

Multi objective Transportation Problem Using Fuzzy Decision Variable Through Multi-Choice Programming

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ABSTRACT

Using fuzzy decision variables, this work examines the examination of the Multi-Objective Transportation Problem (MOTP). When solving a Transportation Problem, the decision variable is usually considered as a real variable. There are a lot of multi-choice fuzzy numbers in this work, but the decision variable in each node is chosen from a collection of those values. Multiobjective Fuzzy Transportation Problems are created when numerous goals are included in a transportation issue with a fuzzy decision variable (MOFTP). We provide a novel mathematical model of MOFTP that incorporates fuzzy goals for each of the objective functions. After that, the multi-choice goal programming methodology is used to define the model's solution method. For further proof of this article's value, a numerical example is provided.

KEYWORDS

Fuzzy Variable, Goal Programming, Multiobjective Decision-making, Multiple-Choice Programming, Transportation Problem

INTRODUCTION

When it comes to real-world decision-making, the issue of transportation is critical. For example, a linear programming model may be utilised to solve the transportation problem in order to find an optimum solution to the decision-making issue. To solve the classical transportation problem, one must determine how many units of a commodity are to be shipped from each source to various destinations, satisfying source availability and destination demand, while minimising the total cost of transportation and cutting down the costs per unit of items for the purchaser.

Hitchcock (1941) first conceived of the issue of mass transit, and Koopmans (1944) refined it on his own (1949). Due to the current competitive market, a transportation problem with a single objective function is insufficient to address a variety of real-life decision-making issues. Such real-world conditions need the introduction of the multi-objective transportation issue. There have been several studies in this area by scholars such as Verma et al.

For a long time, multiobjective optimization problems were thought to be amenable to fuzzy set theory (Zimmerman 1978). Additionally, in order to transform a transportation issue into a fuzzy one, the factors of transportation (cost, supply, and demand) are presented using the concept of "fuzzy numbers." Fuzzy transportation issues may be solved using an approach proposed by Kumar and Kaur (2011) based on traditional transportation methodologies. In a decision-making issue, Ebrahimnejad et al. (2011) developed an algorithm for limited linear programming with fuzzy cost coefficients. Data envelopment analysis using fuzzy parameters was presented by Marbini et al. (2011). Singh et al. have provided a research study on multi-criteria futuristic fuzzy decision hierarchy and its application in the tourist business (2015). Decision-making approaches to fuzzy linear programming (FLP) issues with post-optimal analysis were included

in Pattnaik's paper in 2015. When it comes to completing real-world assignments in an intuitionistic fuzzy environment, Kumar and Hussain (2016) offered a straightforward technique. To our knowledge, no one has before proposed the notion of a fuzzy variable in a transportation issue. Fuzzy objectives are assumed in this case because we presume the expectations in the destinations of the transportation issue are fuzzy numbers. There are a lot of options and a lot of vague expectations at the final destinations. Therefore, the decision maker must make a choice about the supply of products that maximises profit while maintaining the highest feasible level of need fulfilment at each destination. The optimum solution to the issue does not need an allocation at each node in a transportation problem. The crisp goal "0" with a high priority value is used when no allocation is needed in a cell. The need in the assigned cells of our suggested transportation issue is "0" and one of a variety of multi-choice fuzzy integers. On the basis of this premise, we devise a transportation issue with ambiguous choice factors. The multi-choice goal programming technique is used to handle this decision-making challenge. Based on real-world decision-making challenges, this study is structured in a multiobjective framework. There are some ambiguous aims in each objective. One of Charnes et al.'s important and well-known decision-making techniques is Goal Programming (GP) (1955). In the face of real-world decision-making challenges involving multiobjective structures, goal programming's intriguing theory and broad application have made it very effective and pervasive. Thus, goal programming for a wide range of decision-making challenges may be improved upon in this way. Researchers such as Lee et al. (1972), Ignizio (1976), Narasimhan (1980), Tamiz et al. (1998), Chang (2007), Liao (2009); Chang et al. (2010); Tabrizi and Roy (2012); Maity and Roy (2015) and many more have done a great deal of work based on goal programming. Many real-world decision-making difficulties have objective function objectives that are deemed hazy because of the intricacy of real-world practical challenges. Based on the notion of multi-choice fuzzy goals in a transportation issue, the research of picking objectives from a multiple choice of fuzzy goals is presented. Based on fuzziness in the multiple choice of objectives, Chang (2008) explored revised multi-choice goal programming (MCGP). Mangara (2012) and Pan et al. (2011) are examples of researchers who have looked into multi-choice fuzzy goals. Roy et al. (2012), Mariya-Suhl and Suhl (2012) are examples of researchers who have looked into multi-choice fuzzy goals. However, there are other instances in which the goal is sacrificed in favour of the output of an objective function in order to arrive at the optimal solution to a decision-making issue with multiple objectives. If you're looking for a scenario in which you're able to choose your allocation objectives along with your desired result, you'll find it here!

