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Artificial bee colony algorithm for constrained possibilistic portfolio optimization problem

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HIGHLIGHTS

- A possibilistic semi-absolute deviation model with real-world constraints is proposed.
- A modified artificial bee colony (MABC) algorithm is developed to solve the proposed model.
- Real-world constraints have great influence on optimal strategies making.
- MABC algorithm outperforms several heuristic algorithms.

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ABSTRACT

In this paper, we discuss the portfolio optimization problem with real-world constraints under the assumption that the returns of risky assets are fuzzy numbers. A new possibilistic mean-semiabsolute deviation model is proposed, in which transaction costs, cardinality and quantity constraints are considered. Due to such constraints the proposed model becomes a mixed integer nonlinear programming problem and traditional optimization methods fail to find the optimal solution efficiently. Thus, a modified artificial bee colony (MABC) algorithm is developed to solve the corresponding optimization problem. Finally, a numerical example is given to illustrate the effectiveness of the proposed model and the corresponding algorithm.

1. Introduction

Portfolio selection discusses the problem of how to allocate a certain amount of investors' wealth among different assets and form a satisfying portfolio. The mean–variance (M–V) model proposed by Markowitz [1] has become the foundation of the modern finance theory since 1950s. It combines probability with optimization techniques to model the behavior investment under uncertainty. The key principle of the M–V model is to use the expected return of a portfolio as the investment return and to use the variance of a portfolio as the risk measure. After Markowitz's work, a lot of work has been done to improve and extend the standard M–V model in three directions: (i) the simplification of the type and amount of the input data; (ii) the introduction of alternative measures of risk; and (iii) the inclusion of the real-world constraints. In this study we concentrate on the second and third directions.

In the original Markowitz model [1], the risk is measured by the standard deviation or variance. However, as pointed out by Grootveld and Hallerbach in Ref. [2], the distinguished drawback is that variance treats high returns as equally unde-

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sirable as low returns because high returns will also contribute to the extreme of variance. In particular, when probability distribution of security returns are asymmetric, variance becomes a deficient measure of investment risk because it may have a potential danger to sacrifice too much expected return in eliminating both low and high return extremes. Thus, some researchers have proposed various types of portfolio models based on alternative risk measures, e.g., safety-first model [3], mean–semivariance model [4], mean absolute deviation (MAD) model [5], mean semiabsolute deviation models [6,7], maximim model [8], etc. More researches can be found in Refs. [9–11].

In practical financial applications, the portfolio optimization problem has to take into account real features such as transaction costs, cardinality constraint imposing a limit on the number of assets in the portfolio, quantity constraints restricting the proportion of each asset in the portfolio to lie between lower and upper bounds, and minimum transaction lots. Such realistic constraints form mixed integer nonlinear programming problem which falls into the class of considerably more difficult NP-hard problems [12]. Therefore, several researches have focused on the heuristic algorithms for complex constrained portfolio optimization problems. Chang et al. [13] proposed a cardinality constrained mean–variance (CCMV) model, and employed three heuristic algorithms based upon a genetic algorithm (GA), tabu search (TS) and simulated annealing (SA) to solve it. Ehrgott et al. [14] applied four different heuristic solution methods including GA, TS, SA and local search (LS) for the cardinality constrained portfolio problem. Soleimani et al. [15] proposed an improved GA for Markowitz's model with minimum transaction lots, cardinality constraints and market capitalization. Later, Anagnostopoulos and Mamanis [16] presented a computational comparison of five multi-objective evolutionary algorithms, i.e., NSGA-II, SPEA2, NPGA2, PESA and e-MOEA, on the tri-objective portfolio optimization problem. In their study, beyond risk and return they also considered an additional objective which minimizes the number of assets in a portfolio. Apart from the above mentioned, other heuristic algorithms have also been used to solve the constrained portfolio optimization problems, including ant colony optimization (ACO) algorithm [17], neural network (NN) [18], particle swarm optimization (PSO) algorithm [19,20], differential evolution (DE) algorithm [21,22], bacteria foraging optimization (BFO) algorithm [23,24].

