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Research on Optimization of Fresh Cold Chain Based on PCM Passive Temperature Control and Intelligent Algorithms

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Abstract. Against the background of rapid development in the fresh food industry and increasing demand for green and low-carbon logistics, traditional cold chain systems face prominent pain points such as unstable temperature control, high energy consumption, and inefficient scheduling. Taking Muyangsu Cold Chain Co., Ltd. as the research object, this paper proposes a comprehensive optimization scheme integrating PCM passive temperature control, intelligent algorithms, and 5G Internet of Things. By constructing a multi-objective optimization model, introducing improved Sparrow Search Algorithm and Reinforcement Learning-based Whale Optimization Algorithm, and building a combined prediction model, the study systematically optimizes temperature stability, scheduling efficiency, and risk management. The results show that the proposed scheme significantly reduces energy consumption and loss rate while improving logistics efficiency and service reliability. This research provides a replicable technical framework and practical reference for the high-quality development of the fresh cold chain. In addition, this study conducts in-depth investigation and analysis of the company's current operation status and existing problems. The research systematically constructs a multi-dimensional risk assessment and prevention system for cold chain transportation. The proposed technical solution is verified through simulation and real-scenario testing. The research results offer clear guidance for the practical transformation and upgrading of cold chain enterprises. It also provides valuable insights for promoting standardized and intelligent development in the fresh cold chain industry.

Keywords: Fresh cold chain; CPM passive temperature control; intelligent algorithm; cold chain optimization.

1. Introduction

With the rapid growth of fresh e-commerce, the continuous upgrading of residents' consumption, and the vigorous promotion of national policies such as "dual carbon" and rural revitalization, the fresh cold chain industry has entered a critical period of high-quality development [1,2]. As an important link connecting agricultural production and consumer markets, the cold chain directly determines the quality and safety of fresh products, as well as the operational efficiency and sustainability of enterprises [3]. However, traditional cold chain operations, which rely mainly on mechanical refrigeration and manual scheduling, still face prominent challenges, including frequent temperature fluctuations, high energy consumption, excessive product loss, low scheduling efficiency, and weak risk management capabilities [4, 5]. These bottlenecks not only increase operational costs but also restrict the stable development of the fresh supply chain [6].

In recent years, scholars worldwide have carried out extensive research on cold chain optimization. In terms of temperature control, many studies have verified the energy-saving and temperature-stabilizing effects of phase change material (PCM) passive temperature control technology in cold chain scenarios [7,8]. PCM-based insulation structures and composite cold storage materials have been widely used in packaging, vehicles, and warehouses, effectively reducing temperature fluctuations and refrigeration energy consumption. Meanwhile, intelligent optimization algorithms, such as particle swarm optimization and genetic algorithms, have been widely applied to solve scheduling and path planning problems [9, 10]. In addition, with the development of the Internet of Things (IoT) and big data, real-time monitoring and early warning systems have gradually become research hotspots, providing technical support for the digitization of cold chains. Nevertheless, most existing studies focus on single technology or isolated links, lacking systematic integration of PCM technology, intelligent algorithms, and the Internet of Things. Many studies only optimize temperature control or distribution routes separately, ignoring the close coupling among temperature stability, scheduling efficiency, and risk prevention. Moreover, most models do not comprehensively consider uncertain factors such as real-time temperature changes, road congestion, and equipment failures, resulting in insufficient practical guidance for enterprises. There is still a research gap in constructing a closed-loop, multi-dimensional optimization framework for fresh cold chains.

