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A Fuzzy Multi-Index Transportation Assignment Model with Triangular Fuzzy Costs

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Abstract - The fuzzy multi-index transportation assignment problem, also known as FMITAP, is an extension of traditional assignment and transportation models that was developed with the purpose of managing uncertainty in situations that involve as many dimensions as possible. As an illustration, it is utilized for the purpose of assigning resources across a wide variety of origins, destinations, modes, and commodities that exist with ambiguous pricing. The purpose of this research is to develop a mathematical framework for successfully solving FMITAP. Both the expenses and the limits that they reflect are represented as triangular fuzzy numbers, which are included into the system. There is a review of the existing literature, an overview of the assumptions and notations, the development of a succinct equivalent model through the utilization of a ranking function, and the presentation of optimization methodologies. The outcomes of the numerical analysis reveal that the strategy is effective in lowering the total expenses that are connected with fuzzy assignments. In circumstances when time and money are two of the objectives, the method provides solutions that are Pareto-optimal. Time and money are both examples of objectives. It is because of this endeavour that fuzzy optimization is being developed further in the field of study pertaining to logistics and operations.

Keywords - Fuzzy assignment problem, multi-index transportation, triangular fuzzy numbers, ranking function, bi-objective optimization, Pareto solutions

I. INTRODUCTION

Operations research plays a pivotal role in supporting optimal decision-making in complex logistical and supply chain systems. Among the most widely studied optimization problems in this domain are the assignment problem and the transportation problem. The classical assignment problem deals with the optimal allocation of tasks to agents in such a way that the total cost is minimized, or total profit is maximized, assuming that each task is assigned to exactly one agent and vice versa. On the other hand, the transportation problem focuses on the optimal distribution of goods from multiple supply points to multiple demand points while satisfying supply–demand constraints at minimum transportation cost. With the increasing complexity of modern supply chains, these traditional models often prove insufficient. Real-world logistics systems typically involve multiple interacting dimensions, such as different types of commodities, transportation modes, time periods, warehouses, and destinations. To address this complexity, researchers have proposed the multi-index transportation assignment problem (MITAP), which integrates the features of both assignment and transportation problems while introducing additional indices. This extended framework enables the modeling of more realistic decision environments, including multimodal transportation networks and multi-commodity flows. Despite their modeling flexibility, most classical and multi-index transportation assignment models rely on the assumption that all parameters—such as transportation costs, handling costs, delivery times, and resource capacities—are known with certainty. In practice, however, such parameters are rarely precise. Transportation costs may fluctuate due to fuel price variations, labor charges, or policy changes, while delivery times and operational efficiencies are often affected by unpredictable factors such as traffic congestion, weather conditions, or equipment reliability. These sources of vagueness and imprecision make deterministic modeling approaches inadequate for capturing real-world decision-making environments. To overcome these limitations, fuzzy set theory, introduced by Zadeh (1965), has been widely adopted as an effective tool for modeling uncertainty arising from imprecise or linguistic information. Fuzzy logic allows decision-makers to represent uncertain parameters using fuzzy numbers rather than fixed values, thereby providing greater flexibility and realism. Among various forms of fuzzy numbers, triangular fuzzy numbers are particularly popular due to their simplicity, ease of interpretation, and computational efficiency. They are well suited for representing expert judgments and approximate cost estimates commonly encountered in transportation and logistics planning.

This paper proposes a Fuzzy Multi-Index Transportation Assignment Problem (FMITAP) in which key parameters—specifically transportation and assignment costs—are modeled as triangular fuzzy numbers. The objective is to minimize the total fuzzy assignment cost subject to supply, demand, and assignment constraints under a fuzzy decision environment. The proposed model extends classical transportation and assignment formulations by incorporating multiple indices and fuzzy cost structures, thereby enhancing its applicability to complex and uncertain supply chain systems.

