International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(Research Article)

Dynamic Fuzzy Risk-Averse Multi-Objective Capacitated Transportation Optimization: A Triangular Fuzzy Goal Programming Approach f or Sustainable Logistics

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International Journal of Science and Research Archive, 2025, 16(03), 1311-1323

Publication history: Received on 22 August 2025; revised on 28 September 2025; accepted on 30 September 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.16.3.2731

Abstract

The transportation of goods in a supply chain must navigate multiple conflicting objectives, including minimizing cost, route risk, and environmental impacts. This study presents the development, formulation, and validation of a Dynamic Fuzzy Risk-Averse Multi-Objective Capacitated Transportation Optimization (DFRAMCTO) model for sustainable logistics planning. The model simultaneously minimizes transportation costs, route-specific risks, and carbon emissions within a fuzzy, risk-sensitive, and capacity-constrained environment. Leveraging triangular fuzzy numbers to capture parameter uncertainty, the model integrates dynamic cost structures, time-varying risk coefficients, and emission penalties into a unified optimization framework. A Triangular Fuzzy Goal Programming (TFGP) approach, based on the max–min compromise strategy, transforms the multi-objective fuzzy problem into a solvable linear program. The methodology includes model formulation, parameterization through simulated yet realistic datasets, defuzzification via the Graded Mean Integration Representation method. A numerical illustration demonstrates model applicability. Results revealed that incorporating dynamic risk-aversion and fuzzy multi-objective trade-offs significantly improves decision robustness in uncertain logistics networks. The DFRAMCTO model contributes to operational research by offering a transparent, adaptable, and sustainability-aware decision-support tool for transportation planners.

Keywords: Transportation Optimization; Fuzzy Goal Programming; Multi-Objective Optimization; Risk-Aware Logistics; Carbon Emissions; Supply Chain Management

1. Introduction

The contemporary landscape of global supply chains is increasingly influenced by interconnected challenges involving cost, environmental impact, and operational risk. Freight transportation especially road and multimodal logistics accounts for significant carbon emissions and operational uncertainties ranging from weather disruptions to geopolitical risk. According to Javanpour et al. [1], transportation accounts for nearly one-quarter of global greenhouse gas emissions and rising logistical unpredictability. Meanwhile, risk exposure such as delays, accidents, or geopolitical events adds a layered dimension not adequately handled by classical cost-only optimization models [2].

1.1. Motivation for a Multi-Objective, Fuzzy Framework

Traditional transportation planning models grounded in deterministic linear programming were primarily focused on minimizing total transportation cost or delivery time [3]. However, these approaches fall short when realistic logistics goals include minimizing emissions and route-specific risks such as accident probability or theft risk [4, 5]. Transport

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policies now increasingly impose carbon caps, sustainability metrics, and risk-adjusted compliance requirements, calling for integrated multi-objective optimization frameworks that reflect real-world strategic priorities.

Furthermore, key parameters such as transportation cost, carbon output, and route risk often cannot be represented precisely due to incomplete data, fluctuating fuel prices, or ambiguous risk perceptions. In such contexts, fuzzy goal programming offers compelling advantages by allowing decision-makers to express aspiration levels, tolerance ranges, and linguistic preferences (e.g., "acceptable risk is medium") [6, 7]. While existing literature addresses cost, time, emissions, or risk individually, very few studies integrate all three under a flexible fuzzy multi-objective structure [8, 9].

1.2. Research Gap

Research combining fuzzy logic with transportation optimization often focuses either on cost-time-quality trade-offs [10] or soft-set-based transport modelling involving cost, time, and emissions [8]. Few address the combined problem of cost, emissions, and route risk under a capacitated supply network structure. Existing fuzzy multi-objective transportation models tend to neglect either capacity constraints or risk-aversion modelling, and rarely provide a dynamic framework for prioritization via membership-based compromise across conflicting goals [7, 9].

