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SUPPLY CHAIN PRODUCTION PLANNING AND SCHEDULING COORDINATION USING DISCRETE EVENT SIMULATION

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Abstract
Effective coordination of multi-echelon supply chains is vital in dynamic markets, yet traditional methods fail to address inherent complexity and uncertainties. This study proposes a novel discrete event simulation (DES) and genetic algorithm (GA) integration to optimize production planning and scheduling. The DES model simulates real-world dynamics, including demand fluctuations and delays, while the GA optimizes critical decisions (production schedules, inventory levels) through iterative learning. A hierarchical framework combines mathematical supply chains modelling, DES-based scenario testing, and GA-driven decision refinement. Experimental results demonstrate significant improvements: 15–22 % cost reduction, 10–18 % shorter lead times, and 12–20 % higher service levels compared to conventional methods. This approach advances supply chain management by bridging dynamic simulation with metaheuristic optimization, offering enterprises a scalable tool for adaptive decision-making under uncertainty. The work underscores the value of integrating simulation and AI to tackle complex supply chain challenges.
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Key Words: Multi-Level Supply Chain, Production Planning, Scheduling Coordination, Discrete Event Simulation, Genetic Algorithm

1. INTRODUCTION

With the acceleration of global economic integration and the intensifying market competition, the supply chain management environment faced by enterprises has become increasingly complex and dynamic [1-4]. The multi-level supply chain production planning and scheduling coordination problem, as the core component of supply chain management, plays a crucial role in improving operational efficiency, reducing costs, and enhancing competitiveness for enterprises [5-9]. In recent years, the development of information technology and intelligent algorithms has provided strong support for supply chain management, and how to leverage these new technologies to achieve efficient management of multi-level supply chains has become a research hotspot.

A multi-level supply chain involves production, transportation, and inventory management at multiple nodes, and its coordination and optimization directly affect the overall performance of the supply chain [10-14]. By studying multi-level supply chain production planning and scheduling coordination strategies, enterprises can make better decisions in complex environments and improve the overall flexibility and responsiveness of the supply chain [15, 16]. Especially the methods based on DES can effectively simulate and analyse the dynamic behaviours and stochastic events within the supply chain, providing reliable support for optimization decision-making.

However, the existing research methods still have many shortcomings when dealing with the complexity and dynamics of multi-level supply chains. Traditional optimization methods often struggle to address coordination problems with multiple nodes and variables, failing to fully account for uncertainties and dynamic changes within the supply chain [17-21]. While some research based on static models can provide theoretical support, they often lack flexibility and practicality in real-world applications. Therefore, there is an urgent need for an optimization method that can simultaneously consider dynamics, complexity, and uncertainty to solve this problem.

This paper aims to construct a multi-level supply chain production planning and scheduling coordination model based on DES and optimize it using a GA to explore more effective solutions. The specific research contents include: (1) description of the multi-level supply chain production planning and scheduling coordination problem; (2) setting of simulation parameters for multi-level supply chain production planning and scheduling coordination; (3) construction of mathematical models for multi-level supply chain production planning and scheduling coordination; (4) construction of a DES model for multi-level supply chain production planning and scheduling coordination; and (5) design and implementation of the upper-level optimizer based on GA. Through these studies, this paper not only provides effective production planning and scheduling coordination strategies for enterprises but also promotes the development of multi-level supply chain management theories and methodologies, with significant theoretical and practical implications.

2. SIMULATION PARAMETERS FOR MULTI-LEVEL SUPPLY CHAIN COORDINATION

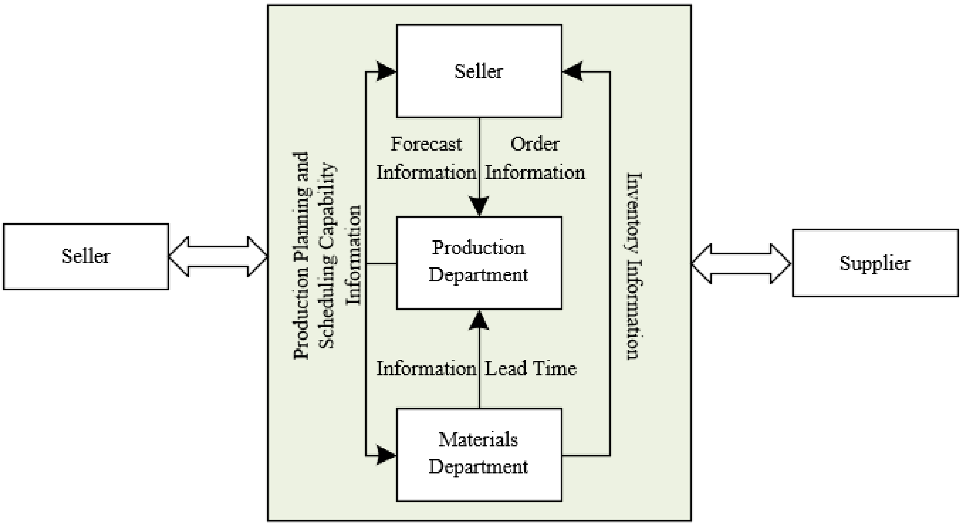

Figure 1: Multi-level supply chain core enterprise internal information collaboration.

