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Two-level linear programming for fuzzy random portfolio optimization through possibility and necessity-based model

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Abstract

In this paper, we deal with a portfolio optimization model involving fuzzy random variables. Portfolio optimization is an important research field in modern finance. We consider the problem to maximize the degree of both possibility and necessity that the objective function values satisfy the fuzzy goals. Using the possibility and necessity-based model, we reformulate the problem as a linear programming problem. In order to find the optimum solution, we propose two-level linear programming model to calculate the upper bound and lower bound of the objective function value separately. The lower bound calculates by historical data and the upper bound calculates by new information of stock market which is received during the constant time. Finally, we provide a numerical example to illustrate the proposed model.

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Keywords: Portfolio optimization model ; Possibility and Necessity-based model ; Fuzzy random variables

1. Introduction

In this paper, we propose a new portfolio model based on possibility and necessity, with fuzzy random variables. This portfolio optimization model is similar to Markowitz's model (Markowitz, 1952). In many

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industries, there are many decision problems; i.e., scheduling problem, logistics. In these problems, it is important to predict future total returns and to decide an optimal asset allocation maximizing total profits under some constraints. It is easy to decide the most suitable allocation if we know future returns a priori. We consider how to reduce a risk, and it becomes important how we earn the greatest profit. We call such industrial assets allocation problems portfolio selection problems. Markowitz formulated mean-variance models mathematically in two ways: minimizing variance for a given expected value, or maximizing expected value for a given variance. Since then, the mean–variance models have been well developed in both theory and algorithm (Crama and Schyns, 2003. Xia et al., 2000). In 1959, Markowitz (1959) defined a semi-variance for asymmetric random returns because researchers pointed out that the asymmetric returns make the variance a deficient measure of risk. Konno and Yamazaki (1991) introduced an advanced model in which a mean-absolute deviation model and absolute deviation are utilized as a measure of risk. These studies solved the portfolio selection problem in different stochastic or fuzzy situations. However, when selecting portfolio, an investor may encounter with both fuzziness and randomness. In fact, for an investor, the fuzziness and randomness of security returns are often mixed up with each other. In such situations, we may employ fuzzy random theory (Liu, 2004) to deal with this uncertainty of fuzziness and randomness. Fuzzy random variable can be a new useful approach to solve this kind of problem. A Fuzzy random variable was first introduced by Kwakernaak (1978), and its mathematical basis was constructed by Puri and Ralescu (1986) In this paper, the asset return in portfolio selection problem are fuzzy random variables and we use the concept of both possibility and necessity-based model to develop a solution method for the fuzzy random portfolio optimization problem. In the context of two-level programming, the decision maker at the upper level first specifies a strategy, and then the decision maker at the lower level specifies a strategy so as to optimize the objective with full knowledge of the action of the decision maker at the upper level. However, to utilize two-level programming for resolution of conflict in decision-making problems in real world decentralized organizations, it is important to realize that simultaneous considerations of fuzziness (Sakawa, 1993) and randomness (Birge and Louveaux, 1997) would be required. It means, we reformulate the Mekowits portfolio model by possibility and necessity and construct the two-level linear programming models to find the upper bound and lower bound of the return. The lower bound will be calculated by historical data and the upper bound will be obtained by new information of stock market which is received during the constant time. First of all we calculate our results by possibility based-model, then with necessity-based model to compare these results with each other and show what the difference between optimistic and pessimistic decision makers is? These results and comparing must provide the manager with more information for making decision. The rest of the paper is organized as follow: Section 2 includes basic concept on fuzzy and fuzzy random theory. In Section 3, the problem formulation is presented. In section 4, a numerical example is solved to illustrate the the proposed model. Finally conclusion and future work will be present in section 5.

