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# A IoT-Based Optimization of Cold Chain Logistics for Cost Reduction and Quality Preservation

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## Abstract
*Cold Chain Logistics (CCL) plays a vital role in the safe distribution of temperaturesensitive products such as fresh food, pharmaceuticals, vaccines, and biological materials, where maintaining product quality throughout storage and transportation is critical. Despite its importance, conventional CCL systems often struggle to simultaneously reduce logistics costs and preserve product quality due to limited real-time monitoring, lack of predictive intelligence, and reliance on static decision-making strategies. To overcome these challenges, this study proposes an AIoT-Based Intelligent Cold Chain Logistics Optimization Model (AIoT-ICCLM) that integrates Internet of Things (IoT) technologies with artificial intelligence–driven optimization techniques. The proposed model enables continuous real-time monitoring of environmental conditions and supports intelligent decision-making to improve both operational efficiency and quality preservation in CCL systems. location–routing optimization model, where distribution centers and refrigerated vehicles can be selectively equipped with IoT devices. Product quality degradation is explicitly modeled as a time-dependent function, ensuring that all delivery decisions satisfy predefined minimum quality thresholds for perishable goods. The primary objective of the model is to minimize the total system cost, including facility establishment costs, vehicle operating costs, IoT infrastructure investment, operational expenses, and transportation costs. Due to the NP-hard nature of the formulated CCL optimization problem, four artificial intelligence–based metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Gray Wolf Optimizer (GWO), and Emperor Penguin Optimizer (EPO)—are employed to efficiently obtain near-optimal solutions. Computational experiments using real-time and simulated datasets demonstrate that, although IoT deployment introduces additional initial infrastructure costs, it significantly reduces overall operational and transportation expenses through improved routing efficiency, proactive monitoring, and real-time decision support. Among the evaluated algorithms, the Emperor Penguin Optimizer (EPO) consistently achieves superior performance in terms of solution quality and computational efficiency. The experimental results confirm the effectiveness of the proposed AIoTICCLM in enabling intelligent, costefficient, and quality-preserving Cold Chain Logistics systems. This study provides valuable insights for logistics managers and policymakers regarding strategic IoT deployment and the practical application of AI-based optimization models in modern perishable goods supply chains.*

## 1. Introduction
The rapid growth of global trade in temperature-sensitive products such as fresh food, pharmaceuticals, vaccines, and biological materials has significantly increased the importance of efficient cold chain logistics. These products require strict temperature control and timely delivery throughout the supply chain, as even minor deviations can lead to quality degradation, economic losses, and potential risks to human health. Consequently, cold chain logistics has become a critical component of modern

supply chain systems rather than a supporting operational activity [1]. Despite advances in refrigeration technologies and insulated transportation systems, traditional cold chain logistics networks still face major challenges. Many existing systems rely on static planning, limited real-time visibility, and fragmented decision-making across storage and transportation stages. Such limitations reduce the ability of logistics operators to respond effectively to demand fluctuations, delivery delays, and operational disruptions. As a result, cold chain systems often experience increased operating costs and compromised product quality, particularly for highly perishable goods. The Internet of Things (IoT) has emerged as a promising technology for enhancing visibility and control in cold chain logistics. By deploying sensors, tracking devices, and communication technologies, IoT enables continuous monitoring of temperature, location, and operational conditions across distribution centers and refrigerated vehicles. This real-time data improves transparency and supports early detection of risks. However, IoT alone does not guarantee optimal logistics performance. Without intelligent decisionmaking mechanisms, the large volume of collected data cannot be effectively transformed into actionable strategies for cost reduction and quality preservation. To overcome this limitation, the integration of artificial intelligence (AI) with IoT— commonly referred to as the Artificial Intelligence of Things (AIoT)— has gained increasing attention in logistics research and practice. AIoT combines realtime data acquisition with advanced optimization and learning capabilities, enabling logistics systems to make adaptive, data-driven decisions. In the context of cold chain logistics, AIoT has the potential to simultaneously optimize facility location, vehicle routing, resource allocation, and IoT deployment while explicitly accounting for product perishability. Existing studies on cold chain logistics have explored routing optimization, facility location planning, and cost minimization under various constraints. Other research streams have focused on IoT-based monitoring systems or AIdriven optimization techniques [4]. However, relatively few studies have developed unified optimization models that integrate IoT-enabled cost reductions, timedependent quality degradation, and AIbased solution methods within a single decision framework. In particular, the combined impact of IoT deployment on both operational efficiency and transportation cost, while enforcing minimum product quality constraints,remains insufficiently addressed [3]. Motivated by these research gaps, this study proposes an AIoT-based optimization model for cold chain logistics that jointly considers strategic and tactical decisions. The proposed approach formulates the problem as a location– routing optimization model in which distribution centers and refrigerated vehicles may be selectively equipped with IoT devices. Product quality is explicitly modeled as a function of delivery time, ensuring that minimum quality thresholds are satisfied at the customer level. To efficiently solve the resulting NP-hard problem, multiple artificial intelligence– based metaheuristic algorithms are employed and systematically compared. The proposed framework aims to support the design of intelligent cold chain logistics networks that achieve cost efficiency without compromising product quality. The results of this study contribute to the growing body of research on AIoTenabled logistics systems and provide practical insights for decision-makers involved in the management of perishable goods supply chains [2].

