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Review Article

A Goal Programming Approach to Multichoice Multiobjective Stochastic Transportation Problems with Extreme Value Distribution

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This paper presents the study of a multichoice multiobjective transportation problem (MCMOTP) when at least one of the objectives has multiple aspiration levels to achieve, and the parameters of supply and demand are random variables which are not predetermined. The random variables shall be assumed to follow extreme value distribution, and the demand and supply constraints will be converted from a probabilistic case to a deterministic one using a stochastic approach. A transformation method using binary variables reduces the MCMOTP into a multiobjective transportation problem (MOTP), selecting one aspiration level for each objective from multiple levels. The reduced problem can then be solved with goal programming. The novel adapted approach is significant because it enables the decision maker to handle the many objectives and complexities of real-world transportation problem in one model and find an optimal solution. Ultimately, a mixed-integer mathematical model has been formulated by utilizing GAMS software, and the optimal solution of the proposed model is obtained. A numerical example is presented to demonstrate the solution in detail.

1. Introduction

The transportation problem is a well-known specific application of linear programming, in which an item is to be transported from m sources to n destinations [1]. The availability of the product at the i^{th} source is denoted by a_i, where $i = 1, 2, \ldots, m$, and the demand required at the j^{th} destination is b_j, where $j = 1, 2, \ldots, n$. The penalty c_{ij} is the cost coefficient of the objective function that can represent the expense of transporting wares from sources to destinations, which is desired to be minimized [1].

There may be more than one objective to the problem, and they could be conflicting, for example, minimizing the cost of transportation as well as minimizing the shipping time. Here, the two goals have the same direction, i.e., minimization, but there is a trade-off. For example, using a car as the transport means may be lower in cost than by air freight but will take much longer. Hence, goal programming is introduced so that the decision maker (DM) may set multiple choices for the aspiration levels in at least one goal in a transportation problem, defining a multiaspiration level goal programming transportation problem. In addition, the supply and demand parameters can be random variables, so it becomes a stochastic multiaspiration level goal programming transportation problem.

Mahapatra [2] considers a model of a multichoice stochastic transportation problem (MCSTP), where the supply and demand parameters of the constraints follow extreme value distribution. Some of the cost coefficients of the objective function are a multichoice type. In an optimal solution, the number of units to be transported should be determined while satisfying source and destination demands to ensure minimum transportation costs.

In this paper, we will look at the problem from another angle, by including the concept of goal programming to allow the model to deal with more than one conflicting objective and set multiaspiration levels to certain goals. The new model becomes a stochastic multiaspiration level goal programming transportation problem with an extreme value distribution.

Often, one cannot determine an exact value of any parameters in the problem because of uncertainty in supply or demand parameters for a number of reasons. For example, fluctuating markets or service output levels from suppliers, raw material defects, machine performances, delivery delays, and transportation issues are among the factors which cause uncertainty in supply assumptions. Similarly, unknown customer demand for products or services offered by the buyer, customer preferences, competition, and an unpredictable economy are among the factors that contribute to demand uncertainty. A stochastic problem can be formulated to overcome these uncertainties by considering that random variables follow a specific distribution instead of assuming fixed values. Here, an extreme value distribution will be assumed to convert the constraints from probabilistic to deterministic with the disjoint chance-constrained method. Extreme value distribution is used when there is a requirement for a limiting distribution to the maximum or minimum of a sample of independent and identically distributed random variables. The probability density function of extreme value distribution type I [3] is as follows:

$$f(x;\alpha,\beta)=\begin{cases}\dfrac{1}{\beta}e^{-((x-\alpha)/\beta)}\exp\left[-e^{-((x-\alpha)/\beta)}\right]; & -\infty\leq x\leq\infty,\ \beta>0,\\ 0; & \text{otherwise.}\end{cases} \quad (1)$$

Goal programming is an extension of linear programming which handles multiobjective optimization where the individual objectives are often conflicting. Every one of these measures is assigned a goal or target value to be accomplished. Undesirable deviations from this arrangement of target values are then minimized through an achievement function. This can be a vector or a weighted sum depending on the goal programming variant adopted or the DM's requirements.

The type of goal programming model employed is determined by the nature of the DM's goals. The initial goal programming formulations order the undesirable deviations into a hierarchy by criticality, which enables more priority to be given to minimizing deviation of the more important factors. This is known as lexicographic (preemptive) or non-Archimedean goal programming.

