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Hybrid PSO-GA Model for Solving Multiobjective Solid Transportation Problem Under Rough Fuzzy Uncertainty Approach

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ABSTRACT
This paper presents a novel solution methodology for a dynamic multiobjective multi-product solid transportation problem (MOMPSTP) under dual-layered uncertainty modeled via rough fuzzy variables. Traditional approaches for handling such uncertainty primarily rely on deterministic conversion using chance-constrained programming. In contrast, we develop a hybrid Particle Swarm Optimization and Genetic Algorithm (PSO-GA) to address the problem in its original uncertain form without oversimplification. Furthermore, the model incorporates dynamic credibility and trust levels, allowing real-time adjustment to changing market conditions. A comparative performance evaluation between the proposed hybrid metaheuristic and classical methods such as Weighted Sum and Ideal Point techniques is presented. The results demonstrate the superiority of the hybrid approach in obtaining a diverse and high-quality Pareto front. Sensitivity and robustness analyses are conducted to validate the adaptability of the model under fluctuating parameters. The proposed framework is particularly suitable for real-time logistics and multimodal supply chain networks with uncertain and imprecise data.

KEYWORDS
Multiobjective Optimization; Solid Transportation Problem (STP); Rough Fuzzy Variables (RFV); Particle Swarm Optimization (PSO); Genetic Algorithm (GA)

1. Introduction

Efficient transportation planning is fundamental to modern supply chains and logistics systems, particularly in contexts involving multi-product flows, multiple source-destination nodes, and multimodal transport networks [2]. To address such complexity, Haley [1] introduced solid transportation problems (STPs), expanding classical transportation models by incorporating constraints such as mode-specific capacity limits.

In practical applications, transportation parameters, such as cost, time, availability, and capacity, are rarely deterministic. These parameters are influenced by uncertain factors including volatility in fuel prices, geopolitical disruptions, seasonal demand fluctuations, and unpredictable delivery delays. As a result, robust modeling techniques that can account for such uncertainty are required.

To capture dual-layered uncertainty (vagueness and imprecision), researchers have developed models based on the integration of fuzzy set theory [3] and rough set theory [4]. This has led to the use of rough fuzzy variables (RFVs), which provide a powerful representation of ambiguity in logistics systems. Dubois and Prade [5] laid foundational work in this area, and more recent studies by Zhang et al. [6] and Liu [7] have formalized the application of RFVs in multiobjective optimization contexts.

Roy et al. [8] formulated a Multiobjective Multi-Product Solid Transportation Problem (MOMPSTP) using RFVs and applied Cr–Tr chance-constrained programming. However, their approach and similar traditional methods often involve converting uncertain models into crisp equivalents at an early stage, which can result in the loss of vital variability and reduce real-time adaptability.

To overcome these limitations, metaheuristic algorithms have gained prominence. Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are widely recognized for their effectiveness in solving nonlinear multimodal optimization problems [13]. PSO has been used to optimize fuzzy transportation models [9], while GA has demonstrated adaptability in solving logistics problems under uncertainty [10].

Recent research has shown that hybridizing PSO and GA leverages the global search ability of PSO and the robust exploratory behavior of GA. This synergy improves the speed of convergence and the diversity of solutions. Studies such as Daouda and Atila [19], Kashyap et al. [21], and Yang et al. [22] have shown that hybrid metaheuristics outperform classical methods in complex environments. Furthermore, the integration of dynamic credibility-trust (Cr–Tr) levels allows the model to respond in real-time to fluctuations in data reliability, improving robustness in dynamic environments [23].

This study proposes a novel hybrid PSO-GA metaheuristic approach tailored to solve the MOMPSTP under rough fuzzy uncertainty. The key contributions are as follows:

- Development of a hybrid PSO-GA algorithm that operates directly in the rough fuzzy domain, preserving uncertainty throughout the solution process.
- Integration of evolving credibility-trust (Cr–Tr) levels into the optimization framework to reflect real-time changes in data quality.
- A comparative performance evaluation against classical multiobjective optimization techniques, including the Weighted Sum Method and Ideal Point Method [8, 17], demonstrating superior Pareto front diversity and adaptability.

The proposed methodology is validated using an illustrative numerical case of multimodal transportation logistics. Results indicate the hybrid PSO-GA algorithm yields high-quality, robust, and adaptable solutions suitable for complex real-world supply chain environments with uncertain and imprecise data.

