

Towards a trusted synchronized decision-making method for social production logistics systems based on blockchain and digital twin

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ABSTRACT

With the growth of personalized demands, manufacturers need to dynamically collaborate with external resources, forming social production logistics systems (SPLS). The complexity and dynamic nature of these systems increase management difficulty, rendering traditional static decision-making methods unsuitable. This study proposes a reliable dynamic collaborative control method for SPLS in discrete manufacturing environments. It aims to provide a secure and controllable collaborative platform for multiple participants, enhancing the system's resilience to disturbances in dynamic environments. A blockchain and digital twin-based trusted synchronized decision-making framework is designed, enabling real-time and reliable acquisition of comprehensive information to support efficient decision-making. Simultaneously, a blockchain smart contract tree-based trusted synchronized decision-making mechanism is proposed to address dynamic disturbances. Utilizing a collaborative optimization algorithm, the "production-distribution-warehousing" collaborative decision model is optimally coordinated to achieve efficient resource allocation and process management. Using the home appliance manufacturing industry chain as a case study, results show that the proposed trusted synchronized control method outperforms the non-trusted synchronized control method, resulting in a 35.3 % reduction in total system costs and an enhancement in the collaborative operational efficiency of the production logistics system, and ensures reliable and efficient system operation in a dynamic demand environment. This research provides valuable references for the operational management of future production logistics systems.

1. Introduction

In the move towards the Industrial 4.0 era, customer demands for products have become increasingly diverse, personalized, and dynamic. Consequently, manufacturers' production systems must exhibit high variability and adaptability to meet these demands [1]. However, continual investments in these manufacturing capabilities impose heavy burdens, potentially hindering the development of core businesses [2]. As a result, manufacturers increasingly turn to outsourcing, crowdsourcing, and close cooperation with external resources to reduce operational costs and swiftly respond to market changes. This shift has fueled the development of social manufacturing (SocialM) mode. In this

mode, manufacturers, logistics providers, and public warehouse operators form social production logistics systems (SPLS) through contractual relationships and production sequencing [3].

Nonetheless, the resource nodes in the SPLS may be unfamiliar with each other, and the lack of trust among multiple decision-makers hampers credible and effective collaboration to achieve set optimization goals. Additionally, the execution of production logistics often faces dynamic disturbances, such as new demand additions, further reducing overall system efficiency. To ensure efficient synchronization between production and logistics subsystems, it is crucial to achieve high coordination in resource allocation, operational planning, and control methods to mitigate the impact of dynamic disturbances and enhance

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the system's resistance to interference and adaptability.

Despite some research beginning to explore the coordinated operation of production and logistics within enterprises, with initial recognition of its potential benefits in certain industrial manufacturing scenarios [4,5,6], studies on the coordinated decision-making theory and applications for social production logistics systems composed of different enterprise nodes remain scarce. Therefore, achieving reliable coordination among multiple subsystems in a dynamic social manufacturing environment to ensure stable system operation is a primary challenge currently faced by SPLS. Specific questions include:

- Traditional optimization methods often focus on local optimization of a single phase (e.g., production) or adopt centralized decision-making approaches (e.g., All-in-one), neglecting the autonomy and privacy of decision-makers. How can we design a global distributed optimization scheduling method that considers the decision-making rights and privacy of each decision-maker to achieve optimal time and quantity coordination in the production logistics system?
- In the face of frequent dynamic disturbances, how can we design a dynamic coordination control mechanism for multiple subsystems that triggers high-precision synchronization response strategies to reduce or eliminate the impact of dynamic disturbances and ensure optimal system operation?
- In an open social manufacturing environment, how can we credibly collect and utilize multi-source real-time data for dynamic simulation optimization, promote trusted data transmission and sharing among decision-making subsystems, and enhance the reliability and operational efficiency of decisions?

To overcome the aforementioned challenges, this study focuses on the coordinated operation of multi-enterprise nodes and multi-tier social production logistics systems within dynamic operational environments. From the perspectives of information, control, and operations research dimensions of systems engineering, systematic solutions are proposed. Firstly, from the information dimension, a blockchain and digital twin-based multi-scale trusted synchronized decision-making framework for SPLS is proposed. This framework aims to comprehensively and reliably acquire real-time data from SPLS and perform dynamic simulation optimization of instructions. Secondly, from the control dimension, a blockchain smart contract tree-based trusted synchronized control mechanism is proposed to effectively reduce the impact of dynamic disturbances. Finally, from the operations research dimension, a collaborative optimization algorithm for two-level multi-subsystem iterative distributed optimization is proposed to enhance the optimization of SPLS.