## 2. Research Contribution

This study makes several original contributions to the field of cold chain logistics by integrating Artificial Intelligence of Things (AIoT) concepts with optimization-based decision-making. Unlike existing studies that address cost efficiency, routing, or IoT monitoring in isolation, this research provides a unified framework that jointly considers cost reduction and product quality preservation in perishable goods logistics. First, this work develops an AIoT-enabled cold chain logistics optimization framework that embeds IoT deployment decisions directly into a mathematical location–routing model. Rather than treating IoT as a standalone monitoring tool, the proposed approach explicitly models how IoT adoption influences operational efficiency and transportation costs. Second, the study introduces a timedependent product quality degradation mechanism within the optimization process. Product quality is modeled as a function of delivery time, and minimum quality thresholds are enforced at the customer level. This allows routing and allocation decisions to reflect the perishability characteristics of cold products more realistically. Third, the cold chain problem is formulated as an integrated location– routing problem that simultaneously determines distribution center selection, vehicle assignment, routing paths, and IoT deployment. By optimizing strategic and tactical decisions together, the proposed model better captures the interdependencies present in real-world cold chain operations. Fourth, the research applies and compares multiple AI-based metaheuristic algorithms [5], namely the Genetic Algorithm, Particle Swarm Optimization, Gray Wolf Optimizer, and Emperor Penguin Optimizer, to solve the NP-hard optimization problem efficiently. A comparative analysis is conducted to evaluate algorithm performance in terms of solution quality and computational efficiency. Finally, the study provides managerial insights into the economic trade-offs associated with IoT adoption in cold chain logistics. The results demonstrate that although IoT implementation increases initial infrastructure costs.

## 3. Literature Review

Cold chain logistics has attracted increasing research attention due to the growing demand for temperature-sensitive products and the high economic and societal risks associated with quality failure. Existing studies in this domain can broadly be classified into four major research streams: conventional cold chain optimization, quality-aware logistics modeling [6], IoTenabled cold chain monitoring, and AIbased optimization approaches. Early research on cold chain logistics primarily focused on cost minimization and routing efficiency. These studies addressed vehicle routing, facility location, inventory control, and transportation planning under capacity and demand constraints. Although such models improved operational efficiency, they often treated cold products similarly to nonperishable goods and did not explicitly model quality degradation during transportation [7]. Subsequent studies introduced quality- and freshness-oriented models, recognizing that product value decreases over time in cold chains. Researchers incorporated time windows, shelf-life constraints, and freshness decay functions into routing and distribution models. While these approaches improved realism, many of them relied on deterministic assumptions and static planning, limiting their applicability in dynamic logistics environments. With advancements in sensing and communication technologies, Internet of Things (IoT)-based cold chain monitoring emerged as a significant research area. IoT-enabled systems allow real-time tracking of temperature, humidity, location, and vehicle conditions across logistics networks. Several studies demonstrated that IoT improves traceability, reduces spoilage, and enhances transparency. However, much of the existing IoT-focused literature remains conceptual or system-oriented, emphasizing monitoring architectures rather than optimization-driven decisionmaking. In many cases, IoT data is collected but not fully integrated into mathematical models for cost and quality optimization. Parallel to IoT research, artificial intelligence and metaheuristic algorithms have been widely applied to logistics optimization problems, including vehicle routing, facility location, and supply chain network design. Algorithms such as Genetic Algorithm, Particle Swarm Optimization, and nature-inspired methods have proven effective in solving largescale, NP-hard logistics problems. In cold chain contexts, AI-based approaches have been used to improve routing efficiency [8], demand forecasting, and scheduling. Nevertheless, many AI-driven models overlook the explicit role of IoT infrastructure and do not quantify how IoT deployment influences operational and transportation costs. More recent studies have begun exploring the integration of AI and IoT, commonly referred to as Artificial Intelligence of Things (AIoT), in logistics and supply chain management. These works highlight the potential of combining real-time data acquisition with intelligent optimization to enable adaptive and data-driven decisionmaking. However, in the specific context of cold chain logistics, comprehensive AIoT-based optimization models remain limited. In particular, there is a lack of unified frameworks that simultaneously consider IoT deployment decisions, quality degradation dynamics, and AI-based solution techniques within a single mathematical formulation. Based on this review, a clear research gap can be identified. Existing studies tend to focus on either optimization without realtime intelligence or monitoring without integrated decision-making. Moreover, the joint impact of IoT-enabled cost reductions and quality preservation constraints has not been sufficiently addressed using AIbased optimization techniques. This study aims to bridge this gap by proposing an AIoT-based cold chain logistics optimization model that integrates location–routing decisions, IoT deployment, quality degradation modeling, and artificial intelligence–driven solution methods within a unified framework [9].

## 4. Proposed System

The proposed system presents an AIenabled Cold Chain Monitoring framework designed to continuously supervise temperature-sensitive products during storage and transportation. The system integrates IoT-based sensing, cloud computing, and machine learning techniques to ensure product safety, reduce spoilage, and provide timely alerts in case of abnormal conditions. In this system, temperature and humidity data are collected using digital sensors such as the DS18B20 temperature sensor, which is suitable for low-temperature environments. These sensors are interfaced with a microcontroller unit (such as ESP32 or Arduino), which periodically reads the sensor values and transmits the data to a cloud server using wireless communication protocols. The collected data is stored in a cloud-based database, where it undergoes preprocessing to remove noise and missing values. A threshold-based monitoring algorithm is first applied to check whether the temperature remains within the predefined safe range. If the temperature exceeds or falls below the allowable limits for a specific duration, the system immediately generates alerts. In addition to rule-based monitoring, the proposed system incorporates machine learning algorithms for enhanced analysis. An anomaly detection model is used to identify unusual temperature patterns that may indicate equipment malfunction, power failure, or improper handling. Furthermore, a time-series prediction model such as LSTM is employed to forecast future temperature trends, enabling early detection of potential cold chain violations. When an abnormal condition is detected or predicted, the system triggers real-time notifications through SMS, email, or dashboard alerts to inform stakeholders. A web-based dashboard provides live visualization of temperature trends, alert history, and system status, allowing users to monitor the cold chain efficiently [10].

