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COORDINATION OF PRODUCTION PLANNING IN MULTI-ECHELON SUPPLY CHAINS: A SIMULATION APPROACH

He, S. H.
School of Logistics, Linyi University, Linyi 276000, China
E-Mail: supremehe@163.com

Abstract
Driven by globalization and diverse market demands, modern multi-echelon supply chains face significant challenges. Effective coordination of resources and information flows between levels is crucial for improving supply chain efficiency and competitiveness. Traditional scheduling methods often fail to capture inter-level synergies and struggle with the dynamic changes and uncertainties in supply chains. To overcome these issues, a coordination strategy based on discrete event simulation was proposed. This strategy includes a multi-objective optimization model that focuses on production efficiency, inventory cost, and delivery time. Discrete event simulation models the production and scheduling processes, enhancing decision support for complex environments. This approach aims to boost the overall operational efficiency and flexibility of the supply chain, providing substantial theoretical and practical benefits.
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Key Words: Multi-Echelon Supply Chain, Production Planning, Scheduling Optimisation, Discrete Event Simulation, Multi-Objective Optimisation

1. INTRODUCTION

Driven by globalisation and digitalisation, modern supply chains have become increasingly complex, particularly multi-echelon supply chains [1, 2]. These supply chains encompass multiple stages and involve various tiers of suppliers, manufacturers, distributors, and consumers. Coordinating production planning and scheduling across these tiers to ensure efficient supply chain operations has emerged as a significant challenge in supply chain management [3-6]. The growing diversity and uncertainty of market demands have rendered traditional supply chain management methods inadequate for addressing the increasingly complex requirements of production planning and scheduling. Consequently, developing effective strategies for production planning and scheduling coordination has become a focal point of research.

Existing approaches, while achieving progress in optimising production and scheduling within single supply chain echelons, often suffer from overly simplistic modelling assumptions, neglect the synergistic effects between different echelons and fail to account for changes in external environments [7-11]. Furthermore, existing production and scheduling methods primarily rely on static analysis, lacking the capacity to effectively address discrete events, dynamic changes, and uncertainties [4, 12]. Many studies also fail to integrate multi-objective optimisation with discrete event simulation, limiting their ability to comprehensively and dynamically consider various factors within the supply chain [13-17]. These limitations restrict the applicability of current methods to the complex production and scheduling challenges faced by real-world multi-echelon supply chains.

This study addresses the issue of production planning and scheduling in multi-echelon supply chains by proposing a coordination strategy based on discrete event simulation. The first aspect of the research involves constructing a multi-objective planning model for production and scheduling in multi-echelon supply chains. This model balances objectives such as production efficiency, inventory costs, and delivery time and employs optimisation methods to resolve coordination challenges. The second aspect focuses on leveraging discrete event simulation to model the dynamic processes within multi-echelon supply chains, enabling the system performance of various production and scheduling strategies to be analysed and providing decision support. This research aims to offer a novel and scientific solution for production and scheduling in multi-echelon supply chains, thereby enhancing overall operational efficiency and flexibility. The findings are expected to hold significant theoretical and practical value.

2. MULTI-OBJECTIVE MODEL FOR PRODUCTION PLANNING IN SUPPLY CHAINS

The management structure of a multi-echelon supply chain is inherently complex, encompassing multiple stages or tiers from raw material suppliers to end consumers. Each tier represents distinct participants or nodes within the supply chain, all of which perform specific roles in the transformation of raw materials into final products. The relationships and cooperation among these tiers are critical. The flow of information, such as demand forecasts, inventory levels, and production plans, and materials, including raw materials, semi-finished goods, and finished products, require high coordination, thereby ensuring the efficient operation and response speed of the supply chain.

Coordination among multiple suppliers and consumers is essential in addressing the production and scheduling challenges in multi-echelon supply chains. The material demands of each consumer are assumed to be known, as are the supply capacities of each supplier. The objective is to determine an optimal scheduling strategy that meets all consumer demands while minimising the number of suppliers involved and ensuring the earliest possible start time for emergency orders. Achieving this objective requires optimisation tailored to the structural characteristics of the multi-echelon supply chain. Specifically, a scheduling model based on tiered priority queues was developed. Within this model, scheduling plans at each tier prioritise the earliest possible start time and the minimal involvement of suppliers. Within each tier, consumers are grouped and assigned to the most suitable supplier groups to ensure the optimality of the scheduling plan. If all materials from a group of suppliers participate in scheduling, the solution for that group is both unique and optimal. However, if a group of suppliers' materials are insufficient to meet the demand, the optimal solution must be selected from all feasible scheduling plans.

