Research on Enterprise Supply Chain Anti-Disturbance Management Based on Improved Particle Swarm Optimization Algorithm

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***Abstract*—A supply chain that is effective and of the highest caliber boosts customer happiness as well as sales and earnings, increasing the company's competitiveness in the market. It has been discovered that the standard supply chain management technique leaves the supply chain with weak supply chain stability because it has a low ability to withstand the manufacturer's production behaviour. An enterprise supply chain resistance management model is built using the study's proposed particle swarm optimisation technique, which is based on a genetic algorithm with stochastic neighbourhood structure, to solve this issue. The suggested technique outperformed the other two algorithms utilised for comparison in a performance comparison test, with a stable particle swarm fitness value of 0.016 after 800 iterative iterations and the fastest convergence. The proposed model was then empirically examined, and the results revealed that the production team using the model completed the same volume of orders in 32 days while making $460,000 more in profit. With scores of 4.5, 4.5, 4.3, 4.3, 4.2, and 4.2, respectively, the team also had the lowest values of the six forms of employee anti-production conduct, outperforming the comparative management style. In summary, the study proposes an anti-disturbance management model for enterprise supply chains that can rationalise the scheduling of manufacturers' production behaviour and thus improve the stability of the supply chain.**

Keywords*—Supply chain; particle swarm optimization algorithm; genetic algorithm; inverse production behaviour; neighbourhood structure

I. Introduction

With the development of the global economy and the intensification of competition, the supply chain of enterprises is faced with more and more disturbances and uncertainties [1]. These disturbances include fluctuations in market demand, changes in raw material prices, natural disasters, etc. which have a huge impact on the operation of the supply chain [2-3]. Therefore, enterprises need to strengthen the anti-disturbance ability of the supply chain to ensure the efficient operation and stability of the supply chain. In supply chain anti-disturbance management, it is an important task to optimize resource allocation and decision-making in the supply chain [4-5]. The traditional particle swarm optimization algorithm often ignores the nonlinear relations and complex constraints in the supply chain, resulting in unstable optimization results and difficult to be applied in practice. Therefore, a new optimization algorithm is needed to solve this problem. In order to solve this problem and improve the anti-disturbance ability of enterprise supply chain, this paper proposes to improve the particle swarm optimization algorithm by using genetic algorithm and random neighborhood structure, and build the anti-disturbance management model of enterprise supply chain based on the improved algorithm. It is hoped that this model can improve the anti-interference ability of supply chain, improve the stability of supply materials, and enhance the market competitiveness of enterprises. The research is of great significance for enterprises to improve supply chain anti-disturbance ability, improve operation efficiency and reduce operation cost. At the same time, the anti-disturbance management method of enterprise supply chain based on improved algorithm also has certain theoretical and practical value, and has certain reference significance for the application and promotion of optimization algorithm. The innovation point of the research is that, considering various variables and uncertainties of the supply chain, genetic algorithm and random neighborhood structure are used to improve the traditional PSO based optimization algorithm, so as to optimize the resource allocation and decision-making in the supply chain, so as to improve the robustness and flexibility of the supply chain. The second section of this research is the in-depth study of the application of particle swarm optimization algorithm and supply chain problems in recent years. The third section analyzes the problems existing in the classical particle swarm optimization algorithm, proposes to improve it by using genetic algorithm and random neighborhood structure, and establishes the enterprise supply chain anti-disturbance management model based on the improved algorithm. The fourth section is the performance comparison test of the improved algorithm proposed in the research, and the practical application effect analysis of the enterprise supply chain anti-disturbance management model. The fifth section is the summary and conclusion of the whole research.

II. Related Works

A particle swarm optimisation technique for multi-objective solutions has been researched by scientists as part of the ongoing advancement of science and technology, and it is now widely employed in many neighbourhoods. To solve the issues with the design of steel pipe support weighing structures, Zakian et al. suggested an optimisation algorithm merging particle swarm algorithm with grey wolf optimiser. The findings of the empirical investigation suggest that the optimisation technique can enhance the structural. The outcomes demonstrated that the optimisation approach might enhance the pipe support structure's structural load-bearing and dimensional binding performance [6]. In an effort to address the issue that thermal coupling can lower the control accuracy of eccentric rotor extruders, Wen et al. proposed a control algorithm based on the particle swarm optimisation algorithm and neuron proportional integral differentiation [7]. After comparison tests, it was found that the algorithm can offset the effect of thermal coupling and improve the control accuracy of eccentric rotor extruders. To solve the issue that it is challenging to locate global peaks of PV arrays under shading conditions, Javed's team suggested a particle swarm optimisation approach in conjunction with adaptive learning. The results of comparative experimental study indicate that the algorithm outperforms conventional algorithms in terms of convergence speed and success rate, operating with an average efficiency of 99.65% [8]. To address the issue of low vehicle guidance accuracy in congested urban networks, Zouari's team suggested a hierarchical interval type 2 fuzzy logic model based on particle swarm optimisation. After conducting a simulation test and analysing the findings, Liu et al. suggested a node localization approach based on the combination of the particle swarm optimisation algorithm and the monkey algorithm. The results indicated that the method produced improved localization effects in terms of node rate and node density [10].

A solution using human capital and digital management was put out by Song et al. to address the issue of high retailer volatility in supply chain integration. According to the empirical analysis's findings, merchants who used this model had a better long-term investment mindset, which improved the supply chain's stability [11]. To solve the problem that green sensitivity has a significant impact on the stability of green supply chains, Long's team created an evolutionary game model that incorporates the green sensitivity of the government, businesses, and consumers. Following empirical analysis, the findings demonstrated that the model can combine the three elements to create a reasonable green sensitivity, upholding the stability of the green supply chain [12]. The outcomes of the comparison experiments demonstrated that this method can increase both the speed and security of hydrogen storage [13]. To attempt to address the issue of supply-demand mismatch in the supply chain for influenza vaccines, Lin et al. proposed a segmented linear function-based procurement model. After comparative experimental analysis, it was demonstrated that the model could coordinate the supply chain for influenza vaccines more effectively by fully taking into account the supply-demand relationship in the supply chain [14]. The results of a comparative experimental examination of a multi-stage mixed integer planning model revealed that it may not only lower logistics costs in the forest supply chain but also satisfy the wood demand of the sector [15].