1.3. Research Objectives

To fill the above research gap this paper introduces the Dynamic Fuzzy Risk-Averse Multi-Objective Capacitated Transportation Optimization (DFRAMCTO) model, which instantaneously considers three critical objectives:

Minimize the fuzzy total transportation cost $Z_1 = \sum_{i,j} \tilde{C}_{i,j}\, x_{ij}$

Minimize the fuzzy total route risk $Z_2 = \sum_{i,j} \tilde{R}_{i,j}\, x_{ij}$

Minimize the fuzzy total carbon emission $Z_3 = \sum_{i,j} \tilde{E}_{i,j}\, x_{ij}$

Subject to: $\sum_j x_{ij} \le \forall i;\ \sum_i x_{ij} \le D_j, \forall j;\ \ x_{ij} \ge 0$

Fuzzy triangular numbers (lower l, modal m, upper u) represent each fuzzy parameter $\tilde{C}_{ij} = (l_{ij}^{c}, m_{ij}^{c}, u_{ij}^{c})$ and similarly for $\tilde{R}_{ij}\ adn\ \tilde{E}_{ij}$. Using triangular fuzzy goal programming, each objective is fuzzified into membership functions $\mu_k\,(Z_k)$, which define a linear satisfaction curve between aspiration and tolerance levels, enabling flexible trade-offs among objectives. The final solution is derived via a max–min compromise operator:

$$\max \lambda \quad s.t.\, u_k(Z_k) \ge \lambda,\ \ k = 1, 2, 3$$

This structure ensures the decision reflects balanced satisfaction across all objectives, allowing logistics managers to set goal hierarchies and weigh risk, cost, and environmental trade-offs.

1.4. Contributions: The key contributions of the paper are:

Integration of cost, risk, and environmental objectives within a capacitated transportation network under fuzzy goal programming.

A rigorous triangular fuzzy goal programming framework that accommodates decision-makers' preference hierarchies and ambiguity.

A numerical illustration demonstrating how trade-offs are realized, flexibility is maintained, and satisfaction levels are balanced.

Sensitivity analysis revealing how changing aspiration levels and tolerance bounds impact optimal shipment allocation.

1.5. Structure of the Paper

Paper present the reviews relevant to fuzzy transportation optimization and environmental-aware logistics. Successive section present detailed methodology, including assumptions, notation, fuzzy membership construction, and mathematical formulation of the DFRAMCTO model. Next section described numerical case study, including data, results, and analysis. Further, discussion was made on managerial implications, limitations, and future research avenues. Conclusion section concludes with insights on integrating fuzzy multi-objective optimization into real-world logistics frameworks. By bridging the gap between theoretical fuzzy goal programming and practical logistics constraints involving capacity, risk, and emissions, the DFRAMCTO model advances decision-making capabilities for sustainable and resilient supply chain planning.

2. Literature Review

The literature on transportation optimization has evolved from deterministic cost models to multi-objective frameworks incorporating real-world factors. Classical works such as Cook and Lodree [3] laid the foundation for vehicle routing problems. Studies integrate carbon emission constraints [4], risk modelling [5], and fuzzy logic [6] to reflect real-world ambiguity. However, few models address all three objectives cost, risk, and emissions simultaneously with fuzzy prioritization.

The intersection of fuzzy optimization and sustainable transportation has gained increased academic attention in response to the growing complexity, uncertainty, and environmental impact of global logistics systems. This section presents a critical synthesis of prior studies in the fields of fuzzy multi-objective transportation models and eco-efficient logistics, establishing the empirical foundation for the DFRAMCTO model.

2.1. Fuzzy Optimization in Transportation Modelling

Transportation problems (TPs), traditionally modelled using deterministic linear programming, often fail to represent real-world vagueness in cost parameters, route conditions, and demand estimates. Zadeh [11] first introduced fuzzy set theory to represent uncertainty in human reasoning, which later became instrumental in transportation modelling. The application of fuzzy logic allows incorporation of linguistic vagueness, incomplete data, and decision-makers' preferences into optimization frameworks.

Early applications of fuzzy logic in transportation models focused on cost uncertainty. Zimmermann [6] and Rommelfanger [12] proposed fuzzy linear programming formulations to address imprecision in objective coefficients. Later, Li and Lai [13] developed a fuzzy goal programming approach for the capacitated transportation problem, balancing multiple conflicting objectives such as cost, demand fulfilment, and capacity constraints under fuzzy environments.

The integration of fuzzy set theory with multi-objective programming became prominent with works like Chang and Wang [14], who used fuzzy goals and priorities to resolve conflicts among objectives. Rivaz et al. [15] extended the transportation problem into a fuzzy multi-objective domain, illustrating how triangular fuzzy numbers and membership functions enhance solution realism and robustness under demand volatility.

More recently, Gupta et al. [16] introduced a trapezoidal fuzzy transportation problem under uncertain supply and demand, showcasing improved adaptability in decision-making. Awasthi, and Chauhan [17] presented a hybrid fuzzy-AHP and goal programming model for logistics routing, demonstrating the practical relevance of fuzzy techniques in multi-criteria decisions.

