Supply Chain Disturbance Management Scheduling Model Based on HPSO Algorithm

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Abstract*—The continuous expansion of business has led to the development of enterprises from vertical integration to horizontal integration, and the interlocking of the supply chain system, but the influence of anti-production behavior factors and the frequent occurrence of disruption events lead to difficulties in supply chain scheduling, which affects the development of enterprises. To address the above problems, the study analyzes the factors influencing counterproductive behavior based on system dynamics, constructs a supply chain disruption management scheduling model on this basis, and solves the supply chain disruption management scheduling model using Hybrid Particle Swarm Optimization algorithm. The findings indicate that the number of non-inferior solutions, uniformity of distribution of non-inferior solutions, dominance ratio of non-inferior solutions, average distance between non-inferior solutions and optimal Pareto, maximum distance, dispersion of non-inferior solutions and coverage of non-inferior solutions of the hybrid particle swarm algorithm are 12.3, 5.283, 0.264, 0.611, 4.474, 4.627, 601.300, respectively in the A condition, 601.300. The number of non-inferior solutions, uniformity of non-inferior solution distribution, dominance ratio of non-inferior solutions, average distance between non-inferior solutions and optimal Pareto, maximum distance, dispersion of non-inferior solutions and coverage of non-inferior solutions for the hybrid particle swarm algorithm under B condition are 12.3, 5.283, 0.264, 0.611, 4.474, In summary, the proposed algorithm has excellent performance and can effectively reduce the impact of interference events, thereby improving the level of supply chain interference management and scheduling, and promoting the sustainable development of this field.

***Keywords*—HPSO algorithm; disturbance management; supply chain; system dynamics; anti-production behavior**

I. Introduction

With the popularization of computer technology and the development of market economy, enterprises are shifting their focus from themselves to supply chain, and supply chain management is particularly important for enterprise management [1-2]. Supply chain management is a management mode that effectively organizes suppliers, manufacturers and distributors to jointly complete product production, transportation and distribution on the premise of minimizing the cost of the entire supply chain [3-4]. However, the supply chain system itself is a complex and dynamic network, which is faced with many challenges from uncontrollable factors both internally and externally, such as resource shortage, equipment failure, and market demand fluctuations. These factors increase the uncertainty and dynamics of the supply chain, making it difficult for traditional supply chain management methods to effectively cope with [5]. At present, how to accurately identify and quantify the influencing factors of employee Counterproductive Work Behavior (CWB) in the supply chain environment and its impact on supply chain performance is a relatively difficult problem [6-7]. In order to better deal with the deterioration effect of CWB and the scheduling deviation of SCM disturbance, in this study, the influence factors of CWB are deeply analyzed, and the corresponding mathematical model is established by using the theory of System Dynamics (SD) to quantify the impact of CWB on supply chain performance. In addition, the research also aims to solve the hybrid model using HPSO algorithm to verify the validity and practicability of the model and provide decision support for enterprises in the face of supply chain disturbance events. Finally, through empirical research, the effect of the proposed model and algorithm in practical application is verified, which provides theoretical basis and practical guidance for the supply chain management of enterprises. This study will integrate SD theory and HPSO algorithm, enrich the research methods and technical means in the field of supply chain management, and provide new perspectives and ideas for the development of supply chain management theory. In addition, this study will provide decision support and practical guidance for enterprises to deal with supply chain disturbance events in actual operations. By optimizing the supply chain scheduling strategy, enterprises will be able to improve the stability and efficiency of the supply chain, reduce operating costs, improve customer satisfaction, and thus enhance the market competitiveness of enterprises. Finally, the research on employee CWB will help enterprises to understand the impact of employee behavior on supply chain performance more comprehensively, and then take targeted management measures to reduce potential losses.

This research is mainly divided into four sections, Section II is a review of relevant research results, Section III is the use of HPSO algorithm to solve the SCIMC model, Section IV is to verify the effectiveness of the HPSO algorithm proposed by the research, and Section V and Section VI is discussion and summary of the research respectively.

II. Related Work

The traditional SC optimization research is mostly focused on transportation and distribution, but rarely involves production optimization algorithm. The findings indicate that the algorithm can effectively reduce the time for computation [8]. Li et al. reduce the maximum time for completion by establishing a task pool and employing a genetic forbidden search algorithm for the production and transportation integration scheduling problem in a hybrid flow shop.

Experimental results confirm that the method can successfully address the scheduling problem for production and transportation integration [9]. Goli et al. employ a cycle duration and integer multiplier technique to coordinate the replenishment cycle of the SC and developed a simulated annealing algorithm to solve the economic lot size and delivery scheduling problems of a multi-stage SC. Simulation experiments demonstrated that the method can reduce the production cost of the SC [10]. Solina et al. proposed a quantitative approach to production and distribution to minimize production and distribution costs with reference to real-life food companies. The findings indicate that the method can significantly improve the performance and sustainability of the SC [11]. Du et al. explored the importance of dynamic optimal production scheduling with demand fluctuations and uncertainties. The study developed a multi-objective genetic algorithm for precast manufacturing based on a dynamic flow shop scheduling model, and simulation studies demonstrated that the method can cope effectively with demand changes [12].

Disruption management is also needed to solve the stochastic disturbance problem because of the real-life uncontrollable factors and SC systems are often affected by many disruptive events that delay production schedules and increase production costs. Lee J et al. designed a joint reactive and proactive airline disruption management method to cope with air traffic disruptions that lead to flight delays, cancellations, and missed passenger connections. The method can predict the probability of future disruptions by estimating the system delays at hub airports. The research data showed that the method can effectively reduce the expected recovery cost of airlines [13]. Jiang et al. constructed an attitude based disruption management model for handling delivery delays to minimize the negative impact of sudden disruptions in the distribution phase of the SC, and designed a heuristic algorithm, and the simulation results verified the effectiveness of the method [14]. Ning et al. addressed the flexible job shop in a comparison experiment with the traditional rescheduling method, the interruption management method improves the stability of the production and processing system under the deterioration effect [15]. Pandi et al. developed a GPU-based adaptive large-neighborhood search technique to address the issue of fleet interruption due to vehicle failure. Simulation experiments indicate that the algorithm can reduce the idle time and operating cost of the fleet under normal operation [16]. Malik A I et al. present a production disruption model for a multi-product single-stage production inventory system to handle the problem of unforeseen disturbances disrupting the entire manufacturing schedule. The data suggest that the effectiveness and superiority of the performance of this production disruption model [17].

In summary, there are many research results about interference management in the field of SC production scheduling, but the majority of the research findings center on the reasonable distribution of negotiated benefits and the optimization of the overall benefits of the SC, ignoring the impact of interference events and CWB of employees, which leads to difficulties in SC scheduling. To address the problem that SC scheduling is easily affected by disruptive events and CWB, this paper analyzes the influencing factors of CWB based on SD theory and establishes SCIMC model, and solves the model by HPSO algorithm.

