IoT-Driven Cold Chain Supply Optimization Utilizing Embedded Systems and Adaptive Communication Protocols

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To enhance the information transparency and monitoring efficiency of the cold chain logistic supply chain, the study adopts the Internet of Things and embedded technology to construct a cold chain logistic supply chain optimization strategy. Firstly, a cold chain logistic supply chain monitoring model based on Internet of Things is constructed. The model covers the whole chain of "sensing-transmission-application". The sensing layer adopts heterogeneous sensor networks and follows the density optimization model for deployment. The network layer utilizes hybrid communication architecture and adaptive routing protocol to ensure efficient and stable data transmission. The application layer realizes the comprehensive supervision of the cold chain logistic supply chain through the three-level data fusion model. Meanwhile, based on embedded technology, it builds intelligent terminals, integrating multi-sensor modules and intelligent peripherals. The results showed that, in the proposed model, the temperature error in the sensitive area decreased by 22.2%, from 0.3 ℃ to 0.1 ℃, and the humidity error decreased by 50%, from 3.0% RH to 1.5%. When the channel utilization was 70%, the transmission delay was 180.6 ms, the transportation cost was reduced by 16.5%, the inventory cost was reduced by 21.6%, and the total loss was reduced by 50.6% (vaccine loss was reduced by 62%). According to the study, the suggested approach considerably raises the cold chain logistic supply chain's monitoring accuracy, data transmission efficiency, path planning rationality, and inventory management efficacy. This effectively optimizes the operation of the cold chain logistic supply chain and provides a feasible technical solution for the development of the industry.

Povzetek: Članek obravnava upravljanje tradicionalnih hladnih verig dobave, npr. hrane. Predlaga IoT–vgrajeni sistem z gostotno optimiziranimi senzorji, hibridno 5G+NB-IoT komunikacijo, tristopenjsko podatkovno fuzijo in adaptivnim PID.

1 Introduction

Cold chain (CC) logistic is the core link connecting the production end and consumption end of fresh food and guaranteeing the safety of medical products circulation. Its operational efficiency is directly related to the well-being of people's livelihood and public health and safety [1]. The need for CC logistics has increased dramatically because to the ongoing rise of the global fresh food e-commerce market and the quick development of the biomedical sector. According to statistics, China's CC logistic market size has jumped from 240 billion yuan in 2018 to nearly 600 billion yuan in 2023. The compound annual growth rate is over 20% [2]. However, the traditional CC logistic system relies on manual inspection and lacks real-time monitoring means. This leads to lagging response to temperature and humidity anomalies, sloppy transportation path planning, high inventory loss and other problems. It not only causes huge economic losses, but also frequently triggers food safety incidents and pharmaceutical product quality risks [3]. At present, academia and industry have carried out a large number of CC monitoring studies based on Internet of Things (IoT) technology. Some scholars deploy temperature and humidity sensors and radio frequency identification (RFID) tags to realize data collection in the transportation environment, and use the network to transmit data to the cloud platform [4]. In path optimization, CC transportation models with time windows are constructed using ant colony algorithms and genetic algorithms. In inventory management, prediction models based on historical sales data are used to optimize the ordering cycle. In addition, blockchain technology has been attempted to be used for CC traceability to construct a whole-process data deposit system from production to consumption due to its tamper-proof characteristics [5]. However, existing studies still have significant limitations. Sensor deployment mostly adopts a uniform density strategy, with insufficient monitoring accuracy in the core area. Data transmission relies on a single communication protocol, which is prone to link congestion in complex road network environments. The embedded terminal's real-time control ability is weak. This makes it difficult to cope with the large lag characteristic of the CC system. Additionally, there is only one means of data security protection.

CC logistic supply chain (SC) optimization is a collaborative upgrade of all aspects of warehousing, transportation and distribution through digital technology, intelligent planning and process reconstruction. It is a systematic improvement process that reduces wastage, improves timeliness, guarantees the quality of temperature-controlled goods and optimizes costs. Li D et al. developed a multi-objective CC logistic model with the goals of maximizing customer happiness, minimizing network costs, and minimizing carbon transaction costs. An enhanced non-dominated sorting genetic algorithm also solved it [6]. Moghaddasi B et al. proposed a mixed integer nonlinear planning model based on balanced scorecard in fuzzy environment to optimize the routing and siting of CC logistic network. The results showed that the model could accurately assess the system cost, optimize the number of distribution centers and routes, and balance customer satisfaction and environmental goals [7]. Ye W combined deep neural network to predict the CC demand of cross-border e-commerce, and comprehensively considered consumption habits and other influencing factors to complete the cold SC management and inventory optimization. The results indicated that the method had a demand prediction accuracy of 96.35%, a precision of 97%, and a recall rate of 94.89% [8]. Li J et al. established a two-stage distribution robust optimization model for the uncertainty of demand, cost and safety risk in pharmaceutical CC. Numerical experiments verified that the model can effectively reduce the total cost of facility construction and transportation. It could guarantee drug safety and SC stability under uncertain environment [9]. To minimize the overall cost, Zhang L et al. integrated refrigeration, damage cost, and carbon emission to create a low-carbon CC distribution center site selection model. The results indicated that this method significantly reduced the integrated cost and carbon emissions. Moreover, the stability of the improved algorithm was better than the traditional intelligent algorithm [10].