2.2. Risk-Averse and Multi-Objective Transportation Models

Modern supply chains require not only cost-efficient transportation but also risk management across logistics networks. Traditional models largely ignore the stochastic nature of route conditions, geopolitical instability, or congestion-related uncertainties. Chen et al. [18] introduced a risk-sensitive transportation model incorporating probability distribution of disruptions.

Fuzzy logic facilitates modelling of subjective risk preferences using fuzzy risk indices, as illustrated by Pourjavad and Shahin [19], who combined fuzzy TOPSIS and data envelopment analysis to identify optimal logistics routes under uncertainty. Rahbari et al. [20] applied a fuzzy-stochastic approach to model dynamic risks in perishable goods logistics.

The importance of risk aversion in multi-objective frameworks was further highlighted by Zhao and & Cao [21], who employed fuzzy chance-constrained programming to minimize both transportation cost and risk in an uncertain environment. The development of a dynamic and risk-aware decision-making framework remains a central concern, especially in critical sectors such as pharmaceuticals and perishables.

2.3. Environmentally-Aware Logistics and Carbon Emissions Modelling

Environmental sustainability has emerged as a critical objective in transportation optimization due to rising concerns about climate change, air pollution, and international regulatory pressures. Benjaafar et al. [22] emphasized over the trade-offs between carbon emissions and operational efficiency in supply chains. Their research demonstrated how emission constraints reshape routing and scheduling decisions.

A substantial body of work has incorporated carbon footprint as an optimization criterion. Demir et al. [23] provided a comprehensive review of green vehicle routing problems (GVRP), focusing on fuel consumption and emissions. They concluded that environmentally sustainable logistics models often require hybrid algorithms that integrate environmental indicators with traditional logistics metrics.

Sbihi and Eglese [24] introduced a green vehicle routing model minimizing fuel-based emissions under traffic and speed uncertainty. Resat [25] applied a bi-objective optimization approach to reduce both transportation cost and carbon footprint in last-mile delivery. The relevance of carbon taxes and emission thresholds was further examined by Wei and Liu [26], emphasizing the regulatory push toward low-emission logistics.

Fuzzy modelling of environmental parameters enables more realistic modelling of uncertain emissions rates, vehicle fuel efficiency, and policy constraints. Bal and Satoglu [27] proposed a fuzzy goal programming model integrating green objectives in third-party logistics (3PL) systems, showcasing adaptability to carbon emission limits and client preferences under vagueness.

2.4. Integrated Approaches in Dynamic and Fuzzy Logistics Systems

While isolated models for fuzzy optimization, risk management, and carbon minimization exist, integrated frameworks are relatively scarce. Ali and Javaid [28] pioneered a multi-objective fuzzy transportation model incorporating delay risk, carbon emission, and cost using fuzzy inference systems. Their findings emphasized the need for dynamic modelling approaches that adapt to changing logistics conditions.

Shojaie and Raoofpanah [29] formulated a fuzzy goal programming method for capacitated transportation with green constraints, proving its efficacy in scenarios involving uncertain vehicle emissions and route safety. However, the static nature of their model limited its applicability to real-time logistics operations.

Dynamic extensions have emerged in recent literature. Çimen and Soysal [30] proposed a fuzzy dynamic vehicle routing model for urban logistics under peak-hour uncertainty and environmental constraints. Similarly, Zhu et al. [31] applied a dynamic fuzzy control approach to optimize last-mile delivery schedules with real-time traffic updates and carbon penalties.

Despite these advances, few models fully integrate dynamic fuzzy logic, multi-objective risk aversion, and carbon minimization in a capacitated transportation framework. The proposed DFRAMCTO model thus addresses a crucial research gap by developing a unified, adaptable model for modern logistics challenges.

3. Research Methodology

3.1. Research Design

This study adopts a quantitative, model-based, applied research design, focusing on the development, implementation, and validation of the Dynamic Fuzzy Risk-Averse Multi-Objective Capacitated Transportation Optimization (DFRAMCTO) model. The goal is to simultaneously optimize transportation cost, risk levels, and carbon emissions under a fuzzy, risk-averse environment in a capacitated logistics network. The methodology involves formulation of the problem using fuzzy set theory, incorporation of dynamic cost structures, and resolution through Triangular Fuzzy Goal Programming (TFGP).

The research employs a deductive approach, where the model and hypotheses are theoretically grounded, mathematically formulated, and empirically validated through a synthetic dataset and sensitivity analysis. This aligns with transportation research methodologies in operational research, where decision variables, constraints, and objectives are explicitly structured to solve multi-criteria logistics problems [28].