In conclusion, merging supply chain research with the superiority of particle swarm optimisation algorithms has been shown in a number of localities, and it is thought that doing so has some research worth. Few academics have merged the two, thus this work uses the particle swarm optimisation algorithm to the creation of an anti-disturbance management model for company supply chains in an effort to close the gap in this research direction. It is believed that this research would increase the ability of business supply networks to withstand disruptions, lay the groundwork for increased business competitiveness, and serve the field of business supply chain management with research data.

III. Research on Anti-Interference Management Model of Enterprise Supply Chain based on Improved Particle Swarm Optimization Algorithm

It is impossible to emphasise how important the supply chain is to business operations, however traditional supply chain management is ineffective at controlling manufacturers' production behaviours, causing the supply chain to be impacted by this issue and having poor stability. This chapter will build an anti-disruption management model for enterprise supply chains based on the improved algorithm by using genetic algorithm and stochastic neighbourhood structure to address the shortcomings of the conventional particle swarm optimisation algorithm.

A. Improved Particle Swarm Optimization Algorithm based on Genetic Algorithm and Random Neighborhood Structure

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique that has strong adaptive and global convergence capabilities [16]. A particle in the PSO algorithm represents a process ordering in a production plant, i.e. a feasible solution to the production scheduling scheme. The particles are initialised and the equations are shown in Eq. (1) and (2).

$$v_{i,j}(t+1)=\omega v_{i,j}(t)+c_1r_1\left[p_{i.j}-x_{i,j}(t)\right]+c_2r_2\left[p_{p,j}-x_{i,j}(t)\right] \quad (1)$$

In Eq. (1), $v_{i,j}(t+1)$ denotes the velocity of the particle at the moment $t+1$ and t denotes the moment t. $x_{i,j}$ denotes the vector of real numbers and $v_{i,j}$ denotes the velocity vector. $p_{i,j}$ and $p_{g,j}$ both denote the current optimal position of the particle. ω denotes the habituation factor and c_1 and c_2 both denote the learning factor. r_1 and r_2 denote the random number between production.

$$x_{i,j}(t+1)=x_{i,j}(t)+v_{i,j}(t+1),\ j\in\{1,2,3,...,n\} \quad (2)$$

In Eq. (2), $x_{i,j}(t+1)$ denotes the particle position iteration at this moment of $t+1$. In the PSO algorithm, information sharing is constructed based on the best position of individual particles with the best position information of the particle population, passing the information to other particles in the search space. Due to the lack of information exchange between each particle, the optimal position of the particle itself changes as the search for the optimal position is continuously updated, and thus the optimal position of the particle population changes as well. Genetic algorithms are a method of searching for optimal solutions that mimics the natural evolutionary process, using processes such as chromosomal gene mutation and crossover [17]. The algorithm can optimise complex problems faster than traditional optimisation algorithms, and this study will use the mutation and crossover processes of the algorithm to change the problem of untimely information interaction in the PSO algorithm to ensure that each particle in the PSO algorithm can interact with each other to achieve information sharing and prevent local search [18]. The mutation operation in the algorithm is shown in Fig. 1.

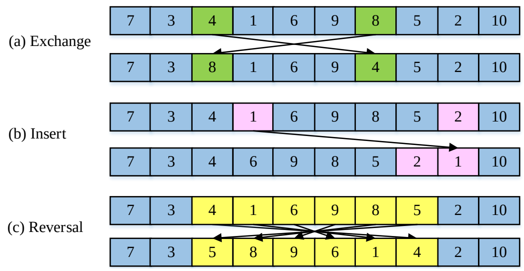


Fig. 1. Schematic representation of the variant operation.

As shown in Fig. 1, the mutation operation is performed separately for the historical best position of the particle and the current best position of the particle population. Different particles have different mutation probabilities, but the mutation operator is selected with the same probability, i.e. the selection of swap, insertion and inversion is the same. Swap variation involves swapping the positions of two randomly selected positions in the particle vector. The insertion variant is a random selection of two positions in a particle vector, which are compared in terms of their numerical size, with the smaller numerical particle being inserted after the larger value. The reversal variation involves randomly selecting two positions in the particle vector and reordering the other particles between the two positions in reverse, i.e. [4,1,6,9,8,5] becomes [5,8,9,6,1,4], as in Fig. 1(c). The crossover operation in the algorithm is shown in Fig. 2.

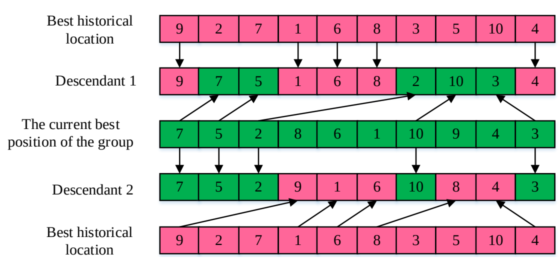


Fig. 2. Schematic diagram of the crossover operation.

As shown in Fig. 2, the historical best positions of the particles after mutation and the current best positions of the particle population are labelled and each is used as a parent to perform the crossover operator. A number of n'(n'<n) positions are randomly selected from the particle historical best positions to form array 1, which is copied directly in the first child according to its position in the parent. The first offspring is directly copied in the first offspring according to its position in the parent, thus completing the first offspring. The second offspring is formed similarly. By means of mutation and crossover operations, it is possible to interact with the information between individual particles in the PSO algorithm and to improve the search accuracy of the PSO algorithm. Although the PSO algorithm is fast in global convergence, local convergence faces the problem of falling into local traps.

