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The system framework of digital twin technology maps the physical process of the fresh-cut flower cold chain in Yunnan for achieving dynamic monitoring and intelligent regulation of carbon emissions

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SUMMARY: *Yunnan is an important production area of fresh-cut flowers in China. The cold chain circulation covers postharvest pre-cooling, cold storage, cold storage transportation and terminal distribution. The existing management mode lacks continuous tracking of the operation status of the cold chain, the node connection efficiency and the change of carbon emissions; the monitoring results are scattered, and the regulation response is lagging, which is difficult to meet the low carbon operation demand under the requirements of high timeliness and high fresh-keeping of fresh cut flowers. Focusing on the entity process of Yunnan fresh cut flowers cold chain, this paper constructed the framework of carbon emission dynamic monitoring and an intelligent regulation system driven by a digital twin. The research content includes the overall architecture design of the system, digital mapping of entity process, multi-source data acquisition and synchronisation of virtual and real, the construction of carbon emission dynamic monitoring model, and the design of intelligent regulation mechanism. In the experimental part, typical cold chain circulation scenarios are selected to test and analyse the pre-cooling, storage, transportation and distribution links. The results show that the system can control the monitoring error of carbon emission of key nodes within 6.8%, the abnormal state recognition rate reaches 93.4%, the early warning response time is reduced by 27.6%, the comprehensive energy consumption per unit batch is reduced by 11.2%, and the carbon emission of transportation is reduced by 9.7%. The results show that the framework can improve the state perception ability, carbon emission monitoring accuracy and regulation efficiency of the fresh cut flower cold chain operation process, which can provide reference for the low-carbon and digital management of Yunnan fresh cut flower cold chain.*

KEYWORDS: *digital twin technology; Yunnan fresh cut flower cold chain; Carbon emission monitoring; Intelligent control; Life cycle assessment method*

1 Introduction

The environmental and operational performance of fresh-cut flower cold chains has become a critical concern in sustainable agri-logistics, particularly in major production regions such as Yunnan. Despite their high sensitivity to environmental and temporal variations, current management approaches remain constrained by fragmented monitoring and the lack of

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integrated mechanisms for real-time state recognition and carbon emission regulation[1, 4, 11, 12, 20]. Fresh-cut flowers retain active post-harvest metabolism, requiring strict temperature control and precise coordination across all stages; even minor deviations can propagate along the chain, resulting in quality degradation, increased waste, and excess energy consumption[1, 6, 8, 20]. At the same time, increasing pressure for carbon accountability demands not only accurate emission quantification but also real-time, proactive regulation, capabilities that conventional post hoc approaches fail to provide [5-7, 11, 20].

The inherent complexity and dynamic interdependence of the fresh-cut flower cold chain necessitate a shift from node-level monitoring to integrated, real-time system-wide state recognition. The circulation process spans pre-cooling, cold storage, refrigerated transportation, and terminal distribution, with tightly coupled material and information flows. System states evolve nonlinearly due to interactions between endogenous factors (e.g., respiration and equipment performance) and exogenous disturbances (e.g., ambient conditions and traffic variability). Consequently, static or segmented monitoring cannot adequately capture system-wide dynamics, limiting the ability to detect deviations or coordinate timely responses, and leading to retrospective identification of inefficiencies and quality losses [10-12, 16, 18].

From an environmental perspective, emissions associated with fresh-cut flowers extend well beyond production to include packaging, refrigeration, transportation, and distribution. Lan et al. demonstrated that these downstream processes significantly reshape the overall carbon footprint structure [1]. The application of Life Cycle Assessment (LCA) provides a systematic framework for quantifying such impacts [1]. In parallel, Bai et al. showed that transportation emissions are strongly influenced by dynamic factors such as route configuration, traffic conditions, and distribution strategies [2]. Further studies have quantified emissions and energy consumption across cold chain operations, highlighting the roles of vehicle load, environmental conditions, equipment performance, and distribution coordination [5-8]. However, these approaches largely rely on static accounting or focus on isolated stages, limiting their ability to support system-wide and real-time carbon management.

Advances in digital technologies, particularly digital twins and IoT-enabled platforms, offer new opportunities for real-time monitoring and integration of cold chain systems. Hu et al. developed a digital twin model for cold storage systems, enabling real-time mapping of operational states [3], while Wu et al. proposed an IoT-driven platform that enhances system visibility and responsiveness [4]. These developments indicate a shift toward process-level digitalization; however, existing applications remain largely confined to individual nodes and lack unified mapping and synchronization across the entire cold chain [3, 4, 10, 12, 14, 16]. Moreover, the integration of real-time state recognition with dynamic carbon emission regulation remains insufficiently explored

To address these gaps, this study proposes a digital twin-driven framework for dynamic carbon emission monitoring and intelligent regulation in the fresh-cut flower cold chain. The study aims to establish a unified physical, virtual mapping across all stages, enable real-time state recognition and anomaly detection through multi-source data integration, and develop a coordinated mechanism for proactive, data-driven carbon emission control. By bridging the gap between system-wide visibility and carbon management, this work contributes to advancing intelligent, low-carbon cold chain systems and provides a scalable approach for sustainable agri-logistics.

2 Related work

The research of digital twin in the field of supply chain has gradually shifted from object visualisation in the early stage to process mapping, state prediction and collaborative decision-making. Kamble et al. reviewed the application of digital twin in sustainable manufacturing supply chain, and pointed out that digital twin can integrate physical objects, business processes and operational data into a unified framework, and has obvious advantages in state perception, process optimisation, and sustainable governance, which provides a theoretical basis for the implementation of digital twin in supply chain [9]. In the agri-food supply chain scenario, Melesse et al. analyzed the implementation process of digital twin, and argued that agri-food products have the characteristics of strong environmental sensitivity, long circulation chain and many participants, and the digital twin system needs to deal with multi-source heterogeneous data, spatio-temporal state changes and cross-node coordination problems at the same time, which is more complex than general industrial processes [10]. Maheshwari et al. introduced digital twin into real-time planning, monitoring and control of the food supply chain, emphasising that its value lies in the realisation of plan modification, state warning and operation control relying on real-time data feedback, rather than staying in static virtual mapping [11]. Huang et al. proposed in the study of food supply chain that the effective operation of digital twin relies on the closed-loop connection between perception, modelling, analysis and decision-making, and only by maintaining continuous interaction between virtual and real space, digital twin can truly serve supply chain governance [12].

Focusing on the issues of supply chain resilience and network collaboration, the research on digital twins is further extended to the level of the chain network. Singh et al. used the grey impact analysis method to explore the role of digital twin in resilient and sustainable manufacturing supply chain, and pointed out that digital twin can improve the system's ability to resist disturbance by enhancing visibility, shortening the time delay of anomaly identification and optimising resource allocation [13]. Yadav et al. analysed the promotion of digital twin in the agri-food supply chain from the perspective of implementation barriers, and pointed out that data heterogeneity, insufficient infrastructure, difficulties in collaboration between organisations, and limited technology adoption capabilities are important factors restricting the implementation of digital twin, which also has reference value for cold chain scenarios [14]. Lim et al. combined supply digital twin with production digital twin, studied the demand disturbance mitigation mechanism in a multi-level network, and proved that the cross-level collaborative twin structure could improve the efficiency of plan adjustment and the accuracy of resource allocation [15].

