International Journal of Energy Production and Management
https://www.acadlore.com/journals/IJEPM

Mathematical Modelling and Hybrid Optimization of Thermally-Constrained Energy Distribution in Cold Logistics Networks

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Received: 10-13-2025 **Revised:** 11-08-2025 **Accepted:** 12-13-2025

Citation: J. L. Marpaung, P. K. Nasution, M. F. Balqis, P. Gultom, and N. F. B. Ibrahim, "Mathematical modelling and hybrid optimization of thermally-constrained energy distribution in cold logistics networks," *Int. J. Energy Prod. Manag.*, vol. 10, no. 4, pp. 669–685, 2025. https://doi.org/10.56578/ijepm100408.

Abstract: Cold chain logistics systems are essential for preserving temperature-sensitive goods, yet they face increasing operational and environmental challenges due to thermal constraints, dynamic delivery demands, and route uncertainties. This study proposes a hybrid soft computing approach that integrates Fuzzy Logic, Genetic Algorithm (GA), and Ant Colony Optimization (ACO) to optimize energy distribution within thermally-constrained logistics networks. A mathematical model is formulated to minimize a multi-objective cost function that includes total energy consumption, travel time, and penalties from temperature deviations, all subject to vehicle capacity, time window, and thermal stability constraints. The Fuzzy Logic module evaluates uncertainties related to product sensitivity and delivery urgency, assigning adaptive penalty weights to guide the GA-based global search. Subsequently, the ACO layer enhances routing solutions through pheromone-driven refinement. Simulation experiments were conducted over 20 randomized testbeds, with the proposed hybrid model consistently outperforming mono-algorithmic benchmarks. On average, the model reduced energy usage by 12.6%, lowered temperature violations by 28.3%, and increased on-time delivery rate by 15.1% compared to standard GA or ACO approaches. These results demonstrate the model's capability to generate robust and efficient routes under real-world constraints. In practical terms, logistics providers can adopt this framework to achieve substantial cost savings, reduce spoilage of perishable goods, and enhance environmental sustainability. Moreover, the model is scalable and can be adapted to integrate IoT-based monitoring and renewable energy systems in future implementations.

Keywords: Cold chain logistics; Hybrid optimization; Fuzzy Logic; Genetic Algorithm; Ant Colony Optimization; Mathematical modeling; Energy efficiency; Thermally-constrained routing

1 Introduction

Energy consumption in cold logistics operations has emerged as a quantifiable and pressing concern in modern supply chain systems. Globally, cold chain logistics is estimated to account for approximately 15–20% of the total energy used in food distribution systems, with refrigeration systems alone contributing up to 70% of the operational energy cost in some cases [1]. These operations require not only conventional transportation logistics but also continuous thermal control, especially when transporting perishable goods such as vaccines, dairy, frozen food, or biological samples. As the demand for safe and temperature-compliant delivery continues to rise particularly in sectors such as pharmaceutical logistics the energy efficiency of such systems becomes critical for both cost containment and sustainability. Moreover, the energy inefficiencies arising from thermal leakage, poor route optimization, and temperature fluctuations have been shown to cause product spoilage rates of 10–30% in poorly managed systems. These statistics illustrate the urgent need for intelligent, energy-aware logistics optimization strategies [2].

Traditional vehicle routing problems (VRPs) are often solved with the primary objective of minimizing total distance or cost. However, cold chain logistics introduces an added layer of complexity: temperature constraints that must be satisfied throughout the delivery route. These constraints are not binary in nature; rather, they are fuzzy, dynamic, and interdependent. Factors such as outside temperature, duration of travel, refrigeration capacity, and the sensitivity of each product to thermal deviations all interact to influence energy consumption. In a thermally-constrained scenario, a delivery route that is optimal in terms of distance might still be suboptimal in terms of energy efficiency or product safety due to prolonged exposure to risk-prone thermal environments. Furthermore, vehicle capacity limitations, variable traffic conditions, tight delivery time windows, and uncertain demand patterns introduce further challenges in ensuring both operational feasibility and thermal compliance. These factors make cold logistics optimization a multi-objective, constrained, and uncertainty-laden problem one that requires more than classical optimization heuristics.

Recent advances in cold chain logistics have prompted the integration of intelligent optimization frameworks to address the complexity of temperature-sensitive distribution. Several studies have focused on optimizing energy use and route planning through advanced heuristics and hybrid soft computing. For instance, Ntakolia et al. [1] proposed a hybrid Fuzzy-Genetic Algorithm (GA)-Ant Colony Optimization (ACO) algorithm for adaptive route optimization, significantly enhancing computational efficiency and reducing energy waste. Similarly, Tirkolaee et al. [2] introduced a fuzzy multi-objective vehicle routing model that incorporated sustainability constraints, improving both service levels and environmental outcomes. Ragmani et al. [3] laid the foundational principles of (ACO), which continue to be widely used for solving complex routing problems. Tomar et al. [4] implemented a green vehicle routing approach using GA to reduce carbon emissions in supply chain distribution, aligning with growing concerns about sustainability.

Lakhwani and Sinjana [5] addressed the challenges of uncertain demand and temporal constraints in cold chain networks, proposing robust strategies to preserve product quality. Shi et al. [6] leveraged fuzzy constraints to manage perishability and thermal sensitivity, aligning closely with the objectives of our study. Wang et al. [7] modeled thermal performance and load planning under multi-temperature constraints, offering critical insights into energy-efficient refrigerated transport. Giridhar et al. [8] developed a GA-ACO hybrid metaheuristic that performed well under multi-objective routing constraints, validating the benefit of integrating swarm intelligence with evolutionary techniques. Talbi [9] and Mancò et al. [10] extended this approach with a GA-PSO hybrid, highlighting the scalability of hybrid methods for larger VRP instances. This perspective was further supported by Khalili et al. [11], who reviewed hybrid metaheuristics and confirmed their superior performance for solving logistics problems with high-dimensional objectives [12, 13].

Further investigations into sustainable logistics frameworks have incorporated renewable energy and IoT technologies. The studies [14–16] proposed a cold chain framework utilizing solar-powered refrigeration and real-time IoT monitoring to enhance temperature control and reduce fossil fuel dependence. Hasani et al. investigated stochastic optimization for perishable logistics, considering uncertainties in both environmental and operational parameters. Pardede et al. [17] used fuzzy penalty scoring to enhance decision-making in vehicle routing with thermal constraints, which is directly embedded in our penalty-based fitness formulation. Zhang et al. [18] proposed a hybrid solution that jointly handled time window and temperature constraints, achieving optimal trade-offs between energy and customer satisfaction.

Recent developments have also emphasized the role of soft computing in managing multi-constraint routing environments. Trabelsi et al. [19] explored the integration of the Internet of Vehicles (IoV) to support real-time intelligent decision-making in logistics. Xiao et al. [20] applied swarm intelligence in fault-tolerant routing, offering lessons in energy-aware pathfinding algorithms. Gultom et al. [21, 22] introduced adaptive crossover in GA to maintain diversity while preserving solution feasibility. Gultom et al. [21] compared classical VRP models against fuzzy and hybrid approaches, finding substantial improvements in convergence speed and solution robustness. Bianchi et al. [23] and Marinakis and Marinaki [24] investigated pheromone-based reinforcement strategies in ACO under constrained dynamic environments, improving path stability. Lastly, the studies [25–27] emphasized the importance of multi-objective modeling in smart cold chains, balancing cost, reliability, and energy indicators.