To solve this problem, a random neighbourhood structure containing insertion neighbourhood, exchange neighbourhood and block exchange neighbourhood was studied [19]. The insertion operation of this neighbourhood structure is highly random, making the neighbourhood structure flexible and guiding the particles to search quickly during production scheduling. The swap operation is decentralised and can lead particles to jump out of local search. Therefore, using this neighbourhood to improve the PSO algorithm not only solves the problem of the algorithm falling into local traps, but also improves the speed and accuracy of the search. The search mechanism of the random structured neighbourhood is to randomly perform one or more insert neighbourhood, swap neighbourhood and block swap neighbourhood operations, the mathematical structure of which is expressed in Eq. (3).

$$f_N = \left(M \oplus \left(C_{pm} \otimes X_{best(g)}\right)\right) \quad (3)$$

In Eq. (3), M denotes the step size for performing the neighbourhood operation; $X_{best(g)}$ denotes the current best position of the X population; and C_{pm} denotes the probability of the diameter neighbourhood operation, which is calculated as shown in Eq. (4).

$$C_{pm} = \begin{cases} (\alpha_1 \le rand() \le \beta_1) \Rightarrow insert(\pi, k_1, k_2) \\ (\alpha_2 \le rand() \le \beta_2) \Rightarrow swap(\pi, k_1, k_2) \\ (\alpha_3 \le rand() \le \beta_3) \Rightarrow blockswap(\pi, B_1, B_2) \end{cases} \quad (4)$$

In Eq. (4), $[\alpha_1, \beta_1]$, $[\alpha_2, \beta_2]$ and $[\alpha_3, \beta_3]$ denote three probability intervals respectively; $rand()$ denotes a random distribution between (0,1); π denotes a scheduling scheme; k denotes an artifact; B denotes a set consisting of two adjacent artifacts; $insert(\pi, k_1, k_2)$ denotes an insertion neighbourhood; $swap(\pi, k_1, k_2)$ denotes an exchange neighbourhood; and $blockswap(\pi, B_1, B_2)$ denotes a block exchange neighbourhood. The parts of the probability region that overlap each other are defined as $COM < I, S, BS >$, and when $rand()$ is between $COM < I, S, BS >$, then the operation of the random neighbourhood is pressed as $insert(\pi, k_1, k_2)$, $swap(\pi, k_1, k_2)$, $blockswap(\pi, B_1, B_2)$. The working schematic of this neighbourhood structure is shown in Fig. 3.

As shown in Fig. 3(a), the position of workpiece 1 in the scheduling plan is randomly determined in $insert(\pi, k_1, k_2)$ and randomly inserted after the position of workpiece 2. As shown in Fig. 3(b), the positions of workpiece 1 and workpiece 2 in the scheduling plan are randomly swapped in $swap(\pi, k_1, k_2)$. The positions of workpiece set 1 and workpiece set 2 are randomly swapped in $blockswap(\pi, B_1, B_2)$ as shown in Fig. 3(c). Combining the above, the PSO algorithm is improved using genetic algorithm with random neighbourhood structure, and the improved algorithm is defined as HPSO-R.

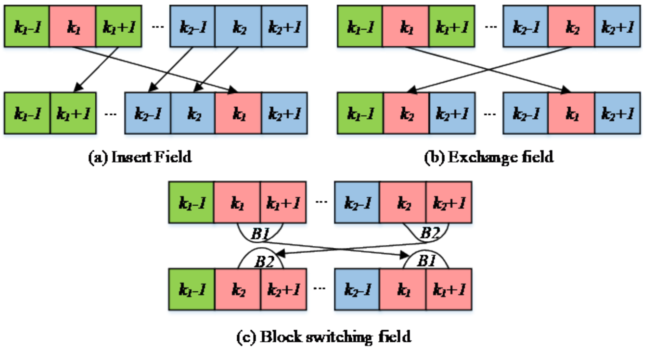


Fig. 3. A Schematic diagram of the domain structure.

B. Construction of Supply Chain Anti-Disturbance Management Model based on Improved Particle Swarm Optimization Algorithm

The supply chain is a network chain structure formed by the whole process of sending products from production to consumers. The supply chain of an enterprise is the lifeblood of the enterprise economy and its stable operation is very important for the development of the enterprise. The schematic diagram of the supply chain structure is shown in Fig. 4.

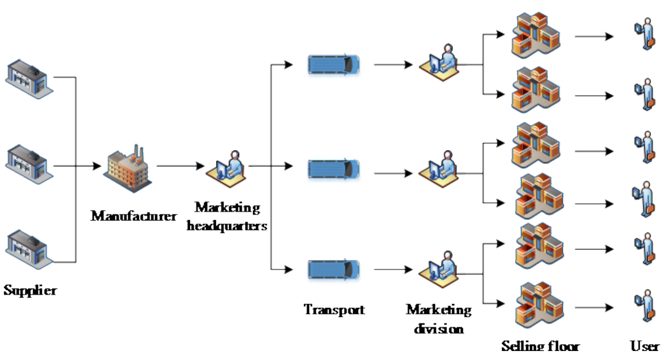


Fig. 4. Supply Chain Schematic diagram.