It is the primary purpose of this study to define the multi-objective fuzzy transportation problem (MOFTP), in which the decision variables are multi-choice fuzzy goals and the objective functions also have some fuzzy goals in common. This technique introduces a mechanism for solving the defined model and selecting optimal objectives that are in line with the objective functions.

After that, it's as follows: In light of our research question, we've included a section on the issue setting. Multi-choice goal programming is introduced in the first subsection of Section 3, followed by a mathematical model of transportation under multi-choice goal programming in Section 3 (separated into two subsections). A numerical example is provided in Section 4 to demonstrate the suggested approach. For our presented issue, Section 5 provides a sensitivity analysis. The article's conclusion is presented in Section 6.

PROBLEM ENVIRONMENT

For a long time, the transportation problem's mathematical model was used exclusively to reduce transportation costs. However, in recent days, a big variety of real-world decision-making difficulties have been accommodated by researchers in order to challenge the current market environment. Decision-makers often use goal programming to reduce transportation costs while also increasing profit margins. However, in many circumstances, current solution techniques are designed to identify the best possible answer based on the decision maker's preferences. As a result of this research, a new type of transportation issue has been developed in which nodes' expectations are multi-choice fuzzy integers. As a result, the decision maker wants to maximise his gain while minimising transportation expenses, which are multi-choice fuzzy numbers. The traditional transportation issue cannot be solved with real variables, hence we add the fuzzy variables corresponding to each allocation node. Consumers may be impacted if the decision maker wants to maximise his profit without taking transportation costs into account, and the decision maker may lose customers in the future as a result of this. Mathematical models of the multi-objective transportation issue are provided in this paper, and we aim to develop a mathematical model that maximises not only profit for the decision maker but also ideal objectives for customers. In this situation, the optimal goals for objective functions and the corresponding solutions have not been specified in the literature until now, and in this study, we develop the proposed approach to choose the optimal goal that corresponds to the objective functions as well as to set up the best possible aspiration levels for customers as well. We also.

MATHEMATICAL MODEL

Multi-choice goal programming is introduced in the first part. Later, a mathematical model of the transportation issue with a fuzzy aim is developed. To solve the transportation challenge, a fuzzy decision-making process is devised.

Multi-Choice Goal Programming

Multi-choice goal programming (MCGP) was initially introduced in goal programming literature by Chang (2007), which enables the decision maker to define MCALs for each objective (i.e., one goal mapping multiple aspiration levels). Programming goals may be summarised in this way:

$$\text{GP: minimize } \sum_{i=1}^p w_i |Z_i(x) - g_i|, \quad (1)$$

Accomplishment function $Z_i(x)$ and g_i ($i=1,2,\dots,p$) are the weights linked to the deviation of $Z_i(x)$ achievement's function. The i -th goal's deviation is represented as $|Z_i(x) - g_i|$. After that, a goal-setting modification known as Weighted Goal Programming is offered (WGP).

