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SIMULATION STUDIES FOR CREDIBILITY-BASED MULTI-OBJECTIVE LINEAR PROGRAMMING PROBLEMS WITH FUZZY PARAMETERS

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Abstract. In this paper, hybrid credibility-based multi-objective linear programming models are provided to optimize expected values of objective functions subject to fuzzy chance-constraints. Triangular or non-linear fuzzy numbers are considered in problem parameters like demands and costs. To handle the uncertainty, the constraints are substituted with credibilistic fuzzy chance-constraints and the objective functions with their expected values. The credibilistic approach offers computational ease by the use of techniques which are similar to the stochastic simulation and applicable to all types of fuzzy numbers. The approach uses expected values and chance-constraints respectively to handle uncertain objective functions and to control the confidence level of fulfilling imprecise constraints. Numerical simulations are presented to compare the expected objective function values.

Keywords: Multiple objective programming, fuzzy parameters, credibility measure, chance-constraints, simulation.

AMS Subject Classification: 90C29, 90C70, 03E72.

1. Introduction

In real life, there are cases in which decisions must be made on the basis of incomplete and imprecise information. In some uncertainty situations when probability distributions cannot be obtained due to lack of historical data, the most pessimistic, the most likely and the most optimistic values can be provided from experts. In order to cope with such decision-making problems under uncertainty, the fuzzy mathematical programming approaches are employed, for a detailed review see [9]. The interest focuses on multi-objective linear programming problems (MOLPPs) with fuzzy coefficients, such as fuzzy unit profits or costs, customer demands, supply capacities, availabilities, unit usages of resources, and processing, completion or travel times. Consider the following decision

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problem with K objectives:

$$\begin{array}{lll} \min & \left(\widetilde{f_1}(x), \widetilde{f_2}(x), \ldots, \widetilde{f_K}(x)\right) & \\ \text{s.t.} & \sum_{j=1}^{n} \widetilde{a_{ij}} x_j \leq \widetilde{b_i}, & i = 1, 2, \ldots, m, \\ & x_j \geq 0, & j = 1, 2, \ldots, n, \end{array} \tag{1}$$

where $\widetilde{f_k}(x) = \sum_{j=1}^{n} \widetilde{c_j^k} x_j$ for $k = 1, 2, \ldots, K$, and $\widetilde{a_{ij}}, \widetilde{b_i}, \widetilde{c_j^k}$ are fuzzy numbers.

The model (1) involves fuzzy parameters but the decision variables are non-fuzzy or crisp numbers. To handle the uncertainty, the constraints are substituted with credibilistic fuzzy chance-constraints and the objective functions with their expected values. After converting this hybrid model into its crisp equivalent, it is transformed into a single-objective programming problem employing compromise programming approach. In this approach, for all conflicting objectives, single-objective programs are solved (by ignoring other objectives) to obtain ideal objective values and less desired ones. The author of this article tries to find optimal compromise solutions, which are optimum at some degree for all objectives. It is assumed that any hierarchical priority levels among objectives do not exist. Simulation of triangular and non-linear types of fuzzy numbers are, furthermore, studied in this paper. To generate triangularly distributed fuzzy numbers, the MATLAB functions "makedist" and "random" are used. Possibility density functions (pdfs), cumulative distribution functions (cdfs), and inverse cdfs are employed for simulation of non-linear fuzzy numbers. Again, MATLAB is utilized to generate samples and to find inverse functions by using the function "polyfit". Also, the function "linprog" is exploited in order to solve decision problems.