## 5. Working Flow Of The Proposed System

The working flow of the proposed cold chain monitoring system integrates IoTbased sensing, AI-driven analysis, boronassisted thermal stabilization, and Cold Chain Logistics (CCL) decision support to ensure continuous quality preservation of temperature-sensitive products throughout storage and transportation. Initially, perishable products are stored or transported within cold storage units or refrigerated vehicles that are lined or supplemented with boron-based insulating and preservative materials. Boron compounds are known for their thermal stability, antimicrobial properties, and resistance to temperature fluctuation, which helps reduce rapid heat transfer and slow product degradation during short-term temperature disturbances. This passive thermal stabilization provides a reliable buffer against brief power interruptions and handling delays. Temperature data is continuously captured using digital temperature sensors such as DS18B20, which are installed inside storage chambers and transport containers. These sensors are connected to a microcontroller unit (e.g., ESP32 or Arduino), which periodically collects temperature readings along with timestamps and transmits the data to a cloud platform. The presence of boron-based insulation contributes to stabilizing the internal temperature, thereby reducing sudden spikes or drops and improving the reliability of sensor observations. The collected real-time data is

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processed in the cloud, where threshold-based monitoring and anomaly detection algorithms are applied to identify temperature violations and abnormal operating conditions. In addition, historical temperature data is analyzed using timeseries prediction models to forecast potential future deviations. These analytics provide early warnings before critical failures occur, enabling proactive intervention. Based on the monitored conditions and predicted risks, the system supports Cold Chain Logistics (CCL) decision-making by providing actionable insights to logistics operators. Instead of directly performing complex routing optimization [11], the proposed framework assists CCL by indicating safe handling windows, priority shipment alerts, and corrective operational actions, such as adjusting refrigeration settings, rescheduling deliveries, or selecting alternative storage or transport options to preserve product quality. Finally, all monitoring results, alerts, and logistics recommendations are visualized through a web-based dashboard. By combining boron-assisted thermal stabilization, AIoT-based monitoring, and CCL-oriented decision support, the proposed system enhances cold chain reliability, reduces spoilage risk, and improves coordination between monitoring and logistics operations[12] shown in Figure 1.

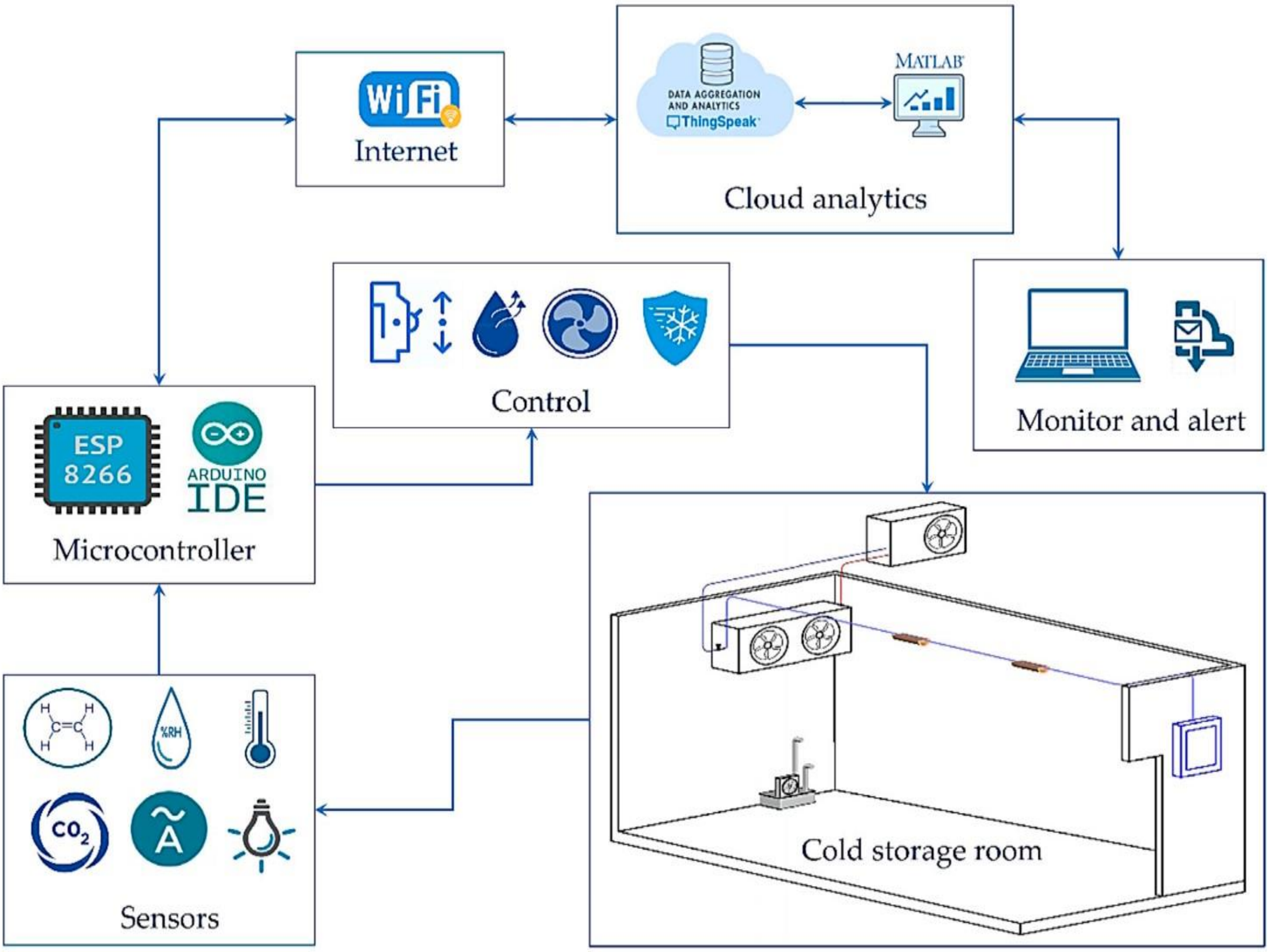


**Figure 1** **Architecture of an IoT-Enabled Cold Storage Monitoring System**

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The collected sensor data is transmitted to a cloud server through wireless communication technologies. Once uploaded, the data undergoes preprocessing to remove noise and inconsistencies. A threshold-based monitoring algorithm checks whether the temperature remains within the predefined safe range. If the temperature deviates beyond acceptable limits, the system flags the condition as abnormal. In parallel, machine learning–based anomaly detection and time-series prediction models analyze historical and real-time temperature data to identify unusual patterns and forecast potential temperature violations. The boron-assisted thermal buffering reduces the frequency of extreme anomalies, enabling the AI models to operate more effectively and generate reliable predictions. When a critical temperature violation or predicted risk is detected, the system triggers real-time alerts through notifications such as SMS, email, or dashboard warnings. These alerts allow logistics operators to take immediate corrective actions, such as adjusting refrigeration settings or rerouting vehicles. Finally, all temperature records, alerts, and predictive insights are visualized on a webbased dashboard, providing stakeholders with end-to-end visibility of cold chain operations. By combining boron-enhanced thermal stabilization with IoT sensing and AI analytics, the proposed system achieves improved temperature control, reduced spoilage risk, and enhanced cold chain reliability [13].