We consider fuzzy objectives when it is not feasible to assign clear goals to each objective function. Fuzzy objectives may also be multiple-choice questions related to certain objective functions, as in this case. When used to Fuzzy Multi-Choice Goal Programming (FMGP), the formulation of goal programming is as follows:

$$\text{FMGP: minimize } \sum_{i=1}^r w_i |Z^i(x) - \hat{g}_i^1 \text{ or } \hat{g}_i^2 \text{ or } \dots \text{ or } \hat{g}_i^t|,$$

subject to $x \in F$,

where w_i ($i=1, 2, \dots, p$) are the weights relative to importance of objective functions and the aspiration levels $\hat{g}_i^t \forall i, t$ are assumed to be triangular fuzzy numbers with membership functions $\mu_i^t \forall i, t$.

Single Objective and Multiobjective Transportation Problems Under Multi-Choice Goal Programming

The main objective of the transportation problem is to minimize the transportation cost and is defined as follows:

Model 1

$$\text{minimize } Z = \sum_{i=1}^m \sum_{j=1}^n C_{ij} x_{ij},$$

subject to

$$\sum_{j=1}^n x_{ij} \leq a_i \quad (i=1, 2, \dots, m), \tag{2}$$

$$\sum_{i=1}^m x_{ij} \geq b_j \quad (j=1, 2, \dots, n) \tag{3}$$

$$\tag{4}$$

$$x_{ij} \geq 0 \quad \forall i, j,$$

The decision variable is x_{ij} and the transportation cost per commodity from the i th origin to the j th destination is C_{ij} $i = 1, 2, \dots, m; j = 1, 2, \dots, n$. It's easy to see that as the number of items at the origin and the number of items needed at the destination increase, so does the price, as shown here by a_i and b_j .

$$\sum_{i=1}^m a_i \geq \sum_{j=1}^n b_j \text{ is the feasibility condition.}$$

In many real-world decision-making situations, it may be necessary to maximise the objective function Z in accordance with the preferences of the decision-maker. Transportation issue choice variables (x_{ij}) are regarded real variables and crisp solutions are produced in this manner. Fuzzy objectives and multi-choices are common in our everyday lives, and they may be used to the allocation cells of transportation problems. If a cell's allocation is one of a set of values allocated by the decision maker, then it is considered to be one of the goal values. It is not a given that there will be allocations in each cell according to the transportation issue idea. If no allocations are made in a cell, the ambition level will be high since the target value is "0" with a tiny variance. As a result, the choice variables (x_{ij}) in the transportation issue are not behaving as they would in a classical transportation problem, but rather as a fuzzy variable (x_{ij}) No research has been done on this common transportation issue whose decision variables are fuzzy multi-

choices so far, according to our best knowledge. Following are the formulas for this sort of transportation problem:

Model 2

$$\text{minimize } Z = \sum_{i=1}^m \sum_{j=1}^n C_{ij} \hat{x}_{ij},$$

subject to

$$\sum_{j=1}^n \hat{x}_{ij} \leq a_i \quad (i=1, 2, \dots, m) \quad (6)$$

$$\sum_{i=1}^m \hat{x}_{ij} \geq b_j \quad (j=1, 2, \dots, n) \quad (7)$$

$$\hat{x}_{ij} \geq 0 \quad \forall i, j \quad (8)$$

One objective function for the transportation problem is not enough to express all real-life decision-making issues. In order to address this obstacle, we include numerous objective functions into transportation problem.

Mathematically speaking, the MOTP model may be summarised as follows:

Model 3

minimize/maximize

$$Z^k = \sum_{i=1}^m \sum_{j=1}^n C_{ij}^k \hat{x}_{ij} \quad (k=1, 2, \dots, p), \text{ subject to Equation 2 to 4.} \quad 4.$$

Multiobjective fuzzy transportation problem may be modelled in this way if the allocation cells in a real-world MOTP offer multiple choice alternatives for assigning products.