III. CONSTRUCTION OF SCIMC MODEL BASED ON HPSO ALGORITHM

The analysis of CWB influencing factors based on SD theory is the premise of SCIMC model construction. Since the SCIMC problem has multi-objective and non-linear characteristics, the study introduces the HPSO algorithm to solve it, and this chapter focuses on the analysis of CWB influence factors based on SD theory and the design of the HPSO algorithm.

A. Analysis of the Factors Influencing Employee CWB Based on SD Theory

SD theory is an effective tool that combines cybernetics, systems theory and information theory and uses computer simulation techniques to study the feedback structure and behavior of systems. It mainly studies the dynamic development law of the system through modeling, simulation and comprehensive reasoning according to the feedback characteristics that the internal components of the system are causal [18]. The main steps of SD theory are shown in Fig. 1.

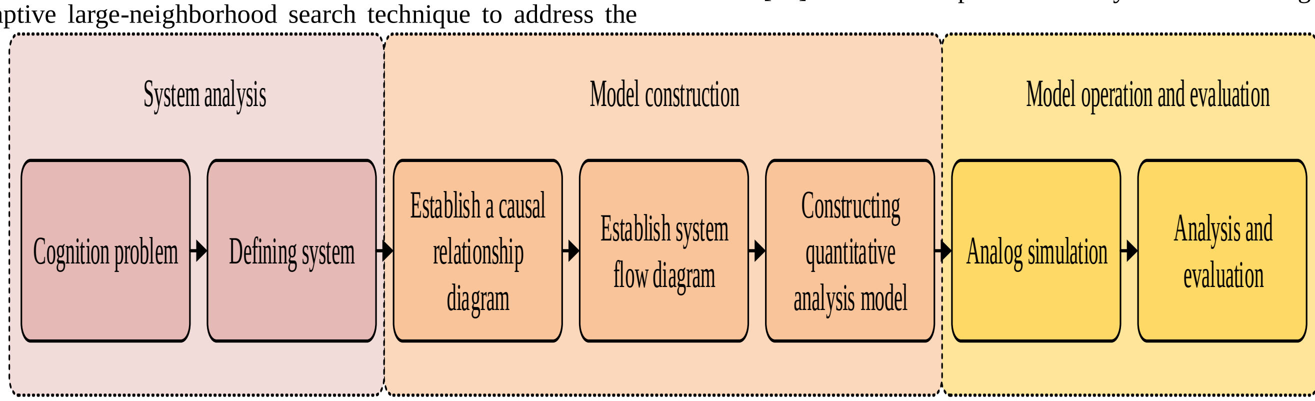


Fig. 1. The main steps of SD theory.

The SD theory in Fig. 1 is mainly composed of three steps: system analysis, model construction, model operation and evaluation. The presence of CWB frequently disrupts the normal running of the production line [19]. To dynamically describe the nonlinear mechanism of CWB, the study uses the SD method as an entry point to explore the influencing factors of CWB. the influencing factors of CWB include job satisfaction A1, sense of organizational justice A2, supervision level A3, team atmosphere positivity A4, group normative level A5, organizational culture building A6, and organizational concern A7. The causal relationship of each influencing factor of CWB is shown in Fig. 2.

Fig. 2 depicts the CWB feedback relationship, which is separated into six major sections. In the first step, which functions as positive feedback, higher job satisfaction lowers the likelihood of CWB incidence, which causes the amount of group norms to rise, and a corresponding decrease in the level of job boredom as an important component of job satisfaction, which further increases job satisfaction. The second part is a negative feedback process, where an increase in organizational justice causes an increase in employee job satisfaction, which decreases the chance of CWB occurrence and leads to an increase in the level of employee burnout, which decreases organizational justice and concern. The third part is the negative feedback process, with the improvement of the organizational supervision mechanism, the team atmosphere positivity and the number of behavior correction is increasing, accompanied by a decrease in the sense of organizational justice and attention, which will bring negative impact on the level of organizational supervision. The fourth part is the positive feedback process, the higher the team climate positivity, the lower the level of group regulation will be, accompanied by employee alienation and increasing job conflict will also lead to a decrease in job satisfaction, which will increase the chances of CWB, further improving the level of organizational regulation and thus increasing the team climate positivity. The fifth part is the positive feedback process, where the increase in the level of group norms makes CWB less likely to occur, thus reducing the level of organizational attention and supervision, making the team gradually looser and further increasing the level of organizational norms. The sixth part is a negative feedback process. The improvement of organizational culture also increases the motivation of the team atmosphere, so the chance of CWB decreases, but the decrease of CWB makes the organization slack, which further reduces the level of attention and organizational culture. The study adds the corresponding state variables, rate variables and auxiliary variables based on the feedback relationship of CWB-related influencing factors, and draw the CWB-SD model flow diagram using Vensim simulation software.

$$\begin{cases} Z_{A1} = 2 + \int_{t0}^{t} (H_1 - H_2)\, dt \\ Z_{A2} = 1 + \int_{t0}^{t} (H_3 - H_4)\, dt \\ Z_{A3} = Z_{A2} \times B_1 + Z_{A6} \times B_2 + Z_{A8} \times B_3 + Z_{A9} \times B_4 \\ Z_{A4,5} = 1.5 + \int_{t0}^{t} (H_5 - H_6)\, dt \\ Z_{A6} = 2 + \int_{t0}^{t} H_9\, dt \end{cases} \quad (1)$$

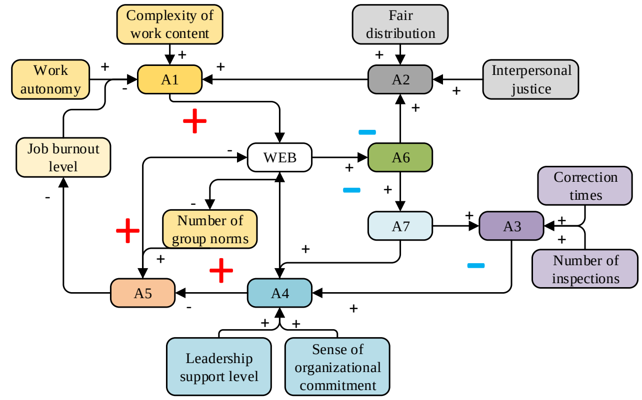


Fig. 2. Feedback relationship between CWB influencing factors.

