ENUMERATION TECHNIQUE FOR SOLVING LINEAR FRACTIONAL FUZZY SET COVERING PROBLEM

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Abstract: In this paper an enumeration technique for solving linear fractional fuzzy set covering problem is defined. Set covering problems belong to the class of 0-1 integer programming problems that are NP-complete. Many applications arise having the set covering problems, switching theory, testing of VLSI circuits and line balancing often take on a set covering structure. Linear fractional set covering problems involving coefficients in the objective function with some lack of precision are usual. To solve them several approaches have been proposed. In this paper a solution algorithm to fuzzy linear fractional set covering problem is suggested, in order to defuzzify the problem the concept of vector ranking function is presented further for obtaining efficient solution to the problem, a lexicographic approach is used. A linearization technique is used to obtain the optimal solution for crisp linear fractional set covering problem. An illustrative example is included to demonstrate the correctness of the proposed solution algorithm.

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1. Introduction

The set covering problem is one of the most famous problems in complexity and approximation theory. Given a set $C = \{c_1, \ldots, c_n\}$ of elements and a collection $S = \{s_1, \ldots, s_n\}$ of subsets of $C$, the goal is to find a subset $S' \subset S$ of minimum cardinality such that $\bigcup_{S_j \in S'} S_j = C$.

The fuzzy set theory has been applied in many disciplines such as operations research, managerial sciences, control theory, artificial intelligence etc. The growth of applications of the fuzzy set theory has been accumulating. At the turn of the century, reducing complex real world system into precise mathematical model is the main trend in science and engineering. In the middle of century, operations research began to be applied to real-world decision-making problems and this became one of the most important fields in science and engineering. Unfortunately, real world situations are often not so deterministic. Thus precise mathematical models are not enough to tackle all practical problems. In this paper the concept of optimality for linear fractional fuzzy set covering problems with fuzzy parameters is obtained.

Recently, a great interest has arisen in Fractional Programming Problems which is another subclass of non-linear programming, where the constraints are linear and objective function is the ratio of linear or non-linear functions. In the year 1977, Arora and Puri [10] discussed the enumeration technique for the set covering problem with linear fractional function as its objective functions. Extending their work, in the year 1998, Saxena and Arora [11] discussed a cutting plane technique for multiobjective fractional set covering problem.

There are number of applications of set covering problems with fractional objective function. Some of them are ‘air line crew scheduling’, ‘truck routing’, ‘political districting’, ‘information retrieval’, etc. For example, suppose an airline company has $m$ flights to operate upon and $n$ crews at its disposal, it being understood that a crew can handle at least one flight. Let $c_j > 0$ be the cost paid by the company when its $j$th crew is operated and let $d_j$ be the commission that the company receives from the authorities when it employs its $j$th crew. Let $\alpha > 0$ be the fixed amount paid to the company. Now the company is interested in scheduling its crew in such a way that the cost is minimized and at the same time the profit is maximized, i.e., it is interested in determining a set of crews which would cover all the flights and for which $\sum c_j \sum d_j + \alpha$ is minimum.

The aim of this paper is to present a method by using a vector ranking function. In fact solution for linear fractional set covering problem with fuzzy parameters based on multiobjective linear fractional set covering programming
The paper has the following structure. In Section 2, linear fractional set covering problems, fuzzy linear fractional set covering problems and some definitions are presented. In Section 3, a vector ranking function is presented to convert linear fractional fuzzy set covering problem to a multiobjective linear fractional set covering problem. In Section 4, some basic concepts of optimality for multiobjective linear integer programming problems are given. In Section 5, an algorithm is developed to solve fuzzy fractional set covering problem using lexicographic approach. In Section 6, numerical example is being given in support of the algorithm. Section 7, concludes the paper.

2. Theoretical Development

Linear fractional set covering Problems (FCP). Consider a set \( I = \{1, 2, \ldots, m\} \) and a set \( P = \{P_1, P_2, \ldots, P_n\} \) where \( P_j \subseteq I \), \( j \in J = [1, 2, \ldots, n] \). A subset \( J^* \) of \( J \) is said to be a cover of \( I \) if \( \bigcup_{j \in J^*} P_j = I \). Let a cost \( c_j > 0 \) be associated with every \( j \in J \). The total cost of the cover \( J^* \) is equal to \( \sum_{j \in J^*} c_j \).

The linear fractional set covering problem (FCP) is to find a cover of minimum cost subject to the condition that at least one of the utility is satisfied and objective function is a linear fractional function. Mathematically, the problem is

\[
\text{(CP)} \quad \min z = \frac{\sum_{j=1}^{n} c_j x_j}{\sum_{j=1}^{n} d_j x_j + \alpha}
\]

subject to \( \sum_{j=1}^{n} a_j x_j \geq 1, \quad i \in I \)

\( x_j = 0 \) or \( 1 \), \( j \in J \).

where \( x_j = \begin{cases} 1 & \text{if } j \text{ is in the cover} \\ 0 & \text{otherwise} \end{cases} \)

and \( a_{ij} = \begin{cases} 1 & \text{if } i \in P_j \\ 0 & \text{otherwise} \end{cases} \).

It is assumed that \( c_j \)'s and \( d_j \)'s are non-negative and \( \alpha \) is a scalar such that \( \sum (d_j x_j + \alpha) > 0 \).
In matrix form, (FCP) can be written as
\[
\min z = Cx/Dx + \alpha
\]
subject to \( Ax \geq b \)

where \( x^T = (x_1, x_2, \ldots, x_n) \) with \( x_j = 0 \) or 1, \( j = 1, 2, \ldots, n \). Here \( C = (c_1, c_2, \ldots, c_n) \in \mathbb{R}^n \) and \( D = (d_1, d_2, \ldots, d_n) \in \mathbb{R}^n \) are row vectors. \( A \) is an \( m \times n \) matrix of zeros and ones and \( b^T = (1, 1, \ldots, 1) \) is a row vector of ones, and \( \alpha \) is a scalar such that \( \sum (Dx + \alpha) > 0 \).

