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A FUZZY APPROCH FOR FINDING INITIAL SOLUTION FOR TRANSPORTATION PROBLEM

BY

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Abstract. Transportation models have wide applications in logistics and supply chain for reducing the cost but the availability, need and unit cost of transportation may not be certain known in real-time applications. Fuzzy numbers are the name given to these ambiguous data. In this study, we investigate a balanced fuzzy transportation problem where the availabilities, requirements and the transportation costs are all triangular fuzzy numbers. In the initial stage, triangular numbers are transformed into crisp numbers using the ranking approach. The Initial Basic Feasible Solution is then obtained in the second step by using several approaches such as the North-West Corner Rule, Least Cost Method and Vogel's Approximation Method. An example in which IBFS is obtained for a transportation problem with fuzzy numbers is presented at the end of the research.

Keywords: transportation problem, triangular fuzzy numbers, ranking technique, initial basic feasible solution.

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1. Introduction

The transportation problem is a subclass of linear programming problems (LPPs) in which the objective is to transport various quantities of a single homogeneous commodity from multiple sources to different destinations in such a way that the total transportation cost is minimized. Transportation models play a crucial role in logistics and supply chain management, where optimizing transportation costs is essential for efficient operations (Hossain and Ahmed, 2020). Traditionally, when the cost coefficients, supply, and demand quantities are known precisely, various algorithms have been developed to solve the transportation problem. However, in real-world applications, these parameters are often uncertain due to factors such as weather conditions, road hazards, traffic disruptions, penalties for delayed deliveries, and fluctuating safety requirements (Chanas and Kuchta, 1996). This inherent uncertainty leads to the formulation of fuzzy transportation problems (FTP).

A FTP is one in which the transportation costs, supply and demand quantities are represented as fuzzy numbers rather than precise values. These fuzzy numbers can be of various types, such as normal, abnormal, triangular or trapezoidal fuzzy numbers (Dubois and Prade, 1983). Most existing approaches for solving FTPs focus on obtaining crisp solutions after defuzzification, rather than directly handling the fuzzy nature of the problem (Liu and Kao, 2004). Several researchers have proposed different techniques for addressing FTPs, including ranking functions and extension principles to convert fuzzy numbers into crisp equivalents, making the problem more manageable within traditional optimization frameworks (Ammar and Youness, 2005; Kaur and Kumar, 2011).

In this study, we investigate a balanced FTP in which all parameters - transportation costs, supply and demand - are represented as triangular fuzzy numbers (TFNs). The initial basic feasible solution (IBFS) is determined using the North-West Corner Method (NWCM), the Least Cost Method (LCM), and Vogel's Approximation Method (VAM) (Kavitha and Pandian, 2012; Chauhan and Joshi, 2013). To assess the efficiency of these methods, we analyze their computational performance and the quality of the obtained solutions through numerical examples. The study provides insights into how different IBFS methods perform in a fuzzy environment and highlights their applicability in handling transportation problems under uncertainty.

2. Preliminaries

Fuzzy numbers are an essential mathematical tool for modeling uncertainty in real-world problems. Among various types, TFNs are widely used due to their simplicity and computational efficiency. A TFN $\widetilde{A}$ is represented by a triplet (a_l, a_m, a_u), where:

- a_l is the lower bound
- a_m is the most plausible value
- a_u is the upper bound (Jolly Puri, 2008; Kaur *et al.*, 2014).

The membership function $\mu_{\tilde{A}}(x)$ of a TFN is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a_l}{a_m-a_l}, & a_l \leq x < a_m \\ \frac{a_u-x}{a_u-a_m}, & a_m \leq x < a_u \\ 0, & otherwise. \end{cases} \tag{1}$$

Further, the α- cut of the TFN $\widetilde{A} = (a_l, a_m, a_u)$ is the closed interval

$$A_\alpha = [a_l + (a_m - a_l)\alpha, a_u + (a_m - a_u)\alpha\,], \alpha \in (0, 1]. \tag{2}$$

Another representation of the TFN is:

$$\widetilde{A} = (a_m - \alpha, a_m, a_m + \beta), \tag{3}$$

where $a_m - \alpha = a_l$ and $a_m + \beta = a_u$ (Dubois and Prade, 1983; Chanas and Kuchta, 1998).