To verify the effectiveness and applicability of the proposed methods, this study investigates the trusted synchronized operation of SPLS consisting of multiple socialized assembly nodes, one distribution node, and one warehouse node. The SPLS primarily includes three stages: production, distribution, and warehousing, each with independent decision-making objectives and information privacy protection requirements, while the objectives of each stage influence each other. Based on the optimization characteristics of SPLS, a mathematical model of SPLS is constructed using a collaborative optimization (CO) algorithm. Numerical case simulations compare the proposed trusted synchronized control (TSC) method with the existing control (non-trusted synchronized control, NTSC) method, demonstrating the effectiveness of the proposed method. Finally, this study analyzes the impact of different numbers of new demand additions on the social production logistics systems and provides valuable management insights.

The rest of this paper is organized as follows. Section 2 introduces related work. Section 3 describes the operational problems and challenges. Section 4 presents the proposed methodology, including the trusted synchronized decision framework for SPLS based on blockchain and digital twin, the trusted synchronized decision mechanism for SPLS based on blockchain smart contract tree, and the coordinated

optimization algorithm for the "production-distribution-storage" collaboration optimization model. Section 5 presents an industrial case study. Section 6 concludes our work.

2. Related work

2.1. Synchronized operation and control of production logistics system

In modern production logistics systems, synchronized decision-making and control have become increasingly important, encompassing the entire process from raw material procurement to product delivery. Various production stages, such as procurement planning, production scheduling, distribution planning, and inventory management, need to work in coordination to enhance system efficiency and response speed through optimized decision-making [7]. Existing research underscores the critical role of synchronized decision-making in production logistics systems. For instance, Luo et al. [8] developed a metaheuristic algorithm to optimize scheduling between factories and warehouses, thereby improving operational efficiency and response speed. Guo et al. [9] proposed an equivalent constraint programming model to address the synchronization of workshop logistics and manufacturing decisions, demonstrating its superior key performance indicators. Li et al. [10] developed a five-stage intelligent manufacturing system that achieved flexible synchronization of production-intralogsitics. Qu et al. [11] from the author's team employed a collaborative optimization method to tackle the production and warehousing optimization problem in paint manufacturing enterprises. Zhang et al. [12] used an analytical target cascading method to optimize the production-transportation-storage process in multi-tier hierarchical structures. Lin et al. [13] studied the "transportation-storage" synchronized decision-making for distribution centers in industrial parks, validating the effectiveness of the collaborative optimization algorithm. Pan et al. [14] investigated the synchronized decision-making of batch workshops and planar warehouses, verifying the feasibility of the collaborative optimization method. Furthermore, Pan et al. [15] explored the synchronized decision-making in a production logistics system comprising multiple workshops, packaging workshops, and warehouses, constructing a mathematical model through goal cascading and validating the method's effectiveness through numerical experiments. Zhang et al. [3] examined the synchronized decision-making of multi-enterprise production logistics in a social manufacturing environment, developing a blockchain-based trusted synchronization service platform, which was validated through industrial case studies. These studies demonstrate that synchronized decision-making and control significantly enhance system efficiency and response speed.

2.2. Multidisciplinary design optimization methods

Multidisciplinary design optimization (MDO) is an advanced optimization technique developed for the design of complex engineering systems. Unlike traditional design methods, MDO achieves global system performance optimization by analyzing the interactions and coupling effects between subsystems [16]. MDO theory decomposes problems, optimizes each subsystem individually, and resolves coupling issues through a coordination mechanism at the system level, ensuring overall design coherence [17,18]. Common MDO methods include collaborative subspace optimization (CSSO), analytical target cascading (ATC) [19], collaborative optimization (CO) [20], and the augmented Lagrangian coordination (ALC) method [21]. These methods use various strategies and techniques to handle and coordinate the interactive effects between multiple subsystems, optimizing the performance of the entire system. MDO is widely applied in the design and optimization of various complex engineering systems, such as aircraft system configuration [22] and vehicle equipment structural design [23].

In recent years, MDO methods have gradually been applied to

various optimization decision-making problems in the manufacturing field. For example, Qu et al. [24] used a hybrid augmented Lagrangian coordination method to optimize the configuration of the industrial cluster assembly supply chain; Wang et al. [25] applied the ALC method to optimize manufacturing resource allocation in shared manufacturing. Zhang et al. [26] researched a data-driven model based on ATC to achieve self-organizing configuration of workshop production logistics. Chen et al. [27] studied a distributed no-idle permutation flow shop scheduling problem based on CO, aiming to minimize completion time and total energy consumption. Zhou et al. [28] applied the CO method to the synchronized scheduling of logistics and processing services in cloud manufacturing, verifying its effectiveness. These studies showcase the practical applications and potential of MDO methods across various fields.