Against this background, taking Muyangsu Cold Chain Co., Ltd. as the research object, this paper proposes an integrated optimization scheme for fresh cold chain operations. The scheme combines PCM passive temperature control, improved intelligent algorithms, and 5G Internet of Things technology, and establishes a multi-objective optimization model covering temperature stability, scheduling efficiency, and risk control. The marginal contributions of this study are as follows: First, a multi-technology fusion framework is constructed to break the limitations of single-technology research and realize the coordinated optimization of multiple links. Second, improved Sparrow Search Algorithm and Reinforcement Learning-based Whale Optimization Algorithm are introduced to enhance the accuracy and robustness of scheduling and prediction. Third, a multi-dimensional risk assessment and prevention system is developed to ensure the safe and stable operation of the cold chain. This research provides practical solutions for the transformation and upgrading of Muyangsu Cold Chain.

2. Integrated Optimization Framework and Core Technologies

2.1. Overall framework design

With the continuous expansion of the fresh food market and the accelerated integration of digital technology and logistics industry, the fresh cold chain has become a critical link connecting agricultural production and consumer consumption. However, traditional cold chain operations still rely on mechanical refrigeration and manual scheduling, which leads to a series of prominent problems such as unstable temperature, high energy consumption, excessive product loss, and low operational efficiency. These bottlenecks not only increase the operating costs of cold chain enterprises but also restrict the sustainable development of the entire fresh supply chain. To address these challenges, this study constructs an integrated optimization framework that combines PCM passive temperature control, improved intelligent algorithms, and 5G Internet of Things technology.

The overall framework is divided into three interconnected layers: data perception layer, algorithm decision layer, and business application layer. The data perception layer serves as the foundation of the entire system, collecting real-time temperature, humidity, vehicle status, equipment parameters, and order information through distributed 5G IoT sensors and terminal devices. The algorithm decision layer is the core engine of the framework, integrating multiple improved intelligent algorithms to achieve demand forecasting, dynamic scheduling, path optimization, and risk early warning. The business application layer provides visualized and standardized management interfaces for cold chain enterprises, covering equipment monitoring, scheduling management, performance analysis, and risk prevention. The overall architecture is illustrated in Figure 1.

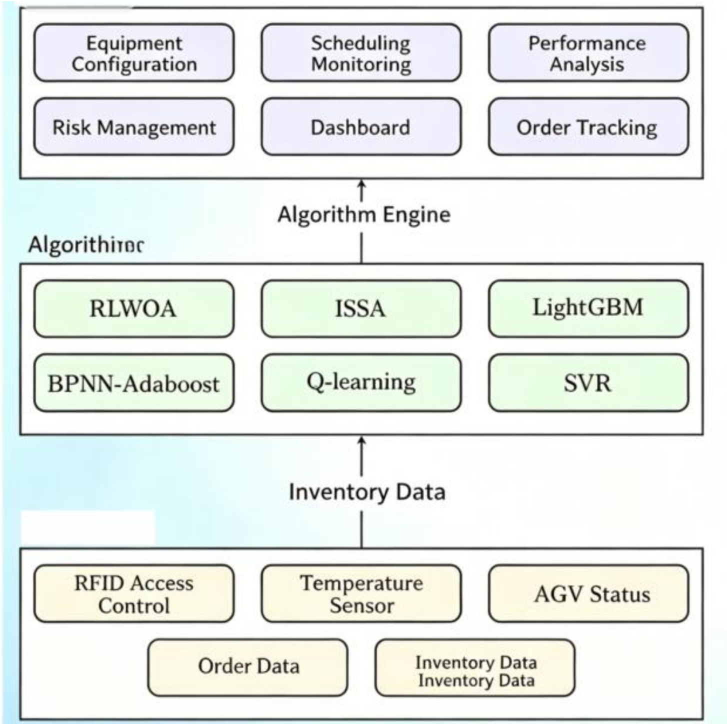

Figure 1. Overall framework of the integrated optimization system.

The proposed framework breaks the limitations of single-technology application and realizes the organic integration of temperature control, scheduling, and risk management. It provides a systematic and replicable technical solution for the green and intelligent transformation of fresh cold chain enterprises.