Existing studies discuss from the perspectives of digital twin framework construction, agro-food supply chain scenario adaptation, real-time monitoring and control, and green cold chain emission reduction, but the research focus and application scope are not consistent. Some literature emphasises the overall architecture and implementation logic of digital twin in supply chain, some focus on dynamic perception and closed-loop control in food or agro-food circulation, and some studies focus on multi-level network collaboration, resilience improvement, and transportation refrigeration emission reduction. In order to more clearly present the main content of related research and its relationship with the research in this paper, Table 1 summarises the research objects, research focuses, technical features and points for reference of the representative literature.

Table 1: Comparison of Related Studies

Author	Research Object	Research Focus	Technical Characteristics	Implications for This Study
Kamble et al.	Sustainable manufacturing supply chain	Digital twin implementation framework	Emphasises system-level mapping and feedback closed loop	Can be used as a reference for overall architecture design
Melesse et al.	Agri-food supply chain	Digital twin implementation analysis	Focuses on multi-source data and scene complexity	Heterogeneous data processing needs to be strengthened
Maheshwari et al.	Food supply chain	Real-time planning, monitoring and control	Emphasises dynamic correction and closed-loop control	Can support the design of monitoring, warning, and regulation
Huang et al.	Food supply chain	Review and conceptual framework	Emphasises integration of perception-modeling-decision	Helps construct the virtual-real synchronisation mechanism
Lim et al.	Multi-echelon supply chain network	Dual-twin collaboration	Highlights cross-level state linkage	Can be used as a reference for node collaborative modelling
Mohan et al.	Green cold chain logistics	Emission reduction of refrigeration units	Focuses on emission control in the transport link	Can provide a reference for transport emission reduction analysis

With the gradual maturity of the supply chain digital twin framework, scholars have begun to pay attention to its evaluation logic and application boundaries. Freese et al. proposed the conceptual framework and evaluation idea of supply chain digital twin, and believed that the system should have basic structures such as object expression, data synchronisation, model update and result verification. Digital twin is not a general information platform, but a virtual-real collaborative system capable of continuous evolution [16]. Hossain et al. combined digital twin with supply chain disruption mitigation strategies, pointing out that digital twin has a strong supporting role in risk identification, strategy adaptation and recovery execution, and their research focus has been extended from state reproduction to operation optimisation in complex scenarios [17]. Monteiro et al. reviewed the research on digital twin from the perspective of regional food supply chain, and believed that the research object had been extended from the internal nodes of the enterprise to the cross-subject circulation network, and digital twin not only served the single operation link, but also served the regional logistics organisation and chain network cooperation [18]. Guo et al. discussed the role of digital twin from the perspective of lean supply chain management, pointing out that it can identify process waste, compress redundant links and improve resource allocation efficiency with fine-grained data, and promote the supply chain operation from experience-driven to data-driven [19].

Compared with the above studies, the green cold chain direction pays more attention to energy consumption control and emission optimisation. Mohan et al. studied the greenhouse gas emission reduction of transportation refrigeration units, and pointed out that the green of the cold chain cannot be simply understood as the shortening of transportation distance. The operation mode of refrigeration equipment, energy structure and transportation organisation mode will all affect the emission results, and cold chain emission reduction has obvious process coupling characteristics [20]. In general, the existing research has provided a foundation for the application of digital twins in the supply chain and food circulation, but there are still few systematic studies on the cold chain of fresh-cut flowers with high time-efficiency and high fresh-preservation requirements.

Existing results mainly focus on the manufacturing supply chain, agro-food network or transportation refrigeration, and lack discussion on the integrated mapping of the whole process of pre-cooling, storage, transportation and distribution. The research on carbon emission also mostly stays at the static accounting and local optimisation level, and the collaborative mechanism of dynamic monitoring, anomaly identification and intelligent regulation for operating state changes still needs to be deepened. In view of the above shortcomings, the fresh cut flower cold chain needs to establish a unified digital mapping relationship in the whole process of pre-cooling, storage, transportation and distribution, and link multi-source perception, carbon emission dynamic monitoring and regulation decision-making into the same technology chain, to improve the synergy of cold chain operation status recognition, emission perception and low carbon regulation.

3 Framework design of the digital twin system

3.1 Overall architecture of the system

The operation process of Yunnan cut flowers cold chain covers multiple links such as pre-cooling, cold storage, cold storage transportation and terminal distribution. There is a continuous coupling relationship between each node in terms of temperature control, operation cycle, equipment load and energy consumption emission. If relying on a single monitoring terminal or segmented information system, it is difficult to uniformly describe the state transfer, energy consumption fluctuation and carbon emission change in the cold chain process. Based on this, this paper builds the overall architecture of the digital twin-driven system, which maps the physical cold chain process and the virtual model space in a bidirectional way. The architecture is composed of a perception and acquisition layer, a data transmission layer, a twin modelling layer, a carbon monitoring layer, a regulation and decision layer, and an application interaction layer, in which the perception and acquisition layer is responsible for data acquisition of temperature and humidity, energy consumption, location, and operation duration. The twin modelling layer is responsible for node object modelling and process mapping. The carbon monitoring layer realises emission accounting of each link. The regulation decision layer outputs temperature control adjustment, path correction and job optimisation strategies. To illustrate the functions of each layer and their coupling relationships, Figure 1 shows the overall system architecture.

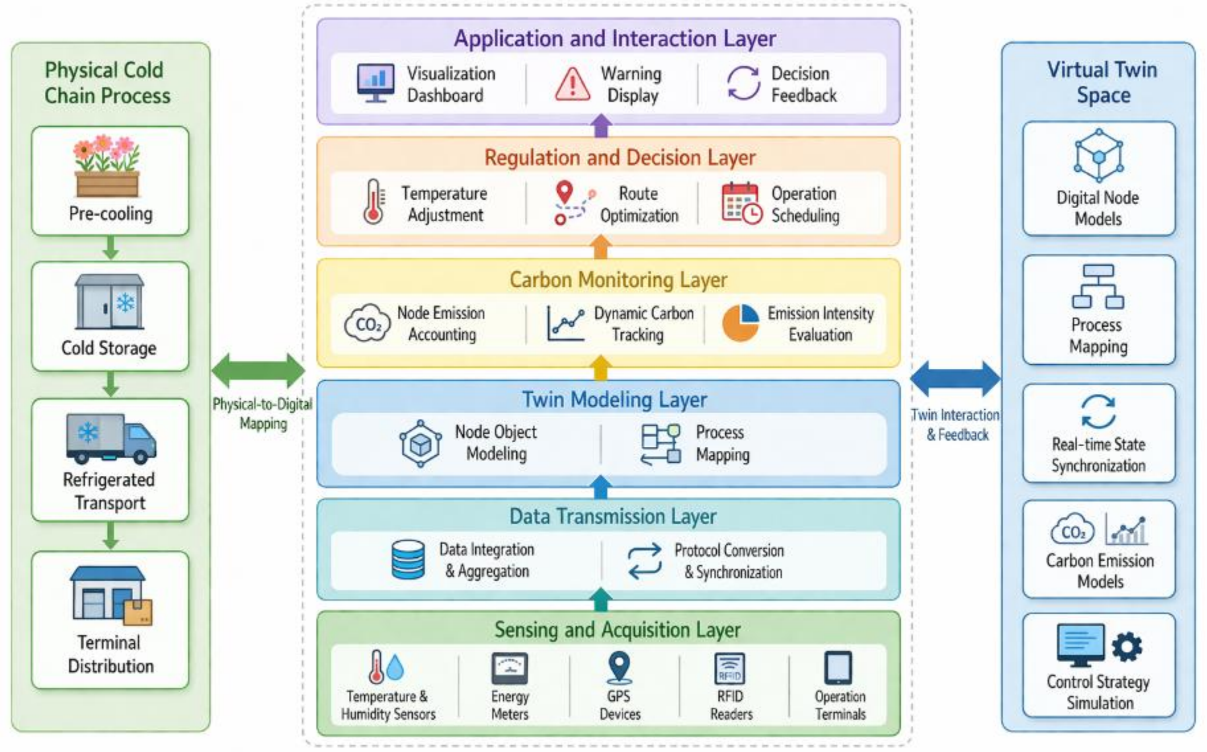

Figure 1: Overall Architecture Diagram of the Cold Chain System for Fresh Cut Flowers in Yunnan Driven by Digital Twin

