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Research Paper

Transportation Planning for Cost Optimization in Cold-Chain Distribution: A Case Study

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Abstract

Cold chain logistics for perishable goods faces increasing challenges in balancing product quality and cost efficiency. This study proposes a mixed integer linear programming (MILP) model that jointly optimizes transportation and inventory decisions in temperature-controlled supply chains by incorporating both transportation and perishability-related holding costs within a multi-node distribution network. A real-world case study based on a ten-node cold chain system in Thailand is used to validate the model. The results indicate that the proposed approach effectively determines routing structures, shipment quantities, and vehicle utilization while accounting for product deterioration. Compared with experience-based planning, the proposed model reduces total logistics cost by 8.02%, primarily through improved transportation efficiency. These findings demonstrate the importance of integrating routing decisions with perishability considerations and highlight the model's potential as a practical decision-support tool for cold chain logistics operations.

Keywords

MILP, Cold Chain, Routing, Perishability, Transshipment, Optimization

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1. INTRODUCTION

The demand for frozen food products in Thailand has expanded rapidly over the past decade, driven by urbanization, shifting consumption patterns, and the growth of modern retail and e-commerce channels. As a leading exporter of frozen seafood and processed foods, Thailand critically depends on cold chain logistics to maintain product quality, safety, and global competitiveness (Aung and Chang, 2014; Mercier et al., 2017; Kuaites and Thungwha, 2025). More broadly, the global demand for fresh and refrigerated products has also increased significantly in recent years, making cold chain logistics an essential component of modern supply chain systems (Yang and Tao, 2023; Xu et al., 2023). However, the transportation of temperature-sensitive products is considerably more complex and costly than conventional logistics operations because it requires continuous energy-intensive refrigeration while products remain highly susceptible to quality deterioration over time (Yang and Tao, 2023). In several countries, including China and India, post-harvest losses of agricultural products during transportation and storage have been reported to range from 10-30%, leading to substantial economic losses and reduced customer satisfaction (Xu et al., 2023). These challenges highlight the growing importance of efficient cold chain management in both developed and emerging markets.

Within the cold chain, transportation represents a critical vulnerability because continuous temperature control must be maintained under dynamic and uncertain operating conditions. Temperature deviations during transit can lead to microbial growth, biochemical degradation, and significant reductions in product shelf life, ultimately resulting in economic losses (Tassou et al., 2010; Laguerre et al., 2013). These risks are exacerbated by the complexity of multi-stage logistics systems, where maintaining consistent temperature control remains challenging (Aung and Chang, 2014). Furthermore, such challenges are particularly severe in tropical environments such as Thailand, where high ambient temperatures increase the likelihood of temperature abuse and accelerate food spoilage (James and James, 2010; Tassou et al., 2010). Recent studies have further emphasized that customer satisfaction in cold chain systems depends not only on delivery timeliness but also heavily on product freshness, which directly influences purchasing decisions and brand loyalty (Ghasemkhani et al., 2022; Pan et al., 2025). Consequently, transportation delays lead not only to higher operational costs but also to increased financial losses associated with product deterioration (Xu et al., 2023; Golestani et al., 2021).

Transportation routing plays a critical role in cold chain performance by influencing travel time, energy consumption, and exposure to temperature fluctuations. Poorly designed routing strategies can accelerate product deterioration and increase food loss due to prolonged transit time and inadequate temperature control (Pérez-Lechuga et al., 2024). Recent studies emphasize that routing decisions should explicitly incorporate product freshness and temperature-dependent quality degradation rather than focusing solely on cost or distance minimization (Ding et al., 2025). However, many traditional routing models still neglect these interactions, limiting their effectiveness in real-world cold chain applications. This limitation is particularly significant in Thailand, where traffic congestion, stochastic travel times, and limited real-time monitoring increase operational uncertainty and complicate temperature management during transportation (Aung and Chang, 2014; Akkerman et al., 2010; Bremer, 2018; Kedigui, 2025). A major challenge in cold chain management is therefore achieving an effective balance between distribution cost and product quality or freshness (Golestani et al., 2021).

