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Creation of a Mathematical Framework for Addressing the Multi-Objective Multi-Item Transportation Challenge Through Linear Programming

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ABSTRACT

Supply chain is a complex area of research because it highlights the non-targeted movement of many commodities across multiple origins and destinations, given the multi-working goal and multi-thing transportation issue, which has vastness in terms of competing objectives. We suggest a systematic mathematical approach using linear programming to address this complex optimization problem. This paper develops a multi-objective linear programming (MOLP) model to optimally minimize cost, time of delivery, and environmental impacts as the first objectives through various published observations. Constraints imposed on the model comprise supply availability, demand allocation requirements, vehicle capacity, and product allocation regulations if multiple products are available. A real practice case study is done using actual operational data in a regional distribution network, optimizing its transportation planning solution approach with WinQSB software to revise the best routes. Results suggest that the balance of conflicting objectives is effectively achieved by the proposed model, leading to a total cost reduction of 18.5%, delivery time reduction of12.3%, as well as lower CO_2 emissions by approximately 15.2%.The research applies the weighted sum-constraint method for Pareto optimization to facilitate decision-making trade-offs, resulting in a comprehensive analysis of trade-offs and potential transportation planning solutions for decision-makers.

1. Introduction

The transportation problem is a fundamental optimization issue in operations research and supply chain management, first introduced by Kantorovich in 1942. However, these problems now face increasingly complex challenges, such as the multicriteria nature and often conflicting goals of freight transport, as well as the transportation of various types of goods in a single journey [1]. Because classical single-objective transportation models have a clear mathematical structure, they are easy to create; however, they often do not reflect the diverse decisions made by any modern supplier on cost minimization considering service level quality, eco-friendliness, and operational flexibility [2]. The multi-item transportation problem generalizes the classical one, considering that several types of products are simultaneously transported on common bi-producible networks, thus introducing added complexity regarding capacity, item-specific restrictions,

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and resource allocation [3]. Multiple objectives are involved, so the goal is not to find optimal solutions but rather sets of Pareto-optimal solutions, implementing trade-offs where achieving beneficial progress in one area may result in negative consequences for another [4]. This paper analyses a practical scenario to bridge the gap between theoretical operations research models and real-world applications. While there are various papers available for unimodal transport solutions, much less work has been dedicated to integrating multimodal objects with varying useful goals and needs onto a single platform; thus, requiring real-world runs using current software [5]. WinQSB allows us not only to solve the model we built but also to bridge from simply doing an exercise on paper to having actual applications in organizations.

1.1 Problem Statement

However, in the context of regional and national distribution networks, the trade-offs become more complex as enterprises must evaluate needs in relation to transportation factors.

This optimizes for price competitiveness, which is associated with transport prices (lower is better), delivery time from the customer's perspective (quicker is desired), and environmental impact through other sustainability targets. This means that these varied objectives can often be at odds; therefore, an advanced optimization process must take place, but rather than finding a unique solution, it will focus on making trade-offs.

1.2 Research Objectives

This paper seeks to:

1. Develop and resolve a broad category of multi-objective multi-item transportation problems. After establishing a practical framework for MIMOTPs, we represent them through mathematical modeling.

2. The nonlinear mathematical model encompasses all potential objective functions, which are as follows:

Let $x \in \mathbb{R}^n$be the vector.

A general can

$$f(x): \mathbb{R}^n \to \mathbb{R}$$

where $f$is any ($\mathbb{R}^n$ to $\mathbb{R}$).

In

$$f(x_1, x_2, \ldots, x_n)$$

where, and be any nonlinear function (e.g., polynomial, exponential, trigonometric, rational, etc.).

Examples:

- $f(x) = x_1^2 + \sin(x_2) + e^{x_3}$
- $f(x) = \frac{x_1^2}{x_2+1} + \log(x_3)$
- $f(x) = \sum_{i=1}^{n} \exp(x_i)$

In summary, anything that is not linear in $qualifies$ as a nonlinear objective function.

3. Current method for achieving Pareto-efficient outcomes Utilizing LP_answers
4. Demonstrate the application of WinQSB software using authentic data with practical characteristics
5. This provides decision-makers with analytical tools to evaluate the effectiveness of transport Policies based on multiple criteria.

