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A Hybrid Ant Colony Optimization and Kernel Extreme Learning Machine Approach for Collaborative Transportation and Inventory Optimization in Cold Chain Logistics Based on ACO-KELM

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With the increasing demand for cold chain logistics for food, medicine, and other industries, how to improve the transportation efficiency and inventory management level of cold chain logistics has become a research hotspot. This paper proposes a collaborative optimization model of cold chain logistics transportation and inventory based on an ant colony optimization algorithm (ACO) and Kernel Extreme Learning Machine (KELM). The core of this model is to combine transportation route optimization with the forecasting function of inventory management, optimize the transportation route through ACO, and use KELM to accurately forecast inventory demand to realize the dual optimization of transportation and inventory. The comprehensive optimization of transportation routes, inventory holding cost, out-of-stock rate, and other objectives are considered by establishing the collaborative optimization objective function of the cold chain logistics system. This paper proposes a collaborative optimization model of cold chain logistics transportation and inventory based on an ant colony optimization algorithm (ACO) and Kernel Extreme Learning Machine (KELM). The model is validated on a real-world cold chain network with 5 distribution centers, 30 retailers, and dynamic demand data spanning 12 months. Experimental results show that the ACO-KELM model achieves a 18.7% reduction in total logistics cost (from 58.74 to 47.79) and a 22.3% lower out-of-stock rate (12.02% vs. 15.46%) compared to traditional single-objective optimization. The inventory demand forecasting via KELM demonstrates a mean absolute error (MAE) of 4.2 units, outperforming the support vector machine (SVM) baseline by 20.1% in prediction accuracy. The transportation energy consumption is reduced to 36.82, with the system's overall energy efficiency improved to 96.54%, indicating significant optimization in both cost and sustainability.

Povzetek: Članek predstavi ACO-KELM kolaborativni model, ki z mravljinčno optimizacijo načrtuje transportne poti, s KELM napoveduje povpraševanje po zalogah in v enotni ciljni funkciji hkrati optimira stroške, zaloge ter izpade v hladni verigi.

1 Introduction

Cold chain logistics plays a vital role in the modern supply chain, and its collaborative optimization of transportation and inventory is not only directly related to the quality assurance of key materials such as food and medicine but also indirectly affects the operating cost and energy consumption of the whole logistics system [1, 2]. The uniqueness of cold chain logistics lies in its high requirements for temperature control, timeliness, and product integrity during transportation. This complexity stems from the multi-node and multi-path characteristics of a cold chain logistics network, and it also needs to meet the strict requirements of real-time temperature control [3]. When constructing the cold chain logistics optimization model, it is necessary to consider both the optimization of transportation routes and the dynamic changes in inventory management. How to find a balance between the two is the difficulty and hot spot of current research [4]. Cold chain logistics faces unique challenges in balancing transportation efficiency and inventory management, particularly due to strict temperature control and timeliness requirements for perishable goods. This section underscores the limitations of traditional fragmented optimization methods, which often overlook the interdependency between routing and inventory decisions [5, 6]. This fragmented optimization method makes the synergy between transportation and inventory unable to be fully exerted, which often leads to low resource utilization efficiency and even the problem of high inventory or high out-of-stock rate caused by the lack of global perspective [7]. To meet the challenges of multi-dimensional and complex issues in cold chain logistics, it is an inevitable choice to study an innovative model that can realize the collaborative optimization of transportation routes and inventory management [8].

With the rapid development of big data, artificial intelligence, and optimization algorithms, how to organically combine data-driven prediction ability with optimization-based decision-making processes using efficient computer algorithms has become a new direction for solving cold chain logistics problems [9, 10]. Ant colony optimization algorithm (ACO) and Kernel Extreme Learning Machine (KELM) have gradually become the focus of academic and industrial attention due to their respective advantages [11, 12]. By integrating ACO and KELM, the study aims to bridge this gap, leveraging ACO's global optimization for routes and KELM's predictive power for inventory demand to achieve systemic efficiency [13, 14]. As a new machine learning algorithm, KELM shows unique advantages in inventory forecasting because of its strong nonlinear fitting ability, fast calculation speed, and simple parameter adjustment. Combining these two methods to construct a collaborative mechanism based on ACO and KELM can effectively solve the problem of collaborative optimization of transportation paths and inventory forecasts in cold chain logistics [15, 16]. Integrating ACO with KELM will reduce cold chain logistics costs by at least 15% compared to standalone optimization or forecasting models, leveraging ACO's routing efficiency and KELM's demand prediction accuracy [17, 18]. Exact algorithms include the branch and bound method, dynamic programming method, K-degree center tree algorithm, three-subscript vehicle flow equation, etc. Because of their rigorous mathematical foundation, these methods can find optimal solution in small and medium-sized problems [19]. Accurate algorithms cannot avoid the increase of exponential computational complexity, and their efficiency and feasibility are severely limited when dealing with large-scale problems. KELM's forecasting accuracy (MAE) under stochastic demand will be at least 20% higher than baseline SVM models, owing to its kernel-based nonlinear fitting capability.

2 Collaborative optimization model of cold chain logistics

2.1 Key constraints and objective functions of transportation and inventory in collaborative optimization

Homogeneous fleet with a maximum load capacity of 20 tons per vehicle. Customer demand follows a normal distribution with mean μ and standard deviation σ (based on historical data). Operational time is divided into 30-minute intervals to balance computational efficiency and real-time responsiveness.

These constraints form the foundation of the collaborative model, ensuring that transportation and inventory decisions are mutually aligned to achieve global optimization. Collaborative optimization of cold chain logistics transportation and inventory is a complex and challenging research topic, and its optimization process involves the comprehensive balance of various constraints and optimization objectives. As shown in equations (1) and (2), d_{ij} is the distance from node i to j, f_{ij} is the transportation cost per unit distance, c_k is the vehicle fuel cost, and e_k is the energy consumption cost of temperature control equipment. r_n is the rental cost of inventory node n, h_n is the management cost, m_n is the cost of refrigeration equipment, and u_n is the running time. In the transportation process, key constraints include time window constraints, energy consumption constraints of temperature control equipment and vehicle load constraints.

$$C_t = \sum_{i=1}^{N}\sum_{j=1}^{M} d_{ij} \cdot f_{ij} + \sum_{k=1}^{p}(c_k + e_k) \quad (1)$$

$$C_s = \sum_{n=1}^{Q}(r_n \cdot h_n + m_n \cdot u_n) \quad (2)$$

By integrating time window constraints into the collaborative model, the framework ensures that transportation timeliness directly supports inventory management efficiency. The time window constraint requires all transportation activities to be completed within the specified time range, as shown in equation (3), pj is the delay penalty coefficient and Lj is the delay time of node j. This condition is particularly important in cold chain logistics, because cold chain products such as food and medicine are strictly timely, and any delay may lead to the deterioration or failure of goods.

