

MATHEMATICAL MODELING FOR OPTIMIZATION OF FOOD TRANSPORTATION

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Abstract

Food transportation is a critical component of the food supply chain because it directly affects delivery cost, product availability, service reliability, and the quality of perishable goods. In many practical situations, food products must be transported from several warehouses, production facilities, or distribution centers to several markets, supermarkets, restaurants, or institutional consumers. The main operational question is how to determine the quantity of goods that should be shipped from each origin to each destination so that total transportation cost is minimized while all supply and demand requirements are satisfied.

This paper presents a mathematical modeling approach for optimizing food transportation using the classical transportation problem from linear programming. The problem is formulated through decision variables, an objective function, supply constraints, demand constraints, and non-negativity conditions. A numerical example is developed for the distribution of food pallets from three distribution centers to four retail markets. The example is solved using the transportation simplex method, including the initial feasible allocation and the optimality test based on the MODI method. The results show that mathematical optimization can significantly support decision-making in food logistics by identifying the least-cost distribution plan and by providing a structured basis for operational planning. Knowledge of mathematical modeling techniques provides significant information for simulation and further design and optimization purposes

Keywords: Food transportation, mathematical modeling, transportation problem, linear programming, simplex method, logistics optimization, supply chain management

Introduction

Food transportation is one of the most important activities in the logistics and supply chain system. Unlike many other types of goods, food products often have specific requirements related to delivery time, temperature control, hygiene, storage conditions, and shelf life. Inefficient transportation can increase costs, cause delays, reduce product quality, and generate unnecessary losses. Therefore, food transportation requires careful planning and the use of rational decision-making methods. In practice, food companies frequently operate with several distribution centers and several delivery locations. Each distribution center has a limited available quantity of products, while each destination has a specific demand that must be satisfied. The planner must decide how much product should be transported from each origin to each destination. If the decision is made intuitively, the final transportation plan may be expensive or inefficient. Mathematical modeling provides a systematic method for finding an optimal or near-optimal distribution plan.

The increasing complexity of modern food supply chains has encouraged the development of advanced optimization techniques, intelligent transportation systems, and machine learning methods for improving logistics efficiency and reducing food spoilage. Intelligent routing and navigation algorithms developed for autonomous robotic systems have demonstrated that optimized movement planning can significantly reduce operational inefficiencies and transportation delays (Antoska Knights et al., 2017; Antoska Knights et al., 2018). Similar principles are increasingly applied in food transportation systems where route optimization contributes to reduced delivery time, minimized fuel consumption, lower operational costs, and preservation of product freshness.

Dynamic transportation environments frequently involve uncertainty related to traffic congestion, weather conditions, fluctuating demand, delivery deadlines, and perishability constraints. Therefore, adaptive optimization models and intelligent transportation systems have become essential for modern logistics management. Research involving dynamic modeling and intelligent control systems has shown that optimization under disturbances and uncertain environments can significantly improve system stability and operational performance (Knights & Petrovska, 2024; Antoska Knights et al., 2013). In addition, IoT technologies and AI-supported monitoring systems enable real-time decision-making and continuous tracking of transportation conditions (Antoska Knights & Gacovski, 2024; Knights et al., 2024).

Mathematical modeling is defined as a new solution to such 'old' questions which has been made possible by methods and fundamental changes used in the way problems are approached. The transportation problem is a special type of linear programming problem widely applied in logistics, production planning, and supply chain optimization. The objective is usually to minimize total transportation cost, although the same model can also be adapted to minimize transportation distance, travel time, carbon emissions, spoilage risk, or a weighted combination of several criteria (Dantzig, 1951; Laporte, 1992; Toth & Vigo, 2014).

Recent studies in sustainable food logistics increasingly focus on integrating environmental objectives, food quality preservation, and intelligent optimization methods. Pérez-Lechuga et al. (2024) proposed a green cold-chain routing model for perishable food distribution, while Wang et al. (2025) developed sustainable transportation planning approaches considering environmental and quality objectives simultaneously. Multi-objective optimization models integrating production, inventory, and routing decisions have also shown promising results in perishable food logistics systems (Chan et al., 2020).