2.3. Blockchain and digital twin in manufacturing

Blockchain (BC), a distributed trusted database technology, ensures the security and immutability of transaction information through linked data blocks, supporting decentralized data interaction, enhancing data transparency, and traceability [29]. Digital twin (DT) creates virtual replicas of physical entities that reflect their status and performance in real-time, predicting maintenance needs, optimizing operations, and improving decision-making efficiency [30]. In manufacturing, digital twin technology is used for equipment management, production optimization, and product lifecycle management, enhancing asset management efficiency and production quality [31]. Blockchain is primarily used in manufacturing for supply chain management, product traceability, and quality control, ensuring the authenticity of information, reducing fraud, and lowering operational costs [32]. In the context of Industry 4.0, blockchain and digital twins, as key technologies, drive the automation and intelligence of industrial processes. Recently, scholars have explored the combined application of these technologies in smart manufacturing. To address the high costs of physical commissioning in manufacturing systems, Leng et al. proposed a digital twin-based remote semi-physical commissioning (DT-RSPC) method designed for open-architecture process-oriented intelligent manufacturing systems [33]. Tao et al. [34] proposed a DT-BC enhanced manufacturing service collaboration mechanism to address the insufficient interaction and trust issues between physical and cyber spaces on industrial internet platforms. Feng et al. [35] studied a self-healing scheme combining digital twins and blockchain to ensure the security of industrial IoT.

Liu et al. [36] proposed a blockchain-based peer-to-peer data interaction method to solve bandwidth competition and latency issues caused by large-scale digital twin system access to enterprise clouds. Jiang [37] et al. developed a blockchain-based digital twin collaboration platform to solve the information sharing challenges among interdisciplinary stakeholders, used for modular integrated construction operations. Li et al. [38] proposed a blockchain-based fine-grained digital twin sharing framework to address the digital challenges of socialized manufacturing resources, accelerating the adoption and iteration of digital twins in social manufacturing. Leng et al. [39] proposed a blockchain smart contract pyramid-driven multi-agent autonomous process control (BSCP-MAAPC) method aimed at Industry 5.0. This approach addresses the issues of low decision-making stability and efficiency associated with traditional centralized production control methods, particularly under frequent disruptions. It enhances the timeliness and adaptability of control, enabling resilient and personalized manufacturing. Further, he researched autonomous decision-making in manufacturing systems under dynamic disturbances, introducing a blockchain smart contract system as the digital twin for decentralized autonomous manufacturing systems, achieving resilience for Industry 5.0 [40].

2.4. Literature summary

Analysis of related studies reveals that current literature on

coordinated operation and control of production logistics system mainly focuses on local optimization and static integration optimization across multiple stages. However, research on coordinated decision-making for multi-level complex production logistics systems in highly dynamic and open manufacturing environments remains insufficient. In the application and research of MDO methods in large system optimization, efforts mainly remain at the stage of static design optimization of collaborative structures and parameters, with few studies dynamically modeling and controlling the operation process of large interconnected systems using MDO methods. Regarding control technologies for production logistics systems, past studies have primarily focused on applying IoT, digital twin, and blockchain technologies to accurately image and simulate specific objects and stages. However, research on virtual modeling of extensive and complex production logistics systems composed of cross-enterprise/units and providing comprehensive, trusted coordination and synchronized control frameworks for distributed independent decision subsystems/units is relatively lacking.

With the continuous advancement of industrial Internet technologies, particularly the development of blockchain and digital twin, innovative solutions have emerged for dynamic production logistics systems in social manufacturing environments. Blockchain is renowned for its unique data transparency and immutability, which significantly enhance trust among various participants. Concurrently, digital twin facilitates real-time information synchronization between the physical world and virtual models, promoting effective information sharing and supporting more precise and efficient decision-making processes. The integration of these two cutting-edge technologies opens new pathways to address the challenges faced by dynamic production logistics systems in social manufacturing environments, particularly demonstrating substantial potential in establishing trusted collaborative decision-making methods.