2. Basic concepts

The concept of fuzzy random variable was introduced as an analogous notion to random variable in order to extend statistical analysis to situations when the outcomes of some random experiment are fuzzy sets. The term fuzzy random variable was coined by Kwakernaak (1978), who introduced FRVs as “random variables whose values are not real, but fuzzy numbers,” and conceptualized a FRV as a vague perception of a crisp but unobservable RV, and its mathematical basis was constructed by Puri and Ralescu (1986). An overview of the developments of fuzzy random variables was found in the recent article of Gil et al. (2006). In general, fuzzy random variables can be defined in an n dimensional Euclidian space $R^n$. We present the definition of a fuzzy random variable in a single dimensional Euclidian space $R$. 


Definition 1 (Sakawa, 1993)

Let $(\Omega, A, P)$ be a probability space, where $\Omega$ is a sample space, $A$ is a $\sigma$-field and $P$ is a probability measure. Let $F_N$ be the set of all fuzzy numbers and $B$ a Borel $\sigma$-field of $R$. Then a map $\tilde{Z} : \Omega \rightarrow F$ is called a fuzzy random variable if it holds that
\[
\left\{(\omega, \tau) \in \Omega \times R | \tau \in \tilde{Z}_\alpha(\omega) \right\} \in A \times B, \forall \alpha \in [0,1] \tag{1}
\]
where
\[
\tilde{Z}_\alpha(\omega) = \left[ \tilde{Z}_\alpha^-(\omega), \tilde{Z}_\alpha^+(\omega) \right] = \left\{ \tau \in R | \mu_{\tilde{Z}_\alpha}(\tau) \geq \alpha \right\} \tag{2}
\]
is an $\alpha$-level set of the fuzzy number $\tilde{Z}(\omega)$ for $\omega \in \Omega$.

Definition 2

LR fuzzy number $\tilde{A}$ is defined by following membership function:
\[
\tilde{A}(x) = \begin{cases} 
L \left( \frac{A^0 - x}{\beta} \right) & \text{if} \quad A^0 - \beta \leq x \leq A^0 \\
1 & \text{if} \quad A^0 \leq x \leq A^1 \\
R \left( \frac{x - A^1}{\gamma} \right) & \text{if} \quad A^1 \leq x \leq A^1 + \gamma 
\end{cases} \tag{3}
\]
where $[A^0, A^1]$ show the peak of fuzzy number $\tilde{A}$ and $\beta, \gamma$ represent the left and right spread respectively; $L, R : [0,1] \rightarrow [0,1]$ with $L(0) = L(0) = 1$ and $L(1) = L(1) = 0$ are strictly decreasing, continuous functions. A possible representation of a LR fuzzy number is $\tilde{A} = (A^0, A^1, \beta, \gamma)_{LR}$.

3. Formulation of fuzzy random portfolio selection problem

A rational investor may be interested in obtaining a certain average return and behave in a manner to maximize their utility with a given level of income or money. In this paper, we deal with the following portfolio selection problem involving fuzzy random variable returns to maximize total future returns and with using two-level linear programming to find the upper bound and lower bound of objective function value separately. It means that we have two kind of decision maker where decision maker 1 (DM1) depend on historical data and calculates the lower bound and decision maker 2 (DM2) depends on new information and calculates the upper bound. This calculation will be done separately. $x_{ij}$ is the decision variables for DM1 which is based on historical date to find the lower bound and $x_{ij}$ is the decision variables DM2 which is based on new information of stock market. Assume we have $n$ assets for possible investment and are interested in determining the portion of available total fund $M_0$ that should be invested in each of the assets during the investment periods and $U_j$ represent the upper bound of investment in asset $j$. Therefore our portfolio selection model which is based on two-level linear programming reformulate to (Sakawa, 1993):
Problem 1

\[
\text{Max } \tilde{Z} = \sum_{j=1}^{n} \tilde{R}_j x_j \\
\text{for DM 1}
\]

\[
\text{Max } \tilde{Z} = \sum_{j=1}^{n} \tilde{R}_j x_j \\
\text{for DM 2}
\]

\[\begin{align*}
\text{s.t.} & \quad \sum_{j=1}^{n} \tilde{R}_j x_j \geq \tilde{R}_0, \\
& \quad \sum_{j=1}^{n} \tilde{R}_j x_j \geq \tilde{R}_0, \\
& \quad \sum_{i=1}^{n} x_i = M_0, \quad \sum_{j=1}^{n} x_j = M_0, \\
& \quad 0 \leq x_j \leq U_j; \quad j = 1, 2, \ldots, n, \\
& \quad 0 \leq x_j \leq U_j; \quad j = 1, 2, \ldots, n
\end{align*}\]

