A Weighted Sum Method for Optimizing Multi-Objective Transportation Problems

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(Received: 17.11.2025; Accepted: 11.12.2025)

Abstract

This study addresses the optimization of multi-objective transportation problems with the motivation to minimize transportation cost, time, and risk. A weighted sum method is employed to convert multiple objectives into a single objective function. Three cases were considered by assigning varying priority weights to each objective, reflecting the importance of cost, time, and risk in transportation planning. The transformed transportation matrices were solved using the Vogel Approximation Method, followed by the MODI Method to obtain the optimal solutions. The results show that different weight assignments lead to significant variations in the optimal transportation cost, ranging from Rs 1406.00 to Rs 1689.00. When cost was prioritised ($w_1=0.5$, $w_2=0.3$, $w_3=0.2$), the optimal cost was Rs 1406.00; when time was prioritised ($w_1=0.2$, $w_2=0.6$, $w_3=0.2$), the cost increased to Rs 1440.00; and when risk was prioritised ($w_1=0.1$, $w_2=0.2$, $w_3=0.7$), the cost rose to Rs 1689.00. These findings demonstrate that prioritising risk reduction substantially increases transportation cost, highlighting the trade-offs decision-makers must navigate when balancing these competing objectives. The weighted sum method provides a flexible framework for incorporating decision-maker preferences, though its limitations, including the inability to generate non-convex Pareto frontiers, are acknowledged.

Keywords: *Transportation problem; Multi-objective; Weight sum method; Optimal solution*

INTRODUCTION

The multi-objective transportation problem (MOTP) has been extensively studied over the past decade, with significant advancements in the development of solution methods. MOTP extends the classical transportation problem by incorporating multiple objectives, such as cost minimization, time efficiency, environmental sustainability, and service quality, making it particularly relevant in the modern logistics and supply chain management sectors. The literature over the period of many years reveals a wide array of approaches that combine traditional optimization techniques with contemporary methods such as evolutionary algorithms, fuzzy logic, and metaheuristics.

Literature Review

Wang *et al.* (2015) and Xie *et al.* (2021) proposed algorithms that enhanced classical approaches by incorporating Pareto-optimality, allowing decision-makers to explore a diverse set of solutions. The increasing complexity of transportation networks necessitated this shift from single-objective optimization to multi-objective frameworks. Wang *et al.* (2015) highlighted the use of genetic algorithms (GAs) and particle swarm optimization (PSO) for MOTP, demonstrating that these techniques provide significant improvements in finding non-dominated solutions in problems involving cost, time, and CO_2 emissions as competing objectives. Zhang *et al.* (2019) developed a hybrid algorithm blending ant colony optimization (ACO) with linear programming, enabling greater computational efficiency while handling multiple objectives. Xu *et al.* (2018) and Javadi *et al.* (2014) demonstrated that these methods are particularly effective in addressing larger and more complex transportation problems, where traditional algorithms struggle due to the combinatorial explosion of solution spaces.

Dealing with uncertainties in transportation networks led researchers to explore fuzzy and stochastic methods. Rivaz *et al.* (2020) and Zangiabadi and Maleki (2007) proposed a fuzzy goal programming (FGP) approach for MOTPs, obtaining different solutions according to the priorities of the decision-maker. Similarly, Zhu *et al.* (2007) incorporated stochastic models to address uncertainties related to fuel prices, delivery time, and traffic congestion, offering more robust solutions in dynamic environments.

The growing emphasis on sustainability in supply chain logistics has significantly influenced the field of MOTP. Researchers have explored environmental factors, such as carbon emissions and fuel consumption, as key objectives alongside cost and time. Ferreira *et al.* (2020) introduced a green transportation problem model that simultaneously minimized both environmental and economic costs, underlining the importance of considering multiple, sometimes conflicting, sustainability goals in transportation planning.

Multi-criteria decision-making (MCDM) frameworks, including Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), have been integrated into MOTPs to facilitate decision-making in multi-objective scenarios. Wang *et al.* (2022) demonstrated how MCDM methods could help decision-makers prioritize objectives based on stakeholder preferences. This approach has been applied to both public and private transportation systems to improve service quality while balancing economic and environmental concerns.