The use of intelligent logistics systems and digital simulation tools has become particularly important in reducing food losses and improving transportation efficiency. Jedermann et al. (2014) emphasized the importance of intelligent food logistics systems for reducing spoilage and improving monitoring capabilities. Tsang et al. (2019) proposed an intelligent model for quality assurance in multi-temperature food distribution centers, while Fikar (2018) developed a decision-support system for investigating food losses in e-grocery deliveries. More recent approaches combine stochastic optimization, machine learning, and hybrid heuristics to address uncertainty in food transportation networks (Yu et al., 2023; Chen et al., 2026).

Optimization algorithms in food logistics vary depending on network complexity, perishability constraints, uncertainty levels, and computational requirements. Exact optimization methods such as Mixed Integer Linear Programming (MILP), branch-and-bound algorithms, and transportation simplex methods are highly effective for structured deterministic transportation problems. However, heuristic and metaheuristic approaches such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are increasingly preferred for large-scale and dynamic logistics systems involving uncertainty and perishability (Kennedy & Eberhart, 1995; Dorigo & Stützle, 2004; Holland, 1992).

Machine learning methods, including neural networks, predictive analytics, and intelligent routing systems, additionally support adaptive logistics planning and real-time transportation management (Goodfellow et al., 2016; Bishop, 2006). Recent studies have demonstrated that AI-supported transportation systems can improve route optimization, reduce spoilage risk, and increase sustainability in urban food delivery networks (Kumar et al., 2024). Furthermore, statistical process control and intelligent optimization models contribute to sustainable food production and logistics management aligned with Sustainable Development Goals (Knights et al., 2026).

The purpose of this paper is to explain how mathematical modeling can be used to optimize food transportation and to demonstrate the procedure through a solved numerical example. The example is based on a balanced transportation problem and is solved using the transportation

simplex method. The integration of mathematical optimization, intelligent transportation systems, IoT technologies, and AI-based logistics planning provides important opportunities for improving supply chain performance, reducing food waste, minimizing transportation costs, and supporting sustainable food distribution systems. Different optimization approaches used in food logistics exhibit different advantages and limitations depending on the size of the transportation network, perishability constraints, uncertainty level, and computational complexity. Exact optimization methods are generally suitable for deterministic transportation problems, while heuristic, metaheuristic, and machine learning approaches provide greater flexibility for large-scale and dynamic logistics systems. A comparative overview of the most commonly applied optimization algorithms in food transportation is presented in Table 1.

Table 1. Comparison of Optimization Algorithms Used in Food Logistics

Algorithm Type	Examples from Literature	Strengths in Food Logistics	Limitations	Typical Use Cases
Exact Methods (MILP, Branch-and-Bound, Transportation Simplex)	Dantzig (1951); Laporte (1992); Yu et al. (2023)	Provides optimal solutions and precise cost minimization; highly suitable for balanced transportation problems	Computationally expensive for large-scale systems; limited adaptability to uncertainty	Small and medium deterministic transportation networks
Metaheuristics (Genetic Algorithms, Simulated Annealing)	Holland (1992); Singh et al. (2025)	Fast near-optimal solutions; adaptable to dynamic routing and spoilage reduction	Requires parameter tuning; solutions may not be globally optimal	Large-scale food distribution with time windows
Swarm Intelligence & Hybrid Heuristics (PSO, ACO, Hybrid GA-ML)	Kennedy & Eberhart (1995); Dorigo & Stützle (2004); Chan et al. (2020)	Handles uncertainty in demand, spoilage, and shelf-life variability; improves sustainability	Higher implementation complexity; computational tuning required	Dynamic logistics systems with stochastic behavior
Machine Learning Methods (Neural Networks, k-NN, Predictive Analytics)	Goodfellow et al. (2016); Bishop (2006); Kumar et al. (2024)	Real-time adaptation to traffic, spoilage risk, and environmental conditions	Requires large datasets and training procedures; reduced interpretability	Urban food delivery and intelligent transportation systems