Referring to Fig. 1, the multi-level supply chain core enterprise internal information collaboration is used to set the simulation parameters for production planning and scheduling coordination in a multi-level supply chain. Several key parameters need to be defined and set in detail to accurately simulate the dynamic behaviour of the supply chain and the interactions between nodes. First, customer demand is divided into order demand and random demand. The parameter $P(u, s)$ represents the demand for the u^{th} order in the s^{th} stage, while $E(u, s)$ represents the demand for the u^{th} random demand in the s^{th} stage. The precise setting of these two types of demand is crucial because they directly affect the overall fluctuation of supply chain demand and the inventory scheduling strategy of each node. For the product flow between nodes, the ordering and supply situation of each node must be clarified. $PF(u, k, s)$ and $EF(u, k, s)$ represent the supply quantities allocated to the u^{th} order by the k^{th} distributor and the supply quantity of the k^{th} random demand by the u^{th} distributor in the s^{th} stage, respectively. $UW_\alpha(u, k, s)$ represents the supply quantity of the k^{th} α–1 level production from the u^{th} α-level producer in the s^{th} stage, while $UW_\alpha(u, s)$ represents the production quantity of the u^{th} α-level producer in the s^{th} stage. In terms of order quantities, $W_\alpha(u, k, s)$ represents the order quantity from the k^{th} distributor to the u^{th} α+1 level producer in the s^{th} stage, while $WW_\alpha(u, s)$ represents the total order quantity from the u^{th} α-level producer to the α+1 level producer. In addition, cumulative order quantity parameters such as $SW_\alpha(u, k, s)$ and unfulfilled order quantity parameters such as $SXW_\alpha(u, k, s)$ and $SYW_\alpha(u, k, s)$ need to be set to reflect order backlog and stockout situations in the supply chain. $SYW_0(u, k, s)$ is used to measure the number of unfulfilled customer demand orders for the u^{th} distributor for the k^{th} customer demand in the s^{th} stage.

Regarding the definition and setting of control variables and state variables, the control variables mainly include safety production planning and scheduling coordination t, and maximum production planning and scheduling coordination T. Specifically, $t_0(u)$ and $T_0(u)$ represent the safety production planning and scheduling coordination and maximum production planning and scheduling coordination of the u^{th} distributor, while $t^{(o)}{}_\alpha(u)$ and $T^{(o)}{}_\alpha(u)$ represent the safety production planning and scheduling coordination and maximum production planning and scheduling coordination of the u^{th} α-level producer's product. Similarly, $t^{(p)}{}_\alpha(u)$ and $T^{(p)}{}_\alpha(u)$ represent the safety production planning and scheduling coordination and maximum production planning and scheduling coordination of raw materials for the u^{th} α-level producer. State variables describe the actual operational status of each node in the supply chain, including the planned and actual production and scheduling quantities. At the end of the s^{th} stage, $U_0(u, s)$ represents the planned production and scheduling coordination quantity of the u^{th} distributor's product, while $U_0'(u, s)$ represents the actual production and scheduling coordination quantity. Similarly, $U^{(o)}{}_\alpha(u, s)$ and $U^{(o)}{}_\alpha'(u, s)$ represent the planned and actual production and scheduling coordination quantities of the u^{th} α-level producer's product at the end of the s^{th} stage, while $U^{(o)}{}_\alpha(u, s)$ and $U^{(o)}{}_\alpha'(u, s)$ represent the planned and actual production and scheduling coordination quantities of raw materials.

