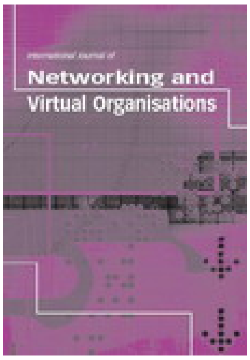


International Journal of Networking and Virtual Organisations

ISSN online: 1741-5225 - ISSN print: 1470-9503
https://www.inderscience.com/ijnvo

Application of particle swarm optimisation in collaborative scheduling of logistics and supply chain

Hongli Liu, Shuang Yang

DOI: 10.1504/IJNVO.2025.10073622

Article History:

Received:	21 February 2025
Last revised:	26 June 2025
Accepted:	30 June 2025
Published online:	05 November 2025

Application of particle swarm optimisation in collaborative scheduling of logistics and supply chain

Hongli Liu* and Shuang Yang

Xi'an Traffic Engineering Institute,
Xi'an, 710300, Shaanxi, China
Email: 17392216060@163.com
Email: 18092025648@163.com
*Corresponding author

Abstract: Traditional logistics and supply chain scheduling often focus on single-objective optimisation and ignore the complexity of multiple objectives, resulting in inefficiency and difficulty in cost control. This paper applies the particle swarm optimisation algorithm (PSO) to the collaborative scheduling of logistics and supply chain to improve transportation efficiency. This paper uses PSO to model logistics and supply chain scheduling problems, studies vehicle routing problems, and comprehensively considers multiple objectives such as transportation cost, inventory cost, and delivery time to optimise logistics transportation routes. Experiments show that after vehicle No. 1 was planned using the PSO algorithm, the transportation time was reduced by 2.1 h, the utilisation rate was as high as 98.2%. This shows that the PSO algorithm has significant advantages in logistics and supply chain collaborative scheduling, can effectively perform multi-objective optimisation, and has fast convergence speed and good stability.

Keywords: logistics and supply chain management; PSO; particle swarm optimisation; collaborative scheduling; production and transportation; vehicle routing problem.

Reference to this paper should be made as follows: Liu, H. and Yang, S. (2025) 'Application of particle swarm optimisation in collaborative scheduling of logistics and supply chain', *Int. J. Networking and Virtual Organisations*, Vol. 33, No. 1, pp.67–86.

Biographical notes: Hongli Liu is an Associate Professor and a Senior Logistics Professional. She serves as a Special Research Fellow of the China Federation of Logistics & Purchasing (CFLP), an Executive Director of the CFLP, an assessor for the Supply Chain Manager certification by the Ministry of Human Resources and Social Security of China, a Director of the Shaanxi Provincial Logistics Society, and an expert in the Comprehensive Bid Evaluation and Review Expert Pool of the Shaanxi Provincial Development and Reform Commission.

Shuang Yang is a Master's degree holder who teaches Logistics Management as a Teaching Assistant at the Xi'an Traffic Engineering Institute's School of Humanities and Management. She is a member of the China Society of Logistics. Her research focuses on the field of logistics and supply chain and main courses include logistics transportation organisation and management, introduction to smart logistics, international trade theory and practice, warehousing and distribution management, and logistics science.

1 Introduction

In the current context of global economic integration, logistics and supply chain management, as the core hubs connecting the production and consumption ends, are becoming more and more important. With the increasingly fierce market competition and the increasing diversification of user needs, enterprises urgently need to achieve efficient collaboration in key links such as production, inventory, and transportation to improve response speed, optimise cost structure, and enhance market competitiveness (Richey et al., 2022; Richey et al., 2023; Akbari and Do, 2021). Especially when facing complex issues such as logistics and supply chain collaborative scheduling, enterprises need to deal with multiple tasks such as production scheduling, transportation organisation, and inventory coordination at the same time, which not only tests their flexibility and adaptability but also puts forward higher requirements for optimisation technology. Most of the existing scheduling methods focus on the optimisation of a certain goal, such as reducing transportation costs or increasing productivity, and often ignore the correlation and trade-off between multiple goals. This kind of single-target method is difficult to effectively take into account multiple aspects such as transportation, inventory, and delivery cycle, resulting in poor overall scheduling effect, cost control, and service levels are difficult to unify. Traditional optimisation strategies lack the ability to find global optimisation, and they often fall into local optimal solutions, making it difficult to cope with the uncertainty brought about by market changes. Therefore, the introduction of intelligent algorithms with strong global search capabilities and multi-objective balancing mechanisms has become a key way to deal with the problem of collaborative scheduling in the modern supply chain.

In order to cope with the limitations of traditional scheduling methods in logistics and supply chain collaboration, PSO has been widely introduced as an effective solution. Inspired by the foraging behaviour of birds in nature, PSO can process multiple decision-making variables in parallel by simulating information interaction and group collaboration between individuals, to achieve the overall optimisation and efficiency improvement of the entire supply chain system (Zhang et al., 2019; Abdelaziz et al., 2020; Son et al., 2021). The algorithm has a simple structure, easy implementation, and good global optimisation performance, which is particularly suitable for large-scale, high-dimensional, and complex optimisation tasks. In the actual supply chain scheduling application, PSO guides the exploration of solution space through the group search mechanism, and gradually approaches the global optimal solution, effectively improving the science and system coordination of scheduling. Based on this, this paper will discuss the specific application path of PSO in logistics and supply chain collaborative scheduling, and conduct systematic research on problem modelling, fitness function design, and algorithm parameter optimisation to improve scheduling efficiency and service quality. The research focus includes vehicle path issues (VRP), combined with multi-objective optimisation ideas, comprehensive consideration of key indicators such as transportation costs, inventory costs, and delivery timeliness, and a more practical and operational scheduling strategy to promote the development of logistics and supply chain management in the direction of intelligence and efficiency.

The main contributions of this research are reflected in the following aspects:

1 With the help of PSO, an efficient intelligent optimisation method has been introduced for the collaborative scheduling of logistics and supply chain, breaking through the limitations of traditional methods in terms of multi-objective coordination and global search capabilities.

2 By constructing a mathematical model covering key variables and a targeted fitness function, the refined expression and optimised solution of the scheduling problem are realised, and the rationality and practical enforceability of the scheme are enhanced.

3 Through experiments, the excellent performance of the proposed algorithm in collaborative scheduling tasks is verified, and it shows high scheduling efficiency and stability, which is of great guiding significance to the production and logistics operations of actual enterprises.

Overall, this research delves into the practical application of PSO in complex logistics and supply chain scheduling, expands the research boundaries of optimisation algorithms in this field, and shows obvious advantages in improving system response speed, reducing operating costs, and improving customer service levels.