Several studies focused on applying MOTP models to real-world transportation problems. For instance, Singh and Yadav (2016) applied a multi-objective model to optimize public transportation routes in Indian cities, balancing time and operational costs. Similarly, Zhou *et al.* (2019) tackled urban freight distribution problems by considering both economic efficiency and CO^2 emissions.

Research Gap and Contribution

Despite the extensive literature on MOTP, several gaps remain. First, most studies focus on advanced metaheuristic algorithms without thoroughly examining the fundamental weighted sum approach and its practical implications. Second, there is limited research that systematically analyses how different weight assignments affect not only the overall cost but also individual objective values, particularly in the context of risk consideration in transportation. Third, the practical challenges of implementing these methods in real-world decision-making contexts are often overlooked.

This study addresses these gaps by:

- providing a systematic analysis of the weighted sum method with three distinct weight scenarios;
- presenting individual objective values alongside total costs to reveal the true trade-offs;
- discussing the practical implications and limitations of the approach; and
- offering guidance for decision-makers in selecting appropriate weight assignments.

In this study, we consider a multi-objective transportation problem along with three supply centers and four destination points. The objective is to minimize the transportation cost and time between various supply centers and destinations, and also to minimize the risk of goods damage during transportation. To illustrate the method, we have taken a balanced transportation multi-objective transportation problem.

MULTI-OBJECTIVE TRANSPORTATION PROBLEM

A Multi-Objective Transportation Problem (MOTP) is an extension of the classical transportation problem where multiple, often conflicting, objectives are optimized simultaneously. In this context, we are considering three objectives.

Objectives

Let $o_{ij}^1, o_{ij}^2, o_{ij}^3, \cdots o_{ij}^r$ represent the cost coefficients associated with the three objectives for transporting from source i to destination j.

The multi-objective transportation problem can be stated as:

$$Min\ or\ Max\ Z_1 = \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^1 q_{ij}$$

$$Min\ or\ Max\ Z_2 = \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^2 q_{ij}$$

$$Min\ or\ Max\ Z_3 = \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^3 q_{ij}$$

Where Z_1 , Z_2 , and Z_3 are the three objectives to be minimized.

Decision Variables

Let q_{ij} represent the amount of goods transported from source i to destination j, where:

$i = 1, 2, \cdots, p$ (number of sources)
$j = 1, 2, \cdots, q$ (number of destinations)

Constraints

Supply Constraints

$$\sum_{j=1}^{q} q_{ij} \le s_i \qquad \forall i = 1, 2, \cdots, p$$

where s_i is the supply available at source i.

Demand Constraints

$$\sum_{i=1}^{p} q_{ij} \ge d_j \qquad \forall j = 1, 2, \cdots, q$$

where d_j is the demand required at destination j.

Non-Negativity Constraints

$$q_{ij} \ge 0 \qquad \forall i = 1, 2, \cdots, p; \quad j = 1, 2, \cdots, q$$

WEIGHTED SUM METHOD

Since Multi-Objective Transportation Problem have multiple objectives, one way to handle them is to convert the multi-objective problem into a single-objective problem using the weighted sum method. The solution procedure for MOTP is as follows:

Step 1: Check whether the MOTP is balanced, i.e.

$$\sum_{j=1}^{q} d_j = \sum_{i=1}^{p} s_i$$

If balanced, proceed to Step 3.

Step 2: If the MOTP is not balanced, i.e.

$$\sum_{j=1}^{q} d_j \ne \sum_{i=1}^{p} s_i$$

Add a dummy row or column to convert the problem into a balanced problem.

