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Research on material whole chain response efficiency improvement model based on network topology optimization

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Abstract With the intensification of competition in the business environment, the efficiency of the whole chain response of materials has become the key to the competition of enterprises. The existing logistics network structure is difficult to balance the timeliness and cost. The study constructs a model to improve the response efficiency of the whole chain of materials based on network topology optimization, and explores the balance between the time efficiency of the whole chain response and the cost of network connection. The network topology-based particle swarm optimization (NTPSO) algorithm is used to construct a fast response system for the whole chain of materials, and the optimization ability of the algorithm is improved by the local path index, weighted connection matrix, and multi-subpopulation learning strategy. Case validation shows that among the three optimization schemes, Scheme 1 achieves the lowest cost of 2481.348 yuan, Scheme 8 reaches the shortest response time of 0.948 hours, and Scheme 5 obtains the highest customer satisfaction of 28.798. After the implementation of this model, the 100-min completion rate of the whole-chain response of the materials is stable at about 95%, the task processing time decreases up to 99.58%, and the user satisfaction (NPS) increases up to 6.63%, which proves that the model can be used to improve the quality and efficiency of the whole-chain response. 6.63%, proving that the model effectively solves the balance between time and cost, and significantly improves the efficiency of the whole chain response.

Index Terms Network topology optimization, Material-wide chain, Response efficiency, Particle swarm algorithm, Chain-wide integration, Fast response

I. Introduction

The current state of the global supply chain (GSC) is at a complex and volatile stage. Nowadays, multiple factors such as epidemics, geopolitical tensions, and energy crises are intertwined, and each link of the global supply chain is affected by various factors, showing complex and dynamic changes. Transportation disruptions, raw material shortages, and labor shortages are commonplace around the world, especially in the period of epidemics, the global manufacturing industry is halted, and a large number of enterprises are unable to obtain sufficient parts or raw materials, and production lines are stalled, even leading to a supply crisis for the whole industry [1]-[5]. The defects of the whole chain supply of materials are exposed, which are presented as the lack of flexibility of the network nodes of static supply in the dynamic response environment, the decrease of the sensitivity of the network node topology, the insufficient sharing of the storage data resources, and the solidification of the network node paths, which lead to the long stagnation time of the transportation transit station, and the chaotic and untimely deployment of the materials, which is more significant in the management of the emergency materials [6]-[9]. Actively applying modern technology to solve the above problems in order to continuously and holistically improve the response efficiency of the whole chain of materials.

With the deepening of globalization and the intensification of market competition, supply chain network optimization becomes more and more important. Supply chain network is a complex and large system involving numerous participants and resources, so the rational design of its topology is crucial for improving efficiency and reducing costs [10], [11]. When it comes to large and complex networks, decision makers and network administrators need to make many choices and decisions to ensure the optimality of the network, and in order to protect the security and performance of the network, network administrators have been exploring different methods to improve the network topology [12]-[14]. Therefore, network topology optimization is a crucial aspect of network design. Network topology optimization techniques are used to improve the efficiency, security, and other metrics of the entire supply chain network by optimizing the connections between the nodes in the supply chain network [15].

In today's competitive business environment, the efficiency of material whole-chain response has become a key factor in the competition of enterprise services. A good supply chain response time can not only improve customer satisfaction, but also significantly enhance the market competitiveness of enterprises. However, the structure of the whole-chain response network has a direct impact on the network connection cost and the whole-chain response time, and there is often a contradictory relationship between the two: the pursuit of the optimal whole-chain response time may lead to a significant increase in the network connection cost, while excessive attention to cost minimization may reduce the whole-chain response time of the network. The core problem faced by the optimization of material full-chain response network is how to find a balance point between these two key indicators, and establish an efficient network structure that can meet the time requirement and control costs at the same time. This problem is more prominent especially for the commerce environment with wide coverage, uneven customer distribution density, diverse demand varieties, and random distribution of demand time points. Existing studies have shown that network topology optimization provides new ideas for solving such problems, but there is still a lack of systematic research that organically combines network topology theory with the improvement of response efficiency of the whole chain of materials. The study takes this as an entry point to construct a model for improving the response efficiency of the whole chain of materials based on network topology optimization, and combines particle swarm algorithm to design the corresponding optimization strategy. Firstly, we analyze three ways to optimize the whole-chain network of materials: to improve the time efficiency under fixed cost, to reduce the cost under fixed time efficiency, and to improve the time efficiency and reduce the cost at the same time, and we establish a mathematical model with the shortest path distance, the whole-chain response time efficiency and the network connection cost as the core parameters. Subsequently, a network topology-based particle swarm optimization algorithm (NTPSO) is proposed to enhance the search and optimization capability of the algorithm through local path metrics, fitness-based normalized edge weights, and individual learning strategies. On this basis, a whole-chain rapid response system containing the functions of shared commerce platform, diversified synergy, dumping combined with modularization of whole-chain response, integration of route planning and rapid payment and settlement is designed. In order to verify the effectiveness of the model, the study uses real cases for experiments to evaluate the practical value of the model by comparing the performance of different schemes in three dimensions: total cost, response time and customer satisfaction. Meanwhile, the task completion rate, average processing time and user experience before and after the implementation of the model are compared and analyzed to comprehensively assess the practical application effect of the model. This study not only theoretically enriches the application of network topology optimization in the field of logistics, but also provides feasible technical solutions and practical guidance for the improvement of the response efficiency of the whole chain of materials, which is of great significance for improving the competitiveness of enterprise services.

II. Material whole chain response efficiency improvement model based on network topology optimization

II. A. Chain-wide material response efficiency network optimization

Figure 1 shows the optimization logic of material whole-chain network, based on the logistics network operation of time competition, the key of enterprise service competition is to improve the customer service experience, and good item whole-chain response time efficiency will bring high customer satisfaction [16]. The structure of the material whole chain network will have an impact on the network connection cost and the whole chain response time, and the whole chain response time and the network connection cost of the material whole chain network are contradictory, the one-sided pursuit of the optimal whole chain response time will significantly increase the connection cost of the whole network, and the one-sided pursuit of the minimum network connection cost will reduce the network whole chain response time. A well-operated whole-chain network should find a balance between whole-chain response time and network connection cost, instead of pursuing the simultaneous optimization of network connection cost and whole-chain response time. There are three ways to optimize the material chain-wide network, the first one is to keep the network connection cost unchanged and improve the chain-wide response time. The second is to reduce the network connection cost while keeping the network chain-wide response time unchanged. The third is to improve the timeliness of the chain-wide response while reducing network connection costs.