Thus, $\tilde{A}$ can also be rewritten in another form as:

$$\widetilde{A} = (a_m, \alpha, \beta). \tag{4}$$

Arithmetic Operations with TFNs

For two TFNs $\widetilde{A} = (a_l, a_m, a_u)$ and $\widetilde{B} = (b_l, b_m, b_u)$, the following arithmetic operations are commonly used:

- Addition: $\widetilde{A} \oplus \widetilde{B} = (a_l + b_l, a_m + b_m, a_u + b_u)$ (5)
- Subtraction: $\widetilde{A} \ominus \widetilde{B} = (a_l - b_u, a_m - b_m, a_u - b_l)$ (6)
- Scalar multiplication:
  $k\tilde{A} = \begin{cases} (ka_l, ka_m, ka_u), & k > 0 \\ (ka_u, ka_m, ka_l), & k < 0 \end{cases}$,($\forall$) k scalar (7)
- Symmetry: $(-\widetilde{A}) = (-a_u, -a_m, -a_l)$ (8)
- Multiplication: $\widetilde{A} \otimes \widetilde{B} = (a', b', c')$, (9)

where

$$a' = \min(a_l b_l, a_l b_u, b_l a_u, b_u a_u) \tag{10}$$

$$b' = a_m b_m \tag{11}$$

$$c' = \max(a_l b_l, a_l b_u, b_l a_u, b_u a_u) \tag{12}$$

- Division: $\widetilde{A} \oslash \widetilde{B} = (a', b', c')$, (13)

where

$$a' = \min\left(\frac{a_l}{b_l}, \frac{a_l}{b_u}, \frac{a_u}{b_l}, \frac{a_u}{b_u}\right) \tag{14}$$

$$b' = \frac{a_m}{b_m} \tag{15}$$

$$c' = \max\left(\frac{a_l}{b_l}, \frac{a_l}{b_u}, \frac{a_u}{b_l}, \frac{a_u}{b_u}\right), b_l \neq 0, b_m \neq 0, b_u \neq 0. \tag{16}$$

Fuzzy arithmetic plays a crucial role in solving optimization problems where uncertainty is present. Several researchers have incorporated these arithmetic operations into fuzzy optimization models, ensuring that uncertainty is handled effectively throughout the decision-making process. An approach that integrates fuzzy arithmetic directly into linear programming models, allowing for the preservation of fuzzy constraints within optimization frameworks, is presented in (Maleki *et al.*, 2000).

Ranking of Triangular Fuzzy Numbers

To compare fuzzy numbers, a ranking function $\Re(\widetilde{A})$ is used to map each fuzzy number $\widetilde{A} = (a_l, a_m, a_u)$ (or $\widetilde{A} = (a_m, \alpha, \beta)$) into a real number. One common ranking method (Chanas and Kuchta, 1998) is the graded mean integration representation, defined as:

$$\Re(\widetilde{A}) = \frac{1}{4}(a_l + 2a_m + a_u) \text{ or} \tag{17}$$

$$\Re(\widetilde{A}) = a_m + \frac{(\beta - \alpha)}{4}. \tag{18}$$

3. Formulation of Fuzzy Transportation Problems and Initial Solution Methods

A FTP is mathematically formulated similarly to the classical problem but incorporates uncertainty through fuzzy values in its parameters. Let $\tilde{s}_i$ represent the fuzzy supply at source i, $\tilde{d}_j$ represent the fuzzy demand at destination j and $\tilde{c}_{ij}$ represent the fuzzy transportation cost from i to j . The decision variable x_{ij} represents the crisp quantity transported between these points. The goal of the FTP is to minimize the total transportation cost, expressed as follows:

$$\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{c}_{ij}\, x_{ij} \tag{19}$$

subject to the following fuzzy constraints:

1. The total quantity transported from each supply source should equal its fuzzy supply:

$$\sum_{j=1}^{n} x_{ij} = \tilde{s}_i, \forall\, i = \overline{1,m} \tag{20}$$

2. The total quantity received at each demand destination should equal its fuzzy demand:

$$\sum_{i=1}^{m} x_{ij} = \tilde{d}_j, \forall\, j = \overline{1,n} \tag{21}$$

3. The transported quantity must be non-negative:

$$x_{ij} \geq 0, \forall\, i = \overline{1,m}, j = \overline{1,n} \tag{22}$$

Since the problem involves fuzzy values, a defuzzification method is typically required to convert fuzzy parameters into crisp equivalents, enabling the use of classical optimization techniques. A ranking function can be applied to assign a crisp equivalent to each fuzzy number, facilitating problem-solving through traditional transportation algorithms (Kumari, 2014; Vasant *et al.*, 2004).

Once the mathematical model of a FTP has been formulated, the following steps are followed to determine an IBFS:

1. Defuzzification of parameters – Convert fuzzy supply, demand and cost values into crisp equivalents using an appropriate ranking function.
2. Check if the problem is balanced – Verify whether the total crisp supply equals the total crisp demand.
   If the problem is unbalanced, a dummy source or destination is introduced to ensure equality, with fuzzy transportation costs typically set to $(0,0,0)$ to avoid influencing the solution.
3. Determining an Initial Basic Feasible Solution Using One of Three Methods: NWCM, LCM and VAM.

Northwest Corner Method (NWCM) for Fuzzy Transportation Problems

The NWCM provides a quick way to generate an initial solution by allocating shipments starting from the upper-left (northwest) corner of the transportation table and proceeding stepwise. This method does not consider transportation costs but ensures all supply and demand constraints are met. When adapted to fuzzy environments, the method follows these steps:

a) Begin allocation at the top-left cell, assigning the maximum possible quantity while maintaining feasibility.
b) If the supply for a source is fully allocated, move to the next source in the same column; if the demand for a destination is fully met, move to the next column in the same row.
c) Repeat the process until all available supply is distributed and all demand is satisfied, ensuring all allocations are completed systematically.

Least Cost Method (LCM) for Fuzzy Transportation Problems

The LCM is a heuristic technique that prioritizes allocations in the lowest-cost cells of the transportation matrix. This approach ensures that the transportation cost remains as low as possible at each step of the allocation process. The fuzzy adaptation of this method follows these steps:

a) Identify the cell with the lowest defuzzified transportation cost in the matrix.
b) Allocate the maximum possible quantity to the selected cell while ensuring feasibility. This means that either the entire supply for the corresponding row or the entire demand for the corresponding column must be satisfied before moving forward.
c) Adjust the remaining supply and demand values accordingly. If the entire supply for a source is exhausted, eliminate that row from further consideration. If the demand for a destination is fully met, eliminate the corresponding column.
d) Repeat the process by selecting the next lowest-cost cell from the remaining available allocations, following the same principles until all allocations are made, and supply and demand constraints are fully satisfied.

The LCM is particularly effective in cases where cost efficiency is a priority, as it systematically seeks to reduce total transportation expenditures.

Vogel's Approximation Method (VAM) for Fuzzy Transportation Problems

VAM is an advanced heuristic that refines the allocation process by incorporating cost penalties, ensuring that the initial feasible solution is closer to optimal. This method prioritizes allocations based on the impact of selecting a particular cell, rather than just its absolute cost. When adapted to a fuzzy environment, VAM follows these detailed steps:

a) Compute cost penalties: For each row and column, determine the penalty by calculating the difference between the lowest and second-lowest cost values after defuzzification. This penalty represents the potential loss incurred if the second-lowest cost cell is chosen instead of the minimum-cost cell.
b) Identify the most significant penalty: The row or column with the highest penalty is selected first, as it indicates the greatest potential cost savings if handled efficiently.
c) Allocate resources to the lowest-cost cell: Within the selected row or column, allocate the maximum feasible quantity to the cell with the lowest transportation cost. This ensures that allocations are made in a manner that minimizes the overall transportation cost.
d) Update supply and demand: After making an allocation, adjust the available supply and demand values accordingly. If a row is completely allocated, remove it from further consideration. If a column is fully satisfied, exclude it from subsequent iterations.
e) Recompute penalties and iterate: Once the allocation is made, recalculate penalties for the remaining rows and columns, then repeat the process until all allocations are completed and the transportation matrix is fully assigned.

The VAM is particularly beneficial in achieving a near-optimal initial solution, reducing the number of iterations required in later optimization phases. By integrating fuzzy costs, this method becomes even more robust in handling uncertainty and making cost-effective allocations in real-world transportation scenarios.

The next section will explore the implementation and comparative performance of these methods in solving FTPs.

4. Numerical Example

To illustrate the methods for determining an IBFS in a FTP, we consider a numerical example that models a real-world transportation scenario. The problem involves three supply sources, each with a limited but uncertain quantity of goods, and four demand destinations that require varying amounts of supplies. The transportation costs, as well as the supply and demand values, are represented using TFNs, capturing the inherent uncertainty in cost estimation and resource availability.

The objective is to determine an initial feasible transportation plan that satisfies all supply and demand constraints while minimizing overall transportation costs. Given the uncertain nature of cost coefficients, the transportation costs between sources and destinations are expressed as fuzzy numbers, reflecting fluctuations in pricing, fuel costs and logistical conditions.

The transportation cost matrix, along with the fuzzy supply and demand values, are presented in the table below.

Table 1
Transportation Cost Matrix and Fuzzy Supply/Demand Values

Supply/ Demand	D1	D2	D3	D4	Supply
S1	(5, 10, 15)	(10, 15, 20)	(5, 15, 20)	(10, 15, 20)	(20, 25, 30)
S2	(10, 15, 20)	(5, 10, 15)	(15, 20, 25)	(5, 10, 15)	(15, 20, 25)
S3	(15, 20, 25)	(10, 15, 20)	(10, 15, 20)	(5, 10, 15)	(20, 25, 30)
Demand	(15, 20, 25)	(10, 15, 20)	(10, 15, 20)	(15, 20, 25)	

The values in the table represent the cost of transporting goods from each supply source to each demand destination in the form of a TFN (a_l, a_m, a_u), where a_l represents the minimum possible cost, a_m represents the most likely transportation cost and a_u represents the maximum possible cost.

Similarly, the supply and demand values are also represented as TFNs, where the actual availability and requirements may fluctuate within the given ranges.

In order to determine an IBFS, the following steps are followed:

1. To convert fuzzy costs, fuzzy supply and demand values into crisp values, we applied the centroid ranking function (17). Applying this formula, the defuzzified cost matrix is:

Table 2
Defuzzified cost matrix

Supply/ Demand	D1	D2	D3	D4	Supply
S1	10	15	13.75	15	25
S2	15	10	20	10	20
S3	20	15	15	10	25
Demand	20	15	15	20	

2. This problem is a balanced one so it will be solved by applying one of the three methods.

Solution using Northwest Corner Method (NWCM)

The NWCM provides a straightforward approach to determining an IBFS in the transportation problem. The allocation begins at the top-left (northwest) corner of the transportation table and proceeds systematically, ensuring that supply and demand constraints are met. As allocations are made, the method moves right when demand is fulfilled and downward when supply is exhausted. This process continues until all resources are fully assigned.

Applying NWCM to the given problem results in the following allocation matrix:

Table 3
Initial Basic Feasible Solution Using NWCM

Supply/ Demand	D1	D2	D3	D4	Supply
S1	20	5			25
S2		10	10		20
S3			5	20	25
Demand	20	15	15	20	

The total crisp transportation cost obtained using the NWCM is 850, while the fuzzy transportation cost is represented as the triangular fuzzy number (500, 850, 1200), where 500 is the lower bound, 850 is the most likely cost, and 1200 is the upper bound.