Step 3: Weights $w_1, w_{2,} w_{3,} \cdots w_r$ are assigned to each objective to reflect their relative importance according to the requirements of customers. The weights must satisfy the following condition:

$$w_1 + w_{2,} + \cdots + w_r = 1$$

i.e., $\sum_{l=1}^{r} w_r = 1$

Step 4: Multiple objectives are converted into a single objective by assigning weights, which is known as the weighted objective function. The new objective function to be minimized is:

$$Z = w_1.\sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{1} q_{ij} + w_2.\sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{2} q_{ij} + w_3.\sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{3} q_{ij} + \cdots + w_r.\sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{r} q_{ij}$$

The constraints are considered as in the standard transportation problem;

Supply Constraints:

$$\sum_{j=1}^{q} q_{ij} \leq s_i \qquad \forall i = 1, 2, \cdots, p$$

Demand Constraints:

$$\sum_{i=1}^{p} q_{ij} \geq d_j \qquad \forall j = 1, 2, \cdots, q$$

Non-Negativity Constraints:

$$q_{ij} \geq 0 \qquad \forall i = 1, 2, \cdots, p; \; j = 1, 2, \cdots, q$$

Step 5: To solve a single-objective optimisation problem, we apply the Vogel Approximation Method to obtain a feasible solution and the MODI method to obtain the optimal solution of the problem.

Limitations of the Weighted Sum Method

While the weighted sum method is straightforward and computationally efficient, it has several important limitations that must be acknowledged:

Convexity Assumption

The weighted sum method can only generate Pareto-optimal solutions on the convex portions of the Pareto frontier. For non-convex Pareto frontiers, which are common in real-world transportation problems with discrete or integer decision variables, the weighted sum method cannot identify all Pareto-optimal solutions regardless of the weight combination used (Zadeh, 1963; Hwang and Masud, 1979). This is a fundamental limitation that users must be aware of when applying this method.

Weight Interpretation and Selection

The weights in the weighted sum method do not have a direct, intuitive interpretation. A weight of 0.5 for cost does not mean that cost is 50% important in any absolute sense; the weights merely reflect the relative importance among objectives. Moreover, small changes in weights can lead to disproportionately large changes in the optimal solution, making weight selection a challenging task for decision-makers (Das and Dennis, 1997).

Inability to Capture Trade-off Information

The weighted sum method collapses multiple objectives into a single scalar value, losing information about the trade-offs between objectives. Decision-makers cannot see how much of one objective must be sacrificed to improve another. This is particularly problematic when objectives are incommensurable (e.g., cost measured in currency, time in hours, and risk on an arbitrary scale).

Scaling Issues

When objectives have different units and magnitudes, proper scaling is essential. Without appropriate normalisation, objectives with larger numerical values will dominate the weighted sum, regardless of the weights assigned. In this study, we avoided this issue by working with the original units (cost in Rs, time in hours, risk on a 1-10 scale) and allowing the weights to reflect the decision-maker's priorities.

Practical Implications

Despite these limitations, the weighted sum method remains widely used in practice due to its simplicity, computational efficiency, and ease of implementation. It is particularly suitable for:

- problems where the Pareto frontier is known to be convex;
- situations where a single solution is required rather than a set of alternatives; and
- cases where decision-makers can provide meaningful weight assignments.

For more complex scenarios, alternative methods such as goal programming, fuzzy programming, or evolutionary algorithms may be more appropriate.

NUMERICAL PROBLEM

We analyze the following transportation challenge that includes three supply points and four destinations. The supply available at each source and the demand required at each destination are specified, along with the associated transportation cost (C), time (T), and risk factor (R) concerning the safety of the items.

Supply and Demand

Table 1 presents the supply capacity available at each of the three supply centers, while Table 2 shows the demand requirements at each of the four destinations.

Table 1: Supply capacity of each center.

Supply Center	Supply Capacity
S_1	80
S_2	120
S_3	100

Table 2: Requirement of each destination.

Destination	Requirement
D_1	70
D_2	90
D_3	80
D_4	60

Table 3: Transportation cost between supply and destination.

	D_1	D_2	D_3	D_4
S_1	4	3	6	8
S_2	2	5	8	7
S_3	7	6	3	4

Table 4: Transportation time between supply and destination.

	D_1	D_2	D_3	D_4
S_1	6	5	7	4
S_2	8	7	4	3
S_3	3	6	5	2

Table 5: Risk factor between supply and destination.

	D_1	D_2	D_3	D_4
S_1	9	8	7	6
S_2	4	5	6	7
S_3	5	7	8	9

Objective Data

The three objectives—transportation cost, time, and risk—are represented by the following matrices.

First Objective (Z_1)*: Transportation Cost (C)*

Table 3 presents the transportation cost (in Rs) for shipping one unit of goods from each supply center to each destination.