Time-dependent routing has been extensively studied in vehicle routing problems with time windows (VRPTW), where mathematical programming approaches provide optimal solutions under temporal constraints. Nevertheless, these models do not explicitly account for perishability effects, leading to an incomplete representation of distribution costs, as time-dependent product deterioration is not incorporated into routing decisions (Yuliza et al., 2023). Classical logistics optimization is grounded in transportation and flow models, beginning with the truck dispatching problem (Dantzig and Ramser, 1959), which established the foundation for the Vehicle Routing Problem (VRP). Subsequent developments Solomon (1987); Toth and Vigo (2002); Laporte (2009) extended VRP to incorporate practical constraints such as time windows, vehicle capacity, and route feasibility. These models provide a strong structural basis for routing decisions but primarily focus on minimizing distance or cost, without considering product-specific characteristics such as perishability.

In parallel, perishable inventory theory Nahmias (1982) emphasizes that product value deteriorates over time, linking holding and transportation delays directly to economic loss. This perspective subsequently led to the development of the Inventory-Routing Problem (IRP), which integrates inventory and routing decisions by balancing transportation frequency and holding costs (Archetti and Speranza, 2016; Campbell and Savelsbergh, 2005). More recent literature has further extended this perspective toward integrated decision-making frameworks that simultaneously consider facility location, inventory management, and transportation routing, commonly referred to as the Location-Inventory-Routing Problem (LIRP) (Pan et al., 2025). Research has shown that integrating these decisions can significantly reduce total system costs compared with solving them independently (Wei et al., 2020). In addition, the incorporation of transshipment strategies and two-echelon distribution structures has improved vehicle utilization efficiency, particularly in high-density logistics networks (Ghasemkhani et al., 2022; Wei et al., 2020). However, despite these advances, most IRP and LIRP formulations still assume simplified deterioration mechanisms and do not explicitly capture temperature-dependent quality degradation, limiting their applicability to realistic cold chain environments.

Cold chain logistics research extends VRP and IRP models by incorporating temperature-related constraints and product quality considerations (Aung and Chang, 2014). A significant body of work has focused on analyzing quality degradation mechanisms. For example, Aiello et al. (2012) used simulation models to evaluate time-temperature effects on shelf life, while Ali et al. (2018) empirically demonstrated that temperature disruptions negatively impact firm performance. Similarly, Tsai and Lo (2024) proposed hybrid decision-support methods to mitigate temperature-related risks. To optimize these increasingly complex systems, recent studies have widely adopted Mixed-Integer Linear Programming (MILP) and non-linear programming approaches capable of handling constraints such as time windows, limited vehicle capacities, and time-dependent deterioration rates (Ali et al., 2021; Golestani et al., 2021; Ghasemkhani et al., 2022). Deterioration functions are often incorporated to transform transportation time into measurable financial losses, thereby enabling more accurate and data-driven managerial decision-making (Yang and Tao, 2023; Golestani et al., 2021). While these studies provide valuable insights into cold chain risks and quality dynamics, many recent international studies primarily focus on metaheuristic algorithms for solving large-scale optimization problems (Ghasemkhani et al., 2022; Pan et al., 2025). Consequently, there remains a significant need, particularly in regional case studies such as Thailand, for comprehensive MILP models that integrate open-routing and transshipment strategies under realistic operational conditions. Such exact optimization approaches are especially important for regional cold chain networks where time and temperature are critical determinants of product quality, operational efficiency, and business sustainability (Wei et al., 2020; Ali et al., 2021).

To address these limitations, this study proposes a single-objective Mixed Integer Linear Programming (MILP) model for cold chain logistics optimization. The proposed framework contributes in three ways. First, it provides a prescriptive, network-wide optimization approach that simultaneously determines routing and commodity flows. Second, it explicitly integrates perishability by monetizing time-dependent quality loss as a holding cost within the objective function. Third, it incorporates a flexible open-routing structure with multicommodity transshipment, enabling a more realistic representation of modern cold chain operations. Unlike recent studies published during 2024-2025, which often consider routing and perishability separately, the proposed framework integrates routing, transshipment, and time-dependent deterioration into a unified MILP model. This integration enables the simultaneous optimization of logistics decisions under quality-related constraints while providing exact solutions suitable for regional cold chain applications. Therefore, this study aims to develop and evaluate an integrated MILP framework for optimizing routing, transshipment, and perishability-related costs in cold chain logistics systems using a real-world case study in Thailand.

2. EXPERIMENTAL SECTION

2.1 Data Description

The dataset was obtained from a third-party cold chain logistics provider in Thailand engaged in frozen food distribution. It comprises shipment records, travel times, and routing schedules collected from daily operations. The underlying distribution network consists of 10 nodes, including depots and customer locations. The raw data were preprocessed by aggregating shipment volumes into arc-based flows and estimating travel times using historical averages. All data were anonymized to ensure confidentiality. The dataset represents a high-demand day in May 2025.