IoT and embedded technology achieve CC logistic whole process temperature dynamic monitoring, path optimization and energy consumption management by deploying intelligent sensors, real-time data acquisition system and intelligent algorithms. The approach can help reduce losses, improve efficiency and promote green and sustainable development while safeguarding the quality of temperature-controlled goods. Pajic V et al. proposed a comprehensive framework for CC temperature monitoring by integrating IoT sensors, intelligent transportation systems and real-time data management. The findings suggested that the framework might protect the quality of temperature-sensitive products and increase the accuracy and dependability of temperature monitoring [11]. Haider A et al. established a tomato CC temperature prediction system based on IoT technology, fusing whale optimization algorithm and extreme learning machine to collect real-time environmental and product temperature data. The results indicated that the model outperformed the traditional machine learning model in terms of precision, recall, and other metrics, and effectively predicted temperature changes to maintain tomato quality [12]. Zhang W et al. combined blockchain technology and genetic algorithm to construct a multi-objective CC path optimization model with time window, considering the multi-objective unification of customer satisfaction and delivery cost. Example validation revealed that the optimization scheme could reduce the distribution cost and improve the efficiency. Blockchain technology could enhance data transparency and path optimization reliability [13]. Fatorachian H et al. qualitatively analyzed the application of Industry 4.0 technologies in CC waste management through focus groups and semi-structured interviews. According to the findings, digital technologies helped to accomplish sustainability targets by drastically reducing waste through predictive maintenance and real-time monitoring [14]. Liu Y et al. established a low-carbon CC vehicle path model with the objective of minimizing the cost per unit of satisfied customers based on the principle of cost-effectiveness. Moreover, a local search genetic algorithm was designed to realize the model solution. Experiments indicated that the appropriate freshness strength could reduce the total cost, and increasing the carbon price could reduce the emission. Meanwhile, the optimization considering time and freshness satisfaction was better [15].

In summary, existing research has made progress around CC logistic SC optimization. However, the current research still has limitations. The deep integration of IoT and embedded technologies in the whole chain is insufficient, and the efficiency of real-time data interaction and multi-system collaboration needs to be improved. Moreover, the landing cost of some technical solutions in complex SC scenarios is high [16]. Therefore, in order to build a whole-process intelligent collaboration system covering monitoring, planning, and execution, the study proposes a CC logistic SC optimization strategy based on IoT and embedded technology. It is anticipated to increase the SC's reactivity to environmental changes, loss control, and temperature-controlled commodity quality assurance. Additionally, it seeks to offer a broadly applicable solution for the effective and environmentally friendly growth of CC logistics.

Existing CC monitoring research often uses a two-level data fusion architecture of "raw data filtering+decision output" (e.g., using Kalman filtering directly to process data for decision-making). This architecture lacks a feature-level fusion link, which results in subtle fluctuations in key parameters, such as temperature and humidity, being ignored. Monitoring errors in sensitive areas often exceed 0.3°C. The three-level data fusion model proposed in this study adds feature level fusion (second level) between filtering (first level) and decision-making (third level). By extracting key features such as temperature and humidity fluctuations and data consistency, temperature monitoring errors in sensitive areas are reduced to 0.1°C. This is 22.2% lower than existing methods and solves the problem of traditional fusion methods' insufficient capture of complex environmental features. Most existing research uses fixed-parameter PID, which has difficulty coping with the common 5-10 second lag characteristics of CC systems. This results in a delayed temperature regulation response and a loss rate of sensitive products, such as vaccines, that often exceeds 30%. The adaptive PID dynamically adjusts parameters by monitoring temperature and humidity deviations in real time. For example, Kp adapts within the range of 0.5 to 2.0. This corrects the control quantity in advance for lag characteristics and reduces the vaccine loss rate to 11.4% (a 62% reduction). This overcomes the limitation of the poor adaptability of fixed-parameter PID to system dynamic characteristics.

2 Methods and materials

2.1 CC logistics SC regulatory model based on the IoT

In the CC logistic SC, due to the problems of information asymmetry and backward monitoring means, the logistics cost is high, the loss is large, and the service quality is difficult to guarantee [17]. Therefore, the study takes IoT technology as the core, and constructs a CC logistic SC supervision model, covering the whole chain supervision system of "sensing-transmission-application", as shown in Figure 1. The model realizes the high-density collection of CC environmental data through the intelligent sensor network in the sensing layer. It utilizes the hybrid communication architecture in the network layer to ensure the real-time and security of data. Moreover, in the application layer, a multi-dimensional data analysis model is used to meet the differentiated needs of government supervision, enterprise operation and consumer traceability.

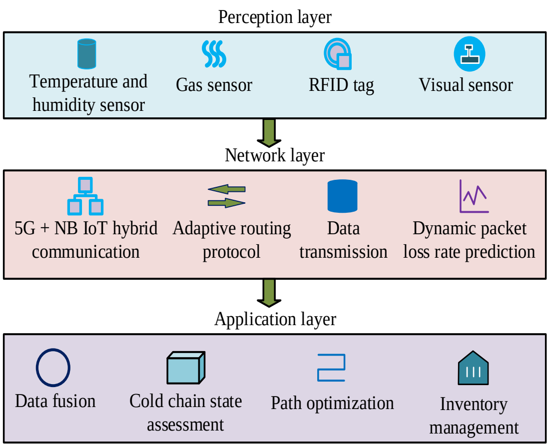

Figure 1: CC logistic SC regulatory model

The sensing layer adopts a heterogeneous sensor network, including temperature and humidity sensors, gas sensors, RFID tags, and vision sensors, to construct a three-dimensional three-dimensional sensing network. The sensor node deployment follows the density optimization model shown in Equation (1).

$$D_{opt} = \arg\min\left(\sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij}^2 \cdot w_{ij} + \lambda \cdot \sum_{k=1}^{p} c_k\right) \tag{1}$$

In Equation (1), D_{opt} is the optimal deployment density matrix. d_{ij} is the Euclidean distance between the i th logistics node and the j th sensor. w_{ij} is the node environment sensitivity weight (taking 1.2 for temperature and humidity sensitivity and 0.8 for gas composition sensitivity). λ is the hardware cost penalty factor (taking value 0.5-1.0). c_k is the single node cost of class k sensors. The environmental sensitivity weight w_{ij} is set based on the tolerance of the region to temperature and humidity fluctuations, such as 1.2 for fresh food areas (sensitive areas) and 0.8 for dry goods areas (non sensitive areas). The monitoring accuracy under different weights is verified through field testing. The hardware cost penalty factor λ is dynamically adjusted based on the unit price of the sensor. When the budget is limited, the ratio is set to 0.8-1.0 to balance the cost. When the budget is sufficient, the ratio is set to 0.5-0.7 to prioritize accuracy.