While NWCM guarantees a feasible solution, it does not account for transportation costs, potentially leading to a higher total transportation cost compared to cost-aware methods such as the LCM or VAM. However, it serves as a useful starting point for further optimization.

Solution using Least Cost Method (LCM)

The LCM is an effective approach for determining an IBFS in the transportation problem by prioritizing cost minimization at each allocation step. The method systematically selects the cell with the lowest transportation cost and assigns as much as possible while ensuring that supply and demand constraints are met. Once an allocation is made, the method updates the remaining supply and demand, repeating the process until all resources are fully assigned.

Applying LCM to the given problem results in the following allocation matrix:

Table 4
Initial Basic Feasible Solution Using LCM

Supply/ Demand	D1	D2	D3	D4	Supply
S1	20		5		25
S2		15		5	20
S3			10	15	25
Demand	20	15	15	20	

The total crisp transportation cost obtained using the Least Cost Method (LCM) is 768.75, while the fuzzy transportation cost is represented as the triangular fuzzy number (400, 775, 1125), where 400 is the lower bound, 775 is the most likely cost, and 1125 is the upper bound.

Although LCM produces a more cost-efficient solution than the NWCM, it does not always guarantee an optimal allocation. However, LCM remains a widely used method due to its simplicity and effectiveness in minimizing initial transportation costs.

Solution using Vogel's Approximation Method (VAM)

The VAM is an improved approach for finding an IBFS in the transportation problem by incorporating a penalty-based selection process to minimize transportation costs from the start. Instead of allocating directly from the northwest corner or selecting the lowest-cost cell at each step, VAM calculates penalties for each row and column based on the difference between the two smallest costs. The row or column with the highest penalty is prioritized, ensuring that allocations are made in a way that minimizes potential cost increases. This process continues iteratively, selecting the least-cost cell within the highest-penalty row or column, allocating the maximum possible amount, and adjusting the supply and demand constraints accordingly.

Applying VAM to the given problem results in the following initial solution, as presented in the table below:

Table 5

Initial Basic Feasible Solution Using VAM

Supply/ Demand	D1	D2	D3	D4	Supply
S1	15		10		25
S2	5	15			20
S3			5	20	25
Demand	20	15	15	20	

The crisp transportation cost for the VAM allocation is 787.5, while the fuzzy transportation cost is represented as the triangular fuzzy number (400, 800, 1150), where 400 represents the minimum possible cost, 800 is the most likely transportation cost, and 1150 is the maximum possible cost.

Comparing the results, NWCM resulted in the highest crisp cost of 850, with a fuzzy cost of (500, 850, 1200), making it the least cost-effective method. VAM provided an improvement over NWCM, reducing the crisp transportation cost to 787.5 and the fuzzy cost to (400, 800, 1150). However, LCM achieved the lowest transportation cost, with a crisp cost of 768.75 and a fuzzy cost of (400, 775, 1125), making it the most cost-efficient method among the three.

While VAM incorporates a penalty-based allocation strategy, it does not always guarantee the lowest transportation cost, as seen in this case. LCM, by prioritizing the lowest-cost cells at each allocation step, resulted in the most cost-effective solution. In contrast, NWCM, which does not consider cost in its allocation process, produced the highest total expense. Therefore, among the tested methods, LCM provides the best initial allocation in terms of cost efficiency. If an optimal solution is pursued, further refinement using optimization techniques such as the MODI method or Stepping Stone Method is recommended to ensure the best possible allocation while addressing potential degeneracy.