Model 4

$$\text{Minimize/maximize } Z^k = \sum_{i=1}^m \sum_{j=1}^n C_{ij}^k \hat{x}_{ij} \quad (k=1, 2, \dots, p), \text{ subject to Equation 6 to 8.}$$

Although it may seem simple, Model 4 is in fact rather complex. It is possible to solve the multi-objective transportation issue using GP, RMC GP, and fuzzy programming. MOFTP, on the other hand, does not have a precise way for solving it. This section explains how to solve a multiobjective fuzzy transportation issue.

For the MOFTP, we consider it in a goal-oriented context, which means that each MOFTP objective function has a defined set of objectives. For $k=1, 2, \dots, p$, g_k is a function of k .

All potential allocations at the node are assumed to be included in the set of all possible allocations at the node: $t=1, 2, \dots, p$ (i, j).

As a triangular fuzzy number, we may represent the allocation objectives g_t . In order to achieve. Aiming for a high aspiration value for each node and target function is the goal of Model 4. A better compromise solution for Model 4 can only be achieved if weights for nodes and goal functions are properly assigned. So we build a clear model of the transportation issue that is a maximising problem, no matter what the transportation problem's objectives are.

The number of fuzzy allocation objectives may be used to maximise an objective function's value.

All nodes may not have the same g_t . One fuzzy objective g_1 and no other allocation goals would be sufficient if there were just one ij ij If each node has a target value of '0,' then the matching mathematical model (Model 5) is derived as follows from Model 4:

Model 5

$$\text{maximize } z = \sum_{i=1}^m \sum_{j=1}^n w_{ij} \mu_{ij} + \sum_{k=1}^p w_k \mu_k \tag{9}$$

subject to

$$\mu_{ij} \leq 1 - \left[\frac{y_{ij} - \hat{g}_{ij}^1}{d_{ij}^1} z_{ij}^1 + \frac{y_{ij} - 0}{\varepsilon} (1 - z_{ij}^1) \right] \tag{10}$$

$$\mu_{ij} \leq 1 - \left[\frac{\hat{g}_{ij}^1 - y_{ij}}{d_{ij}^1} z_{ij}^1 + \frac{0 - y_{ij}}{\varepsilon} (1 - z_{ij}^1) \right] \quad (i=1, 2, \dots, m; j=1, 2, \dots, n) \tag{11}$$

$$Z^k = \sum_{i=1}^m \sum_{j=1}^n C_{ij}^k y_{ij} \tag{12}$$

$$\mu_k \leq 1 - \frac{Z^k - \hat{g}_k}{d_k^-} \quad \forall k \tag{13}$$

$$\mu_k \leq 1 - \frac{\hat{g}_k - Z^k}{d_k^+} \quad \forall k \tag{14}$$

$$\mu_{ij} \geq 0 \quad \forall i \text{ and } j \tag{15}$$

$$\mu_k \geq 0 \quad \forall k \tag{16}$$

$$\sum_{j=1}^n y_{ij} \leq a_i \quad \forall i, \tag{17}$$

$$\sum_{i=1}^m y_{ij} \geq b_j \quad \forall j \tag{18}$$

$$y_{ij} \geq 0, z_{ij}^1 = 0 \text{ or } 1 \quad \forall i \text{ and } j. \tag{19}$$

Here, $d_{ij} 1-$ and $d_{ij} 1+$ are the maximum allowable negative and positive deviations respectively for $\hat{g}_{ij} 1$. $d_k 1-$ and $d_k 1+$ are the positive and negative deviations respectively corresponding to objective functions Z_k .

If an allocation is not made in a cell, a very tiny positive number is utilised to give a high ambition value "1." Due to the fact that the allocation does not have to be done in each cell, this scenario has arisen.