In Eq. (1), Z_{A1} to Z_{A6} represent job satisfaction, organizational justice, organizational supervision level, team atmosphere motivation, group norm level, and organizational culture building level, respectively. B_i H_1 and H_2 represent rates of satisfaction growth and decline, H_3 and H_4 represent the fairness's growth and decline rates, and H_5 and H_6 represent the increase and decrease rates of organizational culture building. The expressions of the number of behavioral corrections Z_{A8} and the monitoring and improvement mechanism Z_{A9} are shown in Eq. (2).

$$\begin{cases} Z_{A8} = 2 + \int_{t0}^{t} H_{10}\, dt \\ Z_{A9} = 2 + \int_{t0}^{t} H_{11}\, dt \end{cases} \quad (2)$$

In Eq. (2), H_9 , H_{10} refer to the rate of increase in the level of organizational culture building and the rate of increase in behavior modification, respectively. The expression of CWB can be obtained from Eq. (1) and Eq. (2), see Eq. (3).

$$Z_{CWB} = Z_1 \times G_1 + Z_2 \times G_2 + Z_3 \times G_3 + Z_4 \times G_4 + Z_5 \times G_5 + Z_6 \times G_6 \quad (3)$$

In Eq. (3) G_i denotes the influence coefficient of each state variable. Human behavior influences the operation and state of the system, and employees' dissatisfaction with their jobs directly leads to an increased chance of CWB and thus negativity. To portray the effect of subjective human behavior on CWB, the study uses employee dissatisfaction to describe the deterioration rate and thus measure the processing time after disturbance, and the dissatisfaction value $Q(R_i)$ is expressed in the range of $x_i < 0$ as shown in Eq. (4) [20].

$$Q(R_i)=\chi(R_i-O_i)^{\beta} \tag{4}$$

In Eq. (4), O_i denotes the initial scheduling scheme and χ is the risk aversion factor. β It refers to the degree of concavity of the value curve, and its value range is $(-\infty,1)$.

When $Q(R_i)=1$, $R_i=O_i+\left(\frac{1}{\chi}\right)^{\frac{1}{\beta}}$, the dissatisfaction function $Q(x_i)$ see Eq. (5).

$$Q(x_i)=\begin{cases}1, x_i \geq R_i \\ \chi(x_i-O_i)^{\beta}, O_i \leq x_i \leq R_i, i=1,2,3,\cdots,n \\ 0, 0 \leq x_i \leq O_i\end{cases} \tag{5}$$

The occurrence of a disturbance event causes O_i to be no longer optimal, and the repair scheduling solution derived according to the specified constraint affects the change in machining position of the corresponding workpiece. The size of the measured disturbance can be expressed in terms of the amount of machining position change, and the dissatisfaction function of the amount of position disturbance $Q(s_j)$ is shown in Eq. (6).

$$Q(s_j)=\begin{cases}1, s_j \geq R_1 \\ \chi_1 s_j^{\beta_1}, 0 \leq s_j < R_1\end{cases} \tag{6}$$

In Eq. (6) s_j denotes relative position perturbation, $R_1=\left(\chi_1^{-1}\right)^{\beta_1^{-1}}$ denotes the upper limit of dissatisfaction tolerance, and employee dissatisfaction Q is shown in Eq. (7).

$$Q=\sum_{j=1}^{n} Q(s_j) \Big/ n \tag{7}$$

Employee psychological dissatisfaction brings about defiance, which lengthens the operation's processing time and subsequently affects the deterioration rate. The deterioration rate function $\theta(s_j)$ is shown in Eq. (8).

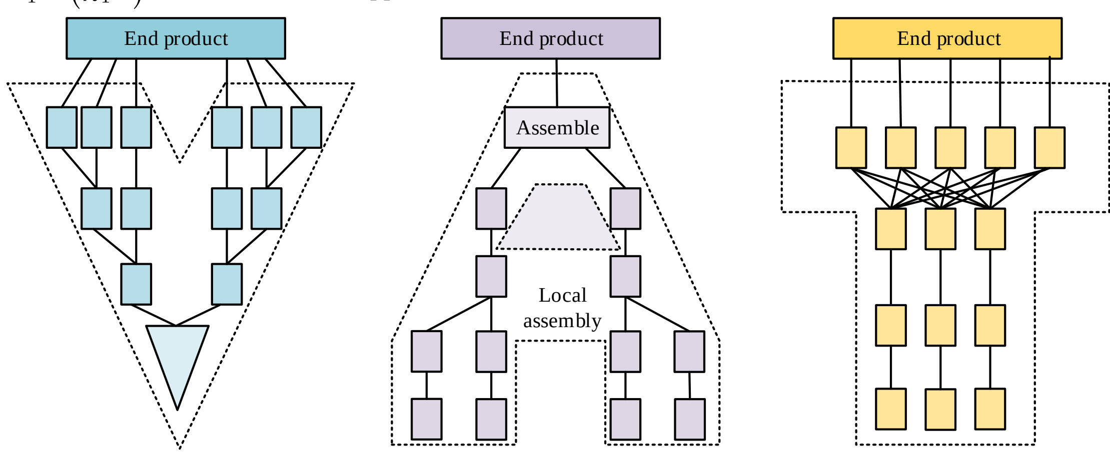
$$\theta(s_j)=\begin{cases}1, s_j > R_1 \square R_2 \cap s_j > R_1 \\ \chi_2 s_j^{\beta_2}, 0 \leq s_j < R_1 \square R_2 \cap 0 \leq s_j < R_1\end{cases} \tag{8}$$

In Eq. (8) $R_2=\left(\chi_2^{-1}\right)^{\beta_2^{-1}}$, then the deterioration rate of operation time θ is shown in Eq. (9).

$$\theta=\sum_{j=1}^{n} \theta(s_j) \Big/ n \tag{9}$$

B. SCIMC Model Construction Based on HPSO Algorithm

Each node enterprise in SC rotates around the core enterprise, forming a fully functional network chain, through regulating the flow of information and cash from acquiring raw resources to producing finished goods, and finally delivering products to consumers through the sales network. According to the different products and manufacturing processes, the SC is split into V-type, T-type and A-type, and the basic structure of the SC is shown in Fig. 3 [21].



(a) Basic structure of V-type supply chain

(b) Basic structure of a-type supply chain

(c) Basic structure of t-type supply chain

Fig. 3. Basic structure of SC.

Fig. 3(a) shows the basic structure of V-type SC, which is the most basic structure in the SC mesh. The success of V-type SC depends on the reasonable arrangement of the critical internal capacity bottlenecks. Fig. 4(b) depicts the basic structure of A-type SC, the overall form of this SC is expressed as convergence type, and A-type SC is generally driven by orders and customers. No market forecast is taken. Fig. 4(c) shows the basic structure of T-type SC, which is a hybrid SC structure that mainly determines the manufacturing standardization of common parts to reduce the complexity. In a two-stage SC with a single manufacturer and supplier, both need to share the task of a batch of orders from customers, the supplier processes the relevant spare parts according to customer demand, and the manufacturer produces according to the spare parts delivered by the supplier, in which the supplier is in a dominant position and the supplier should be satisfied by the manufacturer on each requirement of the order. To increase production effectiveness, the study constructs the SCIMC model, which mainly consists of three parts: initial scheduling, interference management, and cooperation gain, and the initial scheduling is shown in Eq. (10).

$$\min\left\{ f\left(\pi_0{}^s\right)=\sum\nolimits_{j=1}^{n} w_j\cdot C_j,\ f\left(\pi_0{}^m\right)=\sum\nolimits_{j=1}^{n} w'_j\cdot C'_j\right\} \quad (10)$$

