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Applications of Fuzzy Logic to the Transportation Network Design Problem in Multi-Criteria Optimization

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ABSTRACT

This study analyzes the Multi-Objective Transportation Problem using fuzzy decision factors (MOTP). The decision variable in a Transportation Problem is often treated as a real variable. Although this study makes extensive use of multi-choice fuzzy numbers, the decision variable at each node is instead selected at random. When more than one objective must be met in a transportation problem with a ṁ[=fuzzy decision variable, a multiobjective fuzzy transportation problem is posed (MOFTP). Our unique mathematical model of MOFTP includes fuzzy objectives for all of the objective functions. Then, the approach to solving the model is defined using the multi-goal programming technique. An illustrative numerical example is presented to better establish the usefulness of this article.

KEY WORD: Fuzzy Variable; Goal Programming; Multiobjective Decision Making; Multiple-Option Programming; Transportation Problem;

INTRODUCTION

The transportation problem is crucial when making decisions in the real world. For instance, a linear programming model may be used to determine the best course of action for the transportation problem. In order to minimize the overall cost of transportation and the cost per unit of commodities for the buyer, one must calculate how many units of a commodity are to be delivered from each source to different destinations `w5while fulfilling source availability and destination demand.

Hitchcock (1941) originally thought of the problem of mass transportation, and Koopmans (1944) improved it on his own (1949). (1949). A transportation problem with a single objective function is inadequate to meet a wide range of real-world decision-making challenges in today's competitive market. To address such complex real-world scenarios, the multi-objective transportation problem has to be introduced. Scholars like Verma et al. have done a number of studies in this field.

BAD SETTING

For a long time, the primary application of the mathematical model of the transportation issue was cost minimization. However, in recent times, academics have adapted a wide range of real-world decision-making challenges to threaten the existing market structure. Goal programming is often used by decision-makers to lower transportation costs and boost profits. However, modern problem-solving methods are often geared at picking the best option given the decision maker's criteria. This study introduces a novel class of transportation problems in

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which nodes' expectations take the form of fuzzy integers with several possible values. As a result, the decision-maker seeks to maximize profit while minimizing transport costs, all of which are multi-choice fuzzy numbers. Because the classic transportation problem cannot be solved using just real variables, we supplement them with fuzzy variables at each allocation node. If the decision maker is trying to maximize his profit without considering the cost of transportation, he or she may hurt the interests of their clients and risk losing them as a consequence. In this research, we give a mathematical model of the multi-objective transportation problem and set out to create an algorithm that maximizes not just the decision maker's profit but also the consumers' ideal goals. Until now, the literature has lacked a clear specification of the optimal goals for objective functions and the corresponding solutions. Here, we develop the proposed approach to select the optimal goal that corresponds to the objective functions and to establish the best possible aspiration levels for customers. The same goes for us.

STATISTICAL MODEL

In the first section, we present the concept of multi-objective programming. Fuzzy-targeted mathematical model of the transportation problem is constructed afterwards. As a means of addressing the transportation issue, the development of a fuzzy decision-making procedure is proposed.

Objectives Programming with Multiple Options

Chang (2007) was the first to introduce MCGP, which allows the decision maker to define MCALs for each objective, to the goal programming literature (i.e., one goal mapping multiple aspiration levels).

Programming goals may be summarised in this way:

$$\textbf{GP:} \text{minimize} \quad \sum_{i=1}^{p} w_i \left| Z^i(x) - g_i \right|, \tag{1}$$

Accomplishment function Zi(x) and gi (i=1,2,...,p) are the weights linked to the deviation of Zi(xachievement)'s function. The i-th goal's deviation is represented as |Zi(x)–gi|. 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:

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

subject to $x \in F$,

where w_i (i = 1, 2,...,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

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

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

$$x_{ij} \ge 0 \;\; \forall i,j, \tag{4}$$

The decision variable is xij and the transportation cost per commodity from the ith origin to the jth destination is Cii I = 1, 2,..., m; j = 1, 2,..., 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 ai and bj.