The model introduces environment-sensitive weights on the basis of the traditional coverage optimization algorithm to address the demand for differentiated monitoring accuracy in different regions in the CC scenario. The network layer adopts 5G+NB-IoT hybrid communication architecture and designs adaptive routing protocol. The data transmission delay model is shown in Equation (2).

$$\begin{cases} T_{delay} = T_{proc} + T_{trans} + T_{queue} \\ T_{trans} = \dfrac{L}{B} \cdot \left(1 + \dfrac{\alpha}{1-\beta}\right) \end{cases} \tag{2}$$

In Equation (2), T_{proc} is node data processing time. T_{trans} is transmission time. T_{queue} is queue waiting time. L is the packet length. B is channel bandwidth. α is packet loss rate (PLR). β is channel utilization. The study introduces a dynamic PLR prediction module. The link quality is predicted in real time by long short-term memory network (LSTM) network, and the α value is dynamically adjusted so as to improve the transmission efficiency. The application layer constructs a three-level data fusion model. Figure 2 illustrates the data fusion procedure.

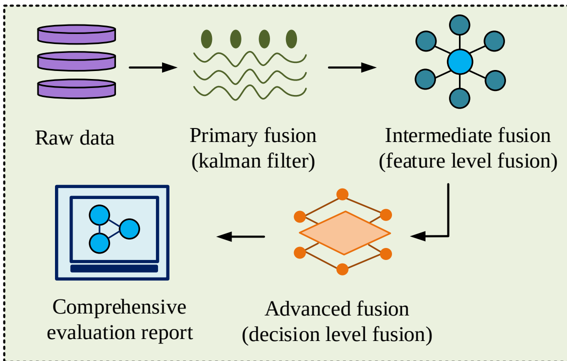

Figure 2: Data fusion process

In Figure 2, the raw data are fused by primary fusion (Kalman filter), intermediate fusion (feature level fusion), and advanced fusion (decision level fusion) to generate a comprehensive assessment report. The primary fusion uses an improved Kalman filter algorithm, as shown in Equation (3).

$$\begin{cases} \hat{x}_k = A\hat{x}_{k-1} + B_u u_k + K_k (z_k - H\hat{x}_{k-1}) \\ K_k = P_{k-1}H^T (HP_{k-1}H^T + R_k + \delta_k)^{-1} \end{cases} \tag{3}$$

In Equation (3), $\hat{x}_k$ is the state estimate. A is the state transfer matrix. B_u is the control matrix. u_k is the control input. K_k is the Kalman gain. z_k is the observation value. z_k is the observation matrix R_k is the observation noise covariance. δ_k is the adaptive noise adjustment factor The study of sensor health assessment module introduced on the basis of extended Kalman filter (EKF). The health index is calculated by fusing the sensor operating voltage, temperature and other parameters through fuzzy logic algorithm, and the noise covariance is adjusted in real time. The CC state assessment adopts the cloud model comprehensive evaluation method to construct the assessment index system $\{C_1, C_2, \ldots, C_n\}$. Among them, the core indexes include deviation error of temperature and humidity C_1, transmission timeliness compliance rate C_2, and package integrity C_3. The comprehensive assessment function is shown in Equation (4) [18].

$$Y = \sum_{i=1}^{n} w_i \mu(C_i) \tag{4}$$

In Equation (4), w_i is the indicator weight. $\mu(C_i)$ is the indicator cloud affiliation function value. The weights are calculated as shown in Equation (5).

$$w_j = \frac{\sum_{i=1}^{m} \left(\prod_{k=1}^{n} \left(a_{ikj} \right)^{1/n} \right)}{\sum_{j=1}^{n} \sum_{i=1}^{m} \left(\prod_{k=1}^{n} \left(a_{ikj} \right)^{1/n} \right)} \tag{5}$$

In Equation (5), a_{ikj} is the fuzzy judgment value of the i th expert on indicators k and j. Figure 3 displays the schematic diagram for the dynamic adjustment of path optimization.

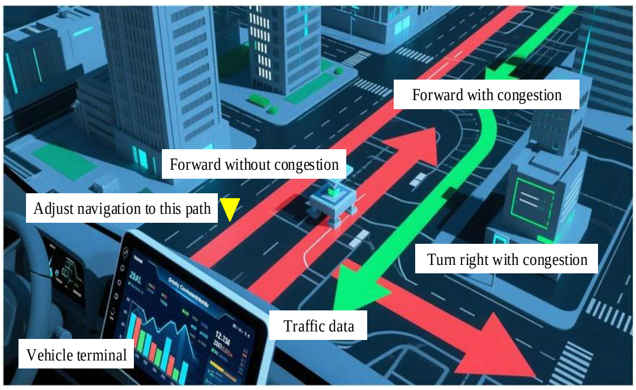

Figure 3: Schematic diagram of dynamic adjustment for path optimization

To avoid crowded areas and increase driving economy, the car automatically chooses the best route based on the amount of road congestion in real time. Equation (6) illustrates how route optimization uses the enhanced Dijkstra method to build the CC transportation network model with time frame.