In the above architecture, the comprehensive operational status of the system can be expressed as:

$$\Phi(t)=\sum_{i=1}^{m}\omega_i\,[\alpha_1 T_i(t)+\alpha_2 H_i(t)+\alpha_3 E_i(t)+\alpha_4 \tau_i(t)+\alpha_5 L_i(t)]+\sum_{i=1}^{m}\beta_i\,C_i(t)+\sum_{i=1}^{m-1}\sum_{j=i+1}^{m}\gamma_{ij}\,R_{ij}(t) \qquad (1)$$

where $\Phi(t)$ represents the comprehensive operation state value of the cold chain system at time t; m represents the total number of cold chain nodes; Let ω_i denote the state weight of the ith node; $T_i(t)$ is the node temperature. $H_i(t)$ is the node humidity; $E_i(t)$ represents the energy consumption of nodes. $\tau_i(t)$ is the node job duration; $L_i(t)$ represents the logistics load intensity of nodes. $\alpha_1 \sim \alpha_5$ are the influence coefficients of each state variable. $C_i(t)$ represents the carbon emission of the node; Let β_i denote the carbon emission weight; R_{ij} represents the coupling transfer strength between node i and node j; Letγij denote the inter-node coupling coefficient. The equation integrates the environment state, energy consumption state, emission state and node coupling relationship into a unified expression, which can provide a model basis for subsequent virtual-real synchronisation, emission monitoring and intelligent regulation.

In general, the architecture can not only realise the digital reconstruction of the entity process of the fresh cut flower cold chain, but also integrate the operation state recognition, carbon emission calculation and control strategy output into the same technology chain, which lays a foundation for the development of subsequent functional modules.

3.2 Digital mapping of the entity process of the fresh-cut flower cold chain

The key to the digital mapping of the physical process in the cold chain of fresh cut flowers is to transform the physical objects, environmental states, operation events and time relationships in each link of pre-cooling, storage, transportation and distribution into computable digital units. Yunnan fresh cut flower cold chain has the characteristics of a long circulation chain, frequent node switching, high ageing requirements and strong quality sensitivity. Temperature fluctuations, loading and unloading detention or abnormal equipment load in any link will be transmitted backwards along the process chain, affecting the fresh-keeping effect and operation energy consumption of subsequent nodes. Digital mapping is not a simple copy of the physical process, but a unified model is constructed around object attributes, state variables, event triggering, and node coupling, so that cut flower batches, pre-cooling equipment, cold storage units, refrigerated vehicles and distribution terminals can obtain recognisable and updatable counterparts in the virtual space. Figure 2 shows the entity process digital mapping structure of the fresh-cut flower cold chain.

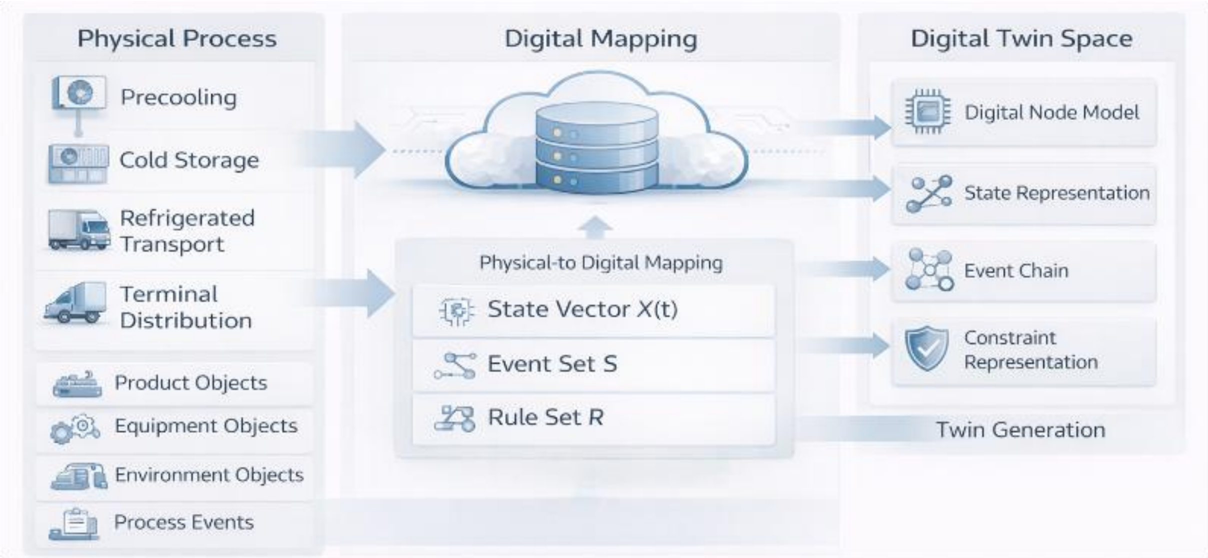

Figure 2: Digital mapping structure of the entity process of the fresh-cut flower cold chain

Node state mapping needs to complete state vector construction first. Let the state of the ith cold chain node at time t be expressed as follows.

$$X_i(t)=\{T_i(t),H_i(t),V_i(t),L_i(t),E_i(t),Q_i(t),\tau_i(t)\} \tag{2}$$

where $X_i(t)$ represents the node state vector, $T_i(t)$ is the node temperature. $H_i(t)$ is the node humidity; $V_i(t)$ represents the moving speed of logistics or the running speed of vehicles; $L_i(t)$ represents the node load level; $E_i(t)$ represents the real-time energy consumption of nodes. $Q_i(t)$ represents the quality state quantity of fresh cut flowers; Let $\tau_i(t)$ denote the node stay or job duration. This formula completes the unified coding of node states and provides the input basis for subsequent virtual-real mapping and synchronous updating.

After the state vector is determined, the mapping relationship between the physical object and the digital object can be written as follows.

$$D_i(t)=f[X_i(t),P_i,S_i,R_i] \tag{3}$$

where, $D_i(t)$ represents the mapping result of the ith node in digital space; f(.) Representation mapping function; P_i represents the physical attribute parameters of nodes. S_i represents the set of node job events. R_i denotes the node rule constraint. The mapping function not only reflects the state of the object itself, but also retains node attributes, job behaviours, and constraints, so that the digital twin can more accurately reproduce the characteristics of the entity process.