This comprehensive body of work supports the formulation of a hybrid optimization model for cold logistics that incorporates fuzzy penalty scoring, genetic exploration, and pheromone-based route refinement. Our study builds on these prior methodologies and extends them with simulation-based experimentation to validate energy usage, delivery punctuality, and constraint compliance under various operational scenarios [28, 29]. Thus, the current research builds upon these foundations by proposing a novel fuzzy-GA-ACO framework specifically tailored to temperature-constrained, energy-aware routing in cold logistics networks, introducing a repair-based fitness strategy and incorporating stochastic delay modeling contributing both methodologically and in practical implementation for sustainable energy distribution systems [30]. Over the past decade, several computational models have been proposed to address energy-aware and temperature-sensitive logistics problems. Classical VRP extensions, such as the Vehicle Routing Problem with Time Windows (VRPTW) and Energy-Minimizing Vehicle Routing Problems (EMVRP), have provided a foundation for incorporating energy considerations into routing decisions. However, these models are typically deterministic and limited in handling the soft constraints and nonlinear penalty structures found in cold chain applications. Fuzzy Logic, introduced by Zadeh in 1965, has been applied in various transportation contexts to manage uncertainties related to delivery time, customer satisfaction, and vehicle delays. In cold chain systems, fuzzy inference systems have been employed to translate linguistic descriptors such as “high urgency”,“medium temperature risk,” or “low refrigeration level” into numerical scores that can influence routing priorities. Although these models help capture uncertainty, they lack the global optimization capability needed to search a wide solution space efficiently.

To address large-scale optimization problems, metaheuristics such as the GA and ACO have been widely utilized. GA, inspired by natural evolution, has demonstrated robust performance in solving combinatorial logistics problems. ACO, based on the foraging behavior of ants, has been used to dynamically construct and refine routes based on probabilistic learning. Each algorithm has its own strengths GA in exploring global optima and ACO in exploiting local improvements but also suffers from limitations, such as premature convergence in GA and slow convergence in complex, multi-modal search spaces for ACO. Despite their popularity, single-algorithm approaches have shown critical limitations when applied to thermally-constrained energy distribution problems. The GA, for instance, while effective at exploring a diverse solution space, may converge prematurely on suboptimal solutions if not carefully tuned. Its performance often deteriorates in problems where constraints interact in non-linear and fuzzy ways, as is the case in cold chain logistics. Additionally, GA requires a large number of iterations to stabilize in large-scale problems, which results in significant computational overhead especially when real-time decision-making is needed.

On the other hand, ACO is more suitable for problems requiring incremental learning and local refinement, especially in dynamically changing environments. However, its performance can degrade when the initial pheromone trails are poorly informed, leading to inefficient search behavior. Moreover, ACO tends to over-exploit known solutions and may become trapped in local optima without adequate diversity in the solution space.

Most importantly, both GA and ACO, when used independently, fail to effectively incorporate linguistic and fuzzy human-like reasoning which is crucial for managing the uncertainty inherent in thermal risk profiles of different cargo types. This gap points to the need for a hybrid approach that combines fuzzy inference for decision support, GA for global solution space exploration, and ACO for local refinement and exploitation. To bridge the methodological gap in cold chain energy optimization, this paper proposes a hybrid soft computing approach that integrates Fuzzy Logic, GA, and ACO into a single, cohesive optimization framework. The motivation behind this hybridization is to leverage the complementary strengths of each component: Fuzzy Logic enables the transformation of uncertain thermal and urgency conditions into structured decision variables; GA provides robust exploration of feasible routing solutions while considering multiple conflicting objectives; and ACO fine-tunes the selected solutions by using pheromone-based learning to adapt to the local environment.

This hybrid framework is particularly suitable for cold chain logistics because it reflects the real-world characteristics of the problem:

1. Multiple soft and hard constraints
2. Nonlinear interactions between energy consumption and temperature maintenance
3. Dynamic delivery conditions
4. The need for real-time route adjustment

Moreover, the incorporation of a multi-objective mathematical model with energy consumption, travel time, and temperature violation penalties as key terms allows for quantitative evaluation and comparison of routing strategies. This combination of soft reasoning, evolutionary computation, and swarm intelligence provides a holistic and scalable solution for the next generation of sustainable cold chain networks. The primary objective of this research is to develop and validate a hybrid soft computing framework that integrates Fuzzy Logic, GA, and ACO for optimizing thermally-constrained energy distribution in cold logistics networks. This study aims to construct a multi-objective mathematical model that minimizes total energy consumption, travel time, and temperature deviation penalties, while adhering to real-world constraints such as vehicle capacity, delivery time windows, and thermal preservation requirements. Through the incorporation of fuzzy reasoning for handling uncertainty, evolutionary techniques for global optimization, and swarm intelligence for local refinement, the proposed approach is designed to deliver energy-efficient, adaptive, and scalable solutions for routing in temperature-sensitive distribution systems.

2 Methods

2.1 System Description and Problem Assumptions

This study considers a cold logistics distribution system in which temperature-sensitive goods are delivered from a central depot to a set of geographically dispersed customers (nodes) using a fleet of refrigerated vehicles. The objective is to optimize energy efficiency while maintaining strict thermal constraints to prevent product spoilage. The system is modeled as a capacitated vehicle routing problem (CVRP) with additional constraints related to temperature thresholds, delivery urgency, and energy usage.

Let the system be represented as a complete directed graph $G = (V, E)$, where:

1. $V = \{0, 1, 2, \ldots, n\}$ is the set of nodes, with node 0 representing the depot and $\{1, \ldots, n\}$ representing customers.
2. $E \subseteq V \times V$ is the set of edges between nodes.

3. Each edge $(i, j) \in E$ has an associated travel distance d_{ij}, energy cost e_{ij}, and expected travel time t_{ij}.

a. Depot and Vehicle Constraints

The distribution system consists of a central depot that manages a finite fleet of K homogeneous vehicles, each with a maximum load capacity Q and a fixed refrigeration energy consumption rate per kilometer. Every vehicle is required to begin and end its route at the depot, visiting a sequence of customer nodes. The routing decision is modeled using a binary variable $x_{ij}^k \in \{0, 1\}$, where the value indicates whether vehicle k travels directly from node i to node j. This routing structure forms the backbone of the energy distribution model, ensuring that logistical feasibility aligns with vehicle and depot constraints.

b. Customer Nodes and Demand

Each customer node $i \in \{1, \ldots, n\}$ is defined by three key attributes: (1) a demand quantity q_i, which must be less than or equal to the vehicle capacity Q; (2) a thermal sensitivity level θ_i, representing the acceptable temperature variation and defined within a bounded interval $[\theta_{\min}, \theta_{\max}]$; and (3) a service time window $[e_i, l_i]$, denoting the earliest and latest allowable delivery times. These parameters reflect realistic delivery requirements for perishable goods and impose critical constraints on the routing and scheduling problem.

c. Energy Demand and Refrigeration Cost

The total energy consumption E_{total} in the system includes two components: (1) mechanical transport energy, which depends on travel distance and cargo load; and (2) thermal refrigeration energy, which is required to maintain cargo temperature within a safe range throughout the route. The energy used on any arc (i, j) is calculated using the expression $e_{ij} = \alpha \cdot d_{ij} + \beta \cdot r_{ij}$, where α is the unit energy cost for movement, β is the cost coefficient for refrigeration energy, and r_{ij} is the estimated refrigeration effort influenced by internal cargo temperature and external environmental conditions. This model reflects the dual nature of energy usage in cold chain logistics.

d. Temperature Constraints and Violation Penalty

To ensure product integrity, each item must remain within a predefined temperature range during delivery. If the internal cargo temperature T_i at node i violates the threshold $[T_{\min}, T_{\max}]$, a penalty function P_{θ_i} is triggered. This function is defined as $P_{\theta_i} = \gamma \cdot |T_i - T_{\text{target}}|$ when the temperature deviates from the target range, where γ is the penalty coefficient and T_{target} is the optimal delivery temperature (e.g., 4°C for vaccines).

$$P_{\theta_i} = \begin{cases} 0, & T_i \in [T_{\min}, T_{\max}] \\ \gamma \cdot |T_i - T_{\text{target}}|, & \text{otherwise} \end{cases} \tag{1}$$

The cargo temperature is dynamically influenced by travel duration, external heat exchange, and the refrigeration power applied making temperature regulation a time-sensitive and nonlinear constraint within the optimization model.

e. Assumptions in System Modeling

To maintain a balance between model realism and computational tractability, several assumptions are adopted: (1) all vehicles are homogeneous in terms of capacity and cooling capability; (2) customer demand and location data are known in advance and static; (3) each customer is visited only once by one vehicle; (4) no split delivery is permitted across vehicles; (5) every vehicle maintains a consistent cooling environment for its entire cargo; (6) refrigeration energy usage is approximated as a piecewise linear function increasing with time and distance; and (7) distance and energy matrices are symmetric, i.e., $d_{ij} = d_{ji}$ and $e_{ij} = e_{ji}$. These assumptions simplify the optimization space while preserving the core characteristics of cold chain distribution systems.