2 Related work

Logistics and supply chain collaborative scheduling is a comprehensive integrated management strategy, the core of which is to optimise the various links in logistics and supply chain to achieve smooth connection and efficient operation between them (Chenna, 2024; Koh et al., 2023). Cai et al. (2023) proposed a new real-time scheduling model and algorithm. There is a new task information release time that can give AGVs a longer time to prepare tasks than existing research. In order to improve energy efficiency and reduce the pollution emissions of replacing ports with electric hydrogen, Pu et al. (2023) proposed a port-integrated energy and container logistics collaborative scheduling method considering electric hydrogen transportation and also constructed a port container logistics assembly line model based on flexible workshop scheduling. As a revolutionary technology that has emerged in recent years, Blockchain technology has great application potential in supply chain operations. Xia et al. (2023) conducted a systematic review of Blockchain-based supply chain case studies. Barman et al. (2022) examined the impact of business strategies in multiple industries on the cooperative market system, proposed a production inventory system with a manufacturer-retailer supply chain, and examined the two-level supply chain model. To solve the problem of supply chain collaboration and improve its effectiveness, Ghazal and Alzoubi (2022) provided a framework based on fusion machine learning. The study of supply chain scheduling and classical logistics has numerous flaws. They frequently concentrate on single-goal optimisation, which makes it challenging to properly account for the complexity of many goals like delivery times, inventory costs, and transportation expenses. This leads to low efficiency and challenging cost control. Second, the global search capabilities of traditional approaches are limited, making it challenging to locate the best answer in a complex and dynamic market environment. Additionally, it is simple to fall into local optimality.

This work makes use of PSO's quick convergence and straightforward structure. The PSO algorithm can comprehensively consider multiple goals and gradually approach the global optimal solution through iterative optimisation, which significantly improves the efficiency of supply chain collaborative scheduling (Li and Li, 2024; Dai, 2023). To enable the company to make decisions that are in line with market changes, Chen and Du (2024) uses the PSO algorithm to optimise the deep learning neural network, improves the model parameter settings, combines the inertial weight strategy of normal distribution attenuation, and proposes a normal distribution attenuation inertial weight particle swarm optimisation (PSO). As the core of vehicle route decision-making in logistics and distribution management, route planning has become a hot topic in logistics and distribution. Cai (2023), a heuristic elastic PSO algorithm is proposed. The A* algorithm is used to provide global guidance on path planning in large-scale grids. The elastic PSO algorithm uses a contraction operation to determine the global optimal path formed by the local optimal node. Wang et al. (2025) aims to build a supply chain financial decision support system based on deep reinforcement learning and PSO algorithms. This research effectively captures the dynamic characteristics of supply chain financial data, optimises model parameters, improves decision-making accuracy and response speed, and further evaluates the impact of the system on improving the financial efficiency of enterprises. Machine scheduling and vehicle scheduling are intertwined because vehicles must transport tasks to machines for processing and machines must complete processing operations before they can be transported. Fontes et al. (2023) proposed a hybrid PSO and simulated annealing technique for scheduling industrial activities and optimising transportation resources. Li et al. (2022) constructed a multi-objective optimisation model with cogeneration system operating cost, pollutant emissions, and energy efficiency as objectives, and proposed a PSO method based on mapping chaos search and nonlinear adaptation.

Recent research has made significant progress in applying PSO algorithms to solve supply chain and logistics coordination scheduling problems; however, some shortcomings remain. For instance, some methods struggle with complex optimisation problems involving multiple objectives and constraints, where the global search capability and convergence speed need improvement. To address these issues, this paper introduces an improved hybrid PSO algorithm. By incorporating nonlinear adaptive strategies and chaotic search mechanisms, the algorithm enhances its global optimisation capabilities and convergence performance. This algorithm is applied to solve multi-objective, multi-constraint supply chain coordination scheduling models, effectively improving the efficiency and practicality of the scheduling solutions.

3 Methods

3.1 Theoretical considerations

The members of the supply chain have differences in goals, geographical distribution, external environment, management strategies, plans, process flow, and operation methods, which leads to different problems to be solved in supply chain collaborative management at different management levels (Rejeb et al., 2021; Alzoubi et al., 2020). At the strategic level, the main focus is on the coordination of goals, and the emphasis is on the construction and strategy design of the supply chain, which mainly involves the coordination of node enterprises at the logical level. At the tactical level, supply chain synchronisation or integration planning is the core. These factors are mostly related to the enterprise logic level, and some involve the physical level. In general, the collaborative scheduling of the supply chain operation layer involves multiple aspects. When considering the storage and transportation connection relationship and capacity constraints between nodes, these factors merge and intersect with each other, forming a more complex scheduling problem. PSO algorithm is a heuristic random search algorithm inspired by the foraging behaviour of birds. In the algorithm, food represents the target, and the bird's position is regarded as a variable, which is then simplified to massless and volumeless particles. These particles move freely in space with a certain initial velocity and record the optimal position of their individuals and groups.

As a typical group intelligence optimisation method, PSO's core idea is derived from the simulation of bird foraging behaviour, emphasising the information sharing and collaboration mechanism between individuals, which makes it show good application potential in the field of logistics and supply chain collaborative scheduling. In this problem, each scheduling scheme is abstract as a particle in the solution space, and the scheduling strategy is continuously optimised through changes in the speed and position of the particles. From the theoretical point of view, the PSO algorithm can not only comprehensively consider multi-objective optimisation factors such as transportation costs, inventory costs, and delivery time, but also has the ability to maintain stability and adaptability in a dynamic environment.

Every potential solution is treated as a particle in the solution space by the PSO algorithm, and these particles track their movements (Chen and Du, 2024; Ji et al., 2021; Song et al., 2020). Particles keep flying in the direction of both the group's ideal position and their historical optimal location. Each particle may remember and modify its speed in order to accomplish this. The following are the formulas for the iteration process of the *i*th particle:

$$x_i(k+1) = y * x_i(k) + a_1 b_1 \left(qe_i(k) - r_i(k)\right) - a_2 b_2 \left(ge(k) - r_i(k)\right) \quad (1)$$

$$r_i(k+1) = r_i(k) + x_i(k+1) \quad (2)$$

Among them, y is the inertia factor, which determines the search range; a_1 and a_2 are learning factors, which allow particles to continuously approach the optimal solution; b_1 and b_2 are random numbers between [0,1].

3.2 Vehicle routing problem (VRP)

When multiple customer points require varying quantities of goods, the logistics vehicle routing problem entails calculating a reasonable driving route by a distribution centre to finish the delivery of goods to each customer point (Konstantakopoulos et al., 2022; Vidal et al., 2020; Rojas Viloria et al., 2021). The main goal of this problem is to minimise the logistics distribution centre's costs while satisfying the demands of every consumer point and a number of limitations. By modifying the vehicle driving route, PSO can be used to examine supply chain logistics vehicle routing issues and efficiently reduce empty loads and detours, increasing the overall efficiency of transportation.