The stability of the enterprise supply chain is mainly influenced by the stability of the products produced by the manufacturer. The study will optimise the manufacturer's production management scheduling model through the HPSO-R algorithm to construct an anti-disturbance management model for the enterprise supply chain. The reasonableness of manufacturers' production management scheduling can be reflected by the counterproductive behaviours generated by employees [20]. Anti-production behaviours are divided into six categories, the first of which is job satisfaction, the equation for which is shown in Eq. (5).

$$L_1 = INTEG(R_1 - R_2, 2) \quad (5)$$

In Eq. (5), the letters L_1, R_1, and R_2 stand for work satisfaction, rate of increase in satisfaction, and rate of drop in satisfaction, respectively. The equation for the second category, organisational justice, is given in Eq. (6).

$$L_2 = INTEG(R_3 - R_4, 1) \quad (6)$$

In Eq. (6), the letters L_2, R_3, and R_4 stand for the organisational sense of justice, the rate at which it is increasing, and the rate at which it is decreasing. Eq. (7)'s equation for the third category, "sense of team climate," is shown.

$$L_3 = INTEG(R_5 - R_6, 1.5) \quad (7)$$

In Eq. (7), L_3 stands for the team's overall environment, R_5 for the rate at which it is improving, and signifies the rate at which it is deteriorating. The level of supervision, which is the fourth category, is determined as illustrated in Eq. (8).

$$L_4 = L_2 \times A_1 + L_6 \times A_2 + L_7 \times A_3 + L_8 \times A_4 \quad (8)$$

L_4 represents the degree of supervision, L_6 represents the degree of organisational culture building, L_7 represents the number of behavioural corrections, L_8 represents the perfection of the supervision mechanism, and $A_i(i = 1, 2, ..., n)$ represents the weighting factor in Eq. (8). Level of group regulation, the fifth category, has an equation that is represented in Eq. (9).

$$L_5 = INTEG(R_7 - R_8, 1.5) \quad (9)$$

In Eq. (9), L_5 stands for the group normative level, R_7 for the rate of increase of the group normative level, and R_8 for the rate of fall of the group normative level. The level of organisational culture building, the equation for which is stated in Eq. (10), is the sixth category.

$$L_6 = INTEG(R_9, 2) \quad (10)$$

In Eq. (10), L_6 stands for the organisational culture's level of development, and R_9 for its pace of growth. Eq. (11) displays the equation for determining anti-productive behaviours.

$$L_7 = L_1 \times F_1 + L_2 \times F_2 + ... + L_6 \times F_6 \quad (11)$$

L_7 stands for unproductive behaviour, and $F_i(i = 1, 2, ..., 6)$ stands for the coefficients of each of the six contributing elements described above in Eq. (11). Fig. 5 illustrates the interrelationship of the variables driving employee unproductive behaviour.

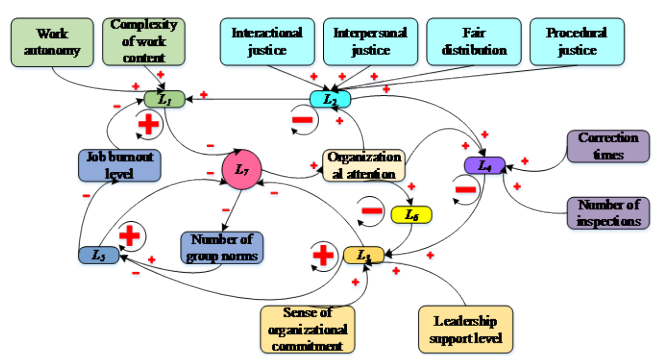


Fig. 5. Plot of anti-productive behavior factors

In the manufacturer's production management scheduling model, the initial scheduling target is calculated as shown in Eq. (12).

$$\min\left\{ f\left(\pi_0{}^{s}\right)=\sum_{j=1}^{n} w_j \cdot C_j ,\ f\left(\pi_0{}^{m}\right)=\sum_{j=1}^{n} w'_j \cdot C'_j \right\} \quad (12)$$

In Eq. (12), j denotes the workpiece; $\pi_0{}^{s}$ is the supplier's initial dispatch time; $\pi_0{}^{m}$ is the manufacturer's initial dispatch time; w_j and w'_j are the supplier's weighting factor and the manufacturer's weighting factor respectively; BBB and C_j are the supplier's completion time and the manufacturer's completion time respectively. To strengthen the resilience to disturbances in the supply chain, the study introduces disturbance management theory to optimise the model. Interference management models the optimisation of individual practical problems and disturbance events, e.g. in the face of machine downtime during a manufacturer's production process, the interference management scheduling objective optimisation equation is shown in Eq. (13).

$$\begin{cases} \min\left\{ f_1\left(\pi'\right)=\sum_{j=1}^{n} w'_j \cdot C'_j ,\ f_2\left(\pi'\right)=\sum_{j=1}^{n} w'_j \cdot \bar{\Delta} t'_0 \right\} \\ \bar{\Delta} t'_0 = \max\left\{ C'_j - \bar{C}'_j , 0 \right\} \end{cases} \quad (13)$$

In Eq. (13), $f_1\left(\pi'\right)$ denotes the optimisation objective of the manufacturer's disturbance repair scheme as well as the initial scheduling scheme, $f_2\left(\pi'\right)$ denotes the minimisation objective and $\bar{C}'_j$ denotes the manufacturer's completion time of the workpiece in the initial scheduling scheme. During the scheduling arrangement of the production product, the cost benefit between the supplier and the manufacturer also needs to be considered, i.e. the objective of maximising the benefits of cooperation, which is calculated as shown in equations (14) and (15).

$$\min\left\{ f_3\left(\pi'\right) = -V_m \cdot V_s \right\} \quad (14)$$

In Eq. (14), V_m denotes the manufacturer's revenue after the disturbance, and V_s denotes the supplier's revenue after the disturbance.

$$\begin{cases} D_j^s \le S_j^m \\ S_j^s, C_j^s \notin \left[t_1, t_2\right], \left(j \in list\right) \\ \left(S_j \ge C_k\right) \vee \left(S_k \ge C_j\right), \forall j,k \in J \end{cases} \quad (15)$$

In Eq. (15), D_j^s denotes the supplier's delivery time; S_j^m denotes the manufacturer's processing start time; C_j^s and C_j^s denote the supplier's processing time and completion time respectively. For the above multi-objective optimisation problem of initial scheduling objective, disturbance management scheduling objective and cooperation revenue maximisation objective, the research proposed HPSO-R algorithm can be used to find the optimal solution for it. The workflow is shown in Fig. 6.