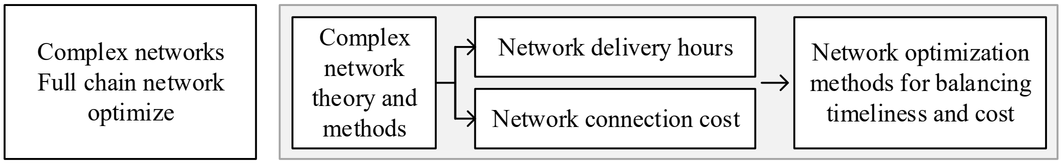

Figure 1: Chain network optimization logic

II. B. ***Model parameters***

The full-chain response network is a network composed of any node and any node pair, the nodes in the network are composed of hub center nodes, transfer nodes at all levels and response nodes at the end of the whole chain, and the network edge is composed of transportation lines connecting each node. The full-chain response network is recorded as graph $G=(V,E,W)$, and the set of network nodes is $V=\{v_1,v_2,v_3,\ldots,v_n\}$, and the number of nodes in the network is $|V|=N$, the set of edges between nodes is $E=\{e_1,e_2,e_3,\ldots,e_n\}$, and the number of edges $|E|=M$, the weight matrix of the adjacency edge distance of the network G is $W=(w_{ij})_{m\times n}$, and w_{ij} is expressed as the weight distance of the adjacency edges of node i and node j. If there is no adjacency edge between node i and node j, then $w_{ij}=\infty$.

II. B. 1) **Shortest path distance**

In a full chain response network, if the shortest path between the starting node and the final node is longer, the more difficult it is to circulate items between the two nodes, and d_{ij} is used to denote the shortest path distance between node i and node j, which is related to the network structure.

In this paper, Floyd algorithm is used to calculate the shortest path distance d_{ij} between nodes in the full chain response network, Floyd algorithm calculates the shortest path distance between all the nodes in the network only once, the specific steps of the algorithm are as follows [17]:

(1)Input edge weight matrix w, node i and node j exist neighboring edges, then $d_{ij}=w_{ij}$, node i and node j do not exist directly adjacent edges and $i\neq j$, then $d_{ij}=\infty$, if $i=j$, then $d_{ij}=0$

(2) Let $k=1$.

(3) Update d_{ij}. For all i,j, if $d_{ik}+d_{kj}<d_{ij}$, then let $d_{ij}=d_{ik}+d_{kj}$, and

(4) Update k such that $k=k+1$.

(5) The algorithm stops if $k=n$ and goes to (3) if $k<n$.

II. B. 2) **Chain-wide response times**

Response efficiency is an important indicator for evaluating service quality, the transportation time between nodes is related to the shortest path distance, the longer the shortest path distance between two nodes, the longer the item delivery time, the response time is also related to the number of nodes passing through the shortest path between node i and node j, and every node that passes by consumes a certain amount of time. The response time between two nodes is also related to the speed of the vehicle, the faster the vehicle travels, the shorter the time required for the response between two nodes. In this chapter, t_{ij} is used to denote the response time between node i and node j with the expression:

$$t_{ij}=x_{ij}\times NPT+\frac{d_{ij}}{v} \tag{1}$$

where x_{ij} denotes the number of nodes passing through on the shortest path from node i to node j (excluding the start node and the target node), NPT denotes the node time lag, i.e., the residence time of the item at the intermediate nodes, and v denotes the vehicle traveling speed.

The number of transit nodes that the item passes through between node i and node j, i.e., the number of transits x_{ij}, is found by Floyd's algorithm. Construct the weighted distance matrix D_0 and the path matrix R_0, and the elements in the path matrix R_0 are r_{ij}. The specific steps are as follows:

(1) Input the edge weight matrix W. w_{ij} denotes the distance of the edge $\{i,j\}$, and if $\{i,j\}\notin E$, then let $w_{ij}=\infty$, and if $i=j$, then $w_{ij}=0$.

(2) For all i,j, let $d_{ij}=w_{ij}, r_{ij}=j, k=1$.

(3) Update d_{ij} and r_{ij}. For all i, ja , if $d_{ik}+d_{kj}<d_{ij}$, then let $d_{ij}=d_{ik}+d_{kj}, r_{ij}=k$.

(4) Update k such that $k=k+1$.

(5) If $k=n$, the algorithm stops, if $k<n$, go to (3).

After n iterations of the algorithm, the shortest distance path matrix R_n is obtained. If $R_{ij}=a$ in the path matrix R_n, it means that node a is the intermediate node of node i and node j, the same method can be used to find all the transit nodes by searching from to the direction of node i and node j, respectively, i.e., all the transit nodes can be found.

The average value of all response times between nodes in the full chain response network is denoted by T, the smaller the value of T, the better the response efficiency of the full chain response network. The average response time T of the full chain response network can be expressed by equation (2):

$$T=\frac{1}{n(n-1)}\sum_{i\neq j}t_{ij}=\frac{1}{n(n-1)}\sum_{i\neq j}(x_{ij}\times NPT+\frac{d_{ij}}{v}) \tag{2}$$

where n is the number of nodes, the number of response paths in the network is $n(n-1)$, x_{ij} denotes the number of nodes passing through on the shortest path from node i to node j (excluding the start node and the target node), NPT denotes the node time lag, i.e., the residence time of the item at the intermediate nodes, and v denotes the vehicle traveling speed.

II. B. 3) Network connection costs

The network connection cost in the material all-chain network is related to the length of the network connecting edges, the longer the total length of the network connecting edges means that more energy is consumed, and if the total length of the network connecting edges is shorter, the more items flow through the network connecting edges.

In this paper, we define the connection cost of the all-chain response network as the total length of the connected edges in the network, and use $Total\_L$ to denote the total length of the connected edges in the all-chain response network, then the network connection cost is expressed by equation (3):

$$Total\_L=sum(sum(A.\times W)) \tag{3}$$

where $sum(sum())$ is the sum of all elements of the matrix in parentheses, $A=(a_{ij})_{n\times n}$ is the adjacency matrix of the network G, when there is an edge between node i and node j in the network, then the element $a_{ij}=1$ in A, when there is no edge connection between node i and node j in the network, then the element $a_{ij}=0$, $W=(w_{ij})_{m\times\pi}$ is the distance weight matrix of the network edges, w_{ij} is the distance weight of node i and node j edge e_{ij}, if there is no edge between node i and node j, then $w_{ij}=\infty$, if $i=j$, then $w_{ij}=0$.