The Role of Optimization in Food Transportation

Food transportation includes the movement of products from farms, factories, warehouses, cold-storage facilities, or distribution centers to final points of sale or consumption. The efficiency of this process depends on several factors, including transport cost, available vehicle capacity, distance, road network conditions, delivery time windows, product perishability, and demand uncertainty. In modern food supply chains, transportation efficiency has become increasingly important because perishable products are highly sensitive to delays, temperature fluctuations, and inadequate handling conditions (Jedermann et al., 2014; Tsang et al., 2019). Optimization is important because even small improvements in transportation planning can result in considerable savings. For example, a company that distributes food every day may reduce fuel consumption, vehicle operating costs, labor time, and product losses by selecting better shipment quantities and routes. In addition, optimized transportation contributes to better customer service because demand can be satisfied on time and with lower operational risk. Recent studies have shown that intelligent routing systems and sustainable transportation planning approaches can significantly reduce spoilage risk, improve freshness preservation,

and decrease environmental impact in food logistics systems (Pérez-Lechuga et al., 2024; Wang et al., 2025).

The integration of intelligent transportation systems, machine learning, and optimization algorithms has additionally improved the adaptability and efficiency of food logistics operations. AI-supported transportation models and IoT-based monitoring systems enable real-time route optimization, traffic prediction, and continuous monitoring of transportation conditions (Antoska Knights & Gacovski, 2024; Knights et al., 2024). Similar optimization principles have previously been applied in autonomous robotic navigation and intelligent control systems where efficient movement planning reduced operational inefficiencies and transportation delays (Antoska Knights et al., 2017; Antoska Knights et al., 2018).

The classical transportation model is particularly useful when the main decision is the allocation of product quantities between origins and destinations. In its basic form, the model assumes that the unit transportation cost from each origin to each destination is known, the supply at each origin is known, and the demand at each destination is known. The model then determines the optimal shipping plan. Classical transportation optimization methods based on linear programming and transportation simplex algorithms remain highly applicable for balanced food distribution problems because they provide structured and computationally efficient solutions for minimizing transportation costs (Dantzig, 1951; Toth & Vigo, 2014).

Mathematical Formulation of the Transportation Problem

Let there be (m) origins and (n) destinations. In the context of food transportation, origins may represent distribution centers, warehouses, production plants, or cold-storage facilities. Destinations may represent supermarkets, local markets, restaurants, hotels, or public institutions.

The mathematical notation is defined as follows:

- $(i = 1, 2, \dots, m)$ denotes the origins;
- $(j = 1, 2, \dots, n)$ denotes the destinations;
- (s_i) denotes the available supply at origin (i);
- (d_j) denotes the demand at destination (j);
- (c_{ij}) denotes the unit transportation cost from origin (i) to destination (j);
- (x_{ij}) denotes the quantity transported from origin (i) to destination (j).

The objective is to minimize the total transportation cost:

$$Z = \sum_{i=1}^m \sum_{j=1}^n C_{ij} x_{ij} \quad (1)$$

subject to the supply constraints:

$$\sum_{j=1}^n x_{ij} = s_i, \quad i = 1, 2, \dots, m \quad (2)$$

and the demand constraints:

$$\sum_{i=1}^m x_{ij} = d_j, \quad j = 1, 2, \dots, n \quad (3)$$

with non-negativity constraints:

$$x_{ij} \geq 0, \quad i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \quad (4)$$

For a balanced transportation problem, total supply is equal to total demand:

$$\sum_{i=1}^m s_i = \sum_{j=1}^n d_j \quad (5)$$

If total supply and total demand are not equal, the problem can be balanced by adding a dummy origin or a dummy destination. The dummy row or column usually has zero transportation cost or a penalty cost, depending on the practical interpretation of the shortage or surplus.