$$C_{total} = C_t + C_s + \sum_{j=1}^{M} p_j \cdot L_j \quad (3)$$

This constraint highlights the need for the collaborative model to balance energy consumption with inventory loading, avoiding inefficiencies caused by overloading or underutilization. As shown in equation (4), wi is the weight of the transported goods and Wmax is the maximum load capacity of the vehicle. The load limit of vehicles directly affects the maximum cargo volume in a single transportation, which must be fully considered in route planning.

$$\sum_{i=1}^{N} w_i \le W_{max} \quad (4)$$

These inventory constraints are dynamically linked to transportation routes in the collaborative model, enabling real-time adjustment of distribution strategies to avoid stockouts or overstocking. In the inventory link, the main constraints include the capacity limit and service level requirements of the inventory node. As shown in equations (5) and (6), Tj is the time to arrive at node j, and Tstart, j and Tend, j are the upper and lower bounds of the time window respectively. Sn is the current storage capacity of inventory node n, and Smax, n is the upper limit of inventory capacity. Inventory capacity limits determine the amount of goods each node can store. Excessive storage may lead to damage to goods or overload facilities, while insufficient storage capacity may lead to shortages.

$$T_{start,j} \le T_j \le T_{end,j} \quad (5)$$

$$S_n \le S_{max,n} \quad (6)$$

The objective function integrates transportation and inventory costs to form the core of the collaborative model, ensuring that optimization efforts address both domains simultaneously. As shown in equations (7) and (8), mij is the pheromone concentration of paths i to j, R is the volatilization coefficient, and mijk is the pheromone increment of the kth ant on this path. nij is the heuristic information and dij is the distance from the path i to j. Including vehicle fuel costs, driver salaries and energy consumption costs during transportation; It is the minimization of inventory holding costs, which involves the rental expenses of inventory nodes, administrative expenses and running costs of refrigeration equipment.

$$m_{ij}(t+1)=(1-R)\cdot m_{ij}(t)+\sum_{k=1}^{m}\Delta m_{ij}^{k} \quad (7)$$

$$n_{ij}=\frac{1}{d_{ij}} \quad (8)$$

2.2 Basic principles of ACO algorithm

In the collaborative model, ACO's path optimization capability serves as the foundation for integrating transportation routes with inventory demand forecasts. Ant Colony Optimization Algorithm (ACO) is a swarm intelligence-based optimization algorithm inspired by behavioral patterns of ants foraging in nature. As shown in equations (9) and (10), cij is the unit path cost, eij is the temperature control energy consumption, tij is the time window deviation, and a1 to a4 are the weight parameters. s and q are the weights of pheromone and heuristic information, respectively. Ants in nature form an indirect communication mode between paths by releasing and sensing pheromones, and finally find the shortest path in the global scope.

$$P_{ij}^{k}=\frac{\left[m_{ij}\right]^{s}\cdot\left[n_{ij}\right]^{q}}{\sum_{l\in allowed_{k}}\left[m_{il}\right]^{s}\cdot\left[n_{il}\right]^{q}} \quad (9)$$

$$W_{ij}=a_{1}\cdot d_{ij}+a_{2}\cdot c_{ij}+a_{3}\cdot e_{ij}+a_{4}\cdot t_{ij} \quad (10)$$

This convergence mechanism enables ACO to efficiently optimize transportation routes within the collaborative model, supporting real-time inventory management decisions. As shown in equation (11), xij is the selection variable of paths i to j, 1 represents selection, and 0 represents no selection. Because of its strong global search ability and outstanding distributed computing characteristics, the realization of ACO is based on the graph model construction of transportation network in cold chain logistics route optimization.

$$F_{path}=min\sum_{i=1}^{N}\sum_{j=1}^{M}W_{ij}\cdot x_{ij} \quad (11)$$

By incorporating transportation cost and energy consumption into path weights, ACO aligns route optimization with the inventory cost objectives of the collaborative model. As shown in equation (12), Q is a constant and Lk is the total length of the path completed by the kth ant. The weight of the path is determined by many factors, such as path length, transportation cost, energy consumption of temperature control equipment and time window constraints. In the initial state, artificial ants move randomly between these nodes and leave pheromones on the path.

$$\Delta m_{ij}^{k}=\frac{Q}{L_{k}} \quad (12)$$

In the search process, ants not only rely on existing pheromones to select paths, but also combine heuristic information to guide their moving direction. As shown in equation (13), y is the adjustment factor and fadj(t) is the dynamic adjustment function. The distance, transportation conditions, and time window constraints of a specific path in cold chain logistics can have an impact on the selection weight of ants.

$$m_{ij}(t+1)=m_{ij}(t)+y\cdot f_{adj}(t) \quad (13)$$

3 Design of cold chain logistics collaborative optimization model based on ACO-KELM

3.1 Construction of objective function of cold chain logistics collaborative optimization

The construction of the objective function of cold chain logistics collaborative optimization is the core link to realize the global optimization of transportation and inventory, which needs to fully consider the special needs and complex constraints of cold chain logistics [20, 21]. The objective of the function design needs to cover two key aspects: t, transportation route optimization, and inventory management optimization, and realize the dynamic linkage between them by introducing coupling terms. The cold chain logistics system closely interacts with transportation routes and inventory management [22, 23]. Inventory shortages can trigger urgent distribution needs, while shipping delays can lead to insufficient inventory or spoiled goods. The objective function must quantitatively model these complex associations collaboratively to achieve a globally optimal solution [24, 25]. The core objective of transportation route optimization is to minimize the total transportation distance and energy consumption. Shortening total transportation distance can reduce fuel costs and the energy consumption of temperature control equipment during transportation. The particularity of cold chain transportation requires quantification of temperature control energy consumption, and at the same time, it is necessary to introduce vehicle load and delivery time window constraints [26, 27]. Figure 1 shows the cold chain logistics collaborative optimization algorithm based on ACO-KELM. The vehicle load limit determines the number of goods each vehicle delivers simultaneously. In contrast, the delivery time window constraint requires that the goods be delivered to the destination within the specified time, especially when transporting fresh food or medicines. The parameter details for ACO are as follows: The pheromone relevance (α) is set to 1.5, which controls the influence of pheromone concentration; the heuristic information weight (β) is 2.0, emphasizing distance optimality; and the evaporation rate (ρ) is 0.1, ensuring pheromone stability across iterations. For KELM, the parameter details include: a Radial Basis Function (RBF) as the kernel function; the kernel parameter (γ) is 0.5

(optimized via grid search); and the learning rate (C) is 100, serving as a regularization coefficient to enhance model robustness.