Specifically, for production and scheduling problems with multiple suppliers and consumers, it is assumed that all consumers purchase materials q in a single transaction. Let T_1, T_2, …, T_v represent the number of suppliers, denoted by v, where the supply capacity of supplier T_u is represented by a_u $(0 < u \leq v)$. The number of consumers is denoted as l, represented by F_1, F_2, …, F_l, where the material demand of consumer F_k is represented by A_k.

$$\sum_{o=1}^{j} a_{ok} \geq A_k \tag{1}$$

$$\sum_{u=1}^{v} a_u \geq \sum_{k=1}^{l} A_k \tag{2}$$

The consumers at echelon g are divided into l' groups. The feasible scheduling plan for the k^{th} group is denoted by $\theta^g{}_k$, while the set of all possible plans for the k^{th} group is represented as $\tau^g{}_k$. If the suppliers in the k^{th} group can fully participate in scheduling, there exists only one optimal plan within $\tau^g{}_k$. Otherwise, the optimal plan $\theta^g{}_k$ must be selected from all candidates in $\tau^g{}_k$, satisfying the following equation:

$$\underset{\theta_k^g \in \tau_k^g}{MIN}\begin{cases} S\left(\theta_k^g\right) \\ V\left(\theta_k^g\right) \end{cases} \tag{3}$$

The optimal scheduling plan for echelon g is subsequently defined as:

$$\theta^g = \bigcup_{k=1}^{l'} \theta_k^g \left(l' \le l\right) \tag{4}$$

To achieve simultaneous optimisation of the dual objectives in Eq. (3), two fuzzy objective sets, $D1$ and $D2$, were introduced. Let s represent the longest transportation time among all suppliers in the k^{th} group at echelon g, and v denote the number of suppliers in this group. θ^g_{1k} is an optimal solution in $MIN_{\theta gk \in \tau gk}\, S(\theta^g{}_k)$, satisfying the earliest possible scheduling start time. Similarly, θ^g_{2k} is an optimal solution in $MIN_{\theta gk \in \tau gk}\, S(\theta^g{}_k)$, satisfying the smallest number of suppliers. $\theta^g{}_k$ is a plan in the k^{th} group at echelon g.

$$\omega_{D1}\left(\theta_k^g\right) = \frac{s - S\left(\theta_k^g\right)}{s - S\left(\theta_{1k}^g\right)} \tag{5}$$

$$\omega_{D2}\left(\theta_k^g\right) = \frac{v - V\left(\theta_k^g\right)}{v - V\left(\theta_{2k}^g\right)} \tag{6}$$

The greater the values of $\omega_{D1}(\theta^g{}_k)$ and $\omega_{D2}(\theta^g{}_k)$, the better the plan $\theta^g{}_k$ satisfying Eqs. (5) and (6). This corresponds to minimising $S(\theta^g{}_k)$ and $V(\theta^g{}_k)$. The larger the value of the following equation, the better it is:

$$c = \beta\omega_{D1}\left(\theta_k^g\right) + \left(1-\beta\right)\omega_{D2}\left(\theta_k^g\right) \tag{7}$$

Thus, $\theta^g{}_k$ that maximises c is considered the optimal plan for the k^{th} group at echelon g.

In the production and scheduling process of a multi-echelon supply chain, the proposed scheduling strategy focuses on meeting consumer demand at each echelon of the supply chain while optimising the utilisation of supplier resources through a grouping-based scheduling approach. Specifically, consumer demands are allocated based on supplier priorities and available schedulable resources. Initially, the multi-echelon supplier priority queue for each consumer was established, after which scheduling tasks for all consumers were carried out sequentially from higher to lower echelons. This process involved grouping consumers based on their remaining material demands and scheduling them according to the demand characteristics of each group. Scheduling begins by evaluating whether the total remaining demand within a group, i.e., the remaining demand for materials by consumers, can be met. If the demand cannot be satisfied, all available suppliers are scheduled. Conversely, if the demand can be met, only a subset of suppliers is scheduled to optimise resource allocation and minimise supplier utilisation. During material allocation, if the total remaining demand of a group exceeds the aggregate supply capacity of all schedulable suppliers, all suppliers are included in the schedule. Materials are then distributed proportionally based on the remaining demand rather than prioritising consumer order urgency, ensuring fairness and efficiency in material scheduling. If the remaining demand can be fulfilled, the scheduling plan is further optimised based on transportation time. Transportation time is calculated by considering the distance between suppliers and consumers, which is determined through GIS network analysis to identify the shortest path. This distance is then combined with the chosen transportation method to determine specific transportation time. For supply chain material storage warehouses, in addition to delivery to consumers, materials must also be transported to material distribution centres. The selection of these distribution centres is optimised based on the transportation time between storage warehouses and distribution centres, ensuring efficient allocation of materials to end consumers.