3. Problem description

3.1. Operational process analysis of SPLS

The paper analyzes a real case study of a cooperative project within the home appliance manufacturing industry chain to explore social production logistics systems (SPLS) driven by resource sharing in a social manufacturing environment (see Fig. 1). The system represents a specific form of a widely production logistics system, emphasizing social collaboration and resource sharing. The case illustrates how manufacturers, logistics companies, and warehousing service providers integrate social production logistics resources based on industrial internet technologies, such as blockchain and digital twin, as well as contractual relationships and production logistics sequences, thereby forming an efficient distributed production logistics network. The case not only reflects the complexities encountered in practical operations but also provides valuable empirical evidence to validate the proposed theoretical method: a trusted synchronized decision-making method based on blockchain and digital twin. By analyzing the case, we aim to demonstrate how the method effectively addresses dynamic disruptions (e.g., dynamic customer demands) and enhances the collaborative efficiency and reliability of the entire system. The SPLS primarily comprises three key stages: production, distribution, and warehousing, which include one or more independent or socialized assembly factories, distribution fleets, and finished goods warehouses.

The production stage employs a typical discrete manufacturing approach, driving the entire process through diversified, small-batch production rhythms. To meet different customers' personalized order requirements, factory assembly lines must promptly switch between different product types, achieving mixed-flow production. During the distribution stage, vehicles adopt a Milk-run cycle pick-up strategy, enhancing loading efficiency and transportation response speed through small-batch, high-frequency transportation. As the products produced by various assembly factories are similar, the Milk-run mode is

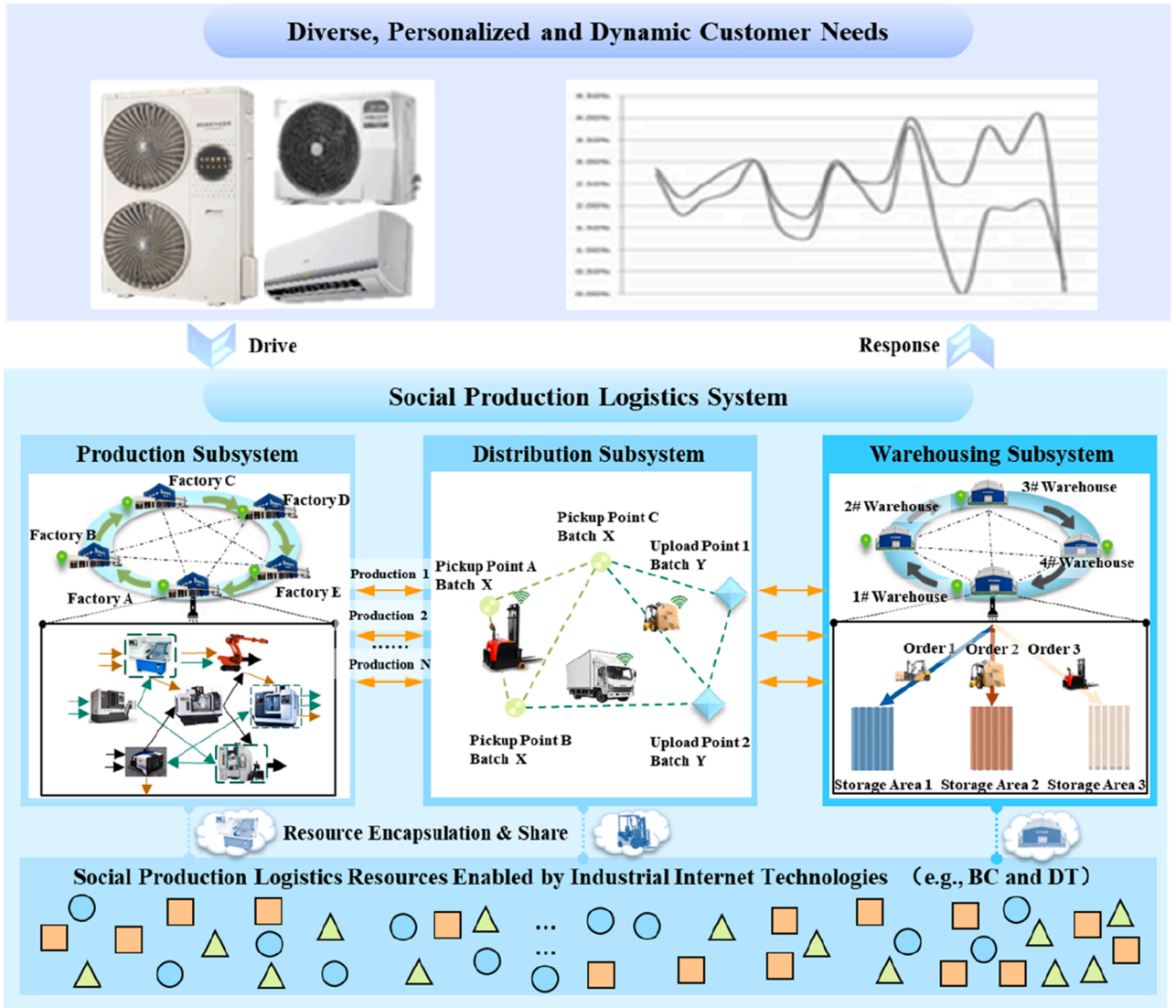


Fig. 1. SPLS driven by personalized demand in Social Manufacturing.