Let us now review the relevant literature which consists of credibility-based multi-objective models with fuzzy coefficients. Ahmadizar and Zeynivand [1] propose a fuzzy bi-objective mixed integer linear programming formulation and a solution technique based on fuzzy chance-constrained programming to a multi-echelon, multi-product, and multi-period supply chain planning problem. In [4], the authors attempt to solve large-scale multi-objective supplier selection problem by using a hybrid method that combines data envelopment analysis and machine learning techniques. Refer to [10] and [15] for other applications to supply chain planning. In [21], the authors explore the role of differential pricing with arbitrage and ordering policies of manufacturers by examining fuzzy marketing and production and utilizing a hybrid multi-objective credibility-based fuzzy optimization model. The authors study fuzzy chance-constraint model to determine optimal decisions for an integrated lot-sizing and price setting model for a manufacturer who faces demand from multiple market segments in [22]. In [5], the authors propose entropy-cross entropy algorithm for multi-objective portfolio optimization models with L-R fuzzy parameters. For an application to multi-objective transportation modeling, the reader may refer to [7]. A bi-objective programming model is developed with fuzzy inputs aiming to maximize agricultural yield productivity and minimize irrigation water shortage in [8]. In [11], compensatory and Pareto-optimal compromise solutions for the multi-objective software product selection problem are obtained via hybrid interactive fuzzy-programming approach. Mohamadi et al. [12] present a credibility-based fuzzy non-linear multi-objective mathematical programming of disaster management problem under uncertainty. For health service network design problem, by using possibilistic approaches, which consider convex combinations of possibility and necessity measures, the authors aim to minimize both the total weighted distance between patient zones and health facilities and the total establishment cost [13]. For other applications to network design, refer to [14] and [19]. In [20], the authors also consider convex combinations of possibility and necessity measures for an allocation problem. The authors present a hybrid credibility-based fuzzy mathematical programming model to cope with uncertainty in green logistics network design problem in [16] . Salehi et al. [17] study a fuzzy multi-objective assembly line balancing problem which tries to minimize the number of stations, purchasing costs, and worker's wages. The authors investigate redundancy allocation problems under fuzziness in [18]. In [24], the authors consider expected objectives and chance-constraints together with level-2 fuzzy parameters of their multi-objective supply chain network design problem combining fuzzy simulation-based genetic algorithm and goal programming approaches. For other applications to type 2 fuzzy numbers, refer to [23] and [25].

The rest of this paper is organized as follows. In the next section, some preliminary information on credibility theory is given. In Section 3, the model that is focused on is briefly given. With an example from the literature, the expected objective function values of the credibilistic model and the simulated ones are compared. Section 4 explains the simulation process for non-linearly distributed parameters. Also, again with an example from the literature, solution steps and error analysis are reported. The paper is concluded with some remarks in Section 5.

2. Preliminaries

In this section, some basic definitions of credibility theory are given.

Definition 2.1. Let Θ be a nonempty set, and 2^{Θ} be the power set of Θ. Each element of 2^{Θ} is called an event. Let ξ be a fuzzy variable with the membership function μ, and t be a real number. The possibility, necessity and credibility of the fuzzy event $\{\xi \geq t\}$ can be given as:

$$\begin{aligned} &Pos\{\xi \geq t\} = \sup_{u \geq t} \mu(u), \\ &Nec\{\xi \geq t\} = 1 - \sup_{u < t} \mu(u), \\ &Cr\{\xi \geq t\} = \tfrac{1}{2}[Pos\{\xi \geq t\} + Nec\{\xi \geq t\}], \end{aligned}$$

respectively. Note that, in the case of equality type of fuzzy event, the possibility is related to membership value.

