Robust Optimization Design of Fresh Food Closed-Loop Supply Chain Network Based on Improved HBA Algorithm: Postprint

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Abstract

To address the fresh food closed-loop supply chain network design problem, a robust optimization model for fresh food closed-loop supply chain networks is established to resolve uncertainties in the supply chain network. First, for a fresh food supply chain network structure encompassing 5 nodes, a multi-period, multi-product mixed-integer programming model is developed with objectives of minimizing cost and environmental impact, which is addressed using fuzzy compromise programming and interval data robust optimization methods; second, based on the original honey badger algorithm, differential evolution principles are introduced to enhance the algorithm' s global search capability and convergence speed; finally, Matlab numerical analysis and simulation examples demonstrate that the proposed robust optimization model and honey badger algorithm exhibit significant advantages in solving fresh food closed-loop supply chain network design problems.

Full Text

Preamble

Robust Optimization Design of Fresh Closed-Loop Supply Chain Network Based on Improved Honey Badger Algorithm

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Abstract: This paper proposes a robust optimization model for fresh food closed-loop supply chain network design to address uncertainties in supply chain networks. First, for a fresh supply chain network structure covering five nodes, a multi-period, multi-product mixed-integer programming model is established with objectives of minimizing cost and environmental impact, processed using fuzzy compromise programming and interval data robust optimization methods. Second, based on the original honey badger algorithm, differential evolution principles are introduced to enhance the algorithm' s global search capability and convergence speed. Finally, numerical analysis and simulation examples in Matlab demonstrate that the proposed robust optimization model and honey badger algorithm offer significant advantages in solving fresh closed-loop supply chain network design problems.

Keywords: closed-loop supply chain network design; fresh supply chain; differential honey badger algorithm; robust optimization

0 Introduction

The design of reverse logistics and closed-loop supply chains has attracted considerable attention from researchers and decision-makers due to issues such as natural resource shortages and the hazards of industrial product residues to human life and the environment. Fresh supply chains have gradually become a research hotspot in the supply chain field because of their perishability and difficulty in regulation.

Most domestic and international research on fresh supply chains focuses on pricing and inventory strategies, preservation efforts, and coordination optimization. Feng et al. [1] constructed decentralized decision-making game models under FOB and CIF pricing modes, considering the characteristics of random output and value loss of fresh agricultural products. Ma et al. [2] studied decision-making issues regarding preservation, carbon emission reduction, and pricing in a three-level cold chain system where third-party logistics undertakes preservation and low-carbon responsibilities for fresh products, proposing a contract incentive mechanism combining wholesale price and two-part tariff. Mohammadi et al. [3] developed a novel coordination mechanism based on preservation technology investment to address spoilage and waste of fresh products, improving overall supply chain profitability. Wen et al. [4] established a three-stage Stackelberg game model involving government, retailers, and farmers considering natural disaster impacts on output, analyzing the government' s optimal subsidy rate and retailers' optimal purchase price under different government subsidy policies and retailer cooperative preferences. Qiu et al. [5] designed a fresh product green supply chain network structure with balanced optimization of cost and carbon emissions for carbon tax policy scenarios, establishing a multi-objective mixed-integer model. Liu et al. [6] designed a "revenue sharing-two-way cost sharing" contract to achieve perfect coordination and Pareto improvement in fresh e-commerce supply chains by constructing centralized and decentralized decision models. Wang et al. [7] built a time-varying consumer utility function affected by freshness and price of fresh agricultural products, establishing a two-level supply chain profit model to determine optimal preservation efforts and pricing.

In closed-loop supply chain network research, Sun et al. [8] established single and dual-channel closed-loop supply chain network decision models based on consumer preferences and fairness concerns. Zhang et al. [9] developed a multi-objective closed-loop supply chain network planning model with fuzzy parameters under uncertain conditions, aiming to minimize cost and environmental impact while maximizing social impact. Dong et al. [10] studied a multi-objective fuzzy optimization design model for fresh closed-loop supply chain networks under power grid interruption, addressing uncertainties in fresh supply chain network design. Zhu et al. [11] examined coordination issues in retailer-led dual-channel closed-loop supply chains, achieving coordination through profit-sharing and cost-sharing contracts. Wang et al. [12] investigated coordination problems in closed-loop supply chains with manufacturer recycling behavior under information asymmetry, using Itô processes to explain the stochastic evolution of recycling rates and constructing decentralized decision models to obtain optimal equilibrium solutions for manufacturers and retailers. Yavari et al. [13] designed an innovative mixed-integer programming robust optimization model for green closed-loop supply chain network design of perishable products under uncertainty. Dey et al. [14] analyzed different game strategies of two competing retailers when manufacturers act as Stackelberg leaders in closed-loop supply chain network design.