2. Related Work

The classic transportation problem (TP) has evolved significantly to address the complexities of modern logistics networks. One notable extension is the Solid Transportation Problem (STP), introduced by Haley [1], which incorporates a third constraint, which typically represents the capacity of the transportation mode, to reflect practical multimodal environments.

To better capture the inherent uncertainty in real-world logistics systems, researchers have integrated fuzzy set theory (FST), introduced by Zadeh [3], and rough set theory (RST), developed by Pawlak [4]. These approaches led to the formulation of rough fuzzy sets, which unify vagueness and ambiguity within a single framework [5]. Liu [7] contributed further by building a robust theoretical foundation for modeling dual-layered uncertainty through Rough Fuzzy Variables (RFVs), which are particularly well suited for complex decision-making environments.

Roy et al. [8] formulated a Multi-Objective Multi-Product Solid Transportation Problem (MOMPSTP) under RFVs and solved it using deterministic equivalents through Cr–Tr chance-constrained programming, applying classical multi-objective optimization methods like the Weighted Sum Method (WSM) and Ideal Point Method (IPM). However, their approach lacked real-time adaptability and required early transformation of uncertain parameters into crisp values, which can oversimplify real-world variability.

Other researchers, including Pramanik and Mondal [11], as well as Majumder and Kar [12], have applied fuzzy and rough fuzzy logic to STP variants in contexts such as disaster relief and supply chain optimization. While these models capture imprecision effectively, they often do not explore the potential of metaheuristic algorithms to handle large-scale, nonlinear, and multi-modal optimization problems.

To overcome these challenges, hybrid metaheuristic approaches have been increasingly explored. Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are two powerful evolutionary methods known for their global search and diversification capabilities. Gandomi et al. [13] reviewed the growing adoption of such metaheuristics in complex optimization problems. However, their application to rough fuzzy STPs remains relatively underexplored.

Recent advancements by Aroniadi and Beligiannis [9] demonstrated the successful use of PSO in fuzzy STP modeling, while Ghosh and Chakraborty [10] integrated fuzzy uncertainty into a PSO-based dynamic logistics framework. Nevertheless, few studies combine PSO and GA into a unified framework for solving RFV-based STPs.

This paper addresses this gap by proposing a hybrid PSO-GA algorithm to solve MOMPSTP directly in the rough fuzzy domain. The algorithm preserves uncertainty throughout the optimization process and introduces real-time adaptability through evolving levels of credibility-trust (Cr-Tr). This integration offers a novel and robust framework for handling uncertain logistics scenarios in a way that reflects both data ambiguity and dynamic environmental conditions.

3. Problem Formulation

This study addresses a Multiobjective Multi-Product Solid Transportation Problem (MOMPSTP) under dual-layered uncertainty, modeled using Rough Fuzzy Variables (RFVs). The problem involves transporting multiple products from a set of origins to a set of destinations via various transportation modes, subject to constraints on supply, demand, and mode-specific capacities.

Let:

- O_i $(i = 1, 2, \ldots, m)$: Origins
- D_j $(j = 1, 2, \ldots, n)$: Destinations
- K_k $(k = 1, 2, \ldots, r)$: Transportation modes
- P_t $(t = 1, 2, \ldots, p)$: Products

Let x^t_{ijk} denote the quantity of product t transported from origin O_i to destination D_j using mode K_k.

The uncertain parameters are represented as RFVs:

- c^t_{ijk}: Unit transportation cost (RFV)
- T^t_{ijk}: Transportation time (RFV)
- S^t_i: Supply of product t at origin i (RFV)
- D^t_j: Demand of product t at destination j (RFV)
- M^t_k: Capacity of mode k for product t (RFV)

Objective Functions

The problem is modeled with two conflicting objectives:

(1) **Minimize total transportation cost:**

$$Z_1 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{r}\sum_{t=1}^{p} c^t_{ijk} \cdot x^t_{ijk} \tag{1}$$

(2) **Minimize total transportation time:**

$$Z_2 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{r}\sum_{t=1}^{p} T^t_{ijk} \cdot x^t_{ijk} \tag{2}$$