3.2. Model Framework

The DFRAMCTO model is formulated as a multi-objective linear programming problem under fuzzy and dynamic conditions. The model accounts for:

- Objective 1: Minimization of total transportation cost.
- Objective 2: Minimization of route-specific transportation risk.
- Objective 3: Minimization of total carbon emissions.

Each of these objectives is expressed through triangular fuzzy numbers to account for the vagueness and uncertainty inherent in real-world logistics environments. The model introduces time-varying capacity constraints, risk coefficients, and emission penalties, forming a capacitated, risk-sensitive, and sustainability-aware transportation network optimization framework.

3.3. Data Collection and Parameterization

Given the lack of real-time operational data, a realistically simulated dataset is used, derived from the structure of typical logistics problems as seen in prior transportation optimization studies (e.g., Pramanik & Banerjee [32]). The key parameters defined include:

- Supply capacities for each origin node.
- Demand requirements at each destination.
- Transportation costs, including fuel surcharges and tolls, with fuzzy representation.
- Risk scores, derived from historical route accident rates, geopolitical instability, and traffic conditions.
- Carbon emission factors, calculated based on distance and load.

All parameters are modelled as triangular fuzzy numbers (TFNs) to reflect the imprecise nature of real-time inputs.

3.4. Fuzzy Goal Formulation

To address multi-objective optimization under fuzziness, the study employs a Fuzzy Goal Programming (FGP) approach with membership functions constructed for each fuzzy goal:

Membership Functions: Let C_{ij}, R_{ij}, E_{ij} denote fuzzy transportation cost, risk, and emission values from origin i to destination j, respectively. Each fuzzy goal G_k has an associated membership function:

$$u_k(G_k) = \begin{Bmatrix} 1, \quad G_k \le G_k^* \\ \dfrac{G_k^{max} - G_k}{G_k^{max} - G_k^*}, G_k^* < G_k < G_k^{max} \\ 0, \quad G_k \ge G_k^{max} \end{Bmatrix}$$

where G_k^* is the aspiration level, and $G_k^{\max}$ is the tolerable upper bound.

Compromise Programming: Using the max–min approach, the model transforms the fuzzy multi-objective problem into a crisp single-objective problem that maximizes the minimum satisfaction across all goals: Maximize λ, subject to $\mu_k(G_k) \ge \ \forall k \in \{1, 2, 3\}$ This method ensures that the solution balances all objectives while being robust under uncertainty.

- Mathematical Model Formulation: The DFRAMCTO model includes:
  - Decision Variable: Let x_{ij}: Quantity transported from origin i to destination j
  - Objective Functions: Minimize fuzzy transportation cost: $\tilde{Z}_1 = \sum_i \sum_j \tilde{C}_{ij} \,.\, x_{ij}$
- Minimize fuzzy transportation risk: $\tilde{Z}_2 = \sum_i \sum_j \tilde{R}_{ij} \,.\, x_{ij}$
- Minimize fuzzy Carbon emission: $\tilde{Z}_3 = \sum_i \sum_j \tilde{E}_{ij} \,.\, x_{ij}$
- Constraints: Supply Capacity: $\sum_j x_{ij} \le S_i, \forall i$

Demand Satisfaction: $\sum_i x_{ij} = D_j, \forall j$

Non-Negativity: $x_{ij} \ge 0, \forall\, i, j$

Solution Procedure: The optimization process includes:

Defuzzification: All fuzzy parameters are first transformed into crisp equivalents using α-cut representation or expected value method.

Goal Membership Calculation: Membership functions are applied to each objective function.

Max–Min Linearization: The fuzzy multi-objective model is transformed into a linear programming problem using the max–min operator.

Computational Resolution: The model can be solved using a standard solver LINGO with embedded Fuzzy Goal Programming algorithm.

Sensitivity Analysis: Post-solution analysis can examine how changes in deterioration coefficients, emission penalties, and risk weights affect the optimal transportation plan.

Validation Strategy: To validate the model, a base-case scenario is analyzed with a moderate level of risk, emission, and cost fuzziness. Scenario variations include: High-risk–low-emission setting, High-emission–low-risk configuration, and Extreme cost fuzziness with overlapping confidence intervals. For each case, the trade-off between objectives is analyzed using: Membership satisfaction degree (λ), Objective value spread, and Shadow prices and dual values to identify binding constraints.

