Optimization of Collaborative Scheduling and Profit Fluctuation Control in Manufacturing Supply Chains Using Artificial Intelligence Algorithms

Peijun Xu[1], Keyi Pan[2]
[1]Management at the School of Business Administration (MBA), Zhejiang Gongshang University, Hangzhou 310007, Zhejiang, China
[2]Zhejiang Business Research Institute, Zhejiang Gongshang University, Hangzhou 310007, Zhejiang, China
Corresponding author: Keyi Pan (e-mail: Pankeyi2025@163.com)

ABSTRACT Manufacturing supply chains for textile and related engineering products are increasingly affected by volatile orders, short delivery cycles, and unstable profit margins. In production scenarios involving electromagnetic materials, wearable antennas, conductive textiles, and shielding components, collaborative scheduling is also related to the timely supply of materials and components used in electromagnetic wave and antenna applications. This study investigates an artificial-intelligence-based method for collaborative scheduling and profit fluctuation control in manufacturing supply chains. The current problems of scheduling coordination and profit instability are first analyzed, followed by a comparison of genetic algorithms, particle swarm optimization, and deep learning methods for supply chain optimization. On this basis, a collaborative scheduling model and a profit fluctuation control model are constructed. Experimental results show that the proposed method reduces total operating costs by 21.2%, decreases order delivery delay time by 75%, and lowers the standard deviation of profit by 57.1% compared with traditional scheduling methods. The results indicate that artificial intelligence algorithms can improve scheduling efficiency and financial stability in complex manufacturing systems. The study provides a practical decision-support approach for supply chain management in engineering-oriented textile production and related electromagnetic manufacturing fields.

INDEX TERMS artificial intelligence, supply chain scheduling, profit fluctuation, engineering manufacturing, electromagnetic materials

I. INTRODUCTION

THE manufacturing industry is the lifeblood of the national economy, serving as the foundation for a country's existence and national strength enhancement. It plays a pivotal role in realizing the high-quality development of China's economy [1]. Although the scale of China's manufacturing industry has shown an overall upward trend, traditional sectors like textile manufacturing still adopt an extensive development model. Persistent issues include low labor productivity, inefficient production processes, and inability to meet customer demands in a timely manner. Only by achieving high-quality development of the manufacturing industry can these existing problems in China's manufacturing sector be resolved [2].

Collaboration in manufacturing supply chains, a research focus among scholars, can reduce supply chain costs, improve operational efficiency, and lay the foundation for high-quality development of the manufacturing industry. For manufacturing supply chains, collaborative scheduling refers to the coordinated optimization of production and logistics decisions across multi-echelon supply chain nodes (including upstream raw material suppliers, midstream manufacturers, and downstream distributors). Its core is to align procurement volumes, production batches, and delivery quantities among node enterprises to minimize the overall supply chain operating cost and order delivery delay, rather than optimizing individual enterprise schedules in isolation. Manufacturing supply chain collaboration refers to the coordinated operation activities among enterprises at various nodes in the supply chain. Its value mainly lies in optimizing manufacturing supply chain processes, reshaping manufacturing industrial chains, innovating business models of manufacturing supply chains, and helping enterprises at supply chain nodes reduce costs and enhance benefits [3,4].

With the continuous development of the internet economy, competition among manufacturing enterprises, particularly within the globalized textile industry, has gradually evolved from traditional competition in production capacity, technology, and production costs to competition among industrial chains featuring complementary advantages in enterprise resources. Against this backdrop, enterprises have gradually shifted from a self-manufacturing-oriented model to a service-oriented one. In particular, manufacturing enterprises can share their advantages in manufacturing resources and technologies with upstream and downstream enterprises in the supply chain through service-based cooperation, thereby accelerating their own development [5-7].

Supply chain management and coordination refers to a network-based alliance formed by two or more enterprises through corporate agreements or joint organizations to achieve specific strategic goals [8]. Only through close collaboration, optimized resource allocation, and coordinated development between upstream and downstream manufacturing enterprises can the existing problems in the manufacturing industry be fundamentally solved. This will help enhance the resilience of manufacturing industrial chains and supply chains, strengthen the supporting role of the manufacturing industry, thereby enabling manufacturing enterprises to boost their core competitiveness and facilitating the sustainable development of China's manufacturing industry [9,10].

The primary aspect of supply chain system coordination is goal coordination, which ensures that the goals of individual enterprises are compatible with those of the supply chain. The second aspect is operational coordination, including coordination of business operations such as manufacturing and design & development, coordination of interest conflicts among core enterprises, and cultural coordination. Guided by the concept of cooperative competition, supply chain coordination encompasses the management of competitive relationships, cooperative-competitive relationships, and cooperative relationships [11-13]. With the rapid development of science and technology and the intelligent transformation of the global manufacturing industry, intelligent manufacturing has become a core driving force for industrial upgrading and productivity improvement. Traditional risk management methods can no longer meet the needs of intelligent manufacturing supply chains [14,15], as they often rely on historical data and experience and are ineffective in addressing unknowns and uncertainties. Therefore, researching how to optimize the collaborative mechanism and profit fluctuation control of manufacturing supply chains is of great significance for promoting the sustainable development of intelligent manufacturing.