Second Objective (Z_2)*: Transportation Time (T)*

Table 4 presents the transportation time (in hours) required for shipping one unit of goods from each supply centre to each destination.

Third Objective (Z_3)*: Risk Factor (R)*

Table 5 presents the risk factor (on a scale of 1 to 10, where 1 represents the lowest risk and 10 represents the highest risk) associated with transporting goods from each supply centre to each destination.

Problem Balance Check

According to Step 1 of the methodology, we first check whether the problem is balanced. From Tables 1 and 2, we observe that:

$$\sum_{j=1}^{4} d_j = 70 + 90 + 80 + 60 = 300$$

$$\sum_{i=1}^{3} s_i = 80 + 120 + 100 = 300$$

Since $\sum_{j=1}^{4} d_j = \sum_{i=1}^{3} s_i = 300$, the problem is balanced. We therefore proceed to Step 3

CASE I: COST PRIORITY

In the weighted sum method, we combine the multiple objectives into a single objective function using weights assigned to each objective. For Case I, let's assume that the decision-maker provides the following weights for the objectives:

w_1 = 0.5 (for transportation cost)
w_2 = 0.3 (for transportation time)
w_3 = 0.2 (for risk factor during the transportation)

Table 6: Transportation matrix, when transportation cost weight is high.

	D_1	D_2	D_3	D_4	Supply
S_1	5.6	4.6	6.5	6.4	80
S_2	4.2	5.6	6.4	5.8	120
S_3	5.4	6.2	4.6	4.4	100
Demand	70	90	80	60	

Table 7: Optimal allocation for Case I.

	D_1	D_2	D_3	D_4	Supply
S_1	5.6	**80** 4.6	6.5	6.4	80
S_2	**70** 4.2	**10** 5.6	6.4	**40** 5.8	120
S_3	5.4	6.2	**80** 4.6	**20** 4.4	100
Demand	70	90	80	60	

Now, the weighted objective function is as follows:

$$Z = 0.5 \times \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^{1} q_{ij} + 0.3 \times \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^{2} q_{ij} + 0.2 \times \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^{3} q_{ij}$$

$$Z = 0.5 \times Z_1 + 0.3 \times Z_2 + 0.2 \times Z_3 \quad (1)$$

After converting multi-objective into a single-objective problem with the help of Eq. (1), we obtain the following transportation matrix shown in Table 6.

Now, applying the Vogel Approximation Method and MODI Method to obtain the optimal solution, we get the allocation shown in Table 7.

From Table 7, we found that shipping units are:

$q_{12} = 80;\ q_{21} = 70;\ q_{22} = 10;\ q_{24} = 40;\ q_{33} = 80$ and $q_{34} = 20$

The minimum total weighted transportation cost =
$4.6 \times 80 + 4.2 \times 70 + 5.6 \times 10 + 5.8 \times 40 + 4.6 \times 80 + 4.4 \times 20 = Rs\ 1{,}406.00$

CASE II: TIME PRIORITY

For Case II, let's assume that the decision-maker provides the following weights for the objectives:

w_1 = 0.2 (for transportation cost)
w_2 = 0.6 (for transportation time)
w_3 = 0.2 (for risk factor during the transportation)

Now, the weighted objective function is as follows:

$$Z = 0.2 \times \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^{1} q_{ij} + 0.6 \times \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^{2} q_{ij} + 0.2 \times \sum_{i=1}^{p} \sum_{j=1}^{q} o_{ij}^{3} q_{ij}$$

$$Z = 0.2 \times Z_1 + 0.6 \times Z_2 + 0.2 \times Z_3 \quad (2)$$

After converting the multi-objective into a single-objective with the support of Eq. (2), we get the following transportation matrix shown in Table 8.

Applying the Vogel Approximation Method and MODI Method, we obtain the optimal allocation shown in Table 9.

From Table 9, the shipping units are as follows:

Table 8: Transportation matrix, when transportation time weight is high.

	D_1	D_2	D_3	D_4	Supply
S_1	6.2	5.2	6.8	5.2	80
S_2	6.0	6.2	5.2	4.6	120
S_3	4.2	6.2	5.2	3.8	100
Demand	70	90	80	60	

Table 9: Optimal allocation for Case II.