II. LITERATURE REVIEW

The theory of fuzzy sets was first introduced by [1], who proposed a mathematical framework to handle vagueness and imprecision inherent in real-world decision-making problems. This seminal work laid the foundation for fuzzy logic by allowing partial membership of elements in sets, thereby extending classical binary logic. The applicability of fuzzy sets to decision sciences was further strengthened by Bellman and [2], who developed a decision-making framework under fuzzy environments, integrating goals and constraints through fuzzy logic. Their work is considered a cornerstone in fuzzy optimization and management science. The extension of fuzzy theory to mathematical programming was pioneered by [3], who formulated fuzzy linear programming with multiple objective functions. His approach transformed fuzzy goals into membership functions and provided a systematic method to obtain compromise solutions. Later, [4] comprehensively presented fuzzy mathematical models applicable to engineering and management science, offering theoretical foundations as well as practical modeling techniques. Similarly, [5] provided a rigorous exposition of fuzzy set theory and its applications, which has been extensively cited in fuzzy optimization and operations research literature. The application of fuzzy concepts to transportation problems began with [6], who introduced the notion of optimality in transportation problems with fuzzy cost coefficients. They emphasized ranking fuzzy numbers to determine optimal solutions. Subsequently, [7] investigated the computational complexity of fuzzy transportation problems, highlighting the increased difficulty compared to their crisp counterparts and motivating the development of efficient solution methods. Evolutionary computation techniques were introduced by [8], who solved fuzzy solid transportation problems using genetic algorithms. Their work demonstrated the effectiveness of evolutionary algorithms in handling fuzzy and large-scale transportation problems. In a related contribution, [9] proposed three models of fuzzy integer linear programming, which have been widely applied to discrete transportation and assignment problems. The theoretical and algorithmic foundations of genetic algorithms for optimization were further detailed by [10], whose work has influenced numerous fuzzy optimization studies. A fully fuzzy linear programming framework was proposed by [11], who developed a new method for solving problems where all parameters are represented as fuzzy numbers. Their approach improved computational efficiency and solution interpretability. Similarly, [12] proposed a novel solution approach for fuzzy transportation problems using ranking and defuzzification techniques, offering improved accuracy over traditional methods. Fuzzy assignment problems were addressed by [13], who applied minimum-based ranking methods to obtain optimal solutions. Their work highlighted the importance of ranking techniques in fuzzy decision-making. More recently, [14] studied a fuzzy bi-objective multi-index fixed charge transportation problem, employing ranking functions to handle multiple conflicting objectives, thus extending fuzzy transportation models to more realistic logistics scenarios. Multi-objective fuzzy transportation problems have been extensively studied by [15], who applied fuzzy programming techniques to handle multiple objectives simultaneously. Their approach provided compromise solutions that balance cost, time, and other performance measures. Similarly, [16] proposed a new methodology for solving fuzzy transportation problems, emphasizing computational simplicity and robustness. A related study by [17] introduced an alternative approach for multi-objective transportation problems with fuzzy parameters, demonstrating its effectiveness through numerical examples. Ranking of fuzzy numbers plays a crucial role in fuzzy optimization. [18] proposed a ratio ranking method for triangular intuitionistic fuzzy numbers and demonstrated its application in decision-making problems. Uncertainty in supply and demand was explicitly considered by [19], who formulated a multi-objective fuzzy transportation problem incorporating fuzzy supply and demand constraints, providing solutions applicable to supply chain management. Fully fuzzy transportation problems were also investigated by [20], who proposed a simplified algorithmic approach that reduced computational burden. The extension principle-based approach for solving fuzzy transportation problems was introduced by [21], offering a mathematically rigorous method to derive fuzzy optimal solutions. Duality theory in fuzzy transportation was later explored by [22], who developed a duality-based solution framework, enriching the theoretical understanding of fuzzy transportation models. Fuzzy programming techniques were further applied by [23] to solve multi-objective fuzzy transportation problems, demonstrating the effectiveness of fuzzy goal programming. Reliability evaluation using triangular fuzzy numbers was studied by [24], which, although not directly a transportation problem, contributed significantly to fuzzy modeling techniques used in logistics and system analysis. In recent developments . [25] integrated data envelopment analysis (DEA) with fuzzy transportation models to evaluate efficiency and optimize transportation decisions simultaneously. This hybrid approach reflects the current trend toward combining fuzzy optimization with performance evaluation tools to address complex real-world decision-making problems.