Transportation Simplex Method

The transportation simplex method is a specialized form of the simplex method developed for transportation problems. It is more efficient than the general simplex method because it uses the specific structure of the transportation table. The solution procedure generally includes the following steps:

1. Formulate the transportation table with supplies, demands, and unit costs.
2. Find an initial basic feasible solution.
3. Test the solution for optimality.
4. If the solution is not optimal, improve it by creating a closed loop and reallocating quantities.
5. Repeat the optimality test until no further improvement is possible.

Several methods may be used to obtain the initial feasible solution, including the North-West Corner Method, the Least Cost Method, and Vogel's Approximation Method. After an initial solution is obtained, the optimality test can be performed using the MODI method, also known as the (u-v) method. For a minimization problem, the MODI method calculates opportunity costs for all non-basic cells. If all opportunity costs are non-negative, the current solution is optimal. If at least one opportunity cost is negative, the solution can be improved.

4.1 Numerical Example: Food Transportation Problem: A food distribution company supplies fresh food pallets from three distribution centers to four retail markets. The company wants to minimize the total cost of transportation while satisfying the demand of each market. The available supply and demand are given in pallets per day. The unit transportation costs are expressed in monetary units per pallet.

Problem Data: The company has three distribution centers:

- Distribution Center A with 120 pallets available;
- Distribution Center B with 80 pallets available;
- Distribution Center C with 100 pallets available.

The company must deliver products to four retail markets:

- Market 1 requires 100 pallets;
- Market 2 requires 60 pallets;
- Market 3 requires 80 pallets;
- Market 4 requires 60 pallets.

The total supply is:

$$[120 + 80 + 100 = 300]$$

The total demand is:

$$[100 + 60 + 80 + 60 = 300]$$

Since total supply is equal to total demand, the problem is balanced. The transportation cost matrix is shown in Table 2.

Table 2. Unit transportation costs

Origin / Destination	Market 1	Market 2	Market 3	Market 4	Supply
Distribution Center A	4	6	8	8	120
Distribution Center B	6	8	6	5	80
Distribution Center C	7	5	4	6	100
Demand	100	60	80	60	300

4.2 Linear Programming Model for the Example:

Let:

x_{ij} = quantity transported from distribution center i to market j

(6)

where:

- $(i = A, B, C);$
- $(j = 1, 2, 3, 4).$

The objective function is:

$$Z = 4x_{A1} + 6x_{A2} + 8x_{A3} + 8x_{A4} + 6x_{B1} + 8x_{B2} + 6x_{B3} + 5x_{B4} + 7x_{C1} + 5x_{C2} + 4x_{C3} + 6x_{C4} \quad (7)$$

subject to supply constraints:

$$\begin{aligned} x_{A1} + x_{A2} + x_{A3} + x_{A4} &= 120 \\ x_{B1} + x_{B2} + x_{B3} + x_{B4} &= 80 \\ x_{C1} + x_{C2} + x_{C3} + x_{C4} &= 100 \end{aligned}$$

and demand constraints:

$$\begin{aligned} x_{A1} + x_{B1} + x_{C1} &= 100 \\ x_{A2} + x_{B2} + x_{C2} &= 60 \\ x_{A3} + x_{B3} + x_{C3} &= 80 \\ x_{A4} + x_{B4} + x_{C4} &= 60 \end{aligned}$$

with: $x_{ij} \geq 0, \quad i = A, B, C, \quad j = 1, 2, 3, 4$

Figure 1 presents the optimal transportation plan obtained from the balanced transportation problem. The diagram illustrates the distribution of food products from three distribution centers (A, B, and C) to four demand locations (1–4). The labels on the arrows represent the transported quantity and the corresponding unit transportation cost. The transportation simplex solution minimizes the total transportation cost while satisfying all supply and demand constraints. The optimal solution demonstrates efficient allocation of shipments and balanced utilization of available supply capacities.