Closed-loop supply chain network optimization design is a typical NP-hard problem. Recent research in this field predominantly employs intelligent algorithms to solve such nonlinear optimization problems [15-17]. The Honey Badger Algorithm (HBA), proposed by Hashim et al. [18] in 2021, simulates the dynamic search behavior of honey badgers digging and foraging for honey. Due to its promising experimental results, simple structure, and effectiveness in solving large-scale optimization problems [19], HBA has broad application prospects. However, the original HBA still has room for improvement in global search capability and convergence speed when handling large-scale problems. Combining it with other algorithms or concepts can enhance its convergence speed and optimization ability.

In summary, research and literature on fresh closed-loop supply chain network optimization design are relatively scarce, and the treatment of uncertain parameters in models is somewhat monolithic. Therefore, this paper establishes a multi-objective optimization model for fresh closed-loop supply chain networks considering environmental impact, adopts fuzzy programming to convert multi-objectives into a single-objective model, and processes uncertain parameters through interval robust optimization. The original HBA algorithm is improved by introducing differential evolution principles to solve the proposed model. Finally, examples verify the feasibility of the model and the superiority of the algorithm.

1.1 Problem Description

This paper investigates a multi-product, multi-period, multi-echelon fresh closed-loop supply chain network design problem comprising suppliers, manufacturers, warehouses, retailers, and collection centers. The supply chain network operates as follows: First, raw materials required for production are transported from suppliers to manufacturers through existing supply chain networks and transportation modes. Products are then shipped from manufacturers to retailers via warehouses. Unsatisfactory products are returned and stored at collection centers, where usable returned items are sent to manufacturers as semi-finished products. Retailer demand and return rates exist in an uncertain state. The specific supply chain network structure is illustrated in Figure 1.

Figure 1. Schematic diagram of fresh closed-loop supply chain network structure

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1.2 Model Assumptions and Symbol Definitions

This paper makes the following assumptions: (a) All facility potential locations, capacities, and cost parameters are predetermined; (b) Each retailer receives all its demand from only one warehouse; (c) All products returned by retailers can only be sent to one collection center, with each retailer sending returned products to only one collection center; (d) A fixed percentage of each product is sent back as returned products to collection centers; (e) Unit transportation costs from suppliers to manufacturers, manufacturers to warehouses, and collection centers to manufacturers are fixed and positively correlated with transportation volume; (f) Transportation costs from warehouses to retailers and retailers to collection centers are static, independent of transportation volume, with pre-allocated trucks making trips between warehouses, retailers, and collection centers each period; (g) Retailers are at fixed locations and facility capacities (suppliers, manufacturers, warehouses, retailers, and collection centers) are limited.

Using a dairy product supply chain network as an example, symbols, parameters, and decision variables are defined as follows:

Symbol Definitions: - A: Set of potential collection center locations, $a \in A$ - I: Products, $i \in I$ - i_b and i_c: Single-source products and reused products respectively, $i_b \in I$, $i_c \in I$ - M: Set of potential manufacturer locations, $m \in M$ - R: Set of fixed retailer locations, $r \in R$ - S: Set of fixed supplier locations, $s \in S$ - t: Time periods, $t \in T$ - W: Set of potential warehouse locations, $w \in W$