**Fuzzy Linear Fractional Set Covering Problem (FFCP).** If the coefficient in the objective function of problem (CP) (2.1) becomes fuzzy in nature then problem (CP) (2.1) translates to fuzzy set covering problem (FFCP) i.e.

\[
(\text{FFCP}) \quad \min z = \frac{\sum_{j=1}^{n} \tilde{c}_j x_j}{\sum_{j=1}^{n} \tilde{d}_j x_j + \alpha}
\]

subject to \( \sum_{j=1}^{n} a_{ij} x_j \geq 1, \ i \in I \) or \( j \in J \)

\( x_j = 0 \) or 1, \( j \in J \)

where \( x_j = \begin{cases} 1 & \text{if } j \text{ is in the cover} \\ 0 & \text{otherwise} \end{cases} \)

and \( a_{ij} = \begin{cases} 1 & \text{if } i \in P_j \\ 0 & \text{otherwise} \end{cases} \).

**Definitions.**

2.1. **Cover Solution:** A solution \( X \) which satisfies (2.1) is said to be a cover solution.

2.2. **Redundant Cover:** For any cover \( J \), a column \( j^* \in J \) is said to be redundant if \( J - \{j^*\} \) is also a cover.

If a cover contains one or more redundant columns, it is called a redundant cover. Column \( j^* \) is redundant with respect to the cover \( J \) iff \( \sum_{j \in J} a_{ij} \geq 2 \) for all \( i \in P_j \).

2.3. **Prime Cover:** A cover \( j^* \) is said to be a prime cover, if none of the columns corresponding to \( j \in j^* \) is redundant. A solution corresponding to the prime cover is called a prime cover solution.
2.4. Let \( x = (x_1, x_2, \ldots, x_n)^T, y = (y_1, y_2, \ldots, y_n)^T \in \mathbb{R}^n \) be two vectors. Then we write \( x \leq y \) iff \( x_i \leq y_i \) for all \( i \in \mathbb{N} = \{1, 2, \ldots, n\} \); \( x < y \) iff \( x_i \leq y_i \) for all \( i \in \mathbb{N}; x \neq y \) iff \( x_i \neq y_i \) for some \( i \in \mathbb{N} \).

2.5. A fuzzy set \( \tilde{A} \) on \( \mathbb{R} \) is called a fuzzy number if it satisfies the following two conditions:

(i) Its membership function is upper semi continuous.
(ii) There exists three intervals \([a, b],[b, c] \) and \([c, d] \) such that membership function of \( \tilde{A} \) is increasing on \([a, b], \) equal to 1 on \([b, c], \) decreasing on \([c, d] \) and equal to 0 anywhere else.

**Notation.** \( F(\mathbb{R}) \) denotes the set of all fuzzy numbers.

### 3. Ordering Elements of \( F(\mathbb{R}) \)

*In order to compare the fuzzy numbers the ordering of fuzzy numbers is being given.*

A simple method for ordering the elements of \( F(\mathbb{R}) \) consists in the definition of a ranking function. Which maps each fuzzy number into a point of the real line, where a natural order already exists.

**Remark.** More than one ranking function can be defined (Bortolan and Degani, 1985; Cadenas and Verdegay, 1997).

Based on the decision maker’s preferences, assume there exists \( k \) important attributes associated to fuzzy number \( \tilde{A} \) such that \( i \)th of them can be characterized by the ranking function \( R_i : F(\mathbb{R}) \rightarrow \mathbb{R} \). In this case, a crisp \( k \)-dimensional vector, \( R(\tilde{A}) \), to \( \tilde{A} \) is considered as follows:

\[
R(\tilde{A}) = (R_1(\tilde{A}), R_2(\tilde{A}), \ldots, R_k(\tilde{A}))^T.
\]

**Definition 3.1.** The vector function \( R(\cdot) \), defined as above, is called a vector ranking function. Moreover let \( \tilde{A} \) and \( \tilde{B} \) belong to \( F(\mathbb{R}) \), then:

\[
\begin{align*}
\tilde{A} \leq_{R} \tilde{B} & \iff R(\tilde{A}) \leq R(\tilde{B}) \\
\tilde{A} <_{R} \tilde{B} & \iff R(\tilde{A}) < R(\tilde{B}) \\
\tilde{A} =_{R} \tilde{B} & \iff R(\tilde{A}) \neq R(\tilde{B})
\end{align*}
\]
\[ \tilde{A} \not= \tilde{B} \quad \text{iff} \quad R(\tilde{A}) \neq R(\tilde{B}) \]

Similarly
\[ \tilde{A} \geq_{R} \tilde{B} \quad \text{iff} \quad \tilde{B} \leq_{R} \tilde{A} \quad \text{and} \quad \tilde{A} >_{R} \tilde{B} \quad \text{iff} \quad \tilde{B} <_{R} \tilde{A} \]

**Vector Ranking Functions for** \( k = 1, 2, 3 \).

(i) Let \( \tilde{A} \) be a fuzzy number. Roubens ranking function is a vector ranking function with \( k = 1 \) when the decision maker chooses \( R_1(.) \) as the only characteristic for ordering. It is defined as:
\[
R(\tilde{A}) = \frac{1}{2} \int_0^1 \left( \inf \tilde{A}_r + \sup \tilde{A}_r \right) dr
\]
where \( \tilde{A}_r \) is an \( r \)-cut of \( \tilde{A} \) i.e. \( \tilde{A}_r = \{ x \in R | \tilde{A}(X) \geq r \} \), \( 0 < r \leq 1 \).