Literature Review

1.3. Classical Transportation Problem Foundation

The transportation problem [1] was first studied by Kantorovich and later developed by Dantzig et al., and it is used to find the most efficient way of transporting products from suppliers to consumers. The classical model deals with the transportation of a single commodity where both supply and demand are deterministic. Such standard problems can be efficiently solved by linear programming methods, particularly the transportation simplex algorithm [6].

1.4. Multi-Objective Optimization Methodologies

Due to the commencement of multiple constraints in modern supply chain systems, optimization of supply chains requires a multi-dimensional approach. Pareto published groundbreaking work in multi-objective optimization, showing that rational decisions must acknowledge the space of trade-offs between competing objectives [7]. Most of the existing literature explores Pareto frontiers utilizing different strategies [8], including weighted sums (composite objective functions), constraint methods (converting additional objectives into constraints), and evolutionary algorithms. Ghaemi et al. overcome complex transportation problems via multi-objective genetic algorithms [8], where the cost of computation is very high compared to its counterpart, linear programming 1. In contrast, certain classical linear programming approaches offer explicit solutions in polynomial time and are thus practically attractive when appropriately posed [10].

1.5. Multi-Item Transportation Extensions

The presence of multiple product categories adds a layer of complexity, making the basic transportation model significantly more complicated. For commodity-level properties, vehicle compatibility constraints, and capacity utilization, Chopra and Meindl (2016) propose multi-product distribution models [11]. In the multi-item problems with time intervals for staging and delivery scheduling, Gupta and Kumar (2019) pointed out the necessity of using sophisticated formulations to maintain computational viability [12].

1.6 Fuzzy and Stochastic Extensions

Transportation-related uncertainty has received growing attention from recent studies. Nayeri et al. The triangular fuzzy number was used to handle uncertain supply and demand parameters, enabling the development of a fuzzy multi-objective transportation model based on the parametric programming method [2] (2024). This class of techniques extends classical linear programming to handle uncertain input data defined in ranges rather than point values [13].

5. Implementation in Optimization Software

The software WinQSB (Quantitative Systems for Business) enables the definition of LP problems in an intuitive environment, plots the participating constraints set, and provides graphical solution methods for small-sized problems alongside systematic sensitivity analysis approaches [14]. Although sophisticated solvers, such as CPLEX and Gurobi, are well-suited for large-scale problem solving, WinQSB remains valuable as an educational tool and for small- to medium-sized real-world applications [15].

1.7. Research Gap and Contribution

Despite extensive research on single-objective multi-item transportation problems or multi-objective single-item problems separately, an integrated approach to addressing the multi-objective multi-item transportation problem with computational practicality remains relatively unexplored. This study aims to (1) formulate an explicit mathematical model that comprehensively encompasses multiple objectives and items; (2) devise procedural methods for the practical implementation of the model; (3) generate and analyze Pareto-optimal solutions in terms of data; and (4) offer policy-making suggestions.

1.8 Critical Review of Literature and Model Positioning

A lot of study work has been carried out in the area of transportation optimization; however, the majority of the existing studies are either on single-objective multi-item models or on multi-objective single-commodity transportation problems, for example:

• Kantorovich (1939) and Dantzig (1963) [1] devised basic linear programming models for single-objective, single-commodity problems, which are computationally efficient but lack the flexibility to meet modern supply chain demands.

• Chopra and Meindl (2016) and Gupta & Kumar (2019) [12] extended these models for multi-item transportation with capacity and compatibility limitations, but considered only cost minimization.

• Multi-objective optimizations were discussed by Pareto (1896), Keeney & Raiffa (1993), and Miettinen (1999), where the balancing of the opposing requirements was emphasized, and approaches such as weighted sum, constraint methods, and evolutionary algorithms were proposed. Despite the theoretical soundness of these techniques, little published research has integrated them with real-world supply chain challenges.

Critical Comparison:

• Many past works deal with either multi-item or multi-objective extensions separately, but this paper unifies both multi-objective and multi-item characteristics in a single linear programming model.

• Ghaemi et al. (2015) and others have also used metaheuristic methods such as evolutionary algorithms for multi-objective routing. However, these methods are usually computationally costly and less interpretable for practitioners than linear programming-based solutions.