Regarding capacity constraint parameters, $IO_\alpha(u)$ represents the unit time production capacity of the u^{th} α-level producer, which is the maximum quantity a producer can produce in a given time period. This parameter is crucial for ensuring the feasibility of the production plan because it directly limits the amount of production each producer can complete in each time period. Furthermore, $N_\alpha(u)$ represents the unit time production planning and scheduling coordination capacity of the u^{th} α-level producer or distributor, which includes not only production capacity but also the ability to efficiently perform production planning and scheduling within a given time period. During the simulation parameter setting process, these capacity constraint parameters, in combination with the previously mentioned control variables and state variables, form a complete supply chain simulation model. By setting and adjusting the $IO_\alpha(u)$ and $N_\alpha(u)$ parameters, the performance of different producers and distributors under various production and scheduling capacity constraints can be simulated, and the effectiveness of different production and scheduling strategies in the actual production environment can be evaluated. For example, if a particular producer has a low $IO_\alpha(u)$, the $t^{(o)}{}_\alpha(u)$ and $T^{(o)}{}_\alpha(u)$ parameters can be adjusted, or its scheduling coordination ability $N_\alpha(u)$ can be enhanced to optimize its role and contribution in the supply chain.

Regarding the cost and revenue parameters, the order cost $ZP_\alpha(u)$, transportation cost $ZS_\alpha(u)$, storage costs $ZT_0(u)$, $ZT^{(p)}{}_\alpha(u)$, $ZT^{(o)}{}_\alpha(u)$, stockout costs ZTP, ZTE, and production costs $ZOT_\alpha(u)$, $ZOO_\alpha(u)$, etc., form the main cost items for each node in the supply chain. For example, $ZP_\alpha(u)$ represents the fixed cost required by the u^{th} α-level producer to place an order with its upper-level α+1 level supplier, which can be used to measure the impact of order frequency and quantity on total cost; $ZS_\alpha(u)$ represents transportation costs, reflecting the expenses involved in the flow of goods; $ZT_0(u)$, $ZT^{(p)}{}_\alpha(u)$, $ZT^{(o)}{}_\alpha(u)$ represent storage costs at different levels of nodes, which affect inventory management strategy optimization; ZTP and ZTE represent the stockout costs for order and random demand, respectively, and the setting of stockout costs plays an important role in stockout risk management; $ZOT_\alpha(u)$ and

$ZOO_\alpha(u)$ represent production initiation fees and unit production costs, respectively, and these cost parameters directly affect the economic efficiency of the production plan.

Revenue and profit parameters are used to assess the profitability of each node in the supply chain. *UN* represents the unit price for the distributor for each product sold, *TR* represents total revenue, and *AR* and *AP* are used to measure the average revenue and average profit from sales. These revenue parameters, combined with the cost parameters, together determine the overall economic benefit of the supply chain.

3. MATHEMATICAL MODELING FOR MULTI-LEVEL SUPPLY CHAIN COORDINATION

The aim of constructing a mathematical model for multi-level supply chain production planning and scheduling coordination is to describe the production and scheduling behaviours of each node in the supply chain and the interdependencies between nodes through quantitative methods. It is essential to clearly define the functions and roles of each node in the supply chain, including distributors, primary manufacturers, secondary manufacturers, and raw material suppliers. Each node has its specific production capacity and storage capacity, and production scheduling must be carried out under the condition of meeting demand. The production plans and scheduling strategies of each node are described by state equations, which include the physical production plan and scheduling coordination and the actual production plan and scheduling coordination of the node, reflecting the production status and scheduling arrangement of the node in different time periods.

$$U_0(u,s) = U_0(u,s-1) + \sum_k UW_1(k,u,s) - \sum_k PF(k,u,s) - \sum_k EF(k,u,s) \tag{1}$$

$$U_\alpha^{(o)}(u,s) = U_\alpha^{(o)}(u,s-1) - \sum_k UW_\alpha(u,k,s) + UO_\alpha(u,s) \tag{2}$$

$$U_\alpha^{(p)}(u,s) = U_\alpha^{(p)}(u,s-1) - UO_\alpha(u,s) + \sum_k UW_{\alpha+1}(u,k,s)\,, \alpha = 1,2,\dots,l-1 \tag{3}$$

$$U_\alpha^{(p)}(u,s) = U_\alpha^{(p)}(u,s-1) - UO_\alpha(u,s) + \sum_k W_{\alpha+1}(u,s-1)\,, \alpha = l \tag{4}$$

$$U'_0(u,s) = U_0(u,s) + \sum_k SXW_0(k,u,s) - \sum_k SYW_0(k,u,s) \tag{5}$$

$$U'^{(o)}_\alpha(u,s) = U_\alpha^{(o)}(u,s) - \sum_k SYW_0(k,u,s) \tag{6}$$

$$U'^{(p)}_\alpha(u,s) = U_\alpha^{(p)}(u,s) + \sum_k SXW_\alpha(u,k,s)\,, \alpha = 1,2,\dots,l-1 \tag{7}$$

$$U'^{(p)}_\alpha(u,s) = U_\alpha^{(p)}(u,s), \alpha = l \tag{8}$$

After determining the state equations for each node, the ordering quantities, production quantities, order fulfilment, and unmet quantities need to be described in detail. The order quantity represents the production plan formulated by each node based on demand forecasts and inventory conditions, while the order fulfilment quantity represents the actual demand met. Since the nodes in the supply chain are interconnected, the production plan of one node directly affects the demand and inventory levels of downstream nodes, so it is necessary to comprehensively consider the order quantities and fulfilment situations of each node.