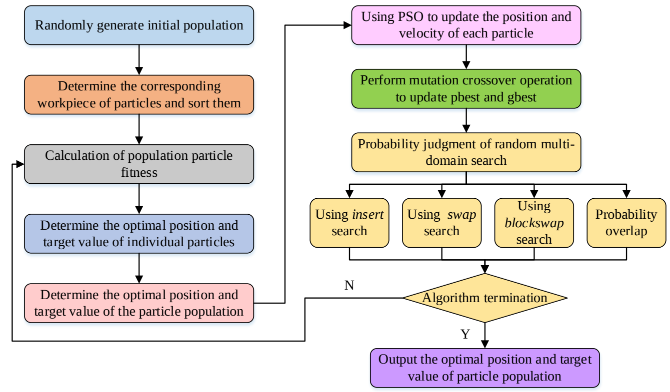


Fig. 6. Workflow of the HPSO-R algorithm.

As shown in Fig. 6, the HPSO-R algorithm is made from the basic PSO algorithm, improved by variation, crossover operations and random neighbourhood structure in the genetic algorithm, and has a higher search accuracy than the traditional PSO algorithm, with superiority in both global search as well as local search. The work flow of the algorithm is as follows: the input data is randomly generated to generate the initial population, and then the fitness value of the population is calculated according to the corresponding workpiece. According to the fitness value, the optimal position and target value of the individual particle are determined, and then the optimal position and target value of the population are determined. After that, the position and velocity of each particle are updated by particle swarm optimization algorithm, and the optimal position and target value of individual particle and the optimal position and target value of group are updated by mutation and cross operation in genetic algorithm. The mutation operation of genetic algorithm is divided into three types, namely exchange mutation, insert mutation and reverse mutation, and the best position of the particle history and the best position of the particle population are respectively changed. The crossover operation is to mark the historical best position of the particle and the current best position of the particle population after the mutation operation, and perform the crossover operator as the parent respectively, and realize the transformation of the historical best position of the particle and the current best position of the particle population through genetics. Through variation and cross operation, the information exchange between individual particles in PSO algorithm can be realized, and the search accuracy of PSO algorithm can be improved. Then the random structure neighborhood is used to perform insertion neighborhood, exchange neighborhood, block exchange neighborhood and probability overlap operations. The insertion operation of the neighborhood structure has a strong randomness, which makes the neighborhood structure change flexibly, and leads the particle to search quickly in the production scheduling process. The exchange operation is decentralized and can guide the particles out of the local search. Using this field can not only avoid PSO algorithm falling into local traps, but also improve the search speed and accuracy of the algorithm. Finally, it is judged whether the optimal position and target value of the particle swarm after searching meet the termination condition of the algorithm, and if so, the result is output. If it is not satisfied, the fitness value of the new population is calculated according to the result, and the previous steps are repeated until the algorithm termination condition is satisfied, and the optimal position and target value of the particle swarm are output. In summary, the improved algorithm not only has high speed and high accuracy, but also will not fall into the local optimal situation, which can strengthen the anti-interference ability of enterprise supply chain.

IV. Results and Discussion

To verify the performance of the HPSO-R algorithm proposed in the study, this study will conduct a comparison test using Visual software and the PSO algorithm, Genetic Algorithm Trade Off Model (GA-TOM) algorithm will be used as the comparison algorithm. The experiment uses the metrics of the Overall Nondominated Vector Generation (ONVG), the Uniformity of Distribution of Non-inferior Solutions (UDNS), the Non Inferior Solution Dominance Ratio (NISD) and the Average Distance between the Non-inferior Solution and the Optimal Pareto Front (ADF) to evaluate the algorithm in a comprehensive manner. An empirical analysis of the research's proposed improved algorithm-based model for the anti-disturbance management of an enterprise's supply chain is then carried out, with workers divided into three groups within a small factory, using the HPSO-R model, the PSO model and the GA-TOM model in a two-month comparative trial. The models will be comprehensively evaluated using indicators such as product completion time and profit in the trial.

A. Comparative Analysis of Performance of Improved Particle Swarm Optimization Algorithm

The performance of the HPSO-R algorithm was tested for comparison. After 10 independent trials under the same conditions, the ONVG and UDNS test results of the HPSO-R algorithm, PSO algorithm and GA-TOM algorithm are shown in Fig. 7, where the larger the ONVG value the stronger the performance and the smaller the UDNS value the better the performance.

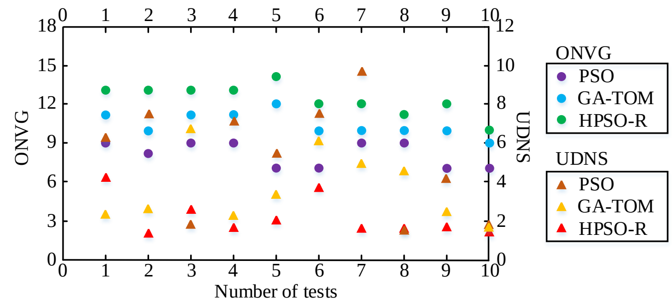
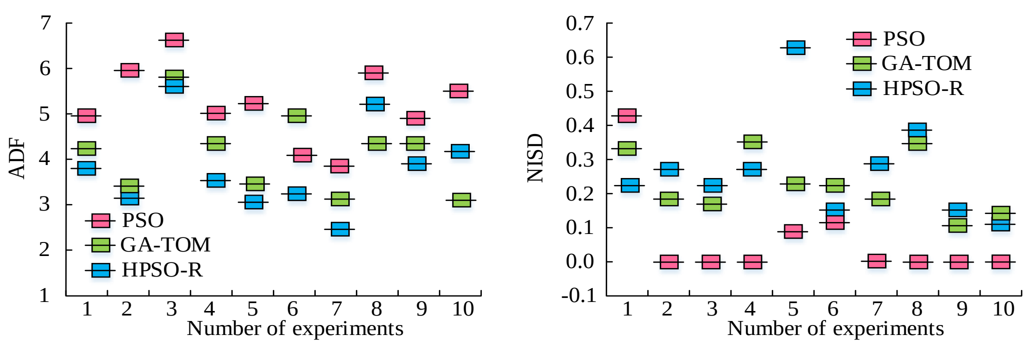