• This study specifically fills the gap in practical implementation by showing the applicability of the proposed model with real operational data and systematic validation, using accessible software (WinQSB) suitable for practitioners and decision makers in small and medium-sized enterprises.

Contribution Over Previous Works:

- The model can be used to bridge the gap between theory and practice by considering real-world restrictions, multi-criteria, and operational data.
- The framework offers a replicable procedure for model deployment, parameter selection, and solution interpretation, which are often lacking in existing literature.

Results are not only reported numerically but also discussed in terms of managerial implications and trade-offs, providing actionable insights for supply chain decision-makers.

2. Methodology

2.1 Mathematical Model Formulation

The multi-objective multi-item transportation problem is structured as follows:

Objective Functions

We aim to simultaneously:

- Minimize total transportation cost:

$$Z_1 = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{p} c_{ijk} \cdot x_{ijk}$$

Where c_{ijk}= unit cost of transporting product $k$from source $i$to destination j.

- Minimize total delivery time:

$$Z_2 = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{p} t_{ijk} \cdot x_{ijk}$$

Where t_{ijk}= time per unit.

- Minimize total environmental impact:

$$Z_3 = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{p} e_{ijk} \cdot x_{ijk}$$

Where e_{ijk}= CO_2 emissions (kg/unit).

Constraints

1. Supply constraint at each source:

$$\sum_{j=1}^{n} \sum_{k=1}^{p} x_{ijk} \leq S_{ik} \forall i, k$$

(S_{ik}: Available quantity of product $k$at source i)

2. Demand constraint at each destination:

$$\sum_{i=1}^{m} x_{ijk} \geq D_{jk} \forall j, k$$

(D_{jk}: Required quantity of product $k$at destination j)

3. Vehicle capacity constraint (if multiple products share vehicles):

$$\sum_{k=1}^{p} w_k \cdot x_{ijk} \leq V_{ij} \forall i, j$$

(w_k: weight/volume per unit of product k, V_{ij}: vehicle capacity for route $i$to j)

4. Item compatibility constraint (if needed):

$$x_{ijk} \leq M \cdot y_{ijk} \forall i, j, k$$

(y_{ijk}: binary indicator if item $k$is assignable on route $i$to j; $M$is a large constant)

5. Non-negativity:

$$x_{ijk} \geq 0 \forall i, j, k$$

Multi-Objective Optimization Approaches

A. Weighted Sum Method: Combine objectives:

$$\text{Minimize } Z = \alpha_1 Z_1 + \alpha_2 Z_2 + \alpha_3 Z_3$$

Where $\alpha_1, \alpha_2, \alpha_3 \geq 0$and $\alpha_1 + \alpha_2 + \alpha_3 = 1$.

B. Epsilon-Constraint Method: Minimize one (e.g., Z_1), subject to constraints on the others:

$$Z_2 \leq \epsilon_2 Z_3 \leq \epsilon_3$$

Where $\epsilon_2, \epsilon_3$are acceptable thresholds.

Let:

- $i \in \{1, \dots, m\}$: Index of sources (suppliers)
- $j \in \{1, \dots, n\}$: Index of destinations
- $k \in \{1, \dots, p\}$: Index of product types (items)

x_{ijk}: Quantity of product $k\ transported$rted from source $i$to destination j

Table 1. Table of Notations

Symbol	Description
x_{ijk}	Quantity of product $k$from source $i$to destination j
c_{ijk}	Cost per unit for i, j, k
t_{ijk}	Time per unit for i, j, k
e_{ijk}	Environmental impact per unit for i, j, k

Table 1. Table of Notations

Symbol	Description
S_{ik}	Supply of product $k$at source i
D_{jk}	Demand of product $k$at destination j
w_k	Weight/volume per unit of product k
V_{ij}	Vehicle capacity on route $i$to j
y_{ijk}	Binary variable for compatibility
M	Large constant (for the big-M method)

2.2 Solution Methodology

2.2.1 Weighted Sum Approach:

The weighted sum approach simultaneously considers individual objectives for multi-objective optimization. Here, " = non-negative weights" and " = the optimal solution for an objective when optimized separately."
By varying the weights of the combinations, many Pareto-optimal solutions can be obtained, allowing the exploration of trade-offs.
Method of constraints (epsilon method):
In the constraint approach philosophy, surplus goals are replaced with bounds:
where = +, within normal limits. Various Pareto-optimal points were obtained by systematically selecting and.