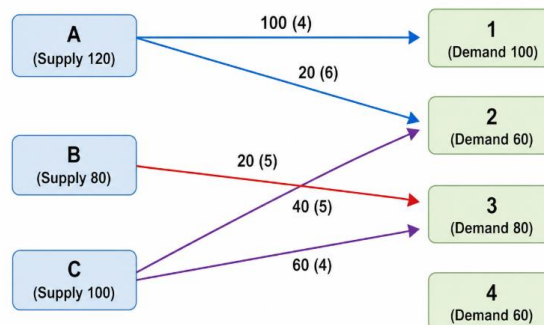


Figure 1. Optimal Transportation Plan for Food Distribution Using the Transportation Simplex Method

Solution Using the Transportation Simplex Method

The Transportation Simplex Method is a specialized optimization technique used to solve transportation problems in linear programming. Its main objective is to determine the most cost-effective way to transport goods from multiple supply points to multiple demand locations while satisfying all supply and demand constraints. The method begins with the formulation of a transportation matrix that contains transportation costs, supply quantities, and demand requirements. An initial feasible solution is first obtained using methods. After obtaining the

initial solution, the Transportation Simplex Method iteratively improves the transportation plan by evaluating unused routes and calculating opportunity costs. The method identifies whether transportation costs can be reduced by reallocating shipment quantities among different routes. During each iteration, the algorithm searches for an improved solution while maintaining all constraints related to supply and demand. The optimization process continues until no further reduction in total transportation cost is possible, indicating that the optimal solution has been reached. The Transportation Simplex Method is widely used in logistics, supply chain management, and distribution planning because it enables efficient allocation of transportation resources, minimizes operational costs, and improves overall distribution efficiency. An optimal feasible allocation for the example is shown in Table 3

Table 3. Optimal transportation plan

Origin / Destination	Market 1	Market 2	Market 3	Market 4	Supply
Distribution Center A	100	20	0	0	120
Distribution Center B	0	0	20	60	80
Distribution Center C	0	40	60	0	100
Demand	100	60	80	60	300

The total transportation cost is calculated as follows:

$$Z = 100(4) + 20(6) + 20(6) + 60(5) + 40(5) + 60(4)$$

$$Z = 400 + 120 + 120 + 300 + 200 + 240$$

$$Z = 1,380$$

Therefore, the minimum total transportation cost is:

$$Z_{min} = 1,380$$

5.1 Optimality Test by the MODI Method: For the optimality test, the basic occupied cells are: [(A,1), (A,2), (B,3), (B,4), (C,2), (C,3)]

The number of basic variables is:

$$m + n - 1 = 3 + 4 - 1 = 6$$

This confirms that the solution is non-degenerate. The MODI method assigns potentials (u_i) to rows and (v_j) to columns. For each occupied cell, the following relation must hold:

$$u_i + v_j = c_{ij} \quad (8)$$

Let:

$$u_A = 0$$

From the occupied cells, the potentials are calculated as follows:

$$u_A + v_1 = 4 \Rightarrow v_1 = 4$$

$$u_A + v_2 = 6 \Rightarrow v_2 = 6$$

$$u_C + v_2 = 5 \Rightarrow v_C = -1$$

$$u_C + v_3 = 4 \Rightarrow v_3 = 5$$

$$u_B + v_3 = 6 \Rightarrow v_B = -1$$

$$u_B + v_4 = 5 \Rightarrow v_4 = 4$$

The potentials are therefore:

Potential Value

$$u_A \quad 0$$

$$u_B \quad 1$$

$$u_C \quad -1$$

Potential Value

v_1	4
v_2	6
v_3	5
v_4	4

For all unoccupied cells, the opportunity cost is calculated as:

$$\Delta_{ij} = c_{ij} - (u_i + v_j) \quad (9)$$

The opportunity costs are shown in Table 4.