II. C. Modeling

II. C. 1) Model description

Firstly, the expected average network delivery time T_p is set according to the nature of this full-chain transportation item, and then the lowest total length of the network connecting edges is taken as the optimization objective, and it is necessary to satisfy that the actual average delivery time T of the full-chain response network is smaller than the expected average delivery time T_p of the full-chain response network. The network optimization model is shown in Eqs. (4) and (5):

$$f=\min(Total_L)=\min(sum(sum(A.\times W))) \tag{4}$$

$$s.t.\quad T\leq T_p \tag{5}$$

where Eq. (4) is the optimization objective of the model in this chapter to minimize the total connectivity cost $Total\_L$ of the full chain response network, $sum(sum())$ denotes the sum of all the elements of the matrix inside the parentheses, $A=(a_{ij})_{n\times n}$ is the adjacency matrix of the network, and $W=(w_{ij})_{m\times n}$ is the connecting edge distance weight matrix of the network. Equation (5) is the constraint of the optimization model, which indicates that the actual average delivery time T of the full chain response network is less than or equal to the expected average delivery time T_p of the network with fixed values.

II. C. 2) Algorithm design

Since the distribution time efficiency is optimal in the fully connected state of the all-chain response network, the algorithm is designed to find the all-chain response network with the smallest network connection cost by starting from the fully connected network and then gradually deleting the least efficient connecting edges in the network, and the deletion of connecting edges needs to satisfy Equation (6):

$$\min(\frac{T^i - T}{Total_L - Total_L^i}) \tag{6}$$

where T is the average distribution time before deleting network edges, T^i is the average distribution time after deleting network edges, $Total\_L$ is the total connection cost of the network before deleting network edges, $Total\_L^i$ is the total connection cost of the network after deleting network edges, and min denotes the cost of selecting the optimal network from among the networks that independently deleted one edge. An optimal network is selected from the comparison of multiple networks that independently remove a connecting edge.

In order to avoid local optimality in the result, in each iteration of the algorithm, two edges are always deleted in the full-chain response network first, and each deletion of a connecting edge minimizes the increment of the average network delivery time while decreasing the same network connection cost, and then a connecting edge is added to the full-chain response network to maximize the decrease of the average network delivery time while increasing the same network connection cost, and the added The connected edge satisfies Equation (7):

$$\max(\frac{T - T^j}{Total_L^j - Total_L}) \tag{7}$$

where T^j is the average delivery time after adding network connectivity, T is the average delivery time before adding network connectivity, $Total\_L^j$ is the total connection cost after adding network connectivity, and $Total\_L$ is the total connection cost before adding network connectivity.

III. Optimization algorithm based on network topology

III. A. Particle swarm optimization based on network topology

III. A. 1) Rationale and metrics for materiel-wide link prediction

Let a_{ij} be the elements of the connection matrix A, $i \in [1, N], j \in [1, N]$. where N is the total number of nodes, and for the PSO algorithm, N is the total number of particles (i.e., population size). Then the matrix A can be expressed by Eq. (8) [18]:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{pmatrix} \tag{8}$$

Therefore, its connection matrix is a 7 × 7 square matrix. Node 1 is connected to node 4, so the elements of the connection matrix $a_{14} = a_{41} = 1$. For nodes that are not connected, the elements of the corresponding connection matrices are 0. In particular, the elements of the diagonal positions of the matrices are 0, indicating that the connection matrices do not contain self-loop structures. The connection matrix of the undirected network topology is a symmetric matrix. There are 12 connected edges in this topology, so this connection matrix has a total of 24 nonzero elements.

According to the definition of connection matrix, it is easy to know that the number of common neighbors $|\Gamma(i) \cap \Gamma(j)|$ of node i and node j can be calculated from the connection matrix according to Equation (9), where $(A^2)_{ij}$ denotes the elements of the i th row and j th column of the matrix A^2. of the matrix A^2. Therefore, the number of common neighbors among all nodes in the network can be represented by the matrix A^2:

$$|\Gamma(i) \cap \Gamma(j)| = \sum_{k=1}^{N} a_{ik} \cdot a_{kj} = (A \cdot A)_{ij} = (A^2)_{ij} \tag{9}$$

Similarly, the number of common 3rd order neighbors $|\Gamma_3(i) \cap \Gamma_3(j)|$ of node i and node j can be computed by Eq. (10), where $(A^3)_{ij}$ denotes the i-row, j-column of matrix A^3 of the element of the matrix A^3:

$$|\Gamma_3(i) \cap \Gamma_3(j)| = \sum_{l=1}^{N}((\sum_{k=1}^{N} a_{ik} \cdot a_{kl}) \cdot a_{lj}) = (A^3)_{ij} \tag{10}$$

Therefore, the number of common neighbors and the number of common 3rd order neighbors of two nodes can be obtained by matrix operations A^2 and A^3, respectively. Therefore, the local path metrics can be expressed as Eq. (11):

$$S = A^2 + A^3 \tag{11}$$

III. A. 2) Topology update based on material-wide link prediction

In order to ensure the computational efficiency of the PSO algorithm, it is required that the information of the particles with good quality can be passed to other particles in the neighborhood as fast as possible, while the information of the particles with poor quality affects other particles as little as possible. For this reason, this paper proposes an adaptation-based normalized edge weight. The specific description is given by Definition 1.

Definition 1: For any connected edge l_{ij} (where i and j denote the two endpoints of the connected edge) within a population network topology, assuming that the optimal fitness in the current network topology is $f_{\min}$ (this paper studies the minimization problem), and the worst fitness is $f_{\max}$, the connected edge l_{ij} has the weight $a_{w,j}$ computed by Equation (12):

$$a_{w,ij} = (\frac{1}{f_{\hat{y}}} - \frac{1}{f_{\max}}) / (\frac{1}{f_{\min}} - \frac{1}{f_{\max}}) \tag{12}$$

where $f_{ij} = (f_i + f_j)/2$. Therefore, all the elements $a_{w,ij}$ form the weighted connectivity matrix A_w, which is represented by Equation (13):

$$A_w = \begin{pmatrix} a_{w,11} & \cdots & a_{w,1n} \\ \vdots & \ddots & \vdots \\ a_{w,n1} & \cdots & a_{w,nn} \end{pmatrix} \tag{13}$$

According to the definition of normalized weights given in Definition 1, it is known that the weight-containing connectivity matrix A_w has the following properties:

Property 1: The connecting edges composed of nodes with less adaptation have more weights in the connectivity matrix. That is, if $f_{ij} < f_{mn}$, then $a_{w,ij} > a_{w,mn}$. where i, j, m, n are nodes in the network (i.e., particles in the PSO).