Starting from a specific distribution centre, a fixed number of delivery vehicles are used to deliver goods to known customer points. In this process, the maximum load capacity of each vehicle and the demand for goods at each customer point are known and fixed. The goal is to design a set of scientific and reasonable logistics distribution routes. These constraints provide important guidance and a basis for the subsequent establishment of a mathematical model for the VRP problem. The mathematical models of the VRP problem studied in this paper are as follows:

$$Min\, h\left(t_{ij}\right) = \sum_i \sum_j \sum_k t_{ij} W_{ijk} \tag{3}$$

$$\sum_i p_i M_{ki} \le P\left(k = 1, 2, \ldots, K\right) \tag{4}$$

$$\sum_i M_{ki} = 1\left(i = 1, 2, \ldots, R\right) \tag{5}$$

$$\sum_i W_{ijk} = M_{kj}\left(j = 1, 2, \ldots, R\right) \tag{6}$$

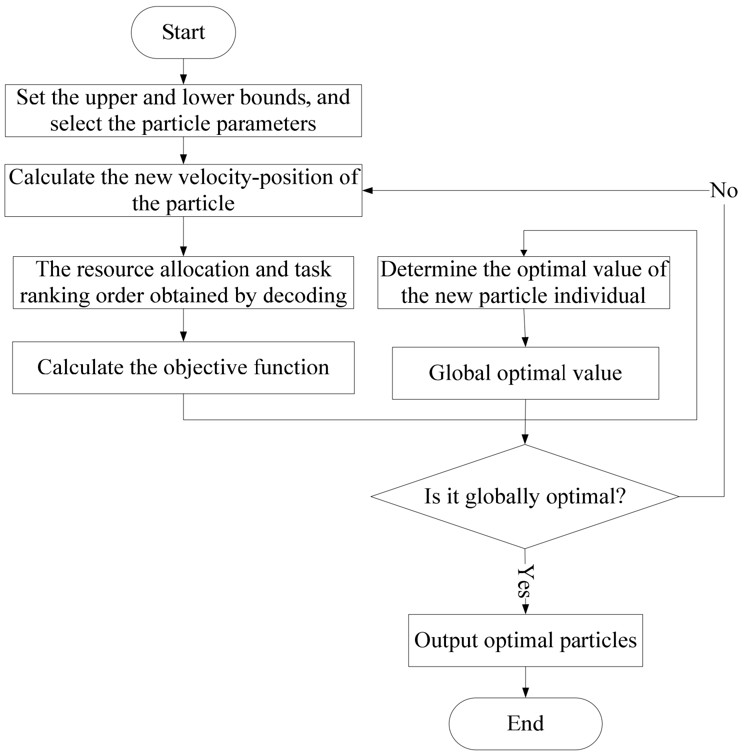
$$\sum_j W_{ijk} = M_{ki}\left(i = 1, 2, \ldots, R\right) \tag{7}$$

t_{ij} represents the logistics distribution cost from customer point *i* to customer point *j*; p_i is the cargo demand of customer point *i*; *P* represents the maximum load limit of the delivery vehicle.

In the field of logistics and supply chain collaborative scheduling, the PSO algorithm has shown significant advantages. The algorithm gradually optimises the vehicle's driving route by simulating the group behaviour and information interaction mechanism of particles, thereby achieving efficient allocation of logistics resources. PSO also performs well in dealing with large-scale transportation problems and can maintain stable computing performance even in the face of complex constraints. Each particle represents a potential vehicle route solution, and its position reflects in detail key information such as the vehicle's departure order, driving route, and the order of customer service. The particle's speed reflects the magnitude and direction of the route adjustment, aiming to optimise the transportation cost or time. In the iterative process, the particle adjusts according to its position, speed, and the optimal solution information in the group constantly approaches the global optimal solution and finally reveals the optimal vehicle route solution. The structure diagram of logistics transportation vehicle route planning based on PSO is shown in Figure 1.

Because of the characteristics of logistics, this paper adopts a coding method based on particle position size. The basic principle is to first clarify the number of workpieces, which is equivalent to the number of population particle dimensions to be set. Assuming there are D workpieces, the position of the *i*th particle in the population can be described by a real number sequence. These real numbers have size attributes, so they can be sorted according to their size to generate a discrete n-dimensional sequence. As the particle position is updated, the sorting changes accordingly, thereby generating a new solution. Taking the scheduling of n processes as an example, a two-dimensional vector group with a particle length of n is constructed. Among them, the first dimension represents the process number, and the second dimension represents the particle's position. During the update process, the particles of the first dimension remain unchanged, while the positions of the particles of the second dimension are arranged in ascending order. The particle positions are rearranged, and the arrangement of the processes also changes. A new solution is generated, and the fitness evaluation is re-performed.

Figure 1 Structure diagram of logistics transportation vehicle route planning based on PSO



In the problem of vehicle path optimisation, PSO adopts an efficient and intuitive path coding strategy, that is, the specific scheduling sequence is represented by the position of the particles. The different dimensions of each particle correspond to different task execution orders so that its location information is directly mapped to the vehicle's driving path scheme. This design makes the change of particle position of practical significance, and the distribution sequence can be dynamically adjusted, so as to achieve continuous optimisation of the path. In the iterative process, the particles continuously correct their positions based on their historical optimal solutions and the globally optimal solutions of the group, which is equivalent to constantly exploring better path arrangements. Each location update may bring about adjustments in the scheduling sequence, which in turn affects the overall distribution efficiency and cost control.

Setting parameters is especially important for enhancing the algorithm's performance. While learning variables dictate how particles combine individual and group experience for speed updates to improve local search accuracy, inertial weights govern the particles' ability to maintain the initial motion trend and impact the algorithm's capacity for global exploration. Convergence can be accelerated and solution quality enhanced with a reasonable setting of these parameters. The PSO method has remarkable stability and applicability, particularly for handling large-scale, high-dimensional logistics scheduling problems. Through the optimisation of the algorithm structure and the fine adjustment of the parameters, high-quality feasible solutions can be obtained in a relatively short period of time to meet the dual needs of efficiency and accuracy in actual scheduling scenarios. Therefore, the application of PSO in complex supply chain systems not only reflects the theoretical depth of algorithm design but also responds to the practical challenges of real problems.