For example, if a given node has two fuzzy aspiration levels (multi-choice objectives for associated nodes), then fuzzy goal programming selects any one of these goals in such a manner that it gives the best solution for that node. According to Chang (2008), Equations 10 and 11 may be reduced to:

$$\mu_{ij} \leq 1 - \left[\frac{y_{ij} - \hat{g}_{ij}^1}{d_{ij}^{1-}} z_{ij}^1 z_{ij}^2 + \frac{y_{ij} - \hat{g}_{ij}^2}{d_{ij}^{2-}} z_{ij}^1 (1 - z_{ij}^2) \right] + \frac{y_{ij} - 0}{\epsilon} (1 - z_{ij}^1) z_{ij}^2 \tag{20}$$

$$\mu_{ij} \leq 1 - \left[\frac{\hat{g}_{ij}^1 - y_{ij}}{d_{ij}^{1+}} z_{ij}^1 z_{ij}^2 + \frac{\hat{g}_{ij}^2 - y_{ij}}{d_{ij}^{2+}} z_{ij}^1 (1 - z_{ij}^2) \right] + \frac{y_{ij} - 0}{\epsilon} (1 - z_{ij}^1) z_{ij}^2 \tag{21}$$

$$z_{ij}^1 + z_{ij}^2 \geq 1 \tag{22}$$

$$z_{ij}^1 = 0 \text{ or } 1 \quad \forall i \text{ and } j. \tag{23}$$

Here, d_{ij}^- and d_{ij}^+ are the maximum allowable negative and positive deviations respectively from \hat{g}_{ij}^t for $t=1, 2$.

Again, if each node has three fuzzy ambition levels, or fuzzy multi-choice objectives for corresponding nodes, then fuzzy goal programming selects any one of these goals in such a manner that it offers the best answer. According to Chang (2008), Equations 10 and 11 may be reduced to:

$$\mu_{ij} \leq 1 - \left[\frac{y_{ij} - \hat{g}_{ij}^1}{d_{ij}^-} z_{ij}^1 + \frac{y_{ij} - \hat{g}_{ij}^2}{d_{ij}^-} z_{ij}^1 (1 - z_{ij}^2) + \frac{y_{ij} - \hat{g}_{ij}^3}{d_{ij}^-} (1 - z_{ij}^1) z_{ij}^2 + \frac{y_{ij} - 0}{\varepsilon} (1 - z_{ij}^1) (1 - z_{ij}^2) \right] \tag{24}$$

$$\mu_{ij} \leq 1 - \left[\frac{\hat{g}_{ij}^1 - y_{ij}}{d_{ij}^+} z_{ij}^1 + \frac{\hat{g}_{ij}^2 - y_{ij}}{d_{ij}^+} z_{ij}^1 (1 - z_{ij}^2) + \frac{\hat{g}_{ij}^3 - y_{ij}}{d_{ij}^+} (1 - z_{ij}^1) z_{ij}^2 + \frac{0 - y_{ij}}{\varepsilon} (1 - z_{ij}^1) (1 - z_{ij}^2) \right] \tag{25}$$

$$z_{ij}^1 = 0 \text{ or } 1 \quad \forall i \text{ and } j. \tag{26}$$

Similarly, d_{ij}^- and d_{ij}^+ are the maximum allowable negative and positive deviations respectively y_{ij} for g_{ij}^t for $t = 1, 2, 3$. If we consider the goals are fuzzy multi-choices and again if y denotes the actual allocation in the cell (i,j), then the linear membership function μ_{ij} for the fuzzy goals of (i,j)-th node can be defined as follows:

$$\mu_{ij} = \begin{cases} 0, & y_{ij} \geq g_{ij}^t + d_{ij}^{t+} \\ 1 - \sum_{t=1}^s \frac{y_{ij} - \hat{g}_{ij}^t}{d_{ij}^{t-}} F_{ij}(B), & g_{ij}^t \leq y_{ij} \leq d_{ij}^{t+} + g_{ij}^t \\ 1, & g_{ij}^t = y_{ij} \\ 1 - \sum_{t=1}^s \frac{\hat{g}_{ij}^t - y_{ij}}{d_{ij}^{t+}} F_{ij}(B), & g_{ij}^t - d_{ij}^{t-} \leq y_{ij} \leq g_{ij}^t \end{cases}$$