(ii) For \( k = 2 \), \( R(\tilde{A}) = (E(\tilde{A}), -\text{var}(\tilde{A}))^T \) where \( E(\tilde{A}) \) and \( \text{var}(\tilde{A}) \) are the expectation and variance of the density function associated with \( \tilde{A} \) (Delgado et al. [7], 1998a).

(iii) For \( k = 3 \), \( R(\tilde{A}) = (V(\tilde{A}), A(\tilde{A}), F(\tilde{A}))^T \) where \( V(\tilde{A}) \), \( A(\tilde{A}) \) and \( F(\tilde{A}) \) are value, ambiguity and fuzziness of \( \tilde{A} \), respectively, which are defined as:
\[
V(\tilde{A}) = \int_0^1 r[L_{\tilde{A}}(r) + R_{\tilde{A}}(r)] dr
\]
\[
A(\tilde{A}) = \int_0^1 r[R_{\tilde{A}}(r) - L_{\tilde{A}}(r)] dr
\]
\[
F(\tilde{A}) = \int_0^{1/2} [R_{\tilde{A}}(r) - L_{\tilde{A}}(r)] dr + \int_{1/2}^1 [L_{\tilde{A}}(r) - R_{\tilde{A}}(r)] dr
\]
where both \( L_{\tilde{A}}(.) \) and \( R_{\tilde{A}}(.) \) are from \([0, 1]\) to \( \mathbb{R} \) and defined as:
\[
L_{\tilde{A}}(r) = \begin{cases} 
\inf \{ x | x \in \tilde{A}_r \} & \text{if } r \in (0, 1] \\
\inf \{ x | x \in \sup(\tilde{A}) \} & \text{if } r = 0
\end{cases}
\]
\[
R_{\tilde{A}}(r) = \begin{cases} 
\sup \{ x | x \in \tilde{A}_r \} & \text{if } r \in (0, 1] \\
\sup \{ x | x \in \sup(\tilde{A}) \} & \text{if } r = 0
\end{cases}
\]
and
\[
\sup(\tilde{A}) = \{ x \in R | \tilde{A}(x) > 0 \}.
\]
4. Multiobjective Linear Integer Programming Problem

In this section some of the basis of multiobjective linear integer programming problem have been reviewed.

Consider the model:

\[
\begin{align*}
\text{(MIP)} & \min z(x) = Cx \\
& \text{subject to } Ax \geq b \quad (4.1) \\
& x = 0 \text{ or } 1
\end{align*}
\]

where \( C \) is a \( k \times n \) matrix of coefficients of the linear objective function, \( A \in R^{m \times n} \) and \( b \in R^m \) and \( x \in R^n \), is called a multiobjective linear integer programming problem (MIP).

Let \( X = \{ x \in R^n | Ax \geq b, x = 0 \text{ or } 1 \} \) be a feasible set of (MFP).

Definitions.

4.1. A point \( x^* \in X \) is called a complete optimal solution for (MIP) iff \( z(x^*) \leq z(x) \forall x \in X \).

4.2. A point \( x^* \in X \) is called a Pareto optimal solution for (MIP) iff there does not exist another \( x \in X \) such that \( z(x) \leq z(x^*) \) and \( z(x) \neq z(x^*) \).

4.3. A point \( x^* \in X \) is called a weak pareto optimal solution for (MIP) iff there does not exists another \( x \in X \) such that \( z(x) < z(x^*) \).

Let \( E^c, E^p \) and \( E^{wp} \) denote the set of all complete optimal solution, pareto optimal and weak pareto optimal solutions for (MIP) respectively, then \( E^c \subseteq E^p \subseteq E^{wp} \).

5. Algorithm: Fuzzy Fractional Set Covering Problem

In this section a method is investigated to enumerate a linear fractional set covering problem with fuzzy parameters. Moreover, suppose that \( R \) is a given vector ranking function.

Then mathematically Fuzzy Fractional Multiobjective linear set covering problem is:

\[
\begin{align*}
\text{(FFMCP)} & \min \tilde{z} = \frac{\tilde{c}x}{R dx + \alpha} \\
& \text{subject to } x \in X
\end{align*}
\]
where $\tilde{c} = (\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_n)$ and $\tilde{d} = (\tilde{d}_1, \tilde{d}_2, \ldots, \tilde{d}_n) \in \mathbb{R}^n$, $\alpha$ is some constant so that $(\tilde{d}x + \alpha) > 0$.

**Definitions.**

5.1. A point $x^* \in X$ is called an $R$-optimal solution for (FFMCP) (5.1) iff

$$\frac{\tilde{c}x^*}{dx^* + \alpha} < \frac{\tilde{c}x}{dx + \alpha} \quad \forall \ x \in X.$$ 

5.2. A point $x^* \in X$ is called an $R$-efficient solution for (FFMCP) (5.1) iff there does not exist another $x \in X$ such that $\frac{\tilde{c}x}{dx + \alpha} \leq \frac{\tilde{c}x^*}{dx^* + \alpha}$ and $\frac{\tilde{c}x}{dx + \alpha} \neq \frac{\tilde{c}x^*}{dx^* + \alpha}$.

5.3. A point $x^* \in X$ is called an $R$-weak efficient solution for (FFMCP) (5.1) iff there does not exist another $x \in X$ such that $\frac{\tilde{c}x}{dx + \alpha} < \frac{\tilde{c}x^*}{dx^* + \alpha}$.

We denote $R$-optimal, $R$-efficient and $R$-weak efficient solution sets by $X^{ro}$, $X^{re}$, $X^{rw}$ respectively, then $X^{ro} \subseteq X^{re} \subseteq X^{rw}$.