Specifically, consumers at echelon g are divided into ml groups based on whether they can request scheduling from the same storage warehouse. For the k^{th} group, the total remaining material demand of all consumers in the group is denoted as A'_k. If schedulable storage warehouses are time-ordered as S^h_{pj}, $S^h_{(p+1)j}$, ..., $S^h_{(p+d)j}$ ($d \geq 0$), their respective material capacities are represented as a_{ok}, $a_{(o+1)k}$, ..., $a_{(o+f)k}$, with the corresponding supply time ordered as a_{ok}, $a_{(o+1)k}$, ..., $a_{(o+f)k}$, with $a_{ok} < a_{(o+1)k} <...< a_{(o+f)k}$. The average transportation time from storage warehouse $T^g_{(o+m)k}$ to all consumers in the k^{th} group is denoted as $a_{(o+m)k}$. In cases where all storage warehouses do not need to participate in the scheduling for the k^{th} group, the scheduling plan can be expressed as follows:

$$\theta^g_{1k} = \left\{ \left(T^g_{ok}, a_{ok}\right), \left(T^g_{(o+1)k}, a_{(o+1)k}\right), \cdots, \left(T^g_{(o+k)k}, A'_k - \sum_{u=o}^{o+j-1} a_{uk}\right) \right\} \quad (0 < j \leq f) \tag{8}$$

In cases where all storage warehouses are required to participate, the plan is expressed as follows:

$$\theta^g_{1k} = \left\{ \left(T^g_{ok}, a_{ok}\right), \left(T^g_{(o+1)k}, a_{(o+1)k}\right), \cdots, \left(T^g_{(o+f)k}, a_{(o+f)k}\right) \right\} \tag{9}$$

The transportation time from the final storage warehouse in the plan θ^g_{1k} is denoted as $S(\theta^g_{1k})$. The schedulable storage warehouses for the k^{th} group are ordered by material quantity as T^g_{o0k}, T^g_{o1k}, ..., T^g_{ofk}, with corresponding material quantities a_{o0k}, a_{o1k}, ..., a_{ofk}, with $a_{o0k} < a_{o1k} <...< a_{ofk}$. When not all storage warehouses in the k^{th} group are required to participate, the plan is given as follows:

$$\theta^g_{2k} = \left\{ \left(T^g_{o0k}, a_{o1k}\right), \left(T^g_{o1k}, a_{o1k}\right), \cdots, \left(T^g_{ofk}, a_{ofk}\right) \right\} \tag{10}$$

The number of transactions completed in plan θ^g_{2k} is represented as $V(\theta^g_{2k})$.

Based on the structural characteristics of the multi-objective planning model for the multi-echelon supply chain, the production and scheduling steps were designed below. Let $F = \{F_1, F_2, ..., F_l\}$, where the initial value of the remaining demand $surplus_j$ for consumer F_l is represented as A_k. The scheduling steps are as follows:

a) The priorities of suppliers and consumers were determined based on consumer demand levels and supplier production capacities.

b) For each echelon in the supply chain, the discrepancies between the supply capacities of storage warehouses, production units, or distributors and the remaining consumer demands were analysed. Let $u = 0$ and $k = 0$.

c) An optimisation function was invoked based on the state of each storage warehouse. Through a multi-objective optimisation algorithm, the optimal allocation scheme of suppliers was determined. Each supplier's supply was proportionally allocated based on demand, considering factors such as transportation distance, inventory cost, and production cost. The optimal combination of suppliers and consumers was calculated. All remaining consumers in F were grouped by their schedulable storage warehouses at echelon u, with those sharing the same storage warehouse forming a group. A total of l groups was created.

d) Based on the optimal supplier allocation plan, materials of each supplier were transported to meet consumer demands. Priority was given to transporting materials to the nearest consumers to minimise transportation costs. During the transportation process, the remaining demands of each consumer were fulfilled as much as possible. If certain consumer demands remain unmet after the first allocation round, subsequent supplier allocations can be carried out until all demands are satisfied or resources are exhausted. For the k^{th} group at echelon u, the total supply of schedulable materials from storage warehouses is represented as SUM, and the total remaining demand of all consumers in the group is denoted as ZL. The function $solveplan$ was invoked to determine the optimal supplier allocation plan, enabling all supplier materials to be transported to the respective distributors. All consumers in the k^{th} group were removed from F.

e) Throughout the production and scheduling process, the real-time operational status of each echelon in the supply chain was monitored. Adjustments to the supply plan and scheduling strategies were dynamically made to account for changes in market demand, production capacity fluctuations, and uncertainties in the transportation process. Whenever new demand variations or production capacity adjustments occur, the optimisation algorithm can be re-executed to reallocate resources, ensuring the efficient operation of the supply chain.