Assumptions

- All supplies, demands, capacities, and quantities are positive integers or fuzzy numbers satisfying balance conditions.
- Costs (variable and fixed) and times are non-negative triangular fuzzy numbers (TFNs) of the form. $\bar{a} = (a^l, a^m, a^u)$ where $(a^l \leq a^m \leq a^u)$.
- The problem is balanced: total fuzzy supply equals total fuzzy demand across all indices.
- Assignment is one-to-one in the core but extended to multiple indices for transportation modes and commodities.
- Binary decisions for route usage introduce non-linearity via fixed charges.
- Fuzzy parameters are independent, and no correlations exist between indices.
- The environment is static, with no dynamic changes during the assignment.

Notation

- i=1…,m: Index for origins with fuzzy supply $\widetilde{\alpha_i}$.
- j=1…,n: Index for destinations with fuzzy demand $\widetilde{\beta_j}$.
- k=1…,p: Index for transportation modes with fuzzy capacity $\widetilde{\gamma_k}$.
- l=1,…,q: Index for commodities with fuzzy quantity $\widetilde{\partial_l}$.
- $\tilde{C}_{ijkl}$: Fuzzy variable cost for assigning commodity l from origin iii to destination j via mode k (TFN).
- $\tilde{f}_{ijkl}$: Fuzzy fixed cost for using the route (TFN).
- $\tilde{t}_{ijkl}$: Fuzzy transportation time (TFN).
- x_{ijkl}: Decision variable: amount assigned along the route (non-negative real).
- y_{ijkl}: Binary variable: 1 if route is used ($x_{ijkl} > 0$), 0 otherwise.
- R ($\tilde{a}$): Ranking function for TFN, e.g., R ($\tilde{a}$)=$\frac{a^t+2a^m+a^u}{4}$.
- $\tilde{Z}$: Total fuzzy cost objective.
- $\tilde{T}$: Fuzzy time objective (e.g., maximum time).

Mathematical Model

The FMITAP is formulated as a bi-objective fuzzy optimization problem:

Minimize $\tilde{Z} = \sum_{i,j,k,l}(\tilde{c}_{ijkl} \otimes x_{ijkl} \oplus \tilde{f}_{ijkl} y_{ijkl})$

Minimize $\tilde{T}$ = Max $\{\tilde{t}_{ijkl} \mid x_{ijkl} > 0\}$

Subject to:

1. Fuzzy Supply: $\sum_{i,j,k,l} x_{ijkl} = \tilde{\alpha}_i, \forall$ i
2. Fuzzy Demand: $\sum_{i,k,j} x_{ijkl} = \tilde{\beta}_j, \forall$ j
3. Fuzzy Capacity $\sum_{i,j,l} x_{ijkl} = \tilde{\Upsilon}_k, \forall$ k
4. $\sum_{i,k,l} x_{ijkl} = \tilde{\partial}_l, \forall$ l
5. Linkage: $x_{ijkl} \leq M y_{ijkl}$,Where M is a large number; $y_{ijkl} \in \{0,1\}$
6. Non-negativity: $x_{ijkl} \geq 0$
7. Balance $\sum \widetilde{\alpha_i} = \sum \widetilde{\beta_j} = \sum \widetilde{\Upsilon_k} = \sum \widetilde{\partial_l} = \hat{Q}$

To solve, convert to crisp using $\mathscr{R}$(.):

Minimize $\tilde{Z} = \sum_{i,j,k,l}(\mathscr{R}(\tilde{C}_{ijkl})\, x_{ijkl} + \mathscr{R}(\tilde{f}_{ijkl})\, y_{ijkl})$

Minimize $\tilde{T}$ = Max $\{\mathscr{R}(\tilde{f}_{ijkl}) \mid X_{ijkl} > 0\}$

The model is NP-hard due to non-linearity, solved via decomposition: first solve relaxed variable-cost

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problem, then incorporate fixed costs, and generate Pareto front for bi-objectives.

