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A Fuzzy Portfolio Model With Cardinality Constraints Based on Differential Evolution Algorithms

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ABSTRACT

Uncertain information in the securities market exhibits fuzziness. In this article, expected returns and liquidity are considered as trapezoidal fuzzy numbers. The possibility mean and mean absolute deviation of expected returns represent the returns and risks of securities assets, while the possibility mean of expected turnover represents the liquidity of securities assets. Taking into account practical constraints such as cardinality and transaction costs, this article establishes a fuzzy portfolio model with cardinality constraints and solves it using the differential evolution algorithm. Finally, using fuzzy c-means clustering algorithm, 12 stocks are selected as empirical samples to provide numerical calculation examples. At the same time, fuzzy c-means clustering algorithm is used to cluster the stock yield data and analyse the stock data comprehensively and accurately, which provides a reference for establishing an effective portfolio.

KEYWORDS

the efficient frontier of the fuzzy portfolio model, Fuzzy c-means clustering algorithm, liquidity, transaction costs, trapezoidal fuzzy numbers

INTRODUCTION

There are considerable data generated in the security markets, and many businesses rely on analysis of these data to excavate information. It is of great theoretical and practical significance that data mining technology is used to establish an effective portfolio investment model to identify the most valuable stock information, through which investors can make the best decision and effectively improve their return on investment (Wang, 2020; Kaur, 2022). The mean-variance portfolio model, initially introduced by Markowitz (Markowitz,1952), quantifies portfolios in terms of their means (returns) and variances (risks), serving as a foundational concept in quantitative investment research. Given the nature of complicated securities markets, investors often bring their subjective preferences into play. Historical returns and risks serve only as reference points for expected returns since they are subject to change and are inherently uncertain. Another influential factor in investment decisions is the liquidity of securities. Like expected returns, turnover rates are also subject to change and

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inherently uncertain (Sui et al., 2020; Song et al., 2021). Konno and Yamazaki introduced the absolute deviation risk function, which overcomes the computational difficulties of the mean-variance model (Konno&Yamazaki,1991). Many scholars have explored portfolio selection using fuzzy theory. Carlsson and Fuller (Carlsson et al., 2002) treated returns as fuzzy numbers, defining possibility means and possibility variances, and proposed a fuzzy possibility portfolio selection model under a no-short-selling condition. Subsequently, various scholars have sought new methods for measuring expected returns (Zhang & Nie, 2003). Chen et al. (2007) and Zeng & Wang (2003) employed the possibility mean and possibility variance of asset returns to measure investment returns and risks, establishing portfolio selection models under financing conditions. In recent years, investors have sought portfolio solutions with a controlled number of securities, avoiding over-diversification when making portfolio selections.

This article utilizes trapezoidal fuzzy numbers to model expected returns and expected turnover rates, providing the possibility-based means of these parameters. We employ the absolute deviation risk function to construct an investment risk measure. To account for transaction costs in the securities market, we establish a fuzzy investment portfolio model with cardinal constraints. Finally, we demonstrate the practical application of this model in the context of the Chinese securities markets, underscoring its effectiveness and reliability. At the same time, the fuzzy c-means clustering algorithm can cluster the daily yield data of stocks, so the stock data samples can be analysed more accurately and comprehensively, which lays the foundation for constructing the portfolio (Begusic & Kostanjcar, 2019). Then, a more reasonable portfolio scheme is obtained.

PRELIMINARY KNOWLEDGE

In the fuzzy set theory, to describe the possibility of a fuzzy event occurring, Zedeh put forward the theory of possibility (Zadeh,1965), which is considered as a critical moment during which the fuzzy set theory experienced the development. Along with the development of the fuzzy set theory, a variety of phenomena of fuzzy uncertainties in the financial market is increasingly attracting the attention of a great number of scholars. Therefore, considerable studies conducted by these scholars employ the fuzzy set theory to address these phenomena of uncertainties that exist in the financial market. It is found that the fuzzy set theory is a powerful analytic tool in studying these phenomena of uncertainties in the stock. Today, the fuzzy portfolio has become a common research focus.

Assume that the fuzzy number A is a fuzzy set of the real numbers (denoted as R) with a bounded support membership function, and this membership function exhibits normality, fuzzy convexity, and continuity. The family of fuzzy numbers is defined as F. Let $A \in F$ be a fuzzy number, and $A(t)$ represents the membership function of A. Here, $\gamma \in [0,1]$ and $[A]^r = \{t \in R \mid A(t) \geq \gamma\}$ denotes a γ- level set of the fuzzy number A.

In the context of level sets of A, denoted as $A^\gamma = [a(\gamma), b(\gamma)]$, Carlsson and Fuller provide the following definitions for upper and lower possibility means in 2001:

$$M^U(A) = 2\int_0^1 \gamma b(\gamma) d\gamma = \frac{\int_0^1 Pos[A \geq b(\gamma)] b(\gamma) d\gamma}{\int_0^1 Pos[A \geq b(\gamma)] d\gamma}$$

$$M^L(A) = 2\int_0^1 \gamma a(\gamma) d\gamma = \frac{\int_0^1 Pos[A \geq a(\gamma)] a(\gamma) d\gamma}{\int_0^1 Pos[A \geq a(\gamma)] d\gamma}$$

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