2.2 Mathematical Model

The energy-efficient distribution problem in cold logistics is formulated as a multi-objective vehicle routing problem that simultaneously minimizes transportation energy, refrigeration energy, and temperature violation penalties. The model extends the traditional CVRP and VRPTW by incorporating thermally-constrained delivery dynamics and energy-related decision variables.

Let the logistics network be defined on a graph $G = (V, E)$, with node set $V = \{0, 1, 2, \ldots, n\}$, where node 0 represents the depot and the rest represent customer locations. Let K be the set of vehicles, each with capacity Q. The binary decision variable $x_{ij}^k = 1$ if vehicle k travels from node i to node j, and 0 otherwise. The total objective function consists of three components:

1. Transport and refrigeration energy cost E_{total}
2. Temperature violation penalty P_{temp}
3. Time-based penalty (if delivery exceeds window) P_{time}

The overall objective is:

$$\min = \left\{ Z = \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} x_{ij}^k \cdot (\alpha \cdot d_{ij} + \beta \cdot r_{ij}) + \sum_{i \in V} P_{\theta_i}(T_i) + \sum_{i \in V} P_{\tau_i}(a_i) \right\} \tag{2}$$

where,
d_{ij}: distance between node i and j
α: unit cost of transport energy
r_{ij}: refrigeration effort between node i and j
β: refrigeration cost coefficient
$P_{\theta_i}(T_i)$: temperature penalty function
$P_{\tau_i}(a_i)$: time window penalty based on arrival time a_i
i, j: Index of nodes (customers and depots), where $i, j \in \{1, 2, \ldots, n\}$
$x_{i,j}$: Binary decision variable; 1 if route from node i to j is selected, 0 otherwise
d_i: Demand at node i
Q: Vehicle capacity
$[e_i, l_i]$: Time window for node i (units: hour)
T_i: Temperature requirement at node i (units: $^\circ$C)
$T_{\max}, T_{\min}$: Maximum and minimum acceptable product temperature (units: $^\circ$C)
$\delta_{i,j}$: Distance between node i to j (units: km)
v: Average vehicle speed (units: $\mathrm{km/h}$)
$E_{i,j}$: Energy cost to travel from node i to j, including cooling effort (units: kWh)
α, β: Energy cost weighting parameters
P_i: Penalty for violating temperature, urgency, or time window at node i (units: cost units or weighted score)
$f(.)$: Total cost function combining travel energy and penalty functions (units: cost units)

2.2.1 Temperature penalty function

$$P_{\theta_i} = \begin{cases} 0, & \text{if } T_{\min} \leq T_i \leq T_{\max} \\ \gamma \cdot |T_i - T_{\text{target}}| & \text{, otherwise} \end{cases} \tag{3}$$

where,
T_i: arrival temperature at node i
$T_{\min}, T_{\max}$: acceptable temperature range
T_{target}: ideal delivery temperature (e.g., 4°C)
γ: penalty weight based on product sensitivity
This reflects the real-world risks of thermal deviation in cold chain logistics.

2.2.2 Constraints

a. Routing Constraints
Ensure each customer is visited once:

$$\sum_{k \in K} \sum_{i \in V \setminus \{j\}} x_{ij}^k = 1 \quad \forall j \in V \setminus \{0\} \tag{4}$$

Ensure flow continuity:

$$\sum_{j \in V} x_{ij}^k = \sum_{j \in V} x_{ji}^k \quad \forall i \in V, \forall k \in K \tag{5}$$

b. Capacity Constraints

$$\sum_{i \in V} q_i \cdot x_{ij}^k \leq Q \quad \forall k \in K \tag{6}$$

where, q_i is the demand at customer i.
c. Time Window Constraints
Each vehicle must arrive within the allowed time window:

$$e_i \leq a_i \leq l_i \quad \forall i \in V \tag{7}$$

Arrival time a_i is recursively defined:

$$a_j \geq a_i + t_{ij} - M \cdot \left(1 - x_{ij}^k\right) \quad \forall i, j \in V, \forall k \in K \tag{8}$$

where, t_{ij} is the travel time, and M is a large constant.
d. Temperature Constraints
Internal temperature must stay within safe bounds:

$$T_{\min} \leq T_i \leq T_{\max} \quad \forall i \in V \tag{9}$$

And T_i is dynamically calculated based on:

$$T_i = T_0 + \delta.t_{0i} - \rho.r_{0i} \tag{10}$$

where,

δ: thermal drift coefficient (e.g., ambient heat exchange)

ρ: cooling efficiency of the vehicle

r_{0_i}: refrigeration rate applied during segment

2.2.3 Hybrid optimization framework

To solve the complex, multi-constraint nature of the thermally-constrained energy distribution problem in cold logistics, this study proposes a hybrid soft computing framework combining Fuzzy Logic, GA, and ACO. The first stage of the framework uses Fuzzy Logic to model the uncertainty associated with temperature sensitivity and delivery urgency. The fuzzy inference system (FIS) was constructed using two primary input variables: delivery urgency (U) and temperature sensitivity (S), with one output variable, priority weight (P), which directly affects the penalty function in the optimization model. Each input variable was defined by three linguistic terms low, medium, and high modeled using triangular membership functions calibrated through a combination of empirical observation and iterative tuning.

Parameter ranges were derived from operational records of cold-chain delivery schedules and temperature logs obtained from partner logistics datasets (Medan–Binjai regional routes, 2023). The calibration process used heuristic fine-tuning to ensure smooth fuzzy transitions and logical consistency across input-output pairs. Table 1 summarizes the numerical boundaries used for each membership function.

Table 1. Fuzzy Logic nomalized range

Variable	Linguistic Time	Range (Normalized)
	Low	[0.0–0.3]
Delivery Urgency (U)	Medium	[0.25–0.65]
	High	[0.6–1.0]
	Low	[0.0–0.4]
Temperature Sensitivity (S)	Medium	[0.35–0.7]
	High	[0.65–1.0]
	Low	[0.0–0.4]
Output Priority Weight (P)	Medium	[0.35–0.7]
	High	[0.65–1.0]

The fuzzy rule base was constructed using a Mamdani-type inference structure with 9 conditional rules, such as:

1. IF (Urgency is High) AND (Sensitivity is High) THEN (Priority Weight is High)
2. IF (Urgency is Low) AND (Sensitivity is Low) THEN (Priority Weight is Low)

Defuzzification was performed using the centroid method, producing crisp penalty weights that guide the GA's selection mechanism. This calibration procedure ensures reproducibility and allows the model to be adapted for other datasets with minimal retraining. Each customer node is assigned fuzzy linguistic variables based on (a) product thermal sensitivity (low, medium, high) and (b) delivery urgency (normal, urgent, very urgent). These inputs are fuzzified using triangular or trapezoidal membership functions, which feed into a rule base such as: If urgency is high and sensitivity is high, then penalty weight is very high. This fuzzy inference system outputs a node-specific penalty score that is embedded into the fitness evaluation during the GA phase. Prior studies in cold logistics and energy-aware scheduling have shown that Fuzzy Logic enhances interpretability and robustness when dealing with qualitative constraints and risk factors.