Property 2: All elements in the connection matrix belong to the interval [0, 1], i.e., $0 \le a_{w,ij} \le 1$.

The connection matrix A_w with weight information is established by introducing the concept of adaptation-based edge weights. In turn, Equation (14) is used to calculate the weighted local path link prediction index S_w, which solves the problem of existing link prediction methods that cannot effectively differentiate the particle fitness. Among them, the local path link prediction indexes with weights for node i and node j are the elements $S_{w,ij}$ of the i th row, j th column of the matrix S_w:

$$S_w = A_w^2 + A_w^3 \tag{14}$$

According to Property 1, it can be seen that in the connection matrix A_w with weighted information, the particle information with good quality (small adaptation) has greater weight. In the network topology update based on link prediction, edges with greater weights have a greater chance of being connected. Therefore, particles with better adaptation can influence more particles and can pass their information to other particles in the neighborhood faster, which in turn improves the search optimization ability of PSO.

III. A. 3) Individual learning strategies

It has been shown that the PSO algorithm based on multiple subpopulation structure is beneficial for particles to perform optimization. Maintaining the diversity of the population during the search process to reduce the occurrence probability of the algorithm falling into local minima is one of the keys to improve the PSO algorithm. In this paper, we adopt the multiple subpopulation structure based on fitness, and use different learning strategies for different subpopulations to improve the diversity of the population, so as to reduce the risk of falling into local minima, and at the same time ensure the overall computational efficiency of the PSO algorithm. In this paper, the parameter λ is used to represent the proportion of the better individuals in the population. The top $|\lambda N|$ individuals are selected to form subpopulation 1, and the remaining ($N - [\lambda N]$) individuals form subpopulation 2. The following describes the individual learning strategies of subpopulation 1 and subpopulation 2 respectively.

(1) Learning strategy of subgroup 1

For subpopulation 1, in order to ensure the diversity of subpopulations and at the same time have a faster convergence speed, this paper uses the network topology-based "integrated learning strategy" to update the speed, as shown in Equation (15). The positions of the particles are updated according to equation (16):

$$v_{id}^{t+1} = \omega_L \cdot v_{id}^t + c \cdot r_{id} \cdot (pbest_{fi(d)d}^t - x_{id}^t) \tag{15}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{16}$$

where the inertia weight ω_L is decreasing with the number of iterations. Larger initial inertia weights result in relatively higher diversity at the beginning of the iteration, while smaller values of inertia weights at the end of the iteration result in relatively faster convergence of the population, as shown in Equation (17):

$$\omega_L = \omega_{ini} - (\omega_{ini} - \omega_{end}) \cdot t / Iter_{\max} \tag{17}$$

ω_{ini} is the value of inertia weight at the beginning iteration, ω_{end} is the value of inertia weight at the final iteration step, and $Iter_{\max}$ is the maximum number of iterations. The inertia weight ω_L is linearly decreasing with the number of iterations, with an initial value of 0.99 and a termination value of 0.2 in this paper.

The integrated learning strategy based on network topology is described below. In order to ensure the diversity of the population, different dimensions of the same particle are learnable from different particles. As shown in Equation (15), $f_i(d) = [f_i(1), f_i(2), ..., f_i(D)]$ denotes the particle number of the learning object selected in the d th dimension of the i th particle. It could be its own $pbest$ or other particles' $pbest$. This flexible selection strategy can fully ensure the diversity of the population and better utilize the information of the population to update the particle velocity. Among them, the selection of the learning object of $pbest$ is a tournament strategy to determine the learning object of each dimension. Firstly, two alternatives $f_1(d)$ and $f_2(d)$ are randomly selected in the neighborhood of the node determined by the topology, and the adaptation values corresponding to the $pbest$ of these two are compared to select the better of the two. When $gbest$ is not updated for consecutive R generations, $f_i(d)$ is re-selected for each particle.

(2) Learning strategy for subpopulation 2

Subpopulation 2 is the particle with relatively poor adaptation value. In order to make this part of the particles can also help to find the excellent region more effectively, this paper comprehensively considers various effective information in its learning strategy. In addition to its own inertia term and its own cognition, the influence of social cognition on the individual is also considered in the learning strategy, as shown in equation (17). Among them, the social cognition comes from the influence of the population optimal solution $gbest$ and the influence of the optimal individual in the neighborhood of the individual determined by the network topology $nbest$. Its position is updated in the same way as subpopulation 1, according to Equation (16):

$$\begin{aligned} v_{id}^{t+1} &= \omega_L \cdot v_{id}^t + c_1 r_1 (pbest_{fi(d)d}^t - x_{id}^t) \\ &+ c_2 r_2 (gbest_d^t - x_{id}^t) \\ &+ c_3 r_3 (nbest_{id}^t - x_{id}^t) \end{aligned} \tag{18}$$

Subcluster 2 not only retains the dimensionally integrated learning strategy of subcluster 1. It also considers the influence of other particles in the neighborhood topology on itself determined by the weighted local path link prediction index. Through the link prediction-based topology updating strategy, the neighbor optimal solution of particles in subpopulation 2 $nbest$ is to take the best particles in the individual's neighborhood as its own social learning object. This is because not only the best particle $gbest$ is considered as the learning object, but also the diversity of the population is not lost due to the fact that the neighborhood information is constantly updated because of the dynamic topology updating strategy. Therefore, this individual learning strategy, while maintaining as much diversity as possible, enables this part of the particles to better focus on discovering the better regions as well.

III. B. ***Algorithm Flow***

Based on the analysis of the link prediction-based topology history new strategy and individual learning strategy in Section 3.1, the flow of the NTPSO algorithm proposed in this paper can be summarized by the flowchart shown in Fig. 2. The specific steps are as follows:

Step 1: Initialization: particle position x, particle velocity v. Set parameters: population size, inertia weights and learning factor. Iterate the counter $i = 0$.