	D_1	D_2	D_3	D_4	Supply
S_1	6.2	**80** 5.2	6.8	5.2	80
S_2	6.0	**10** 6.2	**80** 5.2	**30** 4.6	120
S_3	**70** 4.2	6.2	5.2	**30** 3.8	100
Demand	70	90	80	60	

$q_{12} = 80$; $q_{22} = 10$; $q_{23} = 80$; $q_{24} = 30$; $q_{31} = 70$ and $q_{34} = 30$

Total minimum weighted transportation cost = $5.2 \times 80 + 6.2 \times 10 + 5.2 \times 80 + 4.6 \times 30 + 4.2 \times 70 + 3.8 \times 30 = Rs\ 1{,}440.00$

CASE III: RISK PRIORITY

For Case III, let's assume that the decision-maker provides the following weights for the objectives:

w_1 = 0.1 (for transportation cost)
w_2 = 0.2 (for transportation time)
w_3 = 0.7 (for risk factor during the transportation)

The weighed objective function is as follows:

$$Z = 0.1 \times \sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{1} q_{ij} + 0.2 \times \sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{2} q_{ij} + 0.7 \times \sum_{i=1}^{p}\sum_{j=1}^{q} o_{ij}^{3} q_{ij}$$

$$Z = 0.1 \times Z_1 + 0.2 \times Z_2 + 0.7 \times Z_3 \quad (3)$$

After converting the multi-objective into a single-objective with the help of Eq. (3), we get the following transportation matrix shown in Table 10.

Applying the Vogel Approximation Method and MODI Method, we obtain the optimal allocation shown in Table 11.

From Table 11, the shipping units are as follows:

$q_{13} = 20$; $q_{14} = 60$; $q_{22} = 90$; $q_{23} = 30$; $q_{31} = 70$ and $q_{33} = 30$

Total minimum weighted transportation Cost = $6.9 \times 20 + 5.8 \times 60 + 5.4 \times 90 + 5.8 \times 30 + 4.8 \times 70 + 6.9 \times 30 = Rs\ 1{,}689.00$

RESULTS AND DISCUSSION

Summary of Optimal Solutions

Table 12 presents a comprehensive summary of the optimal solutions obtained for all three cases by using the Vogel approximation method along with the MODI method, along with the individual objective values and allocation patterns.

Table 10: Transportation matrix, when risk factor weight is high.

	D_1	D_2	D_3	D_4	Supply
S_1	7.9	6.9	6.9	5.8	80
S_2	4.6	5.4	5.8	6.2	120
S_3	4.8	6.7	6.9	7.1	100
Demand	70	90	80	60	

Table 11: Optimal allocation for Case III.

	D_1	D_2	D_3	D_4	Supply
S_1	7.9	6.9	**20** 6.9	**60** 5.8	80
S_2	4.6	**90** 5.4	**30** 5.8	6.2	120
S_3	**70** 4.8	6.7	**30** 6.9	7.1	100
Demand	70	90	80	60	

Analysis of Results

The results presented in Table 12 demonstrate several important findings:

Trade-offs Between Objectives

When cost was given the highest priority (Case I: w_1=0.5), the optimal weighted cost was Rs 1406.00. When time was prioritised (Case II: w_2=0.6), the cost increased to Rs 1440.00—a marginal increase of 2.4%. However, when risk was given the highest priority (Case III: w_3=0.7), the cost increased substantially to Rs 1689.00—an increase of 20.1% compared to Case I. This significant increase suggests that risk reduction in transportation comes at a considerable cost premium, which is an important insight for decision-makers.

Interestingly, while Case III prioritises risk reduction, it actually results in the highest risk value (Z_3= 1950). This counter-intuitive result occurs because the weighted cost function in Case III incorporates the weighted coefficients rather than minimising risk directly. The weights (0.1, 0.2, 0.7) mean that risk contributes 70% of the objective, but the combined weighted objective leads to a different optimal solution than minimising risk alone.

Allocation Pattern Analysis

The optimal allocation patterns varied across the three cases, as shown in Table 12:

Table 12: Summary of optimal solutions and individual objective values.