Example 2.1. A triangular fuzzy variable ξ can be determined by a triplet (a, b, c) with $a < b < c$. It is easy to obtain the credibility of the event $\{\xi \geq t\}$ as the following non-increasing piecewise linear function:

$$Cr\{\xi \geq t\} = \begin{cases} 1, & t < a \\ \frac{2b-a-t}{2(b-a)}, & a \leq t < b \\ \frac{c-t}{2(c-b)}, & b \leq t < c \\ 0, & t \geq c \end{cases}.$$

Example 2.2. A non-linear fuzzy variable ξ can be determined by (a, b, c, d) with a membership function:

$$\mu(x) = \begin{cases} 1 - \left(\frac{b-x}{b-a}\right)^2, & a \leq x < b \\ 1, & b \leq x < c \\ 1 - \left(\frac{x-c}{d-c}\right)^2, & c \leq x < d \\ 0, & \text{otherwise} \end{cases}.$$

The credibility of the fuzzy event $\{\xi \geq t\}$ is as follows:

$$Cr\{\xi \geq t\} = \begin{cases} 1, & t < a \\ \frac{1}{2} + \frac{1}{2}\left(\frac{b-t}{b-a}\right)^2, & a \leq t < b \\ \frac{1}{2}, & b \leq t < c \\ \frac{1}{2} - \frac{1}{2}\left(\frac{t-c}{d-c}\right)^2, & c \leq t < d \\ 0, & t \geq d \end{cases}.$$

Definition 2.2. The expected value of the fuzzy variable ξ can be defined as:

$$E\left[\xi\right] = \int_0^{\infty} Cr\{\xi \geq t\}dt - \int_{-\infty}^{0} Cr\{\xi \leq t\}dt$$

provided that at least one of the above two integrals are finite. If ξ is a non-negative fuzzy variable, the second integral equals to 0. It is a representative mean value as in random variables.

Example 2.3. The expected value of a triangular variable (a, b, c) based on its credibility measure is $(a + 2b + c)/4$, and the expected value of a non-linear variable (a, b, c, d) is $(2a + b + c + 2d)/6$.

3. Hybrid Model

Instead of the Model (1), the following multi-objective model with expected objectives and chance-constraints based on the credibility measure is considered:

$$\begin{aligned} \min \quad & \left(E\left[\widetilde{f_1}(x)\right], E\left[\widetilde{f_2}(x)\right], \ldots, E\left[\widetilde{f_K}(x)\right]\right) \\ \text{s.t.} \quad & Cr\left\{\sum_{j=1}^{n} \widetilde{a_{ij}} x_j \leq \widetilde{b_i}\right\} \geq \alpha_i, \quad i = 1, 2, \ldots, m, \\ & x_j \geq 0, \qquad j = 1, 2, \ldots, n, \end{aligned}$$

where $\alpha_i \in [0.5, 1]$ for $i = 1, 2, \ldots, m$, are predetermined satisfactory levels for credibilities to ensure that the constraints hold at some confidence levels. Note that $\widetilde{a_{i1}}, \widetilde{a_{i2}}, \ldots, \widetilde{a_{in}}$ and $\widetilde{b_i}$ should be same type of fuzzy numbers for $i = 1, 2, \ldots, m$.

Example 3.1. Consider the illustrative example of [3]. First, the constraints are replaced with fuzzy chance-constraints in order to handle uncertainty of the constraints. For example, by assuming $\alpha = 0.7$, while converting the first fuzzy chance-constraint:

$$Cr\left\{(6, 12, 14)x_1 + 17x_2 \leq 1400\right\} \geq 0.7 \tag{2}$$

into its crisp equivalent $1400 - 17x_2 = 12.8x_1\lambda_{11} + 14x_1\lambda_{12} + 1400\lambda_{13}$, the additional constraints $\lambda_{11} + \lambda_{12} + \lambda_{13} = 1$ and $\lambda_{11}, \lambda_{12}, \lambda_{13} \geq 0$ are obtained. Then, for the objective functions, the triangular fuzzy coefficients are replaced with their expected values. After following the same procedure for other constraints and all of the objectives, the resulted crisp equivalent formulation is as follows:

$$
\begin{array}{ll}
\max & z_1 = 55x_1 + 100x_2 + 17.5x_3 \\
\max & z_2 = 96x_1 + 77.5x_2 + 50x_3 \\
\max & z_3 = 32.5x_1 + 100x_2 + 75x_3 \\
 & \\
\text{s.t.} & \sum_{j=1}^{3} \lambda_{ij} = 1, \quad i = 1,2,3,4,5,6, \\
 & 1400 - 17x_2 = 12.8x_1\lambda_{11} + 14x_1\lambda_{12} + 1400\lambda_{13}, \\
 & 1000 - 3x_1 - 9x_2 = 8.8x_3\lambda_{21} + 10x_3\lambda_{22} + 1000\lambda_{23}, \\
 & 1750 - 10x_1 - 15x_3 = 13.8x_2\lambda_{31} + 15x_2\lambda_{32} + 1750\lambda_{33}, \\
 & 1325 - 16x_3 = 6.8x_1\lambda_{41} + 8x_1\lambda_{42} + 1325\lambda_{43}, \\
 & 900 - 7x_3 = 14.8x_2\lambda_{51} + 19x_2\lambda_{52} + 900\lambda_{53}, \\
 & 1075 - 9.5x_1 - 4x_3 = 10.3x_2\lambda_{61} + 11.5x_2\lambda_{62} + 1075\lambda_{63}, \\
 & x_j, \lambda_{ij} \geq 0, \quad i = 1,2,3,4,5,6, \ j = 1,2,3.
\end{array} \tag{3}
$$

Now, single-objective programs subject to the constraints of the model (3) are solved one by one to get the best max z_k and the worst min z_k values. In the compromise programming formulation, the minimum satisfaction μ is tried to maximize as following:

$$
\begin{array}{ll}
\max & \mu \\
\text{s.t.} & \mu \leq \frac{z_k - \min z_k}{\max z_k - \min z_k}, k = 1,2,3, \\
 & 0 \leq \mu \leq 1, \\
 & \text{constraints of (3)},
\end{array} \tag{4}
$$

where the optimal solutions are $\mu^* = 0.756$, $x^* = (50.656, 43.132, 37.377)^T$, $z_1^* = 7753.393$, $z_2^* = 10074.553$, $z_3^* = 8762.838$.

In the simulation phase, 1000 triangularly distributed samples are generated for the fuzzy parameters. By using the solver "linprog" in loops, 4000 linear programming problems (individual single objective problems and compromise problems (4)) are solved with generated fuzzy numbers as parameters. Absolute relative errors between the expected objective function values:

$$
e_1 = \frac{|mean\,(z_1) - 7753.393|}{mean\,(z_1)} = 0.0336, e_2 = 0.0869, e_3 = 0.0636.
$$

4. Non-linear Distribution

Similar to trapezoidal distribution [6], the pdf of the non-linear fuzzy number (a, b, c, d) is:

$$
f(x) = \begin{cases} h\left[1 - \left(\frac{b-x}{b-a}\right)^2\right], & a \leq x < b \\ h, & b \leq x < c \\ h\left[1 - \left(\frac{x-c}{d-c}\right)^2\right], & c \leq x < d \\ 0, & \text{otherwise} \end{cases}
$$

where $h = \frac{3}{(c-b)+2(d-a)}$ is the calibration parameter. Note that the sum of all possibilities (total area under the curve) should be equal to 1.

The cdf is as follows:

$$F(x) = \int_{-\infty}^{x} f(t)dt \tag{5}$$
$$= \begin{cases} 0, & x < a \\ \frac{h(x-a)^2(-x-2a+3b)}{3(b-a)^2}, & a \leq x < b \\ \frac{2h(b-a)}{3} + h(x-b), & b \leq x < c \\ \frac{2h(b-a)}{3} + h(c-b) + \frac{h(x-c)(2c^2-6cd+2cx+3d^2-x^2)}{3(d-c)^2}, & c \leq x < d \\ 1, & x \geq d \end{cases}.$$

Example 4.1. Consider the fuzzy transportation problem with two objectives and non-linear fuzzy parameters of [2]:

Suppose that $\alpha = 0.5$. Although having non-linear credibilities, they are linearized with the help of grid points. The crisp equivalent program is as follows:

$$\begin{array}{ll} \min E[z_1] = & 8x_{11} + 40x_{13} + 12x_{22} + 52x_{23} + 28x_{24} + 56x_{31} + 17x_{33} + 20x_{34} \\ \min E[z_2] = & 23x_{11} + 7x_{12} + 12x_{14} + 13x_{21} + 35x_{22} + 48x_{32} + 11x_{33} \\ \text{s.t.} & \sum_{j=1}^{4} \lambda_{ij} = 1, \quad i = 1,2,3,4,5,6,7 \\ & x_{11} + x_{12} + x_{13} + x_{14} = 0\lambda_{11} + 28\lambda_{12} + 32\lambda_{13} + 36\lambda_{14}, \\ & x_{21} + x_{22} + x_{23} + x_{24} = 0\lambda_{21} + 48\lambda_{22} + 52\lambda_{23} + 56\lambda_{24}, \\ & x_{31} + x_{32} + x_{33} + x_{34} = 0\lambda_{31} + 32\lambda_{32} + 36\lambda_{33} + 40\lambda_{34}, \\ & x_{11} + x_{21} + x_{31} = 43\lambda_{41} + 46\lambda_{42} + 49\lambda_{43} + 146\lambda_{44}, \\ & x_{12} + x_{22} + x_{32} = 19\lambda_{51} + 22\lambda_{52} + 25\lambda_{53} + 146\lambda_{54}, \\ & x_{13} + x_{23} + x_{33} = 31\lambda_{61} + 34\lambda_{62} + 37\lambda_{63} + 146\lambda_{64}, \\ & x_{14} + x_{24} + x_{34} = 29\lambda_{71} + 30\lambda_{72} + 35\lambda_{73} + 146\lambda_{74}, \\ & x, \lambda_{ij} \geq 0, \quad i = 1,2,3,4,5,6,7, \ j = 1,2,3,4, \end{array} \tag{6}$$

where 146 is the maximum possible value of total demand. The resulted compromise program for the model (6) is as follows:

$$\begin{array}{ll} \max & \mu \\ \text{s.t.} & z_1 = 8x_{11} + 40x_{13} + 12x_{22} + 52x_{23} + 28x_{24} + 56x_{31} + 17x_{33} + 20x_{34}, \\ & z_2 = 23x_{11} + 7x_{12} + 12x_{14} + 13x_{21} + 35x_{22} + 48x_{32} + 11x_{33}, \\ & \mu \leq \frac{4580-z_1}{4580-563}, \\ & \mu \leq \frac{1834-z_2}{1834-172}, \\ & \mu \in [0,1], \\ & \text{constraints of (6)}, \end{array}$$

where $\mu^* = 0.669$, $z_1^* = 1892.424$, $z_2^* = 722.038$.

To generate non-linear parameters, the inverses of piecewise cubic functions (5) are found by using "polyfit" function of MATLAB. By using the inverse cdfs, non-linearly distributed 5000 fuzzy samples are simulated. The algorithm for Example 4.1 is as follows:

Step 1: Set $t = 1, k = 1$.

Step 2: Repeat while $t \leq 5000$, generate fuzzy parameters $\widetilde{c_{ij}^1}, \widetilde{c_{ij}^2}, \widetilde{a_i}, \widetilde{b_j}$, assign $c_{ij}^1(t), c_{ij}^2(t), a_i(t), b_j(t)$, respectively.