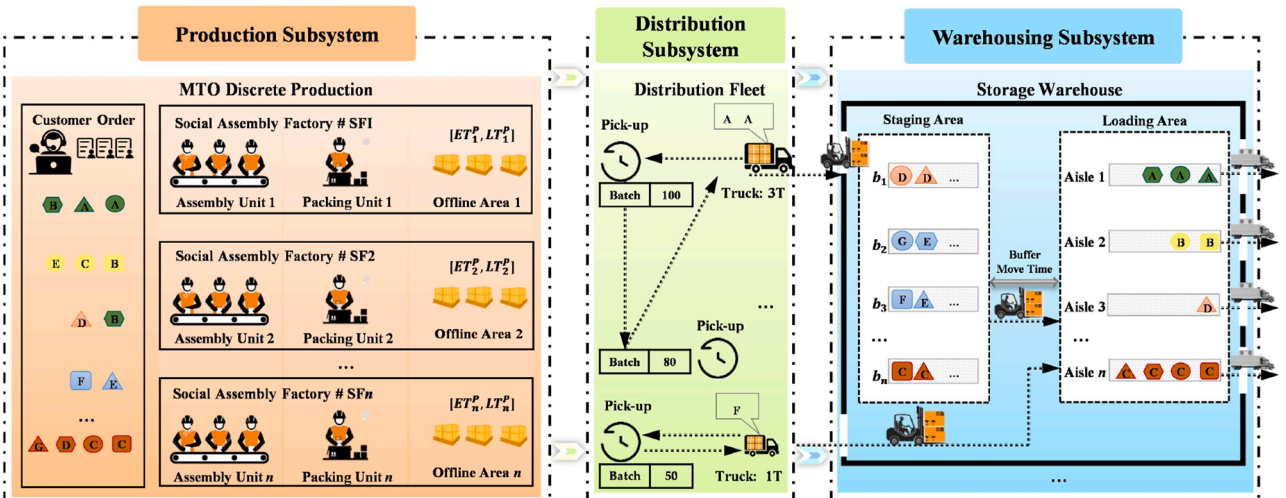


Fig. 2. The operational process for SPLS.

effectively applied in this environment, gradually becoming the primary choice for finished goods logistics in assembly enterprises. Due to land resource constraints in the warehousing stage, warehouse space expansion is limited. To accelerate product circulation and save storage space, a "cross-docking" strategy is implemented, minimizing the handling and storage time of products in the warehouse, and quickly moving products from the receiving point to the shipping point.

The operational process of social production logistics systems for discrete manufacturing is depicted in Fig. 2. It is mainly divided into the planning stage and the execution stage.

- (1) Planning stage. Upon receiving customer demands through the blockchain resource platform, the core manufacturer uses the enterprise resource planning (ERP) system to analyze production capacity, materials, working hours, and costs to confirm the demand. The manufacturer then creates customer orders containing customer information and order details and converts them into production orders through the ERP system, which are then sent to multiple finished goods assembly factories and logistics management nodes. The finished goods assembly factories formulate production plans based on the demand and equipment status and send the relevant information to the finished goods logistics management nodes. The finished goods distribution fleet formulates pick-up plans based on the production plans and resource conditions, while the finished goods warehouse allocates storage locations according to the pick-up plans and storage rules to ensure timely storage and shipping. Due to the discrete production and small-batch order characteristics of the air-conditioning manufacturing industry, manufacturers typically consolidate similar orders into a single production order and produce them in multiple batches to reduce switching times, improve production efficiency, and meet the diverse market demands.
- (2) Execution stage. On the execution plan day, the finished goods assembly factories prepare the required semi-finished products, outsourced components, and purchased parts from various supporting factories. Based on the start time, sequence, and equipment of the assembly production plan, they execute assembly production orders for different product types and quantities, temporarily storing the completed products in a buffer area, awaiting transportation to the warehouse. The finished goods distribution fleet transports the pallets of finished products from the buffer areas of each assembly factory to the finished goods storage warehouse according to the distribution plan's time, pick-up quantity, and travel route. The finished goods storage warehouse stores the pallets in designated locations according to the warehousing plan's entry time, sequence, and storage location. The warehouse department manages the storage and loading of finished products according to customer orders. For efficiency, products from the same order are stored in adjacent locations. If customer order products are in the staging area, they are only transferred to the loading zone when all products are complete, and there is available space in the loading area. Once products meet order requirements and the shipping time arrives, forklift drivers load the pallets onto third-party distribution trucks for delivery.