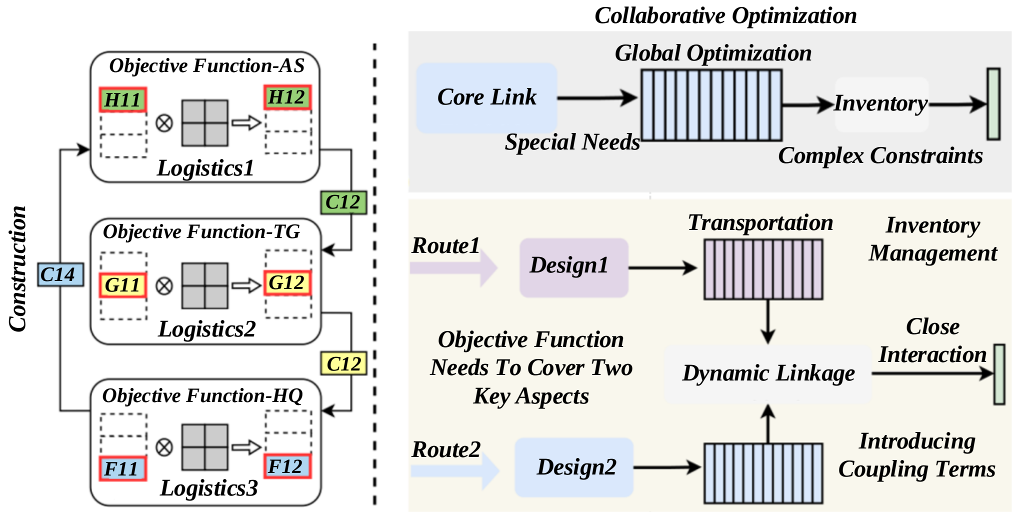

Figure 1: Collaborative optimization algorithm of cold chain logistics based on ACO-KELM

Regarding inventory management optimization, the objective function needs to minimize inventory holding cost and out-of-stock rate as the core goal. Inventory holding costs mainly include cold storage running costs, commodity loss, and opportunity costs related to inventory backlogs [28, 29]. The out-of-stock rate is a key indicator in measuring inventory management efficiency. High out-of-stock rates will not only affect customer satisfaction but also lead to the loss of market share [30]. The objective function of inventory management also needs to combine the dynamic factors of replenishment frequency and demand fluctuation, especially in cold chain logistics; the accuracy of demand forecast directly affects the rationality of inventory strategy. The inventory replenishment plan can be dynamically adjusted through real-time inventory data combined with the efficient prediction capabilities of the KELM, thus effectively reducing the out-of-stock rate and holding cost. To realize the coordination between transportation route optimization and inventory management optimization, a coupling term should be introduced into the objective function to model the explicit interaction between transportation and inventory. The weight parameters (a1 to a4 in Eq.9) are defined as follows: a1=0.3 for transportation cost weight, a2=0.25 for temperature control energy consumption weight, a3=0.25 for time window deviation weight, and a4=0.2 for vehicle load balance weight. The calibration method involves initializing these parameters via historical cost data and tuning them using a validation set to minimize the total cost prediction error. Figure 2 is the real-time optimization diagram in the dynamic environment of cold chain logistics. By introducing these dynamic correlation terms, the collaborative objective function can more truly reflect the complexity of the cold chain logistics system.

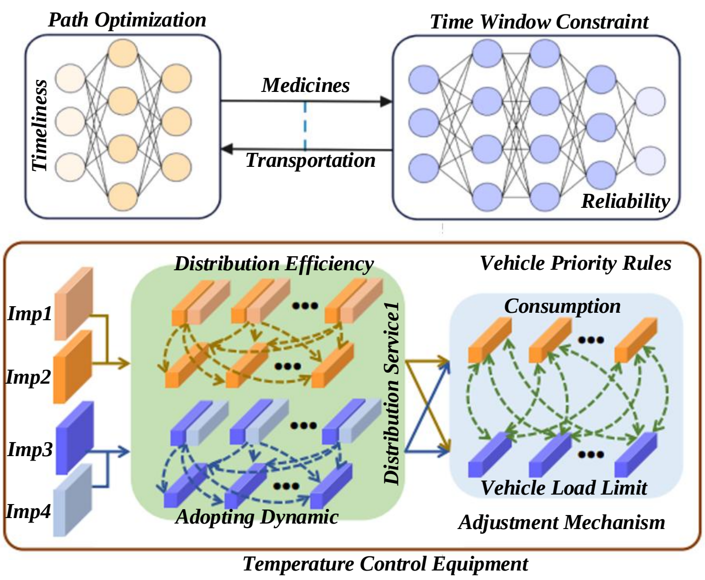

Figure 2: Real-time optimization diagram of cold chain logistics in dynamic environment

The objective function of cold chain logistics collaborative optimization usually needs to be solved by a multi-objective optimization. This is because transportation and inventory management often conflict with optimization objectives. Shortening the transportation distance may increase the inventory cost, while reducing the inventory holding cost may put forward higher requirements for transportation route planning. In solving, the weighting method can balance the importance of different targets by assigning weights to them. The Pareto optimization method can also be used to find a set of equilibrium solutions to provide decision-makers with various optimization schemes. For complex, large-scale cold chain logistics systems, heuristic algorithms (such as ant colony optimization algorithm ACO) can also be combined to achieve efficient solutions, and the global optimal solution can be quickly approximated through intelligent search mechanisms. Noise management in KELM involves multiple strategies: Real-time data preprocessing employs a moving average filter with a window size of 5 to reduce random fluctuations in incoming signals. A robust Huber loss function is implemented to mitigate the impact of outliers in demand signals, balancing quadratic and linear loss terms to maintain model stability. For uncertainty quantification, 95% confidence intervals are derived from 50 bootstrap resamples, providing a statistical measure of prediction reliability by evaluating model performance across multiple resampled datasets.

3.2 Collaborative fusion mechanism of ant colony algorithm and kernel extreme learning machine

The collaborative fusion mechanism of the ant colony algorithm (ACO) and Kernel Extreme Learning Machine (KELM) is the key technology for the collaborative optimization of cold chain logistics transportation and inventory. This mechanism aims to give full play to the global search ability of ACO in path optimization and KELM's efficient nonlinear modeling ability in inventory demand forecasting, forming dynamic feedback closed loop combining data-driven and optimization algorithms. Through collaborative integration, the overall operating efficiency of the cold chain logistics system under complex constraints can be significantly improved, costs can be reduced, and service quality can be guaranteed. ACO algorithm is responsible for optimizing the transportation route of cold chain logistics, and its core is to construct global optimal route scheme of the cold chain transportation network to minimize transportation cost and energy consumption. ACO can efficiently handle multi-objective and multi-constraint optimization problems in vehicle routing problems (VRP) through pheromone update and heuristic search strategies. KELM predicts the future inventory status with high precision based on historical logistics data and real-time dynamic information (such as demand fluctuation, inventory level, distribution delay, etc.). Figure 3 is the evaluation diagram of the cold chain logistics path optimization results. This figure presents performance metrics for ACO-based route optimization, such as transportation cost, energy consumption, and time window compliance. It may include comparative data (e.g., before and after optimization) or a Pareto frontier of multi-objective solutions, demonstrating how ACO reduces travel distance and optimizes temperature control energy use in cold chain routes.