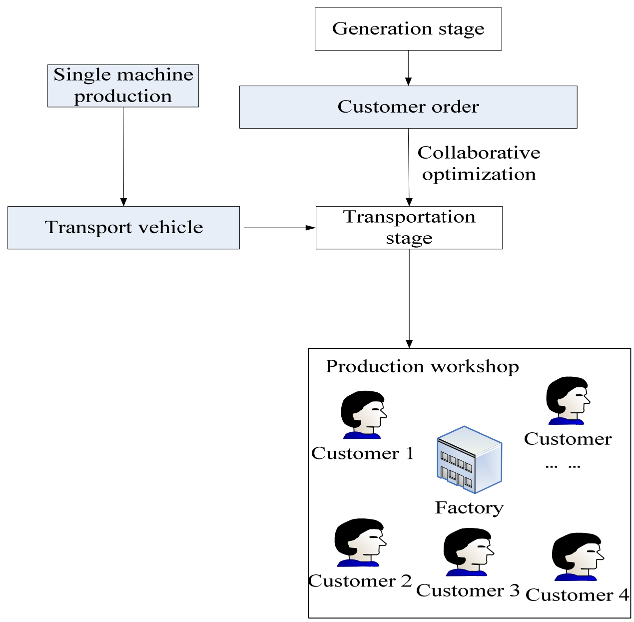
3.3 Collaborative scheduling of production and transportation

PSO is an optimisation method based on group intelligence. Its core idea simulates the information sharing and collaboration mechanism in the foraging process of birds, and it is widely used in logistics and supply chain collaborative scheduling issues. In this algorithm, each scheduling scheme is abstract as a particle in the solution space, and the optimal solution is approximated by constantly updating the position and velocity. The position of the particles represents the specific scheduling strategy, such as transportation path, task sequence, and allocation plan; the speed reflects the direction and amplitude of the adjustment strategy. In the iterative process, each particle updates its state according to its historical optimal solution and the global optimal solution of the group, not only retaining individual experience but also absorbing the wisdom of the group, so as to achieve efficient search. This mechanism not only enhances the convergence ability of the algorithm but also improves the solving quality. Through collaborative optimisation between individuals and groups, PSO effectively balances global exploration and local development and is suitable for complex scheduling optimisation problems.

The core of supply chain management lies in the close coordination of production and transportation. To enhance the competitiveness of the supply chain, it is necessary to achieve the effective integration of these two links. The problem of collaborative scheduling of production and transportation involves two aspects: production sorting and route planning (He et al., 2023; Zhang, 2024). In the production link, manufacturers receive orders from customers from all over the world and arrange production according to production scheduling theory, striving to complete orders and deliver them to customers as quickly as possible. In the transportation link, the transportation start time of the batch and the order of loading orders need to be considered. The PSO algorithm can simultaneously optimise the scheduling scheme of production and transportation to ensure a smooth connection between the two, thereby reducing inventory backlogs and transportation delays. Figure 2 clearly shows the schematic diagram of the production and transportation collaborative scheduling problem based on the PSO studied in this paper.

As shown in Figure 2, a single machine completes the processing of all customer orders in the production process, and the machine is available from time 0. Subsequently, a fleet of the same type is responsible for delivering the orders directly from the factory to the customer's location. The departure time of the vehicle depends on the production completion time of the last order it carries, to achieve the best efficiency of the production process.

Figure 2 Schematic diagram of the production and transportation collaborative scheduling problem based on PSO (see online version for colours)



PSO finds the optimal solution to the problem by simulating cooperation and information sharing between groups (Khalid et al., 2021; Singh and Singh, 2020). In the production and transportation collaborative scheduling problem, each particle represents a potential production and transportation scheduling plan. The position of the particle can be regarded as a specific manifestation of the scheduling plan, while the speed reflects the extent of adjusting the plan. The position of the particle includes the execution order of the production tasks and the allocation of the transportation tasks. The allocation of transportation tasks determines which transportation tools are responsible for each task, as well as the corresponding transportation routes and schedules. The speed of the particle reflects the adjustment of the task sorting and transportation route in the production and transportation scheduling, aiming to approach the optimal solution through continuous iteration. In PSO, to evaluate and optimise the production and transportation scheduling plan, a comprehensive objective function is designed to measure the pros and cons of the plan.

$$h(x) = m_1 * \sum_i B_i + m_2 * \sum_j C_j + m_3 * \sum_i late\ penalty_i \tag{8}$$

Among them, B_i is the completion time of the *i*th production task, and C_j is the transportation time of the *j*th transportation task. The transportation time of each vehicle depends on many factors, and the completion time of the transportation task can be expressed as:

$$C_j = \frac{D_j}{W} + C_{load} + C_{unload} \tag{9}$$

Among them, D_j is the transportation distance from the factory to customer j; C_{load} is the loading time; C_{unload} is the unloading time.

Through the feasible solution, the number of batches and the details of the workpieces contained in each batch can be known, and then the manufacturing span can be calculated. However, the solutions generated in the iterative process may not all be feasible, so these random solutions need to be verified and adjusted to ensure that they meet the actual requirements of the problem. To this end, the batch correction rule is used for adjustment. The specific steps of the correction are as follows: for any batch X_j, if the specific condition $|X_j| - X + |X_{j+1}| \leq X$ is met, the workpiece H^* that arrives at the machine last in the transportation stage from the warehouse to the manufacturer is selected and classified into the batch X_{j+1}. If the condition is not met, a new batch is inserted at a specific position, and the workpiece is classified into this new batch. Through this correction process, the processing start and end times of each batch, as well as the start and end times of transportation, can be accurately calculated. The specific values are shown in Table 1.

Table 1 Batch results

Batch	*Batch start processing time*	*Batch completion time*	*Batch shipping start time*	*Batch shipping end time*
1	6	11	14	18
2	12	15	18	25
3	16	20	26	35
4	22	29	37	47
5	30	35	42	51

As shown in Table 1, the production and transportation schedules of each batch are listed. The first batch is processed from the 6th moment to the 11th moment, and then the transportation is started at the 14th moment and finally completed at the 18th moment. Similarly, the second batch is processed from the 12th moment to the 15th moment, and then the transportation is started at the 18th moment and finally completed at the 25th moment. These data not only clearly show the specific operation process of each batch but also provide valuable information support for the further optimisation of logistics and supply chain collaborative scheduling.

3.4 Collaborative scheduling of inventory and transportation

The joint optimisation problem of inventory and transportation is a logistics storage and transportation management process that comprehensively considers inventory and transportation elements. It mainly studies how to efficiently transport specific types and quantities of items from one or more upstream enterprises to one or more downstream enterprises within a limited or infinite period of time. This problem determines the optimal inventory replenishment quantity, time, optimal transportation volume, and transportation route for each demand point under the constraints of meeting the demand for goods, demand time, and inventory level. Its goal is to minimise the system's total cost or maximise the total benefit. From the perspective of systematisation and integration, the two key functional modules of inventory and transportation in the logistics system are integrated and considered. When formulating vehicle allocation and route optimisation plans, it comprehensively weighs inventory costs and transportation costs, striving to achieve cost optimisation of the entire system. Table 2 displays the key characteristics of the inventory and transportation joint optimisation problem.