Parameter Definitions: - k_i: Return rate of product i - LA_a: Capacity of collection center a - LM_m: Production capacity of manufacturer m - LS_s: Supply capacity of supplier s - LW_w: Capacity of warehouse w - p_i: Product life cycle of product i - FCA_a, FCM_m, FCW_w: Fixed costs for establishing collection center a, manufacturer m, and warehouse w - COM_{imt}: Unit production cost for manufacturer m to produce product i in period t - DR_{irt}: Demand of retailer r for product i in period t - EA_a, EM_m, EW_w: Environmental impact of establishing collection center a, manufacturer m, and warehouse w - EIA_{ia}, EIM_{im}, EIR_{ir}, EIW_{iw}: Environmental impact of storing product i at collection center a, manufacturer m, retailer r, and warehouse w - ETA_{jam}: Environmental impact of transporting product j from collection center a to manufacturer m - ETM_{imw}: Environmental impact of transporting product i from manufacturer m to warehouse w - ETS_{sm}: Environmental impact of transportation from supplier s to manufacturer m - $ETRA_{ra}$: Environmental impact of pre-allocated truck trips from retailer r to collection center a - ETW_{wr}: Environmental impact of pre-allocated truck trips from warehouse w to retailer r - HCA_{ia}, HCM_{im}, HCR_{ir}, HCW_{iw}: Unit inventory costs of product i at collection center a, manufacturer m, retailer r, and warehouse w - Θ_i: Usage coefficient of product i - Q_{ij}: Equals 1 if product j can serve as raw material for product i, otherwise 0 - σ_i: Percentage of returned product i required for producing other products - $PCRA_{irat}$, $PCSM_{smt}$: Unit procurement cost for collection center a to purchase product i from retailer r, and for manufacturer m to purchase raw materials from supplier s in period t - $TCAM_{iamt}$, $TCMW_{imwt}$: Unit transportation costs for product i from collection center a to manufacturer m and from manufacturer m to warehouse w in period t - TCS_{smt}: Unit transportation cost of raw materials from supplier s to manufacturer m in period t - $TCRA_{rat}$, $TCWR_{wrt}$: Fixed transportation costs from retailer r to collection center a and from warehouse w to retailer r in period t - U_{rw}: Equals 1 if product can be shipped from retailer r to warehouse w, otherwise 0 - V_{ra}: Equals 1 if product can be shipped from retailer r to collection center a, otherwise 0

Decision Variables: - N_{imt}: Quantity of product i produced by manufacturer m in period t - ILA_{iat}, ILM_{imt}, ILR_{irt}, ILW_{iwt}: Inventory levels of product i at collection center a, manufacturer m, retailer r, and warehouse w in period t - N_{smt}: Quantity of raw materials shipped from supplier s to manufacturer m in period t - NWR_{iwrt}, NRA_{irat}, NAM_{iamt}, NMW_{imwt}: Quantities of product i shipped from warehouse w to retailer r, from retailer r to collection center a, from collection center a to manufacturer m, and from manufacturer m to warehouse w in period t - OA, OM, OW, OR: Status indicators for collection centers, manufacturers, warehouses, and retailers (value 1 if open, 0 otherwise)

Objective Functions: - Z_1: Minimization of network cost - Z_2: Minimization of environmental impact (measured by CO emissions)

Z_1 comprises total inventory costs across all facilities, total fixed costs for establishing manufacturers, warehouses, and collection centers, total transportation costs between facilities, and total production costs for processing various products.

Z_2 comprises CO emissions from inventory holding at facilities, CO emissions from establishing manufacturers, warehouses, and collection centers, and CO emissions from transportation.

$$
\begin{aligned}
\text{Min } Z_1 = & \sum_{i,m,t} HCM_{im} \times ILM_{imt} + \sum_{i,w,t} HCW_{iw} \times ILW_{iwt} + \sum_{i,r,t} HCR_{ir} \times ILR_{irt} + \sum_{i,a,t} HCA_{ia} \times ILA_{iat} \\
& + \sum_{m} FCM_m \times OM + \sum_{w} FCW_w \times OW + \sum_{a} FCA_a \times OA + \sum_{s,m,t} TCS_{smt} \times N_{smt} \\
& + \sum_{i,m,w,t} TCMW_{imwt} \times NMW_{imwt} + \sum_{w,r,t} TCWR_{wrt} \times U_{wr} + \sum_{r,a,t} TCRA_{rat} \times V_{ra} \\
& + \sum_{i,a,m,t} TCAM_{iamt} \times NAM_{iamt} + \sum_{i,m,t} COM_{imt} \times N_{imt} \\
& + \sum_{i,j,a,m,t} Q_{ij} \times NAM_{iamt} \times PCRA_{irat} + \sum_{i,r,a,t} NRA_{irat} \times PCSM_{smt} \\
& + \sum_{i,m,t} COM_{imt} \times N_{imt} + \sum_{i,j,a,m,t} NAM_{iamt} \times COM_{imt} \times N_{imt} \\
& + \sum_{i,j,a,m,t} Q_{ij} \times NAM_{iamt} \times COM_{imt} \times N_{imt}
\end{aligned}
$$

Constraint (22) ensures each retailer receives products from only one warehouse, while constraint (23) ensures each retailer sends returned products to only one collection center.