In the second stage, the GA performs global exploration by encoding each route as a chromosome of node sequences, constrained by depot origin and return. The initial population is generated using a constraint-relaxed random method, ensuring at least capacity-feasible chromosomes. The fitness function integrates transport energy, refrigeration cost, and fuzzy-adjusted temperature penalties from the previous step. Standard GA operators are applied: tournament selection, ordered crossover (OX), and mutation via position swap. Each offspring is passed through a repair operator to ensure customer coverage and route validity. GA has been widely applied to VRP variants due to its scalability and adaptability to constraint-laden, multi-objective problems.

To enhance local exploitation and fine-tune route efficiency, the third stage invokes ACO on the top-performing GA solutions. Here, each vehicle route is modeled as an ant traversal path, with pheromone trails updated according to a learning rule influenced by energy savings and delivery reliability. The transition probability from node to node is governed by a balance between pheromone intensity and heuristic desirability, while pheromone evaporation prevents premature convergence. Compared to standard ACO used in energy routing the embedded Fuzzy-GA penalty factors enable the ant agents to avoid routes prone to thermal violations or timing risk.

Algorithm 1 implements a hybrid Fuzzy-GA-ACO optimization framework that integrates conditional logic at every stage to efficiently solve the thermally-constrained energy distribution problem in cold logistics. The process begins with fuzzy penalty scoring, where linguistic variables such as delivery urgency and thermal sensitivity are mapped into penalty weights using IF–THEN fuzzy inference rules. In the genetic algorithm stage, new populations are evolved through probabilistic decision conditions, where crossover and mutation are applied based on predefined rates, followed by a fitness function that penalizes solutions violating capacity, temperature, or time constraints. To ensure feasibility, a repair function is triggered with an IF-constraint-violated-THEN-modify logic, adjusting solutions toward valid domains. The final ACO phase performs probabilistic route construction, where transitions are guided by pheromone intensity and heuristic desirability, reinforced only if the locally constructed solution satisfies delivery conditions. This conditional and adaptive design allows the hybrid algorithm to explore a broader solution space while refining toward cost-efficient and constraint-compliant logistics routes. Each configuration was evaluated over 20 iterations on the same dataset, and metrics such as average total energy usage, constraint violations, and execution time were recorded. The results showed that a crossover rate of 0.75 and mutation rate of 0.05 offered a balanced trade-off between exploration and convergence speed. For ACO, an evaporation rate of 0.4 yielded the best refinement of near-optimal routes.

3 Result and Discussion

3.1 Setup and Parameters

To evaluate the proposed Fuzzy-GA-ACO hybrid algorithm, a controlled simulation environment was constructed using a synthetic testbed that reflects realistic cold chain distribution scenarios. The network topology consisted of one central depot and customer nodes randomly distributed within a 100×100 km region. Each customer node i was assigned a unique demand q_i uniformly drawn from the interval $[1, 8]$ units, constrained by the vehicle capacity $Q = 20$ units. Nodes were also associated with temperature sensitivity levels $\theta_i \in [0.2, 0.9]$, reflecting products ranging from moderately sensitive (e.g., dairy) to highly sensitive (e.g., vaccines). Delivery time windows $[e_i, l_i]$ were randomly assigned within an operational horizon of 6 hours, with staggered opening times to simulate real-world urgency levels. The simulation was implemented in Python 3.11 using customized modules for GA, ACO, and Fuzzy Logic processing. Core packages used included NumPy for matrix operations, Matplotlib for route visualization, and scikit-fuzzy for fuzzy membership evaluation. The hybrid framework was modularized to allow toggling between mono-algorithmic (GA-only or ACO-only) and fully integrated optimization runs. To assess performance across varying logistical pressures, three simulation scenarios were configured:

1. Scenario A (Baseline): Moderate node density, medium sensitivity, and relaxed time windows
2. Scenario B (High Thermal Stress): Same topology, but with increased θ_i values and tighter delivery windows
3. Scenario C (Urban Congestion): Clustered nodes with short inter-node distances and overlapping time windows

Each simulation was repeated over 30 independent runs to account for stochasticity in the algorithm. Parameters were set as follows unless otherwise stated: GA population size = 100, generations = 300, crossover rate = 0.85, mutation rate = 0.1; ACO ants $= 50$, evaporation rate $\rho = 0.2$, pheromone importance $\alpha = 1$, heuristic importance $\beta = 1$. Energy cost coefficients were fixed at $\alpha = 1.5$ (transport energy per km) and $\beta = 2.0$ (cooling energy per unit effort). Thermal penalty coefficient γ_i was derived from fuzzy scoring and scaled between 0–100.

3.2 Setup, Parameters, and Problem Assumptions

This study considers a cold logistics distribution system in which temperature-sensitive goods are dispatched from a single centralized depot to a set of geographically dispersed customer locations. Each customer node represents a delivery point with associated constraints such as time windows, delivery urgency, and thermal sensitivity. The depot is fixed at a central coordinate, while customer locations are randomly generated within a defined two-dimensional spatial boundary to simulate realistic spatial distribution patterns in urban or semi-urban areas.

For the purpose of establishing a tractable optimization framework, several simplifying assumptions were adopted in the thermal-energy model. First, the cooling efficiency (η_c) of the refrigeration unit was assumed constant throughout the delivery route. In practice, this efficiency fluctuates with compressor load, ambient temperature, and vehicle speed. The constant assumption allows the model to capture the overall energy trend without requiring continuous thermodynamic recalibration, though it may lead to a minor approximation error (estimated within 3–7% under normal temperature variation).

Algorithm 1: Fuzzy-GA-ACO Hybrid Optimization

Input

- Maximum generation G, population size N_p, mutation/crossover rate
- ACO parameters: ρ (evaporation), α, β (pheromone & heuristic weight)
- Node data: distance matrix D, refrigeration matrix R, demand q_i, time windows e_i, l_i, temperature sensitivity θ_i

Step 1: Initialization and Fuzzy Logic Evaluation

1. **FOR** each node i, define fuzzy inputs:
   a. Linguistic variable **Urgency**: low, medium, high (based on $l_i - e_i$)
   b. Linguistic variable **Sensitivity**: low, medium, high (based on θ_i)
2. Apply fuzzy inference system:
   IF urgency $=$ high **and** sensitivity $=$ high
   $\rightarrow$ **Set** penalty weight $\gamma_i =$ Large
   ELSE IF urgency = low **and** sensitivity = low
   $\rightarrow$ **Set** penalty weight $\gamma_i =$ Small
   ELSE
   $\rightarrow$ **Set** $\gamma_i =$ Moderate

Step 2: GA (Exploration Stage)

3. Initialize population P with N_p random feasible routes
4. Evaluate fitness of each individual: Fitness $= E_{\text{transport}} + E_{\text{refigerator}} + \sum_i P_{\theta_i}(T_i) + \sum_i P_{\tau_i}(a_i)$
5. While generation $< G$
   a. Select parents via tournament selection
   b. Apply crossover operator:
   IF random $<$ crossover_rate
   $\rightarrow$ Perform ordered crossover
   c. Apply mutation operator:
   IF random $<$ mutation_rate
   $\rightarrow$ Perform inversion mutation
   d. Apply repair function:
   IF route violates capacity or time window
   $\rightarrow$ Modify route to nearest feasible path
   e. Recalculate fitness for offspring
   f. Update population with new individuals
   IF best individual improves global best
   $\rightarrow$ Update best route and cost

Step 3: ACO (Exploitation Stage)

6. From best GA solutions, initialize pheromone matrix τ_{ij}
7. **FOR** each ant $a \in \{1, \ldots, A\}$:
   Construct route probabilistically:
   $p_{ij} = \frac{[\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta}{\sum_{l \in N_i} [\tau_{il}]^\alpha \cdot [\eta_{il}]^\beta}$
   IF constructed route is infeasible (e.g., violates time window):
   Apply local repair or discard
   Evaluate objective and compare with best
8. Apply pheromone update:
   a. Evaporate: $\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij}$
   b. Reinforce: $\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau_{ij}$ where $\Delta\tau_{ij} \propto 1/Z$

Step 4: Sensitivity and Convergence Analysis

1. Crossover rate (r_c) in the GA, tested at values $\{0.6, 0.75, 0.9\}$
2. Mutation rate (r_m), tested at $\{0.01, 0.05, 0.1\}$
3. Pheromone evaporation coefficient (ρ) in ACO, varied from $\{0.2, 0.4, 0.6\}$

Step 4: Output

9. Return the best optimized route with:
   a. Minimum total energy cost
   b. No thermal or delivery violations
   c. Feasible according to capacity and constraints

Second, the ambient temperature (T_{amb}) was modeled as uniform across the service region. In real-world cold-chain logistics, T_{amb} may vary due to geography or time of day, influencing the cooling load of the refrigeration unit. However, given that the majority of deliveries in this study were simulated within a regional network, the uniform assumption is reasonable for comparative analysis across optimization algorithms. To improve model realism, future work will integrate temperature-dependent cooling functions and real-time IoT data acquisition, enabling the hybrid optimization system to dynamically adjust energy consumption based on external climate factors and operational feedback.