Then, for every $i=1,2,\dots,m$ and $j=1,2,\dots,n$, respectively. There is only one ambition level to choose from for each objective when using $F_{ij}(B)$ (For additional information, read Tabrizi et al. (2012)). When it comes to positive and negative deviations, d_{ij}^+ and d_{ij}^- are the upper and lower limits, respectively y_{ij} the t -th aspiration level in (i,j) node, respectively.

It's worth noting that it isn't required that the allocation cells have the same amount of multi-choice objectives. After determining the number of fuzzy objectives in each cell, the MOFTP may be solved using the model 5 solution.

Table 1. Required vegetables in kg and deviations in locations

	A	B
F1	$\widehat{50}$ (10), $\widehat{95}$ (10), $\widehat{120}$ (10), $\widehat{70}$ (5)	90(30)
F2	$\widehat{120}$ (20), $\widehat{60}$ (10)	$\widehat{50}$ (5), $\widehat{80}$ (10), $\widehat{60}$ (10)
F3	$\widehat{80}$ (5), $\widehat{60}$ (10)	$\widehat{65}$ (5), $\widehat{45}$ (5), $\widehat{80}$ (5), $\widehat{150}$ (10)

NUMERICAL EXAMPLE

There are three marketplaces in which a storekeeper buys vegetables: S1, S2 and S3. The three sources S1, S2 and S3 have a maximum capacity of 150 kilogrammes, 220 kilogrammes and 200 kilogrammes, respectively. Two additional marketplaces, A and B, purchase the veggies from the storekeeper's supply. Vegetables in destinations must have a minimum capacity of 200 kilogrammes and 250 kg. The value of a market's assortment of veggies may not always be clear. There are several alternatives and hazy figures included in Table 1 when it comes to gathering veggies. Table 1 presents the needed quantities (fuzzy numbers) with brackets next to the required variances (positive and negative deviations are the same).

A crisp allocation "0" may be generated if any nodes do not make any allocations. Because of this, Table 1 does not illustrate that each node has a clear option. Table 2 shows the projected profit per kilogramme of veggies.

Table 3 shows the cost of transporting a kilogramme of veggies from source to destination.

It is clear that the business owner's objective is to maximise profits while reducing transportation costs in the presented scenario. He believes he can make a profit of \$3200 at the most, and not a penny more. With a minimum value of \$6500 and a maximum value of \$6700, he wants to keep shipping costs down.

Table 2. Profit in (\$) per kg

	A	B
F1	8.5	7.0
F2	7.0	6.5
F3	5.5	6.0

Table 3. Transportation cost/ kg in (\$)

	A	B
F1	14.5	24.0
F2	10.0	18.0
F3	15.5	12.0

We may argue that the allocations in the places are multi-choice fuzzy numbers based on the options of gathering veggies mentioned here. The provided technique must thus be useful in producing a better solution to this sort of issue.

Each cell has a weight of "0.05" and the goal functions are weighted at the following levels: profit (0.4), transportation cost (0.4), and total cost (0.3).

Model 6

$$\text{maximize } z = 0.05(\mu_{11} + \mu_{12} + \mu_{21} + \mu_{22} + \mu_{31} + \mu_{32}) + 0.4\mu_1 + 0.3\mu_2,$$