$$\begin{cases} \min Z = \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} + \sum_{i=1}^{n} \left(e_i + l_i \right) \\ s.t. \begin{cases} t_i + d_i \le t_i (x_{ij} = 1) \\ a_i \le t_i \le b_i \\ \sum_{j=1}^{n} x_{ij} = i, \forall i \end{cases} \end{cases} \tag{6}$$

In Equation (6), c_{ij} is the transportation cost from node i to j. x_{ij} is the 0-1 variable. e_i is the early arrival penalty cost (APC). l_i is the late APC. t_i is the arrival time at node i. d_i is the node i dwell time. $[a_i, b_i]$ is the time window constraint. The pseudocode for improved Dijkstra's algorithm is shown in Figure 4.

```
Input: Graph G(V,E), start s, end t, time windows [a_i,b_i], real-time traffic API
Output: Optimal path P

1. Init: dist[s]=0, others=∞; prev[]=-1; T=100 (annealing temp)
2. Every 5min: Update edge weights E(i,j) via traffic API (add penalties for time window violations)
3. Run Dijkstra's to find initial path P0 using dist[] and prev[]
4. Local opt with annealing:
   While T>1:
     Generate P' by swapping 2 nodes in P0
     If cost(P') < cost(P0) or rand() < exp(-ΔC/T): P0=P'
     T *= 0.95
5. Return P0
```

Figure 4: Pseudocode for improved Dijkstra's algorithm

The study introduces a real-time traffic data interface to dynamically update the road segment weights c_{ij} and performs local optimization by simulated annealing algorithm. Inventory management adopts the economic order lot model considering the loss rate to construct the CC inventory cost function, as shown in Equation (7).

$$TC(Q) = \frac{D}{Q} S + \frac{Q}{2} H + D \cdot \theta \cdot C_p \tag{7}$$

In Equation (7), Q is the order quantity. D is the annual demand. S is the single order cost. H is the unit inventory holding cost. θ is the real-time wastage rate. The real-time wastage is calculated as shown in Equation (8).

$$\theta = \theta_0 \cdot e^{k(T-T_0)} \tag{8}$$

In Equation (8), θ_0 is the baseline loss rate. k is the temperature sensitivity factor. T is the actual storage temperature. T_0 is the reference temperature.

2.2 Embedded-based CC logistic SC optimization approach

On the basis of CC logistic SC supervision model, the research is based on embedded technology and advanced Risc machine (ARM) architecture as the core to construct intelligent terminal. It realizes accurate collection of environmental data through multi-sensor fusion, and combines embedded algorithms and blockchain technology to construct a CC logistic SC optimization system. The embedded terminal adopts STM32H750XB main control chip, integrating multi-sensor modules and intelligent peripherals [19]. The embedded hardware composition is shown in Figure 5.

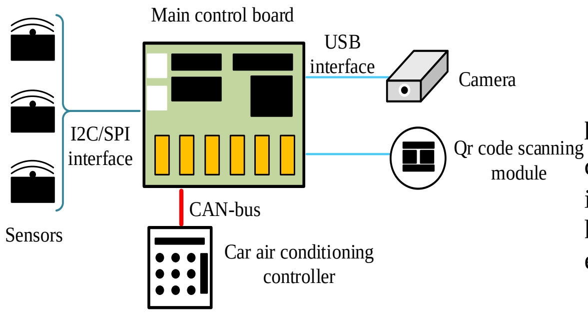

Figure 5: Embedded hardware components

Figure 5 shows that the STM32H750XB main chip is connected to a multi-sensor module via an SPI interface. This setup collects real-time data and sends it to the IoT sensing layer. After preprocessing by the embedded Linux system, the data is transmitted to the network layer via the 5G module. Finally, the vehicle air conditioning is regulated through the controller area network (CAN) bus. As a lightweight blockchain node, it sends transaction data hashes to Fabric nodes via gRPC interfaces for on-chain storage. Large files, such as monitoring videos, are stored in IPFS. Only the hash values are stored on-chain, which achieves real-time synchronization with IoT data and on-chain authentication. The sensor layout follows the spatial correlation model. The sensor array optimization method is shown in Equation (10).

$$\max \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij} - \sum_{k=1}^{p} d_k^2 \tag{10}$$

In Equation (10), r_{ij} is the spatial correlation coefficient between the i th sensor and the j th monitoring point. d_k is the neighboring sensor spacing. The spatial correlation constraint is introduced on the basis of traditional array design to meet the requirement of monitoring density in sensitive areas. The software level is based on the embedded Linux system (kernel version 5.10) to develop the real-time data processing program. Multi-threaded architecture is used to realize task scheduling, as shown in Equation (11) [20].

$$T_s = \sum_{i=1}^{n} \frac{C_i}{1-U_i} \tag{11}$$

In Equation (11), T_s is the maximum schedulable time of the system. C_i is the computation time of the i th task. U_i is the task utilization rate. The rate monotonic scheduling algorithm optimizes task priority to ensure that the data acquisition thread has a higher priority than the interface display thread. This improves the system's real-time performance to the microsecond level. Data encryption adopts the improved advanced encryption standard (AES) algorithm, which introduces chaotic sequences to generate keys, as shown in Equation (12).

$$k_i = tanh(\mu \cdot k_{i-1}(1-k_{i-1})) \tag{12}$$

In Equation (12), μ is the Logistic mapping control parameter (taking values 3.8-4.0). k_i is the key component generated in the i th round of iteration. The initial value sensitivity of the chaotic system enhances the key space, and the key length is extended to 256 bits. The embedded data processing flow is shown in Figure 6.