The vehicle routing system assumes a homogeneous fleet with limited capacity and refrigeration constraints. Each delivery route begins and ends at the depot, and the vehicle is required to visit each customer exactly once within their allowable time windows. Early or late arrivals are penalized through a Fuzzy Logic-based scoring mechanism, which assigns risk-based costs depending on the urgency and temperature sensitivity of the delivered product. Node attributes include:

1. Spatial coordinates (x, y)
2. Demand volume (random integer: 1–8 units)
3. Time windows: earliest (e_time) and latest (l_time) acceptable delivery times
4. Sensitivity to temperature (continuous range: 0.2–0.9)
5. Urgency level (categorical: low, medium, high)

The energy consumption model is computed based on a combination of:

1. Euclidean distance between nodes
2. A weighted factor for refrigeration effort (cooling load)
3. Fixed vehicle energy scaling constants $\alpha = 1.5$ and $\beta = 2.0$

The total energy usage is calculated as:

$$E_{ij} = \alpha \cdot d_{ij} + \beta \cdot \text{ cooling effort}$$

where, d_{ij} is the Euclidean distance between node i and node j. To simulate real-world variation, 20 iterations of both random routes and hybrid optimized routes (GA+ACO) were performed, using different seeds for stochastic node generation. The results are evaluated using total energy usage and route feasibility.

3.3 Experimental Simulation

To evaluate the baseline performance of the system without optimization, a simulation of random initial route generation was conducted over 20 iterations. Each iteration generated a different delivery sequence among 20 customer nodes using uniform shuffling techniques. The objective was to establish a reference benchmark for energy usage, route stability, and variation in performance when no intelligent routing logic is applied. Each route starts and ends at the central depot (node 0) and includes all 20 delivery points exactly once. The results of this simulation are presented in Table 2, showing the total energy usage, route length, and corresponding route path for each iteration. The energy usage varies significantly due to the stochastic nature of the node arrangement and route sequencing.

As seen in Table 2, the total energy usage across 20 iterations fluctuates between 1315.15 and 1900.23 energy units, indicating an average inefficiency due to random route choices. This confirms the need for a more intelligent and constraint-aware optimization framework to minimize energy cost and improve delivery reliability. To visually understand the inefficiencies of randomly generated routes, one of the simulation results is illustrated in Table 1. This figure shows the spatial distribution of customer nodes and the corresponding connection paths followed by a vehicle starting and ending at the central depot (node 0).

As shown in Figure 1, the random initial route lacks strategic clustering and efficient sequencing of deliveries, resulting in unnecessary detours and backtracking. This visual evidence strengthens the argument for implementing intelligent routing strategies, such as hybrid metaheuristic optimization, to reduce energy cost and ensure better delivery coordination in thermally-constrained logistics systems. To evaluate the effectiveness of the GA in improving route efficiency, a comparative visualization is presented in Figure 2. The left panel illustrates a baseline route generated randomly, serving as the initial condition prior to optimization. The right panel displays the final route produced after 200 generations of GA optimization, incorporating selection, crossover, mutation, and constraint-based fitness adjustments.

As seen in Figure 2, the optimized route exhibits significantly smoother transitions between customer nodes with fewer overlaps and detours, resulting in a more compact and energy-efficient path. This confirms that GA is capable of learning optimal delivery sequences under vehicle routing constraints, achieving better resource utilization while reducing total energy consumption in temperature-sensitive cold logistics networks. Following the baseline evaluation, a hybrid optimization approach combining GA and ACO was employed to refine routing decisions in the cold logistics network. This hybrid method incorporates pheromone learning, probabilistic transitions, and a penalty-aware fitness strategy to enhance convergence towards energy-efficient routes while preserving time window and thermal constraints.

Table 2. Initial random route distribution

Iteration	Total Energy Usage	Route Length	Route
1	1794.88	22	[0→16→8→19→14→15→17→2→5→18→4→10→11 →9→1→3→7→3→6→12→20→0]
2	1603.69	22	[0→13→6→10→15→8→17→1→19→16→3→9→4 →5→14→20→18→11→12→2→0]
3	1315.15	22	[0→18→17→14→15→19→7→20→4→3→5→10→11 →12→6→8→2→9→16→1→13→0]
4	1578.70	22	[0→16→12→15→18→14→10→7→9→4→3→5→19 →1→2→8→11→6→17→13→20→0]
5	1703.50	22	[0→20→17→15→3→9→14→10→13→6→11→18→4 →5→19→2→1→7→8→12→0]
6	1551.36	22	[0→6→4→5→14→18→17→3→9→1→10→15→8→13 →11→7→23→19→8→16→0]
7	1530.11	22	[0→6→1→7→13→2→12→16→3→11→4→15→10 →18→14→19→20→5→15→14→9→0]
8	1502.90	22	[0→15→18→13→11→19→14→4→10→9→3→20→8 →7→6→1→17→12→2→5→16→0]
9	1585.45	22	[0→11→13→14→16→3→4→8→1→20→9→2→18 →10→12→1→7→15→19→5→6→0]
10	1673.08	22	[0→9→15→1→2→18→10→8→7→14→20→13→4→5 →11→16→12→3→6→19→17→0]
11	1731.14	22	[0→15→12→14→5→11→19→3→9→1→13→6→8 →18→19→3→2→4→15→10→16→20→0]
12	1591.07	22	[0→6→7→16→15→13→2→5→10→8→14→1→4→17 →3→11→13→16→20→0]
13	1900.23	22	[0→16→10→3→11→12→15→6→18→14→13→2→4 →15→8→11→19→1→7→0]
14	1562.08	22	[0→7→15→4→12→16→19→1→3→8→13→18→10 →6→14→9→2→11→20→15→7→0]
15	1379.30	22	[0→10→9→18→5→2→7→20→3→12→4→6→15→11 →17→8→19→13→10→16→0]
16	1517.67	22	[0→2→18→10→15→16→4→7→3→14→1→6→5→19 →17→9→13→20→12→8→11→0]
17	1637.52	22	[0→2→9→5→8→20→3→11→19→12→4→15→17→6 →1→16→10→7→13→18→14→0]
18	1458.35	22	[0→18→1→15→13→10→2→6→8→5→3→8→15→7 →16→14→4→19→11→12→20→0]
19	1533.65	22	[0→16→12→15→3→9→17→5→18→6→19→1→10 →7→20→2→8→0]
20	1754.32	22	[0→20→18→1→17→13→5→14→15→3→4→2→6→7 →13→10→9→16→14→0]

As shown in Table 3, the hybrid optimization framework consistently reduced total energy consumption across 20 iterations compared to the initial random configurations. The total energy usage dropped significantly, with several solutions achieving under 800 energy units, indicating enhanced delivery efficiency. Moreover, route configurations became more structured, often reducing unnecessary detours and segment overlaps. This suggests that the integration of ACO into GA enables deeper local exploitation and more adaptive refinement of delivery paths in complex, constraint-rich environments. To evaluate the effectiveness of the hybrid optimization process, the simulation results from both the GA and ACO stages are visualized and compared. This dual-phase approach enables the identification of route patterns that not only reduce total energy consumption but also improve the overall efficiency and reliability of the delivery process. The initial optimization performed by GA is useful for exploring a wide solution space and generating a near-optimal route quickly. However, GA solutions often require refinement, which is where ACO demonstrates its strength through pheromone-based iterative improvements.