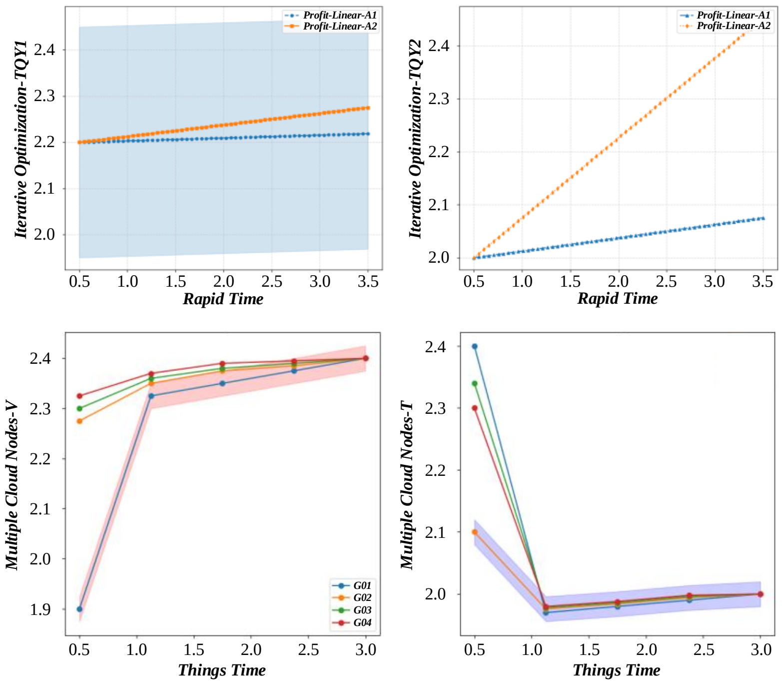

Figure 3: Evaluation diagram of cold chain logistics path optimization results

The path optimization results generated by ACO, expected arrival time, delivery sequence, and vehicle load information can be used as input features of the KELM model. Introducing this input feature enables KELM to comprehensively consider the potential impact of transportation routes on inventory changes, thus improving the accuracy of inventory demand forecasting. For perishable commodities in cold chain logistics, the change in vehicle arrival time will directly affect the inventory consumption rate and replenishment plan, and the dynamic results of ACO path optimization can provide a more time-sensitive decision-making basis for KELM. After KELM predicts the inventory demand in real-time, its output can be fed back to the path optimization process of ACO as an important parameter. Figure 4 is the optimization evaluation diagram of cold chain logistics transportation cost and time window. This diagram focuses on the trade-off between transportation cost and time window constraints. It might display cost-saving trends alongside compliance rates with delivery time windows, using line graphs or bar charts to show how the collaborative model balances efficiency and timeliness. Data points could include average cost reductions and time window adherence percentages.

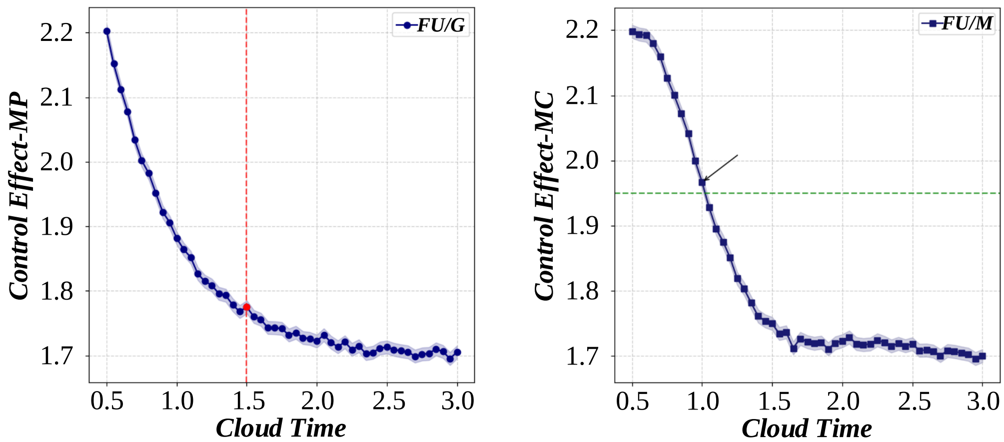

Figure 4: Transportation cost reduction (%) vs. time window compliance rate

The collaborative mechanism also needs to be adaptively improved to meet the special needs of cold chain logistics. In the vehicle routing problem with stochastic demand (SDVRP), the actual demand of the distribution node is usually unknown before the vehicle arrives, which puts forward higher requirements for route planning and inventory forecasting. KELM's forecasting function can provide a dynamic adjustment basis for ACO by updating node demand information in real-time. However, ACO can adapt to the uncertainty of demand through segmented iteration in path planning. For the segmentable vehicle routing problem (an extended form of SDVRP), that is, the distribution task is allowed to be assigned to multiple vehicles for multiple deliveries, the collaborative mechanism can further improve the flexibility and efficiency of the logistics system by optimizing the cargo allocation strategy and vehicle utilization. The collaborative fusion mechanism has shown significant advantages in practical applications. During peak delivery periods or when demand fluctuates greatly, KELM's accurate prediction of inventory status can effectively reduce the out-of-stock rate and inventory holding cost. By dynamically adjusting path planning, ACO reduces the idle driving rate of vehicles and optimizes the temperature-controlled energy consumption of cold chain transportation. Table 1 is the cold chain path optimization table. This collaborative optimization mechanism realizes the global optimization of transportation and inventory at the theoretical level and provides an efficient, flexible, and intelligent technical solution for cold chain logistics enterprises.