There is an obvious state transfer relationship between each node of the fresh-cut flower cold chain. The temperature control quality and operation time of the previous node will change the operation load of the subsequent nodes. The coupling relationship between nodes can be expressed as follows.

$$G_{ij}(t)=\lambda_1\Delta T_{ij}(t)+\lambda_2\Delta\tau_{ij}(t)+\lambda_3\Delta E_{ij}(t)+\lambda_4\Delta Q_{ij}(t) \quad (4)$$

where $G_{ij}(t)$ represents the coupling strength between node i and node j; $\Delta T_{ij}(t)$ is the temperature difference; $\Delta\tau_{ij}(t)$ is the time delay; $\Delta E_{ij}(t)$ represents the change of energy consumption; $\Delta Q_{ij}(t)$ represents the difference of quality states; λ_1 to λ_4 are the weight coefficients. This equation can be used to identify the transfer effects caused by insufficient precooling, storage fluctuations or transportation delays on subsequent links.

In order to further clarify the composition and digital expression focus of various mapping objects in the entity process of the fresh cut flowers cold chain, it is necessary to summarise the basic attributes of product objects, equipment objects, environment objects and process objects, and the relevant content is shown in Table 2.

Table 2: Fresh-Cut Flower Cold Chain Entity Mapping Objects and Main Attributes

Mapping Object Type	Typical Object	Main Attributes	Function of Digital Mapping
Product object	Flower batch, packaging unit	Variety, quantity, initial quality, and packaging method	Describes the basic characteristics of circulation objects
Equipment object	Precooling unit, cold storage equipment, refrigerated vehicle	Power, operating status, load level	Describes refrigeration and operation capability
Environment object	Precooling room, storage area, carriage, delivery point	Temperature, humidity, location, wind speed	Describes environmental changes at nodes
Process object	Warehousing, loading, transportation, signing	Timestamp, operation sequence, residence time	Describes the event chain and process rhythm

Through the above mapping method, the object state, event relationship and node coupling in the fresh cut flower cold chain entity process can be uniformly expressed, which provides a structured basis for subsequent multi-source data acquisition, virtual-real synchronisation, and carbon emission dynamic monitoring.

3.3 Multi-source data acquisition and virtual-real synchronisation

The operation process of the fresh cut flower cold chain involves environmental perception data, equipment operation data, logistics trajectory data and job event data. Different data sources have obvious differences in sampling frequency, transmission mode, time accuracy and data structure. Without a unified collection and synchronisation mechanism, it is difficult to form a continuous process chain among the data of precooling, storage, transportation and distribution links, and the twin state in the virtual space cannot truly reflect the changes of the entity process. The focus of multi-source data acquisition is to build a data input system covering the whole process, which unifies access to the data collected by temperature and humidity sensors, energy metering modules, vehicle GPS, RFID tags, cold storage controllers and operating terminals. Through timestamp correction, outlier elimination and field standardisation processing, the fusion of data from different nodes, different devices and different protocols is realised. Figure 3 shows the process of multi-source data acquisition and virtual-real synchronisation.

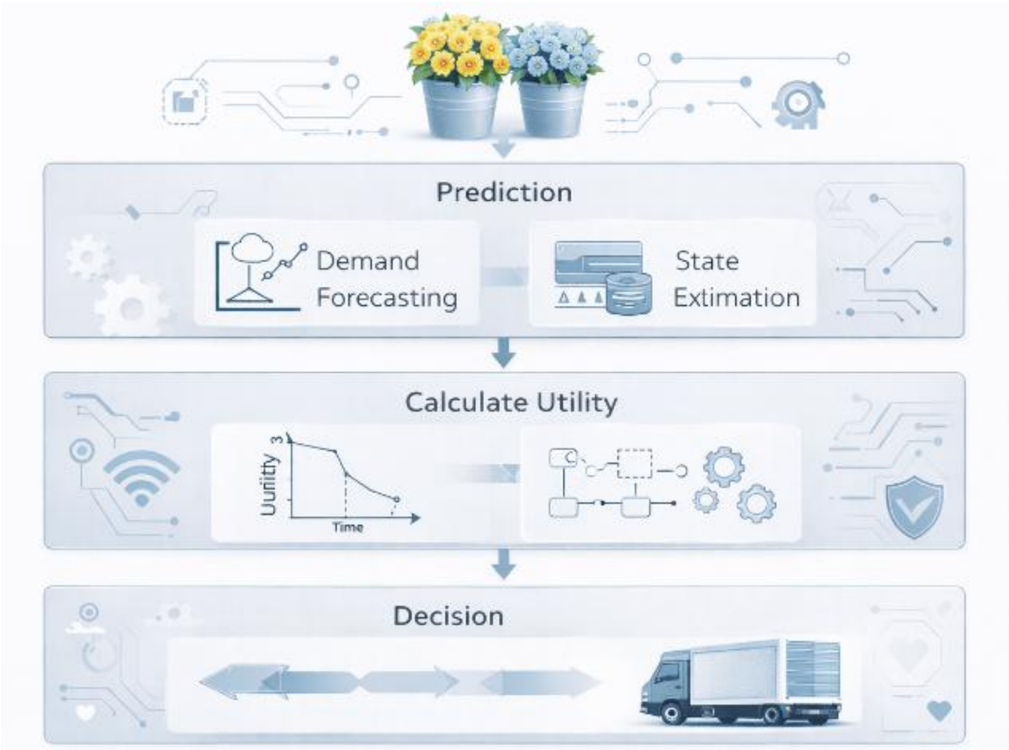

Figure 3: Flow chart of multi-source data acquisition and virtual-real synchronisation

The multi-source data fusion process can be expressed as follows.

$$Z(t)=\sum_{k=1}^{n} \omega_k z_k(t) \tag{5}$$

where Z(t) represents the fused data result at time t; $z_k(t)$ represents the collected value of the KTH data source. n is the number of data sources. Let ω_k denote the fusion weight of each data source. This formula is used to uniformly convert environment, equipment, trajectory and job data into twin model inputs.

The sampling time of different data streams is often not the same, and the time synchronisation error can be expressed as follows.

$$\varepsilon_t=|t_r-t_v| \tag{6}$$

where ε_t denotes the time synchronisation error, t_r represents the time of data recording on the entity side. t_v represents the state update time of the virtual side. This formula is used to measure the degree of deviation of the virtual-real system on the time axis.

After data fusion and time alignment, the twin state update process can be written as follows.

$$\widehat{X}(t+1)=\widehat{X}(t)+\beta\left[Z(t)-\widehat{X}(t)\right] \tag{7}$$

where, $\widehat{X}(t)$represents the virtual node state at time t; $\widehat{X}(t+1)$ represents the updated twin state; Let β denote the synchronisation correction coefficient. This formula enables the virtual model to be continuously modified according to the real-time acquisition results, and keeps the consistency with the entity process changes.

In order to improve the standardisation of multi-source data access and the subsequent synchronisation efficiency, different data types and their collection methods are shown in Table 3.

Table 3: Multi-Source Data Types and Collection Methods

Data Type	Collection Device	Collection Location	Main Purpose
Temperature and humidity data	Temperature and humidity sensor	Precooling room, cold storage, carriage	Monitors environmental status
Energy consumption data	Electricity meter, power meter	Precooling equipment, cold storage unit	Calculates equipment energy consumption
Trajectory data	GPS terminal	Refrigerated vehicle	Monitors transport location and route
Identity data	RFID tag	Flower batch, pallet unit	Identifies batch and circulation object
Operation data	Handheld terminal, controller	Warehousing, loading, and delivery node	Records operation events and timestamps

Through multi-source data acquisition, time alignment and status update, the discrete data in the cold chain entity process can be integrated into a continuous virtual-real synchronisation chain, which provides a reliable data basis for the subsequent dynamic monitoring and abnormal state identification of carbon emissions.

