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A Simulation Study of Operational Processes at a Seafood Cold-Chain Logistics Center Based on Empirical Loss Data

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***Abstract*— This study examines the Dalian Tieyue Cold-Chain Logistics Center and, using the FlexSim platform, develops a cold-chain operations simulation model calibrated with actual loss data. The model jointly considers material flow, labor efficiency, equipment operating states, and fluctuations in the warehousing environment. By fitting to real operational records, it enables dynamic simulation and performance analysis of inbound, outbound, and material-handling processes. The results indicate that inbound operations are the primary source of losses, with equipment waiting and imbalanced workforce scheduling being key limiting factors. On this basis, three categories of measures are proposed—process optimization, improvements to workforce scheduling, and adjustments to warehouse layout—which, when validated via re-simulation, reduce the loss rate by approximately 12%**

***Index Terms*— cold-chain logistics; discrete-event simulation; loss control; FlexSim; process optimization**

I. INTRODUCTION

In recent years, as the seafood consumption market has expanded and quality requirements have risen, cold-chain logistics has assumed an increasingly important role in aquatic product supply chains. However, cold-chain systems are complex and comprise many stages; they are affected by uncertainties related to personnel, equipment, and the environment, which readily lead to higher losses and lower efficiency. Traditional qualitative approaches have difficulty revealing these dynamic relationships, making it urgent to adopt simulation techniques for systematic study. Liu Decai and Zhou Zhijie [1], using Jiangsu Province as a case, employed MATLAB for data processing and compared exponential smoothing, the grey forecasting model, and a combined model based on exponential smoothing and grey prediction to analyze demand for aquatic-product cold-chain logistics. Lv Jing and Chen Yushu [2] used an improved GM(1,1) model together with a backpropagation (BP) neural network to simulate and forecast demand for the cold-chain logistics of aquatic products in Dalian. Li Xiapei [3] applied the grey GM(1,1) model as the basic method to forecast logistics demand for agricultural products in Beijing during the 13th Five-Year Plan period. Yang Fang et al. [4] built a dynamic distribution-center model using AnyLogic simulation technology, analyzed indicators such as turnover, operation time, and resource utilization, and proposed corresponding process and resource optimization schemes to inform practical operations management. Shen Li et al. [5] conducted a refined analysis of the sources of cargo loss and emissions, formulated a distribution-routing optimization model with total-cost minimization as the objective, and solved it using a genetic algorithm. Tuo Wancong [6] established a time-based exponential loss model to characterize the impact of temperature variation on the damage rate of goods. Mirzaei S. et al. [7] proposed a time-dependent linear loss model that directly computes losses in cold-chain transportation by specifying a spoilage rate that varies with time, providing a concise and effective method for evaluating transport-stage losses. Maria Cefola et al. [8] pointed out that cold-chain technology is a key determinant of preservation performance; modern advanced technologies can improve production and handling efficiency, shorten transportation cycles, and reduce spoilage, thereby moving logistics costs toward an optimal level.

FlexSim, a three-dimensional discrete-event simulation platform, can accurately reproduce logistics operations in a virtual environment and enables visual analysis of resource allocation, workflow design, and system bottlenecks. Using empirical data from the Dalian Tieyue Cold-Chain Logistics Center, this paper develops a cold-chain operations simulation model that takes actual loss as a core performance indicator, with the aim of revealing interstage linkages and improvement pathways through data-driven analysis. Sun Chengwei [9] employed FlexSim to simulate a cold-chain distribution center, proposed reasonable measures, and verified them via simulation, thereby reducing both construction and operating costs. Liu Yuxiao [10] used the HL cold-chain distribution center as a case study and applied FlexSim to analyze and optimize operational workflows, increasing order-processing capacity while lowering operating costs. Zhu et al. [11] investigated a fruit-and-vegetable cold-chain distribution center; after collecting baseline data, they built an operational simulation model in FlexSim to identify system bottlenecks and idle resources, and proposed targeted improvements that effectively increased cargo turnover and enhanced the utilization of equipment and labor.