2.2. PCM Passive temperature control technology

2.2.1. Basic principle

Traditional cold chain transportation relies on mechanical refrigeration systems, which must be continuously driven by vehicle engines. This active refrigeration mode has inherent defects: when the vehicle is idling or stopped, the refrigeration system shuts down, leading to rapid temperature rise inside the compartment. During loading and unloading, frequent door openings cause massive heat intrusion, resulting in severe temperature fluctuations. These issues are the main causes of fresh product spoilage and quality degradation.

To solve the above problems, this study adopts Phase Change Material (PCM) passive temperature control technology. PCM is a kind of functional material that can absorb or release a large amount of latent heat during the solid–liquid phase transition process while maintaining a nearly constant temperature. The core heat balance equation of passive temperature control is:

$$Q_{\text{leak}}=m_{\text{PCM}}\cdot\Delta H+m_{\text{PCM}}\cdot c_p\cdot\frac{dT}{dt} \tag{1}$$

Where Q_{leak} represents the total heat leakage into the container, m_{PCM} is the mass of the phase change material, ΔH denotes the phase change enthalpy, c_p is the specific heat capacity, and dT/dt reflects the rate of temperature change. By combining PCM with Vacuum Insulation Panels (VIP), the overall thermal resistance of the container is significantly enhanced, which effectively suppresses heat exchange with the external environment and maintains the internal temperature within a stable range of ±1°C.

2.2.2. Material performance and experimental verification

To ensure the reliability and durability of passive temperature control, this study selects fatty acid-based composite PCM doped with 12% expanded graphite (EG) as the core material. Compared with pure fatty acid PCM, the composite PCM has significantly improved thermal conductivity, reduced supercooling degree, and enhanced cycle stability. A comprehensive performance comparison is presented in Table 1.

Table 1. The impact of six decision variables.

Index	Pure Fatty Acid PCM	Composite PCM (12% EG)	Improvement Rate
Phase Change Temperature (°C)	7.5	7.3	—
Latent Heat of Phase Change (J/g)	159.1	146.7	-7.8%
Thermal Conductivity (W/(m·K))	0.18	1.92	+967%
Leakage Rate (50°C, 8h)	28.7%	2.1%	-92.7%
Supercooling Degree (°C)	3.2	0.8	-75%
Temperature Control Duration at 2~8°C (min)	320	510	+59.4%
Temperature Fluctuation (°C)	±1.5	±0.4	-73.3%

Experimental results show that the composite PCM has a phase change enthalpy of 146.7 J/g and a thermal conductivity of 1.92 W/(m·K), which is 9.67 times higher than that of pure PCM. The leakage rate is reduced from 28.7% to 2.1%, and the supercooling degree is controlled within 0.8°C. After 1000 freeze–thaw cycles, the attenuation rate of phase change enthalpy is only 12.3%, indicating excellent long-term stability.

2.3. Improved intelligent algorithms for prediction and scheduling

2.3.1. STL-SARIMA-ETS-SVR combined prediction model.

Accurate demand forecasting is the premise of efficient cold chain scheduling. Traditional single prediction models often fail to capture the complex nonlinear and seasonal characteristics of fresh demand, resulting in low prediction accuracy. To address this issue, this study proposes a hybrid prediction model integrating STL decomposition, SARIMA, ETS, and SVR algorithms.

The model first uses STL (Seasonal-Trend decomposition using Loess) to decompose the original time series into three components: trend ($\mathrm{T_t}$), seasonal ($\mathrm{S_t}$), and residual ($\mathrm{R_t}$):

$$\mathrm{y_t} = \mathrm{T_t} + \mathrm{S_t} + \mathrm{R_t} \tag{2}$$

Subsequently, SARIMA is applied to fit the trend and residual components to capture linear autocorrelation and seasonal patterns. The ETS (Error-Trend-Seasonal) model is used to model the seasonal component and smooth fluctuations. The SVR (Support Vector Regression) algorithm is employed to fit the nonlinear residual and improve the model’s ability to capture complex relationships. Finally, the weighted fusion method based on inverse error is adopted to integrate the prediction results of each sub-model:

$$\hat{y}_{\mathrm{Comb},h} = w_1 \hat{y}_{\mathrm{STL},h} + w_2 \hat{y}_{\mathrm{ETS},h} + w_3 \hat{y}_{\mathrm{SVR},h} \tag{3}$$