2.2.2 Deployment of the software to be in use

WinQSB can be utilized to solve these types of linear programming problems as follows:

1. Problem Definition Interface: A structured way to show decision variables, limits, and objectives.
2. Solving Engine: Optimal solution derived from the simplex algorithm.
3. Sensitivity analysis tools: Studying the impact of parameter changes and shadow prices.
4. Visualizations of the solution: Representation of the solution space and the constraint region.

2.2.3 Model Validation and Sensitivity Analysis

To verify the practical value and robustness of the proposed mathematical model, further validation processes were carried out as follows:
a. Benchmark Comparison

The optimized solutions achieved from the model were compared with baseline solutions obtained from standard single-objective transportation models and manual allocation procedures. This comparison showed that the multi-objective method always obtained better performance for at least one target (cost, time or environmental effect) without substantial loss in other targets.

b. Sensitivity Analysis

A sensitivity analysis is carried out by adjusting the main parameters such as supply levels, demand needs, cost coefficients, and weights in the weighted sum approach. The impact of these modifications on the ideal solution was documented, demonstrating the model's responsiveness and the compromises that are natural to real-world decision-making.

For example:

- Increasing the weight on environmental impact (α_3) resulted in notable reductions in CO_2 emissions, albeit with minor increases in total cost.

- Small changes in supply availability at a single source led to re-routing in optimal allocations, demonstrating model flexibility.

c. Statistical Validation

Multiple runs with modified input data were performed, where practicable (e.g., simulating demand fluctuations within historical ranges). The results of the objective outcomes were presented as mean and standard deviation values. The stability of the solution was confirmed in the presence of reasonable data uncertainty.

Table 2. Sensitivity Results Example

Scenario	Total Cost	Delivery Time	CO_2 Emissions
Baseline	115,625	17,245	8,890
+10% Demand at D2	122,340	17,860	9,310
Weight on Emissions: 0.6	119,800	17,430	8,620
5% Increase in Supply at S1	114,950	17,190	8,840

The extensive validation emphasizes the robustness of the suggested strategy and its flexibility to changing operational conditions.

3. Applied Case Study
3.1 Problem Definition

The case study of this research is a realistic operational scenario based on regional food distribution patterns in Iraq. The dataset is a combination of real operational data, when accessible, with appropriate assumptions and generated data where direct records were not available.

- The supply and demand estimates were estimated by consulting with local distribution businesses and market studies, and they reflect the average weekly volumes of fresh produce and packaged items in the Baghdad area.
- Transportation costs were estimated using actual vendor price lists and recent fuel and logistics costs, verified by contacting logistics providers.
- The delivery durations and environmental effect coefficients were computed using average travel times and standard emission rates per unit distance and cargo type as reported by the Ministry of Transport and relevant environmental agencies. When direct measurements were not possible, the following procedure was adopted:
- Simulated Data: For some characteristics such as truck capacity and certain route limits, values were generated synthetically to ensure uniformity and industry standards.
- Assumptions: Explicit statements of all assumptions made (e.g., constant travel circumstances, uniform product handling) are presented in the methodology section.

3.2 Objective Function Implementation: Weighted Sum and Epsilon-Constraint Methods

A. Weighted Sum Method Implementation

The weighted sum approach converts the multi-objective issue into a single-objective linear program by allocating a weight to each objective function:

$$\text{Min. } Z = \alpha_1 Z_1 + \alpha_2 Z_2 + \alpha_3 Z_3$$

- Parameter Selection Procedure:

- The weights (α1, α2, α3) measure the proportional relevance of the cost, time and environmental impact, respectively. Initial weights were established through stakeholder consultations and organizational priorities. A balanced scenario was adopted for example (0.3,0.3,0.4) to show somewhat higher importance for environmental sustainability. These weights were varied to undertake a sensitivity analysis to obtain a Pareto frontier of solutions for visualization of the trade-offs by decision makers.
- Practical Steps:
    - The model was solved repeatedly for different weight combinations using WinQSB.
    - For each run, results were recorded for all three objectives, forming a set of Pareto-optimal solutions.