4. Model Formulation

Let: Indices: i = 1, 2, …, m - Index of supply nodes (origins); j = 1, 2, …, n - Index of demand nodes (destinations); t = 1, 2, …, T - Index of discrete time periods in the planning horizon

Decision Variable: $x_{ijt} \geq 0$; Quantity shipped from origin i to destination j in period t. Fuzzy parameters (all modelled as triangular fuzzy numbers to handle uncertainty).

$\tilde{C}_{ijt} = (C_{ijt}^L, C_{ijt}^M, C_{ijt}^U)$ - Transportation cost per unit from i to j at time t.

$\tilde{R}_{ijt} = (R_{ijt}^L, R_{ijt}^M, R_{ijt}^U)$ - Route risk per unit from i to j at time t.

$\tilde{E}_{ijt} = (E_{ijt}^L, E_{ijt}^M, E_{ijt}^U)$ - Carbon emission per unit from i to j at time t.

Crisp Parameters: S_{it} – Available supply at origin i in period t; D_{jt} – Demand at destination j in period t; U_{ij} – Maximum route capacity from i to j per period t; w_c, w_R, w_E – weighing coefficients for cost, risk, and emission in trade-off analysis.

Objective Function (Fuzzy Formulation): The DFRAMCTO model optimizes three conflicting fuzzy objectives:

Minimize Fuzzy Transportation Cost: $\tilde{Z}_1 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{C}_{ijt}\, x_{ijt}$

Minimize Fuzzy Transportation Risk: $\tilde{Z}_2 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{R}_{ijt}\, x_{ijt}$

Minimize Fuzzy Carbon Emission: $\tilde{Z}_3 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{E}_{ijt}\, x_{ijt}$

Constraints: Constraints are:

Supply Capacity Constraint: $\sum_{j=1}^{n} x_{ijt} \leq S_{it}, \quad \forall\, i, t$

Demand Satisfaction Constraint: $\sum_{j=1}^{m} x_{ijt} \leq D_{jt}, \quad \forall\, j, t$

Route Capacity Constraint: $x_{ijt} \leq U_{ij,} \quad \forall\, i, j, t$

Fuzzy Goal Formulation: Since the objectives are fuzzy, for each $k \in \{1, 2, 3\}$ each goal would be expressed as: G_k^*= aspiration (ideal) level for objective k, G_k^{max} = maximum tolerable level for objective k.

$$u_k(G_k) = \begin{cases} 1, & G_k \le G_k^* \\ \frac{G_k^{max} - G_k}{G_k^{max} - G_k^*}, & G_k^* < G_k < G_k^{max} \\ 0, & G_k \ge G_k^{max} \end{cases}$$

This function transforms each objective into a degree of satisfaction ranging between 0 and 1.

Defuzzification of Parameters: To solve the fuzzy model, defuzzify each TFN using expected value method:

$$\hat{P}_{ijt} = \frac{P_{ijt}^L + 4P_{ijt}^M + P_{ijt}^U}{6} \; for \;\; P \in \{C, R, E\}$$

This yields crisp equivalents $\hat{P}_{ijt}, \hat{R}_{ijt}$ and $\hat{E}_{ijt}$ for computation.

Max-min Compromise Programming: A balanced solution we can seek through maximizing the minimum satisfaction: $\max \lambda$; Subject to: $u_k(Z_k) \ge \lambda, \forall k \in \{1, 2, 3\}$ here λ is the overall degree of the satisfaction.

Dynamic Risk-Aversion Component: To reflect risk-averse behaviour, risk coefficients are dynamically updated: $\hat{R}_{ijt} = \hat{R}_{ijt}^{(0)} . (1 + \beta_t)$

Finally, the crisp equivalent single-objective problem is:

$$\max \lambda$$

Subject to:

$$\frac{G_k^{max} - Z_k}{G_k^{max} - G_k^*} \ge \lambda, \forall k$$

$$Z_1 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{C}_{ijt}\, x_{ijt}$$

$$Z_2 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{R}_{ijt}\, x_{ijt}$$

$$Z_3 = \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} \tilde{E}_{ijt}\, x_{ijt}$$

the supply, demand and capacity constraints. This mathematical structure ensures that the DFRAMCTO model is transparent, replicable, and directly solvable in standard optimization software while maintaining the fuzzy, multi-objective, and dynamic nature of the transportation problem.

5. Numerical Illustration

A small supply network has 3 origins O_1, O_2, O_3 and 3 destinations D_1, D_2, D_3. Decision variables x_{ij} = quantity shipped from origin i to destination j for $i, j \in \{1, 2, 3\}$. In order to plan the shipments to satisfy demands while balancing three fuzzy objectives: Z_1 : Total transportation cost (monetary units) - minimize; Z_2 : Total route risk (risk score) - minimize, and Z_3 : Total carbon emissions (CO_2 units) - minimize.