3.2. The operational problems and challenges analysis for SPLS

In SPLS, the stages of final assembly, distribution, and warehousing are typically managed independently by different decision-makers. This independence often results in inconsistent goals and resource constraints, transforming the decision-making process into serial static local optimizations. For instance, if production nodes create final assembly plans from their own perspective without coordinating with logistics nodes, it may lead to mismatched product completion times for the same order. This mismatch can cause issues with order completeness during

warehouse dispatch, affecting temporary storage times, and potentially delaying customer orders. Similarly, if production plans do not consider coordination with finished goods distribution and warehousing, it can result in discrepancies between production schedules, distribution rhythms, and warehousing timings, leading to product backlogs, wasted transportation capacity, and low storage utilization rates. Therefore, failing to orchestrate final product production, distribution, and warehousing plans from a holistic system perspective will cause inefficiencies and hinder the overall cost optimization of the final assembly production logistics system. Despite the independence of decision-making processes for final product production, distribution, and warehousing, these stages are closely linked in actual operations. To achieve smooth overall system operation, enhance efficiency, and reduce costs, it is essential to rely on the local optimization processes of these three stages while making coordinated decisions in terms of time and quantity. Thus, coordinating the limited resources and synchronizing decisions in the stages of final product production, distribution, and warehousing is crucial for improving the operational efficiency and reducing costs of the final assembly system.

In a highly dynamic social manufacturing environment, traditional "production-distribution-warehousing" processes typically use serial static local optimization methods, which are inadequate for meeting modern personalized production demands. This inadequacy mainly stems from a lack of secure, credible, and real-time information exchange, preventing global optimization and dynamic synchronized coordination. To address these issues and ensure low-cost, high-efficiency, and sustainable social production logistics systems, this study faces the following three key challenges:

- (1) The challenge of global optimization scheduling of the system. Traditional optimization methods usually focus on local optimization of individual stages or employ centralized optimization methods, thereby neglecting the autonomy and privacy protection of decision-makers. How can we design a global distributed optimization scheduling method that considers the decision-making rights and privacy of each decision-maker while ensuring optimal coordination of time and quantity in the production logistics system? How does this method ensure globally optimal coordinated operations?
- (2) The challenge of dynamic coordination control mechanism. During the execution of production logistics, social production logistics systems inevitably face various dynamic disturbances. How can we design a dynamic coordination control mechanism for multiple subsystems and formulate high-precision synchronized response strategies to effectively mitigate or eliminate the impact of these disruptions? How can we promptly adjust the actual operation plans of production, distribution, and warehousing stages to achieve optimal operation of the entire production logistics system?
- (3) The challenge of dynamic disturbances trusted sensing and real-time simulation. In an open and dynamic social manufacturing environment, with frequent dynamic disturbances, how can we credibly and accurately collect multi-source real-time operational data from different decision-makers and achieve dynamic simulation optimization? This requires promoting secure and credible data sharing among decision subsystems and effective data interaction. To ensure the reliability, timeliness, and accuracy of the decision-making process, real-time simulation and validation of complex production logistics systems are essential measures. These measures will directly enhance the efficiency and response speed of the entire manufacturing system.

4. The proposed solutions

This study addresses the challenges in the coordinated operation of multi-enterprise nodes and multi-stage social production logistics

systems within dynamic operational environments. By leveraging the dimensions of information, control, and operations research within systems engineering, comprehensive solutions are proposed. Firstly, from the information dimension, a blockchain and digital twin-based multi-scale trusted synchronized decision-making framework for SPLS is proposed. This framework aims to comprehensively and reliably acquire real-time data from SPLS and perform dynamic simulation optimization. Secondly, from the control dimension, a blockchain smart contract tree-based trusted synchronized control mechanism for SPLS is proposed to effectively reduce the impact of dynamic disturbances. Finally, from the operations research dimension, a collaborative optimization algorithm for two-level multi-subsystem iterative distributed optimization is proposed to enhance the optimization of SPLS.

4.1. Blockchain and digital twin-based trusted synchronized decision-making framework for SPLS

To address the challenges in reliably acquiring operational information for large and complex production logistics systems, this paper proposes a multi-scale trusted synchronized decision-making framework based on blockchain and digital twin technologies (see Fig. 3). The framework comprises three main components: the physical resource layer, the blockchain-based twin service layer, and the blockchain-based twin application layer.