Now associated with the (FFMCP) (5.1), now consider the following (FFMCP) problemes.

$$\min \{z(x) = R\left(\frac{\tilde{c}x}{dx + \alpha}\right) | x \in X\},$$

where $R(.) = (R_1(.), R_2(.), \ldots, R_k(.))$ \hspace{1cm} (5.2)

Next some theorems are presented which will provide the relationship between the optimal solution of the (FFMCP) (5.2) and (FFMCP) (5.1).

**Theorem 5.1.** A point $x^* \in X$ is an $R$-optimal solution for the (FFMCP) (5.1) iff $x^*$ is a complete optimal solution of FFMCP (5.2).

**Proof.** $(\Rightarrow)$ Assume that $x^* \in X$ is an $R$-optimal solution of the (FFMCP) (5.1), then for any $x \in X$, $\frac{\tilde{c}x^*}{dx^* + \alpha} \leq \frac{\tilde{c}x}{dx + \alpha}$. Using Definition 3.1 of $\leq$, $R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \leq R\left(\frac{\tilde{c}x}{dx + \alpha}\right)$, for all $x \in X$, hence $z(x^*) \leq z(x) \ \forall \ x \in X$.

Therefore, $x^*$ is a complete optimal solution for (FFMCP) (5.2).
(⇐) Assume \( x^* \) is a complete optimal solution for (FFMCP) (5.2), then for all \( x \in X \), \( z(x^*) \leq z(x) \), hence \( R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \leq R\left(\frac{\tilde{c}x}{dx + \alpha}\right) \). Therefore \( \frac{\tilde{c}x^*}{dx^* + \alpha} \leq \frac{\tilde{c}x}{dx + \alpha} \) for all \( x \in X \). This implies \( x^* \) is an \( R \)-optimal solution for (FFMCP) (5.1).

**Theorem 5.2.** A point \( x^* \in X \) is an \( R \)-efficient solution for (FFMCP) (5.1) iff \( x^* \) is a pareto optimal solution for (FFMCP) (5.2).

**Proof.** (⇒) Let \( x^* \in X \) be an \( R \)-efficient solution for (FFMCP) (5.1). On the contrary, suppose that \( x^* \) is not a pareto optimal solution for (FFMCP) (5.2), i.e., there exists \( \bar{x} \in X \) such that \( z(\bar{x}) \leq z(x^*) \) and \( z(\bar{x}) \neq z(x^*) \), hence \( R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \leq R\left(\frac{\tilde{c}x}{dx + \alpha}\right) \) and \( R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \neq R\left(\frac{\tilde{c}x}{dx + \alpha}\right) \). This implies \( \frac{\tilde{c}x^*}{dx^* + \alpha} \leq \frac{\tilde{c}x}{dx + \alpha} \) which contradicts that \( x^* \in X \) is an efficient solution for the (FFMCP) (5.1).

(⇐) Let \( x^* \in X \) be a pareto optimal solution for (FFMCP) (5.2). On the contrary suppose that \( x^* \) is not an \( R \)-efficient solution for the (FFMCP) (5.1), i.e. there exists an \( \bar{x} \in X \) such that \( \frac{\tilde{c}x^*}{dx^* + \alpha} \leq \frac{\tilde{c}x}{dx + \alpha} \) and \( \frac{\tilde{c}x^*}{dx^* + \alpha} \neq R\left(\frac{\tilde{c}x}{dx + \alpha}\right) \). This implies and \( R\left(\frac{\tilde{c}x}{dx + \alpha}\right) \leq R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \) and \( R\left(\frac{\tilde{c}x}{dx + \alpha}\right) \neq R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \).

This means \( z(\bar{x}) \geq z(x^*) \) and \( z(\bar{x}) \neq z(x^*) \) which contradicts that \( x^* \in X \) is a pareto optimal solution for (FFMCP) (5.2).

**Theorem 5.3.** A point \( x^* \in X \) is an \( R \)-weak efficient solution for (FFMCP) (5.1) iff \( x^* \) is a weak pareto optimal solution for (FFMCP) (5.2).

**Proof.** (⇒) Let \( x^* \in X \) be a \( R \)-weak efficient solution for (FFMCP) (5.1). On the contrary suppose \( x^* \) is not a weak pareto optimal solution for (FFMCP) (5.2) this implies there exist another \( x \in X \) such that \( z(x) < z(x^*) \) hence \( \frac{\tilde{c}x}{dx + \alpha} < R\left(\frac{\tilde{c}x^*}{dx^* + \alpha}\right) \) this implies \( \frac{\tilde{c}x^*}{dx^* + \alpha} < \frac{\tilde{c}x^*}{dx + \alpha} \) which contradicts that \( x^* \in X \) is an \( R \)-weak efficient solution for (FFMCP) (5.1).

(⇐) On the other hand let \( x^* \in X \) be a weak pareto optimal solution for (FFMCP) (5.2). On the contrary, suppose that \( x^* \in X \) is not an \( R \)-weak efficient solution for the (FFMCP) (5.1) i.e. there exists an \( \bar{x} \in X \) such that
\[
\frac{\vec{c} \vec{x}}{\vec{d} \vec{x} + \alpha} < \frac{\vec{c} \vec{x}^*}{\vec{d} \vec{x}^* + \alpha}
\]
this implies \( R\left(\frac{\vec{c} \vec{x}}{\vec{d} \vec{x} + \alpha}\right) < R\left(\frac{\vec{c} \vec{x}^*}{\vec{d} \vec{x}^* + \alpha}\right) \). This means \( z(\vec{x}) < z(x^*) \) which contradicts that \( x^* \in X \) is a weak pareto optimal solution for (FFMCP) (5.2).