Eq. (10) is the optimisation goal for initial scheduling, $\pi_0{}^s$ and $\pi_0{}^m$ refer to the initial scheduling time of suppliers and manufacturers, respectively, w_j and C_j refer to the weighting factor and completion time of suppliers, respectively, and w'_j and C' refer to the weighting factor and completion time of manufacturers, respectively. The expression of interference management is shown in Eq. (11).

$$\min\left\{ f_1\left(\pi'\right)=\sum\nolimits_{j=1}^{n} w'_j\cdot C'_j,\ f_2\left(\pi'\right)=\sum\nolimits_{j=1}^{n} w'_j\cdot \bar{\Delta}t'_0\right\} \quad (11)$$

Eq. (11) is the optimization objective of disturbance management scheduling when the machine is disturbed. $f_1\left(\pi'\right)$ denotes the optimization objective of the manufacturer's balanced disturbance repair solution and initial scheduling solution, and $f_2\left(\pi'\right)$ denotes the minimization objective, where $\bar{\Delta}t'_0=\max\left\{C'_j-\bar{C}'_j,0\right\}$, $\bar{C}'_j$ are the completion times of the manufacturer's artifacts J_j in the initial scheduling solution. The expression of the cooperative gain is shown in Eq. (12).

$$\min\left\{ f_3\left(\pi'\right)=-V_m\cdot V_s\right\} \quad (12)$$

Eq. (12) is the revenue maximization objective of supplier-manufacturer cooperation, and V_m and V_s denote the revenue of the manufacturer and supplier after the perturbation, respectively. The supplier's processing artifacts arrive before the manufacturer can start production, and the expression is $D_j^s\le S_j^m$, where D_j^s denotes the supplier's delivery time and S_j^m is the manufacturer's processing start time. In a product's processing system, neither the supplier nor the manufacturer is allowed to start both workpieces at the same time, see $\left(S_j\ge C_k\right)\vee\left(S_k\ge C_j\right),\forall j,k\in J$. During the time window when the disturbance occurs, the supplier cannot schedule the disturbed workpiece for processing, as expressed in the formula at $S_j^s,C_j^s\notin\left[t_1,t_2\right],\left(j\in list\right)$, where S_j^s and C_j^s denote the supplier's processing time and completion time, respectively. To efficiently optimize the SCIMC model, the study selects the HPSO for solving. Based on the PSO algorithm's great global fast search capability, the HPSO combines the strengths of the variable domain search algorithm's strong local fine search capability, and incorporates the heuristic algorithm obtained from the variational crossover theory related to the genetic algorithm. the HPSO algorithm flow is shown in Fig. 4 [22].

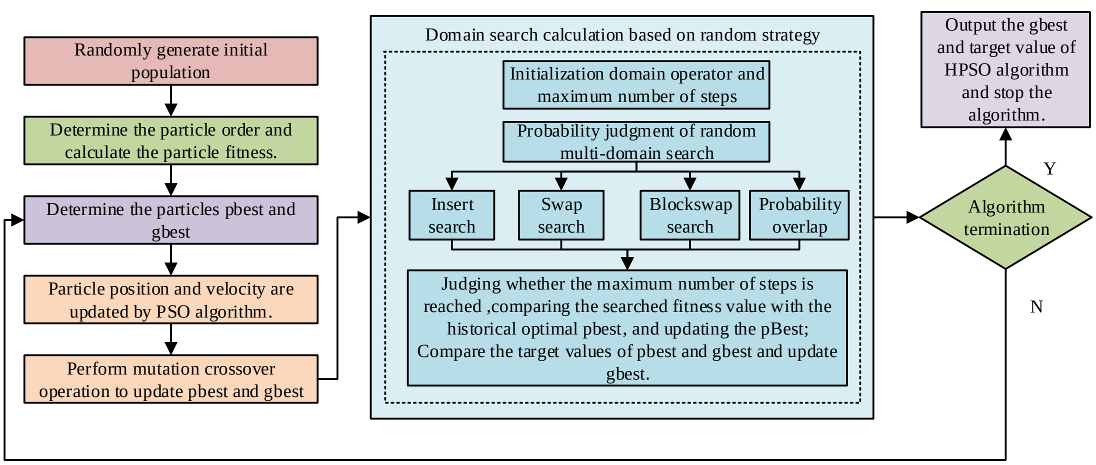


Fig. 4. HPSO algorithm flow.

The HPSO algorithm in Fig. 4 consists of the basic PSO algorithm, variational operations, crossover operations and random field structures. The PSO algorithm first requires particle initialization and particle position initialization, where a particle represents a processing ordering and the particle initialization is to ensure that the processing of a workpiece is unique at the same time. Eq. (13) displays the iterative equation for a particle's velocity at the instant of $t+1$.

$$v_{i,j}(t+1)=wv_{i,j}(t)+c_1r_1\left[p_{i,j}-x_{i,j}(t)\right]+c_2r_2\left[p_{g,j}-x_{i,j}(t)\right] \tag{13}$$

In Eq. (13), w denotes the inertia factor, c_1, c_2 is the learning factor, r_1, r_2 is the arbitrary number generated between $(0,1)$, $p_{i,j}$ and $p_{g,j}$ denote the current and the global optimal position of the particle in the j dimension, respectively, so the iterative formula for the position of the particle at the moment of $t+1$ is Eq. (14)

$$x_{i,j}(t+1)=x_{i,j}(t)+\left|v_{i,j}(t+1)\right|, j\in 1,2,\cdots,n \tag{14}$$

After the initialization of the particle positions, the study also needs to form two new particles by mutating the particle's own best position $pbest$ and the population's best position $gbest$, and the mutated particles are used as the parents to perform the crossover operator based on the process encoding. The PSO algorithm after mutation crossover improves the capability of global search, but the capacity for local search still needs to be improved. To solve this problem, the study introduces a local search strategy with a random domain structure. The stochastic domain structure mainly consists of insertion domain, exchange domain and block exchange domain structure, and its structure is shown in Fig. 5.

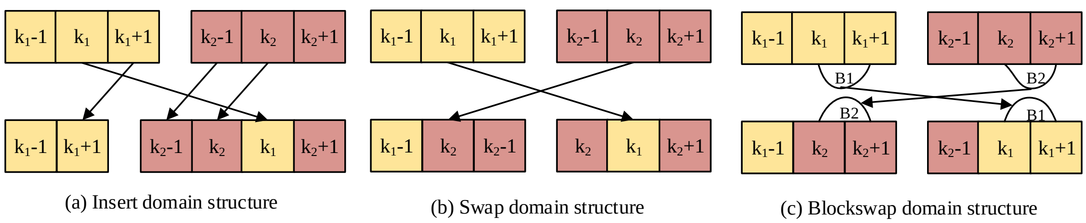


Fig. 5. Schematic diagram of domain structure.