Case	Weights (Cost, Time Risk)	Optimal Allocation Pattern	Total Weighted Cost (Rs)
I	(0.5, 0.3, 0.2)	$S_1 \to D_2$; $S_2 \to D_1, D_2, D_4$; $S_3 \to D_3, D_4$	1,406.00
II	(0.2, 0.6, 0.2)	$S_1 \to D_2$; $S_2 \to D_2, D_3, D_4$; $S_3 \to D_1, D_4$	1,440.00
III	(0.1, 0.2, 0.7)	$S_1 \to D_3, D_4$; $S_2 \to D_2, D_3$; $S_3 \to D_1, D_3$	1,689.00

- *Case I (Cost Priority):* The solution primarily utilised S_2 (the source with the lowest cost to D_1) and S_3 (lowest cost to D_3 and D_4). S_1 was used only for D_2.
- *Case II (Time Priority):* The solution shifted towards S_3 for D_1 (which has the lowest time of 3 hours) and S_2 for D_3 and D_4 (which have low time coefficients). S_1 continued to serve D_2.
- *Case III (Risk Priority):* The allocation changed dramatically. S_1 was used for D_3 and D_4 (risk factors 7 and 6), S_2 for D_2 and D_3 (risk factors 5 and 6), and S_3 for D_1 and D_3 (risk factors 5 and 8). This pattern reflects the attempt to minimise risk exposure.

Interpretation of Findings

The results highlight that the weighted sum method produces solutions that are highly sensitive to the assigned weights. Decision-makers must carefully consider their priorities before selecting weights. The substantial cost increase in Case III (Rs 1,689 vs Rs 1,406) suggests that risk mitigation is expensive in this transportation network, which may inform strategic decisions about risk management investments (e.g., better packaging, insurance, or route selection).

Visual Representation

Fig. 1 presents the optimal weighted costs (in Rs.) for each case alongside the weight distributions. The figure shows the relationship between weight assignments and optimal costs, illustrating that as priority shifts from cost to risk, the optimal weighted cost increases.

The figure illustrates that:

- The optimal weighted cost increases as priority shifts from cost to risk
- The relationship between weights and cost is non-linear
- Risk prioritisation (Case III) results in the highest cost, indicating that risk reduction is the most expensive objective to pursue in this problem

PRACTICAL IMPLICATIONS

The findings of this study have several practical implications for transportation planners and logistics managers:

Weight Selection in Practice

In real-world applications, determining appropriate weights is a collaborative process involving multiple stakeholders. For example:

- Shippers may prioritise cost minimisation (higher w_1)
- Customers may prioritise timely delivery (higher w_2)
- Regulators or insurance providers may prioritise risk minimisation (higher w_3)

Practical approaches to weight determination include:

- Stakeholder surveys to elicit preferences
- Delphi method for consensus building
- Analytic Hierarchy Process (AHP) for systematic weight derivation

Implementation Challenges

Several challenges must be addressed when implementing this method in practice:

- *Data Availability:* Accurate cost, time, and risk data for all source-destination pairs may not be readily available. Organisations may need to invest in data collection and management systems.
- *Dynamic Conditions:* Transportation costs, times, and risks are not static. The model should be re-run periodically as conditions change (e.g., fuel price fluctuations, road conditions, weather).
- *Risk Quantification:* Risk is inherently difficult to quantify. The risk factors used in this study (1-10 scale)