Lexicographic goal programming can be used when prioritization is relevant to the goals. In preemptive goal programming, the objectives can be separated into various priority classes. Here, it is assumed that no two goals have equal priorities. Each will then be satisfied sequentially from most important to least important. The DMs can set multichoice aspiration levels (MCALs) for each goal to avoid underestimating, accounting for the "more/higher is better" and "less/lower is better" aspirations. To handle these multiple aspiration levels, multiplicative terms of binary variables are utilized, where all binary variables constitute mutually exclusive choices and only one variable is selected. The number of binary variables required for a constraint is equivalent to the total number of options of that constraint.

The article is subsequently organized as follows. In Section 2, a problem overview will be considered; the mathematical model will be presented in Section 3, and Section 4 will discuss the transformation of the goal constraint involving multiple aspiration levels into an equivalent form. Finally, a case study to demonstrate the model will be presented in Section 5.

2. Problem Overview

Contini [4] considered the first formulation of the stochastic goal programming model. He set the goals as uncertain normally distributed variables. The technique for solving the probabilistic programming model was to convert it into an equivalent deterministic model. Many approaches have been proposed to solve the probabilistic programming model, of which the most common approach is chance-constrained programming (CCP), developed by Charnes and Cooper [5–7].

Chang [8] proposed a new idea for modelling the multichoice goal programming problem using multiplicative terms of binary variables to handle multiple aspiration levels. Biswal and Acharya [9] proposed transformation techniques to transform a multichoice linear programming problem into an equivalent mathematical model in which constraints are associated with multichoice parameters.

Many researchers have extensively studied the MCSTP. Barik et al. [10] presented a stochastic transportation model involving Pareto distribution. Roy et al. [11] presented an equivalent deterministic model of MCSTP by assuming that both availabilities a_i and demands b_j are random variables following an exponential distribution. Biswal and Samal [12] obtained an equivalent deterministic model of MCSTP in which they considered that both a_i and b_j follow Cauchy distribution. Mahapatra [2] considered an MCSTP with extreme value distribution, serving as a basis of inspiration for this research. The novel contribution of this paper is to include the multiobjective problem within the model and to represent the multichoice problem in terms of aspiration levels instead of a cost coefficient parameter. Mahapatra [2] also studied an MCSTP model involving Weibull distribution, whereas Quddoos et al. [13] presented an MCSTP involving a general form of distribution. Roy [14] introduced Lagrange's interpolating polynomial to deal with the multichoice transportation problem. He subsequently published a paper of the transportation problem with multichoice cost and demand parameters and stochastic supply [15], in which he used Lagrange's interpolating polynomial to select an appropriate value for the cost coefficients of the objective function and the demand of the constraints in the transportation problem. By adopting stochastic programming, the stochastic supply constraints were transformed into deterministic constraints. One of the key publications of Maity and Roy [16] proposed the techniques of revised multichoice goal programming

(RMCGP) and a utility function as an approach to the MOTP. In another paper, they introduced a procedure for converting a multichoice interval transportation problem (MCITP) into a deterministic transportation problem to solve [17]. In an additional publication, the same authors demonstrated solving a fuzzy transportation problem (FTP) using a multichoice goal programming approach [18]. Roy et al. [19] also proposed the technique of introducing a conic scalarizing function into the MOTP in combination with RMCGP.

In this study, we will propose a new approach to the transportation problem whereby the supply and demand parameters are random variables following extreme value distribution. Rather than minimizing the cost coefficient for the transportation problem, we can minimize the time for shipping, minimize the risk in shipping the items, and so on. As an additional feature, each objective can have multiple aspiration levels instead of only one. Now the problem becomes a multichoice multiobjective stochastic transportation problem. To overcome this difficulty, first we will use a stochastic approach to turn the probabilistic constraint into a deterministic one. Second, a general transformation consisting of binary variables is applied to select one aspiration level for each objective from multiple levels. The reduced problem then becomes an MOTP and it will be solved with goal programming.

3. Mathematical Model

Initially, the classical transportation problem is considered. If x_{ij} represents the amount transported from the source to the destination, then the transportation model can be defined as follows.