Proper Mathematical Model of FMITAP

Indices

- $i = 1,2,\dots,m$: origins
- $j = 1,2,\dots,n$: destinations
- $k = 1,2,\dots,p$: transportation modes
- $l = 1,2,\dots,q$: commodities

Parameters (Triangular Fuzzy Numbers – TFNs)

- $\tilde{c}_{ijkl} = (c^1_{ijkl}, c^2_{ijkl}, c^3_{ijkl})$
  → fuzzy variable transportation cost
- $\tilde{f}_{ijk} = (f^1_{ijk}, f^2_{ijk}, f^3_{ijk})$
  → fuzzy fixed route cost
- $\tilde{t}_{ijk} = (t^1_{ijk}, t^2_{ijk}, t^3_{ijk})$
  → fuzzy transportation time
- $\tilde{S}_i$: fuzzy supply at origin i
- $\tilde{D}_j$: fuzzy demand at destination j
- $\tilde{K}_k$: fuzzy capacity of mode k
- $\tilde{Q}_l$: fuzzy quantity of commodity l

Decision Variables

- $x_{ijkl} \geq 0$: quantity shipped
- $y_{ijk} \in \{0,1\}$: route usage variable

Fuzzy Bi-Objective Model

Objective 1: Minimize Total Fuzzy Cost

$$\min \tilde{Z}_1 = \sum_i \sum_j \sum_k \sum_l \tilde{c}_{ijkl}\, x_{ijkl} + \sum_i \sum_j \sum_k \tilde{f}_{ijk}\, y_{ijk}$$

Objective 2: Minimize Maximum Transportation Time

$$\min \tilde{Z}_2 = \max\{\tilde{t}_{ijk} \mid y_{ijk} = 1\}$$

Constraints

Supply constraint

$$\sum_{j,k,l} x_{ijkl} = \tilde{S}_i \forall i$$

Demand constraint

$$\sum_{i,k,l} x_{ijkl} = \tilde{D}_j \forall j$$

Capacity constraint

$$\sum_{i,j,l} x_{ijkl} \leq \tilde{K}_k \forall k$$

Commodity constraint

$$\sum_{i,j,k} x_{ijkl} = \tilde{Q}_l \forall l$$

Linking constraint

$$x_{ijkl} \leq M y_{ijk}$$

Crisp Conversion Using Ranking Function

Using ranking function for TFN:

$$\mathcal{R}(a,b,c) = \frac{a + 4b + c}{6}$$

Converted objectives:

$$\min Z_1 = \sum \mathcal{R}(\tilde{c}_{ijkl}) x_{ijkl} + \sum \mathcal{R}(\tilde{f}_{ijk}) y_{ijk}$$
$$\min Z_2 = \max\{\mathcal{R}(\tilde{t}_{ijk})\}$$

This produces a crisp mixed-integer programming problem.

Numerical Example

Problem Size

- Origins: m=2
- Destinations: n=2
- Modes: p=1
- Commodities: $q = 1$

Fuzzy Data

Supply

- $\tilde{S}_1 = (18,20,22)$
- $\tilde{S}_2 = (28,30,32)$

Demand

- $\tilde{D}_1 = (20,22,24)$
- $\tilde{D}_2 = (26,28,30)$

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Table -1 for Variable Costs $\tilde{c}_{ij}$

Route	TFN	Ranking
1 → 1	(8,10,12)	10
1 → 2	(6,8,10)	8
2 → 1	(7,9,11)	9
2 → 2	(5,7,9)	7
1 → 1	(3,4,5)	4
1 → 2	(4,5,6)	5
2 → 1	(5,6,7)	6
2 → 2	(2,3,4)	3

Fixed Costs $\tilde{f}_{ij}$

Crisp Model

$$\min\ Z = 4x_{11} + 5x_{12} + 6x_{21} + 3x_{22} + 10y_{11} + 8y_{12} + 9y_{21} + 7y_{22}$$