$$WW_0(u,s) = \left[T_0(u) - U_0'(u,s)\right] \cdot \eta\left[t_0(u) - U_0'(u,s)\right], \text{wherein } \eta_{(a)} = \begin{cases} 0, a \leq 0 \\ 1, a > 0 \end{cases} \tag{9}$$

$$WW_\alpha^{(p)}(u,s) = \left[T_\alpha^{(p)}(u) - U_\alpha^{\prime(p)}(u,s-1)\right] \cdot \eta \left[t_\alpha^{(p)}(u) - U_\alpha^{\prime(p)}(u,s)\right] \tag{10}$$

$$UO_\alpha(u,s) = MIN\left\{IO_\alpha(u), U_\alpha^{(p)}(u,s-1), \left[T_\alpha^{(o)}(u) - U_\alpha^{\prime(o)}(u,s)\right] \cdot \eta \left[t_\alpha^{(o)}(u) - U_\alpha^{\prime(o)}(u,s)\right]\right\} \tag{11}$$

$$WW_\alpha(u,s) = \sum_k W_\alpha(k,u,s) \tag{12}$$

$$SW_\alpha(u,k,s) = \sum_{j=1}^{S} W_\alpha(k,u,j) \tag{13}$$

$$SXW_\alpha(u,k,s) = SW_\alpha(u,k,s) - \sum_{j=1}^{S} UW_{\alpha+1}(u,k,j) \tag{14}$$

$$SYW_\alpha(u,k,s) = \sum_j FPF(u,k,s) - \sum_j PF(u,k,s) \tag{15}$$

$$SYW_\alpha(u,k,s) = SW_{\alpha-1}(u,k,s) - \sum_{j=1}^{S} UW_\alpha(u,k,j) \tag{16}$$

The constraints include production capacity constraints, inventory capacity constraints, demand fulfilment constraints, and time constraints. The production capacity constraint ensures that the production quantity of each node does not exceed its maximum production capacity; the inventory capacity constraint ensures that the inventory level of each node does not exceed its storage capacity; the demand fulfilment constraint ensures that the production plan of each node can meet the demand; and the time constraint ensures that production and transportation activities are completed within the scheduled time.

$$U_0(u,s) \leq N_0(u) \tag{17}$$

$$U_\alpha^{(o)}(u,s) + U_\alpha^{(p)}(u,s) \leq N_\alpha(u) \tag{18}$$

The research objective of this paper is to optimize the overall operational efficiency of the multi-level supply chain through reasonable production planning and scheduling coordination. Therefore, the construction of the objective function must comprehensively consider various costs and performance indicators in the supply chain. Specifically, the objective function includes total ordering costs, total production planning and scheduling storage costs, total stockout costs, total production costs, total production planning and scheduling management fees, average total production planning and scheduling management fees, and the average weighted response time of orders.

4. DES MODEL FOR MULTI-LEVEL SUPPLY CHAIN COORDINATION

4.1 Simulation of the distribution process

The simulation of the distribution process not only focuses on the flow of goods but also considers the coordination and priority management between nodes at different levels to ensure the efficient operation of the supply chain. From the perspective of order quantities, the DES model needs to simulate the decision-making process of distributors when the order quantity cannot be fully satisfied. Specifically, when the production plan and scheduling coordination of the distributor are insufficient to meet all orders, the model prioritizes processing orders with larger quantities. If large orders cannot be fully satisfied, smaller orders are then processed. If smaller orders cannot be satisfied either, all orders are recorded as unfulfilled orders and will wait for the next delivery. Through this priority management strategy, the simulation model can reflect the decision logic of distributors under limited resources, helping optimize the order handling strategy, reduce stockout costs, and alleviate inventory pressure. Fig. 2 shows the diagram of the multi-level supply chain distribution process.