Fig. 5(a) shows the insertion field structure, randomly inserting the artifact l before the artifact l_1, where l_1 is any position in the arrangement π before l_1. Fig. 6(b) shows the swap field structure, where the positions of the workpieces l_1 and in the arrangement l_2 π are randomly swapped. Fig. 6(c) shows the block swapping domain structure, randomly swapping the positions of the B_1 and B_2 blocks in the arrangement π. The local search strategy based on the random domain structure is to perform the domain operation with random probability c_{pm} and the random probability c_{pm} is shown in Eq. (15).

$$c_{pm}=\begin{cases}(\alpha_1\le r_1\le\beta_1)\Rightarrow insert\\(\alpha_2\le r_2\le\beta_2)\Rightarrow swap\\(\alpha_3\le r_3\le\beta_3)\Rightarrow blockswap\end{cases} \tag{15}$$

The probability interval overlap is defined in Eq. (15) as $COM<I,S,BS>$, then the priority levels of the domain operations are, in order, the insertion domain, the insertion domain and the block exchange domain.

IV. Performance Analysis of HPSO Algorithm in SCIMC Model

To evaluate how well the HPSO performs in the SCIMC model, the study first requires an analysis of the degree of variation of the WBB under different influencing factors, the experimental software is Visual and the time parameter is set to 20 in months.

Fig. 6 displays the CWB outcomes in various affecting circumstances. From the figure, the CWB changes with time and the degree of CWB change varies under different influencing factors. At the beginning of the simulation, CWB shows an increasing trend with time and reaches saturation at the 7th month, and then decreases rapidly after seven months, and the decreasing trend slows down at the 14th month. Job satisfaction has the greatest impact on CWB, and the level of organizational culture building has the least impact. To optimize the SCIMC model, the study conducted 20 independent numerical experiments on the HPSO algorithm, GA-TOM algorithm, basic PSO algorithm, and ACO algorithm, respectively. The HPSO algorithm's parameters were set with 100 iterations as follows, $w=0.2$, $c_1=c_2=2$, and $c_{pm}=\{[0,0.75],[0.55,0.95],[0.8,0.1]\}$

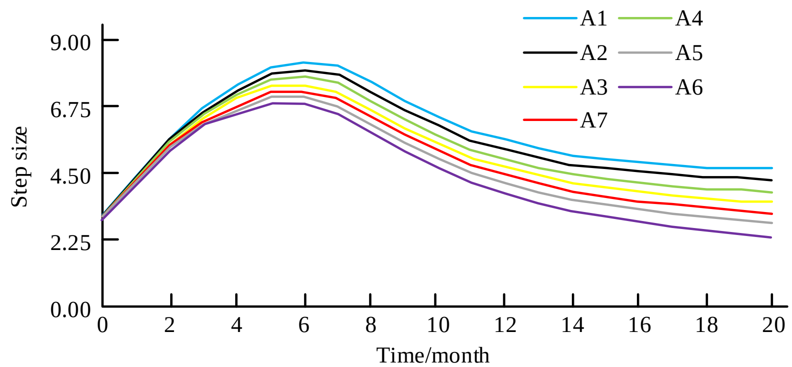


Fig. 6. Comparative analysis of CWB under different influencing factors.

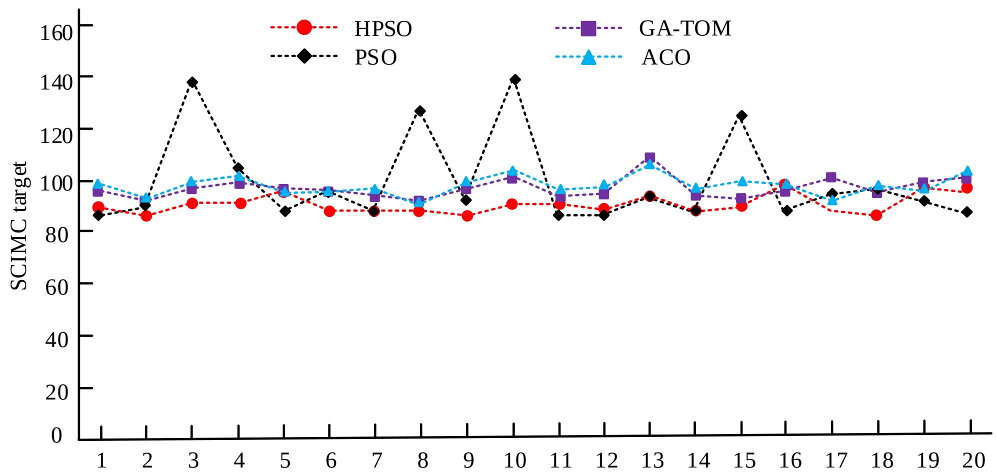


Fig. 7. SCIMC index change curves of four algorithms.

Fig. 7 shows the change curve of SCIMC index of different algorithms. The lower the SCIMC calculation result of the algorithm, the more robust its performance. As can be seen from Fig. 7, the HPSO has a maximum value (MV) of 95.81, a minimum value (IV) of 85.19, and an average value of 89.53. PSO, ACO, and GA-TOM algorithms have MVs of 136.77, 105.45, and 101.37, respectively, the IVs are 86.28, 85.37, and 85.24, respectively, and the average values are 99.09, 90.45, and 89.78, respectively. In summary, the outcomes of the HPSO and the GA-TOM differ less, and the calculation results of HPSO and GA-TOM are lower than the basic PSO and ACO, which proves that HPSO and GA-TOM have better performance in these four algorithms are superior in performance. To compare the performance of HPSO in SCIMC model more scientifically, the study set the machine interference time windows of A $\left[100,125\right]$ and B $\left[125,150\right]$ respectively, and conducted 10 simulation experiments using GA-TOM algorithm as the control group. Performance indicators include the Number Of Non-inferior Solutions (NONS), uniformity of non-inferior solution distribution, UNSD), dominant proportion of non-inferior solution (DPNS), average distance between non-inferior solution and optimal Pareto (DPNS), ADNSOP), maximum distance between non-inferior solution and optimal Pareto (MDNSOP), Noninferior Solution Dispersion, NSD) and Noninferior solution coverage (NSC), in which the larger the values of NONS, DPNS and NSC, the better the performance, and the smaller the values of UNSD, ADNSOP, MDNSOP and NSD, the better the performance.

Fig. 8 illustrates the experimental results of NONS and UNSD for the two algorithms under a working condition. Fig. 8(a) illustrates the NONS results of the two algorithms, the MV of HPSO algorithm is 14, the IV is 10, and the average is 12.3. The GA-TOM algorithm's MV is 12, the IV is 10, and 10.7 is the average. Fig. 8(b) illustrates the UNSD results of the two algorithms, the MV of HPSO algorithm is 9.700, the IV is 1.454, and the average is 5.283; it is higher than the MV of 4.970, the IV of 1.367, and the average of 2.435 for the GA-TOM algorithm.