Fig. 7. ONVG and UDNS for the three algorithms.

As shown in Fig. 7, the ONVG values of the HPSO-R algorithm are 13, 13, 13, 13, 14, 12, 12, 11, 12, 10; the ONVG values of the GA-TOM algorithm are 11, 10, 11, 11, 12, 10, 10, 10, 10, 9; and the ONVG values of the PSO algorithm are 9, 8, 9, 9, 7, 7, 9, 9, 7 The minimum UDNS values of the HPSO-R, GA-TOM and PSO algorithms are 1.6, 1.8 and 1.9, respectively, and the maximum UDNS values are 4.2, 6.8 and 9.6. The overall UDNS values of the HPSO-R algorithm are smaller than those of the other two algorithms. In summary, the HPSO-R algorithm outperforms the other two compared algorithms in terms of ONVG and UDNS, two evaluation metrics. The ADF and NISD test results of the three algorithms are shown in Fig. 8, where the smaller the ADF value the better the performance, and the larger the NISD value the stronger the performance.



(a) ADF (b) NISD

Fig. 8. A for ADF and DPNS for the three algorithms.

As shown in Fig. 8(a), the ADF value of the HPSO-R algorithm is 5.6 at maximum, 2.4 at minimum and 4.1 at average; the ADF value of the GA-TOM algorithm is 5.8 at maximum, 3.1 at minimum and 4.6 at average; and the ADF value of the PSO algorithm is 6.6 at maximum, 4.8 at minimum and 5.8 at average. The ADF value of the HPSO-R algorithm is lower than the other two The ADF values of the HPSO-R algorithm are lower than the other two algorithms. As shown in Fig. 8(b), the NISD value of the HPSO-R algorithm was 0.62 at maximum, 0.11 at minimum, and 0.31 at mean; the NISD value of the GA-TOM algorithm was 0.35 at maximum, 0.11 at minimum, and 0.25 at mean; the NISD value of the PSO algorithm was 0.42 at maximum, 0.0 at minimum, and 0.06 at mean. The NISD value of the HPSO-R algorithm was higher than the other two algorithms. The NISD values of the HPSO-R algorithm were higher than those of the other two algorithms. In summary, the HPSO-R algorithm outperformed the comparison algorithms in terms of ADF and NISD. The experiment reflects the convergence speed of the algorithm by recording the change curve of the particle swarm fitness value during the iterative operation of the algorithm. The smaller the swarm fitness value, the smaller the difference between the result and the optimal solution, and the better the performance of the algorithm. The curves of particle swarm fitness values for the three algorithms are shown in Fig. 9.

According to Fig. 9, which compares the particle swarm fitness curves of the three algorithms, the PSO algorithm begins to stabilise at 0.029 after 200 iterations, followed by the GA-TOM algorithm at 0.021 after 150 iterations, and the HPSO-R algorithm at 0.016 after 100 iterations. The HPSO-R method outperforms the comparative algorithms in terms of performance and has the fastest convergence speed and lowest particle swarm fitness value. In conclusion, the study's evaluation metrics showed that the proposed HPSO-R algorithm performed better than the other two comparative algorithms, proving its superiority.

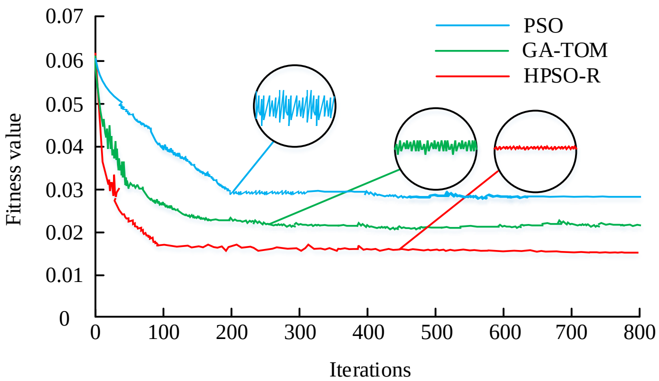


Fig. 9. The particle population fitness value curve of the three algorithms.

B. Analysis of the Effectiveness of the Application of an Enterprise Supply Chain Anti-Disturbance Management Model

In the experiments on the practical application of the anti-disturbance management model of the enterprise supply chain proposed by the study, three groups of employees using the HPSO-R model, the PSO model and the GA-TOM model were assigned the same number of orders, and the experimental results on the order completion time as well as the overall profit are shown in Fig. 10.

From Fig. 10(a), it can be seen that for the same number of orders, the completion time was 59 days for the group using the PSO model, 43 days for the group using the GA-TOM model and 32 days for the group using the HPSO-R model. From Fig. 10(b), it can be seen that the profits of these three groups using the PSO model, the GA-TOM model and the HPSO-R model after completing the same number of orders are \$340,000, \$380,000 and \$460,000 respectively. The group using the HPSO-R model had the shortest time to complete orders and the highest profit, all better than the comparison model. As the value of employee-generated counterproductive behaviour can reflect the rationality of a manufacturer's production management scheduling, the six types of counterproductive behaviour of employees within the three groups using the model were recorded and their experimental results are shown in Fig. 11.