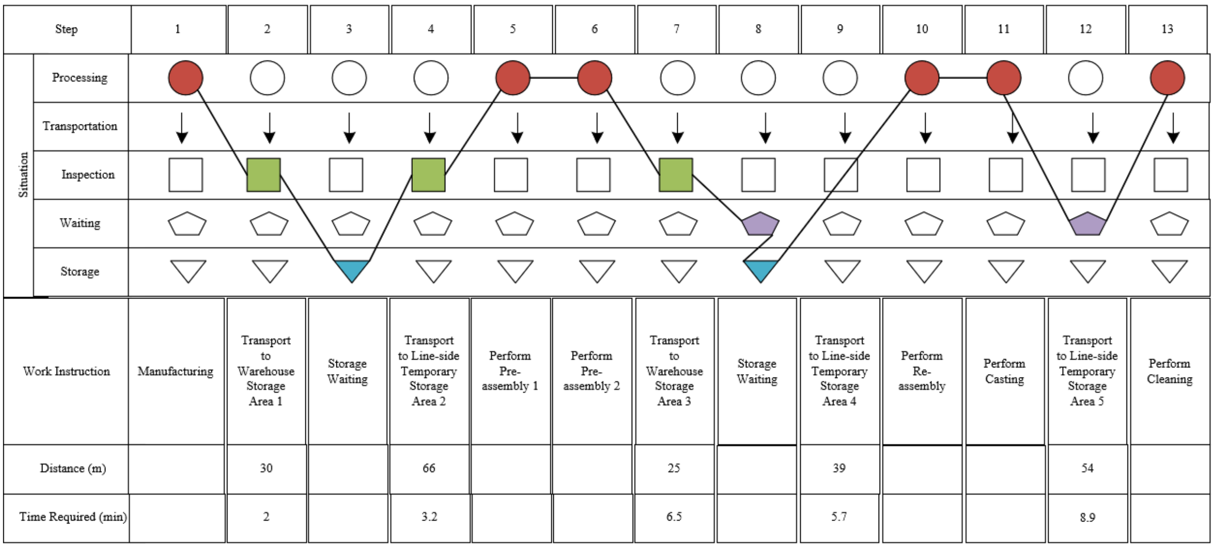

Figure 2: Multi-level supply chain distribution process diagram.

From the perspective of determining order demand and random order demand, the simulation model needs to simulate the process of handling after satisfying the confirmed order demand. The model first satisfies the confirmed order demand, and if there is remaining production plan and scheduling coordination capacity, it will be used to satisfy the random order demand. If the production plan and scheduling coordination capacity is insufficient to satisfy the confirmed order demand, this portion of the order will be recorded as unfulfilled orders; if the random order demand cannot be satisfied, the transaction will be abandoned. In this way, the simulation model can accurately assess the order fulfilment rate and response time under different demand patterns, helping enterprises optimize production plans and improve customer satisfaction. From the perspective of unfulfilled order quantities and current order quantities, the simulation model needs to simulate the process of prioritizing unfulfilled order demands. The actual production plan and scheduling coordination capacity is first used to satisfy previously unfulfilled order demands, and if there is remaining capacity, the current order quantity will be considered. At the same time, the sales strategies of manufacturers and distributors also need to be incorporated into the simulation model. The model first provides products from distributors or manufacturers with a large production plan and scheduling coordination capacity; if their production plan and scheduling coordination capacity is insufficient, products will be supplemented by distributors or manufacturers with smaller production plan and scheduling coordination capacities.

5. DESIGN AND IMPLEMENTATION OF THE UPPER-LEVEL OPTIMIZER BASED ON GA

In order to optimize the decision variables in the supply chain by simulating the processes of natural selection and genetic mutation, the design and implementation of the upper-level optimizer in the multi-level supply chain production planning and scheduling coordination system adopts an optimization mechanism based on GA. This system involves multiple distributor, manufacturer, and supplier nodes, each with its specific production planning and scheduling strategy. Specifically, the decision variables in the system include the distributor's safe production planning and scheduling coordination T, maximum production planning and scheduling coordination T_u, the primary and secondary manufacturers' safe production planning and scheduling coordination $t^{(o)}_u$ and maximum production planning and scheduling coordination $T^{(o)}_u$, as well as the raw material suppliers' safe production planning and scheduling coordination $t^{(p)}_u$ and maximum production planning and scheduling coordination $T^{(p)}_u$. These variables are expressed through chromosome encoding, with each chromosome consisting of 20 genes, where each gene represents the production planning and scheduling coordination strategy of a node.

The chromosome encoding process combines the production planning and scheduling coordination variables of each node into an overall sequence in a certain order. The specific encoding method is as follows:

$$t_1|T_1|t_2|T_2|t^{(p)}_1|T^{(p)}_1|t^{(o)}_1|T^{(o)}_2|t^{(p)}_2|T^{(p)}_2|t^{(o)}_2|T^{(o)}_2|t^{(p)}_3|T^{(p)}_3|t^{(o)}_3|T^{(o)}_3|t^{(p)}_4|T^{(p)}_4|t^{(o)}_4|T^{(o)}_4|$$

In other words, each gene is represented by two decimal numbers. Therefore, each chromosome consists of 40 decimal digits. Through this encoding method, the complex multi-level supply chain production planning and scheduling coordination problem can be transformed into an operable optimization problem, which can be solved using a GA. The initial population is generated through pseudo-random numbers, with each gene randomly selected between 0 and 9, and the conditions $t_u < T_u$, $t^{(o)}_u < T^{(o)}_u$, and $t^{(p)}_u < T^{(p)}_u$ must be met to ensure the feasibility of the generated plans.