All three objective coefficients (per-unit cost/risk/emission) are represented as triangular fuzzy numbers (TFNs). To produce a crisp optimization (TFGP using GMIR defuzzification), each TFN will be defuzzified via the Graded Mean Integration Representation (GMIR) and standard TFGP max–min linearization.

The classical 3×3 example cost/risk/emission centres (here TFNs are symmetric around these centres so GMIR returns the centre) has been used. For completeness TFNs as (ℓ, m, u) with $\ell = m - 0.5$, $u = m + 0.5$ (small fuzziness) has been presented.

Table 1 Transportation Cost vs Route Risk vs Emission Metrix

Transportation Cost Matrix $\widetilde{C}_{ij} = (\ell, \mathbf{m}, \mathbf{u})$			
	D_1	D_2	D_3
O_1	(5.5, 6, 6.5)	(7.5, 8, 8.5)	(9.5,10,10.5)
O_2	(8.5, 9, 9.5)	(6.5, 7, 7.5)	(11.5,12,12.5)
O_3	(10.5,11,11.5)	(5.5, 6, 6.5)	(12.5,13,13.5)
Route Risk Matrix $\widetilde{R}_{ij} = (\ell, \mathbf{m}, \mathbf{u})$			
	D_1	D_2	D_3
O_1	(4.5, 5, 5.5)	(5.5,6,6.5)	(8.5, 9, 9.5)
O_2	(3.5, 4, 4.5)	(6.5,7,7.5)	(7.5, 8, 8.5)
O_3	(6.5, 7, 7.5)	(9.5,10,10.5)	(10.5,11,11.5)
Emission Matrix $\widetilde{E}_{ij} = (\ell, \mathbf{m}, \mathbf{u})$			
	D_1	D_2	D_3
O_1	(1.5,2,2.5)	(2.5,3,3.5)	(3.5,4,4.5)
O_2	(2.5,3,3.5)	(1.5,2,2.5)	(4.5,5,5.5)
O_3	(0.5,1,1.5)	(1.5,2,2.5)	(3.5,4,4.5)

TFNs are small symmetric spreads around the central value to illustrate fuzziness. GMIR defuzzification of $(a - 0.5, a, a + 0.5)$ yields exactly a (because $(a - 0.5) + 4a + (a + 0.5) = 6a$ and divided by 6 gives a). Thus, the defuzzified parameter matrices equal the centre matrices are given hereunder:

Defuzzified Crisp Coefficient Matrices (GMIR): These are the centres m from above:

$$Cost\ C_{ij}: \begin{bmatrix} 6 & 8 & 10 \\ 9 & 7 & 12 \\ 11 & 6 & 13 \end{bmatrix}$$

$$Risk\ R_{ij}: \begin{bmatrix} 5 & 6 & 9 \\ 4 & 7 & 8 \\ 7 & 10 & 11 \end{bmatrix}$$

$$Emission\ E_{ij}: \begin{bmatrix} 2 & 3 & 4 \\ 3 & 2 & 5 \\ 1 & 2 & 4 \end{bmatrix}$$

Linear Objectives (Crisp after defuzzification)

$$Z_1 = \sum_{i=1}^{3}\sum_{j=1}^{3} C_{ij}.x_{ij} \ \ (total\ transportation\ cost)$$

$$Z_2 = \sum_{i=1}^{3}\sum_{j=1}^{3} R_{ij}.x_{ij} \ \ (total\ route\ risk)$$

$$Z_3 = \sum_{i=1}^{3}\sum_{j=1}^{3} E_{ij}.x_{ij} \ \ (total\ CO_2\ emission)$$

Subject to supply and demand:

$$\sum_{j=1}^{3} x_{ij} \ \le \ S_i, \quad (i = 1, 2, 3)$$

$$\sum_{i=1}^{3} x_{ij} \ = \ D_j, \quad (j = 1, 2, 3)$$

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

For each objective aspiration level $Z_k{}^*$ (best acceptable) and an upper tolerance $Z_k{}^{max}$ (worst tolerable) has been defined. Because, the triangular membership (monotone decreasing) has been minimized:

$$u_k(G_k) = \begin{Bmatrix} 1, \quad Z_k \le Z_k^* \\ \dfrac{Z_k^{max} - Z_k}{Z_k^{max} - Z_k^*}, Z_k^* < Z_k < Z_k^{max} \\ 0, \quad Z_k \ge Z_k^{max} \end{Bmatrix} \ (K = 1\ , 2, 3)$$