3. DISCRETE EVENT SIMULATION IN SUPPLY CHAIN PRODUCTION

The virtual simulation modelling of discrete events in multi-echelon supply chain production and scheduling was designed to accurately simulate the interactions and dynamic changes between echelons, thereby providing decision support for production and scheduling. Constructing a virtual scenario for a multi-echelon supply chain requires an in-depth understanding of the structural characteristics of its various tiers, such as raw material supply, manufacturing, warehousing, and logistics. Each echelon involves different resources, facilities, and operational processes. In this environment, discrete events are often triggered by factors such as equipment, processes, or personnel at different echelons and subsequently influence downstream production scheduling. Consequently, the virtual simulation model must precisely reflect the movement and state transitions of these resources and equipment while also capturing the mechanisms by which discrete events are triggered and propagated. To manage the complexity of these hierarchical structures effectively, a three-tiered virtual scenario tree structure was adopted. This structure organises and manages the various stages of the multi-echelon supply chain, such as suppliers, factories, warehouses, and transportation vehicles, through a nested parent-child node architecture. Fig. 1 illustrates the directed graph structure of multi-echelon supply chain production and scheduling relationships.

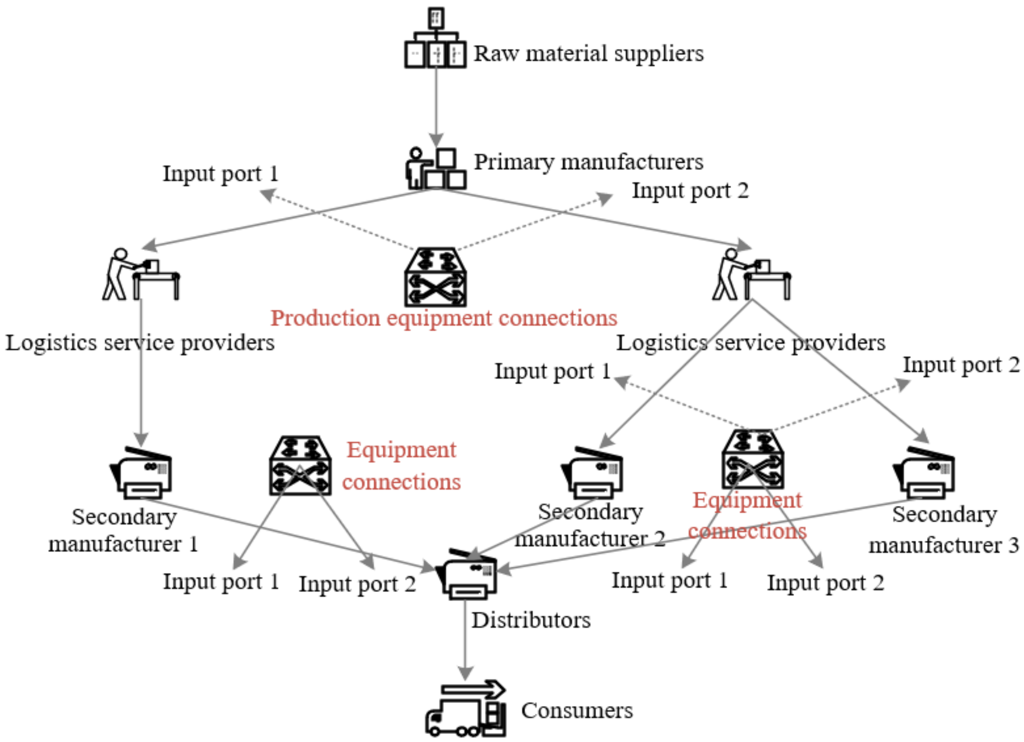

Figure 1: Directed graph structure of multi-echelon supply chain production and scheduling relationships.