4.1.1. Physical resource layer

This layer includes all operational resources and intelligent IoT devices. Operational resources encompass various physical entities in the real world, such as personnel, machinery, materials, vehicles, and facilities. Intelligent IoT devices include passive IoT tags (such as 1D/2D barcodes, RFID tags, iBeacon tags) and active IoT devices (such as positioning terminals, handheld terminals, industrial tablets, wearable devices). Through intelligent transformation, these distributed manufacturing resources in industrial sites are converted into smart objects (SOs) that can be accessed in real-time within the production logistics system.

The core function of this layer is to collect real-time data on production logistics activities, including equipment status, material flow, and personnel distribution. By utilizing various heterogeneous communication networks (such as 5 G, Wi-Fi, and Zigbee), it ensures secure information sharing among broadly distributed manufacturing resources, providing a foundation for real-time monitoring and coordinated decision-making in production logistics activities.

4.1.2. Blockchain-based twin service layer

The blockchain-based twin service layer mainly provides trusted and efficient core services by creating and updating digital twin models with the collected real-time data. Digital twin models, as digital replicas of physical entities, can simulate and predict the behavior of physical entities with high fidelity. Blockchain technology in this layer offers a decentralized and secure data management platform, ensuring data

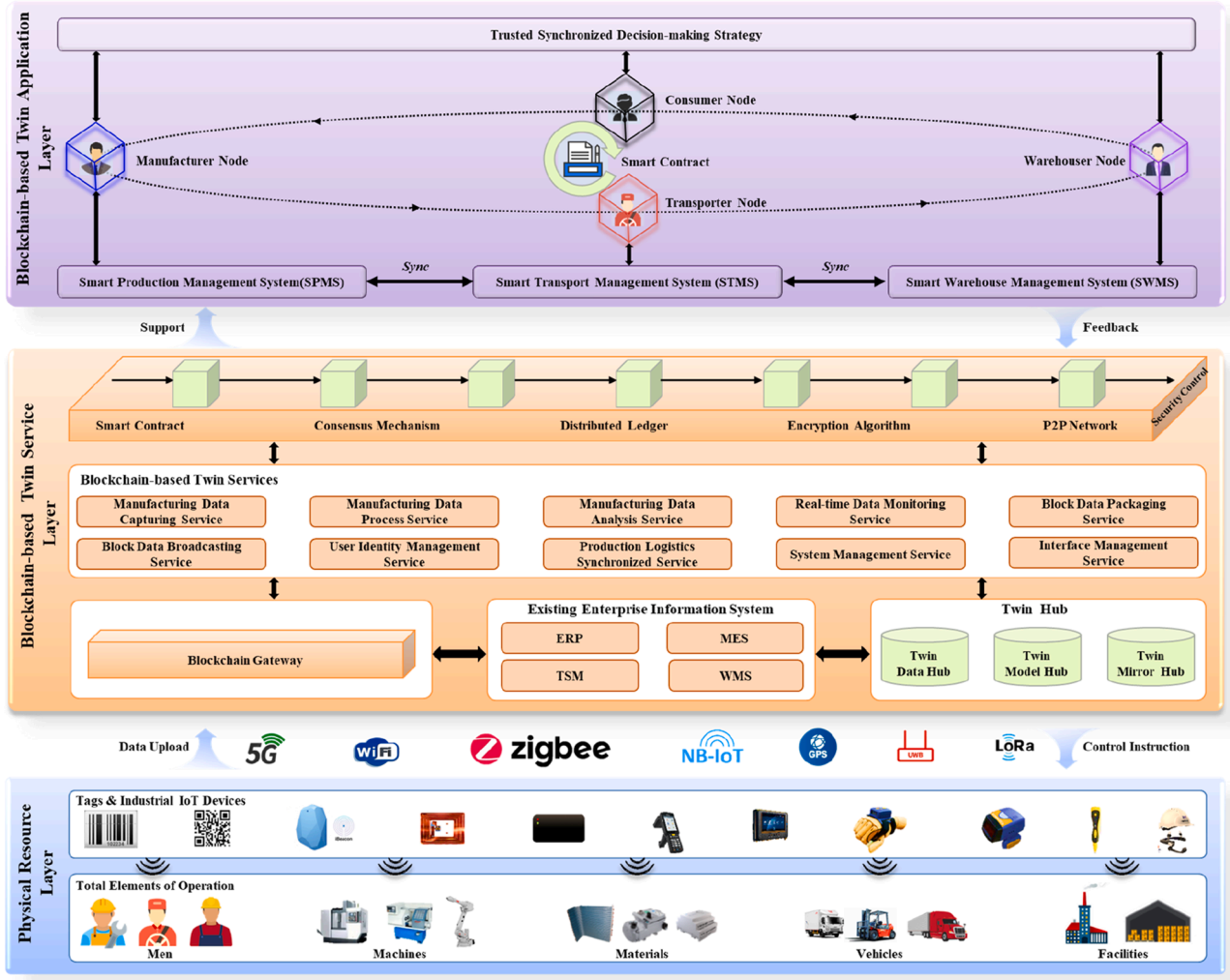


Fig. 3. Blockchain and digital twin-based trusted synchronized decision-making framework for SPLS.

immutability and integrity. The blockchain gateway integrates with existing enterprise information systems (such as ERP; manufacturing execution system, MES; transportation management system, TMS; and warehouse management system, WMS), optimizing the management of real-time data collected by IoT devices. Data requiring high real-time and security requirements is processed through the blockchain gateway to ensure data security and reliability, while routine business data or complex data queries and management are stored in traditional databases to ensure high performance. This dual data storage mechanism supports the efficient operation of SPLS.

The twin center includes the twin data hub, twin model hub, and twin mirror hub, responsible for data storage, model construction and updates, and real-time mirroring of system status, respectively. The main services provided by the blockchain-based twin service layer include: (1) Manufacturing data capturing service. Collecting real-time operational data during manufacturing. (2) Manufacturing data process service. Processing and preparing data for further analysis. (3) Manufacturing data analysis service. Analyzing data to gain insights into production process efficiency and issues. (4) Real-time data monitoring service. Monitoring key parameters during the production process to ensure correct operations. (5) Blockchain data packaging and broadcasting service: Ensuring transaction security and data transparency in the blockchain. (6) User identity management service. Managing user access and authentication. (7) Production logistics synchronized service: Coordinating coupled operations between production and logistics, optimizing resource allocation and subsystem operations. (8) System management service and interface management service. Maintaining overall system operation and interoperability with external interfaces.