Table 2 Main characteristics of the joint optimisation problem of inventory and transportation problems

Topology	Supplier	Single supplier	Single supplier	Multi-supplier	Multi-supplier
	Demand side	Single demand side	Multi-demand side	Multi-demand side	Single demand side
Supply chain consolidation	Two-level supply chain	Two-level supply chain supplier to demand-side two-level			
	Multi-level supply chain	Multi-level supply chain suppliers to middlemen to the demand side			
Cost factor	Inventory cost	Inventory cost purchase fee, cargo holding fee, out-of-stock loss fee, etc.			
	Transportation cost	Transportation costs, distribution, and transportation costs, such as transportation costs related to the distance traveled			
Constraints	Supplier supply capacity, transportation capacity, demand-side storage capacity, demand-side liquidity restrictions				
Demand side demand situation	Requirements are known				
	Random demand				
	Demand unknown				

As shown in Table 2, the topological structure of the supply chain is flexible and allows suppliers and demanders to exist in the form of single or multiple entities, thereby constructing a two-level or even multi-level complex structure. In terms of cost considerations, inventory costs not only cover conventional costs such as purchasing and holding goods but also need to consider the losses caused by out-of-stock; transportation costs are closely related to driving distance, mainly reflected in the distribution link.

The collaborative optimisation of inventory and transportation is a key issue in supply chain management. Its core lies in reasonably weighing the relationship between transportation costs and inventory costs in order to maximise the overall supply chain efficiency. This problem not only requires controlling logistics expenditures but also ensuring that inventory can not only meet market demand but also avoid capital backlogs and excessive storage costs, which have strong complexity and multi-objective characteristics. In response to this challenge, PSO has demonstrated good problem-solving ability with its efficient group intelligent search mechanism. PSO is a useful tool for figuring out how many delivery trucks are best for the strategic layer of the logistics system. The program takes every particle configuration as a particle and dynamically modifies the scheme according to its position and velocity by mimicking the cooperative search process of particles in the solution space. The particles gradually get closer to the ideal configuration during the iterative process, which thoroughly takes into account multifaceted elements including market demand, vehicle utilisation rate, inventory level, and transportation costs. In addition to increasing the system's operational efficiency, this approach lowers total operating costs dramatically, boosts supply chain responsiveness and flexibility, and offers effective resource allocation support in intricate logistical settings.

Inventory cost is a comprehensive consideration, and its formula is:

$$F_{inventory} = \sum_{t=1}^{T} \left(F_g * E_t + F_a * \max\left(0, Z_t - E_t\right) + F_s * \max\left(0, E_t - Z_t\right) \right) \tag{10}$$

E_t represents the inventory at time t; Z_t is the demand; the unit inventory holding cost is F_g; the unit out-of-stock cost is F_a; the unit excess inventory cost is F_s.

In order to optimise inventory and transportation and lower the overall cost of inventory and transportation, cooperative scheduling is essential. By carefully modifying the replenishment and transportation tactics, the PSO algorithm keeps a manageable inventory level and lowers needless transportation costs. A transportation allocation model is developed to more efficiently distribute resources (Zhou et al., 2019). The main goal of this model is to reduce transportation costs by figuring out the best amount to allocate from the material centre to each sub-centre and between sub-centres. The transportation costs are:

$$MinTTC = \sum_{j=1}^{m} \sum_{i=1}^{m} \left[\beta\left(P_{ij}\right) * P_{ij} * d_{ij} + \beta\left(P_{cj}\right) * P_{cj} * d_{cj} \right] * C_{aj} \tag{11}$$

$$\text{s.t.} \quad P_{ij} = \begin{cases} 0 & J_i \le K_i \\ \left[0, J_i - K_i\right], & J_i > K_i \end{cases} \tag{12}$$

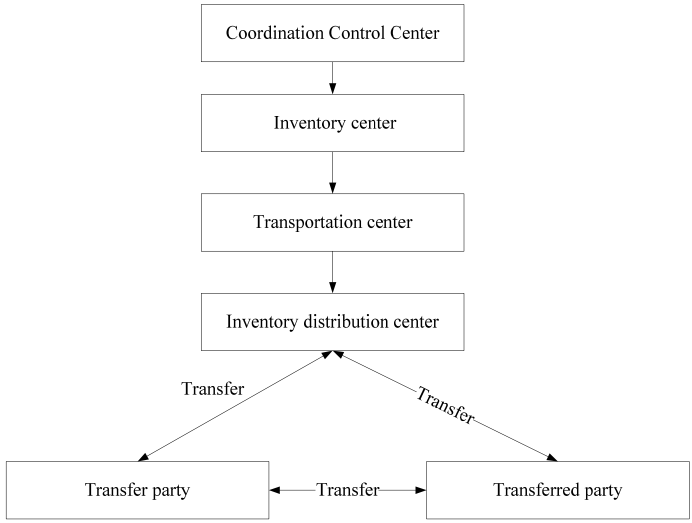
$$P_{cj} = \begin{cases} 0 & J_j > K_j \\ \left[0, J_c - K_c\right], & J_j \le K_j \end{cases} \tag{13}$$

$$P_{ij} = 0\left(i = j\right) \tag{14}$$

According to the constraint, the material sub-centre may distribute items to the out-of-stock sub-centre if it has enough inventory, but the quantity of goods left over after the distribution must be less than its order point. In a similar vein, if the material centre has enough inventory, it may also distribute it to the out-of-stock sub-centre; however, the quantity of inventory left over after the distribution cannot be less than the order point. Figure 3 displays the collaborative scheduling structure diagram for PSO inventory and transportation.

Through repeated iterations and optimisation, the algorithm can determine the best solution, thereby providing strong support for the planning of logistics systems. In short-term operation plans, PSO can also provide solutions for the joint optimisation of inventory and transportation. It dynamically adjusts relevant strategies based on real-time demand, inventory status, and transportation capacity. By optimising the fitness function, the algorithm can efficiently find the optimal inventory allocation and transportation route, which not only ensures inventory stability but also reduces transportation costs.

Figure 3 PSO-based inventory and transportation collaborative scheduling structure diagram

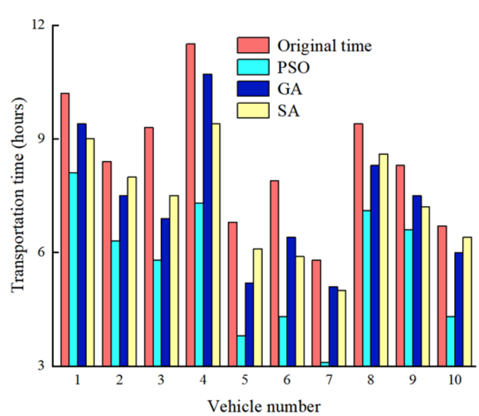


4 Experiments and discussions

4.1 Comparison of transportation time

The use of PSO can well help various vehicles in supply chain logistics to arrange and optimise the routes and maximise the utilisation rate of vehicles. To further demonstrate this advantage, an experimental simulation is conducted to study the vehicles in the upstream and downstream supply chains of a certain enterprise. There are a total of 10 vehicles, each with a different transportation route, and the 10 vehicles are numbered from 1 to 10. By using different methods to plan the transportation routes of these 10 vehicles, the transportation time required for the routes designed based on genetic algorithm (GA), simulated annealing (SA) algorithm, and the method studied in this paper is compared with the original transportation time. The specific comparison results are shown in Figure 4.