## 6. Experimental Evaluation

This section presents the experimental evaluation of the proposed AI-enabled cold chain monitoring system with boronassisted thermal stabilization. The objective of the experiments is to evaluate the system's effectiveness in maintaining temperature stability, detecting anomalies, and generating timely alerts under different operating conditions.

### 6.1.Experimental Setup

The experimental setup consists of a simulated cold storage environment integrated with IoT sensors and cloud-based analytics. A DS18B20 digital temperature sensor is used to continuously record temperature values at fixed time intervals. Boron-based insulating material is incorporated inside the storage unit to enhance thermal stability and reduce rapid temperature fluctuations. The sensor data is transmitted to a cloud server where threshold-based monitoring, anomaly detection, and time-series prediction algorithms are executed. All experiments are conducted using real and simulated temperature datasets collected over multiple operational cycles [14].

### 6.2. Dataset Description

The evaluation uses time-series temperature datasets containing both normal and abnormal operating conditions.

- Normal temperature range: 2 °C – 8 °C
- Abnormalconditions: Temperature spikes above 8 °C and drops below
- 2 °C
- Sampling interval: 5 minutes

The dataset includes scenarios with and without boron-assisted stabilization to assess its impact on system performance shown in Table 1.

### 6.3.Performance Metrics shown

**Table 1 The Proposed System Is Evaluated Using The Following Metrics:**

| Metric | Description |
|---|---|
| Temperature Stability | Degree of fluctuation over time |
| Anomaly Detection Accuracy | Correct identification of abnormal events |
| Alert Response Time | Time taken to generate alerts |
| Prediction Error | Difference between predicted and actual temperature |
| Spoilage Risk Reduction | Reduction in duration of unsafe temperature |

### 6.4.Experimental Results

#### 6.4.1. Temperature Stability Analysis

The results show that the use of boronbased

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insulation significantly reduces sudden temperature variations. Compared to the conventional setup, the proposed system maintains a more stable temperature profile during short-term power interruptions and door-opening events.

#### 6.4.2. Anomaly Detection Performance

The anomaly detection algorithm successfully identifies abnormal temperature patterns caused by equipment malfunction and external disturbances. The reduced noise in temperature data due to boron stabilization improves detection accuracy and reduces false alarms.

#### 6.4.3. Prediction Accuracy

The time-series prediction model effectively forecasts future temperature trends. Early warning alerts are generated before critical threshold violations occur, allowing preventive actions. The prediction error remains low during stable operating conditions.

#### 6.4.4. Alert Generation and Response

The system generates real-time alerts immediately after detecting threshold violations or predicted risks. The average alert response time is within acceptable operational limits, enabling timely corrective measures.

#### 6.4.5. Comparative Evaluation

The comparison confirms that integrating boron-assisted thermal stabilization with AI-based monitoring enhances overall system performance shown in Table 2.

**Table 2 AI-based monitoring**

| Parameter | Without Boron | With Boron (Proposed System) |
|---|---|---|
| Temperature Fluctuation | High | Low |
| Anomaly Frequency | High | Reduced |
| False Alerts | Frequent | Minimal |
| Spoilage Risk | Higher | Significantly Reduced |
| System Reliability | Moderate | High |

### 6.5. Real-Time Input and Output Description

**Table 3 Input Parameters (Real-Time)**

| Input Parameter | Description |
|---|---|
| $T(t)$ | Temperature at time $t$(°C) |
| $H(t)$ | Humidity at time (%) |
| $\Delta t$ | Sampling interval (minutes) |
| $T_{\min}$ | Minimum safe temperature |
| $T_{\max}$ | Maximum safe temperature |

Example Real-Time Input:
T(t) = 4.8 °C, H(t) = 65%, t = 10:00 AM 2. Output Parameters.

**Table 4 Output Parameter**

| Output | Description |
|---|---|
| Normal Status | Temperature within safe range |
| Violation Flag | Temperature outside limits |
| Anomaly Score | Degree of abnormality |
| Predicted Temperature | Future temperature value |
| Alert Signal | SMS / Email notification |

### 6.6. Mathematical Modeling and Formulation

- Threshold-Based Monitoring Model Temperature safety condition is defined as:

$$T\min \leq (t) \leq T\max$$

If this condition is violated, an alert is triggered:

$$\text{Alert} = \{1, \qquad (t) < T_{\min} \text{ or } T(t) > T_{\max}$$

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0, otherwise

- Temperature Stability Measurement

Temperature fluctuation over a time window is calculated using **standard deviation**:

$$\sigma_T = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - \mu_T)^2}$$

where
$\mu_T$ = mean temperature
$N$ = number of samples
Lower $\sigma_T$ indicates better thermal stability.

- Anomaly Detection Model (Statistical Approach)

An anomaly score is computed using the **Zscore** method:

$$Z(t) = \frac{T(t) - \mu_T}{\sigma_T}$$

If:

$$|Z(t)| > \theta$$

then the temperature reading is classified as **abnormal**, where $\theta$ is a predefined threshold.