Constraints (3) and (4) guarantee sufficient input at retailers and warehouses. Constraint (24) requires that all returned products sent from collection centers must be used for remanufacturing production simultaneously. Constraint (25) ensures that inventory levels of product i at each warehouse remain below the total outbound quantity of product i for the next p_i consecutive periods (product i' s life cycle). Constraint (5) states that the quantity returned from each retailer to collection centers is a portion of its demand. Constraint (6) ensures input flow exceeds output flow at each collection center. Constraint (7) balances input and output at each manufacturer. Constraint (8) requires each manufacturer' s output to be at least as much as products shipped from manufacturers to warehouses. Constraints (9)-(12) represent capacity constraints for manufacturers, suppliers, warehouses, and collection centers. Constraints (13)-(16) define inventory levels for each product at manufacturers, warehouses, collection centers, and retailers in each time period. Constraint (17) ensures products can only be produced by existing manufacturers. Constraints (18)-(19) ensure products are shipped from manufacturers to warehouses or collection centers. Constraints (20)-(21) prevent transshipment logistics between non-linked facilities. Constraint (26) ensures retailer inventory levels for each product in each period are less than total demand for the next p_i consecutive periods.

2.1 Multi-Objective Processing

Since the two objective functions Z_1 and Z_2 established in this paper conflict to some extent—when Z_1 performs well, Z_2 may perform poorly—to achieve Pareto optimality, this paper adopts the fuzzy compromise programming method for multi-objective processing. According to the mathematical expressions described in reference [20], the fuzzy compromise programming method is formulated as:

$$L_p(f) = \left[\sum_{i=1}^{k} \lambda_i^p \left(\frac{f_i - f_i^*}{f_i^{\max} - f_i^{\min}} \right)^p \right]^{1/p}$$

where p is a positive integer in $[1, \infty]$; $f_i^* = \min(f_i)$ represents the ideal solution for each sub-objective function f_i; λ_i denotes the weight assigned to each sub-objective, with $\lambda_i \in (0, \infty)$. Thus, the multi-objective model is equivalently transformed as follows:

$$\min \left\{ \max_{i=1,2} \left[w_i \left(\frac{Z_i^* - Z_i}{Z_i^*} \right) \right] \right\}$$

where w_i represents the relative weight of each sub-objective function, calculated as the product of λ_i and p. Different efficient solutions can be obtained by varying parameter p, with the most common values being $p = 1, 2, \infty$.

2.2 Robust Processing

To extend the deterministic model to an uncertain environment, this paper assumes return rates and demand as uncertain parameters. The robust method consists of two stages: first, constructing uncertainty parameter intervals to describe uncertain parameters; second, applying robust counterpart transformation to convert the robust model into an equivalent mixed-integer programming model for solution.

This paper sets uncertainty parameter intervals to consider deviation ranges [21] and proposes a robust counterpart form for the closed-loop supply chain model. Parameters are defined as $d = DR_{irt}$ and $k = K_i$. Uncertain parameters $\tilde{DR}_{irt}$ and $\tilde{K}_i$ are independently and identically distributed within the range $[d - \hat{d}, d + \hat{d}]$ and $[k - \hat{k}, k + \hat{k}]$, symmetrically distributed. Additionally, the uncertainty budget I_0 takes values in $[0, 1]$.

Since demand and return rates are assumed uncertain, and considering the impact of worst-case parameters on the model and algorithm in robust optimization, this paper only considers positive deviations of uncertain parameters for demand and return rates. Uncertain parameters primarily appear in constraints

(3), (5), and (26). Taking constraint (3) as an example, the left side contains uncertain parameters denoted as A_j, $j \in J$, where J represents the index set of uncertain parameters in this constraint. According to reference [21], we define:

$$\tilde{A}_j = A_j + \xi_j \hat{A}_j$$

where A_j is the nominal value and $\hat{A}_j$ represents the maximum deviation of A_j; $\xi_j \in U$, where U is a bounded closed set, and ξ_j is selected from the uncertainty set U to control the bounds of $\tilde{A}_j$. Based on these definitions, constraint (3) can be expressed as:

$$\sum_{j \in J} \tilde{A}_j x_j \leq b$$

The robust counterpart is formulated as:

$$\sum_{j \in J} (A_j + \hat{A}_j \xi_j) x_j \leq b, \quad \forall \xi \in U$$

where μ_1 represents the demand conservatism parameter, $\mu_1 \in [0, |i| \times |r|]$.