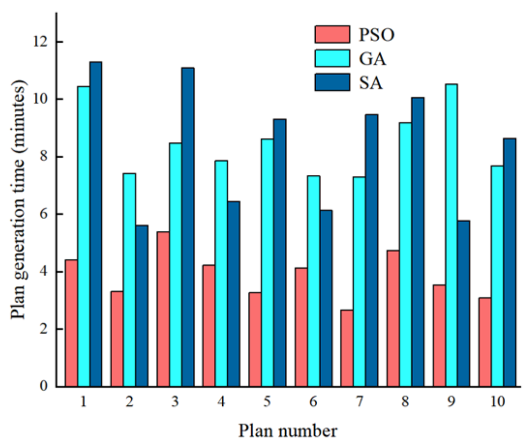
Figure 4 Comparison of transportation time of different methods (see online version for colours)



As shown in Figure 4, the experimental data shows that compared with the original transportation time, the three algorithms have reduced the transportation time to a certain extent. However, the PSO algorithm shows a more outstanding performance. For vehicle No. 1, its original transportation time is 10.2 h, but after the PSO algorithm performs vehicle route planning, the transportation time is 8.1 h, which is reduced by 2.1 h. In contrast, although the GA and SA algorithms have also improved, with transportation times of 9.4 h and 9 h, the effect is still not as good as the PSO algorithm. By comparing the transportation time of the selected vehicles, it is found that the PSO algorithm achieves the shortest transportation time in all cases, which fully demonstrates its efficiency and practicality in dealing with complex supply chain logistics route optimisation problems. The reason why the PSO algorithm is so outstanding is mainly due to its unique swarm intelligence search strategy and powerful global optimisation ability. This enables PSO to quickly find high-quality solutions when dealing with complex optimisation problems containing many variables and constraints, which not only realises efficient transportation route planning but also maximises the efficiency of vehicle use.

By simulating the order location accepted by the manufacturer, the PSO algorithm is used to study the scheduling plan for production and transportation, so as to obtain a specific production and transportation plan. This process can quickly obtain a specific plan using the PSO algorithm, and the calculation speed is very fast. To reflect the advantage of the PSO algorithm in the speed of generating production and transportation plans, 10 different plans are generated, and the time required to generate each plan is compared. The comparison results are compared with the GA and SA algorithms. The specific comparison results are shown in Figure 5.

Figure 5 Comparison of production and transportation plan generation time under different methods (see online version for colours)



As shown in Figure 5, the PSO algorithm is significantly better than GA and SA in the speed of generating production and transportation plans. In the first plan, the PSO algorithm only takes 4.41 min, while GA and SA take 10.45 min and 11.30 min respectively. The PSO algorithm takes 6.04 min and 6.89 min less than GA and SA, respectively, and this time advantage continues in the subsequent plan generation. Among the 10 solutions, the average generation time of the PSO algorithm is 3.87 min, which is 4.61 min and 4.51 min lower than GA and SA, respectively, fully demonstrating its efficient problem-solving ability. In addition, the PSO algorithm is simpler in parameter setting and easy to implement and debug, and further improves its flexibility and practicality in practical applications. Simulating the order location accepted by the manufacturer and using the PSO algorithm to quickly generate high-quality production and transportation scheduling solutions, can not only greatly improve the speed of solution generation but also ensure the quality and feasibility of the solution.

4.2 Algorithm performance comparison

Using PSO to study the collaborative scheduling of logistics and supply chain, it can be found that PSO can coordinate production, inventory, or transportation in the supply chain very well, and has excellent performance in all aspects. Compared with the GA and SA algorithms, the specific comparison results are shown in Table 3.

As shown in Table 3, the PSO algorithm performs outstandingly in terms of vehicle utilisation rate, with an utilisation rate of 98.2%, which is significantly higher than GA's 88.5% and SA's 90.1%. This shows that PSO has significant advantages in optimising vehicle dispatching and improving vehicle efficiency, which helps reduce logistics costs and improve operational efficiency. In terms of production efficiency improvement, the PSO algorithm is 15.61%, which is 5.27% and 6.97% higher than GA and SA respectively. PSO also performs well in reducing inventory backlog and transportation delays, by 20.73% and 18.44% respectively, effectively easing inventory and transportation pressure. In terms of transportation route quality, PSO receives an 'excellent' rating due to its powerful global search and optimisation capabilities, while both GA and SA are rated 'good', further highlighting PSO's advantages in optimising transportation routes and shortening time. In terms of convergence speed, PSO shows fast convergence characteristics, which is significantly better than GA and SA, which means that PSO can find high-quality solutions more efficiently.

Table 3 Study on the performance of collaborative scheduling of logistics and supply chain by different methods

Evaluation indicators	*PSO*	*GA*	*SA*
Vehicle utilisation rate (%)	98.2	88.5	90.1
Production efficiency improvement (%)	15.61	10.34	8.64
Inventory backlog reduction rate (%)	20.73	14.28	11.89
Transportation delay reduction rate (%)	18.44	10.96	12.15
Transportation route	Excellent	Good	Good
Convergence speed	Fast	Medium	Medium
Computational complexity	Medium	High	Medium
Resource consumption	Medium	Medium	High

4.3 Discuss

PSO is an optimisation method based on group intelligence. It is inspired by the foraging behaviour of birds. By simulating this natural phenomenon, PSO simplifies the solution process of traditional optimisation problems and has a strong global search ability. In the field of logistics and supply chain management, PSO can comprehensively consider multiple goals such as transportation costs, inventory costs, and delivery time, and gradually approach the optimal solution through iterative optimisation. In the algorithm, each potential solution is regarded as a particle in the solution space, the position of the particle represents the scheme parameters, and the speed determines the direction and amplitude of the parameter adjustment. PSO regulates the trajectory of particles by introducing inertial weights and learning factors. Inertial weights affect the ability of particles to maintain their original motion trends, thereby controlling the global exploration level of the algorithm; learning factors guide particles to combine individual and group experience to update speed and improve local search efficiency. Parameter configuration is particularly critical to the convergence speed and resolution quality of the algorithm, especially when dealing with large-scale, high-dimensional logistics scheduling.

When applying PSO to VRP, the core goal is to design a scientific and reasonable distribution route to complete all customer distribution at the lowest cost. By treating each path as a particle, PSO dynamically adjusts its position and speed, optimises the driving sequence of the vehicle, effectively reduces no-load and roundabout phenomena, and improves transportation efficiency. Each location update corresponds to the adjustment of the distribution sequence, further optimising the overall path, so as to achieve the dual improvement of scheduling efficiency and cost control. The experimental results show that for vehicles numbered 1, the transportation time is reduced by 2.1 h after the PSO algorithm is planned; at the same time, the vehicle utilisation rate of PSO is as high as 98.2%, which is significantly better than GA's 88.5% and SA's 90.1%.In addition, PSO also has obvious advantages in the speed of generating production and transportation solutions. The average generation time is 3.87 min, which is much lower than the 10.45 min of GA and the 11.30 min of SA. This shows that PSO can not only improve the speed of program generation but also ensure the quality and feasibility of the program.