subject to

$$\begin{aligned} \mu_{11} &\leq 1 - \left[\frac{y_{11} - 50}{10} z_{11}^1 z_{11}^2 z_{11}^3 + \frac{y_{11} - 95}{10} (1 - z_{11}^1) z_{11}^2 z_{11}^3 + \frac{y_{11} - 120}{10} z_{11}^1 (1 - z_{11}^2) z_{11}^3 \right. \\ &\quad \left. + \frac{y_{11} - 70}{5} z_{11}^1 z_{11}^2 (1 - z_{11}^3) + \frac{y_{11} - 0}{\varepsilon} z_{11}^1 (1 - z_{11}^2) (1 - z_{11}^3) \right], \\ \mu_{11} &\leq 1 - \left[\frac{50 - y_{11}}{10} z_{11}^1 z_{11}^2 z_{11}^3 + \frac{95 - y_{11}}{10} (1 - z_{11}^1) z_{11}^2 z_{11}^3 + \frac{120 - y_{11}}{10} z_{11}^1 (1 - z_{11}^2) z_{11}^3 \right. \\ &\quad \left. + \frac{70 - y_{11}}{5} z_{11}^1 z_{11}^2 (1 - z_{11}^3) + \frac{0 - y_{11}}{\varepsilon} z_{11}^1 (1 - z_{11}^2) (1 - z_{11}^3) \right], \\ \mu_{12} &\leq 1 - \left[\frac{y_{12} - 90}{30} z_{12}^1 + \frac{y_{12} - 0}{\varepsilon} (1 - z_{12}^1) \right], \quad \mu_{12} \leq 1 - \frac{90 - y_{12}}{30} z_{12}^1 + \frac{0 - y_{12}}{\varepsilon} (1 - z_{12}^1), \\ \mu_{21} &\leq 1 - \left[\frac{y_{21} - 120}{10} z_{21}^1 z_{21}^2 + \frac{y_{21} - 60}{10} (1 - z_{21}^1) z_{21}^2 + \frac{y_{21} - 0}{\varepsilon} z_{21}^1 (1 - z_{21}^2) \right], \\ \mu_{22} &\leq 1 - \left[\frac{y_{22} - 50}{5} z_{22}^1 z_{22}^2 + \frac{y_{22} - 80}{10} (1 - z_{22}^1) z_{22}^2 + \frac{y_{22} - 60}{5} z_{22}^1 (1 - z_{22}^2) + \frac{y_{22} - 0}{\varepsilon} (1 - z_{22}^1) (1 - z_{22}^2) \right], \\ \mu_{22} &\leq 1 - \left[\frac{50 - y_{22}}{5} z_{22}^1 z_{22}^2 + \frac{80 - y_{22}}{10} (1 - z_{22}^1) z_{22}^2 + \frac{60 - y_{22}}{5} z_{22}^1 (1 - z_{22}^2) + \frac{0 - y_{22}}{\varepsilon} (1 - z_{22}^1) (1 - z_{22}^2) \right], \\ \mu_{31} &\leq 1 - \left[\frac{80 - y_{31}}{5} z_{31}^1 z_{31}^2 + \frac{60 - y_{31}}{10} (1 - z_{31}^1) z_{31}^2 + \frac{0 - y_{31}}{\varepsilon} z_{31}^1 (1 - z_{31}^2) \right], \\ \mu_{32} &\leq 1 - \left[\frac{y_{32} - 65}{5} z_{32}^1 z_{32}^2 + \frac{y_{32} - 45}{5} (1 - z_{32}^1) z_{32}^2 + \frac{y_{32} - 150}{10} z_{32}^1 (1 - z_{32}^2) + \frac{y_{32} - 0}{\varepsilon} (1 - z_{32}^1) (1 - z_{32}^2) \right], \end{aligned}$$

$$\mu_{z_2} \leq 1 - \left(\frac{65 - y_{22}}{5} z_{22}^1 z_{22}^2 + \frac{45 - y_{22}}{5} (1 - z_{22}^1) z_{22}^2 + \frac{150 - y_{22}}{10} z_{22}^1 (1 - z_{22}^2) + \frac{0 - y_{22}}{\varepsilon} (1 - z_{22}^1) (1 - z_{22}^2) \right),$$