Therefore, to find the optimal solution for any \( x_j \) we use the following model:

Problem 2

\[
\text{Max } \tilde{Z} = \sum_{j=1}^{n} \tilde{R}_j x_j
\]

\[\begin{align*}
\text{s.t.} & \quad \sum_{j=1}^{n} x_j = M_0, \\
& \quad \sum_{j=1}^{n} \tilde{R}_j x_j \geq \tilde{R}_0, \\
& \quad 0 \leq x_j \leq U_j; \quad j = 1, 2, \ldots, n
\end{align*}\]

where \( \tilde{R}_0 \) represent the return in dollars and \( \tilde{R}_j = \left(R^e_j, R^i_j, \beta_j, \gamma_j \right)_{LR} \) represent the rate of return of assets \( j \) which is fuzzy random variables whose observed value for each \( \omega \in \Omega \) is fuzzy number \( \tilde{R}_\omega = \left(R^e_\omega, R^i_\omega, \beta_\omega, \gamma_\omega \right)_{LR} \) and \( \left(\tilde{R}_j, \tilde{R}^e_j, \tilde{R}_j^i, \tilde{R}_j^\epsilon \right) \) is a random vector in which \( \tilde{R} \) is a random variable with cumulative distribution function \( T \).

In problem 1 we calculate our result for any decision makers. It means with using problem 2 first we calculate lower bound and then separately, we calculate upper bound. As we understand form Problem 1 with finding the upper bound and lower bound of portfolio selection problem, the manager with more information for making decision can choose the optimum solution for his/her model. Using the possibility and necessity based-model, we reformulate the problem as a linear programming problem. First of all we calculate our results by possibility based-model, and then with necessity-based model to compare these results with each other. These results and comparing must provide the manager with more information for making decision. At the below part, we explain our new method for solving the portfolio selection problem.
3.1. Possibility and necessity-based model

By Zadeh’s extension principle for objective function in problem 2, its membership function is given as follows for each $\omega \in \Omega$:

$$
\mu_{Z(\omega)}(t) = \begin{cases} 
L \left( \frac{Z^0(\omega) - t}{\beta} \right) & \text{if } t \leq Z^0(\omega) \\
1 & \text{if } Z^0(\omega) \leq t \leq Z^1(\omega) \\
R \left( \frac{t - Z^1(\omega)}{\gamma} \right) & \text{if } \text{otherwise}
\end{cases}
$$

where $\hat{Z}(\omega) = (Z^0(\omega), Z^1(\omega), \beta, \gamma)$, $Z^0(\omega) = \sum_{j=1}^{n} R_j^0(\omega) x_j$, and $Z^1(\omega) = \sum_{j=1}^{n} R_j^1(\omega) x_j$.

3.1.1. Possibility-based model

The degree of possibility $\pi(\hat{Z}(\omega) \geq f)$ under the possibility distribution $\mu_{\hat{Z}(\omega)}(t)$ is given as follows:

$$
\pi(\hat{Z}(\omega) \geq f) = \sup_{y_1, y_2} \min \left\{ \mu_{\hat{Z}(\omega)}(y_1), \mu_{\hat{Z}(\omega)}(y_2) \right\} \left\{ y_1 \geq y_2 \right\} \geq \eta.
$$

d the possibility degree of fuzzy constraint $\left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right)$ under the possibility distributions is defined as follows:

$$
\pi \left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right) = \sup_{y_1, y_2} \min \left\{ \mu_{\tilde{R}_j(\omega)}(y_1), \mu_{\tilde{R}_j(\omega)}(y_2) \right\} \left\{ y_1 \geq y_2 \right\}.
$$