Step 2: Evaluate the fitness of the initial population and determine the individuals $pbest, nbest$ and population $gbest$ of the first generation of particles.

Step 3: The loop starts with $i = i + 1$ and the inertia weight ω_L is calculated for each iteration i. Determine whether the topology update condition is satisfied. If it is satisfied, execute Step 3-1, Step 3-2 and Step 3-3, otherwise, skip to Step 4.

Step 3-1: Determine the weighted connection matrix A_w according to Eq. (13).

Step 3-2: Calculate the weighted local path link predictor S_w according to Equation (14).

Step 3-3: Update the neighborhood topology according to algorithm (8) and algorithm (9).

Step 4: Update the velocity and position of particles in the population.

Step 4-1: Sort the particles by the fitness value of the previous generation and divide the population into subpopulation 1 and subpopulation 2 based on the particle division ratio.

Step 4-2: Learning object $fi(d)$ for $pbest$ determined according to the neighborhood topology and tournament strategy. At the same time, select the best neighbor for each particle of subgroup 2 according to the neighborhood topology and determine $nbest$.

Steps 4-3: Update the velocity v of each particle of subpopulation 1 and subpopulation 2 according to Eq. (15) and Eq. (18), respectively, and update the position x of each particle according to Eq. (16).

Step 5: Calculate the fitness value of each particle after updating $pbest, nbest$ and $gbest$.

Step 6: Determine whether the iteration end condition is satisfied, if so, execute step 7, if not, jump to step 3 and continue the iterative loop.

Step 7: Output the global optimal solution $gbest$ and the corresponding fitness value, and the algorithm operation ends.

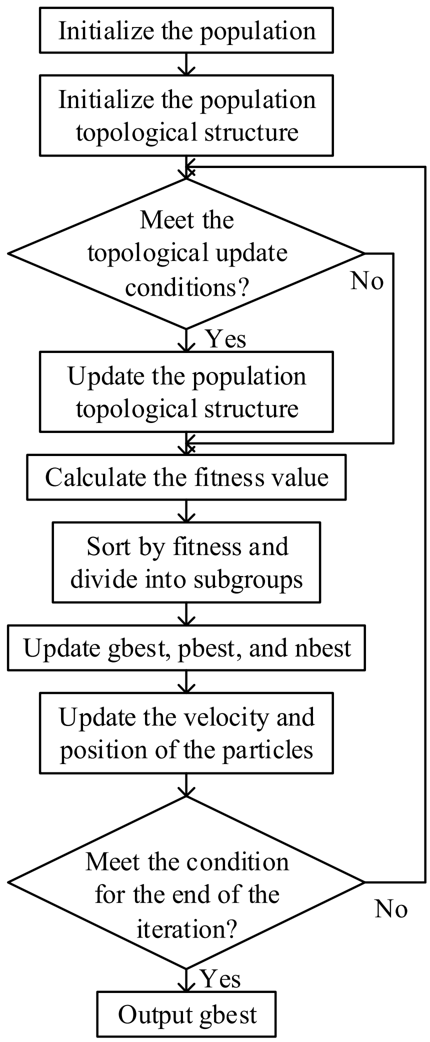

Figure 2: Flowchart of the NTPSO algorithm

IV. Establishment of a framework for improving the efficiency of the whole chain of material response

IV. A. Rapid Response Architecture

From the perspective of material flow, Figure 3 shows the full chain response model diagram. The test mall store stores reached 2578, storage area of 4000 acres, downstream service of more than 20,000 individuals, stores, and small batch, small scale, there is no doubt that should be used in high-efficiency third-party logistics model.

The most downstream stores/shops, individuals are widely distributed, the demand for a variety of needs, the demand for random distribution of time points, which brings challenges to the upstream logistics services, the actual spatial distance can not be shortened, there are only two strategies: one is to improve the response speed of the whole chain, and the second is the integration of information. The whole chain response speed is the average of transportation walking speed, stocking speed, picking speed, addressing speed and picking speed. Under the limitation that the walking speed cannot be accelerated, the only way is to speed up from stocking, picking, addressing and picking operations. In fact, there is no speed faster than the speed of light, and information is spread by speed, the key is the collection of information, processing speed can be very time-consuming, and in the enterprise “firewall” and “corporate power domain” of the barrier, may be slower than the flow of goods. Therefore, it is necessary to consider eliminating these resistance by, firstly, collaborating widely within enterprises, sharing “enterprise power domains”, establishing golden bridge alliances, and making joint pre-decisions, and, secondly, breaking down firewalls between enterprises, realizing interconnectivity, and implementing information integration with the support of e-commerce systems.

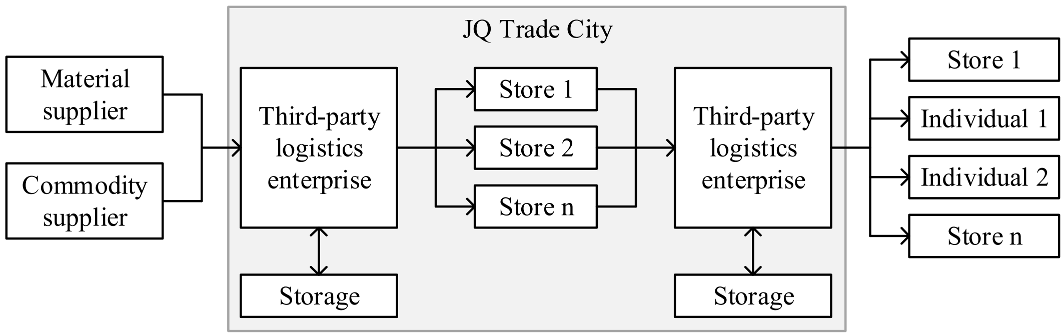

Figure 3: Full chain response model

IV. B. Rapid Response Functional Structure

IV. B. 1) Full chain integration

Today, integrated logistics management has become an advanced management model commonly adopted by major manufacturing companies around the world. Small-scale, decentralized enterprises are unable to meet customer needs with high efficiency and high quality, and enterprises in the test business circle must adopt integrated management strategies to maximize benefits if they want to expand their survival and development space. In order to achieve logistics integration, we must first establish a highly efficient whole chain, so that the procurement logistics, production logistics and sales logistics and business flow, capital flow and information flow can be integrated, so as to meet the customer's requirements in terms of commodity variety, quantity, quality and delivery place, time, mode, price, packaging and so on. Full-chain integration is firstly reflected in the integration of information systems, including the integration of information systems within enterprises and the integration of information systems between enterprises, including the integration of heterogeneous systems. Full-chain integration is also reflected in the integration of resources, and in the environment of commerce and circulation where the subject is the dominant one, the integration of resources can be tuned through the establishment of the subject fund.