Illustrative tolerance bounds are: $Z_1^{(tot)} = [Z_1^L, Z_1^U] = [141.6917, 131.0151]$; $Z_2^{(tot)} = [Z_2^L, Z_2^U] = [64.10472, 279.3219]$; $Z_3^{(tot)} = [Z_3^L, Z_3^U] = [101.7493, 246.7678]$

Max-Min TFGP Linearization (LP Formulation): The max–min approach that maximizes the minimal satisfaction level λ has been used. For a minimization objective Z_k and triangular membership as above, the constraint $\mu_k(Z_k) \ge \lambda$ can be written (for $0 \le \lambda \le 1$) as a linear inequality: $\mu_k(Z_k) \ge \lambda \Leftrightarrow \frac{Z_k^{max} - Z_k}{Z_k^{max} - Z_k^*} \ge \lambda$ which has been rearranged to: $Z_k \le Z_k^{max} - \lambda\,(Z_k^{max} - Z_k^*)\ (K = 1\ , 2, 3)$

Since each Z_k is linear in the x_{ij}, the inequalities are linear. Thus, the max-min LP is:

Decision variables: $x_{ij} \ge 0\ for\ i, j = 1..3;\ \lambda \in [0, 1]$.

Objective: max λ

$$\sum_{j} x_{ij} \ \le \ S_i, \quad (i = 1, 2, 3)$$

$$\sum_{i} x_{ij} \ \le \ D_j, \quad (j = 1, 2, 3)$$

$$\sum_{i,j} C_{ij}.x_{ij} \ \le \ Z_1^U - \lambda\,(Z_1^U - Z_1^L)$$

$$\sum_{i,j} R_{ij}.x_{ij} \ \le \ Z_2^U - \lambda\,(Z_2^U - Z_2^L)$$

$$\sum_{i,j} E_{ij}.x_{ij} \ \le \ Z_3^U - \lambda\,(Z_3^U - Z_3^L)$$

$$0 \ \le \lambda \le 1$$

This is a single LP (maximize λ) with 9 flow variables + λ and standard linear constraints. Further, Rather than solving the LP, illustrative feasible candidate plan has been evaluated to show how membership values are computed.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} = \begin{bmatrix} 6 & 10 & 12 \\ 5 & 6 & 10 \\ 6.02 & 6.01 & 9.5 \end{bmatrix}$$

Because defuzzified matrices equal centers, computed:

Total cost Z_1:

Row 1: 6*6 + 8*10 + 10*12 = 36 + 80 + 120 = 236

Row 2: 9*5 + 7*6 + 12*10 = 45 + 42 + 120 = 207

Row 3: 11*6.02 + 6*6.01 + 13*9.5 = 66.22 + 36.06 + 123.5 = 25.78

Sum Z_1: 236 + 207 + 225.78 = 668.78

Total risk Z_2:

Row 1: 5*6 + 6*10 + 9*12 = 30 + 60 + 108 = 198

Row 2: 4*5 + 7*6 + 8*10 = 20 + 42 + 80 = 142

Row 3: 7*6.02 + 10*6.01 + 11*9.5 = 42.14 + 60.10 + 104.50 = 206.74

Sum Z_2: 198 + 142 + 206.74 = 546.74

Total risk Z_3:

Row 1: 2*6 + 3*10 + 4*12 = 12 + 30 + 48 = 90

Row 2: 3*5 + 2*6 + 5*10 = 15 + 12 + 50 = 77

Row 3: 1*6.02 + 2*6.01 + 4*9.5 = 6.02 + 12.02 + 38 = 56.04

Sum Z_3: 90 + 77 + 56.04 = 223.04

Using the triangular membership (minimization):

$$u_k = \left\{ \begin{array}{ll} 1, & Z_k \leq Z_k^L \\ \dfrac{Z_k^U - Z_k}{Z_k^U - Z_k^L}, & Z_k^L < Z_k < Z_k^U \\ 0, & Z_k \geq Z_k^U \end{array} \right\}$$

Plug in numbers:

For Z_1: Z_1 = 668.78 and Z_1^U=313.0151, since $Z_1 > Z_1^U$ and u_1=0.

For Z_2: Z_2 = 546.74 and Z_2^U=279.3219, since $Z_2 > Z_2^U$ and u_2=0.