3.4 Dynamic monitoring model of carbon emission

The carbon emission of the fresh-cut flowers cold chain has significant process characteristics. Different from the staged summary method under static accounting conditions, the energy consumption level of precooling, storage, transportation and distribution will continue to change with environmental temperature, equipment load, operation time, loading status and path disturbance. The dynamic monitoring model needs to put the node operation status, equipment energy consumption and emission factor into a unified computing framework, so that the carbon emissions of the cold chain can be updated in real time with the progress of the process. In the model construction, pre-cooling equipment, cold storage units, refrigerated vehicles and distribution terminals are taken as the main emission units, and power consumption, fuel consumption, load change and operation time are included as monitoring variables, so as to form a sequential carbon emission expression for the whole process.

Node carbon emission monitoring can be expressed as follows.

$$C_i(t)=\left[\mu_1 P_i(t)\Delta t+\mu_2\int_{t_0}^{t}\left|T_i(\tau)-T_i^*\right|d\tau+\mu_3 L_i(t)\tau_i(t)\right]\gamma_i \tag{8}$$

where, $C_i(t)$ represents the carbon emission of the ith node at time t; $P_i(t)$ represents the real-time power of node equipment; Δt represents the monitoring interval; $T_i(\tau)$ represents the actual temperature of the node; T_i^* represents the target set temperature; $\int_{t_0}^{t}\left|T_i(\tau)-T_i^*\right|d\tau$ denotes the temperature control deviation cumulant. $L_i(t)$ represents the node load level; Let $\tau_i(t)$ denote the node job duration; μ_1, μ_2 and μ_3 represent the influence coefficients of power consumption, temperature control deviation and load duration, respectively. Let γi denote the node emission factor. This equation takes the equipment power, temperature control deviation and operation load into the node emission calculation, which can more truly reflect the emission fluctuation of pre-cooling and storage link.

The transportation link is affected by path length, vehicle load, refrigeration unit power and road running state, and it is easy to cause deviation by estimating mileage alone. The dynamic carbon emission of transportation can be expressed as follows.

$$C_{tr}(t)=\int_{t_0}^{t}\left[\eta_1 F(\tau)+\eta_2 P_r(\tau)+\eta_3 M(\tau)v(\tau)^{-1}+\eta_4\rho(\tau)\right]d\tau \tag{9}$$

where, $C_{tr}(t)$ represents the cumulative carbon emission of the transportation link before time t. $F(\tau)$ represents the fuel consumption rate or equivalent power consumption rate of the vehicle; $P_r(\tau)$ represents the operating power of the refrigeration unit; $M(\tau)$ represents the loading mass of the vehicle; $v(\tau)$ is the speed of the vehicle; $\rho(\tau)$ represents the road congestion or disturbance coefficient of working condition; η_1, η_2, η_3, and η_4 are the emission conversion coefficients of each impact factor. This equation can integrate vehicle driving consumption, refrigeration consumption and road condition disturbance into the transportation emission monitoring process.

At the whole process level, the carbon emission dynamic monitoring of the fresh cut flower cold chain should not only give the emission value of each node, but also reflect the emission intensity and abnormal degree of the unit batch. The comprehensive carbon emission intensity of the whole process can be expressed as follows.

$$I_c(t)=\frac{\sum_{i=1}^{m} C_i(t)+C_{tr}(t)}{Q(t)}\left(1+\kappa_1\frac{\sum_{i=1}^{m}\left|T_i(t)-T_i^*\right|}{m}+\kappa_2\frac{\sum_{i=1}^{m}\tau_i(t)}{\tau^*}\right) \tag{10}$$

where, $I_c(t)$ represents the integrated carbon emission intensity per unit batch at time t; m represents the total number of cold chain nodes; $Q(t)$ represents the quantity or quality of the current batch of fresh cut flowers; κ_1 represents the temperature control deviation correction coefficient; κ_2 is the time lag correction coefficient; Let τ^* denote the standard circulation duration. The equation introduces temperature control deviation and time delay correction on the basis of total emissions, which can identify additional emission risks caused by temperature anomalies and process lag.

The above model integrates node energy consumption, temperature control deviation, transportation conditions and batch circulation efficiency into a unified monitoring framework, which can provide a continuous quantitative basis for subsequent anomaly identification, early warning trigger and intelligent regulation.

3.5 Intelligent control mechanism design

The intelligent control of the fresh cut flower cold chain is not a local correction of a single node parameter, but a multi-objective collaborative optimisation mechanism is constructed around temperature control deviation, carbon emission intensity, operation delay and quality risk. The control layer receives the real-time state vector output from the twin model, and jointly updates the pre-cooling temperature setpoint, the operation intensity of the cold storage unit, the on-board cooling power and the distribution scheduling parameters, so that the system can reduce energy consumption and carbon emissions as much as possible under the condition of ensuring the fresh-keeping quality and aging requirements of fresh cut flowers. The regulation solution is essentially a constrained dynamic optimisation problem, and its comprehensive objective function can be expressed as follows.

$$\min J(t)=\lambda_1\sum_{i=1}^{m}E_i(t)+\lambda_2\sum_{i=1}^{m}C_i(t)+\lambda_3\sum_{i=1}^{m}\left|T_i(t)-T_i^*\right|+\lambda_4\sum_{i=1}^{m}\frac{\tau_i(t)-\tau_i^*}{\tau_i^*}+\lambda_5\sum_{i=1}^{m}\left|Q_i(t)-Q_i^*\right| \quad (11)$$

where, J(t) represents the comprehensive control target value at time t; m represents the number of cold chain nodes; $E_i(t)$ represents the energy consumption of the ith node. $C_i(t)$ represents the carbon emission of the node; Ti(t) represents the actual temperature of the node; Ti∗ denotes the target temperature; $\tau_i(t)$ is the node job duration; Let τ_i^* denote the standard job duration; $Q_i(t)$ represents the current quality state of cut flowers; Q_i^* denotes the desired quality state; λ_1~λ_5 are the weight coefficients of each objective item. The equation simultaneously restricts energy consumption, emission, temperature control error, time delay error and quality deviation, so that the regulation results give consideration to the low carbon target and fresh preservation requirements.

After the objective function is solved, the system iteratively updates the control vector by means of feedback correction, and the update rule can be written as follows.

$$u(t+1)=u(t)-\mu\nabla J(t)+K\left[X^*(t)-X(t)\right]+\sigma\Delta C(t) \quad (12)$$

where, u(t) represents the current control vector; u(t+1) represents the updated control vector; μ is the step size coefficient; Let $\nabla J(t)$ denote the gradient of the objective function; K represents the state feedback gain matrix; $X^*(t)$denotes the desired state vector; X(t) is the real-time state vector. ΔC(t) represents the deviation of carbon emission; Let σ denote the emission correction factor. The equation can introduce the state deviation feedback and emission deviation feedback into the regulation update process at the same time, and improve the adaptability of the control strategy to abnormal working conditions.

After updating the control vector, the state acquisition, exception determination, objective function solving and control instruction issuing should be integrated into a unified computing flow. In order to clearly describe the execution logic of the intelligent control module, Algorithm 1 gives the closed-loop control process of the digital twin system in the cold chain scenario of fresh-cut flowers.