Where $\mathrm{w_1, w_2, w_3}$ are the weights determined by the inverse of the mean absolute percentage error (MAPE) of each sub-model. The results show that the combined model achieves a coefficient of determination ($\mathrm{R^2}$) of 0.8578 and a MAPE of less than 0.23, which is significantly better than single models such as SARIMA, ETS, and SVR. The demand prediction curve is presented in Figure 2.

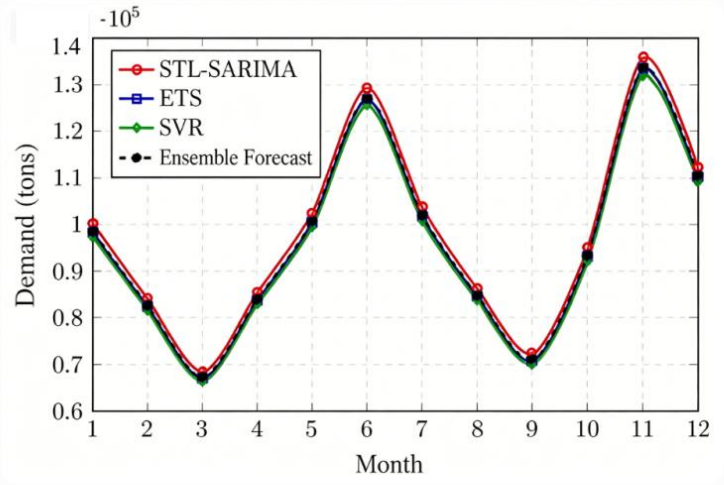

Figure 2. Comparison of demand prediction results.

2.3.2. Improved sparrow search algorithm

Efficient scheduling is crucial for reducing empty driving and improving resource utilization. Traditional Sparrow Search Algorithm (SSA) has limitations such as uneven initial population distribution and easy trapping in local optima when solving complex multi-AGV joint scheduling problems. To overcome these shortcomings, this study proposes an Improved Sparrow Search Algorithm (ISSA) with three core optimizations.

First, Tent chaotic mapping is introduced to initialize the population, which enhances population diversity and uniformity. Second, an adaptive parameter adjustment strategy is designed to dynamically adjust the safety threshold, discoverer ratio, and vigilante ratio during iteration. Third, genetic operators including crossover and mutation are integrated to improve the algorithm's ability to jump out of local optima. The position update formula for discoverers in ISSA is:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \exp\left(-\dfrac{i}{\alpha T}\right), & R_2 < ST \\ X_{i,j}^{t} + Q \cdot L, & R_2 \geq ST \end{cases} \tag{4}$$

Where R_2 is the warning value, ST is the safety threshold, α is a random number, Q follows a normal distribution, and L is an all-ones vector. Simulation results on multiple standard datasets show that ISSA reduces the maximum completion time by approximately 25% compared with SSA, and the convergence speed is increased by 30%. The convergence curves of ISSA and SSA are shown in Figure 3.