As a new strategic management mode, integrated logistics management emphasizes the cooperation between various node enterprises in the whole chain of the test, the establishment of strategic partnership, the organic integration of the internal resources of logistics service providers and the resources of suppliers for management, and the use of operations research methods to carry out global optimization and coordination, to achieve the global dynamic optimal goal, and ultimately achieve a multi-win situation for the whole chain.

IV. B. 2) Chain-wide synergies

In today's market environment, on the one hand, personalized production and customized marketing are the inevitable direction to strengthen the whole-chain management and improve the competitiveness of the whole chain, and on the other hand, the product life cycle becomes shorter and shorter with the development of the society. Since the market environment and consumer demand's are dynamic, if timely information exchange cannot be achieved between upstream and downstream organizations, the whole whole chain will have planning errors, and the wrong beat of any link will lead to the efficiency of the whole chain to decline. In the past, retailers simply passed goods from manufacturers to consumers, playing the role of intermediaries. If the subject trade city wants to achieve synergy in the whole chain, its retailers must be like Wal-Mart, to be involved in the control of the manufacturer's planning operations, to quickly pass the customer's opinions to the manufacturer, to help the manufacturer to improve or research and development of new products, so that the consumer's opinions are quickly passed on to the production, which will greatly improve the speed of response to customer demand information.

IV. B. 3) Modes of operation of the rapid response system

(1) Shared commerce platform

For enterprises and individuals, the test has a unified entrance to the e-commerce platform, 020 service platform, the platform in the realization of the centralized at the same time, to provide personalized services. Through the traditional e-commerce operation of network transactions, including business-to-business, business-to-person, personal-to-person operations, in the mobile Internet and cloud computing technology support, integrated procurement, trading, warehousing, full-chain response, payment and settlement, and other functions, and can allow stores/shops, suppliers and manufacturers, logistics providers, warehousing, banks, customers to share information and synchronize operations.

(2) Diversified synergy

The whole chain management of rapid response is based on synergy. For customers widely distributed, uneven distribution of suppliers and demand for discrete characteristics, the system supports a variety of forms of synergistic operations, including: the so-called horizontal synergy between competitors, allowing commodities to be borrowed between different competitions to reduce out-of-stock losses, support for horizontal synergies between logistics providers, support for the rapid exchange of goods under the common whole-chain response to support the vertical synergies between suppliers and distributors / retailers, and support for logistics providers and customers to quickly respond. Support vertical cooperation between logistics providers and customers to realize zero inventory, or shared inventory.

(3) Combination of dumping and hanging, modularization of whole-chain response

Logistics full chain response unit modular, a logistics unit such as an order, or a parcel, through the modular micro-container, can be realized in a single box, can also be a box of multiple packages. Vehicle cargo box modularization, 80% of the space to hook up modular container, 20% of the space to load large cargo. Container hooked up to the vehicle that shipment, unloading the vehicle that drive. Cold box and operating room temperature box consistent, real-time temperature monitoring, automatic positioning of the box, the operation does not pick box. Outside the city, centralized unloading and loading of boxes, in the city, a single piece of box, pick up the box, up to the seller.

(4) Integration of whole chain response route planning

The distribution of stores/shops and warehouses in the tested trade city is very large, covering about 10 square kilometers, and the customers outside the tested trade city are distributed in 100,000 square kilometers of points. The density of small area is high, and the density of goods in large area is low. Unified route planning and vehicle scheduling are implemented. Stores/shops, customers, and warehouses are all in the same address coding system, picking up and dropping off combined. Whether there are 1,000 orders or 100 orders in one vehicle, pick-up and delivery route planning can be carried out in a visualized context.

(5) Fast Payment and Settlement

Payment and settlement is a specific activity of capital flow in modern full chain management, and fast and barrier-free payment and settlement is a necessary condition to guarantee the fast response of the full chain to the rapid changes in the market. Any node in the whole chain of the test business can use the credit card provided by the test alliance to carry out income and expenditure, and can also quickly obtain the financing services of the “test” alliance fund when cash flow is needed.

V. Case validation

V. A. Full chain of material operation under rapid response

V. A. 1) Operational results

The computer hardware configuration taken for the algorithm experiments was Inter(R)Core(TM) i5-4200M CPU@2.5GHz, 8.00 GB RAM, and the experiments were carried out with MATLAB R2022b under Win10 system. The parameters of the algorithm are set as follows: the number of populations is 50, the maximum number of iterations is 50, the crossover probability is 0.75, the variance probability is 0.2, and the algorithm has an average running time of 23 seconds.

Table 1 shows the results of the operation of the whole chain cooperative operation model, in the model of truck and drone cooperative whole chain response, scheme 1, scheme 8 and scheme 5 are the lowest total cost, the shortest time consuming and the highest satisfaction respectively. The results for total cost, response time, and satisfaction are 2481.348, 0.948, and 28.798, respectively.Since the model in this paper is designed to find the optimal solution for the objective, the number of frontier solutions is too large, and thus only Scenario 1, Scenario 8, and Scenario 5 will be elaborated here.

Table 1: Full chain operation model operation results

Scheme	Full chain running cost	Response time(h)	Customer satisfaction
1	2481.348	1.648	27.539
2	2563.469	1.248	28.148
3	2569.415	1.493	28.636
4	2548.631	1.442	28.547
5	2648.887	1.296	28.798
6	2648.948	1.265	28.612
7	2670.489	1.136	28.745
8	2798.978	0.948	28.631