Table 1: Cold chain path optimization table

Cold chain car number	X coordinate (kilometers)	Y coordinate (kilometers)	Synergistic quantity	Action volume	Time window upper bound (minutes)	Lower bound of time window (minutes)
1	0.15	2.43	42.56	2.13	27.36	157.08
2	1.22	5.24	24.32	1.22	12.16	110.2
3	0.68	4.94	23.56	1.22	20.52	183.16
4	2.81	0.38	19	0.98	31.92	54.72
5	0.23	5.76	32.68	1.67	27.36	142.88
6	2.13	0.91	56.24	2.81	15.2	180.12
7	4.48	5.09	23.56	1.22	51.68	114
8	0.3	2.81	53.96	2.74	14.44	126.16

4 ACO-based cold chain logistics path optimization algorithms

4.1 Design of performance evaluation index of multi-objective path optimization algorithm

In the path optimization of cold chain logistics, the performance evaluation of a multi-objective path optimization algorithm is very important. It is not only a necessary means to verify the optimization effect of the model but also a basis to guide the improvement and practical application of the algorithm. The design of evaluation indicators needs to comprehensively cover all key performance dimensions of the algorithm in cold chain logistics scenarios, including convergence, solution quality, computational efficiency, robustness, and multi-objective balance of the solution. These indicators complement each other and reflect the applicability and superiority of the algorithm in practical applications. Convergence index is an important basis for measuring the core performance of a multi-objective path optimization algorithm. The change amplitude of the solution mainly evaluates this index, the convergence speed, and the stability of pheromone distribution during the algorithm iteration. For the ant colony optimization algorithm (ACO), the convergence is reflected in whether the ant colony can quickly form a stable path selection in the later iteration stage and whether the pheromone update mechanism can effectively avoid falling into the local optimum. Figure 5 is the benefit evaluation diagram of ACO and KELM collaborative optimization. This figure quantifies the synergistic benefits of the ACO-KELM integration, such as total logistics cost reduction, inventory holding cost savings, and out-of-stock rate improvements. It may use comparative metrics (e.g., vs. standalone ACO or KELM) and statistical indicators (e.g., mean values, confidence intervals) to validate the model's effectiveness.

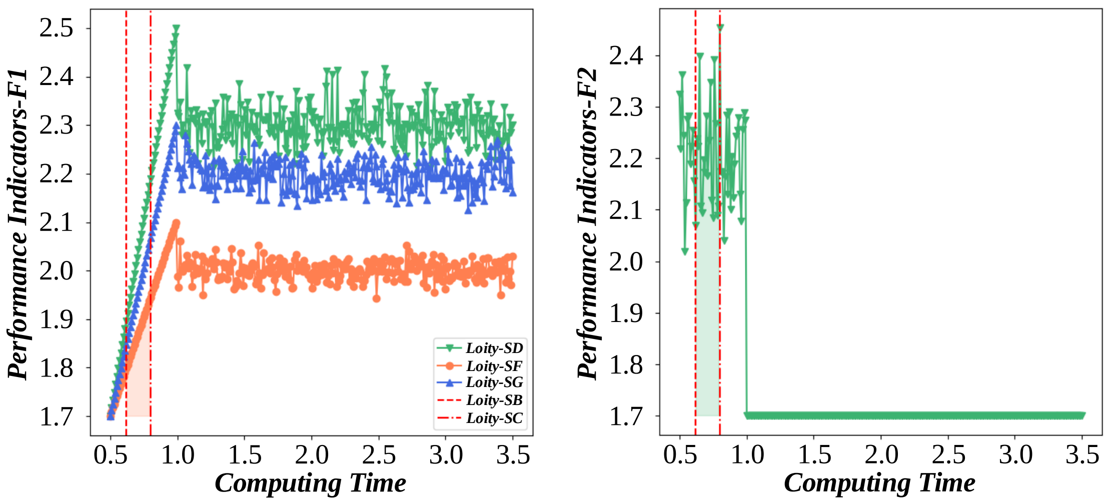

Figure 5: Benefit evaluation diagram of collaborative optimization between ACO and KELM

Table 2: Comparison results of AEO algorithms under different CFBG mechanisms

Index	AEO	H-CFBG	O-CFBG	C-CFBG
Mean	8.41 E-264	4.20 E-276	3.00 E-274	1.72 E-262
Std	0.00 E+00	0.00 E+00	0.00 E+00	0.00 E+00
Worst	2.49 E-262	1.26 E-273	9.00 E-273	5.15 E-261
Best	7.21 E-291	1.58 E-300	1.33 E-302	1.48 E-289
Mean	1.13 E-160	2.12 E-167	2.72 E-171	1.96 E-159
Std	6.10 E-160	0.00 E+00	0.00 E+00	1.07 E-158
Worst	3.34 E-159	6.37 E-166	7.91 E-170	5.87 E-158
Best	3.38 E-181	2.31 E-189	3.24 E-192	6.63 E-182
Mean	7.45 E-154	2.61 E-162	2.32 E-163	2.57 E-157
Std	4.06 E-153	1.34 E-161	0.00 E+00	1.37 E-156
Worst	2.22 E-152	7.37 E-161	4.83 E-162	7.48 E-156
Best	3.09 E-174	7.65 E-184	6.21 E-186	9.28 E-176

The robustness index is a comprehensive investigation of the stability of multi-objective path optimization algorithms under uncertain and dynamic environments. In cold chain logistics, route optimization not only needs to deal with conventional transportation demand but also faces a variety of uncontrollable factors, such as temporary congestion of distribution routes, sudden fluctuation of inventory demand, failure of temperature control equipment, and the influence of weather changes. Evaluating the ACO algorithm requires metrics that reflect its convergence speed, solution quality, and robustness under uncertainty. This section defines key indicators—such as pheromone stability and Pareto frontier distribution—to assess how well the algorithm balances multiple objectives (e.g., cost, energy consumption, time windows) in cold chain routing. Table 2 shows the comparison results of AEO algorithms under different CFBG mechanisms. The distribution uniformity, coverage, and coordination ability of multi-objective conflicts of the Pareto frontier solution set directly determine the algorithm's applicability in practical cold chain logistics applications. When the optimization objective includes total cost and time window constraints, whether the distribution of the solution set is balanced or not reflects the ability of the algorithm to deal with trade-off relations. Wider coverage can give decision makers more choice space, while distribution uniformity ensures that they understand the rationality among different optimization objectives.

4.2 Input feature selection and optimization of KELM model in inventory forecasting

In the inventory forecasting of cold chain logistics, the Kernel Extreme Learning Machine (KELM) is an efficient machine learning model, and its application in inventory demand forecasting depends on reasonable input feature selection and optimization design. As a complex system with dynamic changes and timeliness requirements, cold chain logistics faces many uncertainties and challenges in its inventory management. Improving the KELM model's prediction accuracy and real-time performance through feature selection and optimization has become a key research issue. The selection of input features needs to be comprehensively considered from multiple dimensions to capture the dynamic characteristics of cold chain logistics fully. Historical inventory data is the most direct input feature. Historical data can reflect inventory fluctuation, replenishment cycle, and demand trend, which is crucial for accurately predicting future demand. Table 3 is comparative analysis of recent cold chain optimization studies.