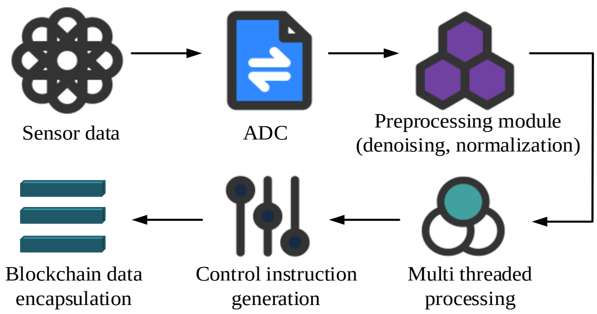

Figure 6: Embedded data processing flow

In the embedded data processing flow, the data collected by the sensors are first converted into digital signals by an analog-digital converter (ADC). Subsequently, these digital signals are fed into a preprocessing module, which is responsible for denoising and normalizing the data. The pre-processed data then proceeds to the multi-threaded processing session. At the same time, the generation of control commands and the encapsulation of blockchain data are performed [21]. The adaptive proportional-integral-derivative (PID) algorithm is used for environmental control. The control quantities in the control model are calculated as shown in Equation (13).

$$u(k) = K_p e(k) + K_i \sum_{j=0}^{k} e(j) T_s + K_d \frac{e(k) - e(k-1)}{T_s} + \Delta u \tag{13}$$

In Equation (13), $u(k)$ is the control quantity. $e(k)$ is the error. K_p, K_i, and K_d are the PID parameters. Δu is the adaptive compensation term. The nonlinear compensation module introduced on the basis of traditional PID solves the large hysteresis characteristics of the CC system. The pseudocode of the adaptive PID algorithm is shown in Figure 7.

```
Input: Target (T0,H0), real-time (T,H), lag τ
Output: Control u (0-100% power)

1. Init: Kp=1.0, Ki=0.5, Kd=0.2; e_prev=0; sum_e=0
2. Loop (Δt=0.1s):
   e = sqrt((T0-T)² + (H0-H)²)
   sum_e += e*Δt; de = (e - e_prev)/Δt
   // Adapt params:
   If e>0.5 and τ>5s: Kp*=1.2; Ki*=0.8; Kd*=1.1
   Else: Kp*=0.9; Ki*=1.1; Kd*=0.9
   u = Kp*e + Ki*sum_e + Kd*de (clamped to 0-100)
   e_prev = e
Return u
```

Figure 7: Pseudocode of adaptive PID algorithm

Blockchain traceability adopts the improved practical Byzantine fault tolerance (PBFT) consensus mechanism. Node weights are calculated as shown in Equation (14).

$$w_j = \frac{\eta_j \cdot \tau_i}{\sum_{i=1}^{n} \eta_j \cdot \tau_i} \tag{14}$$

In Equation (14), η_j is the node historical transaction success rate. τ_i is the node hardware performance index. Multi-source data fusion adopts sparse representation algorithm to construct the observation model, as shown in Equation (15).

$$\begin{cases} y = \Phi x + noise \\ \hat{x} = \arg\min \|x\|_1 \quad s.t. \|y - \Phi x\|_2 \le \varepsilon \end{cases} \tag{15}$$

In Equation (15), y means the observation vector. Φ means the observation matrix. x means the sparse signal. $noise$ means the noise. ε means the noise tolerance limit. The reconstruction speed is enhanced by improved orthogonal matching pursuit (OMP), which is combined with hardware acceleration to realize real-time fusion. The pursuit data structure uses Merkle-Patricia tree, and the transaction hash is computed as shown in Equation (16).

$$H(Tx) = SHA - 256(Tx \oplus nonce \oplus prevHash) \tag{16}$$

In Equation (16), $SHA-256$ is the cryptographic hash function. Tx is the transaction data. $nonce$ is the random number. $prevHash$ is the front block hash value. The study introduces a timestamp encryption module to ensure that the transaction time cannot be tampered with. The blockchain traceability architecture diagram is shown in Figure 8.

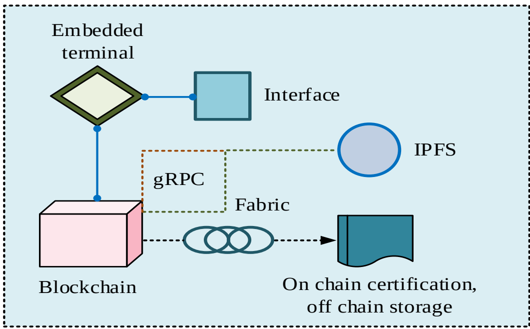

Figure 8: Blockchain traceability architecture diagram

The blockchain backing architecture has embedded terminals as light nodes responsible for data interaction and storage tasks. The architecture communicates efficiently with Fabric backing nodes through the gRPC interface to ensure data security and consistency. When dealing with large file data, the InterPlanetary File System (IPFS) is utilized for storage to achieve off-chain storage, thus reducing the pressure of on-chain storage. Through the method of "on-chain deposit + off-chain storage", the embedded terminal can record and verify data in real time, ensuring data integrity and traceability.

3 Results

3.1 Experimental design and data collection

The simulation experiment is based on MATLAB Simulink to build a CC logistic network containing 10 transportation nodes, 5 distribution vehicles, and 3 types of typical goods (fresh food, vaccines, and pharmaceutical reagents). The field test selects a CC logistic enterprise in the Yangtze River Delta region and deploys intelligent terminals in 20 transportation vehicles and 5 storage nodes. It covers 200 kilometers of transportation routes from Shanghai to Nanjing and continuously collects data for 30 days. The experiment takes temperature and humidity monitoring accuracy, data transmission delay, path optimization efficiency, and inventory cost reduction rate as the core evaluation indexes. It also compares the performance difference between the traditional supervision model (based on GPS+RFID) and the proposed model. Table 1 displays the setup of the experimental environment.