V. A. 2) Comparison of Programs

The full chain response path diagram is shown in Figure 4, where solid lines represent the truck's driving path, and dashed lines represent the drone's driving path. Scheme 1 is the full chain response scheme with the lowest total cost, with the total cost of the full chain response being 2481.348 yuan, response time being 1.648 hours, and customer satisfaction being 27.539. The specific full chain response scheme is shown in Table 2. A total of 4 trucks depart from the full chain response center: Truck 1 is equipped with 1 drone, and its path travels from the full chain response center to customer points 19, 18, 22, 21, stop point 9, customer point 11. The first full chain response by the drone attached to the truck departs from customer point 18 to serve customer point 23 and then returns to the truck at customer point 22. The second response is from customer point 22 to serve customer point 20, then returning to the truck at customer point 21. The third full chain response departs from stop point 9 to service customer point 10 before returning to the truck at customer point 11. Finally, the truck with the drone returns to the full chain response center. Truck 2's path goes from the full chain response center to stop point 12, customer point 13, customer point 16, customer point 17, and ultimately returns to the full chain response center. Truck 3 is equipped with 1 drone, and its path goes from the full chain response center through customer points 1, 2, 3, 8, stop point 15, customer point 6. The first full chain response carried out by the drone departs from customer point 2, sequentially serving customer points 5, 4, and 3 before returning to customer point 7. The second full chain response departs from customer point 3 to serve customer point 7 and then returns to the truck at customer point 8, ultimately returning to the full chain response center. Truck 4 is also equipped with a drone, and its path goes from the full chain response center through customer points 6, 24, 26, stop point 29, and customer point 14. The drone's first full chain response departs from customer point 24 to serve customer point 30 before returning to the truck at customer point 26. The second response is from customer point 26 to serve customer point 28 before returning to the truck at stop point 29. The third response departs from stop point 29 to serve customer point 25 and then returns to stop point 27. Finally, the truck carries the drone back to the full chain response center.

Table 2: Full chain response scheme

Solution 1		
Truck number	Truck path	Drone path
1	0→19→18→22→21→9→11-0	18→23→22
		22→20→21
		9→10→11
2	0→12→13→16→17→0	/
3	0→1→2→3→8→15→6→0	2→5→4→3→7
		3→7→8
4	0→6→24→26→29→14→0	24→30→26
		26→28→29
		29→25→27

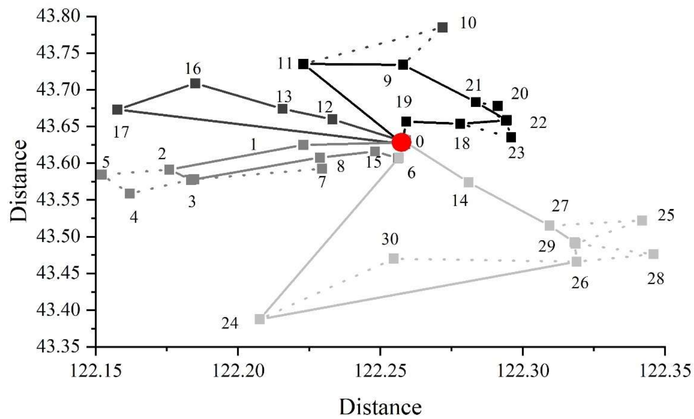

Figure 4: Solution 1 whole chain response path

Scenario 8 is the shortest time-consuming full-chain response scenario, with a total full-chain response cost of 2,798.978 yuan, a full-chain response time of 0.948 hours, and a customer satisfaction of 28.631. The specific full-chain response scenarios are shown in Table 3. The full-chain response path diagram is shown in Fig. 5 the solid line represents the truck traveling path and the dashed line represents the drone traveling path. Unlike scenario 1, scenario 8 has 5 truck main paths and 7 drone paths.

Table 3: Full chain response scheme

Solution 1		
Truck number	Truck path	Drone path
1	0→19→9→11→12→0	9→10→11
		16→17→5
2	0→13→16→5→2→1→0	3→7→8→7
		5→4→2
3	0→15→30→6→0	15→24→30
4	0→14→27→25→0	27→29→26→28→25
5	0→23→22→18→0	22→20→21→18

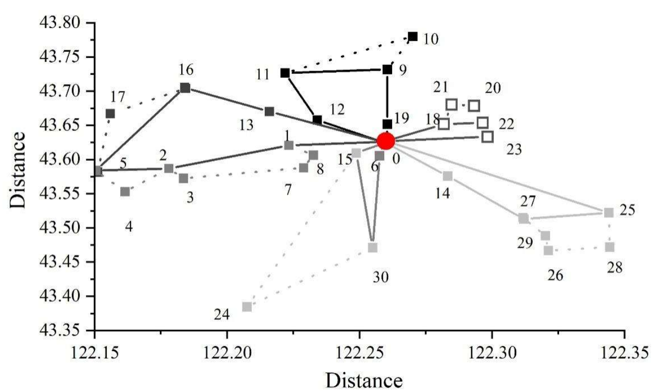

Figure 5: Solution 8 whole chain response path

Scenario 5 is the scenario with the highest level of satisfaction, with a total cost of 2648.887 yuan for the full chain response, a full chain response time of 1.296 hours, and a customer satisfaction level of 28.798. The specific full chain response scenarios are shown in Table 4. A total of five trucks carrying one UAV each depart from the full chain response center. The full-chain response path diagram is shown in Fig. 6, with two paths for the drone paths of Truck 1, Truck 2, Truck 3, and Truck 4, and one path for the drone path of Truck 5.

Table 4: Full chain response scheme

Solution 1		
Truck number	Truck path	Drone path
1	0→12→13→1→15→0	13→16→17→1
		15→6→0
2	0→8→2→3→7→15→0	2→5→4→3
		0→24→30
3	0→30→29→27→14→0	29→25→14→29
		29→26→28
4	0→22→21→18→19→0	0→23→22
		22→20→21
5	0→19→9→11→0	9→10→11

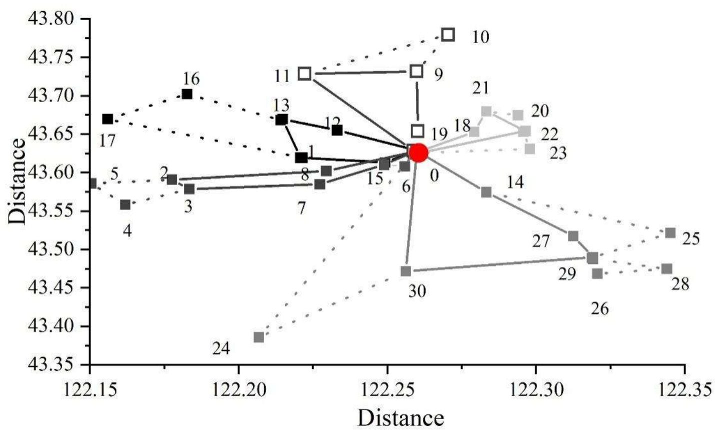

Figure 6: Solution 5 whole chain response pat

V. B. Response efficiency analysis

V. B. 1) Mission completion rate

Figure 7 shows the average problem processing timeframe and timely completion rate, according to the problems shown in the July survey report, the plan was designed based on the network topology optimization of the whole chain response efficiency model, which has been used in late July 2022, and from the implementation of the use of the first results, the monitoring of the task completion status in November 2023 is as follows: at first, the material whole-chain response 100min completion rate and the quality control 24h completion rate Before 2022/11/28, they were unstable, with completion rates fluctuating between [0.05,1] and [0.3,0.85], respectively. After half a year of operation, the response and QC completion rate tends to stabilize, and the response 100min completion rate is stabilized at about 95%.