$\sum_{i=1}^{m} a_i \geq \sum_{j=1}^{n} b_j$ 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 (xij) 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 (xij) in the transportation issue are not behaving as they would in a classical transportation problem, but rather as a fuzzy variable (xij) 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

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

subject to

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

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

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

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

$$Z^k = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}^{k} x_{ij} \; (k = 1, 2, \ldots, p), \text{ subject to Equation 2 to} \qquad 4.$$

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

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

Although it may seem simple, Model 4 is in fact rather complex. It is possible to solve the multi-objective transportation issue using GP, RMCGP, 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,...., p, gk 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,...,p (i,j).

As a triangular fuzzy number, we may represent the allocation objectives gt. 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 gt. One fuzzy objective g1 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

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

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

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

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

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

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

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

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

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

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

Here, dij 1− and dij 1+ are the maximum allowable negative and positive deviations respectively for ˆgij 1 . dk 1− and dk 1+ are the positive and negative deviations respectively corresponding to objective functions Zk .

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:

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

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

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

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

Here, dij t− and dij t+ are the maximum allowable negative and positive deviations respectively from ˆgij 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:

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

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

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

Similarly, d^{t-}_{ij} and d^{t+}_{ij} are the maximum allowable negative and positive deviations respectively ij ij for $\hat{g}^{t}$ 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:

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

Then, for every i=1,2,...,m and j=1,2,...,n, respectively. There is only one ambition level to choose from for each objective when using Fij(B) (For additional information, read Tabrizi et al. (2012)). When it comes to positive and negative deviations, dt+ and dt are the upper and lower limits, respectively ij 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

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

subject to

$$\mu_{11} \le 1-\left[\frac{y_{11}-50}{10}z_{11}^1 z_{11}^2 z_{11}^3+\frac{y_{11}-95}{10}\left(1-z_{11}^1\right)z_{11}^2 z_{11}^3+\frac{y_{11}-120}{10}z_{11}^1\left(1-z_{11}^2\right)z_{11}^3\right.$$

$$\left.+\frac{y_{11}-70}{5}z_{11}^1 z_{11}^2\left(1-z_{11}^3\right)+\frac{y_{11}-0}{\varepsilon}z_{11}^1\left(1-z_{11}^2\right)\left(1-z_{11}^3\right)\right],$$

$$\mu_{11} \le 1-\left[\frac{50-y_{11}}{10}z_{11}^1 z_{11}^2 z_{11}^3+\frac{95-y_{11}}{10}\left(1-z_{11}^1\right)z_{11}^2 z_{11}^3+\frac{120-y_{11}}{10}z_{11}^1\left(1-z_{11}^2\right)z_{11}^3\right.$$

$$\left.+\frac{70-y_{11}}{5}z_{11}^1 z_{11}^2\left(1-z_{11}^3\right)+\frac{0-y_{11}}{\varepsilon}z_{11}^1\left(1-z_{11}^2\right)\left(1-z_{11}^3\right)\right]$$

$$\mu_{12} \le 1-\left[\frac{y_{12}-90}{30}z_{12}^1+\frac{y_{12}-0}{\varepsilon}\left(1-z_{12}^1\right)\right],\ \mu_{12} \le 1-\left[\frac{90-y_{12}}{30}z_{12}^1+\frac{0-y_{12}}{\varepsilon}\left(1-z_{12}^1\right)\right],$$

$$\mu_{21} \le 1-\left[\frac{y_{21}-120}{10}z_{21}^1 z_{21}^2+\frac{y_{21}-60}{10}\left(1-z_{21}^1\right)z_{21}^2+\frac{y_{21}-0}{\varepsilon}z_{21}^1\left(1-z_{21}^2\right)\right],$$

$$\mu_{22} \le 1-\left[\frac{y_{22}-50}{5} z_{22}^{1} z_{22}^{2}+\frac{y_{22}-80}{10}\left(1-z_{22}^{1}\right)\right) z_{22}^{2}+\frac{y_{22}-60}{5} z_{22}^{1}\left(1-z_{22}^{2}\right)+\frac{y_{22}-0}{\varepsilon}\left(1-z_{22}^{1}\right)\left(1-z_{22}^{2}\right)],$$