2.2 Mathematical Model

In this section, we present a mixed-integer linear programming formulation that minimizes total logistics cost, decomposed into two components: transportation costs and perishability-related holding costs. The model represents a flexible multi-destination flow network that supports multi-commodity transshipments and permits open routing (i.e., vehicles need not return to their origin depot), thereby reflecting realistic cold-chain operational practice.

The model parameters and decision variables are defined below.

- i, j origin and destination locations (pickup and drop-off nodes) i and j, respectively.
- $C_{(i,j)}$ transportation cost for moving goods from location i to location j (THB/trip), representing the cost per trip.
- $T_{(i,j)}$ travel time on the route from i to j (minutes).
- S_i vehicle stock (number of vehicles) stationed at location i (vehicles). Use this to represent available vehicle capacity at node i.
- q_k demand quantity associated with shipment k.
- N set of all nodes /locations, indexed by i, j.
- A set of all possible arcs (i, j) and $A \subset N \times N$.
- K set of all shipment flows, indexed by k.
- $o(k)$ the origin node for shipment k.
- $d(k)$ the destination node for shipment k.
- h holding (inventory) cost per unit per minute (THB/unit/minute). Given $h = 0.5$.
- Cap vehicle capacity per trip (units/trip). Given $Cap = 450$ units/trip.

Decision variables:

- $x_{(k,i,j)}$ quantity of goods transported from node i to node j for shipment k (units).
- $y_{(i,j)}$ number of vehicle trips scheduled on the route from i to j (trips). This can also be interpreted as trip frequency over the planning horizon.

Objective Function

$$\min Z = \sum_{(i,j)\in A} C_{(i,j)} y_{(i,j)} + h \sum_{k\in K} \sum_{(i,j)\in A} T_{(i,j)} x_{(k,i,j)} \quad (1)$$

Constraints

Demand flow (conservation) for each k and node n:

$$\sum_{j:(n,j)\in A} x_{(k,n,j)} - \sum_{i:(i,n)\in A} x_{(k,i,n)} = \begin{cases} q_k, & n = o(k), \\ -q_k, & n = d(k), \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Vehicle capacity linking (for every $(i, j) \in A$):

$$\sum_{k\in K} x_{(k,i,j)} \le Cap \cdot y_{(i,j)}, \text{ or } \sum_{k\in K} x_{(k,i,j)} \le 450 \cdot y_{(i,j)}. \quad (3)$$

Vehicle availability. For every origin $i \in N$,

$$\sum_{j:(i,j)\in A} y_{(i,j)} - \sum_{j:(j,i)\in A} y_{(j,i)} \le S_i. \quad (4)$$

Route feasibility: For $(i, j) \notin A$,

$$y_{(i,j)} = 0 \text{ and } x_{(k,i,j)} = 0. \quad (5)$$

Domains:

$$x_{(k,i,j)} \ge 0 \text{ (integer), and } y_{(i,j)} \in \mathbb{Z}^+. \quad (6)$$

The variable $x_{(k,i,j)}$ is defined as an integer to reflect practical logistics operations, where goods are transported in discrete, indivisible units (e.g., boxes or shipment units). Using continuous variables would allow fractional quantities, which are not physically meaningful in this context.

3. RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from both the experience-based planning approach and the proposed Mixed Integer Linear Programming (MILP) model. The analysis provides a comprehensive evaluation of system performance under realistic operational conditions. First, the existing experience-based transportation planning is examined as a baseline scenario to reflect current industry practice. Next, the optimized results derived from the MILP model are presented, highlighting improvements in routing decisions, resource utilization, and cost efficiency. Finally, a comparative analysis is conducted to assess the performance gains achieved by the proposed approach, with particular emphasis on the trade-off between transportation cost and perishability-related holding cost. The results provide quantitative evidence and managerial insights into improving cold chain logistics operations.

3.1 Preliminary Planning under Experience-Based Control

This section presents experience-based transportation planning, which serves as the baseline scenario for comparison. The planning decisions are derived from operational experience without the support of real-time data or mathematical optimization. The analysis focuses on route structure, vehicle utilization, and cost components, including transportation and inventory holding costs. Such heuristic and experience-driven planning approaches remain common in practical cold-chain operations, particularly in developing logistics environments where integrated optimization systems are not fully implemented (Aung and Chang, 2014; Bremer, 2018).