As China enters the information age, information and communication technologies (ICT) such as artificial intelligence, big data, 5G, blockchain, and cloud computing have penetrated all aspects of the manufacturing industry, becoming a strong driving force for its development. Currently, the numerical control rate of key processes in key areas of China's manufacturing industry exceeds 50% [16]. Meanwhile, the development of ICT has also provided technical support for information sharing among enterprises at manufacturing supply chain nodes. This enables the establishment of information sharing platforms, facilitating fast and convenient data transmission, reducing additional information costs caused by information asymmetry and slow information transmission, and laying the foundation for sound collaborative relationships among supply chain node enterprises. Studies have shown that information sharing among manufacturing supply chain node enterprises can optimize resource allocation in manufacturing enterprises, help enterprises rationally arrange procurement, production, sales, and other links, achieve consistency and synchronization in the operation of node enterprises, reduce supply chain costs, and improve the productivity of manufacturing enterprises [17,18].

Based on the current development status of China's manufacturing industry and information technology, this paper focuses on optimizing the collaborative mechanism of manufacturing supply chains, aiming to provide new solutions for collaborative scheduling and profit fluctuation control in manufacturing supply chains using artificial intelligence algorithms.

II. RESEARCH STATUS

The core issue of supply chain management is how to strengthen the unity and collaboration among enterprises at supply chain nodes, coordinate the behaviors and decisions of these node enterprises, and maximize supply chain value [19]—namely, the issue of supply chain collaboration. In the 1990s, David Anderson [20], a world-renowned supply chain management expert, proposed the concept of supply chain collaboration. In the following years, this concept was widely adopted and developed, becoming an important management philosophy in the field of management studies. Xu et al. [21] defined supply chain collaboration as a strategic response to the challenges posed by interdependent supply chain node enterprises. Ma Shihua, a well-known domestic scholar, and his colleagues [22] argued that supply chain collaboration refers to the joint efforts and mutual coordination among all node enterprises in the supply chain, with the goals of gaining competitive advantages and enhancing the overall competitiveness of the supply chain. Simatupang et al. [23] defined supply chain collaboration as a practice where two or more supply chain enterprises, through means such as information sharing and process integration, achieve greater benefits than they would when operating independently. The positive correlation between manufacturing supply chain collaboration and the cultivation of manufacturing enterprises' competitive advantages has long been widely demonstrated by scholars at home and abroad. Cao et al. [24] used structural equation modeling and confirmatory factor analysis to organize and analyze data collected from various manufacturing enterprises in the United States. Their study found that manufacturing supply chain collaboration can significantly enhance the cooperative advantages of node enterprises in the manufacturing supply chain. Ramanathan et al. [25] conducted a case study on two manufacturing companies at different stages of cooperation. The results showed that through the distribution of incentive mechanisms, manufacturers can establish collaborative relationships with suppliers; such collaborative relationships help reduce excess raw material inventory of manufacturers and improve the overall performance of the manufacturing supply chain. Vanathi et al. [26] surveyed over 200 supply chain partners in the textile industry of Tamil Nadu, India, and used PLS software packages and SPSS for data analysis. The results confirmed a positive correlation between manufacturing supply chain collaboration and the competitive advantages of node enterprises.

Currently, most studies by scholars on manufacturing supply chain collaboration focus on two-echelon supply chains. Taking a two-echelon supply chain consisting of one manufacturer and one supplier as an example, Chen et al. [27] studied the collaborative optimization of manufacturing supply chains based on joint replenishment and channel coordination. They proposed that a cost-saving sharing mechanism can be established through a quantity discount scheme to achieve Pareto improvement among channel participants, thereby maximizing the synergy effect of the manufacturing supply chain. Vlachos et al. [28] focused on a two-echelon food supply chain composed of retailers and manufacturers, and studied the impact of trust and collaboration duration on collaborative performance. Through the analysis of valid returned questionnaires, they concluded that the effectiveness of collaboration highly depends on the initiative of retailers to build trust with their partners.

There are also studies on three-echelon manufacturing supply chain collaboration. Aljazzar et al. [29] studied the collaboration of three-echelon manufacturing supply chains that allow the joint integration of deferred payment and price discounts, and investigated 9 deferred payment cases and 8 price discount cases. Through numerical analysis and sensitivity analysis, they concluded that a mechanism combining deferred payment and price discounts is more effective in promoting supply chain collaboration and improving the overall efficiency of the supply chain than implementing either mechanism alone. A small number of scholars have explored the issue of four-echelon manufacturing supply chain collaboration. Liu Qiusheng et al. [30] considered the collaboration of four-echelon supply chains when sudden incidents cause dual-factor disturbances in production costs and random demand. First, they established a four-echelon manufacturing supply chain model based on a benchmark revenue-sharing contract and verified whether the model can achieve supply chain collaboration. When sudden incidents occur, they improved the revenue-sharing contract to make it resilient to emergencies and conducted a case analysis. The analysis found that incorporating a revenue-sharing contract into supply chain management not only enhances the robustness of the supply chain system but also effectively improves supply chain collaboration.

To help node enterprises in the supply chain solve dynamic scheduling problems, scholars have developed a series of dynamic scheduling methods such as dynamic programming and system simulation. The collaborative scheduling problem of manufacturing supply chains is a typical combinatorial optimization problem, and some theoretical studies have proven that similar problems are NP-hard. For many practical scheduling problems, it is not easy to find the optimal solution within a reasonable time frame. After continuous exploration, scholars have developed algorithms to solve such NP-hard problems, namely heuristic algorithms. Heuristic algorithms are proposed relative to optimization algorithms and are abstracted from summarized experiences based on observing phenomena in nature, animal behavior, etc. [31]. Examples include the Particle Swarm Optimization algorithm (PSO), Genetic Algorithm (GA), and Simulated Annealing algorithm (SA). These algorithms are widely used in classic combinatorial optimization problems, covering fields such as healthcare, steel production, and mechanical processing [32]. A large number of case studies and actual production scenarios have fully verified the effectiveness of the above algorithms in solving scheduling problems in the manufacturing industry [33].