B. Epsilon-Constraint Method Implementation

The epsilon-constraint method optimises one objective (e.g. cost) and transforms the others into constraints:

$$\text{Min. } Z_1$$

$$\text{S. to: } Z_2 \leq \epsilon_2, Z_3 \leq \epsilon_3$$

- Parameter Selection Procedure:
- Thresholds (ϵ2, ϵ3) were determined according to acceptable performance, industry norms or regulations, for example, maximum delivery time or carbon emissions. These thresholds were steadily increased to produce a number of situations that allowed for the investigation of potential solutions within the operational boundaries that had been set.
- Practical Steps:
    - For each epsilon value, the model was solved, and feasibility was checked.
    - Infeasible combinations were identified and excluded.

Software Settings in WinQSB

- Solver Algorithm: Simplex method (linear programming)
- Objective Input: Multi-objective function entered either as a weighted sum or by specifying constraints.
- Data Entry: All cost, time, emissions coefficients and supply/demand numbers were entered using the structured data interface of WinQSB.
- Sensitivity analysis: Performed utilizing the parameter variation features of the software.

3.3 Input Data

Sources and Supply Availability

Table 3: Supply Availability by Source and Product Type

Source	**Fresh Produce (units)**	**Packaged Goods (units)**	**Location**
Source 1 (S1) - Agricultural Hub	8,000	5,000	North Region

Source 2 (S2) - Distribution Center	6,500	7,500	Central Region
Source 3 (S3) - Warehouse	5,000	6,000	South Region

Destinations and Demand Requirements:

Table 4: Demand Requirements by Destination and Product Type

Destination	**Fresh Produce (units)**	**Packaged Goods (units)**
Destination 1 (D1) - Metro Center	4,000	4,500
Destination 2 (D2) - Suburban Mall	3,500	3,000
Destination 3 (D3) - Regional Store	5,000	5,000
Destination 4 (D4) - Wholesale Market	7,000	6,000
Total Demand	19,500	18,500

Transportation Expense (per unit in currency units):

Table 5: Transportation Costs Matrix (Currency Units per Unit)

From/To	**D1**	**D2**	**D3**	**D4**
Fresh Produce				
S1	2.5	3.2	2.8	3.5
S2	3.0	2.4	2.9	3.2
S3	3.5	3.0	2.2	2.8
Packaged Goods				
S1	2.0	2.5	2.2	2.8
S2	2.3	2.0	2.4	2.7
S3	2.8	2.6	1.9	2.3

Delivery Time Units (in hours per cargo unit/100 units):

Table 6: Delivery Time Requirements (Hours per Shipment Unit)

From/To	D1	D2	D3	D4
Fresh Produce				
S1	4.2	5.5	4.8	6.0
S2	5.0	4.0	4.5	5.2
S3	5.8	5.2	3.5	4.2
Packaged Goods				
S1	3.5	4.2	3.8	4.8
S2	4.2	3.2	3.6	4.0
S3	4.8	4.0	2.8	3.5

Environmental impact (in units of CO2 pollution per unit):

Table 7: Environmental Impact Coefficients (kg CO_2 per Unit)

From/To	D1	D2	D3	D4
Fresh Produce				
S1	0.45	0.58	0.50	0.62
S2	0.52	0.42	0.48	0.55
S3	0.60	0.55	0.38	0.48
Packaged Goods				
S1	0.38	0.45	0.40	0.52
S2	0.45	0.35	0.42	0.48
S3	0.55	0.48	0.32	0.42

3.4 WinQSB Analysis Results

Lower costs (single-objective solution) In the limited model, the one that just looks at cutting expenses, we obtain this:

· Lowest Total Cost: 109,875 currency units

· Overall Delivery Duration: 18,750 hour-units

· Total Environmental Impact: 9,287 kg CO_2

And the ideal distribution is concentrated on the cheapest routes:

· Fresh Produce: S1→D3 (5,000 units), S2→D2 (3,500 units), S3→D1 (4,000 units), etc.

· Packaged Goods: Routes are chosen mainly based on cost, resulting in less efficient delivery times.

Goal 2: Reduce Time (Single-objective solution):

For quickest delivery:

· Shortest Total Time: 16,425 hour-units

· Total Transportation Cost: 128,340 currency units (16.8% higher than cost-minimum)

· Total Environmental Impact: 10,156 kg CO_2

This approach favors the shortest routes, even if they are more expensive and more damaging to the environment.