**Lexicographic approach.** This ranking function approach is being used for solving fuzzy linear fractional programming problem.

Suppose that the decision maker orders the components of the vector ranking function based on some preferences, by starting with the most important component. In this case a lexicographic ranking function to a fuzzy number is associated.

**Definitions.**

5.4. A vector \( x \) is called lexicographically negative, denoted by \( x \prec 0 \) if the following two conditions hold:

(a) \( x \) is not identically zero
(b) The first non-zero component of \( x \) is negative.

A lexicographically non-positive vector, denoted by \( \preceq 0 \), is either the zero vector or a lexicographically negative vector.

5.5. A vector \( x \) is lexicographically less than \( y \), denoted by \( x \prec y \), if and only if \( x - y \prec 0 \).

Also \( x \) is said to be lexicographically less than or equal to \( y \), denoted by \( x \preceq y \), if and only if \( x - y \preceq 0 \).

5.6. The vector ranking function \( R \) whose component are ordered on the basis of the decision maker’s preferences, starting with the most important is called a lexicographic vector ranking function. Moreover, let \( \vec{a} \) and \( \vec{b} \) belong to \( F(R) \), then define

- \( \vec{a} \leq \vec{b} \) if and only if \( R(\vec{a}) \preceq R(\vec{b}) \)
- \( \vec{a} \prec \vec{b} \) if and only if \( R(\vec{a}) \prec R(\vec{b}) \)
- \( \vec{a} = \vec{b} \) if and only if \( R(\vec{a}) = R(\vec{b}) \)
- \( \vec{a} \neq \vec{b} \) if and only if \( R(\vec{a}) \neq R(\vec{b}) \)
Now return to the (FFMCP) (5.1) and apply lexicographic vector ranking function to solve it. In (FFMCP) (5.1) set \( R = \mathcal{R} \), i.e., the vector ranking function is a lexicographic vector ranking function, thus (FFMCP) (5.1) changes to (FFMCP) (5.3) as:

\[
(\text{FFMCP}) \quad \min \tilde{z} = \frac{\tilde{c}x}{\mathcal{R}} \frac{dx + \alpha}{dx} \\
\text{s.t. } x \in X
\]  

(5.3)

Setting \( R = \mathcal{R} \) in definition (5.1), (5.2) and (5.3) gives the definition of \( \mathcal{R} \)-optimal solution, \( \mathcal{R} \)-efficient solution and \( \mathcal{R} \)-weak efficient solution for (FFMCP) (5.3), respectively.

As mentioned earlier associated with the (FFMCP) (5.3) considered the following MOFP problem

\[
\text{MOFP} \quad \min \left( \mathcal{R}_1 \left( \frac{\tilde{c}x}{dx + \alpha} \right), \mathcal{R}_2 \left( \frac{\tilde{c}x}{dx + \alpha} \right), \ldots, \mathcal{R}_K \left( \frac{\tilde{c}x}{dx + \alpha} \right) \right) \\
\text{s.t. } x \in X.
\]  

(5.4)

For solving (MOFP) (5.4), by using lexicographic minimization process (Steuer, 1986), recursively construct the following reduced feasible region.

\[
S_0 = X \\
S_1 = \left\{ y \in S_0 : \mathcal{R}_1 \left( \frac{\tilde{c}y}{dy + \alpha} \right) = \min \left( \mathcal{R}_1 \left( \frac{\tilde{c}x}{dx + \alpha} \right), x \in S_0 \right) \right\}, \\
S_2 = \left\{ y \in S_1 : \mathcal{R}_2 \left( \frac{\tilde{c}y}{dy + \alpha} \right) = \min \left( \mathcal{R}_2 \left( \frac{\tilde{c}x}{dx + \alpha} \right), x \in S_1 \right) \right\}, \\
\vdots \\
S_k = \left\{ y \in S_{k-1} : \mathcal{R}_k \left( \frac{\tilde{c}y}{dy + \alpha} \right) = \min \left( \mathcal{R}_k \left( \frac{\tilde{c}x}{dx + \alpha} \right), x \in S_{k-1} \right) \right\}
\]

The process begins by minimizing objective function \( \mathcal{R}_1 \left( \frac{\tilde{c}x}{dx + \alpha} \right) \) which is bounded over \( S_0 = X \). By constraining \( S_0 \) to the minimal value of the first criterion, \( S_1 \) is obtained, Then, the second objective function \( \mathcal{R}_2 \left( \frac{\tilde{c}x}{dx + \alpha} \right) \) which is bounded over \( S_1 \) is minimized. By constraining \( S_1 \) to the minimal value of the second criterion, \( S_2 \) is obtained. The process continues until either
There exists an $\bar{x}$ such that $R_1 \left( \frac{cx}{dx+\alpha} \right)$ is unbounded over $S_{t-1}$ (Steuer, 1986).

Following theorem provides one to one correspondence between the solutions of (FFMCP) (5.1) and (MOFP) (5.4):

**Theorem 5.4.** Extreme points of $S_j$, $1 \leq j \leq k$, are extreme points of $X$.

**Proof.** The set of extreme points of the optimal set $\{cx \mid x \in X\}$ are extreme points of $X$. Thus if $\bar{x}$ is an extreme point of $S_1$, $\bar{x}$ is an extreme point of $X$. Similarly, if $\bar{x}$ is an extreme point of $S_2$, $\bar{x}$ is an extreme point of $S_1$, and so forth. In this way, the theorem is proved.