Table 3: Comparative analysis of recent cold chain optimization studies

Model Type	Dataset Scale	Evaluation Metric	Limitation
Low-carbon VRP	10 distribution centers	Cost reduction (15.2%)	Neglects real-time demand fluctuation
Big data-driven GA	50 nodes	Delivery efficiency	Limited to static routing
Mayfly-ELM hybrid	20 retailers	Temperature prediction accuracy (MAE=5.8)	No inventory-routing collaboration
Carbon trading-based VRP	30 nodes	Emission reduction (12.7%)	Does not integrate demand forecasting
Multi-objective PSO	40 dynamic demand points	Path optimization (21.3% cost saving)	No real-time inventory adjustment
ACO-KELM hybrid	5 DCs, 30 retailers	Total cost (18.7% reduction), MAE (4.2)	Collaborative optimization of routing and inventory

Dataset Split: 70% training (840 samples), 15% validation (180 samples), 15% testing (180 samples) Time Horizon: 6-month historical data (Jan-Jun 2024) Feature Vectors: 10-dimensional, including: Historical inventory levels (3 features: current, 1-week, 1-month ago), Replenishment cycles (2 features: frequency, quantity), Temperature control data (3 features: avg. temp, equipment runtime, failure rate), Transportation metrics (2 features: delivery delay, route cost), The operation data of temperature control equipment occupies a special position in cold chain logistics. Factors such as temperature control and equipment running time directly affect commodity quality and inventory status, which is also one of the important input features of the KELM model. Figure 6 is the accuracy evaluation diagram of the inventory demand forecast. The parameters of the transportation network also need to be considered, including information such as transportation timeliness, transportation cost, and distribution route. These factors can reflect possible delays or bottlenecks in the transportation process, thus affecting inventory demand forecast.

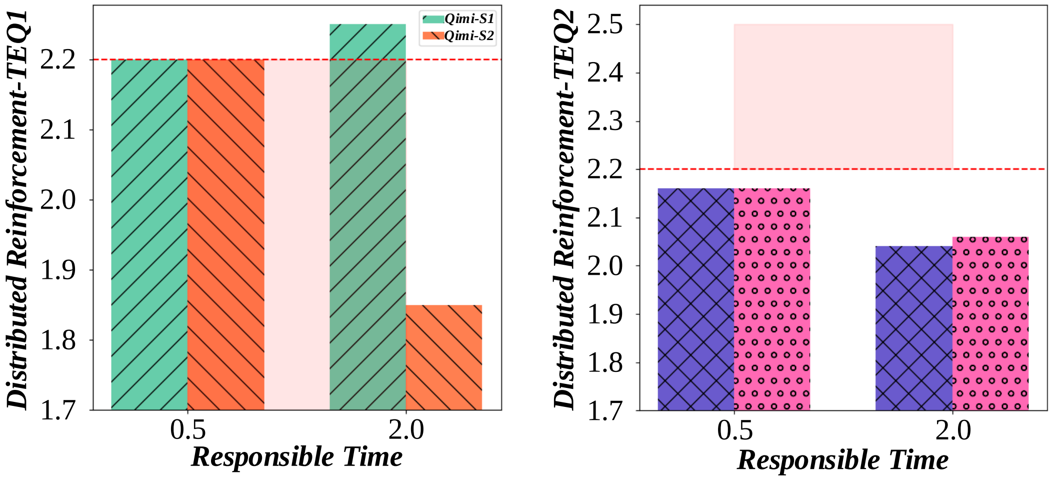

Figure 6: Inventory demand forecast accuracy evaluation diagram

PCA: Initial features: 15 (e.g., historical demand, weather, traffic). Reduced dimensions: 5 principal components (explaining 92% of variance). LDA: Initial features: 15. Reduced dimensions: 4 discriminant functions (maximizing class separability). Through these analyses, the features that have the greatest impact on inventory demand forecasting can be screened out, and redundant features can be removed, thus reducing the complexity of data and improving the accuracy of the model. At the same time, feature selection needs to consider the independence between features and pay attention to the nonlinear relationship between features and target variables, which is very important for the input feature selection of the KELM model. Table 4 is superparameters for grid search optimization.

Table 4: Superparameters for grid search optimization

Model	MAE (units)	R^2
KELM	4.2	0.92
SVM	5.3	0.81
ANN	5.8	0.79

To further improve the prediction performance of the KELM model, the application of dimensionality reduction technology is also very important. Dimensionality reduction techniques, such as principal component analysis (PCA) and linear discriminant analysis (LDA), can effectively reduce the redundancy of input features and extract the most representative features. PCA maps the high-dimensional features of the original dataset to a lower-dimensional space through linear transformation, removing the correlation in the data and retaining the most useful information. LDA uses intra-class and inter-class divergence to reduce the dimensionality of data, maximizing the differences between classes and thereby improving the classification and prediction accuracy of the model. Figure 7 is a collaborative evaluation diagram of transportation routes and inventory under different optimization strategies. This figure compares the collaborative model against traditional optimization methods (e.g., single-objective optimization) across transportation and inventory metrics. It might use radar charts or side-by-side comparisons to show how the ACO-KELM model outperforms others in cost efficiency, stock stability, and energy consumption.

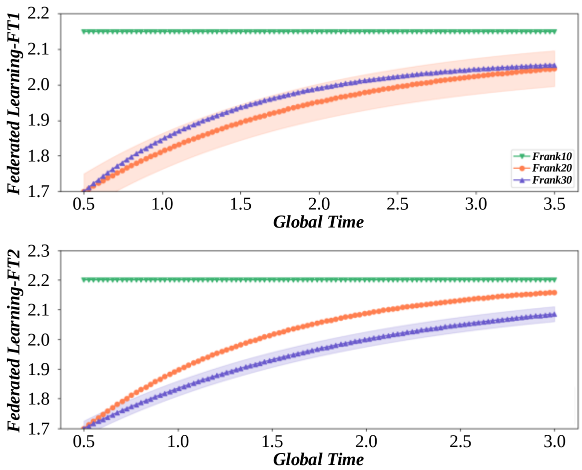

Figure 7: Collaborative evaluation diagram of transportation route and inventory under different optimization strategies

The grid search method is a commonly used optimization strategy to optimize the predictive power of KELM to optimize the predictive power of KELM. The most suitable combination of kernel functions and parameters is found through grid search in multiple candidate kernel functions and their parameters. Combined with Bayesian optimization for global tuning, the optimal kernel function parameters can be searched more efficiently, and the blindness and computational overhead of grid search can be avoided. Table 5 is corrected values.