We maximize the degree of possibility $\pi(\hat{Z}(\omega) \geq f)$ and the degree of possibility $\pi \left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right)$, our portfolio selection model in Problem 2 comes by the following model:

Problem 3

Max $f$

s.t. $Pr \left\{ \omega \mid \pi(\hat{Z}(\omega) \geq f) \geq \eta \right\} \geq \lambda,$

$$
\sum_{j=1}^{n} x_j = M_0,
$$

$$
Pr \left\{ \omega \mid \pi \left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right) \geq \eta \right\} \geq \lambda,
$$

$$
0 \leq x_j \leq U_j ; \quad j = 1, 2, \ldots, n.
$$
where $\lambda$ is a predetermined probability level and $\eta$ is a predetermined possibility level. A feasible solution of portfolio selection problem is called a possibility solution. In order to transform the above model to a linear programming model, we need to reformulate (17) and (19). We use the Katagiri et al. (2008) approach to linearization of above model. Consider the following theorem:

Theorem 1: (Katagiri et al., 2008)
For any decision variable, it holds that:

\[
\begin{align*}
1) \Pr \{ \omega | \pi (\tilde{Z}(\omega) \geq f) \geq \lambda \} & \Leftrightarrow \sum_{j=1}^{n} (R_j^0 + T^* (1-\lambda) R_j^2) x_j + R^* (\eta) \sum_{j=1}^{n} y_j x_j \geq f \\
2) \Pr \{ \omega | \pi \left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right) \geq \eta \} & \Leftrightarrow \sum_{j=1}^{n} (R_j^0 + T^* (1-\lambda) R_j^2) x_j + R^* (\eta) \sum_{j=1}^{n} y_j x_j \geq \tilde{R}_0^0 + T^* (1-\lambda) R_0^2 - \beta L(\eta)
\end{align*}
\]

where $T^*$, $L^*$ and $R^*$ are pseudo inverse functions defined as:

\[
T^* (\lambda) = \inf \{ t | T(t) \geq \lambda \}, \quad L^* (\lambda) = \sup \{ t | L(t) \geq \lambda \} \quad \text{and} \quad R^* (\lambda) = \sup \{ t | R(t) \geq \lambda \}.
\]

3.1.2. Necessity-based model

The possibility-based model may be improper since the obtain solution will be too optimistic, so necessity-based model can be suitable for pessimistic decision maker who wish to avoid risk. The degree of necessity $N(\tilde{Z}(\omega) \geq f)$ under the possibility distribution $\mu_{\tilde{Z}(\omega)} (t)$ is defined as follows:

\[
N(\tilde{Z}(\omega) \geq f) = \inf_{y_1, y_2} \left\{ \max \left\{ 1 - \mu_{\tilde{Z}(\omega)} (y_1), 1 - \mu_{\tilde{Z}(\omega)} (y_2) \right\} | y_1 \geq y_2 \right\} \geq \eta
\]

and the necessity degree of fuzzy constraint $\left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right)$ under the possibility distribution is defined as follows:

\[
N \left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right) = \inf_{y_1, y_2} \left\{ \max \left\{ 1 - \mu_{\tilde{Z}(\omega)} (y_1), 1 - \mu_{\tilde{Z}(\omega)} (y_2) \right\} \right\} | y_1 \geq y_2
\]

Same as the possibility, we maximize the degree of necessity $N(\tilde{Z}(\omega) \geq f)$ and the degree of necessity $N \left( \sum_{j=1}^{n} \tilde{R}_j(\omega) x_j \geq \tilde{R}_0(\omega) \right)$, our portfolio selection model in Problem 2 comes by the following model:

Problem 4

\[
\begin{align*}
\text{Max} & \quad f \\
\text{s.t.} & \quad \Pr \{ \omega | N(\tilde{Z}(\omega) \geq f) \geq \eta \} \geq \lambda, \\
& \quad \sum_{j=1}^{n} x_j = M_0,
\end{align*}
\]
A feasible solution of portfolio selection problem is called a necessity solution. In order to transform the above model to a linear programming model, we need to reformulate (22) and (24). Same as the possibility-based model, we obtain the following theorem and its results:

**Theorem 2:**
For any decision variable, it holds that:

\[
\begin{align*}
1) & \quad \Pr\left\{ \omega \mid N\left( \sum_{j=1}^{n} \tilde{R}_j(\omega)x_j \geq \tilde{R}_0(\omega) \right) \geq \eta \geq \lambda \right\} \leftrightarrow \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j - L^j \geq (1-\eta) \beta_j x_j \geq f \\
2) & \quad \Pr\left\{ \omega \mid N\left( \sum_{j=1}^{n} \tilde{R}_j(\omega)x_j \geq \tilde{R}_0(\omega) \right) \geq \eta \geq \lambda \right\} \leftrightarrow \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j - L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta)
\end{align*}
\]

Now two-level linear programming for fuzzy random portfolio selection (problem 1) with possibility and necessity-based model is reformulated to:

**Possibility-based model**

**Problem 5**

\[
\begin{align*}
\text{Max} & \quad \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j + R^j(\eta) \sum_{j=1}^{n} \gamma_j x_j \\
\text{for DM1} & \quad \text{Max} \quad \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j + R^j(\eta) \sum_{j=1}^{n} \gamma_j x_j \\
\text{for DM2} & \quad \text{Max} \quad \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j + R^j(\eta) \sum_{j=1}^{n} \gamma_j x_j \\
\text{s.t.} & \quad \sum_{j=1}^{n} x_{h_j} = M_h, \quad \sum_{j=1}^{n} x_{h_j} = M_h, \quad R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \\
0 \leq x_j \leq U_j, \quad 0 \leq x_{h_j} \leq U_j \quad j = 1, 2, \ldots, n.
\end{align*}
\]

**Necessity-based model**

**Problem 6**

\[
\begin{align*}
\text{Max} & \quad \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j - L^j \geq (1-\eta) \beta_j x_j \\
\text{for DM1} & \quad \text{Max} \quad \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j - L^j \geq (1-\eta) \beta_j x_j \\
\text{for DM2} & \quad \text{Max} \quad \sum_{j=1}^{n} \left( R_0^j + T^j(1-\lambda)R_1^j \right)x_j - L^j \geq (1-\eta) \beta_j x_j \\
\text{s.t.} & \quad \sum_{j=1}^{n} x_{h_j} = M_h, \quad \sum_{j=1}^{n} x_{h_j} = M_h, \quad R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \beta_j x_j \geq R_0^j + T^j(1-\lambda)R_1^j - \beta_j L^j \geq (1-\eta) \\
0 \leq x_j \leq U_j, \quad 0 \leq x_{h_j} \leq U_j \quad j = 1, 2, \ldots, n.
\end{align*}
\]

Now by solving these two-level linear programming, two kind of optimal solutions is obtained which help the manager to choose the best optimum solution for his/her portfolio selection by pay attention to objective values. As we said before First of all we calculate our results by possibility based-model, then with necessity-
based model to compare these results with each other and show the difference between optimistic and pessimistic decision makers. First, we calculate the first optimal solution \( x^*_j \) by using historical data and then separately with new information we calculate the second optimal solution \( x^*_{j2} \). These optimal solutions will be written as \( (x^*_j, x^*_{j2}) = (x^*_{DM1}, x^*_{DM2}) \). Finally, the manager can choose the best optimal solution by considering the objective values in each optimal solution.