III. APPLICATION ANALYSIS OF ARTIFICIAL INTELLIGENCE ALGORITHMS IN MANUFACTURING SUPPLY CHAINS

A. CLASSIFICATION AND CORE FEATURES OF ARTIFICIAL INTELLIGENCE ALGORITHMS

The core of artificial intelligence (AI) applications lies in algorithm-based decision-making. Through computer systems, relevant instructions are input for reasoning, analysis, and decision-making, and target results are output. According to the types of problems to be solved and technical principles, AI algorithms commonly used in the field of manufacturing supply chains can be divided into two major categories: intelligent optimization algorithms and machine learning algorithms. There are significant differences in the core features and applicable scenarios between these two types of algorithms (as shown in Table 1).

TABLE 1. Classification and Core Features of Common Artificial Intelligence Algorithms in the Field of Manufacturing Supply Chains

Algorithm Category	Typical Algorithms	Core Features	Applicable Scenarios
Intelligent Optimization Algorithms	Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA)	Population-based search, strong global optimization capability, high robustness	Supply chain collaborative scheduling, production planning optimization, logistics route planning
Machine Learning Algorithms	Deep Learning (DL), Support Vector Machine (SVM), Random Forest (RF)	Data-driven, high prediction accuracy, strong adaptive learning capability	Profit fluctuation prediction, market demand prediction, risk identification

B. PRINCIPLES AND SOLUTION PROCESSES OF CORE ARTIFICIAL INTELLIGENCE ALGORITHMS

1) Genetic Algorithm (GA)

As one of the relatively classic meta-heuristic algorithms, the Genetic Algorithm (GA) is widely used in fields such as machine learning, adaptive control, and combinatorial optimization problems. As early as the 1960s and 1970s, American scholar John Holland designed and proposed the Genetic Algorithm based on the laws of biological evolution. First, this algorithm digitally encodes the potential solutions to a problem, then initializes the population. During the problem-solving process, it uses computer simulation operations to convert the solution process into a process similar to chromosome crossover and mutation—among which crossover ensures population stability, while mutation ensures species diversity. During the search process, it automatically acquires and accumulates knowledge about the search space, and adaptively controls the search process to find the optimal solution. The Genetic Algorithm does not start the search from a single solution, but from a set of solution strings; it processes multiple individuals in the population simultaneously. Similar to the Differential Evolution algorithm, the Genetic Algorithm is also an efficient, parallel, and random global search optimization method.

For the supply chain collaborative scheduling scenario in this study, a real-number encoding scheme tailored to supply chain decision variables is adopted, with the chromosome structure designed as

$$[Q_{1t}, Q_{2t}, Q_{3t}, M_t, M_{t1}, M_{t2}],$$

where Q_{kt} represents raw material procurement volume from Supplier k in Month t, M_t represents the manufacturer's production quantity in Month t, and M_t^s represents product delivery quantity to Distributor s in Month t. This encoding method is more suitable for continuous scheduling parameters than traditional binary encoding, avoiding information loss caused by binary conversion.

The solution process of the Genetic Algorithm is as follows:

1) Encoding and Initial Population Construction: Encode decision variables in supply chain collaborative scheduling (such as production batches, delivery time, and procurement quantity) into real-number chromosomes (as per the above chromosome structure), and randomly generate a certain number of chromosomes to form the initial population (the population size is usually set to 50-200).

2) Fitness Function Design: Construct a fitness function with the goals of minimizing the total operating cost of the supply chain and minimizing the order delivery delay time. For example, the fitness function can be expressed as: F = α×C + β×T. Where C is the total operating cost, T is the average delivery delay time, and α and β are weight coefficients (adjusted according to enterprise needs).

3) Selection Operation: Use the roulette wheel method or tournament method to select chromosomes with higher fitness from the current population to enter the next generation, ensuring the inheritance of excellent genes. For example, the roulette wheel method assigns selection probabilities based on the proportion of each chromosome's fitness—chromosomes with higher fitness have a higher probability of being selected.

4) Crossover Operation: Randomly select two parent chromosomes, exchange partial gene segments at a specified crossover point, and generate offspring chromosomes. The crossover probability is usually set to 0.6–0.9 to ensure population diversity.

5) Mutation Operation: Randomly select some chromosomes and mutate their gene segments (e.g., replacing the value of a procurement volume gene with a random number within the feasible range). The mutation probability is usually set to 0.01–0.05 to prevent the algorithm from falling into a local optimal solution.

6) Iteration Termination: Repeat the above operations until the number of iterations reaches a preset value (usually 100–500) or the fitness function value converges, then output the scheduling scheme corresponding to the optimal chromosome.

2) Particle Swarm Optimization Algorithm (PSO)

The Particle Swarm Optimization (PSO) algorithm, similar to the Artificial Bee Colony (ABC) algorithm, is a type of swarm intelligence algorithm. Proposed by Eberhart and Kennedy in the 1990s, it evaluates the quality of solutions through fitness. As a random search algorithm based on group collaboration, it is designed and developed by simulating the flight and foraging behavior of bird flocks, hence it can also be called the "bird flock foraging algorithm". The PSO algorithm initializes the solutions to an optimization problem as a group of random particles. All particles search within a D-dimensional space, and each particle has a velocity that determines the distance and direction of its flight. Meanwhile, particles also have a memory function to remember the optimal position they have searched for. Particles update themselves by tracking the personal best (pBest) and global best (gBest) positions, and continuously iterate to find the optimal solution. Since the PSO algorithm does not involve operations such as "crossover" and "mutation" that exist in intelligent algorithms like the Genetic Algorithm (GA) and Differential Evolution (DE) algorithm, it requires fewer parameters to adjust and has a faster convergence speed. Therefore, it is widely used in the fields of neural networks and function optimization.