II. SIMULATION MODEL DEVELOPMENT

This section clarifies the research object and objectives, and then presents the overall framework of the simulation model, modeling assumptions, parameter settings, and model

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validation methods, providing the technical foundation for subsequent experiments.

A. Overall Model Structure

The model adopts a modular design and consists of four components: an operations-process module, a resource module, a control module, and a data-collection module. The operations-process module defines the main stages that materials pass through—arrival, inspection, put-away, in-warehouse handling, picking, consolidation, loading, and outbound. The resource module includes dock workers, forklifts, racking and buffer areas. The control module schedules job sequences and task assignment. The data-collection module records key indicators such as task time, waiting time, and loss rate.FlexSim links modules through logic nodes and an event-driven mechanism, ensuring dynamic interactions as time advances so that the model can reflect the real operating cadence of the logistics center and the emergence of resource conflicts.

B. Modeling Assumptions

To facilitate subsequent implementation of the simulation logic and parameter calibration, this section—after clarifying the research subject and boundary conditions—first summarizes the key assumptions adopted for modeling. The table below lists the core assumptions in the format "ID—Assumption—Notes," highlighting key points such as temperature control, equipment reliability, worker efficiency, and capacity constraints.

ID	Assumption	Notes
H1	Storage temperature remains within bounded fluctuations; once cargo leaves the optimal temperature range, it enters a loss stage.	Simplifies environmental effects.
H2	Forklifts and handling equipment experience random failures; time between failures follows an exponential distribution.	Captures equipment reliability.
H3	Worker efficiency follows a normal distribution N(μ = 70%, σ = 10%) and decays with continuous working time.	Reflects fatigue and shift differences.
H4	Operations follow first-in-first-out (FIFO); storage capacity is capped at 90%.	Matches real operating rules.

Table1. Modeling Assumptions

C. Parameter Settings And Data Sources

The parameters mainly come from the logistics center's operating records and on-site surveys conducted from June to September 2024. After fitting, the goods' interarrival times follow a Gamma distribution; the mean interarrival time for tuna is approximately 137.21 s, and for sweet shrimp and botan shrimp is 91.66 s and 109.77 s, respectively. Arrival batch sizes follow a lognormal or triangular distribution. The handling-related loss rate is set at 0.05%. Equipment speeds, worker movement rates, and operation delays are shown in Table 2.

Type	Parameter	Value / Distribution	Units	Notes
Labor	Loading/unloading speed	0.8	m/s	Empirical measurement
Equipment	Pallet jack speed / delay	1.0 / 10 s	—	Average operation
Equipment	High-reach forklift speed / delay	1.5 / 20 s	—	Calibrated with literature
Equipment	Time between failures / repair time	Exp(480) / Exp(30)	—	Minutes as units
System	Arrival-intensity surge	+30% (peak hours)	—	10:00–12:00, 14:00–16:00

Table 2. Parameter Settings

D. Model Validation

To ensure validity, simulation outputs were compared against monitored data for average processing time, equipment utilization, and loss rate. Deviations between simulated and observed values were all below 5%, indicating that the model captures the real system's characteristics well.

III. SIMULATION EXPERIMENTS AND RESULTS

A. Experimental Design

The simulation covers 15 days, with daily runs from 08:30 to 17:30. Ten replications are performed and averaged to reduce stochastic error. A baseline scenario (S0) and four improvement scenarios (S1–S4) are designed to evaluate the impacts of resource allocation and operational strategies.

S0: Current operating mode (baseline)
S1: Increase forklift count by 10%
S2: Worker rotation policy; any single continuous low-temperature assignment ≤ 2 hours
S3: Optimized task sequencing to reduce loading/unloading waits
S4: Widen aisles by 0.3 m and adjust slotting/layout

B. Simulation Results

The overall loss rate is 3.25%, with inbound losses accounting for roughly 55% of total losses. Average processing time in inbound is 26% higher than in outbound. During peak periods, queue lengths in the dock area rise markedly and average waits exceed 20 minutes.