Table 1 presents the aggregated transportation planning results by origin node. The results indicate that node N8 accounts for the largest proportion of system flow and logistics cost, with a total flow of 2,729 units and a total logistics cost of THB 343,687.5, of which holding cost accounts for the majority. This finding is consistent with prior cold-chain studies reporting that quality deterioration and temperature-related losses frequently dominate overall logistics expenses in perishable food distribution systems (Mercier et al., 2017; James and James, 2010). This highlights the critical role of N8 as a central hub and a major source of perishability-related cost. The concentration of flows through hub nodes is also consistent with network-based logistics studies, where centralized transshipment structures improve consolidation efficiency but may increase operational dependency on a limited number of nodes (Akkerman et al., 2010).

In contrast, nodes such as N5 and N2 exhibit relatively lower total costs, suggesting more balanced routing structures and shorter holding durations. Overall, the results confirm that cost distribution is highly uneven across nodes, with high-flow nodes contributing disproportionately to total system cost, primarily driven by time-dependent deterioration effects. The detailed arc-level transportation plan is provided in Tables 2 and 3.

3.2 Numerical Experiment

This section reports the numerical experiments conducted to evaluate the feasibility and practical applicability of the proposed Mixed Integer Linear Programming (MILP) model. The analysis focuses on three aspects: optimal resource allocation, cost structure, and the operational value of the integrated framework defined in Equations (1)-(6).

The case study is based on real-world data from a Thai cold chain distribution company operating a network of ten hubs (denoted N_1–N_{10}). The dataset fully specifies the model parameters, including transportation cost ($C_{(i,j)}$), refrigerated travel time ($T_{(i,j)}$), demand ($D_{(i,j)}$), and vehicle availability (S_i), consistent with the definitions in the proposed formulation (Equations (1)-(6)). The key parameter settings are a holding (perishability) cost rate of $h = 0.5$ THB/unit/minute and a vehicle capacity of $Cap = 450$ units/trip, which are incorporated into the objective function (1) and capacity constraint (3), respectively.

Applying the model to this dataset yields the following results. Table 4 reports shipment flows and associated holding costs across arcs. Table 5 presents the optimal number of trips and transportation costs between nodes. Table 6 summarizes the selected freight transportation routes and shipment volumes, highlighting the role of transshipment in the network. Finally, Table 7 presents the optimal objective value and the overall system configuration obtained from the proposed MILP model.

Table 4 presents the quantity of goods transported (Flow) between nodes i and j in the logistics network, together with the corresponding holding cost for each route. Here, i denotes the origin node and j denotes the destination node. The variable Flow represents the quantity of goods transported from i to j in each cycle, while Hold Cost indicates the associated inventory holding cost. For example, the row "N1 N2 316 5846" indicates that 316 units are transported from node N1 to node N2, resulting in a holding cost of 5,846 THB. Table 4 supports the analysis of freight movement patterns across the network, identifies high-cost or high-volume routes, and facilitates informed decision-making regarding logistics optimization. It can also highlight bottlenecks or areas where inventory costs are significant, supporting effective inventory and supply chain management.

The concentration of holding cost on several major arcs reflects the sensitivity of cold-chain systems to travel time and temperature exposure. Similar observations were reported by Aiello et al. (2012) and Laguerre et al. (2013), who demonstrated that prolonged transportation duration significantly accelerates quality degradation in perishable food logistics. This finding also suggests that reducing travel time on high-volume arcs may generate larger economic benefits than uniformly reducing transportation cost across the entire network. From a managerial perspective, prioritizing refrigeration efficiency and scheduling improvements on these critical routes may substantially reduce deterioration-related losses.

As reported in Table 5, high-demand arcs (e.g., N2-N3, N8-N7) require multiple trips, indicating capacity pressure in key corridors. For example, the row "N2 N3 2 2465 4930" indicates that goods are transported from node N2 to node N3 with a total of 2 trips, where each trip costs 2,465 THB, resulting in a total transportation cost of 4,930 THB. Table 5 allows for identification of routes with high transportation frequency or cost, provides insights into overall logistics expenses, and supports the optimization of transportation planning and resource allocation within the supply chain. The need for multiple trips on several high-demand arcs also reflects classical vehicle-routing behavior under limited vehicle capacity constraints. Similar capacity-driven routing patterns have been widely discussed in VRP literature (Solomon, 1987; Toth and Vigo, 2002). The occurrence of multiple trips on several arcs directly reflects the effect of the vehicle-capacity constraint defined in Equation (3). This demonstrates that fleet availability and vehicle capacity are critical operational parameters influencing overall routing efficiency.