This study applies PSO to the collaborative scheduling of logistics and supply chains, fully demonstrating its outstanding advantages in multi-objective optimisation, dynamic adaptation, and computational efficiency. PSO can effectively coordinate multiple optimisation goals such as transportation costs, inventory costs, and delivery time, and quickly generate high-quality scheduling plans when the market and supply chain environment changes, reflecting good flexibility and practicality. The experimental results show that PSO is superior to traditional methods in vehicle path planning, collaborative scheduling of production and transportation, and collaborative optimisation of inventory and transportation, and provides a new technical path for logistics and supply chain management. Compared with the existing research, this work is innovative at both the theoretical and application levels. In theory, the convergence characteristics, computational complexity, and the impact of key parameters on the performance of PSO are analysed in depth, which lays the foundation for subsequent algorithm improvement; in application, through actual cases and data analysis, the effectiveness of PSO in improving efficiency and reducing costs is verified, which provides strong support for practice.

Although the PSO algorithm has shown good optimisation ability in experiments, there are still certain limitations in this research. When applied to larger-scale or more complex logistics and supply chain scheduling issues, the computational efficiency and quality of solutions may decrease. In addition, the research mainly focuses on the performance of algorithms in a static environment, and the adaptability to dynamic market demand and supply chain fluctuations still needs to be verified. The experience derived from this shows that when applying intelligent optimisation algorithms, their applicable scope and limitations should be fully evaluated, and the algorithms and parameters should be rationally selected according to the characteristics of specific problems. Future research can be carried out in many ways: first, improve the structure of the PSO algorithm and enhance its ability to handle large-scale problems; secondly, try to integrate PSO with other optimisation algorithms to build hybrid algorithms to enhance the solving ability; strengthen application testing in actual scenarios and promote the transformation of research results. Through continuous exploration in the above directions, it is expected to provide more effective solutions and technical support for the collaborative scheduling of logistics and supply chains.

Overall, this paper systematically explores the application of PSO in logistics and supply chain collaborative scheduling, highlighting its advantages in multi-objective optimisation, such as transportation costs, inventory expenses, and delivery times. Despite certain limitations, PSO demonstrates significant potential due to its flexibility and adaptability in addressing complex market and supply chain demands. As the algorithm continues to be optimised and its applications expand, PSO is expected to become a crucial tool for driving innovation and development in logistics and supply chain management, bringing about significant changes.

5 Conclusions

Collaborative scheduling of logistics and supply chains is crucial in modern enterprise operations, which profoundly affects production efficiency and customer satisfaction. However, traditional methods are unable to cope with changing market and customer demands when dealing with this complex problem. To this end, this paper studies the collaborative scheduling of logistics and supply chains based on the global search capability and fitness function of the PSO algorithm. PSO comprehensively considers multiple objectives such as transportation costs, inventory costs, and delivery time, and generates practical solutions under given constraints. Through iterative optimisation, PSO can avoid local optimal solutions and gradually approach the global optimal solution, thereby locking in the best scheduling solution. In terms of vehicle route planning, this algorithm significantly reduces empty loads and detours by optimising driving routes and improves overall transportation efficiency. In the field of collaborative scheduling of production and transportation, the PSO algorithm ensures a seamless connection between production and transportation, reduces inventory backlog and reduces transportation delays. In the collaborative scheduling of inventory and transportation, the algorithm maintains reasonable inventory levels and reduces unnecessary transportation expenses through precise strategic adjustments.

Conflicts of interest

All authors declare that they have no conflicts of interest.

References

Abdelaziz, F.B., Alaya, H. and Dey, P.K. (2020) 'A multi-objective particle swarm optimization algorithm for business sustainability analysis of small and medium sized enterprises', *Annals of Operations Research*, Vol. 293, No. 2, pp.557–586, https://doi.org/10.1007/s10479-018-2974-0

Akbari, M. and Do, T.N.A. (2021) 'A systematic review of machine learning in logistics and supply chain management: current trends and future directions', *Benchmarking: An International Journal*, Vol. 28, No. 10, pp.2977–3005, https://doi.org/10.1108/BIJ-10-2020-0514

Alzoubi, H., Ahmed, G., Al-Gasaymeh, A. and Kurdi, B. (2020) 'Empirical study on sustainable supply chain strategies and its impact on competitive priorities: the mediating role of supply chain collaboration', *Management Science Letters*, Vol. 10, No. 3, pp.703–708, https://doi.org/10.1016/j.ijpe.2019.07.002

Barman, A., Das, R. and Pijus, K.D. (2022) 'An analysis of optimal pricing strategy and inventory scheduling policy for a non-instantaneous deteriorating item in a two-layer supply chain', *Applied Intelligence*, Vol. 52, No. 4, pp.4626–4650, https://doi.org/10.1007/s10489-021-02646-2

Cai, L. (2023) 'Decision-making of transportation vehicle routing based on particle swarm optimization algorithm in logistics distribution management', *Cluster Computing*, Vol. 26, No. 6, pp.3707–3718, https://doi.org/10.1007/s10586-022-03730-z

Cai, L., Li, W., Luo, Y. and He, L. (2023) 'Real-time scheduling simulation optimisation of job shop in a production-logistics collaborative environment', *International Journal of Production Research*, Vol. 61, No. 5, pp.1373–1393, https://doi.org/10.1080/00207543.2021.2023777

Chen, M. and Du, W. (2024) 'Dynamic relationship network and international management of enterprise supply chain by particle swarm optimization algorithm under deep learning', *Expert Systems*, Vol. 41, No. 5, p.e13081, https://doi.org/10.1111/exsy.13081

Chenna, K. (2024) 'Optimizing decision-making in supply chains: a framework for AI and human collaboration using SAP technologies', *International Journal of Research in Computer Applications and Information Technology (IJRCAIT)*, Vol. 7, No. 2, pp.824–835, https://doi.org/10.5281/zenodo.14044969

Dai, T. (2023) 'Research on enterprise supply chain anti-disturbance management based on improved particle swarm optimization algorithm', *International Journal of Advanced Computer Science and Applications*, Vol. 14, No. 8, pp.936–927. doi: 10.14569/IJACSA.2023.01408102.