The NONS and UNSD variation curves of the two algorithms under B working condition are presented in Fig. 9. The NONS variation curves for the two algorithms are displayed in Fig. 9(a). The maximum, minimum and average values of the HPSO algorithm are 12, 9 and 10.4, respectively, and the values of the GA-TOM algorithm are 11, 8 and 9.3, respectively. Fig. 8(b) shows the UNSD variation curves of the two algorithms, the MV of the HPSO algorithm is 10.500, the IV is 2.526 and the average is 6.132, The MV of GA-TOM algorithm is 12.26, the IV is 1.769, and the average is 5.936. Combining the results of Fig. 8 and Fig. 9, HPSO algorithm is marginally superior to GA-TOM algorithm in terms of the number of non-inferior solutions.

The CM, Dav and Dmax experimental results of the two algorithms under working conditions A and B are shown in Table I. As can be seen from Table I, the experimental results of DPNS, ADNSOP and MDNSOP for the two algorithms under A and B working conditions are presented in Fig. 1. The average of DPNS for the HPSO algorithm is 0.264 and that for the GA-TOM algorithm is 0.069. The average of ADNSOP for the HPSO algorithm is 4.474 and that for the GA-TOM algorithm is 4.485. The average value of MDNSOP for the HPSO algorithm is 4.627 and that for the GA-TOM algorithm is 4.638. The average values of DPNS, ADNSOP, and MDNSOP for the HPSO algorithm are 0.114, 3.104, and 3.189, respectively, for the B condition, and the average values of DPNS, ADNSOP, and MDNSOP for the GA-TOM algorithm are 0.066, 3.110, and 3.193, respectively. In terms of the link between the non-inferior solution set dominance and the separation of non-inferior solutions from the ideal Pareto front, the HPSO method surpasses the GA-TOM.

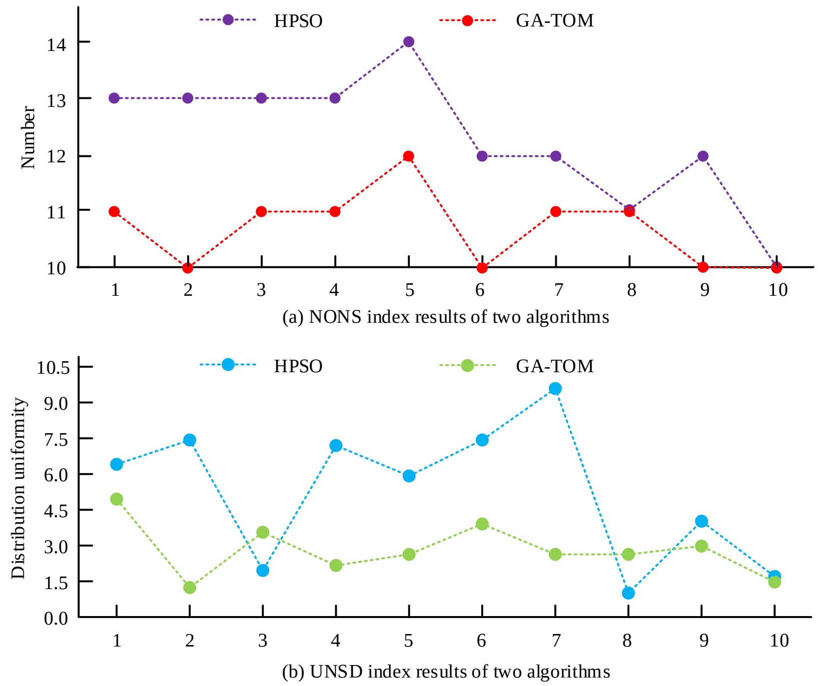


Fig. 8. NONS and UNSD results of two algorithms under ‘A’ working condition.

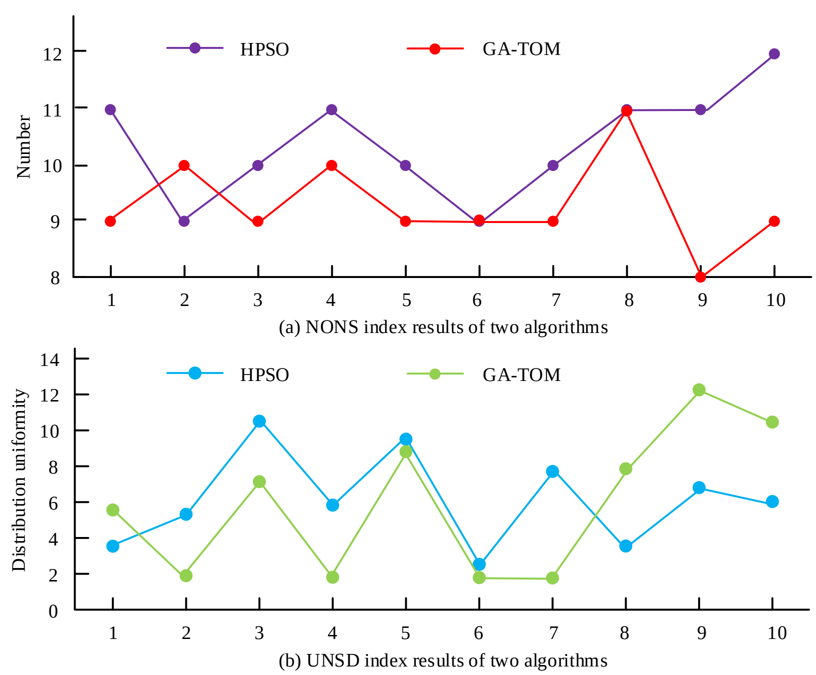


Fig. 9. NONS and UNSD results of two algorithms under ‘B’ working condition.

TABLE I. DPNS, ADNSOP AND MDNSOP RESULTS OF TWO ALGORITHMS UNDER 'A' AND 'B' WORKING CONDITIONS

Working condition	Performance index	Algorithm	Maximum	Minimum	Mean
A	DPNS	HPSO	0.814	0.112	0.264
		GA-TOM	0.398	0.000	0.069
	ADNSOP	HPSO	8.028	2.497	4.474
		GA-TOM	8.031	2.512	4.485
	MDNSOP	HPSO	8.264	2.595	4.627
		GA-TOM	8.278	2.611	4.638
B	DPNS	HPSO	0.401	0.000	0.114
		GA-TOM	0.239	0.000	0.066
	ADNSOP	HPSO	3.744	2.601	3.104
		GA-TOM	3.748	2.610	3.110
	MDNSOP	HPSO	3.845	2.681	3.189
		GA-TOM	3.849	2.683	3.193