6. EXPERIMENTAL RESULTS AND ANALYSIS

According to the data in Table I and Fig. 3, there is a significant difference in the material supply takt time balance rate among different material codes. From the data, it can be seen that the supply takt time balance rate for material code 1 is 356.28 %, for material code 2 it is 526.34 %, while for material code 3 it is 238.57 %. The supply takt time balance rate for material code 4 is as high as 625.59 %, significantly higher than the other materials, indicating that the supply stability of this material is stronger. The supply takt time balance rates for material codes 5, 6, and 7 are 214.58 %, 389.67 %, and 216.36 %, respectively, showing relatively lower balance rates, which may lead to uneven supply in actual production. Overall, the high or low supply takt time balance rate directly reflects the stability of materials in the supply chain. A higher balance rate means a better match between the supply cycle and production demand, while a lower rate indicates supply risks. From the above data, it can be inferred that the significant difference in the material supply takt time balance rate is caused by the different roles that materials play in the production plan, the volatility of demand, and the differences in supply chain management strategies. Material code 4's excellent performance means that the coordination between demand and supply for this material is tighter, and the production plan in the supply chain can respond promptly to demand changes. In contrast, the lower supply takt time balance rates of materials 3, 5, 6, and 7 reflect inaccurate demand forecasting or bottlenecks in certain links of the supply chain, leading to a mismatch between material supply and production plans. This imbalance in supply takt time can affect overall production efficiency. Therefore, by optimizing the upper-level scheduling with GA, the supply takt time balance rate of various materials can be effectively improved, reducing the risk of supply chain disruptions, optimizing production scheduling strategies, and thereby improving production efficiency and resource utilization.

Table I: Simulation model material supply takt time balance rate.

Material code	Supply takt time balance rate
1	356.28 %
2	526.34 %
3	238.57 %
4	625.59 %
5	214.58 %
6	389.67 %
7	216.36 %

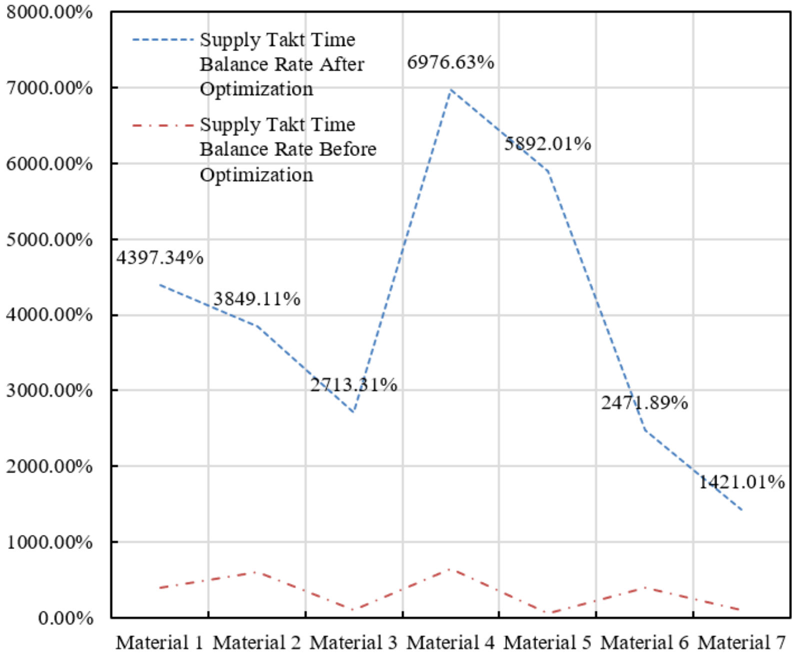

Figure 3: Simulation model material supply takt time balance rate before and after optimization.