As it can be seen from Fig. 11, all three groups of employees reached their highest values of counterproductive behaviour at around day 20 of the trial. The highest values for the six categories of counterproductive behaviour were 7.1, 7.0, 6.8, 6.7, 6.4 and 6.1 in the group using the PSO model; 5.6, 5.5, 5.3, 5.2, 5.1 and 5.0 in the group using the GA-TOM model; and The HPSO-R model group had the lowest production behaviour values, indicating that the group had the most rational production management scheduling. A sample of completed goods from each group was checked and the pass rate of goods was counted, while manufacturers were invited to rate the perception of using the three models out of 10. The results of the experiment are shown in Fig. 12.

As it can be seen from Fig. 12(a), at one month into the trial, the commodity pass rate was 65% with a manufacturer rating of 6.3 in the PSO model group, 75% with a manufacturer rating of 7.1 in the GA-TOM model group, and 83% with a manufacturer rating of 8.2 in the HPSO-R model group. As it can be seen from Fig. 12(b), at two months into the trial, the PSO model group had a commodity qualification rate of 66% and a manufacturer rating of 6.6, the GA-TOM model group had a commodity qualification rate of 78% and a manufacturer rating of 7.9, and the HPSO-R model group had a commodity qualification rate of 92% and a manufacturer rating of 9.1. Combining the above experimental results, it can be seen that the anti-disturbance management model of the enterprise supply chain based on the HPSO-R algorithm proposed in the study is better than the comparison model when applied in practice.

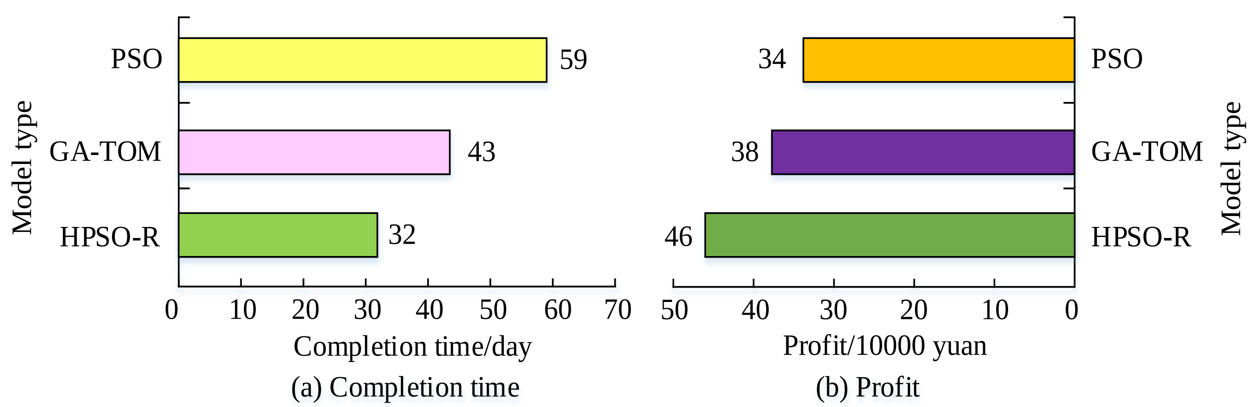


Fig. 10. Time to completion and profit.

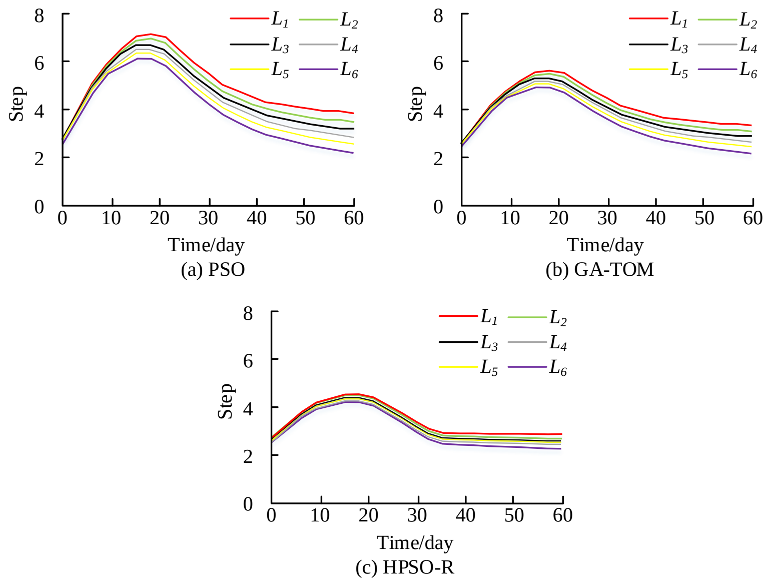


Fig. 11. Comparison of antiproductive behavior.

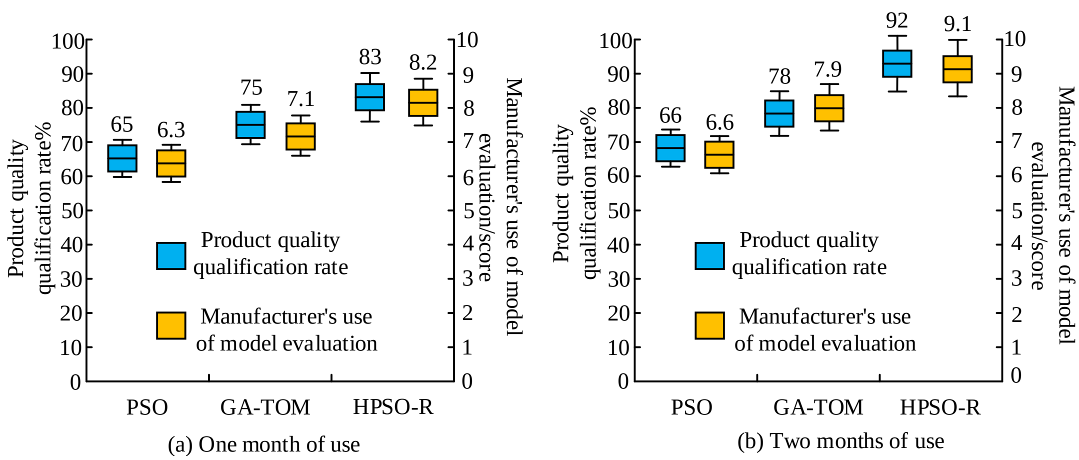


Fig. 12. Pass rate of goods and manufacturer score.