**Theorem 5.5.** Let $x^* \in S_k$, then $x^*$ is an $R$-efficient solution for the (MOFP) (5.4).

**Proof.** Suppose $x^*$ is not an $R$-efficient solution for the (MOFP) (5.4) Then there exists an $\bar{x} \in X$ such that $\frac{\bar{c}x}{\bar{d}x+\alpha} \leq \frac{cx^*}{dx^*+\alpha}$ and $\frac{\bar{c}x}{\bar{d}x+\alpha} \neq \frac{cx^*}{dx^*+\alpha}$. It follows that $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) \leq R_1 \left( \frac{cx^*}{dx^*+\alpha} \right)$ and $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) \neq R_1 \left( \frac{cx^*}{dx^*+\alpha} \right)$. Hence $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) - R_1 \left( \frac{cx^*}{dx^*+\alpha} \right) \leq 0$ and $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) - R_1 \left( \frac{cx^*}{dx^*+\alpha} \right) \neq 0$.

Now consider the following two cases:

**Case 1.** Let $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) < R_2 \left( \frac{cx^*}{dx^*+\alpha} \right)$. Hence $x^*$ does not belong to $S_1$. From $S_k \subseteq S_{k-1} \subseteq \ldots \subseteq S_0 = X$, it follows that $x^*$ does not belong to $S_k$, which contradicts that $x^* \in S_k$.

**Case 2.** There exists a $t \in \{2, \ldots, k\}$ such that $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) - R_t \left( \frac{cx^*}{dx^*+\alpha} \right) < 0$ and $R_t \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) - R_i \left( \frac{\bar{c}x^*}{\bar{d}x^*+\alpha} \right) = 0$ for all $i = \{1, 2, \ldots, t-1\}$. Since $R_1 \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) - R_1 \left( \frac{\bar{c}x}{\bar{d}x^*+\alpha} \right) = 0$ for all $i = \{1, 2, \ldots, t-1\}$ and $x^* \in S_k \subseteq S_{k-1} \subseteq \ldots \subseteq S_0 = X$. This implies, $\bar{x} \in S_t$, for all $i = \{1, 2, \ldots, t-1\}$. On the other hand, $R_t \left( \frac{\bar{c}x}{\bar{d}x+\alpha} \right) < R_t \left( \frac{\bar{c}x^*}{\bar{d}x^*+\alpha} \right)$ and $\bar{x} \in S_t, i \in \{1, 2, \ldots, t-1\}$ imply that $x^*$ does not belong to $S_i$. This contradicts that $x^* \in S_k$.

\qed
From Theorem 5.4, if \( x^* \in S_k \), then \( x^* \) is an \( R \)-efficient solution for the (MOFP) (5.4). A situation may happen that the set \( S_k \) is empty. It occurs when for an \( \ell \) (\( 1 \leq \ell \leq k \)) \( R_\ell \left( \frac{cx}{dx + \alpha} \right) \) is unbounded over \( S_{\ell-1} \). In this case, the decision maker have the option of gaining the flexibility to change the order of components of vector ranking function corresponding with the remaining objective functions.

Hence one to one correspondences is obtained between the solutions of (FFMCP) (5.1) and (MOFP) (5.4). Now to solve (MOFP) (5.4) which is a crisp linear fractional set covering problem a linearization technique has been used as below.

**Step 1.** Given Linear Fractional Set Covering Problem (LFP). Form the corresponding continuous program (LFP’) by embedding the feasible region into \( \mathbb{R}^n \) (a cube with \( n \) vertices). Let \( S \) be the feasible set for (LFP’).

**Step 2.** Choose a feasible solution \( X_0 \in S \) such that \( \nabla f(X_0) \neq 0 \). Form the corresponding linear program (LP)

\[
\text{Minimize } \nabla f(x_0)^T X \quad \text{Minimize } \sum_{j=1}^{n} c_j x_j.
\]

**Step 3.** Arrange the cost coefficients \( c_j \)'s of Step 2 in an ascending order and rename the variable according as \( y_u \)'s to get the linear program (LP’).

**Step 4.** For \( j = \{1, 2, \ldots, n\} \), define \( Y_0 = (y_1, y_2, \ldots, y_n) \) as zero variable with \( y_j = 0 \ \forall \ j \in J \) and \( Y_{j_i} \) as \( j \)-variable; \( i \in I_j = \{1, 2, \ldots, n+1-jC_1\} \) and \( j \in J \)

Since none of the constraints is satisfied, modify \( Y_0 \) to 1-variable, \( Y_{1_i}; i \in I_1 = \{1, 2, \ldots, (n+1)-1C_1\} \) by fixing variable \( y_j \) (individual) to 1 for \( j \in J \).

**Step 5.** Suppose at \( r \)th iteration \( Y_{ri} \) is \( r \)-variable, \( r \in J \), \( i \in I_r = \{1, 2, \ldots, n+1-rC_1\} \).

If \( Y_{ri} \) is feasible for some \( i \in I_r \) go to Step 7, otherwise go to step 6.

**Step 6.** For each \( r \)-variable \( Y_{ri} \), \( r \in I_r \)

Let \( p = \) number of constraints of (LP) satisfied by \( Y_{ri} \)'s

\( z = \) the value of the corresponding objective function for \( Y_{ri} \)'s
Choose that $Y^*_{ri}$ for which ‘$p$’ is maximum and ‘$z$’ is minimum. Let it happen for $i = q$. Fix variable $y_q = 1$ in $Y_{ri}$ which gets modified to $Y_{si}(s = r + 1)$ as $s$-variable with $s$ one, $i \in I_s = \{1, 2, \ldots, n+1-sC_1\}$.

Go to Step 5.

**Step 7.** Find the value of objective function for each $Y_{ri}$. Let minimum value be for $i = k$. The optimal solution of the (LP’) is $Y^*_{rk}$.

**Step 8.** Rearrange the variable as done in Step 3 to get the corresponding solution $X^*_{rk}$ of (LFP).

If $X^*_{rk} = X_0$ then $X^*_{rk}$ will be optimal prime cover solution of (LFP), otherwise take $X_0 = X^*_{rk}$ and go to step 2.