Algorithm 1 Intelligent Regulation Mechanism
Input: real-time state vector X(t), target state X*(t), emission threshold set Θ
Output: control vector u(t+1)
Initialize twin state \hat{X}(t), control vector u(t), objective value J(t)
While the system is running do
  Acquire multimodal data stream from precooling, storage, transport, and delivery nodes
  Update twin state \hat{X}(t) by state synchronisation and feature fusion
  Compute node emission C_i(t) and batch emission intensity I_c(t)
  Evaluate temperature deviation, time-delay deviation, and quality deviation
  If C_i(t) >Θ_i or ||X(t)-X*(t)|| >εthen
    Solve constrained objective function J(t)
    Generate candidate control set U={temperature adjustment, power adjustment, routing adjustment, scheduling adjustment}
    Select optimal action u(t+1) with minimum objective value
    Dispatch control command to physical nodes
  Else
    Keep current control vector and continue monitoring
  End If

Feed execution result back to twin model
End While
Return u(t+1)

This mechanism connects real-time perception, state synchronization, goal solving, feedback iteration and control issuance into a unified closed loop, which can provide a computational basis for pre-cooling regulation, storage load control, transportation refrigeration optimization and distribution scheduling correction.

4 Experimental results and performance analysis

4.1 Experimental scenarios and data sources

The typical business chain in the cold chain circulation of fresh cut flowers in Yunnan is selected as the experimental scene, covering four links: post-harvest pre-cooling, cold storage, cold storage transportation and terminal distribution, and a test environment corresponding to the actual operation process is constructed. The data of temperature and humidity in the pre-cooling room, equipment power and batch cooling time were collected in the pre-cooling link. In the storage link, the data of cold storage temperature fluctuation, unit operating power, inventory residence time and in-out and in-out events were collected. In the transportation link, the data of vehicle position, carriage temperature, refrigeration unit power, running speed and road state were collected. The data of terminal residence time, environmental exposure time and signing completion time were collected in the distribution link. To ensure the continuity and contrast of the experimental results, the scene data were collected from the real-time sensor collection, the vehicle terminal record and the operation log summary at the same time. Figure 4 shows the experimental scenario and the relationship between data flow.

Figure 4: Experimental scenario and data source structure diagram

Different experimental links have obvious differences in the number of monitoring objects, sampling frequency, monitoring period and effective data amount, which will directly affect the subsequent carbon emission monitoring accuracy and regulation effect analysis. In order to improve the completeness of the description of the experimental scene, the data sources and their statistical characteristics of each link are summarised, and the relevant content is shown in Table 4.

Table 4: Statistics of Experimental Scenarios and Data Sources

Link	Number of Monitoring Objects	Sampling Frequency	Monitoring Period	Valid Data Volume	Main Data Content
Precooling	6 groups of precooling equipment, 18 batches	1 time/min	7 d	6048	Temperature and humidity, equipment power, and cooling time
Storage	2 cold storage areas, 24 cargo locations	1 time/5 min	10 d	5760	Storage temperature, unit power, residence time, inbound and outbound records
Transport	4 refrigerated vehicles, 16 trips	1 time/min	8 d	9216	GPS location, operating speed, carriage temperature, refrigeration power
Delivery	5 delivery nodes, 20 batches	1 time/10 min	6 d	1728	Residence time, exposure time, signing time
Total	—	—	—	22752	Multi-source experimental data of the whole cold chain process

4.2 Evaluation index setting

In order to test the monitoring ability and regulation effectiveness of the digital twin system in the cold chain scenario of fresh cut flowers, the evaluation indicators were carried out from four dimensions: monitoring accuracy, anomaly identification, response efficiency and emission reduction effect. Index design not only serves for result comparison, but also undertakes the role of model output verification, state identification verification and regulation performance quantification. The monitoring accuracy is used to measure the deviation degree between the output carbon emission value of the system and the reference measured value, the anomaly recognition rate is used to test the system's ability to capture abnormal conditions such as temperature control imbalance, energy consumption sudden increase and operation delay, the response time reduction rate is used to reflect the linkage efficiency of the early warning link and the regulation link, and the emission reduction rate is used to evaluate the low-carbon optimization effect of the overall operation of the system after investment.

The monitoring error is expressed by the mean absolute percentage error and is calculated as follows.

$$\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{C_i^{ref}-C_i^{pre}}{C_i^{ref}}\right|\times 100\% \qquad (13)$$

In the formula, MAPE represents the average absolute percentage error; n represents the number of samples; C_i^{ref} represents the reference carbon emission value of the i-th sample; C_i^{pre} represents the system monitoring value.

The abnormal recognition rate can be expressed as:

$$R_a=\frac{N_{tp}}{N_{tp}+N_{fn}}\times 100\% \tag{14}$$

where, R_a represents the anomaly recognition rate; N_{tp} represents the number of correctly identified anomaly samples. N_{fn} represents the number of abnormal samples that are not identified.

The early warning response time reduction rate is calculated as follows.

$$\eta_t=\frac{T_0-T_1}{T_0}\times 100\% \tag{15}$$

where, η_t represents the response time reduction rate; T_0 represents the average response time of the original system; T_1 represents the average response time of the digital twin system.

The comprehensive emission reduction rate is expressed by the comparison of carbon emissions before and after regulation, and the calculation formula is as follows.

$$\eta_c=\frac{C_0-C_1}{C_0}\times 100\% \tag{16}$$

where, η_c represents the comprehensive emission reduction rate; C_0 represents the total carbon emission before regulation; C_1 represents the total amount of carbon emissions after regulation.

There are differences in sample sources and judgment criteria for each evaluation index. In order to ensure the consistency of subsequent result analysis, the calculation object and judgment basis of the core index are uniformly set, and the specific content is shown in Table 5.

Table 5: Evaluation Index Judgment Criteria

Index Name	Calculation Object	Judgment Basis
Monitoring error	Monitored carbon emission value and reference value of each node	Less than 8%, based on measured converted value
Anomaly recognition rate	Labeled anomaly event samples	Greater than 90%, based on manual review results
Response time reduction rate	Anomaly warning and disposal process	Greater than 20%, compared with the original manual process
Comprehensive emission reduction rate	Whole-process emission data before and after regulation	Greater than 5%, based on the emission level without regulation

The above indicators can reflect the comprehensive performance of the system in monitoring, identification, response and emission reduction more completely, and the subsequent analysis will be carried out accordingly.

4.3 Analysis of the dynamic monitoring effect of carbon emission

The dynamic monitoring effect of carbon emission is mainly analysed from three aspects: monitoring accuracy, node adaptability and anomaly recognition ability. In the experiment, four types of nodes, including pre-cooling, storage, transportation and distribution, were taken as objects, and the carbon emission monitoring values output by the system were compared with the reference values obtained by the measured energy consumption and emission factor conversion. At the same time, the abnormal state recognition results were statistically analysed by combining the labelled abnormal event samples. The results show that the digital twin system can track the carbon emission change trend of different nodes more stably, the monitoring curve is consistent with the reference curve as a whole, and it still has a good fitting effect in the period of large load fluctuation and strong temperature control disturbance. Figure 5 shows the comparison between the change in the carbon emission monitoring value and the reference value in a typical experimental cycle.