The hierarchical structure of the scenario tree enables each node to independently control its movement and state transitions, thereby facilitating precise simulation of inter-echelons interactions. For example, consider a point in space undergoing translation. Let the translational distances of a geometric figure along the *a*-axis, *b*-axis, and *c*-axis be denoted by S_a, S_y, and S_c, respectively. The translation matrix *v* is expressed as follows:

$$\lambda = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ S_a & S_b & S_c & 1 \end{bmatrix} \tag{11}$$

Additionally, a fixed rotation angle σ about the *a*-axis was applied. The corresponding rotation matrix *E* is represented as follows:

$$E = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & COS\sigma & SIN\sigma & 0 \\ 0 & -SIN\sigma & COS\sigma & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} \tag{12}$$

Finally, a scaling coefficient η was assigned to each axis to generate the following transformation matrix *W*:

$$W = \begin{bmatrix} \eta_a & 0 & 0 & 0 \\ 0 & \eta_b & 0 & 0 \\ 0 & 0 & \eta_c & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

Supply chains frequently experience various unexpected events, such as the completion of part processing, equipment failures, or transportation delays. The occurrence of these events is often unpredictable and has profound implications for subsequent production scheduling. Traditional simulation methods based on fixed clocks are insufficient for handling such irregular discrete events. In a multi-echelon supply chain system, discrete events can occur independently at different nodes and are often interconnected, influencing the flow and operations of the entire supply chain. To accurately simulate sporadic and irregularly occurring events during production and scheduling processes, a discrete event simulation clock advancing mechanism was established in this study. This mechanism incorporates three distinct types of clock systems, each with specific functions and tasks, ensuring that the simulation process accurately reflects the temporal sequence of events while effectively managing state transitions within the system.

The global simulation clock serves as the primary clock controlling the entire simulation process, responsible for synchronising and advancing all discrete events. At a certain simulation timestep, the global clock checks all events within the system and determines which event needs to be processed next. Local discrete event simulation clock primarily handles unpredictable and sudden events, such as machine failures or changes in orders. When such events occur, the local clock is triggered, prompting the system to adjust and respond accordingly. This mechanism ensures that the system captures event timing with precision and processes them swiftly. Local continuous system simulation clock is dedicated to modelling continuous activities within the supply chain, such as the operation of machinery or the ongoing transportation of materials. Although these activities are continuous, their precise tracking in the simulation process requires a dedicated local clock. The collaboration of these three clocks enables the simulation of both discrete and continuous events within multi-echelon supply chains. This approach enhances the flexibility and realism of the simulation system, allowing the complex processes of production and scheduling in supply chains to be accurately reproduced. In this simulation framework, the occurrence time of events is denoted as s'. Variables Z, F, and D represent logistics vehicles, resource objects, and event types, respectively. The initial state of an event is represented as Y, and its expected state as α_0. The set of continuous events to be processed within the target time period is denoted as R. Each event r to be processed is represented as follows:

$$r = (s', Z, F, D, \alpha_0, \alpha), r \in R \tag{14}$$

Let event identifiers be represented by p, and simulation time by ω. The relationship between the discrete event simulation time and the event occurrence time in a multi-echelon supply chain system can be characterised as follows:

$$rs' \leq \omega \leq r_{p+1}s' \tag{15}$$

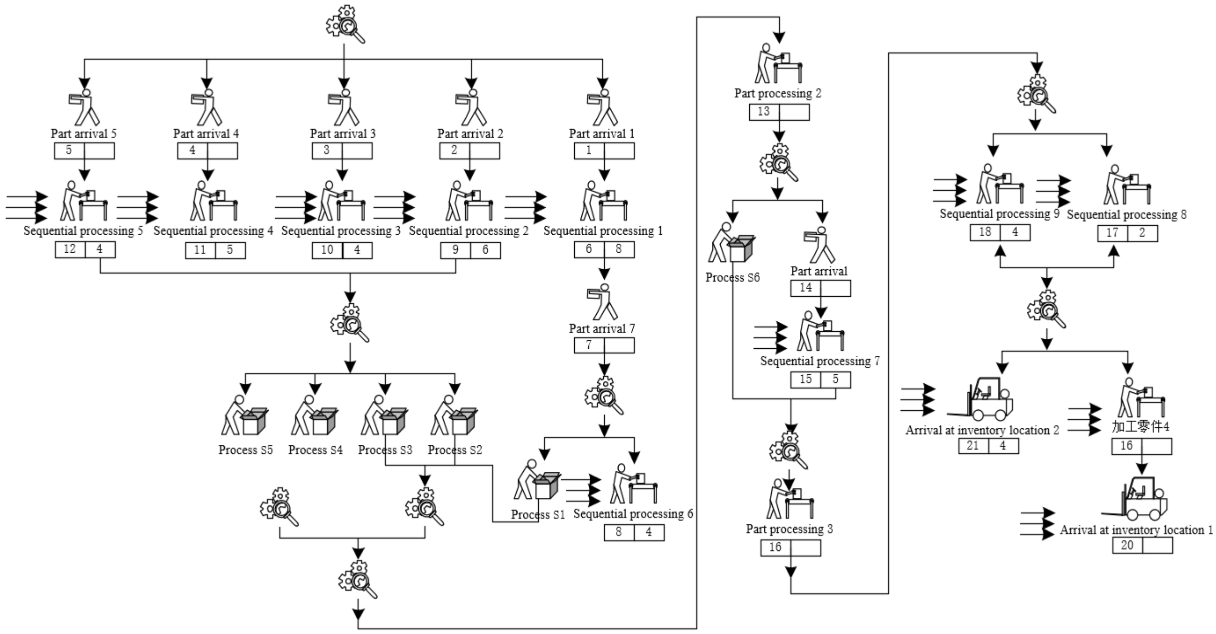

Figure 2: Discrete event simulation behaviour units for production and scheduling in multi-echelon supply chains.

In multi-echelon supply chains, the production and scheduling processes often involve a large number of operational units and multiple interaction stages, each associated with specific events and state transitions. To address this complexity, a virtual simulation model for production and scheduling processes in multi-echelon supply chains was constructed using the IDEF3 process modelling method. This approach simplifies complex sequential operations and accurately simulates the occurrence and handling of discrete events. Fig. 2 illustrates the discrete event simulation behaviour units. The use of IDEF3 enables the sequential operational logic between various stages to be effectively captured and expressed. This method employs finite automata diagrams to visually represent the temporal sequence and causal relationships of discrete events. Specifically, by modelling the processing procedures and defining state transition rules for each discrete event, the operational sequence, resource scheduling, and interdependencies within production stages can be depicted in detail. Let the set of discrete states be denoted as Ξ, the event set as I, and the discrete state transition mapping function as μ. The initial state is represented by w_0. The computation of the finite automata diagram H is given as follows:

$$H = (\Xi, I, \mu, w_0) \tag{16}$$

Assume the state nodes of three discrete events are represented by O, G, and K. The events associated with supply chain participant O are denoted as γ_1, γ_2, and γ_3. For node G, the corresponding events are represented by π_1, π_2, and π_3. For node K, the associated events are denoted as n_1, n_2, and n_3.

$$\Xi = \{O, G, K\} \tag{17}$$

$$I = \{\gamma_1, \gamma_2, \gamma_3, \pi_1, \pi_2, \pi_3, n_1, n_2, n_3\} \tag{18}$$

$$w_0 = O \tag{19}$$

4. EXPERIMENTAL RESULTS AND ANALYSIS

The research background of this study involves a typical multi-echelon supply chain system with multiple suppliers and consumers. Table I provides a detailed overview of the production demands of different consumers. Consumers F_1 and F_2 have a demand of 122,152 and 7,748 units, respectively. Table II presents the material inventory information of the suppliers and warehouses. Each supplier (T_1 to T_9) has varying quantities of material in stock, with the types and quantities of these materials being crucial for the raw material requirements in the production process. As shown in Table I, the relationship between the demand quantities from consumers and the material inventory levels of suppliers determines the priority for production and scheduling. As shown in Table II, given the varying stock levels across suppliers T_1 to T_9, material shortages may occur, indicating a need for efficient management of material procurement, production planning, and inventory replenishment.

Table I: Production demand list for the multi-echelon supply chain.

Consumer	F_1	F_2
Demand	122152	7748

Table II: Information on materials stored in the suppliers' material storage warehouses.

Supplier	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
Material quantity	601	612	623	41256	31254	25621	21452	55121	23514

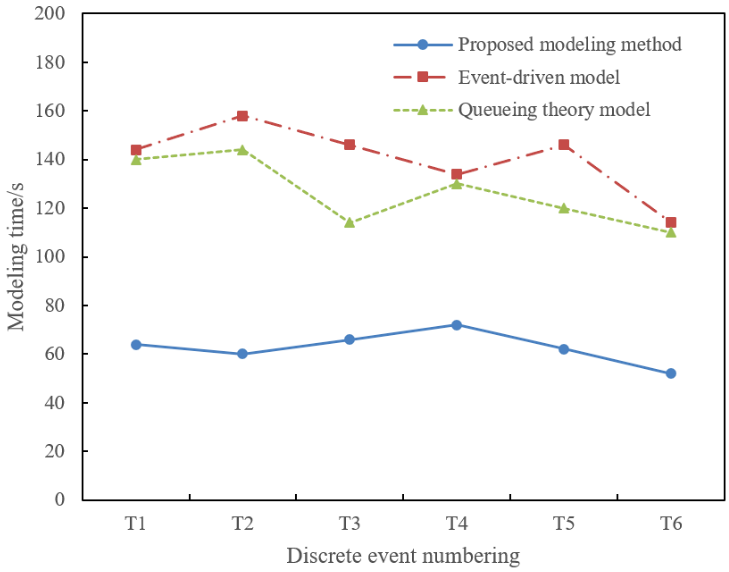

Figure 3: Virtual simulation modelling time for different methods.