All the above literatures assume that the security returns are random variables. However, if there is not enough historical data, it is more reasonable to assume them as fuzzy variables. Since Zadeh introduced the fuzzy set theory, many researchers have studied portfolio selection problem in fuzzy environments, such as Tanaka and Guo [25], Carlsson et al. [26], Vercher et al. [27], Smimou et al. [28], Chen et al. [29], Sadjadi et al. [30], Wang et al. [31], Kamdem et al. [32], Tsaur [33]. Though great progress has been made in fuzzy portfolio selection problems, none of the above-cited papers incorporate real-world constraints such as transaction costs and cardinality constraints. Recently, various fuzzy portfolio models with complex constraints have been proposed, and solved by heuristic algorithms. Li and Xu [34] applied GA algorithm to solve a fuzzy portfolio selection model with cardinality and buy-in thresholds constraints. Lin and Liu [35] used GA for the fuzzy multiobjective portfolio selection problem with minimum transaction lots. Chen and Zhang [36] applied PSO algorithm for the admissible portfolio selection problem with transaction costs. Bermúdez et al. [37] applied GA algorithm for a bi-objective fuzzy portfolio selection problem with cardinality constraints. Later, Gupta et al. [38] developed a hybrid intelligent algorithm integrating fuzzy simulation and genetic algorithm to solve a tri-objective fuzzy portfolio model with cardinality constraints. Zhang et al. in 2014 [39] presented an improved DE algorithm for a multi-period fuzzy lower semi-deviation model with risk control. Liu and Zhang [40] applied GA algorithm to solve a multi-period fuzzy portfolio optimization model which includes transaction costs, cardinality constraint and minimum transaction lots.

ABC algorithm is a relatively new meta-heuristic algorithm first developed by Karaboga [41], which is inspired by the intelligent behavior of honey bee swarm. Some researches [42–44] demonstrate that ABC is simple in concept, few in parameters, easy for implementation and more effective than some other population-based algorithms such as GA, PSO, ACO and DE. Therefore, ABC algorithm has aroused much interest and has been successfully used in different fields, such as function optimization, neural networks training, image processing, data mining, scheduling, and engineering design. For a detailed list of ABC usage please see recent comprehensive surveys on ABC [45–47]. In addition to the above mentioned applications, nowadays, some researchers have applied ABC algorithm for portfolio optimization problems. For example, Wang et al. [48] proposed an improved ABC algorithm for solving CCMV model and compared the results with those obtained by Chang et al. [13]. Later, for the same model, Chen et al. [49] and Tuba and Bacanin [50] used standard ABC algorithm and improved ABC algorithm by hybridization with firefly algorithm (FA) to solve it, respectively. Recently, Hsu [51] developed an integrated approach based on data envelopment analysis (DEA), ABC and genetic programming (GP) for the portfolio selection problem. Chen et al. [52] proposed an improved ABC algorithm to solve a fuzzy mean–variance portfolio selection model under four kinds of transaction costs, and compared it with standard ABC and GA.

In summary, there is few research on constructing fuzzy portfolio selection model by using semiabsolute deviation as risk measurement under the real-world constraints, and then solving the corresponding model by ABC algorithm.

The purpose of this paper is to construct a mean-semiabsolute deviation portfolio model based on the possibility theory and to develop an efficient heuristic approach based on ABC algorithm for solving proposed model. The main contributions of our paper can be summarized as follows. We propose a possibilistic mean-semiabsolute deviation portfolio model including transaction costs, cardinality and quantity constraints, in which for a given return level, the investor penalizes the negative semiabsolute deviation that is defined as a risk. Meanwhile, we present a MABC algorithm for the solution, in which chaotic initialization based on logistic map is used to produce initial population, and a hybridization method of ABC and PSO is presented to further improve the performance of ABC. Finally, we give a numerical example to illustrate the idea of our model and demonstrate the effectiveness of the designed algorithm.