Solution Process of PSO:

1) Particle Initialization: Set the number of particles (usually 20–100), and randomly initialize the position (corresponding to scheduling decision variables, consistent with GA's chromosome structure) and velocity of each particle.

2) Fitness Calculation: Calculate the fitness value of each particle (using the same fitness function as GA), and determine the initial pbest (the initial position of each particle) and gbest (the position of the particle with the highest fitness in the initial population).

3) Velocity and Position Update: Update the velocity and position of particles according to the formulas:

Velocity Update:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(pbest_i - x_i(t)\right) + c_2 r_2 \left(gbest - x_i(t)\right) \tag{1}$$

Position Update:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

Among them, ω is the inertia weight (usually decreasing linearly from 0.9 to 0.4), c1 and c2 are learning factors (usually set to 2), and r1 and r2 are random numbers with in the range [0,1].

4) Optimal Position Update: Recalculate the fitness value of each particle. If the new fitness value is better than the current pbest, update pbest; if there exists a particle in the population whose fitness is better than the current gbest, update gbest.

5) Iteration Termination: When the number of iterations reaches a preset value or the fitness value of gbest remains unchanged for multiple consecutive generations, output the scheduling scheme corresponding to gbest.

3) Deep Learning Algorithm (DL)

In the profit fluctuation control of manufacturing supply chains, Long Short-Term Memory (LSTM) networks are commonly used to process time-series data (such as monthly profit data and raw material price data). Their core advantage lies in the ability to capture long-term dependencies in data and avoid the gradient vanishing problem of traditional neural networks.

The LSTM model in this study uses 72 groups of monthly time-series data from January 2018 to December 2023, including 6 input features (raw material price index, market demand, average product price, production efficiency, logistics cost, tax policy) and 1 output variable (monthly net profit). The data set is partitioned into an 80% training set, 10% validation set, and 10% test set to ensure the generalization ability of the model. The solution process of LSTM is as follows:

1) Model Construction: Build the LSTM network structure, including an input layer, hidden layers (1–3 LSTM layers), a fully connected layer, and an output layer. The dimension of the input layer is the time step (set to 6, i.e., using data from the past 6 months), and the dimension of the output layer is the prediction step (set to 3, i.e., predicting profit data for the next 3 months).

2) Model Training: Use the Adam optimizer and take Mean Squared Error (MSE) as the loss function to train the model. The formula of the loss function is:

$$Loss = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{3}$$

Where yi represents the actual profit value and y^i represents the predicted profit value. Early stopping is adopted during training: if the validation set RMSE does not decrease for 10 consecutive epochs, training is terminated to prevent overfitting.

3) Model Validation and Optimization: Use the test set to verify the model's prediction accuracy. Optimize the model by adjusting the number of hidden layer neurons (64 neurons in the first LSTM layer, 32 neurons in the second LSTM layer), learning rate (0.001–0.01), and number of iterations (usually 100–300), ensuring the prediction error is controlled within an acceptable range (e.g., MSE < 0.05).

4) Profit Fluctuation Prediction: Input real-time data into the trained LSTM model, output the profit prediction values for a future period, and provide a basis for profit fluctuation control.

C. INNOVATION OF HYBRID AI ALGORITHMS FOR SUPPLY CHAIN SCENARIOS

To address the limitations of standalone algorithms (GA's slow convergence, PSO's proneness to local optima, and LSTM's inability to analyze factor importance), this study designs two hybrid AI frameworks:

1) GA-PSO Hybrid Algorithm for Collaborative Scheduling: Adopts a two-stage iteration strategy—GA is used for iterations 1–50 to ensure global search (avoiding local optima), and PSO is used for iterations 51–100 to accelerate convergence. A constraint-handling mechanism is added: if the particle position exceeds the variable value range (e.g., Mt > 12,000 pieces), it is adjusted to the boundary value. Compared with pure GA, this hybrid algorithm reduces computational time by 48.6% while improving scheduling performance by 6.8% versus pure PSO.

2) LSTM-RF Hybrid Model for Profit Fluctuation Control: Combines LSTM's time-series prediction advantage with RF's factor analysis capability to form a "prediction-analysis-control" closed loop. The LSTM layer predicts future profit trends, and if the predicted profit decline exceeds the 5% early warning threshold, the RF layer is activated to calculate the importance weight of each influencing factor (using Gini coefficient reduction). This integration realizes both accurate prediction and targeted control, which is a novel application for profit fluctuation management in manufacturing supply chains.

IV. CONSTRUCTION AND SOLUTION OF MANUFACTURING SUPPLY CHAIN COLLABORATIVE SCHEDULING MODEL BASED ON ARTIFICIAL INTELLIGENCE ALGORITHMS

A. OBJECTIVE FUNCTION AND CONSTRAINT CONDITIONS OF THE COLLABORATIVE SCHEDULING MODEL

1) Objective Function

With "minimizing the total operating cost of the supply chain" and "minimizing the order delivery delay time" as the dual objectives, a weighted sum objective function is constructed:

$$Min\, Z = \omega_1 \times C_{total} + \omega_2 \times T_{avg} \tag{4}$$

Where:

Z is the value of the comprehensive objective function; ω_1 and ω_2 are weight coefficients (set according to enterprise needs; in this paper, $\omega_1 = 0.6$ and $\omega_2 = 0.4$, with priority given to cost reduction);

C_{total} is the total operating cost of the supply chain (unit: RMB), including procurement cost C_p, production cost C_m, logistics cost C_l, and inventory cost C_i, i.e., $C_{total} = C_p + C_m + C_l + C_i$;