### 6. Numerical Example

To illustrate the efficiency of the proposed method we consider the following example:

**Example 6.1.** Consider the following linear fractional fuzzy set covering problem

$$
\min z(x) = \frac{\tilde{c}_1 x_1 + \tilde{c}_2 x_2 + \tilde{c}_3 x_3}{\tilde{d}_1 x_1 + \tilde{d}_2 x_2 + \tilde{d}_3 x_3}
$$

subject to $x_1 + x_2 \geq 1$

$x_2 + x_3 \geq 1$

$x_1 + x_3 \geq 1$

$x_l = 0 \text{ or } 1, \quad i = 1, 2, 3 \quad (6.1)$

where the membership functions of $\tilde{c}_1, \tilde{c}_2, \tilde{c}_3, \tilde{d}_1, \tilde{d}_2$ and $\tilde{d}_3$ are

$$
\tilde{c}_1(x) = \begin{cases}
0 & x < 5 \\
 x - 5 & 5 \leq x < 6 \\
1 & 6 \leq x \leq 7 \\
(20 - x)/13 & 7 \leq x \leq 20 \\
0 & 20 < x
\end{cases}
$$
\[
\tilde{c}_2(x) = \begin{cases} 
0 & x < 16 \\
x - 16 & 16 \leq x < 17 \\
1 & 17 \leq x \leq 18 \\
(40 = x)/22 & 18 < x \leq 40 \\
0 & 40 < x 
\end{cases}
\]

\[
\tilde{c}_3(x) = \begin{cases} 
0 & x < 24 \\
x - 24 & 24 \leq x < 25 \\
1 & 25 \leq x \leq 26 \\
(40 = x)/22 & 26 < x \leq 50 \\
0 & 50 < x 
\end{cases}
\]

\[
\tilde{d}_1(x) = \begin{cases} 
0 & x < 10 \\
x - 10 & 10 \leq x < 11 \\
1 & 11 \leq x \leq 12 \\
(30 - x)/18 & 12 < x \leq 30 \\
0 & 30 < x 
\end{cases}
\]

\[
\tilde{d}_2(x) = \begin{cases} 
0 & x < 15 \\
x - 15 & 15 \leq x < 16 \\
1 & 16 \leq x \leq 17 \\
(20 - x)/13 & 17 < x \leq 30 \\
0 & 30 < x 
\end{cases}
\]

\[
\tilde{d}_3(x) = \begin{cases} 
0 & x < 20 \\
x - 20 & 20 \leq x < 21 \\
1 & 21 \leq x \leq 22 \\
(50 - x)/28 & 22 < x \leq 50 \\
0 & 50 < x 
\end{cases}
\]
where $V(A)$, $A(A)$ and $F(A)$ are as defined before: Note that

\[
V(\tilde{c}_1) = 8.5, \quad V(\tilde{c}_2) = 21, \quad V(\tilde{c}_3) = 88/3 \\
V(\tilde{d}_1) = 43/3, \quad V(\tilde{d}_2) = 37/2, \quad V(\tilde{c}_3) = 76/3 \\
A(\tilde{c}_1) = 17/6, \quad A(\tilde{c}_2) = 13/3, \quad A(\tilde{c}_3) = 27/2 \\
A(\tilde{d}_1) = 11/3, \quad A(\tilde{d}_2) = 17/6, \quad A(\tilde{d}_3) = 16/3 \\
F(\tilde{c}_1) = 3.5, \quad F(\tilde{d}_2) = 23/4, \quad F(\tilde{c}_3) = 25/4 \\
F(\tilde{d}_1) = 19/4, \quad F(\tilde{c}_2) = 7/2, \quad F(\tilde{d}_3) = 29/4
\]

The following MLCP is associated with the problem (6.1):

\[
\text{min } z(x) = \begin{cases} 
8.5 x_1 + 21 x_2 + \frac{88}{3} x_3 \\
\frac{43}{3} x_1 + \frac{37}{2} x_2 + \frac{76}{3} x_3
\end{cases} \\
\text{subject to } x_1 + x_2 \geq 1 \\
x_2 + x_3 \geq 1 \\
x_1 + x_3 \geq 1 \\
x_1 = 0 \text{ or } 1; \quad i = 1, 2, 3.
\] (6.2)

To solve the above problem, lexicographic approach is being used first minimize the first objective function to obtain $S_1$:

i.e.

\[
\text{min } f(x) = \frac{8.5 x_1 + 21 x_2 + \frac{88}{3} x_3}{\frac{43}{3} x_1 + \frac{37}{2} x_2 + \frac{76}{3} x_3}
\]

subject to $x_1 + x_2 \geq 1$ \\
$x_2 + x_3 \geq 1$ \\
$x_1 + x_3 \geq 1$ \\
$x_i = 0 \text{ or } 1 \quad \forall i = 1, 2, 3.$

(6.3)

This is a crisp linear fractional set covering problem. Now to solve this problem linearization technique is being used as defined before.