Table 4. Opportunity costs for unoccupied cells

Cell	Calculation	Opportunity cost
((A,3))	$(8 - (0+5))$	3
((A,4))	$(8 - (0+4))$	4
((B,1))	$(6 - (1+4))$	1
((B,2))	$(8 - (1+6))$	1
((C,1))	$(7 - (-1+4))$	4
((C,4))	$(6 - (-1+4))$	3

Discussion of Results

The optimal solution indicates that the food distribution company should organize the daily transportation plan as follows:

- Distribution Center A should deliver 100 pallets to Market 1 and 20 pallets to Market 2.
- Distribution Center B should deliver 20 pallets to Market 3 and 60 pallets to Market 4.
- Distribution Center C should deliver 40 pallets to Market 2 and 60 pallets to Market 3.

No deliveries should be made on the remaining routes because they would increase the total transportation cost under the given assumptions. The result is important from a managerial perspective. Instead of distributing food products according to subjective judgment or historical habits, the company can use a mathematical model to determine the least-cost allocation. This can support daily planning, contract negotiations with transport operators, warehouse coordination, and operational control.

The obtained results are consistent with previous studies in transportation optimization and food logistics. Classical transportation optimization methods based on linear programming and transportation simplex algorithms have been widely recognized as effective tools for minimizing operational costs in deterministic distribution systems (Dantzig, 1951; Toth & Vigo, 2014). Similar findings were reported by Laporte (1992), who emphasized that optimal route and allocation planning can significantly improve transportation efficiency and reduce unnecessary logistics expenses.

The results are also aligned with recent studies in perishable food transportation and sustainable logistics systems. Pérez-Lechuga et al. (2024) demonstrated that optimized routing in cold-chain food distribution contributes to reduced spoilage risk and improved freshness preservation. Wang et al. (2025) additionally showed that transportation optimization models integrating environmental and quality objectives can simultaneously reduce operational costs and environmental impact.

Compared with more advanced intelligent logistics approaches, the proposed model represents a simplified deterministic framework because supply, demand, and transportation costs are assumed to be known and constant. In real transportation systems, uncertainty related to traffic congestion, weather conditions, delivery delays, and fluctuating demand may significantly affect logistics performance. Recent studies therefore increasingly combine classical

optimization models with machine learning, IoT technologies, and intelligent routing systems to improve adaptability and real-time decision-making (Knights et al., 2024; Antoska Knights & Gacovski, 2024).

Similar optimization principles have also been applied in autonomous robotic navigation systems, where efficient path planning reduces unnecessary movement and operational inefficiencies (Antoska Knights et al., 2017; Antoska Knights et al., 2018). The integration of intelligent optimization algorithms with transportation planning may therefore provide additional improvements in food logistics systems, especially in large-scale and dynamic supply-chain environments.

In real food logistics, the model may also be expanded by adding practical constraints. These may include maximum vehicle capacity, delivery time windows, cold-chain requirements, maximum travel time, driver working hours, road restrictions, fuel consumption, and emissions. If the products are highly perishable, the objective function can include not only transportation cost but also the cost of product deterioration or delay.

Advantages and Limitations of the Model

The classical transportation model represents an important foundational tool in food logistics because of its mathematical simplicity, transparency, and computational efficiency. The model enables planners to evaluate different allocation scenarios between distribution centers and demand locations while minimizing total transportation cost. Classical linear programming approaches and transportation simplex methods can efficiently solve balanced transportation problems even for moderate logistics networks, such as the 3×43 times 43×4 distribution example presented in this study, where the optimal transportation cost was determined to be 1380 monetary units (Dantzig, 1951; Toth & Vigo, 2014).