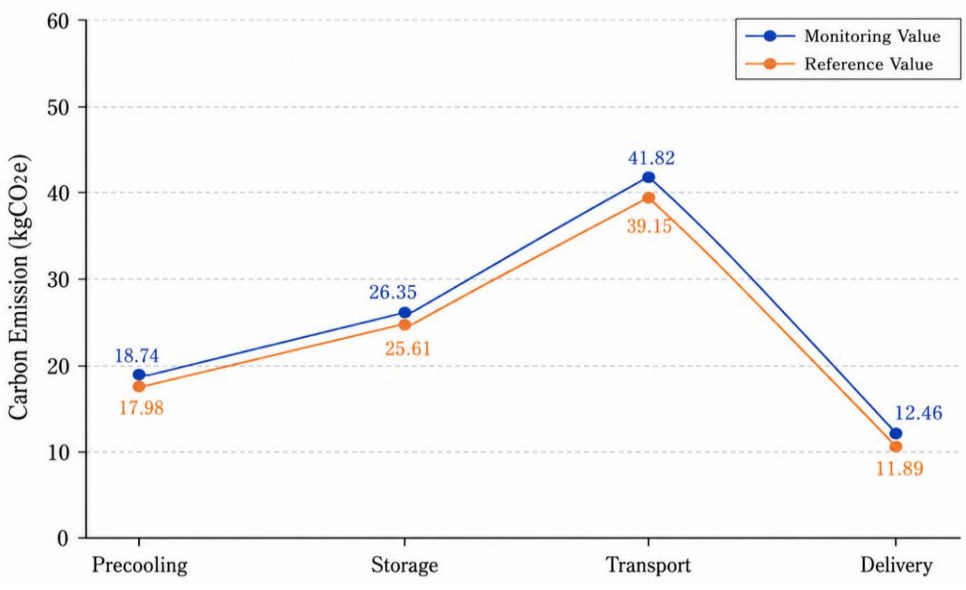

Figure 5: Comparison of carbon emission monitoring values and reference values

From the results of the sub-nodes, the monitoring error of the pre-cooling and storage links is relatively small; the main reasons are that the equipment operating boundary is more stable, the power change law is clearer, and the model has a strong ability to fit the state of the fixed scene. The transportation and distribution link is greatly affected by road state, docking frequency and environmental exposure duration, and the error level is slightly higher, but overall is still within a controllable range. Table 6 shows the statistics of the monitoring results of each node.

Table 6: Dynamic Monitoring Results of Carbon Emissions at Each Node

Link	Average Monitoring Value /(kgCO2e)	Reference Value /(kgCO2e)	Relative Error /%	Anomaly Recognition Rate /%
Precooling	18.74	17.98	4.2	94.1
Storage	26.35	25.61	2.9	95.3
Transport	41.82	39.15	6.8	92.7
Delivery	12.46	11.89	4.8	91.6
Average	24.84	23.66	4.7	93.4

The average monitoring error of the system for carbon emissions of the four types of nodes is 4.7%, and the maximum error occurs in the transportation link, which is 6.8%, still not exceeding the accuracy range set in the abstract. The anomaly recognition rate reaches 93.4% on average, which indicates that the system can effectively identify temperature control anomaly, energy consumption surge and emission fluctuation caused by operation delay. Overall, the digital twin system has a good dynamic perception ability of carbon emissions in the cold chain scenario of fresh cut flowers, which can provide more reliable data support for subsequent early warning triggering and intelligent regulation.

4.4 Analysis of intelligent regulation effect

The effect analysis of intelligent control mainly investigated the state feedback speed of the digital twin system after the abnormal trigger, the efficiency of control strategy generation and the improvement of operation indicators after execution. In the experiment, the control layer takes real-time state vector, carbon emission intensity and node deviation as input, and jointly corrects the pre-cooling setting temperature, cold storage unit power, vehicle cooling intensity and distribution scheduling parameters. The control process operates in a closed-loop mode of "anomaly detection -- state evaluation -- candidate policy generation -- objective function solver -- control instruction issuance -- result writeback". The anomaly detection module is responsible for identifying temperature control deviation, energy consumption surge and time delay accumulation, and the policy generation module constructs a candidate control set according to constraints. The control layer selects the optimal strategy according to the comprehensive objective function and sends it to the entity node. Figure 6 shows the comparison results of the main operation indicators before and after the investment of intelligent regulation.

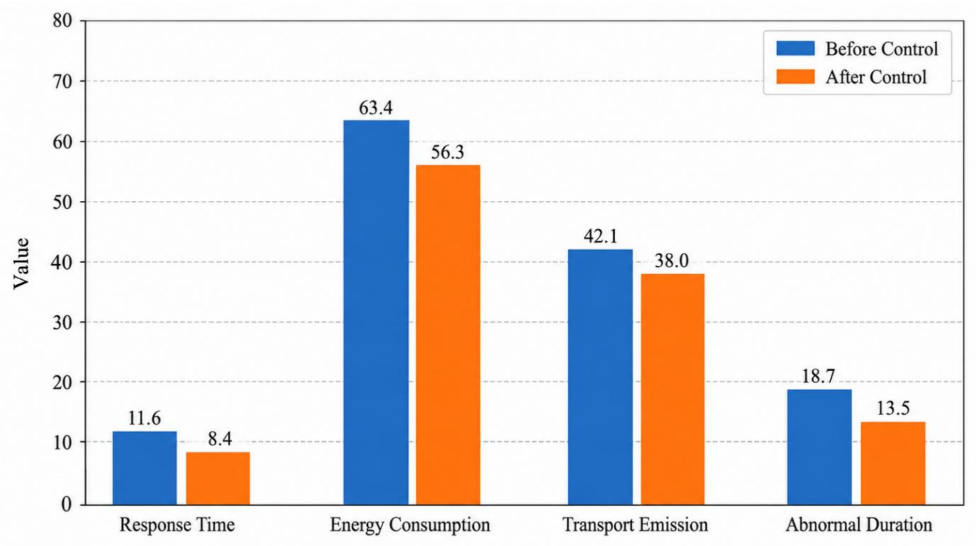

Figure 6: Comparison of main operating indicators before and after intelligent control

From the perspective of the control link, the original mode mainly relies on manual interpretation and step-by-step disposal, and there is an obvious time delay between data upload, anomaly confirmation and execution feedback. Especially in transportation and distribution scenarios, node distribution is discrete and road conditions fluctuate frequently, which makes it difficult for control instructions to act on the entity system in time. After the digital twin system is connected, the edge acquisition end writes the temperature, power, position, operation time and other data into the twin model in real time. The model layer quickly triggers the early warning decision according to the state residual and emission deviation, and the optimisation module updates the control vector according to the current load, standard temperature control interval and time constraints, so that the control decision is changed from serial manual disposal to parallel computing driven. The test results show that the average warning response time of the system is reduced from 11.6 minutes to 8.4 minutes, and the reduction is 27.6%, which indicates that the digital twin closed-loop mechanism has obvious advantages in shortening the time link from state recognition to control execution.

At the level of energy consumption and emission reduction, the regulatory effect is mainly reflected in two types of mechanisms. One class is an operating parameter correction oriented to fixed nodes. The pre-cooling and storage link dynamically adjusted the start-stop threshold and power output interval of the unit by comparing the deviation between the set temperature and the actual temperature in real time, which reduced the ineffective energy consumption caused by frequent switching of equipment and excessive cooling. The other category is the joint scheduling correction for mobile nodes. In the transportation scenario, the system synchronously corrects the intensity of the refrigeration unit and the distribution sequence according to the temperature fluctuation of the carriage, the vehicle loading quality and the road condition disturbance coefficient, so as to reduce the emission load per unit time in the transportation stage. The distribution link reduces the terminal compensation cooling demand by compressing the docking time and reducing the environmental exposure time. The relevant results are shown in Table 7.