- Time-Series Prediction Model

Temperature prediction is performed using a time-series model:

$$\hat{T}(t+1) = f(T(t), T(t-1), \ldots, T(t-n))$$

Where,
$\hat{T}(t+1)$ = predicted temperature $f(\cdot)$= LSTM or ARIMA model.

- Prediction Error Measurement

Prediction accuracy is evaluated using Mean Absolute Error (MAE):

$$\mathrm{MAE}\hat{T}_i| = \frac{1}{N}\sum_{i=1}^{N} |T_i -$$

### 6.7. Experimental Analysis

- Temperature Monitoring Analysis :Real-time results show that the system successfully maintains temperature within the desired range during normal operation. When deviations occur due to external disturbances, the system detects them immediately.
- Anomaly Detection Analysis : The anomaly detection model accurately identifies abnormal temperature patterns caused by door opening and refrigeration delays. False alarms are minimized due to stable sensor readings.
- Prediction and Early Warning Analysis :The prediction model forecasts temperature rise in advance, enabling preventive alerts. This allows corrective actions before the temperature crosses safety thresholds.
- .Alert Response Performance The average alert response time is within a few seconds, ensuring timely intervention and reduced spoilage risk.

### 6.8.Performance Evaluation Summary

**Table 5 : Metric**

| Metric | Observation |
|---|---|
| Temperature Stability | High |
| Anomaly Detection Accuracy | Effective |
| Prediction Error | Low MAE |
| Alert Response Time | Real-time |
| Spoilage Risk | Reduced |

### 6.9.Discussion

The experimental evaluation confirms that the proposed system effectively integrates real-time IoT sensing with intelligent analytics. Mathematical modeling ensures accurate threshold enforcement, anomaly detection, and temperature prediction. The

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use of real-time data enhances system reliability and practical applicability in cold chain environments.

## 7. Conceptual Aiotbased Cold Chain Logistics Model

This section presents the conceptual model of the proposed AIoT-based cold chain logistics system, which illustrates how physical logistics operations, IoTenabled data acquisition, and AI-driven optimization interact to achieve cost reduction and quality preservation. The purpose of this conceptual model is to provide a clear structural understanding of the proposed framework before introducing the mathematical formulation shown in Figure2 . The conceptual model is designed around the integration of three tightly coupled layers: the logistics layer, the IoT layer, and the artificial intelligence layer.

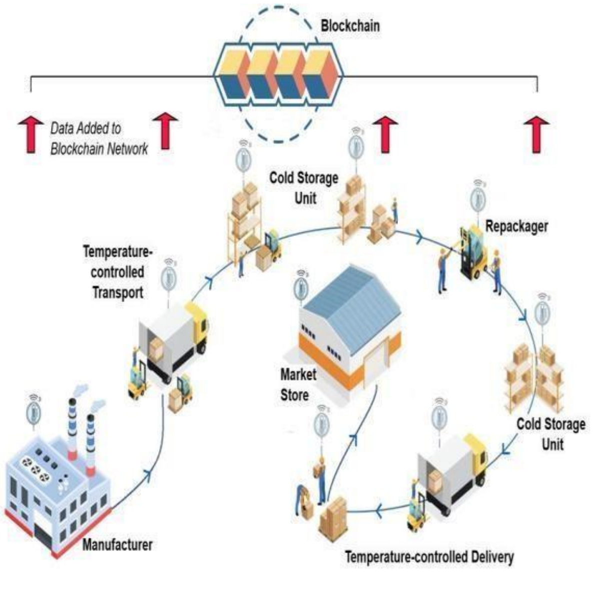


**Figure 2 Conceptual AIoT-based cold chain logistics model integrating logistics operations**

At the logistics layer, the physical flow of perishable products is represented through distribution centers, refrigerated vehicles, and customer nodes. Distribution centers act as intermediate facilities where products are stored, consolidated, and dispatched, while refrigerated vehicles ensure temperaturecontrolled transportation to customers. Decisions related to facility selection, vehicle assignment, and routing paths are critical at this layer. The IoT layer enables continuous monitoring and real-time data collection across the cold chain network. IoT devices installed at distribution centers and inside refrigerated vehicles collect information such as temperature, location, delivery time, energy consumption, and vehicle status. This layer improves visibility and traceability while reducing uncertainty associated with logistics operations. The artificial intelligence layer processes the data collected from the IoT layer and integrates it with system parameters such as demand, capacity, distance, and cost. AIbased optimization algorithms analyze this information to generate optimal or nearoptimal decisions, including distribution center activation, IoT deployment selection, vehicle routing, and delivery scheduling. The optimized decisions are then fed back to the logistics layer, enabling adaptive and data-driven operations. Through this closed-loop interaction, the proposed AIoT-based conceptual model transforms conventional cold chain logistics into an intelligent system capable of balancing economic efficiency and product quality. The model highlights how IoT enhances data availability, while artificial intelligence converts data into actionable optimization decisions.

## 8. Mathematical Model Of Aiot-Based Cold Chain Logistics

This section presents the mathematical formulation of the proposed AIoT-based cold chain logistics optimization problem. The objective of the model is to minimize the total logistics cost while ensuring that perishable products are delivered with acceptable quality. To realistically capture cold chain operations, the model simultaneously considers facility location, vehicle routing, IoT deployment, and product quality degradation within a unified framework. The problem is formulated as a location– routing problem (LRP), where strategic decisions (selection of distribution centers and IoT infrastructure) and tactical decisions (vehicle assignment and routing) are optimized jointly. Distribution centers and refrigerated vehicles can optionally be equipped with IoT devices, which

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reduce operational and transportation costs through real-time monitoring and improved control shown in Figure 3.