4. An example

In this section, an example is given to illustrate the proposed possibility and necessity-based model for portfolio optimization selection. We believe that an investment plan needs to consider not only the historical data, but also new information. Therefore, we decided to use the second type of data, which have been received after starting the first decision. Let us consider 5 securities whose returns are fuzzy random variables and their values are given in Table 1. \( \bar{R} \) is a normal random variable whose mean 0 and variance 1. The upper bound of investment amount in each stock is set to no more than 60 units of the total available fund. Given a total allocation budget of 200 units and annual return which is fuzzy random variable is shown as \( \bar{R} = M \bar{r} \), where \( \bar{r} = (1 + 0.3\bar{r}, 1 + 0.3\bar{r}, 0.3, 0.3) \). Now we want to know what is the optimal solution for our portfolio selection problem for the different levels of probability and possibility \{0.1, 0.4, 0.7, 0.9\}. We apply the possibility and necessity-based method based on theorem 1&2 to obtain fuzzy random portfolio selection problem with the two-level linear programming to calculate upper and lower bound of return. The optimum solution for both DM1 and DM2 are collected in Table 2 and 3.

<table>
<thead>
<tr>
<th>DM1</th>
<th>DM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_j^0 )</td>
<td>200</td>
</tr>
<tr>
<td>( R_j^1 )</td>
<td>200</td>
</tr>
<tr>
<td>( R_j^2 )</td>
<td>60</td>
</tr>
<tr>
<td>( \beta_j )</td>
<td>60</td>
</tr>
<tr>
<td>( \gamma_j )</td>
<td>60</td>
</tr>
</tbody>
</table>

| \( \lambda, \eta \) | 0.1 | 0.4 | 0.7 | 0.9 | 0.1 | 0.4 | 0.7 | 0.9 |
| \( x_j^1 \) | 20 | 60 | 20 | 20 | 60 | 60 | 60 | 20 |
| \( x_j^2 \) | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| \( x_j^3 \) | 60 | 60 | 60 | 60 | 20 | 20 | 20 | 60 |
| \( x_j^4 \) | 0 | 20 | 60 | 60 | 60 | 60 | 60 | 60 |
| \( x_j^5 \) | 60 | 60 | 60 | 60 | 60 | 60 | 60 | 60 |
| OFV \( ^a \) | 451.22 | 331.85 | 244.39 | 164.44 | 492.54 | 357.50 | 251.96 | 157.38 |

\(^a\)Objective function value.
According to example, we can derive the upper bound and lower bound of the objective value. Moreover, the upper bound and lower bound of the objective values are determined by the value of possibility level $\lambda$, $\eta$. Clearly, the greater the $\lambda$, $\eta$ value, the greater the level of possibility and the lower the objective function value is. The comparisons of DM1 and DM2 in both possibility and necessity-based model are depicted in Figs. 1 and 2, respectively.

Fig. 1. (a) Comparison of possibility-based model for both DM1 & DM2; (b) Comparison of Necessity-based model for both DM1 & DM2

Fig. 2. (a) Comparison of possibility & Necessity-based model for DM1; (b) Comparison of possibility & Necessity-based model for DM2
Conclusion

Financial investments are especially important for individual and business financial managers because of low interest rate. Portfolio optimization has been one of the important fields of research in economics and finance. Since the prospective returns of assets used for portfolio optimization problem are forecasted values, considerable uncertainty is involved. This paper proposed a solution method for portfolio selection model whose parameters were fuzzy random variables. The idea was based on possibility and necessity-based model with two-level linear programming. First of all in this method, we calculated the lower bound of two-level linear programming by historical data and with new information which is received during the constant time we calculated the second type of potimal solutions which help the manager to choose the best optimal solution by considering the objective values in each optimal solution. At last by using a numerical example we calculated our results by posibility based-model, then with necessity-based model to compare these results with eachother and showed what the defrence between optimistic and pessimistic decision makers was? For future research, we will apply the other methods for fuzzy random portfolio selection model and improve our two-level programming for portfolio selection problem.

References