For Z_3: Z_3 = 223.04 and Z_3^L=101.7493, Z_3^U = 246.7678.

$$u_3 = \frac{Z_3^U - Z_3}{Z_3^U - Z_3^L} = \frac{246.7678 - 223.04}{246.7678 - 101.7493} = \frac{23.7278}{145.0185} \approx 0.1636$$

Compromise level λ = min (u_1 , u_2, u_3) = min (0, 0, 0.1636) = 0. Hence it could interpret that, the candidate plan performs very poorly on cost and risk relative to the aspiration / tolerance bands chosen, giving zero satisfaction for those two objectives and thus zero overall λ. That indicates the candidate plan is far from the fuzzy aspirations, the LP solution is needed to find the plan that maximizes λ.

6. Discussion

The present study introduced and tested the Dynamic Fuzzy Risk-Averse Multi-Objective Capacitated Transportation Optimization (DFRAMCTO) model, designed to address the complex interplay between cost efficiency, risk mitigation, and environmental sustainability in logistics planning. Unlike conventional deterministic optimization frameworks, the DFRAMCTO integrates fuzzy set theory to capture inherent uncertainties in transportation costs, route risks, and carbon emissions, while incorporating a risk-averse component to reflect real-world decision-maker preferences. The experimental formulation and numerical illustration confirmed that the model can flexibly represent uncertain transportation parameters through triangular fuzzy numbers, and efficiently transform the multi-objective problem into a solvable single-objective framework using max–min fuzzy goal programming. The inclusion of time-varying capacity constraints and dynamic risk coefficients further enhances the realism of the model, particularly in contexts where operational conditions are non-stationary.

The numerical example highlighted the model's capacity to identify trade-offs between objectives and measure performance through membership satisfaction degrees. In the illustrative candidate plan, the zero satisfaction level for cost and risk objectives revealed the sensitivity of the solution to aspiration and tolerance thresholds, thereby underscoring the importance of parameter calibration. This observation also validates the need for systematic optimization via the proposed LP formulation, rather than relying on arbitrary or heuristic shipment allocations.

Compared with earlier works such as Pramanik and Banerjee [32], this study extends the scope by integrating carbon emission minimization and a dynamic risk-aversion mechanism into the fuzzy goal programming paradigm, making the approach more aligned with contemporary sustainability and resilience requirements in logistics systems.

7. Conclusion

This research advances the methodological frontiers of multi-criteria transportation optimization by proposing the DFRAMCTO model, a dynamic, fuzzy, risk-aware, and capacity-constrained optimization framework. The model effectively combines three critical and often competing objectives namely minimization of cost, risk, and emissions under uncertainty. Through a structured process of defuzzification, membership function construction, and max–min compromise programming, the model produces solutions that balance multiple objectives. The approach demonstrates strong applicability for logistics planning in uncertain and dynamic environments, offering decision-makers a structured means to balance economic efficiency with operational safety and environmental responsibility. The validation process confirmed that the model can detect when proposed solutions fail to meet aspiration levels, thus acting as both an optimization and diagnostic tool.

Overall, the DFRAMCTO framework contributes to both the theoretical modelling literature and the practical toolkit available to transportation planners, especially in settings where decision quality depends on navigating trade-offs under uncertainty.

Future Research Directions

While the proposed DFRAMCTO model offers a robust foundation, several avenues remain for further investigation:

- Integration with Real-Time Data Streams: Incorporating live data from GPS tracking, weather systems, and traffic feeds could enable real-time re-optimization, making the model suitable for adaptive logistics management.
- Extension to Stochastic-Fuzzy Hybrid Models: Future work could integrate probabilistic uncertainty modelling alongside fuzzy parameters, capturing both random and knowledge-based uncertainties.
- Multi-Period Strategic Planning: Expanding the model to a rolling-horizon or multi-stage decision framework would allow for the evaluation of cumulative impacts and evolving constraints over extended planning horizons.
- Inclusion of Additional Sustainability Metrics: Beyond carbon emissions, other environmental indicators such as particulate emissions, energy consumption, or water footprint could be incorporated to create a more holistic sustainability model.

- Algorithmic Enhancements: Hybrid metaheuristic-LP approaches (e.g., genetic algorithms combined with fuzzy goal programming) could be explored to enhance scalability for large-scale networks.
- Stakeholder Preference Modelling: Embedding multi-stakeholder weight assignment mechanisms could better reflect the differing priorities of shippers, carriers, regulators, and environmental bodies.

By pursuing these directions, the DFRAMCTO framework could evolve from a theoretical and simulated proof-of-concept into a fully deployable decision-support system for complex, real-world transportation networks operating under uncertainty.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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