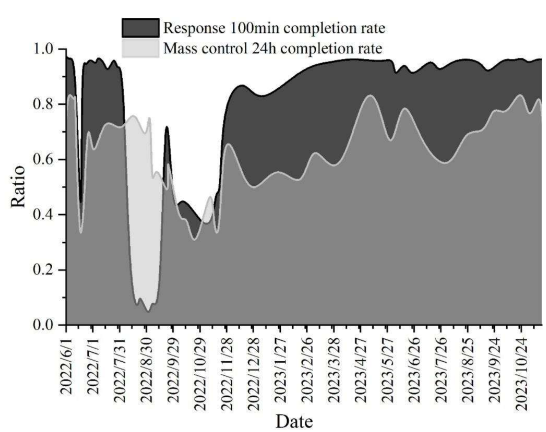

Figure 7: Average problem processing time and timely completion rate

V. B. 2) Average task processing time

Figure 8 shows the average task processing time, from the data monitoring between March 28, 2023 and November 16, 2023, it can be seen that there is a huge drop in the average task processing time, and the extreme deviation of the whole monitoring interval is 7,584, which is a drop of 99.5798%. As the backlog of problems before implementation is quite large, the centralized solution makes the performance of the average task processing time not as fast as the response to the improvement of the task completion rate, but through a period of improvement, it is obvious that the task processing time after March 28, 2023 has been kept at a stable low position, around 300, which shows that after the improvement of the network topology-particle swarm algorithm, the material full chain of backlog issues processing is completed, the same manpower can cope with the current daily task processing order volume, there is no pile-up problem is not processed in time or too late to deal with the phenomenon[19]-[21].

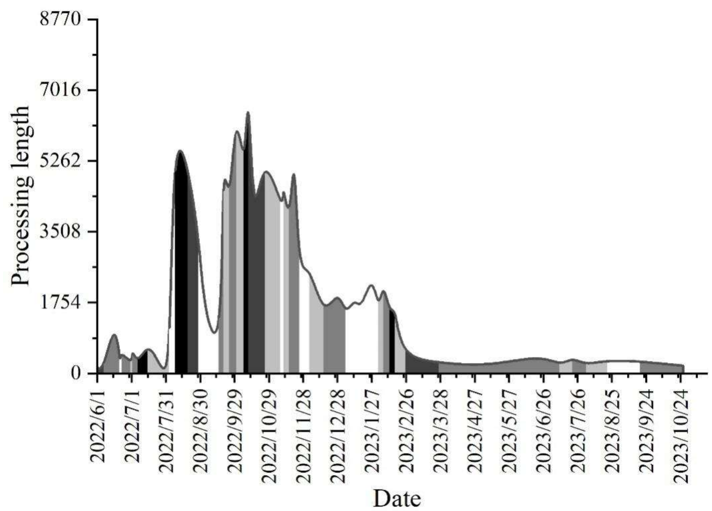

Figure 8: Average task time

V. B. 3) User experience

In this paper, we still follow the designed model to investigate the user experience and compare and observe the impact of the improvement on the user experience.

Figure 9 shows the trend of user satisfaction in the past 6 months, which shows that the recommendation degree of users to the whole chain of materials is rising from July to October, comparing with July, the recommendation degree in October has been significantly improved, and the value of user satisfaction (NPS) has also increased by 6.6261% as a result. After the overall improvement strategy came into effect, the initial results have been seen, data monitoring after the improvement of the three months of August, September and October material whole chain response to the main related items impact is the user response performance and customer service, refunds of the service has significantly improved. Compared to September, overall satisfaction with response fulfillment services in October increased by 0.7007%, which includes not only response fulfillment speed, but also response-related services, including the speed of response personnel coming to pick up the goods when returning or exchanging goods, and whether or not there are any delivery errors in the response.

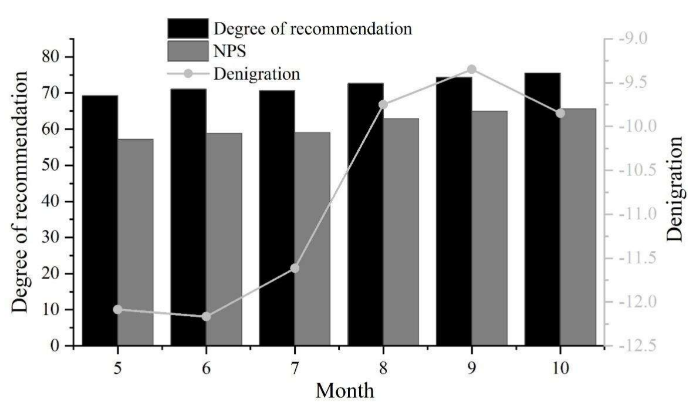

Figure 9: The trend of user satisfaction in nearly six months

VI. Conclusion

The material full-chain response efficiency improvement model based on network topology optimization constructed in this study successfully solves the problem of balancing the full-chain response timeframe and network connection cost. Through the application of NTPSO algorithm, the optimization of the network structure of the whole chain of materials is achieved, and three solutions with different focuses are provided: the lowest cost solution (2481.348 yuan), the shortest response time solution (0.948 hours) and the highest customer satisfaction solution (28.798). The actual application results show that the model has achieved remarkable results in the whole-chain operation of materials: the 100min completion rate of material response has stabilized at about 95%, the average processing time of the task has been reduced from the original peak to about 300, with a reduction of 99.58%, the customer recommendation degree has been significantly improved, and the overall satisfaction of users with the response fulfillment service has been increased by 0.70% from the previous year. Meanwhile, the establishment of the whole-chain rapid response system has realized information system integration, resource integration and cross-enterprise synergy, and provided a scalable systematic solution for the whole-chain management of materials.

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