Table 1. Aggregated Transportation Planning Results Under Experience-Based Planning

			Transportation		
Origin	Total Flow	Trips	Cost (THB)	Holding Cost (THB)	Total Cost (THB)
N1	658	6	18,072.50	49,959.50	68,032.00
N2	706	6	18,750.00	41,002.50	59,752.50
N3	473	6	27,400.00	44,688.50	72,088.50
N4	532	6	28,737.50	52,765.00	81,502.50
N5	433	6	22,375.00	30,019.50	52,394.50
N6	575	4	17,550.00	43,222.50	60,772.50
N7	896	3	15,050.00	66,517.50	81,567.50
N8	2,729	9	57,900.00	285,787.50	343,687.50
N9	565	3	24,375.00	82,065.00	106,440.00
N10	498	2	9,622.50	54,843.00	64,465.50

Table 2. Detailed Arc-Level Transportation Plan for Nodes N1-N4

Origin	Destination	Flow (units)	Trips	Transportation cost (THB)	Holding cost (THB)	Total cost (THB)
N1	N2	24	1	810.0	444.0	1,254.0
N1	N3	81	1	3,150.0	4,050.0	7,200.0
N1	N4	70	1	2,350.0	3,150.0	5,500.0
N1	N5	30	1	1,637.5	855.0	2,492.5
N1	N6	92	1	3,850.0	6,624.0	10,474.0
N1	N8	361	1	6,275.0	34,836.5	41,111.5
N2	N1	62	1	782.5	1,054.0	1,836.5
N2	N3	247	1	2,465.0	8,645.0	11,110.0
N2	N4	73	1	2,800.0	3,613.5	6,413.5
N2	N5	69	1	2,327.5	2,760.0	5,087.5
N2	N6	30	1	3,525.0	1,755.0	5,280.0
N2	N8	225	1	6,850.0	23,175.0	30,025.0
N3	N1	89	1	3,100.0	4,361.0	7,461.0
N3	N2	24	1	2,425.0	852.0	3,277.0
N3	N4	71	1	5,125.0	5,186.5	10,311.5
N3	N5	9	1	4,650.0	648.0	5,298.0
N3	N6	71	1	4,075.0	4,721.5	8,796.5
N3	N8	209	1	8,025.0	28,319.5	36,344.5
N4	N1	13	1	2,312.5	539.5	2,852.0
N4	N2	98	1	2,900.0	4,802.0	7,702.0
N4	N3	69	1	5,225.0	5,520.0	10,745.0
N4	N5	18	1	3,600.0	1,107.0	4,707.0
N4	N6	99	1	6,300.0	10,246.5	16,546.5
N4	N8	235	1	8,400.0	30,550.0	38,950.0

Table 6 summarizes the freight transport routes and associated shipment volumes under experience-based planning. Each route represents a feasible path with its corresponding flow distribution across segments. The frequent use of intermediate nodes confirms the operational value of transshipment in cold-chain distribution networks. This finding is aligned with integrated inventory-routing studies showing that coordinated transshipment structures can reduce transportation inefficiencies and improve network-wide resource utilization (Archetti and Speranza, 2016; Campbell and Savelsbergh, 2005).
Example interpretation:

Example 1: Row: "2 N1-N2-N3 81-81". This is the 2nd shipment in sequence. The route is from N1 to N2 to N3. 81 units are shipped from N1 to N2, and another 81 units from N2 to N3 along the route.

Example 2: Row: "36 N4-N5-N8-N7-N10 69-69-69-69". 36$^{\text{th}}$ shipment in order. Route: N4 → N5 → N8 → N7 → N10. 69 units are moved in each segment (N4-N5: 69, N5-N8: 69, N8-N7: 69, N7-N10: 69).