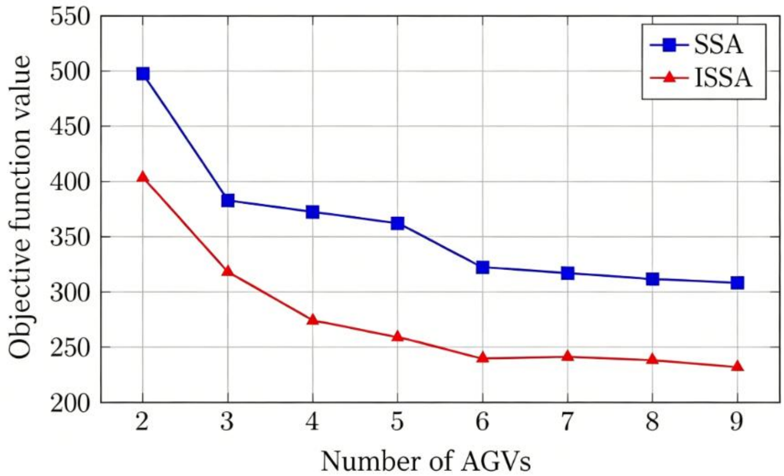

Figure 3. Convergence curve of ISSA and SSA.

2.3.3. Reinforcement Learning-Enhanced Whale Optimization Algorithm

The hyperparameter selection of machine learning models significantly affects prediction accuracy. Traditional Whale Optimization Algorithm (WOA) relies on fixed probability strategies, which are prone to local optima. This study proposes a Reinforcement Learning-enhanced Whale Optimization Algorithm (RLWOA) by introducing Q-learning.

The Q-learning agent dynamically selects three update strategies (encircling prey, spiral hunting, random search) according to the current population state. The Q-value update formula is:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \underset{a}{max} Q(S_{t+1}, a) - Q(S_t, A_t)] \quad (5)$$

Where α is the learning rate, γ is the discount factor, and R_{t+1} is the reward function. RLWOA is used to optimize the hyperparameters of the LightGBM supply prediction model. The optimization results are shown in Table 2.

Table 2. Hyperparameter optimization results of RLWOA-LightGBM

Prediction Category	R2	MSE	MAPE	Optimal Hyperparameter Combination
Pallet Outbound Supply	0.821	52.6	0.213	(165, 8, 0.08, 5)
Case Outbound Supply	0.789	38.7	0.228	(150, 6, 0.12, 4)
Unit Outbound Supply	0.792	39.1	0.225	(152, 6, 0.11, 4)

The optimized LightGBM model achieves $R^2 > 0.78$ and MAPE < 0.23, which effectively improves the accuracy and robustness of supply prediction.

2.4. Integrated optimization results

The proposed integrated optimization framework is applied to the actual operation of Muyangsu Cold Chain. A comprehensive evaluation is conducted from multiple dimensions including temperature control, energy consumption, loss rate, scheduling efficiency, and on-time rate.

The results show that after optimization, the energy consumption for refrigeration is reduced by 40–60%, the fresh product loss rate drops from 8–12% to below 3%, the vehicle emptying rate decreases from 35% to below 20%, and the order on-time rate increases from 85% to above 96%. The overall optimization effect is visualized in Figure 4.

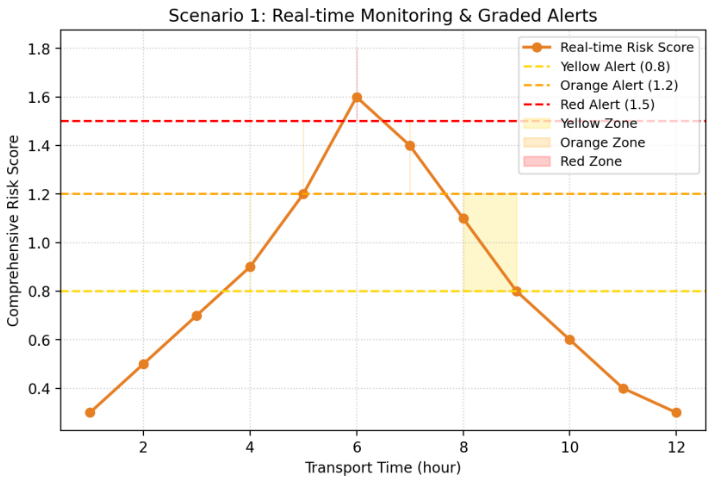

Figure 4. Optimization effect.