Forklift utilization averages 63%, while handlers average 72%. Some forklifts are underutilized, indicating imbalanced equipment allocation. Overall storage utilization rises from 20% initially to 37% by day 15, suggesting a dynamically stable system over the simulated horizon.

C. Loss And Processing-Time Analysis

Loss rates differ significantly by commodity and stage. Tuna—sensitive to temperature and handled in larger batches—shows the highest loss rate (3.8%); sweet shrimp the lowest (2.7%); and botan shrimp about 3.1%. Inbound dwell time and loss rate exhibit a strong positive correlation ($r = 0.82$, $p < 0.01$), indicating that longer waits directly increase losses.

D. Equipment And Labor Utilization Analysis

Worker efficiency declines with time due to fatigue, and forklift utilization peaks around 10:00 and 15:00. Under the S2 rotation policy, average operating efficiency improves by 6%, and working-time distributions become more balanced.

E. Bottlenecks And System-Balance Analysis

Bottlenecks are concentrated in the loading/unloading area and at the entrance to the freezer zone. Heat-map analysis shows excessive task density in these regions during peaks, impeding overall flow. Widening main aisles and optimizing task sequences reduce flow time by about 9% and increase throughput by 7%.

F. Summary

The experiments highlight the central role of inbound operations in loss formation. Misaligned labor and equipment scheduling, queueing in dock areas, and aisle congestion are the main bottlenecks. Moderate adjustments to processes and resources effectively improve efficiency and reduce losses.

IV. OPTIMIZATION ANALYSIS

A. Problem Diagnosis

① Low inbound efficiency and long cargo dwell times;

② Uneven equipment allocation with large variations in forklift utilization;

③ Worker fatigue disrupts overall cadence;

④ Suboptimal aisle layout causes congestion.

B. Optimization Measures

① Process optimization: adjust loading/unloading order, prioritize high-risk items, and shorten dwell time;

② Workforce optimization: implement shifts and flexible task assignment, add staff during peaks;

③ Equipment optimization: add backup forklifts and refine dispatching rules;

④ Layout improvement: widen main aisles and re-plan slotting.

C. Re-Simulation Evaluation

After implementing the measures, average operating efficiency rises by 8.1%, and the loss rate drops from 3.25% to 2.85%. Average waiting time in the dock area decreases by 22%, and equipment utilization surpasses 70%. The optimized system runs more smoothly with a more balanced resource load.

D. Comprehensive Evaluation

To provide an intuitive comparison of the overall effectiveness of the optimization schemes, this section summarizes the performance of each scenario in terms of loss and efficiency. The table below presents the average loss rate, efficiency gains, and primary improved indicator for S0–S4, which can be used to prioritize implementation and guide the optimization roadmap.

Scenario	Avg. Loss Rate (%)	Efficiency Gain (%)	Primary Improved Indicator
S0	3.25	—	Baseline state
S1	3.10T	4.5	Equipment utilization
S2	3.05	6.0	Labor efficiency
S3	2.92	7.3	Process smoothness
S4	2.85	8.1	Integrated optimization

Table3. Results Analysis

E. Summary

With stable temperature control and cadence maintained, the optimized system achieves dual improvements in efficiency and quality. Simulation confirms that streamlining processes and balancing resources are key to reducing losses in cold-chain logistics centers.

V. CONCLUSIONS AND OUTLOOK

Using FlexSim, this study builds a simulation model for operations in a seafood cold-chain logistics center and reveals the mechanisms behind loss formation in the workflow. The inbound stage is identified as the critical influence point, with uneven equipment and labor scheduling and corridor congestion as the main bottlenecks. Optimizing processes, configuring resources rationally, and improving layout significantly reduce losses and improve efficiency. Future work can integrate temperature-control monitoring and energy-consumption analysis to provide a comprehensive performance evaluation of cold-chain systems.

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