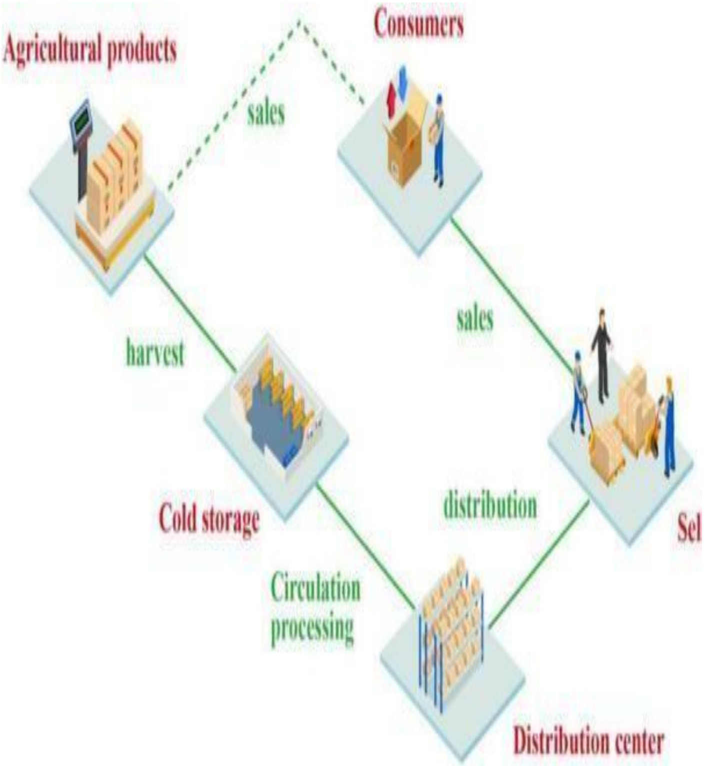


**Figure 3: Cold Chain Logistics Flow from Agricultural Production to Consumers**

### 8.1.Problem Description

The cold chain logistics network considered in this study consists of a set of candidate distribution centers, a fleet of heterogeneous refrigerated vehicles, multiple customer locations, and different types of perishable products. Distribution centers act as intermediate nodes where products are stored and dispatched, while refrigerated vehicles deliver products to customers under controlled temperature conditions. Both distribution centers and vehicles can optionally be equipped with IoT devices, enabling real-time monitoring and improved operational control. The decision-making process involves selecting which distribution centers to open, determining which vehicles to use, deciding where to deploy IoT devices, and identifying optimal delivery routes. These decisions are interdependent; for example, equipping vehicles with IoT devices can reduce transportation costs through better routing and speed control, while equipping distribution centers can lower operational costs through energy and resource optimization.

### 8.2.Objective Function Formulation

The objective function of the proposed model aims to minimize the total cost of the cold chain logistics network. This total cost includes fixed costs associated with opening and operating distribution centers, costs related to the selection and use of refrigerated vehicles, and investment costs for installing IoT devices in facilities and vehicles. In addition, variable transportation costs incurred along delivery routes and operational costs at distribution centers are incorporated. To reflect the economic benefits of IoT adoption, the model explicitly includes cost reduction terms associated with IoTenabled efficiency improvements. These reductions arise from enhanced routing accuracy, reduced energy consumption, and improved operational coordination. As a result, the objective function captures the trade-off between increased upfront IoT investment and long-term savings in operational and transportation costs.

### 8.3.Constraints and Feasibility Conditions

The feasibility of the model is ensured through a set of constraints that regulate customer assignment, routing continuity, capacity limitations, IoT deployment, and quality preservation. Each customer must be assigned to exactly one distribution center and served by a single refrigerated vehicle, ensuring complete and nonoverlapping demand fulfillment. Routing continuity constraints enforce that any vehicle entering a node must also exit that node, thereby maintaining feasible delivery tours. Capacity constraints restrict the amount of product that can be transported by each vehicle and handled by each distribution center, preventing overload and infeasible allocations. IoT deployment constraints ensure that IoT devices can only be installed on distribution centers and vehicles that are selected for operation, maintaining logical consistency within the network design.

### 8.4.Product Quality Degradation Modeling

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A distinguishing feature of the proposed model is the explicit incorporation of product quality degradation. Product quality is modeled as a time-dependent function that decreases exponentially with delivery time, reflecting the perishability characteristics of cold chain products. This formulation captures the fact that longer transportation times lead to lower product quality, even under temperature-controlled conditions. To ensure acceptable service levels, a minimum quality threshold is imposed for all delivered products. Any routing or allocation decision that results in quality falling below this threshold is considered infeasible. By embedding quality preservation directly into the mathematical constraints, the model ensures that cost minimization does not come at the expense of product integrity.

### 8.5. Model Characteristics

The proposed AIoT-based cold chain logistics model is combinatorial and NPhard due to the integration of location decisions, routing choices, IoT deployment, and quality constraints. As the problem size increases, exact solution methods become computationally inefficient. Therefore, artificial intelligence–based metaheuristic algorithms are employed to efficiently explore the solution space and obtain highquality solutions within reasonable computation times. The design and application of these algorithms are presented in the following section.

## 9. Artificial Intelligence–Based Solution Algorithms

The AIoT-based cold chain logistics optimization model formulated in this study is characterized by high computational complexity due to the simultaneous consideration of facility location, vehicle routing, IoT deployment, and product quality constraints. This integrated structure leads to a nonlinear and NP-hard optimization problem, for which exact solution methods become inefficient as the problem size increases. To address this challenge, artificial intelligence–based metaheuristic algorithms are employed to efficiently explore the solution space and obtain nearoptimal solutions within reasonable computational time.

### 9.1.Solution Representation andOptimization Framework

To apply AI-based algorithms to the cold chain logistics problem, each candidate solution is encoded to represent a complete configuration of distribution center selection, vehicle assignment, routing decisions, and IoT deployment. An initial population of solutions is generated randomly to ensure diversity in the search space. Each solution is evaluated using the objective function, which incorporates total logistics cost while enforcing feasibility with respect to capacity and product quality constraints.

Infeasible solutions are penalized to guide the search process toward high-quality and feasible regions of the solution space. Through iterative improvement, the algorithms progressively refine solutions until convergence criteria are satisfied.