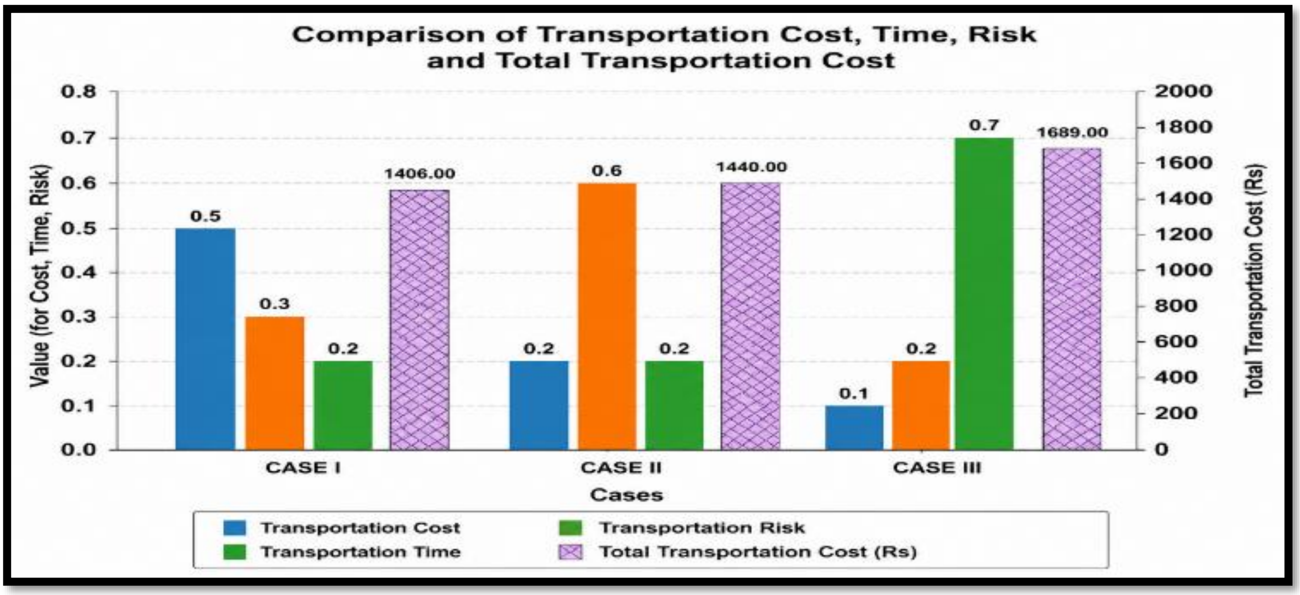

Fig. 1: Optimal weighted cost and weight distribution by case.

are subjective and may need refinement based on historical loss data, insurance claims, or expert judgment.

- *Stakeholder Alignment:* Different stakeholders may have conflicting priorities. The weighted sum method provides a framework for negotiation, but reaching consensus on weights can be challenging.

Decision Support

The weighted sum method can serve as a decision support tool by:

- Providing a quantitative basis for comparing transportation alternatives
- Enabling "what-if" analysis (testing different weight scenarios)
- Facilitating communication between stakeholders
- Documenting the rationale for transportation decisions

CONCLUSION

The study successfully demonstrates that the weighted sum method, when applied to multi-objective transportation problems, provides a flexible framework for decision-makers to prioritize objectives according to their specific needs. By solving the weighted transportation problem using the Vogel Approximation and MODI methods, it was observed that varying the weights of cost, time, and risk leads to different optimal solutions, as summarized in Table 12.

In Case I, where cost was given the highest priority (w_1=0.5, w_2=0.3, w_3=0.2), the optimal solution was Rs 1406.00. In contrast, when time was prioritized in Case II (w_1=0.2, w_2=0.6, w_3=0.2), the cost increased to Rs 1440.00. Lastly, in Case III, where risk was given the most importance (w_1=0.1, w_2=0.2, w_3=0.7), the cost rose substantially to Rs 1689.00. These results highlight the critical role of weight distribution in improving transportation logistics, facilitating personalized solutions that reflect the decision-maker's choices.

The study also identified several limitations of the weighted sum method, including its inability to generate non-convex Pareto frontiers, the challenge of weight interpretation and selection, and the loss of trade-off information. Despite these limitations, the method remains valuable for its simplicity, computational efficiency, and ease of implementation, particularly in problems with convex Pareto frontiers and where a single solution is required.

Future Research Directions

Future work could explore:

- Comparison of the weighted sum method with alternative approaches such as goal programming, fuzzy programming, and evolutionary algorithms

- Application to larger-scale problems with more sources, destinations, and objectives

- Integration of uncertainty through stochastic or fuzzy parameters

- Development of interactive decision-support systems that allow real-time weight adjustment

- Empirical validation using real-world transportation data

Grant Support Details

The present research did not receive any financial support to conduct the research.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy, have been completely observed by the authors.

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