C. *Comparative Analysis of Improved Algorithm Performance is discussed*

In the comparative test of the performance of the improved algorithm, ONVG, UDNS, NISD, ADF and the particle swarm fitness value of the algorithm are proposed as evaluation indexes. Among them, ONVG, UDNS, NISD and ADF are all evaluation indexes of non-dominated ranking problems. Non-dominant ranking is to divide all non-dominant individuals into the first non-dominant optimal layer, and formulate and assign a shared virtual fitness value. The already stratified individuals are then ignored and the division continues, with a second non-dominant layer appearing, which also develops and assigns a shared virtual fitness value, and so on until all population individuals are stratified. This has the advantage of good individual fitness values and also maintains population diversity. Therefore, it is applied to the performance comparison of multi-objective optimization algorithms. Singh et al. adopted non-dominated ranking index to verify the optimization algorithm of multi-objective problem in the dynamic balance mechanism of cleaning device of agricultural thresher. The results show that the proposed method is feasible, that is, non-dominated ranking index is universal for the detection of multi-objective optimization algorithm [21]. In the study of the basic method of non-orthogonal multiple access which has been envisaged as the fifth generation cellular network, Kumaresan's team used the fitness value of each iteration of the algorithm to evaluate the particles in the validation of the adaptive user clustering algorithm based on the particle swarm optimization algorithm. The results show that the proposed algorithm has advantages. That is, the particle swarm fitness value algorithm detection of the algorithm is scientific [22]. Therefore, it is feasible to use ONVG, UDNS, NISD, ADF and the particle swarm fitness value of the algorithm as the evaluation index of the algorithm in the experiment. In ten comparison tests, the ONVG values of HPSO-R algorithm are 13, 13, 13, 13, 14, 12, 12, 11, 12 and 10, respectively, which are greater than the other two comparison algorithms, indicating the optimal performance of the algorithm. The minimum UDNS values of HPSO-R algorithm are 1.6 and the maximum UDNS values are 4.2, respectively, which are both lower than the other two comparison algorithms, indicating that the algorithm has the best performance. The maximum ADF value of HPSO-R algorithm is 5.6, the minimum is 2.4, and the average value is 4.1, all of which are lower than the other two comparison algorithms, indicating that the algorithm has the best performance. The maximum NISD value of HPSO-R algorithm is 0.62, the minimum is 0.11, and the average value is 0.31, all of which are greater than the other two comparison algorithms, indicating that the algorithm has the best performance. The smaller the particle swarm fitness value is, the smaller the gap between the operation result and the optimal solution, that is, the better the algorithm performance. In the iterative test, the particle swarm fitness value of HPSO-R algorithm is finally stable at 0.016, the lowest value, and the fastest convergence speed, which is better than the comparison algorithm. In summary, the HPSO-R algorithm proposed in this study has the advantages of fast running speed and high accuracy, and its performance is better than the comparison algorithm.

V. Conclusion

A robust company supply chain is crucial to the successful growth of a business. The production practises of manufacturers have a greater impact on the supply chain than any other of the different links that make it up. The study suggests combining evolutionary algorithms and random neighbourhood structures to improve the particle swarm optimisation method in order to address this issue, and it then completes the building of the enterprise supply chain's anti-disturbance management model using the revised algorithm. When the modified method was tested for comparative performance, it outperformed both the PSO algorithm and the GA-TOM algorithm with maximum ONVG and NISD values of 14 and 0.62, respectively, and minimum UDNS and ADF values of 1.6 and 2.4, respectively. The algorithm outperforms the comparison algorithms in both the quickest convergence rate and the smallest particle swarm fitness value, which is steady at 0.016 after 800 iterations. In a trial of the practical application effects of the model proposed in the study, it was found that the production team using the model had the shortest time and highest profitability in completing the same order volume, 32 days and $460,000 respectively. Additionally, in the experiment, the members of this group outperformed both the PSO model and the GA-TOM model by having the lowest values for each of the six forms of anti-production behavior—4.5, 4.5, 4.3, 4.3, 4.2, and 4.2, respectively. At one month into the experiment, the group employing this model had a manufacturer score of 8.2 and a merchandise conformance rate of 83%. The model group's pass rate and manufacturer score at the halfway point of the testing were 92% and 9.1, respectively. In conclusion, the study's anti-disturbance management model of the company supply chain may realistically schedule the behaviour of manufacturers with regard to production, hence enhancing the stability of the supply chain.

In the study of the influence of behavioral factors, although the measurement method is obtained, the parameters are selected by direct reference to the values in the existing literature. In the subsequent work, empirical studies can be conducted according to different enterprises and environments, so as to be closer to the actual situation. In supply chain management, because the member enterprises of the supply chain are independent economic entities, their interests and goals are different, so the coordination and decision-making problem is more complicated and diversified, and it is urgent to study it deeply. At the same time, this model is not strong enough for the connection and coordination between all links in the supply chain. How to do a good job in the connection between all links is also a problem to be further studied in the future.

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