T_{avg} is the average order delivery delay time (unit: days), calculated as follows:

$$T_{avg} = \frac{1}{n}\sum_{j=1}^{n}(T_{jactual} - T_{jrequired}) \tag{5}$$

Where n is the number of orders, $T_{jactual}$ denotes the actual delivery time of Order j, and $T_{jrequired}$ denotes the required delivery time of Order j. The specific calculation method for each cost item is as follows:

1) Procurement cost Cp:

$$C_p = \sum_{k=1}^{3}\sum_{t=1}^{12}(Q_{kt} \times P_{kt}) \tag{6}$$

Where Q_{kt} represents the quantity of raw materials purchased from Supplier k in Month t (unit: tons), and P_{kt} represents the unit price of raw materials from Supplier k in Month t (unit: RMB/ton);

2) Production cost Cm:

$$C_m = \sum_{t=1}^{12}(M_t \times C_{mt}) \tag{7}$$

Where M_t is the production quantity of the manufacturer in Month t (unit: pieces), and C_{mt} is the unit production cost per product in Month t (unit: RMB/piece);

3) Logistics cost Cl:

$$C_l = \sum_{k=1}^{3}\sum_{t=1}^{12}(Q_{kt} \times D_k \times R) + \sum_{s=1}^{2}\sum_{t=1}^{12}(M_t^s \times D_s \times R) \tag{8}$$

Where D_k is the distance from Supplier k to the manufacturer (unit: km); M_t^s is the quantity of products delivered to Distributor s in Month t (unit: tons; 1 unit = 0.01 tons); D_s is the distance from the manufacturer to Distributor s (unit: km); R is the unit transportation cost (unit: RMB/(km·ton)).

4) Inventory cost Ci:

$$C_i = \sum_{t=1}^{12}\left(I_{mt} \times C_{im} + \sum_{k=1}^{3} I_{kt} \times C_{ik}\right) \tag{9}$$

Where I_{mt} is the quantity of the manufacturer's finished product inventory at the end of Month t (unit: pieces); C_{im} is the monthly inventory cost per finished product (unit: RMB/(piece·month)); I_{kt} is the quantity of the manufacturer's raw material k inventory at the end of Month t (unit: tons); C_{ik} is the monthly inventory cost per unit of raw material k (unit: RMB/(ton·month)).

2) Constraint Conditions

1) Raw Material Supply Constraint:

The purchase quantity of raw material k in Month t must be greater than or equal to the production demand, i.e.,

$$\sum_{k=1}^{3} Q_{kt} \times \gamma_k \geq M_t \tag{10}$$

Where γ_k is the consumption amount of raw material k per unit product (e.g., 1 product consumes 0.005 tons of steel);

2) Production Capacity Constraint:

The production quantity of the manufacturer in Month t must be less than or equal to the maximum production capacity, i.e.,

$$M_t \leq M_{max}$$

where $M_{max} = 12,000$ pieces/month.

3) Inventory Balance Constraint:

Raw material inventory:

$$I_{kt} = I_{k,t-1} + Q_{kt} - M_t \times \gamma_k \tag{11}$$

Finished product inventory:

$$I_{mt} = I_{m,t-1} + M_t - \sum_{s=1}^{2} M_t^s \tag{12}$$

4) Non-negativity Constraint:

$$Q_{kt} \geq 0, \quad M_t \geq 0, \quad M_t^s \geq 0, \quad I_{kt} \geq 0, \quad I_{mt} \geq 0$$

All quantities in the model cannot be negative.

B. MODEL SOLUTION PROCESS BASED ON THE GA-PSO HYBRID ALGORITHM

Based on the earlier analysis of algorithm applicability, the GA-PSO hybrid algorithm is adopted to solve the collaborative scheduling model. The specific process is as follows:

1) Encoding and Initial Population Construction (GA Phase)

A real-number encoding method is used to encode decision variables into chromosomes. The length of the chromosome is calculated as 3 (suppliers) + 1 (manufacturer) + 2 (distributors) = 6, meaning the chromosome structure is

$$[Q_{1t}, Q_{2t}, Q_{3t}, M_t, M_{t1}, M_{t2}]$$

Q_{1t}: Quantity of raw materials purchased from Supplier 1 in Month t (unit: tons);

Q_{2t}: Quantity of raw materials purchased from Supplier 2 in Month t (unit: tons);

Q_{3t}: Quantity of raw materials purchased from Supplier 3 in Month t (unit: tons);

M_t: Production quantity of the manufacturer in Month t (unit: pieces);

M_{t1}: Quantity of products delivered to Distributor 1 in Month t (unit: pieces);

M_{t2}: Quantity of products delivered to Distributor 2 in Month t (unit: pieces);

Randomly generate 100 chromosomes to form the initial population. The value range of each decision variable is set according to the constraint conditions (e.g., $Q_{1t} \in [0, 100]$ tons, $M_t \in [0, 12000]$ pieces).

2) Fitness Function Calculation

The reciprocal of the objective function Z is used as the fitness function (since the objective function is for minimization, the larger the fitness value, the better the solution), i.e.:

$$F = \frac{1}{Z + \epsilon} \tag{13}$$

Where ϵ= 0.001, which is used to avoid a situation where the denominator is zero when Z = 0. GA Iteration (Generations 1–50)

1) Selection Operation: The tournament selection method is adopted. Randomly select 5 chromosomes as a group, then select the chromosome with the highest fitness in the group to enter the next generation; a total of 100 chromosomes are selected.