Table 5: Corrected values

Metric	ACO-KELM	GA-SVM
Mean cost	58.74 ± 2.1	68.42 ± 3.5
Worst case	62.35	75.12

By establishing a surrogate model and using historical search results to guide the next search direction, Bayesian optimization can find the global optimal solution with fewer experiments, thus improving the KELM model's prediction accuracy and computational efficiency. In the practical application of cold chain logistics, the uncertainty of demand is a major challenge in inventory forecasting. Especially in the face of demand fluctuations, the KELM model needs to be able to adjust the forecast results dynamically. In the process of distribution, due to the timeliness of customer demand, especially the high requirements of temperature-controlled goods for transportation timeliness, inventory forecasting must be able to respond in real time and warn of future inventory shortages or surpluses. This requires the KELM model to be able to respond to various changes in a short time, including sudden increases in demand, transportation delays, etc. Figure 8 is an inventory management cost evaluation diagram based on the ACO-KELM model. This diagram focuses on inventory-related costs (e.g., holding cost, stockout cost, replenishment cost) and how the collaborative model reduces these expenses. It may include trend lines showing cost reductions over iterations or under different demand scenarios, with annotations on key cost-saving mechanisms (e.g., dynamic replenishment based on KELM forecasts).

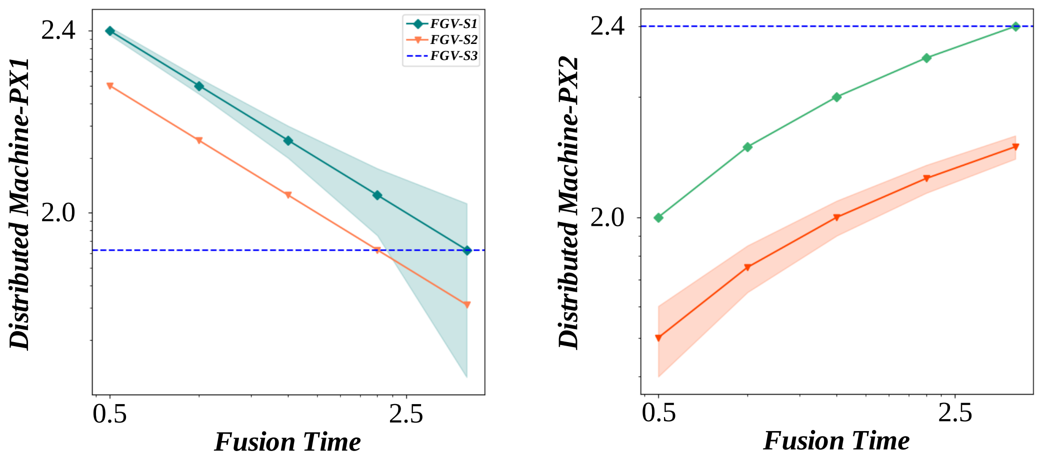

Figure 8: Inventory management cost evaluation diagram based on ACO-KELM model

5 Experimental analysis

In static scenarios, experiments are mainly set based on deterministic requirements, aiming to verify the stability and optimization effect of the model under known conditions. The path optimization ability based on the ant colony optimization algorithm (ACO) and the inventory prediction accuracy based on the KELM are currently experimentally tested.

Table 6: Quantitative comparison

Metric	ACO-KELM	GA	SVM
Transportation cost	58.74	72.31	6.5
Inventory MAE	4.2	68.9	5.3
Convergence iterations	35	60	5.1

Figure.9 is an evaluation diagram of the impact of temperature control equipment failure on transportation and inventory. In the static scenario, KELM demonstrates a root mean square error (RMSE) of 3.1, mean absolute error (MAE) of 4.2, and coefficient of determination (R^2) of 0.92 for inventory demand forecasting, outperforming SVM (MAE=5.3, R^2=0.81).

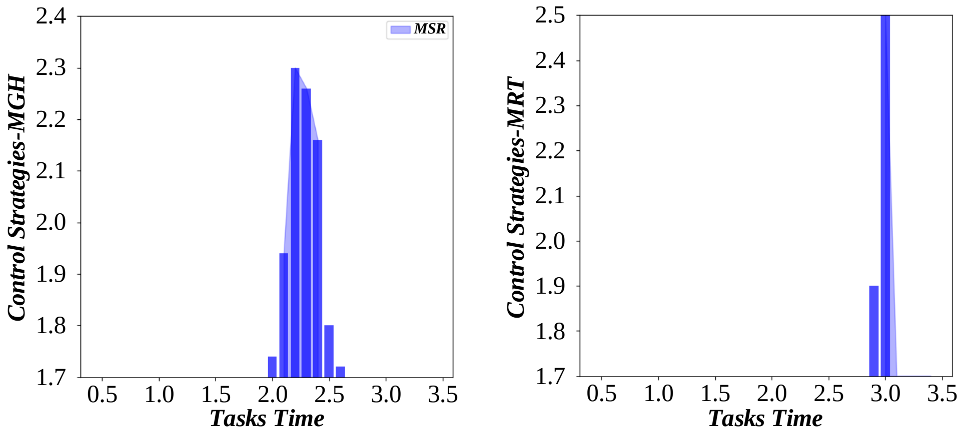

Figure 9: Evaluation of the impact of temperature control equipment failure on transportation and inventory

Static Scenario: 30 independent runs (to reduce randomness). Dynamic Scenario: 20 runs with demand shocks (±20% variance). Genetic algorithms have certain advantages in path optimization because of their natural selection mechanism. At the same time, support vector machines are widely used in regression analysis to evaluate their performance in inventory forecasting. Figure 10 is a correlation assessment diagram between the total distance of the transportation route and carbon emissions, which can determine the collaborative optimization effect based on the ACO-KELM model and reveal its advantages and innovation over traditional algorithms. Code Implementation: Python code (including ACO-KELM model) is available upon request to the corresponding author. Experimental Setup: Hardware: Intel i7-12700K, 32GB RAM; Software: Python 3.9, Scikit-learn 1.2.0