Table 7: Comparison of Intelligent Regulation Effects

Index	Before Regulation	After Regulation	Change Range
Average warning response time /min	11.6	8.4	-27.6%
Comprehensive energy consumption per batch /(kWh/batch)	63.4	56.3	-11.2%
Carbon emissions in transport link /(kgCO2e/vehicle-trip)	42.1	38.0	-9.7%
Duration of temperature control abnormality /min	18.7	13.5	-27.8%
Average operation delay /min	9.3	7.1	-23.7%

After the investment in intelligent regulation, the comprehensive energy consumption per unit batch was reduced from 63.4 kWh to 56.3 kWh, with a reduction of 11.2%. Carbon emissions from transport decreased from 42.1 kgCO2e/ vehicle to 38.0 kgCO2e/ vehicle, a decrease of 9.7%. The abnormal duration of temperature control and the average operation delay decreased synchronously, indicating that the control strategy not only plays a role in a single energy consumption index, but also forms a linkage optimisation of state stability, scheduling efficiency and emission control. On the whole, the digital twin system has strong state feedback, control calculation and execution coordination capabilities, which can provide stable technical support for the low-carbon operation of the fresh cut flower cold chain.

4.5 Comparison of system performance

In order to further verify the comprehensive applicability of the digital twin system in the cold chain scene of fresh flowers, this paper compared it with the traditional manual monitoring method and the conventional Internet of Things monitoring system. The comparison dimensions include carbon emission monitoring error, anomaly recognition rate, average response time, and comprehensive emission reduction rate. The traditional manual monitoring method mainly relies on manual inspection and segmentation recording, and the data update cycle is long, and the anomaly identification has an obvious lag in anomaly identification. The conventional IoT monitoring system can collect node data online, but there are still limitations in cross-node correlation modelling, emission dynamic calculation and control linkage. The digital twin system connects monitoring, identification, analysis and execution into a unified technology chain through entity process mapping, state synchronous update and regulation closed-loop computation. Figure 7 shows the standardised comparison results of the three systems on the main performance metrics.

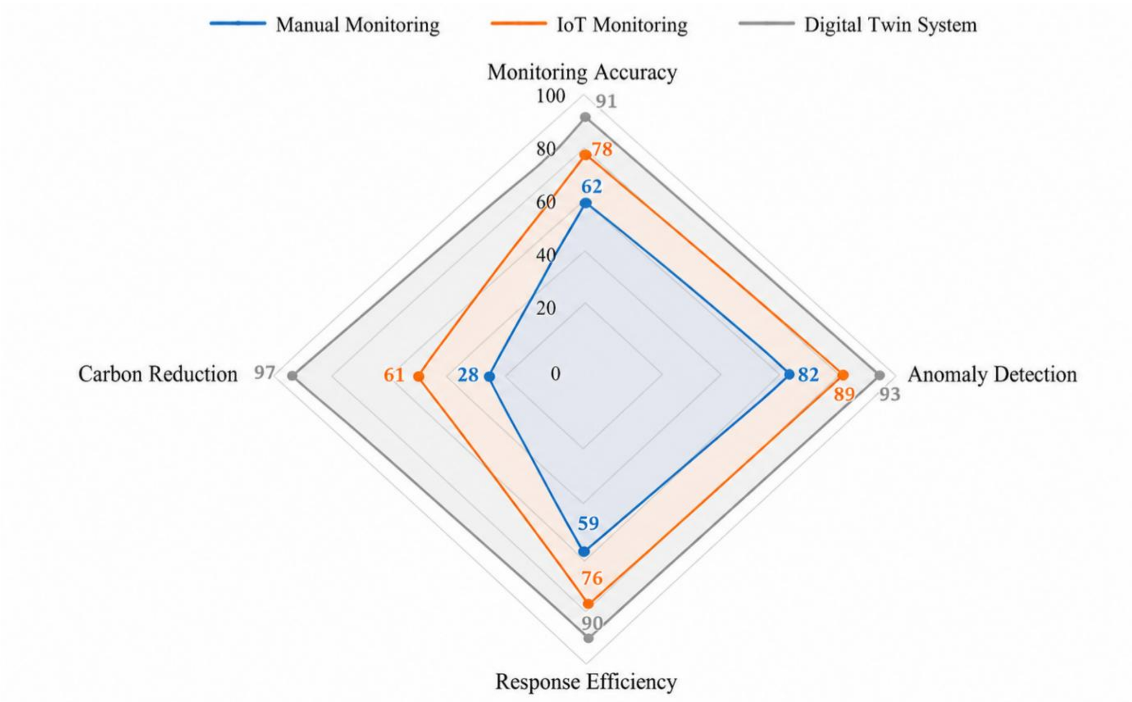

Figure 7: Standardised comparison of main performance indicators of different systems

From the standardised results, the digital twin system is better than the control scheme in the dimensions of monitoring accuracy, anomaly identification, response efficiency and emission reduction ability. To illustrate the comparison results more intuitively, the main performance data are summarised, as shown in Table 8.

Table 8: Comparison of Different System Performance

System Type	Monitoring Error /%	Anomaly Recognition Rate /%	Average Response Time /min	Comprehensive Emission Reduction Rate /%
Manual monitoring system	12.4	81.7	14.2	2.8
Conventional IoT system	8.9	88.6	10.7	6.1
Digital twin system	4.7	93.4	8.4	9.7

The digital twin system shows stronger advantages in monitoring accuracy, anomaly identification and response efficiency, and the comprehensive emission reduction rate has reached the highest level. This shows that in the cold chain scenario of fresh cut flowers, it is difficult to meet the requirements of low-carbon pipe control in the whole process by relying solely on manual recording or general online monitoring, and the digital twin system has higher comprehensive performance in engineering applications.

5 Conclusion

Focusing on the problems of decentralised state perception, lagging carbon emission monitoring and insufficient regulation linkage in the operation process of Yunnan fresh cut flowers cold chain, this paper constructed a framework of carbon emission dynamic monitoring and an intelligent regulation system driven by a digital twin. The system was designed from the aspects of the overall system architecture, entity process digital mapping, multi-source data acquisition, virtual-real synchronisation, carbon emission dynamic monitoring model and intelligent regulation mechanism. Pre-cooling, storage, transportation and distribution are integrated into the digital space, and the cold chain node states, equipment operating parameters, process events and emission variables are expressed collaboratively, forming a closed-loop technology chain from data acquisition, state modelling, emission calculation, to regulation and execution. In the experimental part, the monitoring ability and control performance of the system are verified by combining with a typical cold chain circulation scenario of fresh-cut flowers.

The experimental results show that the constructed system can well track the carbon emission changes of key nodes in the fresh cut flower cold chain, the monitoring error is controlled within 6.8%, and the abnormal state recognition ability and early warning response efficiency show a good level. After the investment in intelligent regulation, the system has made significant improvements in comprehensive energy consumption control and transportation link emission reduction, indicating that the digital twin technology can improve the state perception accuracy, regulation efficiency and low-carbon operation ability in the operation process of the fresh cut flower cold chain. On the whole, this study provides a feasible technical path for the digitalisation, low-carbon, and intelligent management of the Yunnan cut flower cold chain. Further research can be carried out to further improve the model accuracy, cross-scenario adaptability and system generalisation ability by combining a larger range of samples, multi-season operating conditions and more fine-grained emission parameters.

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