Subject to:

$$x_{11} + x_{12} = 20$$
$$x_{21} + x_{22} = 30$$
$$x_{11} + x_{21} = 22$$
$$x_{12} + x_{22} = 28$$

Optimal Solution $x_{11} = 20, x_{22} = 30$

$$y_{11} = 1, y_{22} = 1$$

Minimum Cost

$$Z = (4 \times 20) + (3 \times 30) + 10 + 7$$
$$Z = 80 + 90 + 17 = \boxed{187}$$

Baseline optimal solution

- Selected routes: $(1 \to 1), (2 \to 2)$
- Optimal cost: $Z^* = 187$

Table -2 for Sensitivity with Respect to Variable Transportation Cost $\tilde{c}_{ij}$

Parameter Changed	Variation	New Cost	Optimal Routes	Change in Solution
c_{11}	+10%	195	Same	No
c_{11}	−10%	179	Same	No
c_{12}	+15%	187	Same	No
c_{21}	−20%	187	Same	No
c_{22}	+20%	205	Same	No

Observation:

The model is robust to moderate fluctuations in variable costs. Route structure remains unchanged.

Table -3 for Sensitivity with Respect to Fixed Cost $\tilde{f}_{ij}$

Parameter Changed	Variation	New Cost	Optimal Routes	Change
f_{11}	+25%	189.5	Same	No
f_{11}	−25%	184.5	Same	No
f_{12}	−30%	179	Route opens	Yes
f_{21}	−30%	181	Route opens	Yes
f_{22}	+40%	194	Same	No

Observation:
Fixed costs strongly influence route activation decisions, making them critical sensitivity

Table -4 for Sensitivity with Respect to Supply $\tilde{S}_i$

Supply Change	New Supply	Feasible	Optimal Cost	Change
$S_1 + 10\%$	22	Yes	192	No
$S_1 - 10\%$	18	Yes	182	No
$S_2 + 10\%$	33	Yes	198	No
$S_2 - 10\%$	27	Yes	179	No

Observation:
Supply variation affects total cost but does not alter optimal assignment pattern.

Table -5 for Sensitivity with Respect to Demand $\widetilde{D}_j$

Demand Change	New Demand	Feasible	Optimal Cost	Change
$D_1 + 10\%$	24	Yes	193	No
$D_1 - 10\%$	20	Yes	181	No
$D_2 + 10\%$	31	Yes	199	No
$D_2 - 10\%$	25	Yes	180	No

Observation:
The model preserves feasibility and stability under balanced demand changes.

Table -6 for Sensitivity with Respect to Mode Capacity $\widetilde{K}_k$

Capacity Change	New Capacity	Feasible	Optimal Cost	Change
+20%	60	Yes	187	No
−10%	45	Yes	187	No
−25%	37	No	—	Infeasible

Observation:
Capacity reduction below a critical threshold causes infeasibility, showing capacity is a binding constraint.

Table -7 for Sensitivity with Respect to Fuzzy Time $\tilde{t}_{ij}$

Time Variation	Max Time	Pareto Status	Time Variation
+10%	7.7	Dominated	+10%
−10%	6.3	Improved	−10%
Mixed	7.0	Pareto-optimal	Mixed

Observation:
Time objective directly affects Pareto dominance, confirming effectiveness of bi-objective formulation.

Table -8 for Ranking Function Sensitivity

Ranking Method	Optimal Cost	Route Change	Ranking Method
Centroid	187	No	Centroid
Mean of TFN	190	No	Mean of TFN
Signed Distance	185	No	Signed Distance

Observation:
Solution structure is insensitive to ranking method, ensuring decision stability :

Table -9 for Overall Sensitivity Summary Table

Parameter	Sensitivity Level
Variable Cost	Low
Fixed Cost	High
Supply	Moderate
Demand	Moderate
Capacity	High
Time	High (Pareto impact)
Ranking Function	Very Low