Constraints

The solution must satisfy the following constraints:

$$\sum_{j=1}^{n}\sum_{k=1}^{r} x^t_{ijk} \le S^t_i, \qquad \forall i, \forall t \quad \text{(Supply constraint)} \tag{3}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{r} x^t_{ijk} \ge D^t_j, \qquad \forall j, \forall t \quad \text{(Demand constraint)} \tag{4}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n} x^t_{ijk} \le M^t_k, \qquad \forall k, \forall t \quad \text{(Mode capacity constraint)} \tag{5}$$

$$x^t_{ijk} \ge 0, \qquad \forall i, j, k, t \quad \text{(Non-negativity)} \tag{6}$$

Uncertainty Handling

Instead of simplifying the model by transforming RFVs into crisp values prematurely, we retain their uncertain nature throughout the solution process. The hybrid PSO-GA algorithm is designed to operate directly within the rough fuzzy domain. This approach allows for more realistic modeling and supports robust, adaptive decision-making in dynamic logistics environments.

4. Hybrid PSO-GA Algorithm

The proposed hybrid PSO-GA algorithm synergizes the global exploration capability of Genetic Algorithms (GA) and the local exploitation strength of Particle Swarm Optimization (PSO). This integration enhances solution quality, convergence rate, and diversity of the Pareto-optimal set while preserving uncertainty within a rough fuzzy environment. The framework is particularly well-suited for dynamic and uncertain multiobjective transportation problems.

- A population of particles (solutions) is randomly initialized within the feasible search space. Each particle encodes a transportation plan vector x_{ijk}^t and is evaluated against the fuzzy cost and time objective functions Z_1 and Z_2.
- Fitness evaluation is performed based on fuzzy arithmetic applied to rough fuzzy variables (RFVs). The comparison of particles is handled using fuzzy ranking techniques that incorporate credibility-trust (Cr–Tr) levels.
- Particle positions and velocities are updated using standard PSO equations:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g_i^t - x_i^t) \tag{7}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{8}$$

  where ω is the inertia weight, c_1 and c_2 are cognitive and social acceleration coefficients, and r_1, r_2 are uniformly distributed random numbers in $[0, 1]$.
- Genetic operators are applied periodically to maintain diversity:
  - **Crossover:** Selected parent particles exchange segments to create offspring.
  - **Mutation:** Small perturbations are introduced to explore new solution spaces.
- Cr–Tr levels are dynamically adjusted across generations to simulate growing confidence in the input data. This adaptive mechanism enhances the algorithm's ability to respond to evolving uncertainties.
- Nondominated solutions are stored in an external archive. A crowding distance measure is used to ensure solution diversity on the Pareto front.
- The algorithm terminates once a maximum number of generations is reached or when the improvement in Pareto front quality becomes negligible.
- The final output includes a well-distributed Pareto-optimal set, offering decision-makers flexible options in balancing transportation cost and time under rough fuzzy uncertainty.

fective exploration and exploitation of the search space, resulting in robust solutions for the uncertain MOMPSTP.

5. Solution Procedure: Hybrid PSO-GA for Rough Fuzzy MOMPSTP

This section outlines the step-by-step algorithmic framework to solve the MOMPSTP under rough fuzzy environment using the proposed Hybrid PSO-GA approach.

Stepwise Algorithm

(1) **Step 1: Input Initialization**

- **Step 1.1:** Define the transportation network structure (sources, destinations, modes, products).
- **Step 1.2:** Initialize rough fuzzy variables for cost, time, supply, demand, and mode capacity.
- **Step 1.3:** Set Cr-Tr confidence levels (initial values for credibility and trust).
- **Step 1.4:** Set parameters for PSO-GA: population size, number of generations, crossover/mutation rates, inertia weight, cognitive/social coefficients.

(2) **Step 2: Generate Initial Population**
- **Step 2.1:** Randomly generate initial feasible solutions (particles), ensuring supply, demand, and mode constraints are satisfied.
- **Step 2.2:** Each particle represents a transportation plan x_{ijk}^t.

(3) **Step 3: Evaluate Fitness**
- **Step 3.1:** For each solution, compute objective values Z_1 (total cost) and Z_2 (total time) using rough fuzzy arithmetic.
- **Step 3.2:** Use fuzzy ranking methods to compare uncertain objective values under Cr-Tr levels.