Table 1: Experimental environment configuration

Module type	Hardware model	Key parameter	Software version	Functional positioning
Master chip	STM32H750XB	480MHz main frequency, 1MB memory	Embedded Linux 5.10	Multi sensor fusion control
Communication module	Huawei MH5000-32	5G NR Sub-6GHz	Driver v1.2.3	High speed data transmission
Sensor group	SHT30+MQ-135	Temperature and humidity accuracy ± 0.1 ℃/± 1.5% RH	Data Collection Driver v3.0	Real time monitoring of environmental parameters
Blockchain node	Hyperledger Fabric	Consensus algorithm improvement PBFT	2.5.0	Data certification and traceability
Simulation platform	MATLAB R2023a	YALMIP Toolbox	/	Model effectiveness simulation verification

A total of 128,640 valid data are captured during the experimental period, including temperature and humidity data (65% of the total), transportation path data (20%), and inventory transaction data (15%). A comparison of sensor deployment parameters is shown in Table 2. In the proposed model, the sensor deployment density is 5 nodes/m^3 in the middle of the refrigerated compartment (temperature and humidity sensitive area). The non-sensitive area at the two ends is 2 nodes/m^3. The data are collected at a frequency of 10Hz (dynamic transportation phase) and 5Hz (static warehousing phase), and are transmitted in real time to the cloud server via 5G network.

Table 2: Comparison of sensor deployment parameters

Regional type	Sensitive area	Non-sensitive area
Traditional uniform deployment	3 nodes /m^3	3 nodes /m^3
Proposed model	5 nodes /m^3	2 nodes /m^3
Monitoring accuracy improvement rate	22.2%	5.3%

3.2 Effectiveness of CC logistic SC regulatory model

The comparison results of temperature and humidity monitoring accuracy are shown in Figure 9. In Figure 9(a), the mean values of the errors of the traditional and proposed models in the sensitive area are 0.3°C and 0.1°C. The errors in the non-sensitive area domain are 0.5°C and 0.43°C, respectively. In Figure 9(b), the mean values of the errors of the traditional model in the sensitive area and non-sensitive area domain are 3.0%RH and 4.0%RH, respectively. The mean values of the errors of the proposed model are 1.5%RH and 3.8%RH, respectively. In the temperature and humidity sensitive area, the monitoring accuracy of the proposed model is improved by 22.2% compared with that of the traditional model. Whereas, the accuracy of non-sensitive area domain is improved by 5.3%. This is mainly due to the introduction of environmentally sensitive weights in the density optimization model. This model allocates monitoring resources differently to ensure accuracy in the core area.

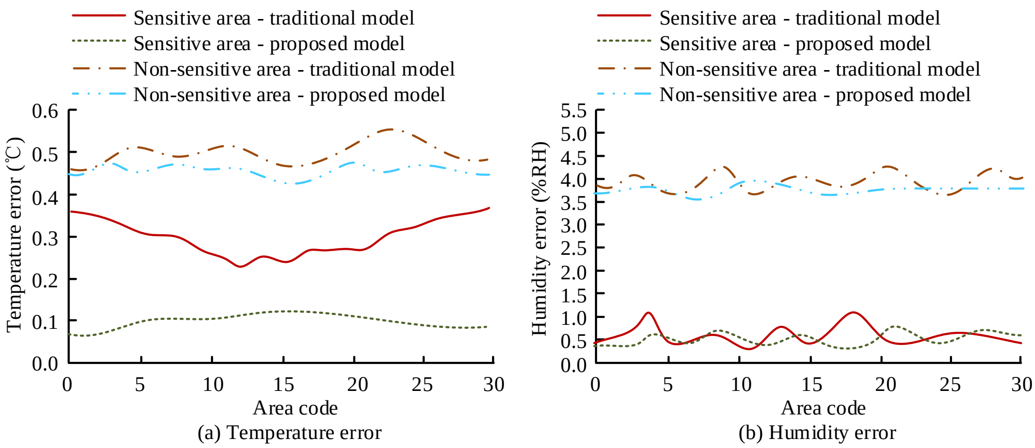

Figure 9: Comparison results of temperature and humidity monitoring accuracy

The data transmission delay and reliability comparison is shown in Figure 10. Figure 10(a) shows the transmission delay comparison. With the increase of channel utilization, the transmission delay both show an increasing trend. When the channel utilization is 30%, the transmission delay is 85.3ms and 54.2ms for the traditional model and the proposed model, respectively. When the channel utilization is 70%, the transmission delay is 382.3ms and 180.6ms for the traditional model and the proposed model, respectively. In Figure 10(b), the

PLR of the proposed model are lower than the traditional model. When the channel utilization is 70%, the PLR of the proposed model is 3.5%, which is 70.8% lower than the traditional model. The combination of 5G+NB-IoT hybrid communication architecture and LSTM dynamic packet loss prediction module optimizes the routing strategy in real time and reduces the queue waiting time and link congestion.