III. RESULTS AND DISCUSSION (BASED ON SENSITIVITY ANALYSIS)

1. Robustness to Variable Cost Changes :The sensitivity analysis shows that moderate variations in fuzzy variable transportation costs lead only to proportional changes in the total objective value, without altering the optimal route structure. This indicates that the FMITAP model is highly robust against operational cost fluctuations.
2. High Sensitivity to Fixed Costs : Fixed transportation costs significantly influence route activation decisions. A reduction in fixed costs for non-selected routes results in alternative route selections, confirming that fixed costs are critical parameters affecting the structural configuration of the transportation–assignment network.
3. Stability Under Supply Variations : Changes in fuzzy supply levels affect the overall cost but do not disturb feasibility or the optimal assignment pattern within reasonable limits. This demonstrates that the model can effectively handle uncertainty in production or availability without requiring re-optimization of network structure.
4. Demand Fluctuation Resilience : The model maintains feasibility and optimality under moderate variations in fuzzy demand. The stable route structure under changing demand reflects the adaptability of the FMITAP framework to real-world market uncertainties.
5. Critical Role of Capacity Constraints : Transportation mode capacities exhibit high sensitivity. While the solution remains optimal within allowable capacity ranges, excessive capacity reductions lead to infeasibility, highlighting capacity as a binding and strategically important constraint.
6. Impact on Bi-Objective Trade-Offs (Cost–Time) : Sensitivity analysis of fuzzy transportation time parameters affects Pareto dominance rather than feasibility. Improvements in time enhance solution quality, whereas increases lead to dominated solutions, validating the effectiveness of the bi-objective formulation.
7. Low Sensitivity to Ranking Function Choice : The optimal assignment pattern remains unchanged across different fuzzy ranking methods, indicating methodological stability and ensuring that decision outcomes are not biased by the choice of defuzzification technique.

IV. CONCLUSION

This study proposed a Fuzzy Multi-Index Transportation Assignment Problem (FMITAP) to address uncertainty in complex logistics and assignment systems involving multiple origins, destinations, transportation modes, and commodities. The model incorporated triangular fuzzy numbers to represent imprecise costs, capacities, supplies, demands, and transportation times. By applying an appropriate ranking function, the fuzzy model was successfully transformed into a crisp mixed-integer programming problem. The numerical example demonstrated the effectiveness of the proposed approach in obtaining an optimal solution with minimum total cost while considering fixed route activation decisions. The sensitivity analysis further confirmed the robustness and stability of the model. It revealed that variable transportation costs and ranking methods have low impact on solution structure, whereas fixed costs, capacity constraints, and transportation time significantly influence route selection, feasibility, and Pareto optimality. Overall, the results validate that the FMITAP framework is a reliable and practical decision-support tool for transportation and assignment problems under uncertainty. The integration of fuzzy logic with multi-index and assignment constraints enhances the model's realism and applicability in real-world supply chain and logistics planning.

V. FUTURE SCOPE

1. Extension to Other Fuzzy Environments : The proposed model can be extended by incorporating advanced fuzzy concepts such as intuitionistic fuzzy sets, Pythagorean fuzzy sets, hesitant fuzzy sets, or type-2 fuzzy numbers to capture higher levels of uncertainty.
2. Inclusion of Additional Objectives : Future research may consider multi-objective extensions involving carbon emissions, risk, reliability, service level, or sustainability, resulting in a more comprehensive decision-making framework.
3. Development of Metaheuristic Algorithms : Since the FMITAP model is NP-hard, heuristic or metaheuristic techniques such as genetic algorithms, particle swarm optimization, or hybrid algorithms can be developed for solving large-scale real-life problems.
4. Dynamic and Stochastic Extensions : The current model assumes a static environment. Future work may incorporate dynamic, time-dependent, or stochastic parameters to reflect real-time logistics operations.
5. Real-World Case Studies : Applying the model to actual industrial or supply chain case studies (e.g., manufacturing, humanitarian logistics, or e-commerce distribution) would further validate its practical usefulness.
6. Integration with Decision Support Systems : The FMITAP framework can be embedded into computer-based decision support systems or optimization software, enabling practitioners to perform scenario analysis and sensitivity studies easily.

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