In summary, introducing $\tilde{d}_j$ to represent demand uncertainty in the supply chain, we have $\tilde{d}_j = d_j + \hat{d}_j \xi_j$, where $\xi_j \in U$, $j \in J$, and ξ_j is an independent random variable controlling $\tilde{d}_j$. Based on the above definitions and rules, auxiliary variable Y_j is introduced. With uncertainty budget $I_0 \in [0, 1]$, the relevant constraints and robust equivalent model Z^* are obtained. In the constraints, $\varepsilon = \tilde{DR}_{irt} \times \tilde{K}_i$ and $\beta^* = \frac{\hat{\varepsilon}}{\varepsilon}$. Additionally, $\mu_2 \in [0, |i| \times |r| \times |t|]$.

The robust model becomes:

$$\min\{Z_1, Z_2\}$$

subject to the original constraints with robust counterparts.

3.1 Encoding

Considering the multi-level, multi-period complexity of supply chain network design problems, this paper adopts matrix real-number encoding. Assume population size is P', the Q-th generation population $W_Q = \{K_1, K_2, \dots, K_{P'}\}$, where K_j represents the j-th individual in generation Q, $j \in [1, P']$, $Q \in [1, t_{\max}]$. Define $K_j = (C_{ab})_{m \times n}$, where C_{ab} denotes matrix elements, $a \in [1, m]$, $b \in [1, n]$. The matrix size K_j relates to the number of levels and nodes in the supply chain network, and matrix elements C_{ab} primarily reflect logistics or supply relationships with upper-level suppliers. For example, if K_j is a 3×4 matrix, the supply chain network model has 3 levels with a maximum of 4 nodes, and

$C_{21} = (53, 0, 48, 0)$ indicates that the first node at level 2 receives 53 units from the first node and 48 units from the third node of the upper-level supplier.

3.2.1 Population Initialization

The fundamental idea of HBA is optimization through simulating honey badger foraging behavior. Equation (34) initializes the number of honey badgers (population size N) and their respective positions:

$$x_i = lb_i + r_1 \times (ub_i - lb_i)$$

where r_1 is a random number in $[0, 1]$, x_i represents the position of the i-th honey badger in population N, and lb_i and ub_i are the lower and upper bounds of the search domain, respectively.

3.2.2 Predation Intensity

The predation intensity of honey badgers relates to prey concentration intensity and distance to the i-th honey badger. I_i represents prey odor intensity; higher intensity results in faster movement, and vice versa. It is defined as:

$$I_i = \frac{S}{4\pi d_i^2}$$

where S represents prey concentration and odor intensity, and d_i denotes the distance between prey and the i-th honey badger.

3.2.3 Update Density Factor

The density factor (α) controls time-varying randomness to ensure smooth transition between algorithm phases. According to equation (36), the decreasing factor α is updated with iteration count to reduce temporal randomness:

$$\alpha = C \times \exp\left(-\frac{t}{t_{\max}}\right)$$

where $t_{\max}$ represents maximum iteration count and C is a constant greater than 1 (default value 2).

3.2.4 Update Particle Position

As described above, HBA particle position updating employs two modes: "digging mode" and "honey mode." The algorithm uses a flag F to change search direction, ensuring more rigorous scanning of the search space to escape local optima.

1) Digging Mode: In digging mode, honey badger movement follows a heart-shaped trajectory simulated by equation (37):

$$x_{new} = x_{prey} + F_1 \times \beta \times I_i \times x_{prey} + F_2 \times \alpha \times d_i \times \cos(2\pi r_3) \times \cos(2\pi r_4) \times (x_{prey} - x_i)$$

where x_{new} represents the new position, x_{prey} denotes the global best position (prey location), $\beta \geq 1$ (default 6) describes the honey badger' s food acquisition ability, d_i is the distance between prey and the i-th honey badger, r_3, r_4, and r_5 are three distinct random numbers between 0 and 1, and F_1 is a direction change flag determined by equation (38):

$$F_1 = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{otherwise} \end{cases}$$

where r_6 is a random number in $[0, 1]$. In digging mode, honey badgers primarily rely on prey odor intensity I_i, prey distance d_i, and time search influence factor α.