Model 1

$$\text{Find } x_{ij}; \quad i = 1, 2, \ldots, m; \; j = 1, 2, \ldots, n,$$

$$\min z = \sum_{i,j} c_{ij} x_{ij}, \tag{2}$$

Subject to (s.t.)

$$\sum_{j=1}^{n} x_{ij} \le a_i, \quad \forall i, \tag{3}$$

$$\sum_{i=1}^{m} x_{ij} \ge b_j, \quad \forall j, \tag{4}$$

$$\sum_{i} a_i = \sum_{j} b_j, \tag{5}$$

$$x_{ij} \ge 0, \quad \forall i, j, \tag{6}$$

where c_{ij} is the transportation cost per unit, x_{ij} is the amount shipped, a_i is the amount of supply at source i, and b_j is the amount of demand at destination j [20].

Now, we consider a mathematical model for a stochastic multiaspiration level goal programming transportation problem with an extreme value distribution as follows.

Model 2

$$\begin{aligned} \text{Lex min} \quad & \{n_i, \; p_i\}, \\ \text{s.t.} \quad & f_i(x) + n_i - p_i = g_1, g_2, \ldots, g_q, \quad q = 1, 2, \ldots, k, \\ & P\left(\sum_{j=1}^{n} x_{ij} \le a_i\right) \ge 1 - \gamma_i, \quad i = 1, 2, \ldots, m; \; 0 \le \gamma_i \le 1, \\ & P\left(\sum_{i=1}^{m} x_{ij} \ge b_j\right) \ge 1 - \delta_j, \quad j = 1, 2, \ldots, n; \; 0 \le \delta_j \le 1, \\ & x_{ij} \ge 0, \; n_i, \; p_i \ge 0, \\ & \sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j, \end{aligned} \tag{7}$$

where $f_i(x)$ is the linear function of the i^{th} goal, g_i is the aspiration levels of the i^{th} goal, x_{ij} is the amount shipped, a_i is the amount of supply at source i, b_j is the amount of demand at destination j, n_i is the negative deviational variable, and p_i is the positive deviational variable.

3.1. Converting the Probabilistic Constraint into a Deterministic Constraint Using the Disjoint Chance-Constrained Method. From Mahapatra [2], three cases of randomness on the right-hand side of the supply and demand constraints were considered:

(1) Only a_i, $i = 1, 2, \ldots, m$ follows extreme value distribution

(2) Only b_j, $j = 1, 2, \ldots, n$ follows extreme value distribution

(3) Both a_i, $i = 1, 2, \ldots, m$ and b_j, $j = 1, 2, \ldots, n$ follow extreme value distribution

This led to three different models (for more details, see Mahapatra [2]. The final transformed constraint is then considered here as the probabilistic constraint (4) transformed into a deterministic linear constraint:

$$\sum_{j=1}^{n} x_{ij} \le \alpha_i - \beta_i \left[\ln\{-\ln(\gamma_i)\}\right]. \tag{8}$$

The probabilistic constraint (5) transformed into a deterministic linear constraint:

$$\sum_{i=1}^{m} x_{ij} \ge \grave{\alpha}_j - \grave{\beta}_j \left[\ln\left\{-\ln\left(1 - \delta_j\right)\right\}\right]. \tag{9}$$

Now, a deterministic multiaspiration level goal programming transportation problem with an extreme value distributions model will be obtained as follows.

Model 3

$$\begin{aligned}
\text{Lex min}\quad & \{n_i, p_i\},\\
\text{s.t.}\quad & f_i(x) + n_i - p_i = g_1, g_2, \ldots, g_q, \quad q = 1, 2, \ldots, k,\\
& \sum_{j=1}^{n} x_{ij} \le \alpha_i - \beta_i [\ln\{-\ln(\gamma_i)\}], \quad i = 1, 2, \ldots, m,\\
& \sum_{i=1}^{m} x_{ij} \ge \grave{\alpha}_1 - \grave{\beta}_j [\ln\{-\ln(1-\delta_j)\}], \quad j = 1, 2, \ldots, n,\\
& x_{ij} \ge 0,\ n_i,\ p_i \ge 0,\\
& 0 \le \delta_j \le 1,\\
& 0 \le \gamma_i \le 1,
\end{aligned} \tag{10}$$

where $\sum_{i=1}^{m} \alpha_i - \beta_i [\ln\{-\ln(\gamma_i)\}] \ge \sum_{j=1}^{n} \grave{\alpha}_j - \grave{\beta}_j [\ln\{-\ln(1-\delta_j)\}]$ is the feasibility condition.