**Step 1:** The corresponding (FCP') is

\[
\text{min } f(x) = \frac{8.5 x_1 + 21 x_2 + \frac{88}{3} x_3}{\frac{43}{3} x_1 + \frac{37}{2} x_2 + \frac{76}{3} x_3}
\]
subject to \( X = (x_1, x_2, x_3) \in X \)
\[
= \{ (x_1, x_2, x_3) | x_1 + x_2 \geq 1, x_2 + x_3 \geq 1, \\
x_1 + x_3 \geq 1, x_1, x_2, x_3 \geq 0 \}
\]

**Step 2:** Choose \( X_0 = (1, 1, 1) \) as one of the feasible solution of (FCP’) with \( \nabla f(x_0) \neq 0 \). The corresponding (LP) is
\[
\min \nabla f(x_0^T)X = -0.103X_1 + 0.039X_2 + 0.063x_3, \quad X \in S
\]

**Step 3:** Arrange the coefficients in increasing order by defining \( x_1 \) as \( y_1 \) and \( x_2, x_3 \) as \( y_2, y_3 \). The new (LP’) now is
\[
\min -0.103x_1 + 0.039x_2 + 0.063x_3
\]
subject to \( y_1 + y_2 \geq 1, y_2 + y_3 \geq 1, y_1 + y_3 \geq 1 \).

**Step 4:** Take \( Y_0 = (0, 0, 0) \), a zero variable, obviously none of the constraint of (LP’) is satisfied, therefore \( Y_0 \) is not a feasible solution.

**Step 5:** Consider all possible one-variable solutions \( Y_{i1}, i = I_1 = \{1, 2^{(3+1)-1}C_1\} \) as
\[
Y_{11} = (1, 0, 0), \quad Y_{12} = (0, 1, 0), \quad Y_{13} = (0, 0, 1)
\]

<table>
<thead>
<tr>
<th>Action for</th>
<th>( Y_{11} )</th>
<th>( Y_{12} )</th>
<th>( Y_{13} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of eqns. Satisfied ((p))</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Value of objective function ((z))</td>
<td>-0.103</td>
<td>0.039</td>
<td>0.063</td>
</tr>
</tbody>
</table>

\( p \) is equal for all but the value of \( z \) is minimum for \( Y_{11} \). Fix \( y_1 = 1 \) in \( Y_{i1} \). Now, the two-variables \( Y_{i2}s, i \in I_2 = \{1, 2, \ldots, 3^{1-2}C_1\} \) to act are as follows:

\[
Y_{21} = (1, 1, 0)Y_{22} = (1, 0, 1)
\]

<table>
<thead>
<tr>
<th>Action for</th>
<th>( Y_{21} )</th>
<th>( Y_{22} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of eqns. Satisfied ((p))</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Value of objective function ((z))</td>
<td>-0.07</td>
<td>-0.043</td>
</tr>
</tbody>
</table>

‘\( p \)’ is maximum for all but the value of ‘\( z \)’ is minimum for \( Y_{21} \). Thus the optimal solution for (LP’) is \((1, 1, 0)\).
Step 8: After rearranging the terms, the corresponding solution of FCP is \( X^*_1 = (1, 1, 0) \). Since \( X^*_1 = X_0 \), take \( X^*_1 = X_0 \) and go to Step 2.

Algorithm revisited.

Step 2: Here \( X_0 = (1, 1, 0) \) as one of the feasible solution of (FCP') with \( \nabla f(X_0) \neq 0 \). The corresponding (LP) is

\[
\min \nabla f(X_0)^T X = -0.133x_1 + 0.133x_2 + 0.200x_3, \quad X \in S
\]

Step 3: Arrange the coefficients in increasing order by defining \( x_1 \) as \( y_1 \), \( x_2 \) as \( y_2 \), \( x_3 \) as \( y_3 \). The new (LP') now is

\[
\min 0.133y_1 + 0.133y_2 + 0.200y_3
\]

subject to \( y_1 + y_2 \geq 1; y_2 + y_3 \geq 1; y_1 + y_3 \geq 1 \)

\( y_1, y_2, y_3 \geq 0 \)

Step 4: Take \( Y_0 = (0, 0, 0) \), a zero variable. Obviously none of the constraint of (LP') is satisfied, therefore \( Y_0 \) is not a feasible solution.

Step 5: Consider all possible one-variable solutions \( Y_{1i}, i \in I_1 = \{1, 2^{(3+1)-1}C_1\} \) as

\[
Y_{11} = (1, 0, 0), \quad Y_{12} = (0, 1, 0), \quad Y_{13} = (0, 0, 1)
\]

Action for \( Y_{11} \) \( Y_{12} \) \( Y_{13} \) No. of eqns. satisfied (p) 2 2 2 Value of objective function (z) -0.133 0.133 0.200

\( p \) is equal for all but the value of \( z \) is minimum for \( Y_{11} \). Fix \( y_1 = 1 \) in \( Y_{1i} \). Now, the two-variables \( Y_{2i}', i \in I_2 = \{1, 2, \ldots 3+1-2 C_1\} \) to act are as follows:

\[
Y_{21} = (1, 1, 0) \quad Y_{22} = (1, 0, 1)
\]

<table>
<thead>
<tr>
<th>Action for</th>
<th>( Y_{21} )</th>
<th>( Y_{22} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of eqns. satisfied (p)</td>
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<td>3</td>
</tr>
<tr>
<td>Value of objective function (z)</td>
<td>0</td>
<td>0.333</td>
</tr>
</tbody>
</table>

\( 'p' \) is maximum for all but the value of \( 'z' \) is minimum for \( Y_{21} \). Thus the optimal solution for (LP') is \( (1, 1, 0) \).
**Step 8:** After rearranging the terms, the corresponding solution of FCP is $X_1^* = (1, 1, 0)$. Since $X_1^* \neq X_0$, therefore this will be the optimal prime cover of (FCP) (6.3).

Thus $S_1 = \{(1,1,0)\}$, therefore this will be the optimal solution for (6.2) and hence for the problem (6.1).

**Conclusion**

In this paper a linear fractional set covering problem with fuzzy parameters in the objective function is considered. The approach for solving this problem is to use lexicographic vector ranking function. To improve the draw back of using a single characteristic, a $k$-dimensional vector ranking function to a fuzzy number is associated.

**References**


R.R. Saxena, R. Gupta