2) Honey Mode: In honey mode, honey badgers following honeyguides to beehives can be simulated by equation (39):

$$x_{new} = x_{prey} + F_1 \times \alpha \times d_i \times r_7$$

where r_7 is a random number in $[0, 1]$, and α and F_1 are determined by equations (36) and (38). Equation (39) shows that honey badgers search near the currently discovered prey position x_{prey} based on distance information d_i. This search behavior is influenced by the time-varying factor (α).

3.3 Differential Honey Badger Algorithm

To improve the original honey badger algorithm' s tendency to fall into local optima and slow convergence when handling large-scale problems, this paper introduces the crossover and mutation principles from the Differential Evolution Algorithm (DEA) into the original HBA, forming the Differential Honey Badger Algorithm (DHBA). By executing differential evolution crossover and mutation strategies when selecting new positions and individuals, DHBA achieves broader global search range and greater population diversity. The specific DE/rand/1/bin crossover-mutation strategy is as follows:

1) Mutation Strategy:

$$V_{i,j} = X_{prey} + F_2 \times (X_{r_8,j} - X_{r_9,j})$$

where X_{prey} represents the current optimal position in the search region, F_2 is a scaling coefficient (constant in $(0,1)$), and $X_{r_8,j}$, $X_{r_9,j}$ are random individuals from the population, with r_8, r_9 being distinct integers from population N.

2) Crossover Operation:

$$U_{i,j} = \begin{cases} V_{i,j} & \text{if } \mathrm{rand}(0,1) \leq CR \\ X_{i,j} & \text{otherwise} \end{cases}$$

where $\mathrm{rand}(0,1)$ is a uniformly distributed random number in $(0,1)$, and CR is the crossover probability in $[0,1]$. The DHBA algorithm flow is illustrated in Figure 2.

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4 Example Verification

This paper uses a dairy product manufacturer in Shenyang as an example. The company' s supply chain network covers five administrative districts within the city, comprising 5 nodes including 3 suppliers, 5 manufacturing centers, 4 warehouses, 17 retailers, and 3 collection centers. The company primarily produces two types of dairy products, with collection centers only recycling one product type and considering only a fixed single transportation mode. Based on actual enterprise conditions, all parameter values follow uniform random distributions: demand uncertainty $\tilde{DR}_{irt} \in [400, 2000]$, return rate uncertainty $\tilde{K}_i \in [0,1]$. Specific parameter settings are shown in Table 1.

4.1 Robust Model Verification

To verify the stability and feasibility of the proposed robust optimization model, five test problems were generated for demand uncertainty scenarios, with parameters shown in Table 1. Sensitivity analysis was conducted between demand uncertainty $\tilde{DR}_{irt}$ and supply chain network cost/environmental impact functions, with the range set to $[400, 1400]$. Considering market competition, supply chain network design should prioritize enterprise benefits and costs, followed by environmental impact. Therefore, based on comprehensive practical considerations, weights w_1 and w_2 were set to 0.7 and 0.3, respectively, with retailer return rate set at 0.2.

Using DHBA for calculation based on Table 1 and actual case data, the variation of objective function values with demand uncertainty is shown in Figure 3 (unit: demand/ton).

Figure 2. DHBA algorithm flow

Table 1. Parameter settings

Parameter	Range
LS_s, LM_m, LW_w, LA_a	10000~40000
HCM_{im}, HCW_{iw}, HCA_{ia}, HCR_{ir}, Θ_i, COM_{imt}	0.04~1
FCM_m, FCW_w, FCA_a	5000~80000
TCS_{smt}, $TCMW_{imwt}$, $TCAM_{iamt}$, $PCRA_{irat}$, $PCSM_{smt}$	10~40
$TCWR_{wrt}$, $TCRA_{rat}$, DR_{irt}	500~3000
ETS_{sm}, ETM_{imw}, ETW_{wr}, ETR_{rc}, ETA_{jam}, EM_m, EA_a	0.9~4.56

Table 2. Robust model test problems

Test Problem	DR_{irt}

Table 3 compares objective functions between robust and deterministic models under demand uncertainty. The results show that the robust model demonstrates significant advantages over the deterministic model, with average total cost function Z_1 decreasing by 34.37% and average environmental impact function Z_2 decreasing by 22.71%.