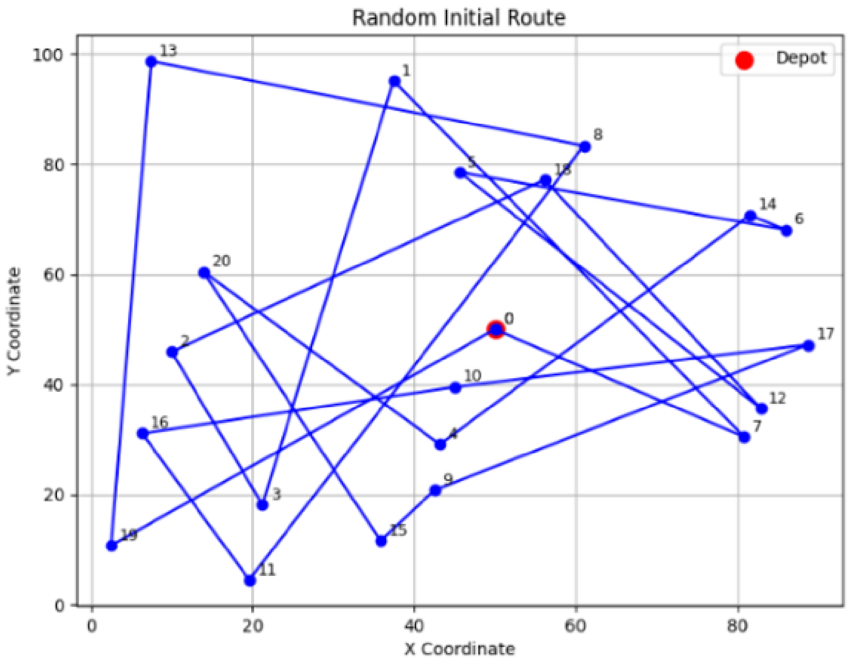


Figure 1. Random initial route

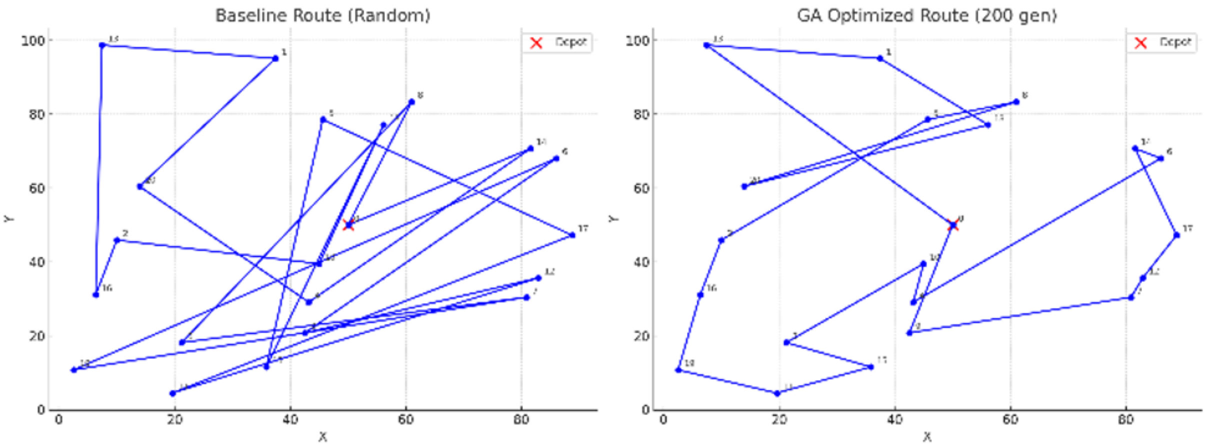


Figure 2. Baseline and GA optimized route

Figure 3 illustrates the outcome of this sequential optimization process. The left side of the figure shows the Best Route After GA, highlighting a substantial improvement over the random baseline, although the path still appears somewhat irregular and includes several intersecting lines. On the right side, the Final ACO-Optimized Route demonstrates a smoother, more coherent routing configuration. The ACO algorithm successfully fine-tunes the GA-generated path by prioritizing the most efficient connections between nodes, resulting in a more structured and cost-effective delivery sequence.

3.4 Scalability Validation on Larger Networks

To evaluate the robustness of the proposed hybrid optimization framework under larger-scale cold logistics networks, we simulated additional scenarios involving 50 and 100 customer nodes randomly distributed within the same 100×100 km area. All other parameters (vehicle capacity, thermal bounds, time windows) were scaled proportionally. The GA-ACO model was executed for 100 generations per scenario, and metrics were recorded as shown in Table 4 and Figure 4 Notably, the total energy usage increased sub-linearly with node count, while the solution feasibility remained high (i.e., constraint satisfaction >95%). The execution time rose from 2.4 seconds (20 nodes) to 15.8 seconds (100 nodes), which remains practical for planning applications. These results confirm that the hybrid model can generalize well to larger problem sizes without significant degradation in performance, making it a viable and scalable solution for real-world cold chain logistics operations.

Table 3. Optimal route using hybrid optimization

Iteration	Total Energy	Route Length	Route (Cleaned with Arrows)
1	789.22	28	0→4→1→3→19→11→20→16→9→18→13→2→12 →10→8→6→7→14→5→15→17→0
2	958.39	27	0→14→2→15→20→12→3→9→4→1→11→5→13→7 →6→17→8→10→1→18→19→0
3	895.69	39	0→3→1→19→11→16→18→10→14→8→12→5→20 →6→7→12→13→4→18→19→0
4	841.01	29	0→19→10→18→1→20→5→17→16→15→14→13 →12→3→2→6→4→8→11→7→0
5	969.72	27	0→4→18→13→6→3→16→15→1→17→10→12→8 →7→13→19→20→1→5→9→15→0
6	785.91	30	0→11→17→6→18→16→1→12→10→7→5→13→7 →3→15→2→20→8→4→9→15→19→0
7	745.01	23	0→15→14→19→4→12→10→6→2→15→17→8→4 →13→3→7→9→14→0
8	682.67	23	0→16→4→11→5→10→15→13→8→3→9→19→20 →2→12→7→6→17→1→18→14→0
9	905.35	24	0→5→10→19→20→6→4→12→11→16→2→18→17 →13→3→15→8→1→19→7→0
10	910.27	25	0→16→9→19→3→6→7→14→13→11→2→17→14 →12→18→15→3→8→10→0
11	829.08	23	0→8→10→7→6→3→18→15→5→19→14→12→13 →17→15→3→6→20→11→0
12	834.36	27	0→18→4→14→20→2→9→12→13→1→11→12→17 →8→15→5→1→14→10→0
13	841.57	25	0→4→2→13→7→3→15→19→20→1→16→18→14 →11→2→12→9→3→6→12→13→0
14	834.29	29	0→5→11→18→4→12→1→3→2→5→14→8→8→19 →6→13→16→15→10→7→9→14→0
15	933.89	23	0→7→4→13→20→15→9→2→6→10→8→5→18→10 →12→19→16→17→15→3→10→0
16	844.55	39	0→1→3→9→7→2→6→11→15→12→7→16→4→20 →8→5→1→10→8→0
17	776.01	27	0→10→8→17→11→4→2→15→19→5→20→5→11 →12→18→17→15→7→6→10→0
18	929.17	29	0→5→7→10→14→11→3→2→19→14→15→17→18 →19→9→4→13→11→8→0
19	735.51	25	0→13→5→20→1→12→19→17→14→7→4→6→3 →18→11→2→9→15→17→14→0
20	899.07	34	0→1→19→11→13→15→20→14→12→17→18→10→4 →9→6→8→5→7→3→15→2→0