If $\sum\limits_{i=1}^{3} a_i(t) < \sum\limits_{j=1}^{4} b_j(t)$ go to Step 3. Otherwise, solve

$$\begin{array}{ll} \min & \sum\limits_{i=1}^{3}\sum\limits_{j=1}^{4} c_{ij}^1(t)x_{ij} \\ \text{s.t.} & \sum\limits_{j=1}^{4} x_{ij} \leq a_i(t), \quad i=1,2,3, \\ & \sum\limits_{i=1}^{3} x_{ij} \geq b_j(t), \quad j=1,2,3,4 \\ & x_{ij} \geq 0, \quad i=1,2,3, j=1,2,3,4, \end{array} \tag{7}$$

and assign $\left(x_{ij}^1\right) = \left(x_{ij}^*\right)$. Solve

$$\begin{array}{ll} \min & \sum\limits_{i=1}^{3}\sum\limits_{j=1}^{4} c_{ij}^2(t)x_{ij} \\ \text{s.t.} & \text{constraints of (7)}, \end{array}$$

and assign $\left(x_{ij}^2\right) = \left(x_{ij}^*\right)$. Set

$$z_1^{\min}(\text{or } z_1^{\max}) = \min\ (\max) \left\{ \sum_{i=1}^{3}\sum_{j=1}^{4} c_{ij}^1(t)x_{ij}^1, \sum_{i=1}^{3}\sum_{j=1}^{4} c_{ij}^1(t)x_{ij}^2, \right\},$$

$$z_2^{\min}(\text{or } z_2^{\max}) = \min\,(\max) \left\{ \sum_{i=1}^{3}\sum_{j=1}^{4} c_{ij}^2(t)x_{ij}^1, \sum_{i=1}^{3}\sum_{j=1}^{4} c_{ij}^2(t)x_{ij}^2, \right\}.$$

Solve the compromise program:

$$\begin{array}{ll} \max & \mu \\ \text{s.t.} & z_1 = \sum\limits_{i=1}^{3}\sum\limits_{j=1}^{4} c_{ij}^1(t)x_{ij} \\ & z_2 = \sum\limits_{i=1}^{3}\sum\limits_{j=1}^{4} c_{ij}^2(t)x_{ij} \\ & \mu \leq \frac{z_1^{\max}-z_1}{z_1^{\max}-z_1^{\min}}, \\ & \mu \leq \frac{z_2^{\max}-z_2}{z_2^{\max}-z_2^{\min}}, \\ & \mu \in [0,1], \\ & \text{constraints of (7)}, \end{array}$$

and set $\left(x_{ij}^3\right) = \left(x_{ij}^*\right)$. Store $f_1(k) = \sum\limits_{i=1}^{3}\sum\limits_{j=1}^{4} c_{ij}^1(t)x_{ij}^3$, $f_2(k) = \sum\limits_{i=1}^{3}\sum\limits_{j=1}^{4} c_{ij}^2(t)x_{ij}^3$ and $m(k) = \mu^*$. $k := k+1$.

Step 3: $t := t+1$ and go to Step 2.

Step 4: Return $mean\,(f_1)$, $mean\,(f_2)$ and $mean\,(m)$.

An if-then rule is written, because in a transportation setting if the total supply is less than the total demand, an infeasibility occurs. To avoid such cases, remember that $\alpha = 0.5$. Absolute relative errors between the expected objective function values:

$$e_1 = 0.0094, e_2 = 0.0195, mean\,(\mu^*) = 0.6715.$$

5. Conclusions

In this study, optimal decisions for hybrid models combining fuzzy chance-constraints and expected values of objective functions are discussed. The approach uses expected values and chance-constraints respectively to handle uncertain objective functions and to control the confidence level of fulfilling imprecise constraints. In case there are conflicting objectives and uncertainty, the credibilistic approach offers computational ease. With a little effort, error analysis can be provided by the use of techniques which are similar to the stochastic simulation and applicable to all types of fuzzy numbers. Also, the method can be adapted to the other interactive fuzzy multi-objective solution techniques including goal programming.

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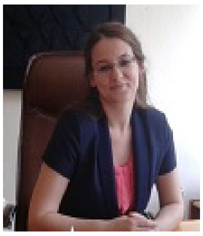

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