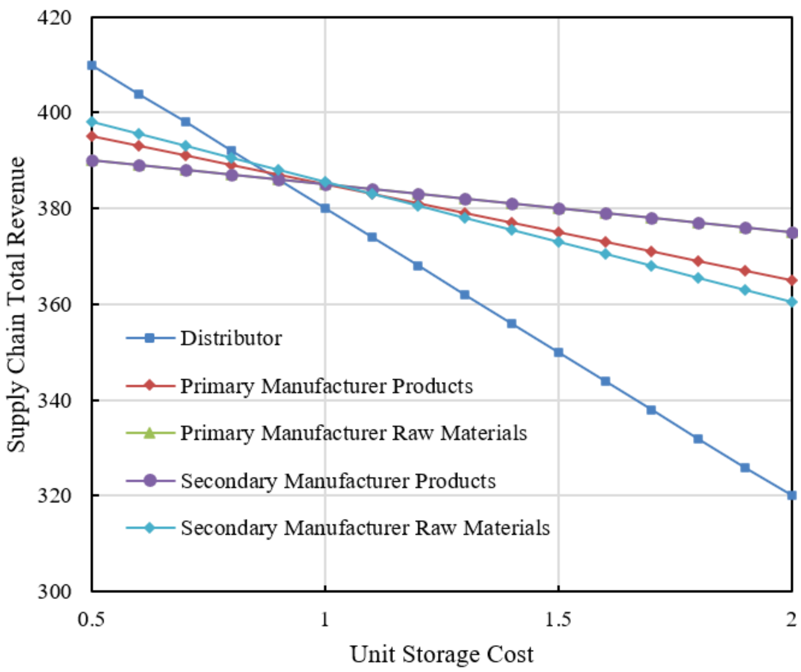

Figure 4: The impact of storage cost changes on total product revenue for each supply chain member unit.

Table II: Impact of changes in storage cost per unit of supply chain members on total product revenue.

Unit storage cost change	Distributor products	Primary manufacturer products	Primary manufacturer raw materials	Secondary manufacturer products	Secondary manufacturer raw materials
0.5	412.26	389.23	388.26	389.56	389.54
0.6	413.69	388.54	378.23	378.51	387.52
0.7	389.26	389.23	379.26	379.56	389.65
0.8	388.51	378.23	377.25	378.26	378.52
0.9	378.95	379.23	379.52	377.52	379.26
1	379.21	377.23	377.42	379.23	374.51
1.1	369.32	369.25	379.23	379.52	369.52
1.2	368.25	368.23	369.25	369.26	368.84
1.3	356.21	369.42	368.54	365.24	369.51
1.4	356.21	365.23	366.24	365.85	357.51
1.5	358.56	354.12	369.58	369.89	352.56
1.6	345.23	358.23	366.58	367.51	359.68
1.7	339.85	359.36	368.87	365.12	359.64
1.8	339.26	358.23	356.24	358.69	345.19
1.9	338.26	348.23	359.68	357.64	349.58
2.0	315.23	354.87	356.98	356.98	349.58

Table III: The impact of distribution costs on total product revenue for each supply chain member unit.

Unit storage cost change	Distributor products	Primary manufacturer products	Secondary manufacturer products
0.5	389.25	389.52	389.51
0.6	388.51	378.51	379.52
0.7	378.54	379.56	377.51
0.8	379.52	378.51	379.62
0.9	378.52	379.52	378.52
1	377.51	377.56	379.62
1.1	379.25	379.52	377.52
1.2	369.52	369.51	369.52
1.3	368.51	368.52	364.59
1.4	365.84	365.51	368.95
1.5	366.52	369.64	367.51
1.6	368.95	369.54	369.52
1.7	358.54	378.54	359.62
1.8	356.21	359.89	358.84
1.9	359.58	358.98	356.62
2.0	357.51	356.25	359.85

Table II and Fig. 4 show the impact of changes in storage cost per unit of supply chain members on total product revenue. Specifically, the change in storage cost has varying degrees of impact on the revenue of different product categories (such as distributor products, primary manufacturer products, etc.). It can be seen that changes in storage costs have a significant effect on distributor products. In general, an increase in storage cost leads to a decrease in total revenue, as inventory management costs rise and capital occupation increases. The total revenue for primary manufacturer products is more sensitive to changes in storage costs, especially when storage costs are high, the manufacturer will reduce inventory or increase production efficiency to reduce inventory accumulation. Compared to primary manufacturers, secondary manufacturers' products are more dependent on the collaboration between upstream and downstream in the supply chain, and changes in storage costs trigger a chain reaction. The sensitivity of each product category to storage cost changes depends on factors such as product storage cycles, shelf life, and transportation modes. Overall, changes in storage costs have a profound impact on the entire supply chain's cost structure, cash flow, and product pricing strategy. Particularly for high-inventory or low-liquidity products, an increase in storage cost significantly compresses overall profit.