The integrated framework effectively addresses the core pain points of traditional cold chains and provides a practical and replicable solution for the green and intelligent transformation of cold chain enterprises.

3. Multi-dimensional Risk Assessment and Prevention System

3.1. Risk identification and index system

Fresh cold chain operations involve complex links and multiple uncertain factors, and risks may spread and amplify along the supply chain. To systematically identify and assess potential risks, this study conducts a comprehensive risk analysis covering five dimensions: technology, safety, supply chain, cost, and market. A three-level risk assessment index system with 19 core indicators is constructed based on the entropy weight-TOPSIS method, as shown in Table 3.

Table 3. Cold chain transportation risk assessment index system.

Target Layer	Criterion Layer (Primary Indicators)	Indicator Layer (Secondary Indicators)	Indicator Attribute
Comprehensive Risk of Fresh Cold Chain Transportation	Technical Risk	PCM Performance Degradation Rate	Negative
		Intelligent Algorithm Prediction Error Rate	Negative
		Sensor Data Accuracy	Positive
	Operational Safety Risk	Temperature Compliance Rate	Positive
		Average Response Time to Abnormal Events	Negative
		On-time Delivery Rate	Positive
	Supply Chain Risk	Supplier Qualification Rate	Positive
		Order Fluctuation Amplitude	Negative
		Upstream and Downstream Information Collaboration Rate	Positive
	Cost Risk	Unit Transportation Cost	Negative
		Asset-liability Ratio	Negative
	Market Risk	Customer Concentration Degree	Negative
		Market Share Growth Rate	Positive
	Environmental Risk	Unit Transportation Carbon Emissions	Negative
		Number of Environmental Compliance Rectifications	Negative
	Organizational Culture Risk	Certified Staff Employment Rate	Positive
		Employee Turnover Rate	Negative
		Safety Training Completion Rate	Positive

Technical risks mainly include PCM performance degradation, insufficient algorithm robustness, and system compatibility issues. Long-term repeated freeze–thaw cycles may lead to phase separation and enthalpy attenuation of PCM. Experimental data show that the enthalpy attenuation rate of pure fatty acid PCM reaches 23.6% after 87 cycles, while composite PCM only has 4.1% attenuation. Safety risks include temperature control failure, driver irregularities, road accidents, and equipment failures. In traditional cold chains, the average abnormal response time is as long as 47 minutes, which may lead to large-scale fresh spoilage.Supply chain risks involve upstream pre-cooling irregularities, downstream demand fluctuations, and information asymmetry. The lack of real-time data sharing among links may lead to untimely risk response and chain reaction accidents.Cost risks include high initial investment and fluctuating energy prices. Market risks include fierce competition and high customer concentration, which may affect the stable operation of enterprises.

3.2. Multi-dimensional prevention strategies

For technical risks, high-stability composite PCM is selected, and algorithm robustness is enhanced through multi-scenario training. A compatible IoT system is built to ensure stable data transmission. Standardized operating procedures are formulated, and full-process real-time monitoring is implemented. An emergency response mechanism is established to shorten the abnormal response time to within 15 minutes.

A diversified customer structure is built, and a supplier evaluation system is established. A collaborative information platform is constructed to realize real-time data sharing and supply chain coordination.

To identify the core risk sources restricting the stable operation of the fresh cold chain and provide targeted guidance for risk prevention, this study conducts a sensitivity analysis on key risk factors based on the constructed multi-dimensional risk assessment system. The analysis quantifies the impact weight of each risk driver on the overall cold chain operation risk, and the results are visualized in Figure 5.