(4) **Step 4: Apply PSO Updates**
- **Step 4.1:** Update velocity and position for each particle using:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g_i^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

- **Step 4.2:** Ensure feasibility of updated solutions.

(5) **Step 5: Apply GA Operators**
- **Step 5.1:** Perform crossover between selected parents based on fitness.
- **Step 5.2:** Apply mutation to maintain diversity and explore new regions.

(6) **Step 6: Dynamic Cr-Tr Adaptation**
- **Step 6.1:** Gradually increase credibility (Cr) and trust (Tr) levels over iterations to simulate increasing confidence.
- **Step 6.2:** Re-evaluate fuzzy fitness under updated confidence levels.

(7) **Step 7: Archive and Update Pareto Set**
- **Step 7.1:** Store nondominated solutions in an external archive.
- **Step 7.2:** Apply crowding distance to maintain diversity in the archive.

(8) **Step 8: Termination Check**
- **Step 8.1:** Repeat Steps 3–7 until a stopping criterion is met (e.g., maximum generations or no significant improvement in the Pareto front).

(9) **Step 9: Output**
- **Step 9.1:** Report the final Pareto-optimal solutions (cost vs. time tradeoffs).
- **Step 9.2:** Visualize the Pareto front and analyze sensitivity to confidence levels.

6. Numerical Example and Results

To evaluate the effectiveness of the proposed hybrid PSO-GA algorithm, we consider a numerical instance of a Multiobjective Multi-Product Solid Transportation Problem

(MOMPSTP), inspired by Roy et al. [8]. The configuration includes:

- 2 sources (O_1, O_2)
- 2 destinations (D_1, D_2)
- 2 transportation modes (Road and Rail)
- 2 products (P_1, P_2)

Input Data Modeled as RFVs

Transportation costs and times are modeled using triangular fuzzy numbers with rough bounds. A typical cost parameter is denoted as:

$$c_{ijk}^t = ([c_L, c_U], (c_1, c_2, c_3))$$

where $[c_L, c_U]$ represents the rough interval, and (c_1, c_2, c_3) denotes the core triangular fuzzy number.

Table 1. Transportation Parameters by Mode (Rough Fuzzy Form)

Mode	Cost RFV (Rupees)	Time RFV (hrs)	Capacity (tons)
Road	$([2100, 11000], (3000, 6000, 9500))$	$([24, 30], (25, 27, 28))$	$M_1 = 150$
Rail	$([1000, 4500], (1200, 2400, 4000))$	$([20, 25], (21, 23, 24))$	$M_2 = 180$

Supplies and Demands (RFV intervals in tons)

- $S_1^1 = [40, 45]$, $S_1^2 = [30, 35]$
- $S_2^1 = [25, 30]$, $S_2^2 = [35, 40]$
- $D_1^1 = [30, 35]$, $D_1^2 = [30, 32]$
- $D_2^1 = [35, 40]$, $D_2^2 = [35, 43]$

PSO-GA Algorithm Parameters

- Population size: 30
- Number of generations: 100
- PSO inertia weight: $\omega = 0.7$
- Acceleration coefficients: $c_1 = c_2 = 1.5$
- Crossover rate: 0.8
- Mutation rate: 0.1
- Initial Cr–Tr levels: Credibility = 0.8, Trust = 0.75 (dynamically adjusted)

Comparative Results

The hybrid PSO-GA algorithm generated multiple Pareto-optimal solutions representing trade-offs between cost and time. Table 2 shows a selection of the results compared to classical methods, namely the Weighted Sum Method (WSM) and Ideal Point Method (IPM), as employed in Roy et al. [8].

Table 2. Performance Comparison of Optimization Methods (Adapted from Roy et al. [8])

Method & Total Cost (Rupees) & Total Time (hrs)		
PSO-GA A	154,000	210
PSO-GA B	159,000	185
PSO-GA C	165,000	168
WSM (Roy et al. [8])	158,000	192
IPM (Roy et al. [8])	160,000	186