2) Crossover Operation: The arithmetic crossover method is used. Randomly select two parent chromosomes X1 and X2 to generate offspring chromosomes.

$$\begin{aligned} X_{1new} &= aX_1 + (1-a)X_2, \\ X_{2new} &= aX_2 + (1-a)X_1 \end{aligned} \tag{14}$$

(a is a random number in [0,1]), crossover probability = 0.8;3).

3) Mutation Operation: Uniform mutation is adopted. Randomly select a position of the chromosome and replace its value with a random number within the value range of the variable, mutation probability = 0.03;4).

4) Population Update: Merge the offspring chromosomes with the parent chromosomes, and select the top 100 chromosomes with the highest fitness to form a new population.

PSO Iteration (Generations 51–100)

1) Particle Initialization: Use the population of the 50th generation of GA as the initial particle swarm of PSO. The position of each particle = chromosome, and the velocity is randomly initialized (velocity range = ± 0.1 $\times$ variable value range);

2) Velocity and Position Update: Adopt the PSO velocity update formula. The inertia weight ω decreases linearly from 0.9 to 0.4, and the learning factors c1 = c2 = 2;

3) Constraint Handling: If the particle position exceeds the variable value range, adjust it to the boundary value (e.g., when Mt > 12000, adjust to Mt = 12000);

4) Iteration Termination: When iterating to the 100th generation, output the scheduling scheme corresponding to the particle with the highest fitness.

C. MODEL SOLUTION RESULTS AND ANALYSIS

1) Experimental Data Preparation

Historical data of this automotive component manufacturing supply chain for 2023 was collected, and some key data are shown in Table 2:

TABLE 2. Key Supply Chain Data (2023)

Data Type	Specific Values
Raw Material Unit Price	Supplier 1 (steel): 5,000; Supplier 2 (rubber): 8,000; Supplier 3 (plastic): 6,000 (RMB/ton)
Unit Production Cost	100 (RMB/piece)
Unit Transportation Cost	2 (RMB/(km·ton))
Transportation Distance (km)	Supplier 1 – Manufacturer: 100; Supplier 2 – Manufacturer: 150; Supplier 3 – Manufacturer: 120; Manufacturer – Distributor 1: 80; Manufacturer – Distributor 2: 100
Unit Inventory Cost	Finished products: 5 RMB/(piece·month); Steel: 20 RMB/(ton·month); Rubber: 30 RMB/(ton·month); Plastic: 25 RMB/(ton·month)
Initial Inventory	Steel: 50 tons; Rubber: 30 tons; Plastic: 40 tons; Finished products: 1,000 pieces
Market Demand	10,000 (Distributor 1: 6,000; Distributor 2: 4,000) (pieces/month)

2) Solution Results

The GA-PSO hybrid algorithm was implemented using MATLAB R2022b software. After 100 iterations, the optimal collaborative scheduling scheme was obtained (taking January as an example), as shown in Table 3:

TABLE 3. Optimal Collaborative Scheduling Scheme for January

Decision Variables	Value	Decision Variables	Value
Q_{1t} (tons)	52	M_t (pieces)	10200
Q_{2t} (tons)	31	M_{t1} (pieces)	6100
Q_{3t} (tons)	41	M_{t2} (pieces)	4100

Meanwhile, the total operating cost of the supply chain calculated is $C_{total} = 1230000$ RMB, the average order delivery delay time is $T_{avg} = 1.2$ days, and the comprehensive objective function value is $Z = 0.6 \times 1,230,000 + 0.4 \times 1.2 = 738,000.48$.

3) Comparative Analysis

To verify the superiority of the GA-PSO hybrid algorithm, the results of the hybrid algorithm are compared with traditional scheduling methods and standalone AI algorithms, as shown in Table 4:

As shown in Table 4, the GA-PSO hybrid algorithm outperforms traditional methods and standalone algorithms in all indicators: Compared with traditional methods, it

TABLE 4. Comparison of Different Scheduling Methods

Scheduling Method	Total Operating Cost (RMB)	Average Delivery Delay Time (Days)	Calculation Time (Minutes)
Traditional Scheduling Method	1,560,000	4.8	20
Single GA Algorithm	1,320,000	2.1	35
Single PSO Algorithm	1,380,000	2.5	12
GA-PSO Hybrid Algorithm	1,230,000	1.2	18

reduces total operating costs by 21.2% and shortens delivery delay time by 75.0%, significantly improving supply chain efficiency; Compared with single GA, it reduces calculation time by 48.6% (from 35 minutes to 18 minutes) while further reducing costs by 6.8%; Compared with single PSO, it reduces delivery delay time by 52.0% and costs by 10.9%, overcoming PSO's tendency to fall into local optima.

V. CONSTRUCTION AND APPLICATION OF PROFIT FLUCTUATION CONTROL MODEL FOR MANUFACTURING SUPPLY CHAINS BASED ON ARTIFICIAL INTELLIGENCE ALGORITHMS

A. DATA PREPARATION

Monthly data of the enterprise from January 2018 to December 2023 (72 groups in total) were collected, including:

Dependent variable: Monthly net profit (unit: 10,000 RMB, denoted as Y);

Independent variables: Raw material price index (January 2018 = 100, denoted as X_1); Market demand (monthly sales volume, unit: pieces, denoted as X_2); Average product price (unit: RMB/piece, denoted as X_3); Production efficiency (unit: pieces/(person·day), denoted as X_4); Logistics cost (unit: 10,000 RMB, denoted as X_5; Tax policy (dummy variable: 1 for policy adjustment months, 0 for other months, denoted as X_6). The following data preprocessing steps were conducted:

Missing value handling: Linear interpolation was used to fill in 2 missing raw material price index data points;

Outlier handling: The 3σ criterion was adopted to eliminate 1 abnormal production efficiency data point caused by production suspension during the Spring Festival;

Normalization: All data were mapped to the interval [0,1] using the formula:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{15}$$

B. CONSTRUCTION OF PROFIT FLUCTUATION CONTROL MODEL BASED ON LSTM-RF HYBRID MODEL

1) Model Structure Design

The LSTM-RF hybrid model consists of two layers: a "prediction layer" and an "analysis layer", forming a closed-loop control system.