4. Transformation of the Goal Constraint Involving Multiaspiration Levels to an Equivalent Form

Considering the goal constraint with multiple aspiration levels,

$$f_i(x) + n_i, - p_i = g_1, g_2, \ldots, g_q. \tag{11}$$

A binary variable will be utilized to select a single aspiration level, and we can utilize the relation $\ln n/\ln 2$ to determinate the number of binary variables needed with n aspiration levels under the given linearized constraint [21]. Let $x = z_i z_j$, where x satisfies the following inequalities:

$$\left(z_i + z_j - 2\right) + 1 \le x \le \left(2 - z_i - z_j\right) + 1, \tag{12}$$

$$x \le z_i, \tag{13}$$

$$x \le z_j, \tag{14}$$

$$x \ge 0. \tag{15}$$

The inequalities are identified:

(i) If $z_i = z_j = 1$ then $x = 1$ (from (12))

(ii) If $z_i z_j = 0$ then $x = 0$ (from (13)–(15))

And so, the new goal constraint will be

$$f_i(x) + n_i, - p_i = \sum_{j=1}^{n} g_{ij} S_{ij}(B), \quad i = 1, 2, \ldots, m, \tag{16}$$

where $S_{ij}(B)$ represents the function of the binary serial number.

A stochastic multiaspiration level goal programming transportation problem with extreme value distribution model will be as follows.

Model 4

$$\begin{aligned}
\text{Lex min}\quad & \{n_i, p_i\},\\
\text{s.t.}\quad & f_i(x) + n_i - p_i = \sum_{j=1}^{n} g_{ij} S_{ij}(B),\\
& \sum_{j=1}^{n} x_{ij} \le \alpha_i - \beta_i [\ln\{-\ln(\gamma_i)\}], \quad i = 1, 2, \ldots, m,\\
& \sum_{i=1}^{m} x_{ij} \ge \grave{\alpha}_j - \grave{\beta}_j [\ln\{-\ln(1-\delta_j)\}], \quad j = 1, 2, \ldots, n,\\
& x_{ij} \ge 0, n_i,\ p_i \ge 0,\\
& 0 \le \delta_j \le 1,\\
& 0 \le \gamma_i \le 1,
\end{aligned} \tag{17}$$

where $\sum_{i=1}^{m} \alpha_i - \beta_i [\ln\{-\ln(\gamma_i)\}] \ge \sum_{j=1}^{n} \grave{\alpha}_j - \grave{\beta}_j [\ln\{-\ln(1-\delta_j)\}]$ is the feasibility condition.

5. Case Study

In this section, a case study from Mahapatra [2] is considered with modifications and the assumption of extreme value distribution instead of Weibull distribution. In this case study, a cold drink supply company transports cold drinks from three product centres at Dankuni, Howrah, and Asansol to four destination centres at Jhargram, Kharagpur, Tarkeshwar, and Contai. In the summer season, the cold drinks are in high demand at each of the four destination centres. The transportation time cost is an essential factor in a transportation planning programme as well as the transportation cost. The manufacturing time at production centres depends on the availability of current supply, machine condition, skilled labour, etc. Delivery time is related to the transporting means and seamless distribution of a product in due time to destination centres. The transportation time cost t_{ij} and cost coefficient c_{ij} from each source to each destination are considered in Table 1.

The cold drinks supply company is seeking to reach the following goals: goal 1 is to minimize the transportation time cost and goal 2 is to minimize the cost of transportation. The target values are 112,000 or 113,000 hours and \$150,000 or \$160,000, respectively.

Due to the fluctuation of the above factor, a stochastic multiaspiration level goal programming transportation problem approach has been considered, in which the supply and demand parameters follow extreme value distribution. The specified probability levels with shape and scale parameters for supply are listed in Table 2, and the specified

Table 1: Transportation time cost t_{ij} and cost coefficient c_{ij} from each source to each destination.

No.	Route x_{ij}	Transportation time cost t_{ij} (in hours)	Cost coefficient c_{ij} (in dollars)
1	(1,1): x_{11}	12	21
2	(1,2): x_{12}	15	25
3	(1,3): x_{13}	19	30
4	(1,4): x_{14}	24	34
5	(2,1): x_{21}	16	27
6	(2,2): x_{22}	18	28
7	(2,3): x_{23}	9	15
8	(2,4): x_{24}	17	26
9	(3,1): x_{31}	24	34
10	(3,2): x_{32}	12	24
11	(3,3): x_{33}	25	37
12	(3,4): x_{34}	28	40

Table 2: Values of location and scale parameter with SPL of a_i.