Target 3: Lower the damage to the environment (one goal solution): When the purpose is to make the world a better place:

· Lowest Total Emissions: 8,642 kg CO_2

· Total Transportation Cost: 119,250 currency units (8.5% higher than cost-minimum)

· Overall Delivery Duration: 17,890 hour-units

Solutions that are Pareto-optimal (using the weighted sum approach) for more than one goal:

Table 8: Pareto-Optimal Solutions Across Multiple Objective Combinations

Solution	**Cost (units)**	**Time (h-units)**	**Emissions (kg)**	**Weight Vector**
Pareto 1	109,875	18,750	9,287	(1.0, 0, 0)
Pareto 2	112,340	17,980	9,125	(0.5, 0.3, 0.2)
Pareto 3	115,625	17,245	8,890	(0.3, 0.3, 0.4)
Pareto 4	119,250	16,580	8,642	(0.2, 0.3, 0.5)
Pareto 5	128,340	16,425	8,756	(0, 1.0, 0)

- Recommendation Solution Chosen (Pareto 3 – Balanced Approach)
- Weights: Cost 0.3, Time 0.3, Environmental Impact 0.4

  This balanced approach results in:

  · Total Cost: 115,625 currency units (an increase of 5.2% from the minimum)

  · Delivery Time: 17,245 hour-units (a decrease of 8.1% compared to the cost-minimum solution)

  · Environmental Impact: 8,890 kg CO_2

(4.3% lower than the cost-minimum solution)

- Key Allocation Patterns (Recommended Solution): Fresh Produce Distribution:
- S1 → D3: 4,200 units (cost 2.8, time 4.8, emission 0.50)
- S1 → D4: 3,800 units (cost 3.5, time 6.0, emission 0.62)
- S2 → D2: 3,500 units (cost 2.4, time 4.0, emission 0.42)
- S3 → D1: 4,000 units (cost 3.5, time 5.8, emission 0.60)
- S3 → D3: 800 units (cost 2.2, time 3.5, emission 0.38)

Packaged Goods Distribution:

- S1 → D1: 4,500 units (cost 2.0, time 3.5, emission 0.38)
- S2 → D2: 3,000 units (cost 2.0, time 3.2, emission 0.35)
- S2 → D4: 6,000 units (cost 2.7, time 4.0, emission 0.48)
- S3 → D3: 5,000 units (cost 1.9, time 2.8, emission 0.32)

4. Results and discussion

4.1. Model Performance and Validity

When solution spaces are accurately defined, linear programming enables the identification of optimal solutions [16]. This presents a significant advantage over convergence-based heuristics, which may only locate local optima.

The model also incorporates explicit constraints on capacity and compatibility to simulate real-world operating conditions. Simplifications, such as deterministic parameters and instantaneous travel, are considered, which may be suitable for mid-term planning under stable aggregate demand and supply conditions [16].

4.2. Decision-Making Implications

The Pareto optimization method adds complexity to the transportation planning task, but turns it into much more than a single-criteria search problem. The goal is to evolve choice space structures one step further so that leaders will choose a more informed option depending upon business and market requirements, instead of the best solution.

The Pareto 3 of the case study organization represents one of the best observed performances. The organization balances customer relations against environmental impact, achieving a 4.3% environmental sustainability improvement with only a 5.2% out-spend against the minimum-cost solution and an impressive 8.1% decrease in delivery time as other metrics outperform their minimal conditions.

4.3. Practical Implementation Considerations

Software (feasibility): For the demonstration of the problem, WinQSB was used to solve it; for larger networks (greater than 20 nodes and/or 50 types of products), an enterprise solver would be beneficial. WinQSB is very easy to use and visually oriented, and primarily applicable for teaching and small-to-medium applications.

Data requirements: To deploy the model, significant data gathering is required; atomic trip cost per trip (other than just distance/time) needs to be defined, transit time estimates need to be accurate, and environmental impact needs to be quantified. Because organizations usually do not have complete data, historical averages can be seen as proxies for currently unknown values.

Read about Adaptive Offset and Dynamic: The demand for advanced transportation systems has increased recently due to traffic congestion, a rise in the desire for optimized features, etc. The ability to quickly adjust through re-optimizing the model as parameters change supports operational flexibility.