Based on the data presented in Fig. 3, differences in virtual simulation modelling time are observed between the event-driven model, the queueing theory model, and the multi-objective planning model proposed in this study. In the case of various suppliers, the event-driven model generally exhibits higher simulation modelling time. For instance, the simulation modelling time for T_1 to T_6 is 144, 158, 146, 134, 146, and 114 time units, respectively. In comparison, the queueing theory model shows relatively lower simulation time, with data points of 140, 144, 114, 130, 120, and 110 time units. The multi-objective planning model proposed in this study has comparatively shorter simulation time, with the modelling time for T_1 to T_6 recorded as 64, 60, 66, 72, 62, and 52 time units, respectively. These results demonstrate a clear advantage in simulation modelling time for the coordination strategy based on discrete event simulation technology proposed in this study. From the experimental findings, it is evident that the multi-objective planning model not only excels in optimising production plans and scheduling but also offers significant advantages in terms of virtual simulation modelling efficiency. Compared with the traditional event-driven model and the queueing theory model, the method proposed in this study greatly reduces simulation time and enhances efficiency, which holds substantial significance for practical supply chain management and decision-making.

Table III: Supplier priority queue.

Priority level	0	1	2	3
F_1	T_1	T_2	T_3	T_5, T_6, T_7, T_8, T_9
F_2	T_2	T_3	T_4	T_5, T_6, T_7, T_8, T_9

Table IV: Distance/time from material storage warehouses to consumers in the multi-echelon supply chain.

Supplier	T_5	T_6	T_7	T_8	T_9
F_1	815/12.9	1158/19.3	1789/31.2	2456/42.3	1789/32.1
F_2	925/16.3	1247/21.5	2145/32.8	2689/42.6	2148/32.6
Average time	13.52	18.9	31.24	41.3	31.46

According to the supplier priority queue shown in Table III, F_1 and F_2 were assigned to different priority levels for material scheduling. The demand for F_1 and F_2 is 122,152 and 7,748 units, respectively (Table I). These demands need to be met by scheduling materials from multiple suppliers. During the experimental process, scheduling was performed in the order of the priority queue. Initially, in the level 0 scheduling phase, 600 units of material were scheduled for F_1 and F_2 from suppliers T_1 and T_2, respectively. At this point, the remaining demand for F_1 was 135,640 units, and for F_2, it was 8,426 units. This process demonstrated how material allocation was performed based on supplier priorities, ensuring that demand is met on time. As scheduling progresses, the demand for F_1 and F_2 decreased at each level, reflecting the dynamic distribution of materials within the supply chain. Then during the level 1 scheduling phase, supplier T_3 allocated 687 and 44 units of material to F_1 and F_2, respectively, leaving remaining demands of 126,857 and 7,362 units. In the level 2 scheduling phase, supplier T_4 allocated 348,852 and 2,149 units of material to F_1 and F_2, respectively, reducing their remaining demand to 82,654 and 4,113 units. This process illustrated how material allocation was fulfilled through hierarchical scheduling across suppliers, reflecting the coordination and resource allocation efficiency within the supply chain. In practical applications, such a scheduling strategy effectively optimises production plans by reducing inventory pressure, improving production efficiency, and shortening delivery cycles through rational priority-based scheduling.

According to the experimental results shown in Table IV, during the level 3 scheduling phase, the remaining demand for F_1 and F_2 was 86,245 units. At this stage, the number of suppliers involved was no less than one, and the total supply from suppliers exceeded the remaining demand, meaning not all suppliers need to participate in the scheduling. In order to optimise the transportation process, a global shortest path algorithm was employed to determine the shortest distances and transportation time from F_1 and F_2 to each supplier, thereby selecting the most appropriate suppliers for scheduling. Table IV presents the distances and transportation time between different suppliers and consumers within the multi-echelon supply chain, specifically listing the transportation time from F_1 and F_2 to each supplier (such as T_5, T_6, T_7, T_8, and T_9). For example, the transportation time from F_1 to T_5 is 12.9 time units, and from F_2 to T_5, it is 16.3 time units, with average transportation time of 13.52 and 18.9 time units for F_1 and F_2, respectively. The main objective of this step is to reduce transportation time and costs by rationally selecting suppliers, thus enhancing the operational efficiency of the supply chain.