Tables 4-6 present the detailed results of shipment flows, transportation decisions, and routing structures derived from the proposed optimization model. Rather than focusing on in-

Table 3. Detailed Arc-Level Transportation Plan for Nodes N5-N10

Origin	Destination	Flow (units)	Trips	Transportation Cost (THB)	Holding Cost (THB)	Total Cost (THB)
N5	N1	90	1	1,602.5	2,610.0	4,212.5
N5	N2	45	1	2,447.5	1,845.0	4,292.5
N5	N3	59	1	4,775.0	4,248.0	9,023.0
N5	N4	13	1	3,650.0	825.5	4,475.5
N5	N6	15	1	4,300.0	1,290.0	5,590.0
N5	N8	211	1	5,600.0	19,201.0	24,801.0
N6	N2	104	1	3,250.0	5,928.0	9,178.0
N6	N4	81	1	5,950.0	8,343.0	14,293.0
N6	N5	87	1	4,275.0	7,438.5	11,713.5
N6	N8	303	1	4,075.0	21,513.0	25,588.0
N7	N8	356	1	4,625.0	30,438.0	35,063.0
N7	N9	129	1	7,300.0	17,995.5	25,295.5
N7	N10	411	1	2,625.0	18,084.0	20,709.0
N8	N1	164	1	6,425.0	16,236.0	22,661.0
N8	N2	446	1	6,900.0	45,715.0	52,615.0
N8	N4	254	1	8,525.0	33,782.0	42,307.0
N8	N5	228	1	5,750.0	21,090.0	26,840.0
N8	N6	281	1	4,100.0	20,372.5	24,472.5
N8	N7	801	2	9,650.0	67,284.0	76,934.0
N8	N9	555	2	16,550.0	81,307.5	97,857.5
N9	N7	66	1	7,525.0	8,712.0	16,237.0
N9	N8	499	2	16,850.0	73,353.0	90,203.0
N10	N7	93	1	2,497.5	3,813.0	6,310.5
N10	N8	405	1	7,125.0	51,030.0	58,155.0

Table 4. Quantity of Gods Transported and Holding Cost

i	j	Flow (units)	Hold Cost	i	j	Flow (units)	Hold Cost
N1	N2	316	5846	N6	N8	414	29394
N1	N4	337	15165	N6	N9	234	45396
N1	N5	195	5557.5	N7	N10	411	18084
N1	N8	450	43425	N7	N8	405	34627.5
N2	N1	418	7106	N7	N9	129	17995.5
N2	N3	456	15960	N8	N1	418	41382
N2	N6	225	11137.5	N8	N2	446	45715
N2	N8	372	21762	N8	N5	228	21090
N3	N2	193	6851.5	N8	N6	281	20372.5
N3	N6	280	18620	N8	N7	801	67284
N4	N2	279	13671	N8	N9	321	47026.5
N4	N5	253	15559.5	N9	N7	115	15180
N5	N1	222	6438	N9	N8	450	66150
N5	N8	446	40586	N10	N7	93	3813
N6	N2	272	15504	N10	N8	405	51030

dividual entries, the analysis highlights key operational insights that are critical for managerial decision-making. First, Table 4 reveals that holding (perishability-related) costs are highly concentrated on specific arcs with both high flow volume and long travel times, particularly those connected to central transshipment nodes such as N8. This indicates that certain nodes act as critical consolidation points where delays significantly amplify quality-related costs. From a managerial perspective, these nodes represent priority targets for operational improvements, such as reducing handling time, improving scheduling, or investing in enhanced refrigeration capacity.

Second, Table 5 indicates that most transportation routes operate with a low number of trips (typically one or two), suggesting that the model efficiently utilizes vehicle capacity under

Table 5. Number of Trips and Transportation Costs between Nodes i and j

i	j	Trips	TripCost	Cost	i	j	Trips	TripCost	Cost
N1	N2	1	810	810	N6	N8	1	4075	4075
N1	N4	1	2350	2350	N6	N9	1	11175	11175
N1	N5	1	1637.5	1637.5	N7	N10	1	2625	2625
N1	N8	1	6275	6275	N7	N8	1	4625	4625
N2	N1	1	782.5	782.5	N7	N9	1	7800	7800
N2	N3	2	2465	4930	N8	N1	1	6425	6425
N2	N4	1	2800	2800	N8	N2	1	6900	6900
N2	N6	1	3525	3525	N8	N5	1	5750	5750
N3	N2	1	2425	2425	N8	N6	1	4100	4100
N3	N6	1	4075	4075	N8	N7	2	4825	9650
N4	N2	1	2900	2900	N8	N9	1	8275	8275
N4	N5	1	3600	3600	N9	N7	1	7525	7525
N5	N1	1	1602.5	1602.5	N9	N8	1	8425	8425
N5	N8	1	5600	5600	N10	N7	1	2497.5	2497.5
N6	N2	1	3250	3250	N10	N8	1	7125	7125