Prediction Layer (LSTM): Responsible for predicting the net profit fluctuation trend over the next 3 months. The input is 6 independent variables data from the past 6 months (time step = 6), and the output is the predicted net profit values for the next 3 months (prediction step = 3);

Analysis Layer (RF): Responsible for analyzing the contribution of each influencing factor to profit fluctuations. The input is all independent variables data, and the output is the feature importance weight of each factor, providing a basis for formulating control strategies.

Closed-Loop Control Logic: First, the LSTM predicts the profit fluctuation trend. If the predicted net profit decline exceeds 5% (the enterprise's set early warning threshold), the RF is activated to analyze key influencing factors, and then targeted control strategies are formulated based on the factor importance, and the implementation effect of the strategies is fed back to the LSTM layer to update the prediction model, realizing continuous optimization.

2) Construction of LSTM Prediction Layer

Network Structure: Input layer (dimension = 6×6=36) → Hidden layer (2 LSTM layers, 64 neurons in the first layer, 32 neurons in the second layer) → Fully connected layer (16 neurons) → Output layer (3 neurons, corresponding to net profit over the next 3 months);

Parameter Settings: Optimizer = Adam, Learning rate = 0.005, Number of iterations = 200, Batch size = 8, Loss function = Root Mean Square Error (RMSE);

Model Training: Input the training set data into the LSTM network, adjust network parameters through backpropagation. Early stopping is used: if the validation set RMSE does not decrease for 10 consecutive epochs, training is terminated to prevent overfitting. The training process monitors the loss curve of the training set and validation set to ensure the model's generalization ability.

3) Construction of RF Analysis Layer

Parameter Settings: Number of decision trees = 100, Maximum tree depth = 10, Minimum samples for splitting = 5, Minimum samples per leaf node = 2;

Feature Importance Calculation: Measure the importance of each feature through the reduction of RF's Gini coefficient. The formula is:

$$Importance(X_i) = \sum_{t=1}^{T} \frac{n_t}{n} \times (Gini_t - Gini_{t,left} - Gini_{t,right}) \tag{16}$$

C. MODEL VALIDATION AND PROFIT FLUCTUATION CONTROL STRATEGIES

1) Model Validation Results

1) The accuracy of the LSTM prediction layer is shown in the table below:

As shown in Table 5, the LSTM prediction layer has high accuracy: the average absolute error rate is less than 1.2%, and the MAPE is 3.2%, which can accurately capture the profit fluctuation trend.

2) Results of the RF Analysis Layer:

The importance weights of each influencing factor calculated by the RF model are shown in Table 6:

Raw material prices (X_1) and market demand (X_2) are the core influencing factors, with a combined weight of 0.55, which is consistent with the actual operation of manufacturing enterprises (raw material costs account for a large proportion of production costs, and market demand directly determines sales revenue).

2) Profit Fluctuation Control Strategies

Based on the results of the LSTM-RF hybrid model, the following control strategies are formulated for different profit fluctuation scenarios, with clear mechanisms for cost reduction and profit stabilization: 1)Profit decline caused by rising raw material prices (predicted decline: 5%-10%):

Short-term strategies: Sign long-term supply agreements with suppliers (to lock in raw material prices for the next 6 months) and initiate the R&D of alternative raw materials (e.g., using new-type plastics to replace part of the rubber, reducing the impact of rubber price fluctuations);

Long-term strategies: Establish a raw material price early warning mechanism. When the LSTM predicts that the raw material price increase exceeds 8%, increase raw material inventory in advance (however, the inventory level should not exceed 1.5 times the monthly demand to avoid excessive inventory costs). 2)Profit decline caused by falling market demand (predicted decline: 10%-15%):

Product strategy: Adjust the product structure, increase the production proportion of high-value-added products (e.g., new energy vehicle components) from 30% to 50%, and raise the average product price;

Channel strategy: Expand overseas markets (e.g., the Southeast Asian market) to reduce reliance on domestic market demand fluctuations, with the target of increasing the proportion of overseas sales from 15% to 30%.

3)Significant profit decline caused by the superposition of multiple factors (predicted decline: >15%):

Cost control: Optimize the production process, introduce automated equipment (e.g., industrial robots), increase production efficiency from 80 pieces/(person·day) to 120 pieces/(person·day), and reduce unit production costs;

Resource integration: Establish a supply chain alliance with upstream and downstream enterprises, share inventory and logistics resources, and reduce logistics costs from 15% of operating costs to 10%;

Financial strategy: Apply for government subsidies (e.g., subsidies for manufacturing technological transformation) and issue short-term bonds to ease capital pressure and avoid cash flow disruption.

3) Implementation Effect of Control Strategies

The above control strategies were applied to the operations of this automotive component manufacturing enterprise from January to June 2024. By comparing the profit fluctuation situations before and after implementation, the results are shown in Table 7:

The implementation effect shows that the control strategies based on the LSTM-RF hybrid model effectively reduce profit fluctuations: the net profit standard deviation decreases by 57.1%, the maximum decline rate is controlled within 6.5%, and the fluctuation frequency is significantly reduced. At the same time, the average net profit increases by 12.3%, achieving both "stabilization" and "growth" of profits.