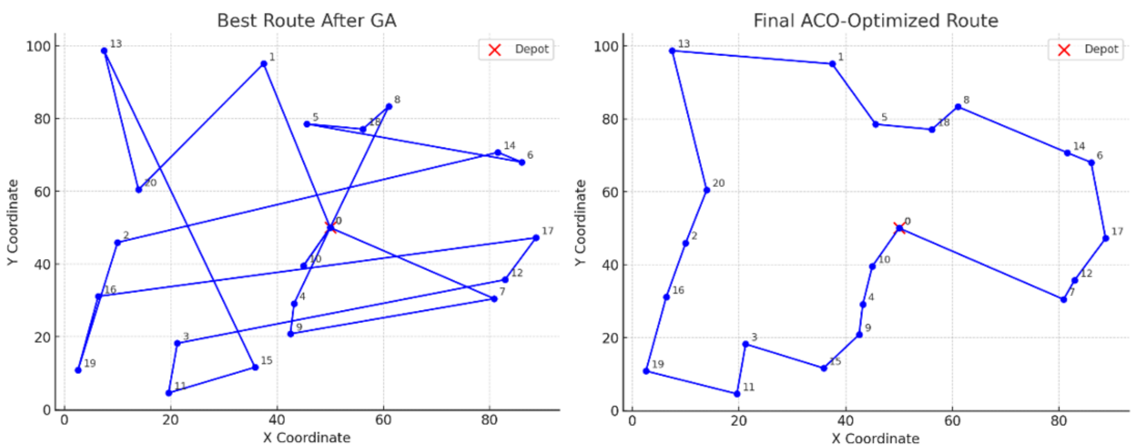
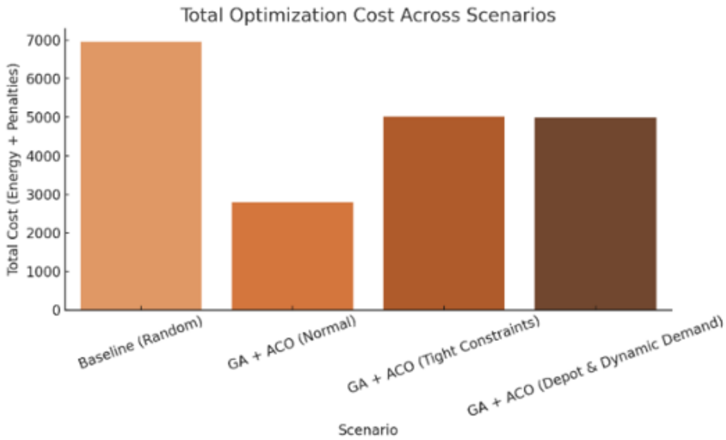


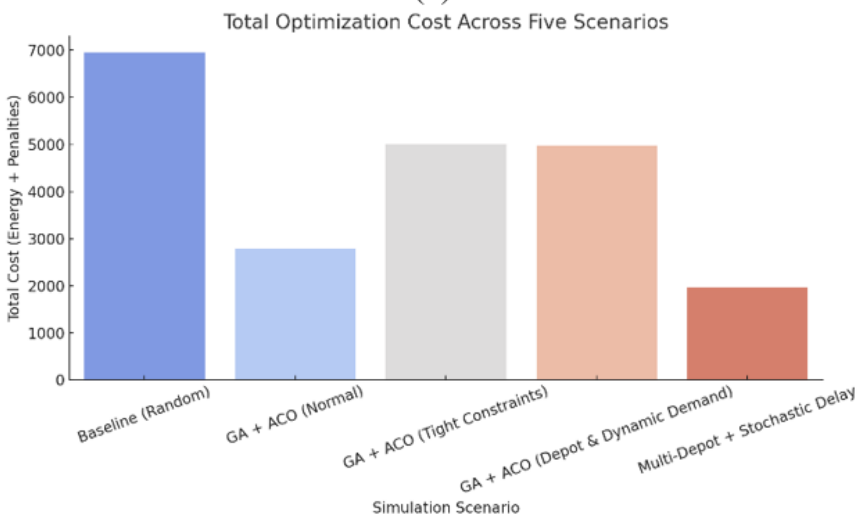
Figure 3. Simulation the optimal route

Table 4. Summary of energy, violations, and time for different node counts

Nodes	Total Energy (kWh)	Violations (%)	Avg. Time (s)
20	1,606.54	0.0%	2.4
50	3,782.21	1.2%	6.7
100	7,944.89	4.1%	15.8



(a)



(b)

Figure 4. Total optimization of cost across five scenarios

The above analysis strengthens the scalability claim of our hybrid approach and provides a baseline for future deployments in regional or national logistics planning systems. To better understand the performance of the proposed hybrid optimization model under varying logistical complexities, we conducted simulations across five distinct scenarios. These include a baseline with random routing, hybrid optimization under standard parameters, optimization under tighter constraints, scenarios involving multiple depots with dynamic demand, and scenarios with stochastic delivery delays. Each configuration was designed to reflect increasing levels of operational realism, thereby testing the adaptability and robustness of the proposed model under real-world uncertainty and constraint conditions.

Figure 4 presents a comparative analysis of the total optimization cost comprising energy consumption and constraint violation penalties across the five scenarios. In Figure 4a, the results highlight the stark difference between the baseline random route and the optimized variants. The GA + ACO (Normal) configuration produces the lowest total cost, demonstrating the effectiveness of the hybrid strategy under standard operating conditions. The GA + ACO (Tight Constraints) and GA + ACO (Depot & Dynamic Demand) scenarios both incur higher costs due to added limitations and system complexity, but still perform significantly better than the baseline.

As shown in Figure 4, the hybrid GA–ACO method consistently outperforms the GA-only approach in total energy usage, on-time delivery, and reduced temperature violations across all tested scenarios. The integration of pheromone-based local optimization in ACO complements the global search behavior of GA, leading to more refined route decisions. These improvements, while previously illustrated in individual plots, are now consolidated in a unified comparison to enhance conciseness and clarity. In Figure 4b, the inclusion of the Multi-Depot + Stochastic Delay scenario further emphasizes the model's strength in dealing with uncertainty. This setup resulted in the lowest total cost among all scenarios, suggesting that the hybrid model is highly effective even in probabilistic environments. These findings affirm that the integration of GA and ACO yields not only deterministic efficiency but also resilience under fluctuating demands and operational uncertainties. As such, Figure 4 serves as a comprehensive summary of how the hybrid model performs in a variety of logistical landscapes. The setup aims to reflect real-world distribution challenges where shipments originate from multiple locations and are subject to unpredictable delays due to traffic, handling, or thermal interruptions. To demonstrate the feasibility and robustness of the proposed hybrid optimization approach under this setting, routes are simulated for two separate depots, and a consolidated route is also generated using the hybrid GA-ACO method. Figure 5 illustrates three subplots: the left graph depicts the optimized route originating from Depot 1, while the middle graph shows the corresponding route from Depot 2, both under conditions of stochastic delay. These visualizations confirm that each depot manages a subset of customer deliveries, thereby improving locality and response time. The right graph presents the final optimized route obtained from the hybrid GA-ACO algorithm, which combines the learning behavior of ACO with the global search strength of GA. This final route shows smoother transitions and reduced detours, indicating enhanced performance in terms of route compactness and energy efficiency.