Table 6. Representative Freight Transport Routes under the Proposed Model

Order of ship-ment	Routes	The amount of goods transported along the route (Unit)
1	N1-N2	24
2	N1-N2-N3	81-81
3	N1-N4	70
4	N1-N5	30
5	N1-N2-N6	92-92
6	N1-N8-N7	96-96
7	N1-N8	84
8	N1-N8-N9	84-84
9	N1-N8-N7-N10	97-97-97
10	N2-N1	39
11	N2-N3	11
12	N2-N4	73
13	N2-N1-N5	69-69
14	N2-N6	30
15	N2-N1-N8-N7	42-42-42
16	N2-N1-N8	16-16
17	N2-N6-N9	67-67
18	N2-N1-N8-N7-N10	31-31-31-31
...	...	...
88	N10-N7	61
89	N10-N8	13
90	N10-N7-N9	32-32

the given constraint (Cap = 450). However, routes with multiple trips, such as N2-N3 and N8-N7, indicate high-demand corridors that may serve as potential bottlenecks. Increasing vehicle availability or reallocating fleet resources along these critical routes could further improve system performance and reduce total logistics cost.

Third, Table 6 highlights the structure of optimal routing decisions, where a significant number of shipments are routed through intermediate nodes rather than direct origin-destination paths. These findings confirm the strategic role of transshipment in reducing overall cost. Routes passing through nodes such as N8 and N2 appear frequently, indicating that these nodes function as key hubs within the network. While this structure improves cost efficiency, it also introduces dependency on a limited number of nodes, which may increase operational risk in the event of disruptions. Such dependency may increase network vulnerability during disruptions, which has also been identified as a major challenge in resilient cold-chain logistics systems (Ali et al., 2018).

From a strategic standpoint, the results suggest three key managerial implications. First, reducing travel time and delays on high-flow arcs can substantially decrease holding costs, which dominate total logistics expenses. Second, identifying and strengthening high-demand routes can mitigate bottlenecks and improve service reliability. Third, while transshipment improves efficiency, it requires careful management of hub operations to avoid congestion and risk concentration.

Table 7. Summary of Optimization Results

Status	Objective	h	Cap
Optimal	911,264	0.5	450

Overall, the analysis demonstrates that the proposed model not only provides optimal routing solutions but also offers actionable insights for improving cold chain logistics performance through better resource allocation, network design, and operational control.

From the experiment, under the parameter settings (h =

Table 8. Comparison of Before and After Transportation Planning Results

Performance indicator	Before: Experience-based planning	After: MILP optimization	Difference	Change (%)
Total transportation trips (trips)	51	32	-19	-37.25
Transportation cost (THB)	239,832.50	143,535.00	-96,297.50	-40.15
Holding cost (THB)	750,870.00	767,729.00	+16,859.00	+2.24
Total logistics cost (THB)	990,702.50	911,264.00	-79,438.50	-8.02

0.5, $Cap = 450$), the proposed model identified the minimum total logistics cost of THB 911,264 (Table 7). The total cost is composed of transportation cost (THB 143,535) and holding (perishability-related) cost (THB 767,729), indicating that quality-related costs dominate overall logistics expenses in cold chain systems. This result further supports recent cold-chain optimization studies emphasizing that routing decisions should explicitly account for freshness deterioration and time-temperature exposure rather than focusing solely on transportation efficiency (Pérez-Lechuga et al., 2024; Ding et al., 2025).

This result highlights the critical importance of explicitly incorporating perishability into routing decisions. In particular, the high proportion of holding cost suggests that neglecting time-dependent product deterioration may lead to significantly suboptimal solutions. This finding is consistent with prior studies emphasizing the economic impact of time-temperature exposure on product quality (Aiello et al., 2012; Ali et al., 2018). However, unlike these studies, which primarily evaluate quality degradation, the proposed model integrates perishability directly into a prescriptive optimization framework, enabling decision-makers to balance transportation and quality-related costs simultaneously. In particular, the dominance of holding cost (over 80% of total cost) indicates that perishability is the primary driver of logistics performance in cold chain systems.