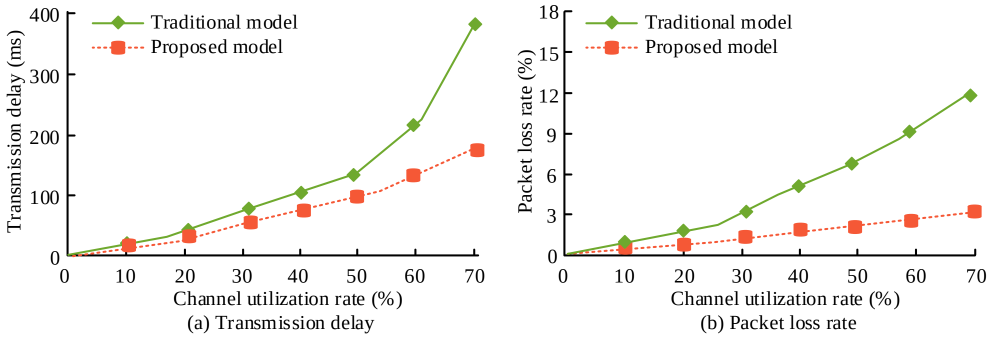

Figure 10: Data transmission delay and reliability comparisons

Comparison of the accuracy of the comprehensive assessment of CC status is shown in Table 3. The proposed model adopts the cloud model comprehensive evaluation method with three-level data fusion technique. The deviation error of temperature and humidity assessment is reduced from 15.1% to 8.5%. The transmission timeliness compliance rate increases from 72.2% to 91.3%. The accuracy rate of packaging integrity detection increases from 80.5% to 95.4%. The composite evaluation result has an agreement of 92.5% with actual CC accidents, which is 16.8% higher than the 75.7% of the traditional model. The three-level data fusion and cloud model evaluation method effectively improves the processing capability of multi-source data. This enables the regulatory model to identify CC abnormalities more accurately. However, in areas with weak infrastructure such as rural areas, the 5G signal coverage rate is often below 60%. To reduce packet loss, the system automatically switches to NB-IoT mode, reducing the data transmission frequency from 10Hz to 2Hz. In response to signal fluctuations, an LSTM model is used to predict packet loss trends 10 s in advance, triggering a local 500MB cache. After signal recovery, batch uploads are made. Testing in a remote area shows that this strategy improves transmission reliability by over 85%.

Table 3: Comparison of the accuracy of the comprehensive assessment of the state of the CC

Evaluation indicators	Traditional model	Proposed model	Error reduction	Improvement of accuracy rate
Deviation error of temperature and humidity	15.1%	8.5%	6.6%	/
Transmission timeliness compliance rate	72.2%	91.3%	/	19.1%
Accuracy rate of packaging integrity detection	80.5%	95.4%	/	14.9%
Actual CC accidents	75.7%	92.5%	/	16.8%

3.3 CC logistic SC optimization effectiveness evaluation

For the path optimization effect, the experiment compares the difference between Dijkstra's algorithm and the improved algorithm with time window in terms of transportation time, cost, and punctuality. The results of path optimization performance comparison are shown in Figure 11. In Figure 11(a), the average transportation time of Dijkstra's algorithm and the research improved algorithm is 210min and 175min, respectively. In Figure 11(b), the transportation cost under the research improved algorithm is 710 yuan/trip, which is reduced by 16.5% compared with Dijkstra's algorithm. In Figure 11(c), the punctuality rates under the Dijkstra algorithm and the research improved algorithm are 78.2% and 94.1%, respectively. The results show that the improved Dijkstra algorithm combines real-time traffic data and time window constraints to effectively improve the dynamic adaptability of path planning. This reduces the time and cost loss and meets the strict requirements of CC transportation on time and punctuality.

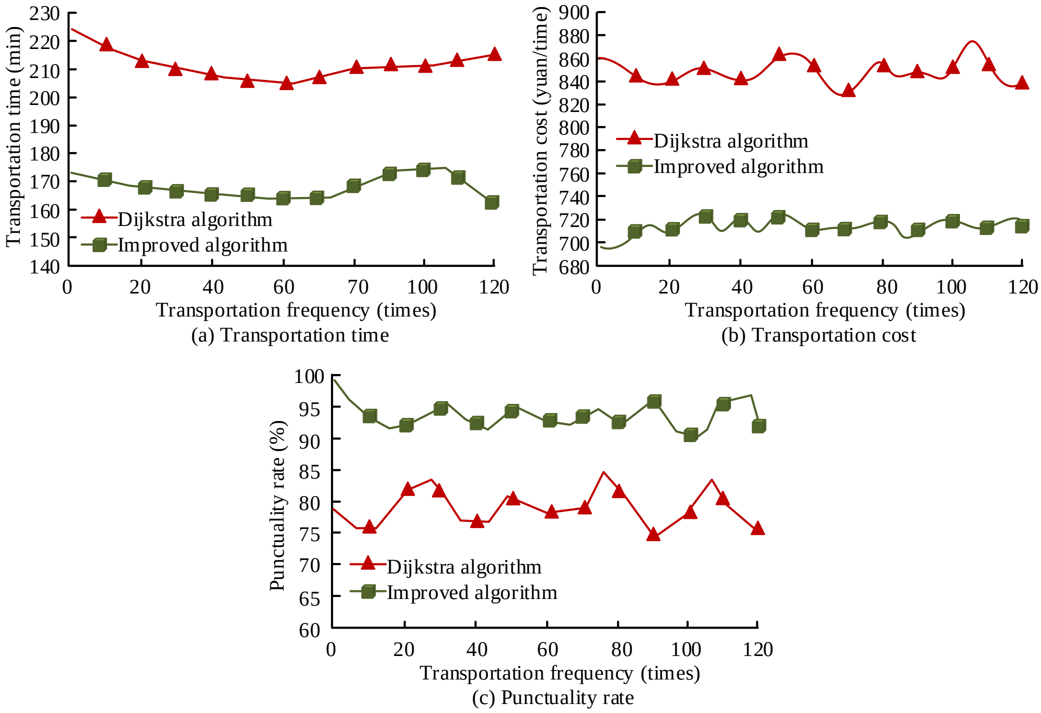

Figure 11: Path optimization performance comparison results

The comparison of inventory cost and loss rate is shown in Table 4. The proposed model dynamically adjusts the loss rate through real-time monitoring of temperature and humidity, which reduces the annual inventory cost from 125,000 yuan to 98,000 yuan, a reduction of 21.6%. The annual loss is reduced from 850kg to 420kg, which is 50.6% lower. Among them, the loss of temperature-sensitive goods (e.g., vaccines) is especially reduced by 62%. The effectiveness of environmental data-driven inventory management is validated. The results show that the improved model achieves precise optimization of inventory strategy by adjusting the wastage rate through real-time sensing of environmental data. This reduces both inventory holding costs and goods wastage. This has significant benefits especially for high-value, perishable pharmaceutical products.