Table V: List of material storage warehouse combination plans for the multi-echelon supply chain.

Material storage warehouse combination plan	Number of suppliers	Emergency start time	*c* value
[(T_5, 31214) (T_7, 829) (T_8, 54123)]	3	41.5	0.5
[(T_5, 30112) (T_6, 24156) (T_7, 7798) (T_9, 22154)]	4	31.5	0.74
Stop	0	0	0

Table VI: Production planning and scheduling plans for the multi-echelon supply chain.

Supplier	Logistics destination	Material quantity	Supplier	Logistics destination	Material quantity
T_1	F_1	612	T_4	F_2	2154
T_2	F_2	624	T_5	N	31256
T_3	F_1	558	T_6	N	24561
T_4	F_2	34	T_7	N	7789
T_5	F_1	36256	T_9	N	22356

Based on the experimental results shown in Tables V and VI, different material storage warehouse combination plans were proposed under the dual objectives of minimizing the emergency start time and the number of suppliers. The study also conducted optimisation and selection based on these objectives. Specifically, the plan with the earliest emergency start time includes combinations of materials from multiple suppliers to various material storage warehouses. One such plan is [(T_5, 30112) (T_6, 24156) (T_7, 7798) (T_9, 22154)], which results in an earliest emergency start time of 31.5 hours. The core advantage of this plan lies in its ability to meet emergency demands in the multi-echelon supply chain within the shortest time, thus minimizing production downtime or delivery delays caused by time delays. On the other hand, the plan with the fewest suppliers as the objective selected the material storage warehouse combination [(T_5, 31214) (T_7, 829) (T_8, 54123)], involving a total of three suppliers. The optimisation focus of this plan is on reducing the number of suppliers, thereby simplifying supply chain management, lowering coordination complexity, and reducing communication and logistics costs associated with multiple suppliers. By balancing and selecting between the two optimisation objectives (with a *c* value of 0.5), the optimal plan (the second plan based on the *c* value) achieved a balance between the emergency start time and the number of suppliers. This ultimately resulted in the optimal production scheduling and material distribution plan, as shown in Table VI.

Through the application of the above optimisation strategies, the experiment demonstrated that a rational trade-off between emergency start time and the number of suppliers in multi-echelon supply chains can significantly enhance the overall response efficiency of the system. The optimised plan not only ensures the earliest emergency response time but also simplifies supply chain management by reducing the number of suppliers. This approach lowers management costs and reduces resource wastage. In practical applications, such optimisation methods can provide decision support for supply chain managers, enabling a quick response to sudden demands and ensuring that delivery deadlines are met while reducing supply chain complexity. Furthermore, the use of discrete event simulation technology allows this optimisation process to be precisely simulated in dynamic and volatile supply chain environments, providing strong tools and theoretical support for improving system performance.

5. CONCLUSION

This study addresses the production planning and scheduling problem in multi-echelon supply chains by proposing a coordination strategy based on discrete event simulation technology. The aim is to achieve efficient supply chain management and optimisation through the integration of the multi-objective planning model and the simulation technique. By balancing multiple objectives, such as production efficiency, inventory costs, and delivery time, the proposed multi-objective planning model provides a comprehensive solution for production and scheduling in supply chains. The second part of the study employed discrete event simulation modelling to simulate the dynamic process of multi-echelon supply chains, analysing system performance under different production scheduling strategies and offering scientific decision support. The experimental results indicate that the coordination strategy based on discrete event simulation technology offers significant advantages, particularly in terms of simulation time. Compared to the traditional event-driven model and the queuing model, the proposed method can notably reduce simulation time and improve computational efficiency. Furthermore, the design of optimised supplier priority queues, material storage warehouse combinations, and production planning and scheduling plans effectively enhanced supply chain operational efficiency and responsiveness, providing strong support for decision-making in real production scheduling.

Although the coordination strategy based on discrete event simulation technology shows promising application prospects in multi-echelon supply chain production scheduling, certain limitations remain. First, the multi-objective planning model may encounter computational resource and time constraints when dealing with extremely complex supply chain networks. As the scale of the supply chain expands, additional optimisation algorithms may be required to enhance the model's capacity. Secondly, the simulation model used in the experiments is primarily based on theoretical derivations and assumptions, lacking a deep integration with real enterprise data. Future research could focus on validating the model's practicality and accuracy through closer alignment with actual supply chain systems.

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