$$\mu_{22} \le 1-\left[\frac{50-y_{22}}{5} z_{22}^{1} z_{22}^{2}+\frac{80-y_{22}}{10}\left(1-z_{22}^{1}\right)\right) z_{22}^{2}+\frac{60-y_{22}}{5} z_{22}^{1}\left(1-z_{22}^{2}\right)+\frac{0-y_{22}}{\varepsilon}\left(1-z_{22}^{1}\right)\left(1-z_{22}^{2}\right)],$$

$$\mu_{31} \le 1-\left[\frac{80-y_{31}}{5} z_{31}^{1} z_{31}^{2}+\frac{60-y_{31}}{10}\left(1-z_{31}^{1}\right)\right) z_{31}^{2}+\frac{0-y_{31}}{\varepsilon} z_{31}^{1}\left(1-z_{31}^{2}\right)],$$

$$\mu_{32} \le 1-\left[\frac{y_{32}-65}{5} z_{32}^{1} z_{32}^{2}+\frac{y_{32}-45}{5}\left(1-z_{32}^{1}\right)\right) z_{32}^{2}+\frac{y_{32}-150}{10} z_{32}^{1}\left(1-z_{32}^{2}\right)+\frac{y_{32}-0}{\varepsilon}\left(1-z_{32}^{1}\right)\left(1-z_{32}^{2}\right)],$$

$$\mu_{32} \le 1-\left[\frac{65-y_{32}}{5} z_{32}^{1} z_{32}^{2}+\frac{45-y_{32}}{5}\left(1-z_{32}^{1}\right)\right) z_{32}^{2}+\frac{150-y_{32}}{10} z_{32}^{1}\left(1-z_{32}^{2}\right)+\frac{0-y_{32}}{\varepsilon}\left(1-z_{32}^{1}\right)\left(1-z_{32}^{2}\right)],$$

$$Z^1=8.5\, y_{11}+7.0\, y_{12}+7.0\, y_{21}+6.5\, y_{22}+5.5\, y_{31}+6.0\, y_{32},$$
$$Z^2=14.5\, y_{11}+24\, y_{12}+10\, y_{21}+18\, y_{22}+15.5\, y_{31}+12\, y_{32},$$
$$\mu_1 \le 1-\frac{3200-Z^1}{200},$$

$$\mu_2 \le 1-\frac{Z^2-6500}{200},$$

$$y_{11}+y_{12} \le 150,$$
$$y_{21}+y_{22} \le 220,$$
$$y_{32} \le 200,$$
$$y_{11}+y_{21}+y_{31} \ge 200,$$
$$y_{12}+y_{22}+y_{32} \ge 250,$$
$$z_{11}^{1}+z_{11}^{2} \ge 1,$$
$$z_{11}^{1}+z_{11}^{3} \ge 1,$$
$$z_{31}^{1}+z_{31}^{2} \ge 1,$$
$$z_{21}^{1}+z_{21}^{2} \ge 1,$$
$$0 \le \mu_{ij} \le 1,$$
$$0 \le \mu_{p} \le 1,$$
$$y_{ij} \ge 0,\ z_{ij}^{1}=0\, or\, 1 \quad \forall i, j \text{ and } p.$$

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:

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

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:

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

SENSITIVITY ANALYSIS

In this paper, we take a close look at the MOFTP (multiobjective transportation problem with fuzzy choice variables). The numerical example demonstrates how the proposed method can be used to solve MOFTP issues with unknown choice variables. This work's decision variables are fuzzy integers, making direct comparisons to existing models impossible. A general multi-objective transportation problem may be solved using goal programming or updated multi-choice goal programming. To evaluate our findings, we developed a mathematical model using the enhanced multi-choice goal programming procedure, and we solved it to get the following result::

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

$$x_{11}=0.0;\ x_{12}=98.0;$$
$$x_{21}=220.0;\ x_{22}=0.0;$$
$$x_{21}=0.0;\ x_{32}=162.33.$$

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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