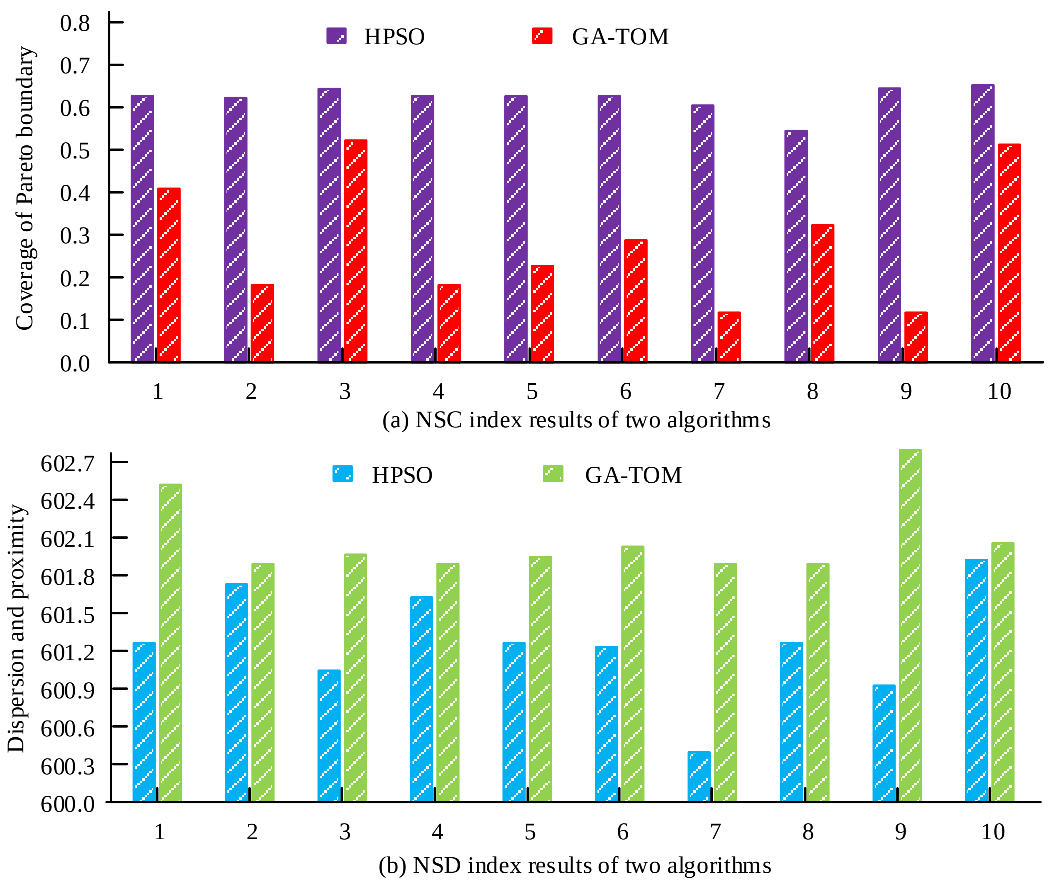
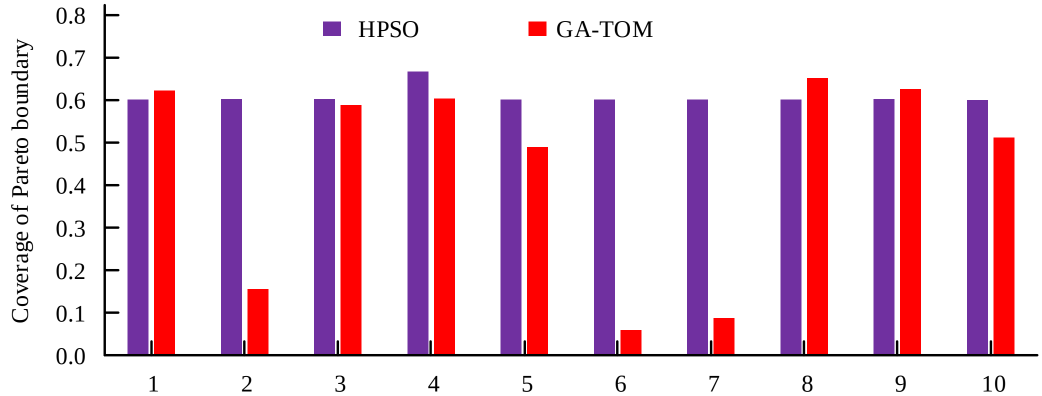
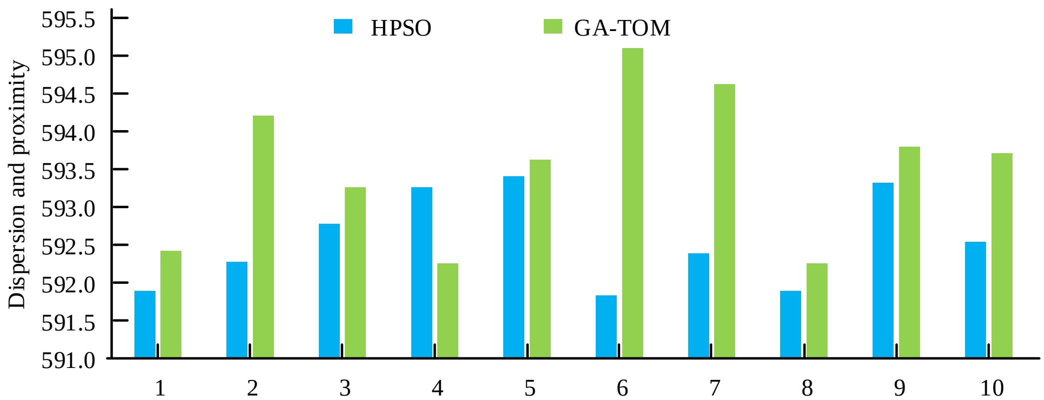


Fig. 10. NSC and NSD results of two algorithms under 'A' working condition.

Fig. 10 shows the experimental results of NSC and NSD for both algorithms under 'A' working condition. Fig. 10(a) shows the NSC results of both algorithms, the MV of HPSO algorithm is 0.638, the IV is 0.570, and the average is 0.611. The MV of GA-TOM algorithm is 0.511, the IV is 0.124, and the average is 0.298, The IV is 600.581 and the average is 601.300; it is lower than the MV of 602.753, the IV of 600.849 and the average of 601.961 of GA-TOM algorithm.



(a) NSC index results of two algorithms



(b) NSD index results of two algorithms

Fig. 11. NSC and NSD results of two algorithms under 'B' working condition.

TABLE II. COMPARES THE RESULTS OF EACH INDEX OF THE PROPOSED ALGORITHM AND THE TRADITIONAL ALGORITHM IN THE ACTUAL SUPPLY CHAIN INTERFERENCE MANAGEMENT SCHEDULING PROCESS

Evaluation index	Traditional algorithm	Research and propose algorithms
Response time	48 hours	24 hours
Cost saving	5%	12%
Customer satisfaction	75%	88%
Robustness	Intermediate	High
Expandability	Finitude	Good
Innovativeness	There is no	There are

The NSC and NSD variation curves of the two algorithms under B working condition are presented in Fig. 11. The NSC variation curves for both techniques are demonstrated in Fig. 11(a), the maximum, minimum and average values of HPSO algorithm are 0.667, 0.600 and 0.611, respectively. The values of GA-TOM algorithm are 0.652, 0.059 and 0.440, respectively. Fig. 11(b) demonstrates the NSD variation curves of both algorithms, the MV of HPSO algorithm is The MV of the HPSO algorithm is 593.407, the IV is 591.833, and the average is 592.54. The MV of the GA-TOM algorithm is 595.101, the IV is 592.251, and the average is 593.524. Combining the Fig. 10 and Fig. 11, the HPSO algorithm outperforms the GA-TOM algorithm in terms of non-inferior solution coverage, dispersion, and approximation. Finally, in order to carry out the practical application effect of the proposed algorithm, it is applied to the actual supply chain interference management scheduling process. In order to comprehensively evaluate the application effect of the proposed algorithm in the actual supply chain interference management and scheduling process, this study adopts response time, cost saving, customer satisfaction, robustness, scalability and innovation as evaluation indicators. The results of each indicator of the proposed algorithm and the traditional algorithm in the actual supply chain interference management and scheduling process are shown in Table II.