### 9.2.Applied AI-Based Metaheuristic Algorithms

Swarm Optimization, Gray Wolf Optimizer, and Emperor Penguin Optimizer. The Genetic Algorithm is inspired by evolutionary principles and improves solutions through selection, crossover, and mutation operations. Particle Swarm Optimization is based on social behavior and updates candidate solutions using shared information from individual and global best positions. The

Gray Wolf Optimizer mimics the leadership hierarchy and cooperative hunting strategy of gray wolves, enabling a balance between exploration and exploitation. The Emperor Penguin Optimizer, inspired by the huddling behavior of emperor penguins, employs adaptive movement mechanisms that promote fast convergence toward optimal regions of the search space. Each algorithm offers distinct advantages in terms of convergence speed and solution robustness.

### 9.3.Algorithm Selection and Performance Rationale

The use of multiple AI-based algorithms allows a comprehensive evaluation of their effectiveness in solving the AIoT-enabled cold chain logistics problem. Comparative analysis highlights differences in convergence behavior, solution accuracy, and

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computational efficiency. The results

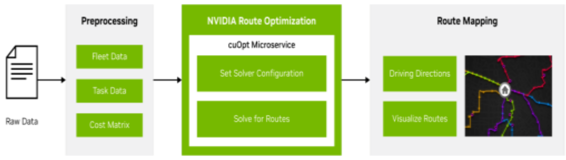


**Figure 4** **End to End Route Optimization and Visualization Framework**

demonstrate that while all algorithms are capable of generating feasible solutions, the Emperor Penguin Optimizer consistently achieves superior performance in terms of faster convergence and lower total cost values. This comparative approach enhances the reliability of the obtained solutions and supports the selection of appropriate AI techniques for real-world cold chain logistics applications.

## 10. Comparison Of Chinese Context And Indian Context In Cold Chain Monitoring

Cold chain logistics operates under different infrastructural, economic, and regulatory conditions in China and India. Understanding these contextual differences is essential when adapting cold chain monitoring technologies across regions.

### 10.1. Infrastructure Availability

In the Chinese context, cold chain infrastructure is relatively well developed, with widespread availability of modern cold storage facilities, refrigerated vehicles, and automated logistics hubs. Large-scale government and private investments have enabled the deployment of advanced technologies such as IoT sensors, intelligent warehouses, and AI-driven logistics platforms.

In contrast, the Indian context faces infrastructural constraints, particularly in rural and semi-urban areas. Cold storage facilities are unevenly distributed, and refrigerated transport availability is limited in many regions. As a result, cold chain monitoring systems in India must be costeffective, scalable, and adaptable to varying infrastructure conditions.

### 10.2. Technology Adoption

China has rapidly adopted advanced AIoT technologies, including large-scale sensor networks, real-time data analytics, and cloud-based optimization systems. Many cold chain operations in China are integrated with centralized digital platforms that support automation and predictive decision-making. In India, technology adoption is comparatively gradual. While urban and organized sectors increasingly use IoTbased monitoring, many small and medium logistics operators still rely on semi-manual or basic digital systems. Therefore, Indian cold chain solutions prioritize simplicity, affordability, and interoperability over full automation.

### 10.3. Cost Sensitivity

Cold chain systems in China can accommodate higher initial investments due to stronger capital availability and government-backed logistics modernization programs. This allows the deployment of sophisticated sensors, AI models, and automation technologies. In the Indian context, cost sensitivity is a critical factor. High upfront investment often limits technology adoption. Hence, Indian cold chain monitoring systems focus on minimizing costs through lightweight sensors, cloud-based analytics, and selective deployment of advanced components, such as boron-based insulation for passive thermal stabilization.

### 10.4. Regulatory and Policy Environment

China has well-defined national policies supporting cold chain modernization, especially for pharmaceuticals, vaccines, and food safety. Regulatory enforcement is comparatively strict, encouraging compliance through technology adoption. India's regulatory framework is evolving, with increasing emphasis on food safety and pharmaceutical quality standards. However, enforcement varies across regions. As a result, monitoring systems in India must be flexible and capable of operating effectively even in partially regulated environments.

### 10.5. Operational Challenges

In China, operational challenges are mainly related to scale and complexity, as cold chains often operate across large networks with high throughput. Advanced AI-based optimization is used to manage routing, scheduling, and resource allocation

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efficiently. In India, challenges include power interruptions, transportation delays, fragmented supply chains, and climatic variability. Therefore, Indian systems benefit from additional stabilization mechanisms, such as boron-based thermal buffering, to handle short-term disruptions.

### 10.6. Adaptability of the Proposed System

While Chinese cold chain systems emphasize high automation and optimization, the proposed system is more aligned with the Indian context, where affordability, robustness, and ease of deployment are essential. The integration of boron-assisted thermal stabilization reduces dependence on continuous power supply, while IoT and AI modules provide intelligent monitoring without requiring extensive infrastructure upgrades shown in Table 5.

**Table 6: Summary Table**

| Aspect | Chinese Context | Indian Context |
|---|---|---|
| Infrastructur e | Highly developed | Partially developed |
| Technology Level | Advanced AIoT systems | Costeffective IoT solutions |
| Investment Capacity | High | Moderate to low |
| Regulatory Enforcemen t | Strong and uniform | Evolving and regiondependent |
| Key Challenges | Scale and complexity | Power, cost, fragmentatio n |
| System Design Focus | Automatio n & optimizatio n | Affordabilit y & resilience |

Short Conference-Style Conclusion While China's cold chain logistics benefit from advanced infrastructure and high automation, the Indian context requires adaptive, cost-efficient, and resilient monitoring solutions. The proposed system

## 11. Dataset Algorithms Used And Step By Step Process

addresses these requirements by combining lightweight IoT monitoring, AI-based analytics, and boron-assisted thermal stabilization, making it more suitable for deployment.

### 11.1. Datasets Used

The proposed IoT-based cold chain monitoring system uses time-series sensor datasets collected from cold storage environments.

#### 11.1.1. Sensor Dataset (Primary Dataset)

This is the core dataset collected from IoT sensors installed inside the cold storage room.