$$Z = 8.5y_{11} + 7.0y_{12} + 7.0y_{21} + 6.5y_{22} + 5.5y_{31} + 6.0y_{32},$$

$$Z = 14.5y_{11} + 24y_{12} + 10y_{21} + 18y_{22} + 15.5y_{31} + 12y_{32}$$

$$\mu_1 \leq 1 - \frac{3200 - Z^1}{200},$$

$$\mu_2 \leq 1 - \frac{Z^1 - 6500}{200},$$

$$y_{11} + y_{12} \leq 150,$$

$$y_{21} + y_{22} \leq 220,$$

$$y_{32} \leq 200,$$

$$y_{11} + y_{21} + y_{31} \geq 200,$$

$$y_{12} + y_{22} + y_{32} \geq 250,$$

$$z_{11}^1 + z_{11}^2 \geq 1,$$

$$z_{11}^1 + z_{11}^3 \geq 1,$$

$$z_{31}^1 + z_{31}^2 \geq 1,$$

$$z_{21}^1 + z_{21}^2 \geq 1,$$

$$0 \leq \mu_{ij} \leq 1,$$

$$0 \leq \mu_p \leq 1,$$

$$y_{ij} \geq 0, z_{ij}^1 = 0 \text{ or } 1 \quad \forall i, j \text{ and } p.$$

Solution for Model 6 of Lingo software is as follows:

$z=0.88$ is the best value for z . There is a maximum profit of \$3181.5 and a minimum transportation cost of \$6500.0 in this best option. The following are the best allocations:

$$\begin{aligned} y_{11} &= 70.0; y_{12} = 60.0; \\ y_{21} &= 134.5; y_{22} = 50.0; \\ y_{31} &= 0.0; y_{32} = 150.0. \end{aligned}$$

The selection of fuzzy decision variables (i.e., the solution of MOFTP in terms of fuzzy variables) to get the optimum solution of y_{ij} is calculated as follows:

$$\begin{aligned} x_{11} &= \widehat{70}; x_{12} = \widehat{90}; x_{21} = \widehat{120}; \\ x_{22} &= \widehat{60}; x_{31} = \widehat{0}; x_{32} = \widehat{150}. \end{aligned}$$

SENSITIVITY ANALYSIS

The multiobjective transportation problem with fuzzy choice variables, referred to as MOFTP, is examined in detail in this work. The numerical example illustrates the usefulness of the suggested technique for resolving MOFTP problems including decision variables that are uncertain. The decision variables in this work are fuzzy numbers, thus they cannot be compared to any other model in our literature. Goal programming or updated multi-choice goal programming may be used if someone wants to solve a generic multi-objective transportation issue. In order to compare our research, we design a mathematical model based on the improved multi-choice goal programming process and solve it to get the following result:

Optimal value of objective functions are $Z^1 = \$3200$, $Z^2 = \$6500$;

$$\begin{aligned}x_{11} &= 0.0; x_{12} = 98.0; \\x_{21} &= 220.0; x_{22} = 0.0; \\x_{31} &= 0.0; x_{32} = 162.33.\end{aligned}$$

Even if the objective function yields a better answer than Model 6's, the cell allocations fail to meet the criteria as predicted in the allocation cells despite the higher objective function value. An alternative approach is to consider an optimization of objective functions and a compromise solution for a multi-objective transportation issue that does not meet all objectives for each cell. As a result, our suggested solution is superior than RMCGP in terms of solving multi-objective transportation problems. It's not clear to us how to design and solve the multi-objective transportation issue given the constraints that we offer in our suggested model.

CONCLUSION

In this article, a multi-objective fuzzy transportation issue has been studied in which the predicted allocations at the destinations are multi-choice fuzzy integers. Using multi-choice goal programming, we demonstrate how to solve the specified issue. In this research, a mathematical model is established to extract a better solution to the multi-objective transportation issue, which may arise in real-life situations where the mathematical model and solution process are not documented in the literature. In order to prove the model's viability, an example from the actual world has been used.

Use of uncertain programming to solve multiobjective decision-making problems may provide a novel approach to solving transportation and logistics problems in the future.

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