Table 3. Comparison of robust and deterministic models under uncertain demand

Model	$Z_1/10^5$	$Z_2/10^5$
Robust Optimization Model	[values]	[values]
Deterministic Model	[values]	[values]

4.2 Sensitivity Analysis

To further verify model reliability, sensitivity analysis was conducted on retailer return rates. As shown in Figure 3, cost and environmental functions exhibit similar trends within $[400, 800]$. However, within $[800, 1400]$, as retailer demand increases, supplier and manufacturer shipment and production volumes increase rapidly, causing costs to rise sharply. The environmental cost function shows relatively moderate fluctuation with demand uncertainty, primarily due to weight settings. In reality, upper-level decision-makers in supply chains can determine weight allocation based on actual policies and preferences.

Figure 3. Influence of demand on supply chain cost and environmental cost

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4.3 Algorithm Performance Testing

To comprehensively evaluate DHBA performance, it was compared with mainstream algorithms including Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Improved Whale Optimization Algorithm (IWOA) [22], and original Honey Badger Algorithm (HBA) in Matlab R2018b. The computational environment was: R7-4800H RTX2060 processor, 16GB RAM, Windows 11 operating system.

Five test problems were generated for the objective functions (Table 4), with node parameters from Table 1. Population size was set to 50 and maximum iterations to 400. To verify the multi-objective robust optimization model and avoid randomness, two weight scenarios were tested: $(w_1, w_2) = (0.5, 0.5)$ and $(0.8, 0.2)$. DHBA, NSGA-II, and IWOA were applied to solve the model, with results shown in Table 5 and algorithm comparison in Figure 4.

Table 4. Test problems

Test Problem	Description

Table 5. Optimal solutions under two weight scenarios

Algorithm	$(0.5, 0.5)$ $Z_1/10^6$	$(0.5, 0.5)$ Time/s	$(0.8, 0.2)$ $Z_1/10^6$	$(0.8, 0.2)$ Time/s
DHBA	[optimal]	[time]	[optimal]	[time]
NSGA-II	[value]	[time]	[value]	[time]
IWOA	[value]	[time]	[value]	[time]
HBA	[value]	[time]	[value]	[time]

The results show that DHBA's ability to obtain optimal solutions exceeds NSGA-II and IWOA under both weight scenarios, demonstrating the effectiveness and feasibility of the differential evolution honey badger algorithm for solving multi-objective problems. However, DHBA is not perfect—its local search speed still has room for improvement compared to NSGA-II.

Figure 4 reveals that in the initial phase $[0, 30]$, HBA's convergence speed slightly exceeds DHBA, NSGA-II, and IWOA, while the other three have similar initial convergence rates. In interval $[32, 51]$, DHBA converges rapidly, outperforming the others. In $[55, 90]$, IWOA shows optimal convergence speed, but excessively fast mid-stage convergence can easily lead to local optima, which could be improved by introducing other global search strategies. NSGA-II' s optimization capability ranks second to DHBA, with similar convergence speed.

Figure 4. Average function value and iteration solution speed

The results indicate that while HBA' s initial convergence speed exceeds DHBA, NSGA-II, and IWOA, it falls into local optima. Figure 4 visually demonstrates the significant difference between HBA and DHBA optimal values, validating the effectiveness of introducing differential evolution principles to improve HBA' s global optimization capability. Overall, DHBA performs best in optimal value selection, though its convergence speed requires further enhancement. Future research could improve HBA by adjusting parameters and refining the dynamic search patterns of digging and honey modes.

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5 Conclusion

This paper establishes a multi-objective optimization model for fresh closed-loop supply chain network robust optimization design and solves it using DHBA. Key conclusions are:

a) A multi-objective function minimizing network cost and environmental impact was established, processed using fuzzy compromise programming and interval data robust optimization methods for uncertain parameters.

b) The original HBA algorithm was enhanced by introducing differential evolution mutation and crossover strategies to improve search capability and convergence speed. Comparison with NSGA-II, IWOA, and original HBA in Matlab simulations demonstrates that DHBA features fast convergence and superior optimal value search advantages for multi-objective NP-hard problems.

c) Real-world fresh closed-loop supply chain networks involve more uncertainty factors. This paper considered demand and return rate uncertainties. Future research will incorporate distribution time and product freshness impacts on closed-loop supply chain design to ensure greater practical relevance.

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Note: Figure translations are in progress. See original paper for figures.