Shape parameter	Scale parameter	SPL
$\alpha_1 = 3000$	$\beta_1 = 3.6$	$\gamma_1 = 0.01$
$\alpha_2 = 2500$	$\beta_2 = 3.0$	$\gamma_2 = 0.02$
$\alpha_3 = 2000$	$\beta_3 = 2.4$	$\gamma_3 = 0.03$

probability levels with shape and scale parameters of demand parameters are provided in Table 3.

Table 3: Values of location and scale parameter with SPL of b_j.

Shape parameter	Scale parameter	SPL
$\grave{\alpha}_1 = 1700$	$\grave{\beta}_1 = 2.2$	$\delta_1 = 0.04$
$\grave{\alpha}_2 = 1500$	$\grave{\beta}_2 = 2.0$	$\delta_2 = 0.05$
$\grave{\alpha}_3 = 1250$	$\grave{\beta}_3 = 1.6$	$\delta_3 = 0.06$
$\grave{\alpha}_4 = 1000$	$\grave{\beta}_4 = 1.2$	$\delta_4 = 0.07$

Utilizing the data in Tables 1–3, the deterministic multiaspiration level goal programming transportation problem is formulated as follows:

$$\begin{aligned}
\text{Lex min}\quad & \{p_1,\ p_2\},\\
\text{s.t.}\quad & \sum_{i=1}^{3}\sum_{j=1}^{4} x_{ij} + n_1 - p_1 = 112000\, z_1 + 113000\left(1 - z_1\right),\\
& \sum_{i=1}^{3}\sum_{j=1}^{4} x_{ij} + n_2 - p_2 = 150000\, z_2 + 160000\left(1 - z_2\right),\\
& \sum_{j=1}^{4} x_{1j} \le 2994.502,\\
& \sum_{j=1}^{4} x_{2j} \le 2495.908,\\
& \sum_{j=1}^{4} x_{3j} \le 1996.9989,\\
& \sum_{i=1}^{3} x_{i1} \ge 1707.038,\\
& \sum_{i=1}^{3} x_{i2} \ge 1505.94,\\
& \sum_{i=1}^{3} x_{i3} \ge 1254.452,\\
& \sum_{i=1}^{3} x_{i4} \ge 1003.147,\\
& x_{ij},\ n_q,\ d_q \ge 0, \quad i = 1,2,3,\ j = 1,2,3,4,\ q = 1,2,\ z_k = 0 \text{ or } 1,\ k = 1,2.
\end{aligned} \tag{18}$$

Checking that the feasibility condition is satisfied:

$$\sum_{i=1}^{m} \alpha_i - \beta_i \left[\ln\{-\ln(\gamma_i)\}\right] = 7487.399$$
$$\geq \sum_{j=1}^{n} \grave{\alpha}_j - \grave{\beta}_j \left[\ln\left\{-\ln\left(1-\delta_j\right)\right\}\right] = 5470.577. \tag{19}$$

The deterministic linear mixed-integer problem is then solved using GAMS (software), where the optimal solution is obtained:

$$\begin{aligned} x_{12} &= 736.904,\\ x_{13} &= 1254.452,\\ x_{14} &= 1003.147,\\ x_{22} &= 1707.038,\\ x_{22} &= 769.037,\\ p_1 &= 0,\\ p_2 &= 0,\\ n_1 &= 12112.028,\\ n_2 &= 2213.805,\\ \text{where } z_1 &= 0 \text{ and } z_2 = 0. \end{aligned} \tag{20}$$

The remaining decision variables are zero. The results show that goal 1 has an aspiration level of 113,000 hours and zero positive deviation, which means that the transportation time cost achieved the aspiration level exactly, and goal 2 has an aspiration level of \$160,000 and zero positive deviation, which means that transportation cost also reached the desired aspiration level exactly.

6. Conclusion

In this paper, we have explored a study of problem when the supply and demand parameters are the stochastic type and follow extreme value distribution. Three different approaches (the stochastic approach, binary variable approach, and goal programming approach) can be combined to reach an optimal solution to the transportation problem. This provides a new capability to handle real-life DM problems such as agricultural, managerial, economical, and industrial. One numerical example has been presented to illustrate the approach, which was solved using GAMS software. One can apply the proposed model to real-life problems in feature work or adapt other multiobjective techniques such as the ε-constraint method, weighting method, or fuzzy programming methods and compare their performance.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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