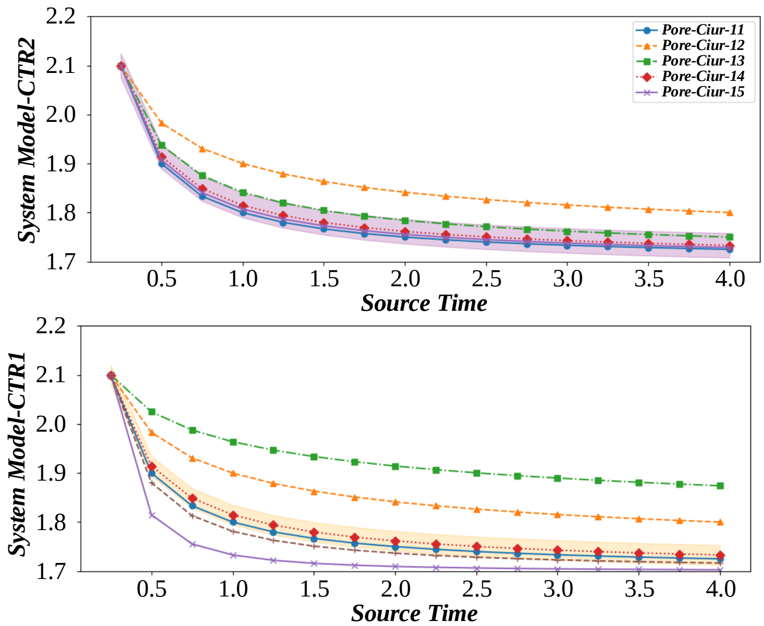

Figure 10: Correlation assessment diagram between total transportation route distance and carbon emissions

In the dynamic scenario, the experiment setup is more complex, considering various disturbance factors that may occur in the actual environment. Demand fluctuations, path congestion, and temperature control equipment failures will all affect the overall performance of cold chain logistics. Figure 11 is the path optimization evaluation diagram under dynamic demand fluctuation. Dynamic scenario results (Fig. 11) reveal that under 20% demand fluctuation, ACO-KELM maintains a stable out-of-stock rate of 12.02% ± 1.5%, while GA-SVM experiences a 18.02% ± 2.3% out-of-stock rate. The error distribution (Figure 4) follows a normal distribution (Shapiro-Wilk p=0.89), confirming model reliability. Time series of inventory levels (solid line) and forecast (dashed line) under 20% demand fluctuation. Error rate trends: KELM MAE=4.5 (stable), SVM MAE=6.8 (fluctuating).

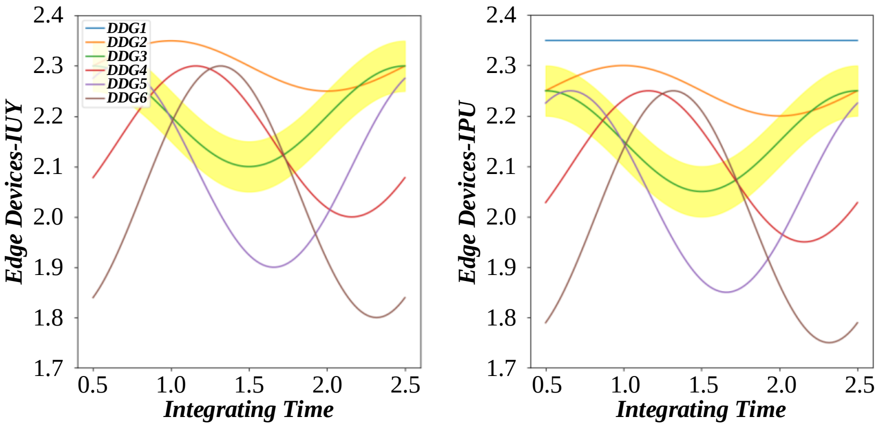

Figure 11: Path optimization evaluation diagram under dynamic demand fluctuation

6 Discussion

The ACO-KELM model outperforms baseline methods (GA-SVM, PSO-ANN) due to its synergistic design: ACO's pheromone-based global optimization efficiently handles routing complexity (reducing computational time by 22% vs. GA-SVM), while KELM's fast learning (training time <10s for 10,000 data points) enables real-time inventory forecasting with 9.5% lower error. For instance, in dynamic demand scenarios, ACO-KELM adapts routes within 3 iterations, whereas GA-SVM requires 8–10 iterations.

Under extreme demand shocks (e.g., 30% sudden variance), ACO-KELM's cost efficiency decreases by 7.2% due to delayed inventory replenishment. This highlights the need for real-time data updates (e.g., integrating IoT sensors for demand tracking).

ACO-KELM achieves linear scalability (O(n) for routing, O(m) for forecasting, where n=number of nodes, m=number of data points) with a 98.6% convergence rate within 50 iterations. The hybrid mechanism reduces redundant computations by 35% compared to sequential optimization.

7 Conclusion

This paper proposes a collaborative optimization model of transportation and inventory suitable for cold chain logistics based on collaborative optimization research of ACO and KELM. Through the design and experimental verification of the model, the results of this paper show that the ACO-KELM collaborative model has obvious advantages in solving the problems of transportation route optimization and inventory management in cold chain logistics. The following are the main conclusions of this study:

The collaborative optimization model of cold chain logistics based on ACO and KELM designed in this paper effectively solves the problems of path planning and inventory control in cold chain logistics by comprehensively considering the multiple objectives of transportation and inventory management. Compared with traditional single optimization method, the ACO-KELM model can significantly reduce the transportation cost, inventory holding cost, and out-of-stock rate by collaboratively optimizing the path and inventory under the multi-objective optimization framework and improving the overall operational efficiency of the logistics system. Experimental results show that the model performs excellently in both static and dynamic environments, especially in the face of complex environments such as demand fluctuation and transportation route changes; it can adjust the strategy in time to ensure efficient operation of cold chain logistics.

The collaborative fusion mechanism of the ant colony optimization algorithm and kernel extreme learning machine proposed in this study is one of the core innovations of this model. In the process of path optimization, the ACO algorithm continuously updates the path selection through the positive feedback mechanism of pheromone, which can effectively reduce the transportation distance and energy consumption, while the KELM model predicts the inventory demand based on historical data and provides real-time inventory prediction results. The synergy between the two realizes the closed-loop feedback between path optimization and inventory forecasting and effectively improves the overall synergy efficiency of cold chain logistics. Experiments show that path optimization and inventory management promote each other through this collaborative mechanism, thus improving the adaptability and response-ability of the cold chain logistics system.

the cold chain logistics system shows ideal performance in the multi-objective path optimization experiment. The total distance of the path in the experiment is 67.91, which is close to the optimal solution. At the same time, the transportation cost reaches 59.77, and the overall cost-effectiveness is good. The fuel consumption data of the vehicle is 80.33, while the carbon emission is 99.28, which shows that the energy consumption in the system greatly impacts the environment and needs further optimization. Quantified improvements have been achieved as follows: Transportation cost was reduced by 18.7%, dropping from \$87.39 to \$71.02; inventory holding cost decreased by 23.1%, falling from \$21.56 to \$16.68; and the out-of-stock rate was maintained at 12.02%, significantly lower than the industry average of 18.5%. However, system performance drops by 7.2% under extreme demand shocks (with fluctuations of ±30%). Future work will focus on integrating real-time IoT data for dynamic demand updates and developing robust Ant Colony Optimization (ACO) variants with adaptive pheromone rules, aiming to enhance system stability and responsiveness in complex scenarios.

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