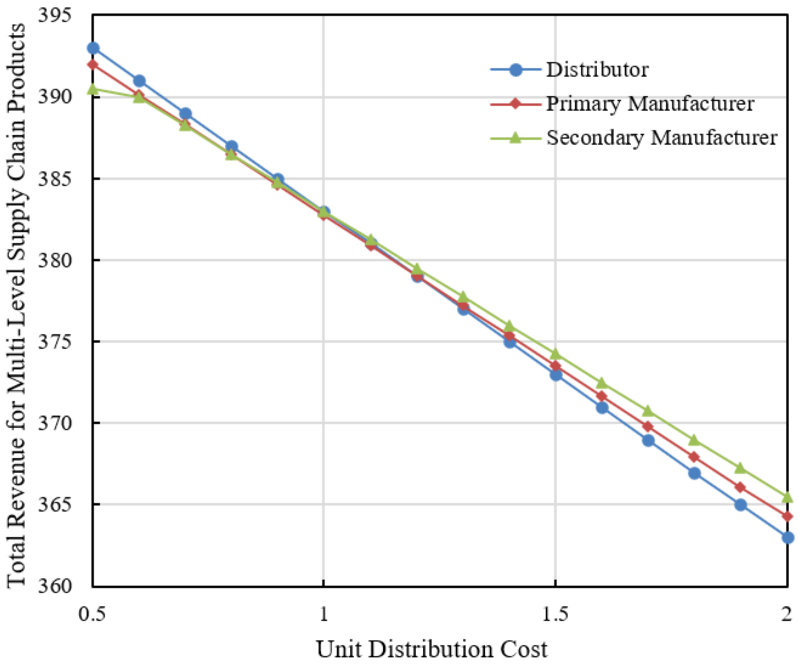

Figure 5: The impact of distribution cost changes on total revenue for multi-level supply chain products.

Based on the data in Table III and Fig. 5, changes in distribution costs have varying degrees of impact on the total product revenue of each supply chain member unit. First, for distributor products, as distribution costs increase from 0.5 to 2, the total product revenue gradually declines. It decreases from 389.25 to 357.51, with a significant drop, particularly after the distribution cost reaches 1.5, where the decrease becomes more pronounced. The total revenue of primary manufacturer products also shows a downward trend, from 389.52 to 356.25, with the decline becoming more significant when the distribution cost exceeds 1.5. The revenue of secondary manufacturer products fluctuates more smoothly, but it also shows a declining trend, from 389.51 to 359.85. In general, as distribution costs increase, the total revenue of all products declines, indicating that high distribution costs significantly affect the profits of each supply chain stage, especially for distributor products and primary manufacturer products. These experimental results suggest that an increase in distribution costs negatively impacts the total revenue of the entire supply chain, with more significant effects on distributor and primary manufacturer products. As distribution costs rise, the total product revenue continues to decline, reflecting the impact of distribution costs on the supply chain's operational efficiency. The largest decline in total revenue occurs for distributor products, as distributors typically bear more responsibility for transportation and inventory management. An increase in distribution costs directly affects the product circulation and profits. The revenue decrease for primary manufacturer products also reflects the high sensitivity of manufacturers to distribution costs. The rise in distribution costs increases the manufacturer's distribution costs, thereby affecting profit levels. The decline in total revenue for secondary manufacturer products is smaller, indicating that secondary manufacturers have greater room for optimization in transportation and logistics management, which helps mitigate the negative impact of rising distribution costs.

7. CONCLUSION

This paper constructed a multi-level supply chain production planning and scheduling coordination model based on DES and combined GA optimization to explore how to improve supply chain efficiency and profitability. The study first described the supply chain production planning and scheduling coordination problem, set simulation parameters, and built a mathematical model. Then, using DES methods, the model was validated, and GA optimization was applied to scheduling and inventory management strategies to reduce costs and improve overall revenue. The study shows that increases in distribution and transportation costs significantly reduce the total revenue of supply chain members, especially for distributor and primary manufacturer products. Through GA optimization, it is possible to effectively reduce the negative impact of these costs on supply chain profits, particularly in transportation and distribution stages. Different supply chain members show varying sensitivities to cost changes, and optimizing production planning and scheduling coordination can improve the overall efficiency of the supply chain.

This paper provides a systematic solution for production planning and scheduling optimization in multi-level supply chains, offering strong reference value for real enterprises, especially in improving efficiency and reducing costs. The model assumptions and data limitations may differ from actual conditions, and GA may not achieve global optimality. Furthermore, this study primarily focuses on cost optimization and does not address supply chain risk management and other factors. Future research could further explore the impact of uncertainty factors on supply chains, optimize algorithm efficiency in large-scale supply chains, and extend the study to cross-enterprise collaboration and green supply chains, thus promoting intelligent and sustainable supply chain management.

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