It can be clearly seen from Table II that the proposed algorithm has significant advantages compared with traditional algorithms in the actual supply chain interference management scheduling process. First, in terms of response time, the new algorithm is able to react within 24 hours, while the traditional algorithm takes 48 hours, which indicates that the new algorithm has a faster reaction speed. Secondly, in terms of cost savings, the new algorithm achieved a cost savings of 12%, much higher than the traditional algorithm of 5%, showing higher economic benefits. In addition, the new algorithm also showed a significant improvement in customer satisfaction, reaching 88 percent compared to 75 percent for the traditional algorithm, indicating that the new algorithm was better able to meet customer needs. In addition, the proposed algorithm also shows strong advantages in robustness, scalability and innovation, and has high stability and adaptability. Therefore, it can be concluded that the proposed algorithm has excellent performance and wide application prospects in the actual supply chain interference management scheduling process.

V. Discussion

With the deepening of globalization and networking, supply chain has become the core component of modern enterprise operation. The complexity, dynamics and uncertainty of supply chain bring unprecedented challenges to enterprises. Especially in recent years, due to the global epidemic, trade war, natural disasters and other multiple factors, the stability of the supply chain has been seriously threatened, resulting in a series of problems such as rising enterprise costs, delayed delivery, and decreased customer satisfaction. In order to cope with these challenges, supply chain interference management has gradually attracted the attention of enterprises and academia. SCDM aims to ensure supply chain continuity and stability by identifying, assessing, preventing and responding to disruptive events in the supply chain. However, the traditional supply chain optimization methods are often powerless in the face of complex and dynamic interference events. Therefore, how to effectively manage and dispatch the interference events in the supply chain has become an urgent problem in the field of supply chain management. This study aims to build an efficient and flexible supply chain interference management scheduling model by introducing HPSO algorithm. HPSO algorithm combines the advantages of particle swarm optimization algorithm and other optimization techniques, and can achieve global optimization and fast convergence in complex and dynamic environments. By applying HPSO algorithm, this study is expected to provide a new solution and method for supply chain interference management, help enterprises improve the stability and efficiency of supply chain, reduce operating costs, and enhance customer satisfaction.

The performance of HPSO algorithm in SCIMC model is analyzed and verified by experiments. Firstly, the variation degree of CWB under different influencing factors was analyzed. The results show that job satisfaction is the most influential factor on CWB, while the influence of organizational culture building level is relatively small. This finding is similar to the research results obtained by Bilandi's team in 2021, and this result provides a valuable reference for optimizing SCIMC model, suggesting that more attention should be paid to improving job satisfaction in practical applications [23]. Secondly, through independent numerical experiments on HPSO algorithm, GA-TOM algorithm, basic PSO algorithm and ACO algorithm, it is found that the results of HPSO algorithm and GA-TOM algorithm have little difference, and are better than the basic PSO algorithm and ACO algorithm. This shows that HPSO algorithm and GA-TOM algorithm have higher stability and efficiency in solving SCIMC model. The above results coincide with the research results of XX et al. on HPSO algorithm in 2022 [24]. In order to investigate the performance of HPSO algorithm more scientifically, the research also sets up the machine interference time window in A condition and B condition, and carries out the simulation experiment. The experimental results show that HPSO algorithm is slightly better than GA-TOM algorithm in terms of the number of non-inferior solutions. HPSO algorithm also shows some advantages in the dominant relation of the non-inferior solution set and the distance of the non-inferior solution from the optimal Pareto front. The research results are similar to the performance test results of the improved HPSO algorithm conducted by Zhang's team in 2020 [25].

In summary, the experimental results of this study verify the superior performance of HPSO algorithm in multiple performance indicators, providing strong support for the optimization of non-inferior solution coverage, dispersion and approximation, etc., and the conclusions obtained in this study are also consistent with the conclusions of the latest research. In future research, it is necessary to further explore the application potential of HPSO algorithm in other optimization problems, and constantly improve and improve the algorithm to improve its solving efficiency and stability. At the same time, we will also pay attention to the influence mechanism of key factors such as job satisfaction on the degree of CWB change, with a view to providing more targeted suggestions and guidance for solving practical problems.

VI. Conclusion

With the increasing growth of the economy, the market competition model has undergone a new change, and the traditional competition of enterprise units has been converted into the competition of SC units. Effective SC management can bring more economic benefits to enterprises, but since the SC itself is a dynamic and complex system, its internal is susceptible to disruptive events and the deterioration effect brought by CWB, which leads to hindering the production operation of enterprises. To address this difficulty, the study uses the HPSO algorithm to solve the behavior-based SCIMC model. The experimental results show that the HPSO algorithm for SCIMC objective calculates the MV of 95.81, the IV of 85.19, and the average value of 89.53, which is less difficult than the GA-TOM algorithm with the MV of 101.37, the IV of 85.24, and the average of 89.78. The average of NONS, DPNS, and NSC for the HPSO algorithm under ‘A’ working condition are 12.3, 0.264 The average of ADNSOP, MDNSOP, and NSD for the HPSO algorithm are 4.474, 4.627, and 601.300, which are lower than those of 4.485, 4.638, and 601.961 for the GA-TOM algorithm. The average of ADNSOP, MDNSOP, and NSD of HPSO algorithm are 3.104, 3.189, and 592.54, which are lower than 3.110, 3.193, and 593.524 of GA-TOM algorithm. In summary, the HPSO algorithm proposed in this study has robust performance, can effectively solve SCIMC problems, and promote the development of supply chain scheduling. However, the research still needs to be deepened, especially in considering the multi-benefit objectives of each node enterprise and the complex and changeable negotiation scheduling process. Looking forward to the future, the research in this field can be expanded in the aspects of multi-objective optimization, dynamic scheduling, application of game theory, integration of big data and artificial intelligence, and practical application verification, so as to reveal the internal law of supply chain interference management scheduling more comprehensively, and provide enterprises with more targeted and practical supply chain management strategies. Through these forward-looking discussions and practices, it is expected to promote the research of supply chain interference management scheduling to a new height.

FUNDINGS

The research is supported by: Jiangsu University Philosophy and Social Science Research Project ——Research on the ecological development path of Jiangsu cultural tourism industry from the perspective of "double carbon" (2022SJYB0678).

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