Fontes, D.B.M.M., Homayouni, S.M. and Goncalves, J.F. (2023) 'A hybrid particle swarm optimization and simulated annealing algorithm for the job shop scheduling problem with transport resources', *European Journal of Operational Research*, Vol. 306, No. 3, pp.1140–1157, https://doi.org/10.1016/j.ejor.2022.09.006

Ghazal, T.M. and Alzoubi, H.M. (2022) 'Fusion-based supply chain collaboration using machine learning techniques', *Intelligent Automation and Soft Computing*, Vol. 31, No. 3, pp.1671–1687, https://doi.org/10.32604/iasc.2022.019892

He, P., Li, K. and Tian, Q. (2023) 'Research on the collaborative scheduling of spare parts production and transportation based on 3D printing technology', *Chinese Journal of Management Science*, Vol. 31, No. 4, pp.239–249, https://doi.org/10.16381/j.cnki.issn1003-207x.2020.0780

Ji, X., Zhang, Y., Gong, D. and Sun, X. (2021) 'Dual-surrogate-assisted cooperative particle swarm optimization for expensive multimodal problems', *IEEE Transactions on Evolutionary Computation*, Vol. 25, No. 4, pp.794–808, DOI: 10.1109/TEVC.2021.3064835.

Khalid, Q.S., Azim, S., Abas, M., Babar, A.R. and Ahmad, I. (2021) 'Modified particle swarm algorithm for scheduling agricultural products', *Engineering Science and Technology, An International Journal*, Vol. 24, No. 3, pp.818–828, https://doi.org/10.1016/j.jestch.2020.12.019

Koh, S.L., Jia, F., Gong, Y., Zheng, X. and Dolgui, A. (2023) 'Achieving carbon neutrality via supply chain management: position paper and editorial for IJPR special issue', *International Journal of Production Research*, Vol. 61, No. 18, pp.6081–6092, https://doi.org/10.1080/00207543.2023.2232652

Konstantakopoulos, G.D., Gayialis, S.P. and Kechagias, E.P. (2022) 'Vehicle routing problem and related algorithms for logistics distribution: a literature review and classification', *Operational Research*, Vol. 22, No. 3, pp.2033–2062, https://doi.org/10.1007/s12351-020-00600-7

Li, F. and Li, T. (2024) 'Economic modeling and simulation in the industrial supply chain model using particle swarm optimization algorithm', *International Journal of Innovative Computing, Information and Control*, Vol. 20, No. 1, pp.163–179, DOI: 10.24507/ijicic.20.01.163.

Li, M., Yang, S. and Zhang, M. (2022) 'Power supply system scheduling and clean energy application based on adaptive chaotic particle swarm optimization', *Alexandria Engineering Journal*, Vol. 61, No. 3, pp.2074–2087, https://doi.org/10.1016/j.aej.2021.08.008

Pu, Y., Liu, H., Wang, J. and Hou, Y. (2023) 'Collaborative scheduling of port integrated energy and container logistics considering electric and hydrogen-powered transport', *IEEE Transactions on Smart Grid*, Vol. 14, No. 6, pp.4345–4359, DOI: 10.1109/TSG.2023.3266601.

Rejeb, Abderahman, Keogh, J.G., Simske, S.J., Stafford, T. and Treiblmaier, H. (2021) 'Potentials of blockchain technologies for supply chain collaboration: a conceptual framework', *The International Journal of Logistics Management*, Vol. 32, No. 3, pp.973–994, https://doi.org/10.1108/Ijlm-02-2020-0098

Richey Jr., R.G., Chowdhury, S., Davis-Sramek, B., Giannakis, M. and Dwivedi, Y.K. (2023) 'Artificial intelligence in logistics and supply chain management: a primer and roadmap for research', *Journal of Business Logistics*, Vol. 444, pp.532–549, https://doi.org/10.1111/jbl.12364

Richey, R.G., Roath, A.S., Adams, F.G. and Wieland, A. (2022) 'A responsiveness view of logistics and supply chain management', *Journal of Business Logistics*, Vol. 43, No. 1, pp.62–91, https://doi.org/10.1111/jbl.12290

Rojas Viloria, D., Solano-Charris, E.L., Munoz-Villamizar, A. and Montoya-Torres, J.R. (2021) 'Unmanned aerial vehicles/drones in vehicle routing problems: a literature review', *International Transactions in Operational Research*, Vol. 28, No. 4, pp.1626–1657, https://doi.org/10.1111/itor.12783

Singh, G. and Singh, A. (2020) 'A hybrid algorithm using particle swarm optimization for solving transportation problem', *Neural Computing and Applications*, Vol. 32, No. 15, pp.11699–11716, https://doi.org/10.1007/s00521-019-04656-1

Son, P.V.H., Duy, N.H.C. and Dat, P.T. (2021) 'Optimization of construction material cost through logistics planning model of dragonfly algorithm–particle swarm optimization', *KSCE Journal of Civil Engineering*, Vol. 25, No. 7, pp.2350–2359, https://doi.org/10.1007/s12205-021-1427-5

Song, X-F., Zhang, Y., Guo, Y.N., Sun, X.Y. and Wang, Y.L. (2020) 'Variable-size cooperative coevolutionary particle swarm optimization for feature selection on high-dimensional data', *IEEE Transactions on Evolutionary Computation*, Vol. 24, No. 5, pp.882–895, DOI: 10.1109/Tevc.2020.2968743.

Vidal, T., Laporte, G. and Matl, P. (2020) 'A concise guide to existing and emerging vehicle routing problem variants', *European Journal of Operational Research*, Vol. 286, No. 2, pp.401–416, https://doi.org/10.1016/j.ejor.2019.10.010

Wang, Z., Shen, Z., Chew, J., Wang, Y. and Hu, K. (2025) 'Intelligent construction of a supply chain finance decision support system and financial benefit analysis based on deep reinforcement learning and particle swarm optimization algorithm', *International Journal of Management Science Research*, Vol. 8, No. 3, pp.28–41, https://doi.org/10.53469/ijomsr.2025.08(03).03

Xia, J., Li, H. and He, Z. (2023) 'The effect of blockchain technology on supply chain collaboration: a case study of Lenovo', *Systems*, Vol. 11, No. 6, p.299, https://doi.org/10.3390/systems11060299

Zhang, H. (2024) 'Research on optimization of dispatching command in railway transportation production', *Mechanical and Electronic Control Engineering*, Vol. 6, No. 6, pp.168–170, https://doi.org/10.37155/2717-5197-0606-56

Zhang, X., Du, K.J., Zhan, Z.H., Kwong, S., Gu, T.L. and Zhang, J. (2019) 'Cooperative coevolutionary bare-bones particle swarm optimization with function independent decomposition for large-scale supply chain network design with uncertainties', *IEEE Transactions on Cybernetics*, Vol. 50, No. 10, pp.4454–4468, DOI: 10.1109/TCYB.2019.2937565.

Zhou, G., Wang, Y. and Zhen, J. (2019) 'Study on optimization decision model of oil allocation and transportation based on entropy weight and AHP', *Ship Electronic Engineering*, Vol. 39, No. 11, pp.154–158, DOI: 10.3969/j.issn.1672-9730.2019.11.038.