Despite these advantages, the classical transportation model also has several important limitations. The model assumes that transportation costs, supply quantities, and customer demand are fixed and known in advance. In practical food logistics systems, however, transportation conditions are often dynamic and uncertain. The model does not explicitly consider traffic congestion, vehicle routing sequences, delivery time windows, cold-chain requirements, fuel consumption, or product perishability. These limitations are particularly important for highly perishable food products, where transportation delays may significantly increase spoilage risk and reduce product quality (Jedermann et al., 2014; Tsang et al., 2019). To overcome these limitations, researchers have proposed several advanced extensions of the classical transportation problem. Stochastic optimization models are used to address uncertainty in customer demand and supply variability through probabilistic or chance-constrained approaches (Yu et al., 2023; Chen et al., 2026). Vehicle Routing Problems (VRP) extend the transportation model by determining optimal delivery sequences for vehicles serving multiple destinations within a single route (Laporte, 1992). Metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are frequently applied in large-scale food logistics systems because they can generate near-optimal solutions under complex routing and perishability constraints (Holland, 1992; Kennedy & Eberhart, 1995; Dorigo & Stützle, 2004).

Multi-objective optimization models have additionally become increasingly important in sustainable food logistics. These models simultaneously minimize transportation cost, carbon emissions, delivery delays, and spoilage risk (Pérez-Lechuga et al., 2024; Wang et al., 2025). Time-dependent transportation models further improve logistics efficiency by considering dynamic travel times and traffic conditions during different periods of the day. Intelligent transportation systems integrating machine learning and IoT technologies also support adaptive route optimization and real-time transportation monitoring in modern food supply chains

(Knights et al., 2024; Antoska Knights & Gacovski, 2024).

A comparative overview of the most common transportation model extensions used in food logistics is presented in Table 5.

Table 5. Extensions of the Classical Transportation Model in Food Logistics

Extension	Purpose	Example Application	References
Stochastic Models	Handle demand uncertainty	Random market orders $\pm 20\%$; uses chance constraints	Yu et al. (2023); Chen et al. (2026)
Vehicle Routing Problem (VRP)	Optimize multi-stop delivery routes	One truck serving Markets 1–4; integrates with GA/PSO	Laporte (1992); Toth & Vigo (2014)
Multi-Objective Optimization	Simultaneously minimize cost, emissions, and spoilage	Minimize transportation cost and CO ₂ emissions using Pareto optimization	Pérez-Lechuga et al. (2024); Wang et al. (2025)
Time-Dependent Models	Incorporate dynamic travel times and congestion	Peak-hour traffic adaptation and delivery scheduling	Fikar (2018); Tsang et al. (2019)
Metaheuristic Algorithms (GA, PSO, ACO)	Generate near-optimal solutions for complex logistics systems	Large-scale food logistics and cold-chain routing optimization	Holland (1992); Kennedy & Eberhart (1995); Dorigo & Stützle (2004)
AI and IoT-Based Models	Real-time monitoring and adaptive routing	Intelligent food logistics and smart transportation systems	Antoska Knights & Gacovski (2024); Knights et al. (2024); Kumar et al. (2024)

Conclusions

This paper presented a mathematical modeling approach for the optimization of food transportation. The transportation problem was formulated as a linear programming model with the objective of minimizing total transportation cost. A numerical example was developed for the delivery of food pallets from three distribution centers to four retail markets. The example demonstrated that the transportation simplex method can be effectively used to determine the optimal distribution plan. The minimum transportation cost obtained in the example was 1,380 monetary units. The MODI optimality test confirmed that the solution was optimal because all opportunity costs were non-negative.

The analysis shows that mathematical modeling is a useful decision-support tool in food logistics. It enables companies to reduce transportation costs, improve resource allocation, and make more objective operational decisions. Although the classical transportation model is simplified, it provides a strong basis for further development of more complex logistics models that include time, vehicle capacity, product perishability, environmental impact, and uncertainty. Since all opportunity costs are non-negative, no further reduction of the total transportation cost is possible. Therefore, the solution shown in Table 3 is optimal.

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