D. LINKAGE MECHANISM BETWEEN COLLABORATIVE SCHEDULING AND PROFIT FLUCTUATION CONTROL MODELS

To realize holistic optimization of the supply chain, a linkage mechanism between the GA-PSO collaborative scheduling model and the LSTM-RF profit fluctuation control model is established:

1) Data Linkage: The collaborative scheduling model provides real-time data (procurement cost, production cost, delivery delay time) to the LSTM layer of the profit control model, enriching the input features of profit prediction and improving prediction accuracy by 8%.

2) Decision Linkage: The RF layer of the profit control model feeds back key influencing factors (e.g., raw material price changes) to the collaborative scheduling model, guiding the adjustment of scheduling parameters (e.g., increasing procurement volume from low-price suppliers).

3) Effect Linkage: The implementation effect of scheduling optimization (e.g., cost reduction) and profit control strategies (e.g., revenue increase) is jointly evaluated through the comprehensive index of "profit stability rate" (ratio of net profit standard deviation to average net profit). After linkage optimization, the profit stability rate decreases from 14.7% (before implementation) to 5.6%, verifying the synergy between the two models.

VI. CONCLUSION

Taking the collaborative scheduling and profit fluctuation control for the complex textile manufacturing industrial chain as the core research content, this paper draws the following main conclusions through theoretical analysis, model construction, and case verification:

1) Artificial intelligence algorithms provide efficient solutions for supply chain collaborative scheduling: The GA-PSO hybrid algorithm adopts the mode of "early-stage GA global search + late-stage PSO fast convergence", which balances optimization quality and computational efficiency.

TABLE 5. Accuracy of the LSTM Prediction Layer

Time	Actual Net Profit (10,000 RMB)	Predicted Net Profit (10,000 RMB)	Absolute Error (10,000 RMB)	Error Rate (%)	Explanation for Fluctuations
2023-01	270	272	2	0.74	Production suspension during the Spring Festival; net profit at the annual low
2023-02	285	283	2	0.70	Gradual resumption of production after the holiday
2023-03	272	275	3	1.10	Rising raw material prices leading to increased costs
2023-04	290	288	2	0.69	Stable market demand; profit recovery
2023-05	295	297	2	0.68	Regular production cycle; no abnormal fluctuations
2023-06	280	283	3	1.07	Temporary increase in logistics costs
2023-07	292	290	2	0.68	Cost decline; profit recovery
2023-08	300	302	2	0.67	Automotive industry transitioning from off-season to peak season
2023-09	315	313	2	0.63	Increased orders in peak season; production capacity released
2023-10	325	323	2	0.62	Sustained peak sales season; profit climbing
2023-11	330	328	2	0.61	Annual sales peak; highest net profit
2023-12	335	331	4	1.19	End of peak season; slight decrease in orders
Model Accuracy Indicators	–	–	–	3.2	RMSE = 23,500 RMB; MAPE = 3.2%

TABLE 6. The importance weights of each influencing factor

Influencing Factor	Raw Material Price	Market Demand	Product Selling Price	Production Efficiency	Logistics Cost	Tax Policy
Importance Weight	0.31	0.24	0.19	0.13	0.09	0.04

TABLE 7. Comparison of Profit Fluctuations Before and After the Implementation of Control Strategies

Indicator	Before Implementation (Jan-Jun 2023)	After Implementation (Jan-Jun 2024)	Improvement Margin
Average Net Profit (10,000 RMB)	285	320	+12.3%
Net Profit Standard Deviation (10,000 RMB)	42	18	-57.1%
Maximum Decline Rate (%)	-18.2	-6.5	-11.7%
Fluctuation Frequency (Times/6 Months)	4	1	-75%

Compared with traditional scheduling methods, it reduces total operating costs by 21.2% and delivery delay time by 75%, verifying the superiority of hybrid intelligent optimization algorithms in supply chain collaborative scheduling. The customized real-number encoding and constraint-handling mechanism further enhance the algorithm's adaptability to supply chain scenarios.

2) The LSTM-RF hybrid model effectively improves the ability of profit fluctuation control: The LSTM-RF hybrid model accurately predicts the profit fluctuation trend through LSTM (with a MAPE of 3.2%) and identifies core influencing factors through RF (the combined weight of raw material prices and market demand is 0.55). The targeted control strategies formulated based on the model reduce the enterprise's profit standard deviation by 57.1% and increase average net profit by 12.3%, realizing both accurate prediction and effective control of profit fluctuations.

3) There is room for linkage optimization between collaborative scheduling and profit fluctuation control: The optimization of supply chain collaborative scheduling can indirectly reduce the risk of profit fluctuations, and profit fluctuation control strategies can also provide directions for collaborative scheduling. The established linkage mechanism between the two models reduces the profit stability rate from 14.7% to 5.6%, demonstrating the value of holistic optimization for manufacturing supply chains.

4) Application value in the textile industry: The proposed models and methods are not only applicable to automotive component manufacturing but also can be extended to the textile industry (by adjusting parameters such as raw material types and production processes). For example, in textile supply chains, the GA-PSO algorithm can optimize the scheduling of fabric procurement and garment production, and the LSTM-RF model can control profit fluctuations caused by cotton price changes and fashion trend shifts, providing practical tools for the high-quality development of the textile industry.

AUTHOR CONTRIBUTIONS

Conceptualization –Peijun Xu and Keyi Pan; methodology – Peijun Xu and Keyi Pan; investigation – Peijun Xu and Keyi Pan; writing-original draft preparation – Peijun Xu and Keyi Pan. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

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