Table 4: Inventory cost compared to wastage rate

Indicator	Traditional model	Proposed model	Cost/loss reduction rate
Annual inventory cost (yuan)	125000	98000	21.6%
Annual loss (kg)	850	420	50.6%
Among them: vaccine loss amount (kg)	300	114	62.0%
Ordering cycle (days)	15	12	20.0%
Inventory turnover rate (times/year)	4	6	50.0%

A comparison of blockchain traceability performance is shown in Figure 12. In Figure 12(a), the average transaction time of the improved blockchain system is about 200ms, which is reduced by 75.0% compared to the traditional database. In Figure 12(b), the throughput averages of the traditional database and the improved blockchain system are about 500tps and 1200tps. The results show that the combination of the improved PBFT consensus mechanism and IPFS storage improves the system efficiency while guaranteeing the data tampering. The embedded terminal as a light node realizes real-time data uplinking and fast traceability, which meets the demand for data security and efficient interaction in the CC SC.

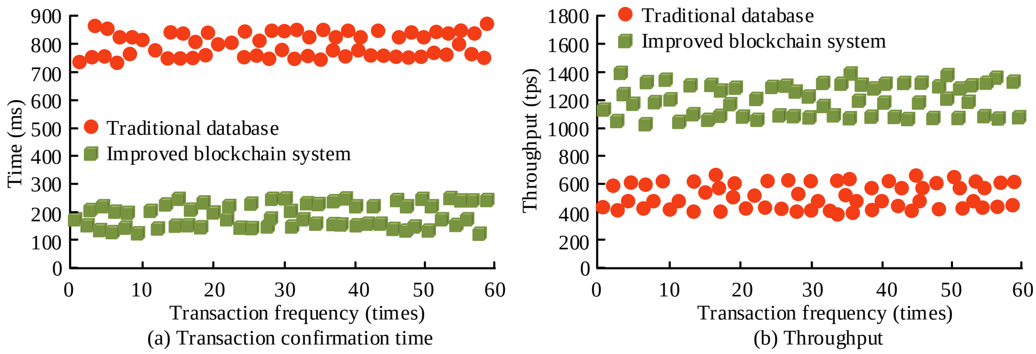

Figure 12: Blockchain traceability performance comparison

The system performance test results under different environments are shown in Table 5. Under high temperature and low temperature environment, the monitoring accuracy fluctuation of the system is less than 3%. It indicates that it has strong adaptability to extreme temperatures. In the rural weak network environment, the increase of transmission delay is limited, and the network robustness is good. The delay growth is less than 20% when the number of nodes is expanded fivefold, reflecting good scalability. The system operates without fault under high load to verify the stability of the system. In summary, the system is stable in complex environments and can meet the application requirements of different scenarios.

Table 5: System performance test results under different environments

Environment type	Key indicators	Result data
High temperature environment (35 ℃)	Monitoring accuracy fluctuation in sensitive areas	±2.8%
Low temperature environment (-10 ℃)	Monitoring accuracy fluctuation in sensitive areas	±2.5%
Rural weak network environment	Transmission delay changes (compared with cities)	Increase<15%
Node expansion (20→100 nodes)	Transmission delay variation	Increase<20%
High load for 24h	System stability (trouble free operation)	100%

4 Discussion and conclusion

The goal of the project was to build an IoT and embedded technology-based CC logistic SC optimization system in an attempt to address the issues of high cost and high loss brought on by information asymmetry and backward monitoring methods in the conventional CC logistic SC. First, IoT regulatory model covering “sensing-transmission-application” was constructed. Meanwhile, the intelligent terminal was constructed based on embedded technology of ARM architecture, integrating multi-sensor fusion, adaptive PID control, and improved PBFT blockchain traceability technology. The results revealed that the mean value of temperature error of the proposed model in temperature and humidity sensitive region was reduced from 0.3°C to 0.1°C, and the mean value of humidity error was reduced from 3.0% RH to 1.5%. At 30% channel utilization, the data transmission delay was reduced from 85.3ms to 54.2ms. In the comprehensive assessment of CC status, the deviation error of temperature and humidity assessment was reduced from 15.1% to 8.5%. The transmission timeliness compliance rate increased from 72.2% to 91.3%. The accuracy rate of packaging integrity detection increased from 80.5% to 95.4%. Route optimization reduced shipping time by 35min, cost by 16.5%, inventory cost by 21.6% and wastage by 50.6%. In the improved blockchain system, the average transaction time was reduced from 800ms to 200ms and throughput was increased from 500tps to 1200tps. The study shows that the combination of IoT and embedded technology can significantly improve the precision, transmission efficiency and decision-making science of CC supervision, and realize the optimal allocation of resources and loss control. The limitations of the study are that the experimental scenarios only cover the Yangtze River Delta region, and the stability of sensors in extreme environments still needs to be verified. Future research directions include expanding multi-region experiments, optimizing edge computing capability, and exploring the deep integration with digital twin technology. This can further enhance the intelligence and adaptive level of the CC SC.

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Data availability

The data supporting the findings of this study are available within the article.

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