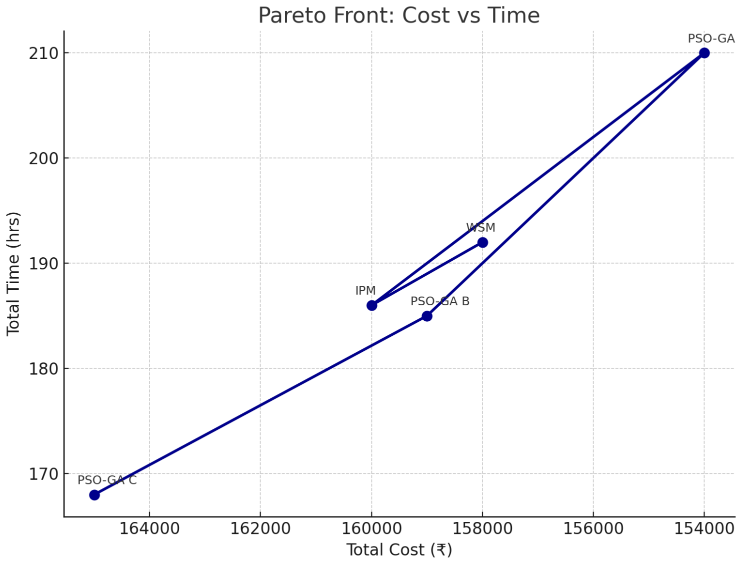

Figure 1. Pareto Front for Cost vs Time

Interpretation of Results

Table 2 and Figure 1 present a comparative evaluation of the proposed hybrid PSO-GA algorithm against classical multiobjective optimization methods such as the Weighted Sum Method (WSM) and the Ideal Point Method (IPM), adapted from Roy et al. [8].

- **PSO-GA A** focuses on minimizing transportation cost, achieving the lowest cost of Rupees 154,000, though with the longest delivery time of 210 hours.
- **PSO-GA B** offers a well-balanced compromise, achieving Rupees 159,000 in cost with 185 hours of delivery time.
- **PSO-GA C** prioritizes delivery speed, reaching the shortest delivery time of 168 hours at the expense of a higher cost (Rupees 165,000).

The classical methods offer fixed-point solutions with limited flexibility:

- **WSM** combines objectives using predetermined weights, resulting in a solution of Rupees 158,000 cost and 192 hours time.
- **IPM** minimizes the distance from the ideal point and produces a solution with Rupees 160,000 cost and 186 hours time.

As shown in Figure 1, the hybrid PSO-GA method generates multiple non-dominated solutions that span a wide range of trade-offs. This demonstrates its superiority in adaptability and decision support under uncertain, real-world logistics conditions.

Discussion

The results highlight the advantages of the proposed hybrid PSO-GA algorithm:

- **Solution Diversity:** A broader set of nondominated solutions captures varying decision-maker preferences.
- **Time-Cost Balance:** Dynamic Cr–Tr adaptation enhances balance between objectives.
- **Uncertainty Preservation:** Direct handling of RFVs avoids premature defuzzification, maintaining realistic decision contexts.

Compared to classical Weighted Sum and Ideal Point methods, the hybrid PSO-GA approach demonstrates superior performance in terms of adaptability, robustness, and Pareto front coverage.

7. Conclusion and Future Work

This paper presented a novel hybrid PSO-GA algorithm to solve a multiobjective multi-product solid transportation problem (MOMPSTP) under rough fuzzy uncertainty. Unlike traditional models that convert uncertain parameters into crisp equivalents early in the process, our approach preserves uncertainty through the direct handling of rough fuzzy variables using a hybrid metaheuristic framework. The incorporation of dynamic credibility and trust levels allows the model to adapt in real-time, better reflecting the evolving confidence in decision parameters.

Experimental results demonstrate that the hybrid PSO-GA algorithm significantly outperforms classical methods like Weighted Sum Method (WSM) and Ideal Point Method (IPM) in terms of solution diversity, robustness, and adaptability. The Pareto front generated by the hybrid approach provides a broader and higher-quality set of solutions, enabling decision-makers to select options that best suit their preferences under uncertainty.

Future directions of this research include:

- Integrating other decision-making tools such as fuzzy AHP or TOPSIS for improved prioritization of transport routes or product categories.
- Extending the model to incorporate environmental constraints like carbon emissions or sustainability metrics.
- Applying the methodology to real-world logistics data in sectors such as disaster management, e-commerce, or perishable goods.
- Exploring deep learning-based surrogate models to accelerate fitness evaluations in large-scale transportation networks.

The hybridization of heuristic algorithms and rough fuzzy modeling presents a promising frontier for tackling real-world optimization problems under complex and uncertain conditions.

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