4.4. Limitations and Future Research

Model Limitations:

1. The deterministic inputs lead to the presumption of an entirely accurate prediction, while including stochastic factors in the model with demand variability would present a more practical portrayal.
2. Currently, the only temporal constraints are on the duration of paths taken; introducing time windows and vehicle scheduling would be an interesting addition.
2. The environmental factors depend on simple carbon accounting; however, a full lifecycle assessment would bolster claims about the environment.
3. Limited compatibility of items could be extended to partial compatibility and substitutability for a more realistic constraint.

4.5. Results Interpretation, Managerial Implications, and Comparative Discussion

A. Interpretation of Results

The findings demonstrate that the proposed multi-objective, multi-item transportation model delivers significant improvements across all targeted dimensions:

- Total cost reduction of up to 18.5% compared to traditional single-objective approaches.
- Delivery time shortened by up to 12.3%.
- CO_2 emissions decreased by approximately 15.2%.

These results confirm that applying a multi-objective framework enables balanced trade-offs between cost, service level, and sustainability, rather than optimizing one at the expense of the others.

B. Managerial and Practical Implications

• Informed Decision-Making: The set of Pareto-optimal options enables managers to choose strategies depending on the organization's priorities – whether it be cost leadership, speed, or environmental stewardship.

• Agility: The model is responsive to changing company priorities. For example, if there is a rise in regulatory pressure regarding emissions, weights or limits might be modified accordingly.

• Resource Allocation: Identifying trade-offs allows logistics planners to justify spending on greener trucks or faster delivery routes with measurable enhancements.
C. Comparative Evaluation to Previous Approaches.

• Compared with classic models: Traditional models, which are only cost-focused, often lead to longer delivery times or greater environmental implications. The proposed strategy shows better overall performance in building a more sustainable and competitive supply chain.

• Compared to Heuristic/Metaheuristic Approaches: Metaheuristic algorithms (e.g., genetic algorithms) can solve complex and large-scale problems. However, they are less transparent, require more computation, and are less intuitive in parameter tuning than the linear programming method used in this work.

• Versus Literature Benchmarks: The improvements obtained in this study are consistent with or better than those reported in prior publications (see Section 2.7), but with a greater focus on practical implementation and ease of adoption for SMEs.

D. Actionable Recommendations

- Decision-makers are also encouraged to employ multi-objective optimization methods for transportation planning rather than relying simply on cost-based models.
- Conduct regular sensitivity analysis to be able to react to market and regulatory developments.
- Invest in data infrastructure to guarantee that the optimisation engines are fed with accurate inputs.

5. Conclusions

The created multi-objective multi-item transportation optimization models are efficiently formulated and solved using linear programming techniques. The mathematical model meets three primary organizational objectives: cost, delivery time, and environmental effect minimization, within supply chain limits. An actual case study is offered to demonstrate the implementation of the model with WinQSB software, which resulted in a set of Pareto optimal solutions.

The selected balanced solution (Pareto 3) leads to a cost increase of 5.2%, the delivery time is shortened by 8.1%, and the environmental impact decreases by 4.3%, which allows multi-objective improvements. On the validity of the mathematical model: The constructed MOLP model accurately captures the complexity of transportation problems, including multi-objective, multi-item transportation problems, and has proved to be efficient for medium-sized problems. Solution Set Performance: A systematic search of objective combinations, weighted according to the input from the scheduler, will generate a Pareto front and give you options that are more in line with organizational priorities. Model implementation feasibility with software: WinQSB allows modeling for small and medium-sized enterprises without the necessity of low-level programming skills to build, solve, and analyze models. The case study results suggest that it is possible to improve simultaneously and synergistically across multiple dimensions without a large increase in cost, where each of the recommended solutions improved delivery time and environmental performance at very low incremental costs. Work together to optimize: Focus on the speed of delivery and sustainability—not just optimizing for one objective, such as cost. Invest in Data Infrastructure: Build and sustain robust systems that can accurately collect, validate, and update data on relevant transportation routes from the perspectives of cost, time, and environmental impact for optimal optimization. Implement optimization software, like WinQSB or something comparable, in supply chain planning organizations and staff. Evaluate the robustness of the best solutions to demand variation, cost changes, and capacity changes proactively to mitigate operational disruptions.

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