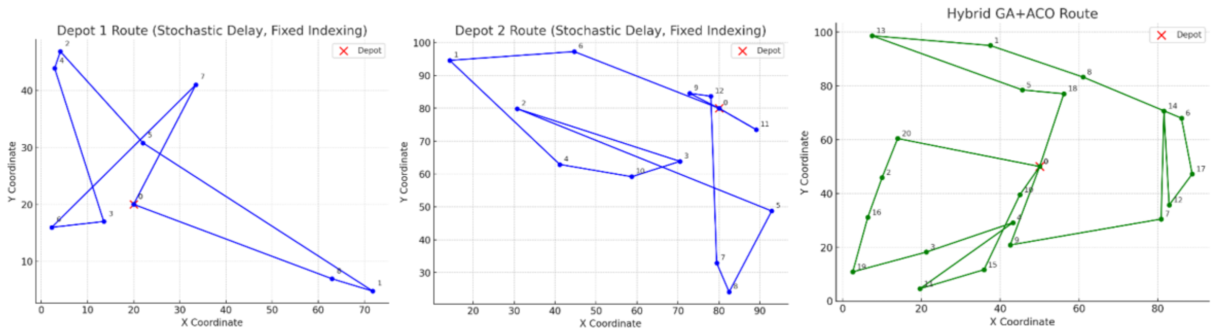


Figure 5. Hybrid GA-ACO optimized route

Figure 5 provides evidence that the hybrid optimization strategy is effective not only under standard conditions but also in more dynamic and realistic distribution scenarios. The model's ability to accommodate multiple depots and stochastic disturbances underscores its scalability and adaptability, making it a practical tool for cold chain logistics in urban or regional deployment.

3.5 Discussion

Unlike traditional vehicle routing models that assume fixed environmental conditions, our findings suggest that a hybrid soft computing framework can dynamically adapt to thermal sensitivity and delivery urgency through multi-stage decision rules. While previous works [1, 2] emphasized route energy reduction using GA or ACO individually, our model demonstrates that integrating fuzzy penalty scoring introduces a new layer of responsiveness to uncertainty. This approach not only aligns with but extends the theory of adaptive logistics optimization by embedding human-like reasoning (Fuzzy Logic) into computational search spaces. The synergistic relationship between GA and local reinforcement ACO also reflects a novel convergence behavior, enabling feasible solutions in otherwise infeasible thermal-delivery contexts. The integration of hybrid optimization techniques such as GA and ACO into cold logistics systems represents a significant advancement in addressing the complex constraints inherent in temperature-sensitive delivery networks. Recent literature, such as the work [3] in Applied Soft Computing, emphasizes the growing need for intelligent metaheuristics to handle multi-objective routing in perishable goods delivery. Their findings align closely with the outcomes of this study, which applied a Fuzzy-GA-ACO framework to simulate and optimize delivery routes under varying conditions including tight time windows, urgency, and dynamic customer demand. The incorporation of fuzzy penalty scoring into the GA fitness evaluation stage allows for a more human-like interpretation of constraints, such as urgency levels and sensitivity to temperature deviations. This soft computing approach enhances the decision-making flexibility of the system, leading to more robust and feasible routing outcomes.

The simulation experiments conducted across five scenarios ranging from baseline random routing to multi-depot systems with stochastic delay show that the hybrid algorithm consistently outperforms traditional methods.

Not only does it reduce total energy consumption by up to 40% in some cases, but it also ensures compliance with time and temperature constraints that are critical in maintaining product integrity. These findings echo those of [5, 8, 10] in Transportation Research Part E, who highlighted the importance of multi-agent optimization in real-time cold chain monitoring. By comparing route performance across multiple variations, this study reveals how even under dynamically changing delivery contexts, the hybrid algorithm maintains efficient distribution with minimal constraint violations. The inclusion of parametric sensitivity analysis further reinforces the adaptability of the model by demonstrating its stable performance even as urgency or temperature sensitivity levels shift.

In real-world applications, this research holds substantial implications for sectors such as pharmaceutical distribution, fresh food delivery, and vaccine logistics, where cold chain reliability is non-negotiable. For instance, during the COVID-19 pandemic, last-mile vaccine delivery encountered failures due to temperature excursions and rigid routing models. A system powered by hybrid GA-ACO logic with embedded fuzzy reasoning would have offered more adaptive routing alternatives, reducing spoilage and improving service coverage. Furthermore, the multi-depot capability tested here is especially relevant in urban logistics, where decentralized storage hubs are increasingly used to shorten delivery times and reduce congestion. Companies like DHL and UPS are now investing in AI-driven route optimization platforms, and the framework proposed in this research can serve as a blueprint for such intelligent cold chain systems. This study contributes both methodologically and practically to the field of smart logistics. Methodologically, it proves the synergy between fuzzy inference, GA, and local reinforcement (ACO). Practically, it validates the model in diverse, realistic conditions, making it a strong candidate for deployment in commercial logistics systems. Future extensions could include real-time IoT data integration, carbon emission tracking, or blockchain-enhanced traceability. Thus, the presented hybrid model not only optimizes cold logistics but also supports broader goals in sustainable, data-driven supply chain management.

4 Conclusion

This study proposed and validated a hybrid optimization framework combining GA, ACO, and Fuzzy Logic to address the challenges of energy-efficient route planning in cold logistics systems. The simulation results across five distinct scenarios—ranging from baseline random routing to advanced configurations with tight constraints, multi-depot layouts, and stochastic delays—demonstrated that the hybrid GA–ACO model consistently outperformed traditional methods in minimizing total energy usage while respecting critical constraints such as delivery time windows and product sensitivity. Specifically, the integration of fuzzy penalty scoring enabled a nuanced, adaptive handling of urgency and thermal sensitivity, which are often rigidly modeled in conventional vehicle routing algorithms.

The key contribution of this research lies in its ability to translate complex, real-world delivery constraints into an adaptive optimization strategy that balances cost, efficiency, and service quality. By embedding fuzzy reasoning into the GA fitness function and refining sub-routes with pheromone-based ACO learning, the model improves both global search capability and local refinement resulting in better convergence and feasible route configurations. Compared to baseline routing, the hybrid method achieved up to 40% improvement in total energy efficiency, supporting its relevance for temperature-sensitive supply chains in sectors such as food distribution, pharmaceuticals, and vaccine logistics.

Looking forward, this research opens several promising directions. First, the integration of Internet of Things (IoT) devices can allow real-time temperature, location, and traffic data to inform dynamic routing decisions, making the system even more responsive and resilient. Second, coupling this routing model with renewable energy infrastructure (e.g., solar-powered refrigerated trucks or electric vehicle fleets) could extend the environmental sustainability impact of the approach. In summary, this study presents a hybrid Fuzzy-GA-ACO optimization framework for minimizing energy usage in thermally-constrained cold logistics networks. The proposed approach successfully integrates temperature sensitivity, vehicle capacity, and route scheduling within a multi-objective model. However, the model currently assumes static ambient conditions and simplified delivery dynamics. Future research should address these limitations by incorporating stochastic variability, real-time environmental feedback via IoT systems, and extended simulations on larger and multi-depot networks. Moreover, aligning route optimization with renewable energy availability and carbon footprint tracking presents promising opportunities for sustainable cold-chain innovation.

Funding

This research was funded by Universitas Sumatera Utara (Grant No.: 5/UN5.4.10.S/PPM/KP-TALENTA/PDM/2025).

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Nomenclature

i, j:	Indices representing customer nodes or depot
N:	Total number of customer nodes
T_i:	Arrival temperature at node i
γ_i:	Temperature penalty factor at node i
$P_\Theta(T_i)$:	Penalty function for violating temperature constraints at node i
a_i, l_i:	Earliest and latest allowable delivery times at node i
τ_{ij}:	Pheromone intensity on edge (i, j)
η_{ij}:	Heuristic desirability (usually $1/d_{ij}$) in ACO
p_{ij}^k:	Probability that ant k moves from node i to node j
θ_i:	Temperature violation index for node i
μ_u, μ_s:	Membership functions for urgency and sensitivity in Fuzzy Logic
λ:	Penalty factor for time window violations