5. Conclusions

In this study the Initial Basic Feasible Solutions for a fuzzy transportation problem were determined using three different methods: the Northwest Corner Method, the Least Cost Method and Vogel's Approximation Method. Different than the traditional transportation problems where cost, supply and demand are represented as crisp values, this study considers triangular fuzzy numbers to model transportation cost, supply and demand, leading to a representation that is more realistic when dealing with uncertainty in decision-making. To support comparative analysis, the fuzzy parameters were defuzzified into crisp values. Then, to generate an initial feasible solution, each method was run to assess its efficiency.

The outcome highlights that the Least Cost Method provided the most cost-effective initial solution, achieving the lowest crisp transportation cost of 768.75, against to 787.5 for Vogel's Approximation Method and 850 for Northwest Corner Method. Variation in the corresponding fuzzy transportation costs was identified, with the Least Cost Method yielding (400, 775, 1125), Vogel's Approximation Method producing (400, 800, 1150) and the Northwest Corner Method resulting in (500, 850, 1200). These findings suggest that the Least Cost Method outperforms both Vogel's Approximation Method and the Northwest Corner Method. This leads to minimization of the transportation costs, turning the Least Cost Method into the preferred choice when selecting an initial solution for further optimization.

It is to highlight that Vogel's Approximation Method, despite its structured penalty-based allocation, did not lead to the best solution in this situation. Whilst Vogel's Approximation Method balances cost efficiency with a strategic allocation process, the Least Cost Method's lead to a better allocation via direct cost-minimization approach. On the other hand, the Northwest Corner Method provided the least cost-efficient solution, because it does not take the transportation costs into consideration when making allocations. Since the most effective IBFS method could vary depending on features of the problem, these results highlight that the selection of the method should be much dependent on the context.

Another target of the study was to analyze the quantities being transported from each source to each destination but computed both in crisp values (after defuzzification) and fuzzy values (before transformation). The resulted allocation matrices from each method showed the way how supply was distributed across demand points while fulfilling the constraints. Future research could explore preserving the fuzzy nature of transportation costs throughout the optimization process, rather than relying on initial defuzzification, to enhance adaptability in decision-making.

MATLAB scripts were developed to implement these methods. Computational validation would enable automatic allocation and cost comparison. The scripts processed fuzzy values, performed defuzzification and applied each method to generate an initial solution. They ensure a robust framework for future fuzzy analysis of transportation.

While this study focused on determining IBFSs, an important future step is to determine the optimal solution for a fuzzy transportation problem. Future research will analyze various optimization techniques such as the Modified Distribution Method (MODI) or the Stepping Stone Method, thus to refine the initial allocations and further minimize transportation costs. Moreover, advanced approaches could be analyzed to enhance solution accuracy, e.g. metaheuristic algorithms specifically designed for fuzzy environments. By optimizing transportation targets while preserving the fuzzy nature of the problem, the present study intends to provide to more efficient and practical decision-making frameworks for real-world supply chain and logistics problems.

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O ABORDARE FUZZY PENTRU DETERMINAREA SOLUȚIEI INIȚIALE A PROBLEMEI DE TRANSPORT

(Rezumat)

Modelele de transport au aplicații extinse în logistică şi lanțul de aprovizionare, fiind utilizate pentru reducerea costurilor, însă, în aplicațiile reale, disponibilitatea, cererea şi costul unitar al transportului pot să nu fie cunoscute cu exactitate. Numerele fuzzy sunt folosite pentru a descrie aceste date ambigue. În acest studiu, investigăm o problemă de transport echilibrată în care disponibilitățile, necesarul şi costurile de transport sunt reprezentate prin numere fuzzy triunghiulare. În prima etapă, aceste numere triunghiulare sunt transformate în valori crisp folosind o metodă de ordonare. Apoi, în a doua etapă, este determinată Soluția Inițială Fezabilă de Bază (IBFS) utilizând mai multe metode, printre care Regula Colțului de Nord-Vest, Metoda Costului Minim şi Metoda de Aproximare a lui Vogel. La finalul studiului, este prezentat un exemplu numeric în care se obține o soluție inițială pentru o problemă de transport cu numere fuzzy.