Furthermore, the model demonstrates the effectiveness of transshipment and flexible routing in reducing total logistics cost. The results show that optimal solutions frequently utilize intermediate nodes rather than direct shipment, reflecting the benefits of network-wide coordination. This observation aligns with the structural insights of classical VRP and IRP models (Toth and Vigo, 2002; Archetti and Speranza, 2016), which emphasize the importance of routing flexibility and coordinated decision-making. Compared with conventional VRP formulations, the proposed framework provides greater operational flexibility through open-routing and multicommodity transshipment, which are increasingly recognized as important characteristics in modern cold-chain systems (Leng et al., 2024).

Nevertheless, the proposed model extends these frameworks by incorporating open-routing structures and explicitly linking routing decisions with perishability costs. Unlike traditional VRP models that focus solely on transportation efficiency, and IRP models that primarily capture inventory trade-offs, this study provides an integrated representation that simultaneously accounts for routing, transshipment, and time-dependent quality loss.

Overall, the findings demonstrate that integrating routing optimization with perishability considerations leads to more realistic and cost-efficient solutions in cold chain logistics. The model not only improves operational efficiency but also provides a quantitative basis for evaluating trade-offs between transportation decisions and product quality preservation, which is essential for decision-making in temperature-sensitive supply chains.

3.3 Benchmark Comparison with Baseline Planning

A benchmark comparison between the experience-based planning approach and the proposed MILP model shows clear improvements in system performance (Table 8). First, the number of transportation trips decreases from 51 to 32 (–37.25%), indicating better vehicle utilization and shipment consolidation. Second, transportation cost is reduced significantly from THB 239,832.50 to THB 143,535.00 (-40.15 %), showing that the model effectively improves routing efficiency. In contrast, holding (perishability-related) cost increases slightly from THB 750,870.00 to THB 767,729.00 (+2.24%), as the model selects routes that improve overall system efficiency rather than minimizing local costs. This trade-off reflects the typical behavior of integrated inventory-routing systems, where global optimization may accept localized increases in holding-related cost to achieve lower overall system cost (Archetti and Speranza, 2016). The slight increase in holding cost indicates that the optimization framework prioritizes global system efficiency over locally optimal routing decisions. Such behavior is common in integrated logistics optimization, where minimizing total system cost may require accepting marginal increases in individual cost components. The observed reduction in transportation trips and routing cost is consistent with prior optimization-based cold-chain studies, where integrated routing strategies improved fleet utilization and reduced redundant transportation activities (Leng et al., 2024; Nan et al., 2025).

Overall, total logistics cost decreases from THB 990,702.50 to THB 911,264.00 (-8.02%). This confirms that the MILP model achieves better trade-off between transportation and holding costs compared to conventional planning. These results demonstrate that incorporating perishability into routing decisions leads to measurable cost savings and improved operational efficiency, supporting the practical value of the proposed approach. Overall, the comparative results support the growing consensus in recent cold-chain logistics research that integrated optimization models outperform heuristic or experience-based planning approaches in terms of cost efficiency and operational coordination (Iyer and Robb, 2024).

4. CONCLUSION

This study develops a mixed integer linear programming (MILP) framework that integrates routing, transshipment, and time-dependent perishability into a unified cold chain optimization model. The results show that the proposed approach reduces total logistics cost from THB 990,702.50 to THB 911,264.00 (-8.02%), primarily driven by a significant reduction in transportation cost (-40.15%) and the number of trips (-37.25%), despite a slight increase in holding cost (+2.24%). These findings highlight the importance of explicitly capturing the trade-off between transportation efficiency and perishability-related costs, confirming that routing decisions based solely on distance or cost may lead to suboptimal system performance. By explicitly incorporating product deterioration into the decision framework, the model provides an effective decision-support framework for route planning, transshipment, and capacity allocation under quality constraints. In contrast to conventional routing models that primarily minimize transportation distance or cost, the proposed framework explicitly integrates perishability-related holding cost into routing and transshipment decisions. This enables a more realistic representation of cold-chain operations where product quality deterioration is economically significant. However, the model is limited by assumptions of deterministic travel times, constant holding costs, and fixed vehicle capacity. Future research should extend this framework by incorporating stochastic travel times, dynamic demand, and route-dependent deterioration, along with large-scale validation to enhance its applicability in real-world cold chain systems. In addition, computational complexity may increase significantly for large-scale logistics networks with stochastic parameters, requiring the development of decomposition methods or metaheuristic algorithms for future implementation.

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