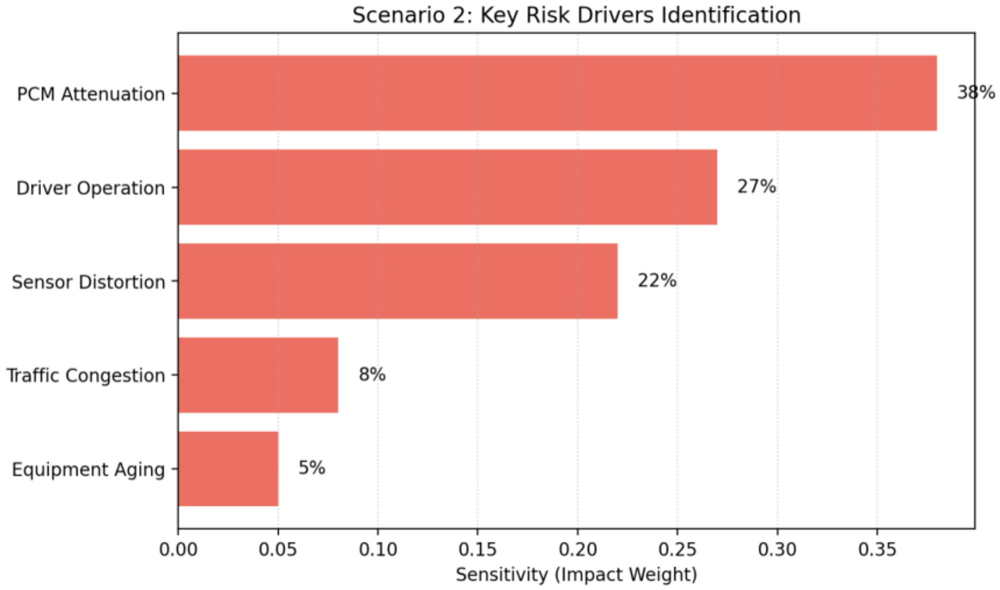

Figure 5. Schematic diagram of end-to-end product tracking and intelligent monitoring.

The sensitivity analysis results show that PCM performance attenuation is the most critical risk driver, contributing 38% to the overall risk, which is closely related to the long-term stability of the passive temperature control system and directly determines the quality safety of fresh products. Driver irregular operation and sensor data distortion are the second and third most important risk factors, with impact weights of 27% and 22% respectively, indicating that human factors and data reliability are the key links affecting the accuracy of cold chain monitoring and the effectiveness of risk early warning. In contrast, traffic congestion and equipment aging have relatively limited impacts, accounting for only 8% and 5% of the total risk. This result confirms that the risk prevention work of fresh cold chain should focus on the maintenance of PCM materials, standardized operation training for drivers, and the upgrade of sensor equipment, so as to realize the accurate identification and effective control of core risks.

4. Conclusions

This study constructs an integrated optimization framework for fresh cold chain operations that combines PCM passive temperature control, improved intelligent algorithms, and 5G Internet of Things technology. Taking Muyangsu Cold Chain as the research object, the paper systematically optimizes the three core dimensions of temperature control, scheduling efficiency, and risk management, and verifies the optimization effect through simulation and real-scenario application.

The results show that the proposed scheme significantly reduces refrigeration energy consumption by 40%–60%, cuts the fresh product loss rate to below 3%, increases the order on-time rate to over 96%, and improves the risk early warning accuracy to 92.5%, effectively solving the prominent pain points of traditional cold chains such as unstable temperature, high energy consumption, and weak risk management. The framework has strong practical feasibility, providing replicable technical solutions and management references for the green and intelligent transformation of fresh cold chain enterprises.

For future research, this work can be further expanded in multiple directions. First, more real-time data such as weather changes and road conditions can be incorporated to build a more adaptive dynamic optimization model. Second, digital twin technology can be introduced to realize full-process visual monitoring and simulation of cold chain operations, further improving the intelligence level of the system. Third, the research scope can be extended to cross-regional and cross-border cold chain scenarios to verify the generalizability of the framework in more complex application environments.

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