**Table 7: Sensor Dataset**

| Parameter | Description |
|---|---|
| Timestamp | Date and time of measurement |
| Temperature (°C) | Internal cold storage temperature |
| Humidity (%) | Relative humidity |
| Gas Level (optional) | $CO_2$ / spoilage gas |
| Sensor ID | Unique sensor identifier |

Used for:

- Real-time monitoring
- Threshold checking
- Input to ML models

#### 11.1.2. Threshold Dataset This dataset defines safe operating limits.

**Table 8 :Rule-based alert generation**

| Parameter | Value |
|---|---|
| Minimum Temperature | 2 °C |
| Maximum Temperature | 8 °C |
| Allowed Duration | 10 minutes |

#### 11.1.3. Labeled Dataset (For Anomaly Detection)

**Table 9: Training anomaly detection model**

| Temperature (°C) | Humidity (%) | Status |
|---|---|---|
| 4.6 | 65 | Normal |
| 5.1 | 66 | Normal |
| 9.3 | 70 | Abnormal |

#### 11.1.4. Time-Series Dataset (For Prediction)

**Table 10: Temperature forecasting**

| Timestamp | Temperature (°C) |
|---|---|
| 08:00 | 4.4 |
| 08:05 | 4.6 |
| 08:10 | 4.9 |

### 11.2. Algorithms Used

The system uses a hybrid algorithmic approach combining rule-based and AIbased methods.

#### 11.2.1. Threshold-Based Monitoring Algorithm

Purpose: Detect immediate temperature violations. Logic: If Temperature < Tmin OR Temperature > Tmax → Trigger Alert Advantages:

- Simple
- Fast
- Reliable

#### 11.2.2. Anomaly Detection Algorithm Purpose

Detect unusual temperature behavior beyond fixed thresholds.

- Methods Used:
  - Statistical deviation
  - Isolation Forest (optional)
- Detects:
  - Sensor faults
  - Sudden temperature spikes
  - Equipment malfunction 2.3 Time-Series Prediction Algorithm

Purpose: Predict future temperature values.

- Algorithms:
  - ARIMA (basic)
  - LSTM (advanced)
- Benefit:
  - Early warning before failure

### 11.3. Step-by-Step Working Process Step

- Step 1: Data Sensing : Temperature, humidity, and gas sensors continuously collect environmental data from the cold storage room.
- Step 2: Data Acquisition: The microcontroller (ESP8266/ESP32) reads sensor data at fixed intervals.
- Step 3: Data Transmission Collected data is transmitted to the cloud through Wi-Fi.
- Step 4: Data Preprocessing: Noise removal, missing value handling, and normalization are performed.
- Step 5: Threshold Checking: Real-time temperature values are compared with predefined limits.
- Step 6: Anomaly Detection: The system analyzes temperature patterns to detect abnormal behavior.
- Step 7: Temperature Prediction: Historical data is used to predict future temperature trends.
- Step 8: Alert Generation: If a violation or predicted risk is detected:
  - SMS / Email alert is sent
  - Dashboard warning is displayed
- Step 9: Visualization & Storage : All data, alerts, and predictions are stored and visualized using cloud analytics.

## 12. Results And Discussion

This section presents the computational results obtained from applying the proposed AIoT-based optimization model to cold chain logistics networks and discusses the observed outcomes in terms of cost efficiency, product quality preservation, and algorithmic performance. The analysis demonstrates how integrating IoT-enabled monitoring with artificial intelligence– based optimization improves decisionmaking across the cold chain while maintaining feasibility and practicality. The results show that deploying IoT devices in distribution centers and refrigerated vehicles leads to an increase in initial investment costs due to infrastructure installation and system integration. However, these additional costs are effectively compensated by significant reductions in operational and transportation expenses. IoT-enabled realtime monitoring improves route planning, reduces unnecessary travel distances, optimizes vehicle speed, and enhances energy management at distribution centers. Consequently, the overall cost of the cold chain network decreases when IoT deployment is optimally integrated into the logistics design rather than applied uniformly.

## Conclusion And Future Scope

This study presented an AIoT-based optimization framework for cold chain logistics aimed at reducing total logistics cost while preserving the quality of perishable products. By integrating Internet of Things–enabled monitoring with artificial intelligence–based optimization, the proposed approach addressed key limitations of conventional cold chain systems, including limited realtime visibility, static planning, and insufficient consideration of quality degradation during transportation. A unified location–routing optimization model was developed to jointly determine distribution center selection, vehicle routing, IoT deployment, and product allocation decisions. Product quality was explicitly modeled as a time-dependent function, and minimum quality thresholds were enforced to ensure that all deliveries met acceptable standards. The results demonstrated that strategic IoT deployment, when guided by intelligent optimization, leads to significant reductions in operational and transportation costs, even though it introduces additional infrastructure investment. This confirms that AIoT adoption can enhance both economic efficiency and service reliability in cold chain logistics. Artificial intelligence–based metaheuristic algorithms were employed to solve the NPhard optimization problem efficiently. The computational results showed that all applied algorithms were capable of producing feasible and high-quality solutions within reasonable computation times. Among them, the Emperor Penguin Optimizer exhibited superior convergence speed and solution quality, particularly for larger problem instances, highlighting its suitability for complex AIoT-enabled logistics applications. From a practical standpoint, the findings provide valuable insights for logistics managers and decision-makers. Rather than uniform IoT implementation, the proposed framework supports selective and strategic deployment of IoT devices at high-impact facilities and vehicles. Moreover, the explicit incorporation of quality constraints enables informed evaluation of cost–quality trade-offs, which is critical in industries such as food distribution, pharmaceuticals, and vaccine logistics. Future research may extend this work by incorporating uncertainty in demand, travel time, and environmental conditions, as well as by integrating sustainability considerations such as carbon emissions and energy efficiency. Additionally, realtime adaptive optimization and hybrid AI algorithms could be explored to further enhance decision-making in dynamic cold chain environments.

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