By utilizing blockchain technologies such as smart contracts, consensus mechanisms, distributed ledgers, encryption algorithms, and peer-to-peer networks, this layer offers high automation and real-time data processing capabilities, optimizing resource allocation and process management, enhancing the response speed of the production logistics system, and ensuring system security, trustworthy and controllable.

4.1.3. Blockchain-based twin application layer

The top layer, the blockchain-based twin application layer, leverages real-time operational data and core services from the underlying layers to provide trusted and efficient applications to manufacturers, logistics providers, warehousing providers, and customers. This layer aims to enhance production efficiency, optimize logistics operations, and improve the flexibility of warehousing management through advanced application management systems. The main application management systems include: (1) Smart production management system. Optimizes production plans and processes to achieve automated scheduling and refined management, thereby improving production efficiency. (2) Smart distribution management system: Manages and optimizes the routes and schedules for goods distribution, reducing transportation costs and enhancing distribution efficiency. (3) Smart warehousing management system: Monitors storage conditions and logistics flows within warehouses, automatically adjusting inventory levels in response to market demand changes, ensuring efficient inventory management.

When the production logistics system encounters dynamic disturbances, such as order demand changes or equipment failures, managers can use visualization tools to monitor the entire production logistics process in real time and invoke preset blockchain smart contracts. The smart contracts assess the impact of dynamic disturbances and automatically trigger multi-scale trusted coordinated decision-making mechanisms, executing appropriate strategies to mitigate the effects of disruptions on system operations and maintain or restore the stability of the production logistics system. Therefore, the blockchain-based twin application layer not only improves system responsiveness and flexibility but also ensures the reliability and efficiency of production logistics operations, providing support for the optimal operation of large-scale complex production logistics systems.

4.2. Blockchain smart contract tree-based trusted synchronized decision-making mechanism for SPLS

• Trusted synchronized decision-making mechanism

This study proposes a trusted synchronized decision-making mechanism for SPLS based on blockchain smart contract tree (see Fig. 4). The aim is to enhance trust among different manufacturing entities and achieve dynamic, multi-stage coordinated operations. The mechanism utilizes blockchain technology to provide a decentralized, collaboratively maintained network platform for various manufacturing entities, reducing trust costs and increasing information transparency. The mathematical structure of blockchain ensures credibility without reliance on a single center or third-party, addressing the trust deficit among manufacturing entities in untrusted environments.

In terms of trustworthy data support, the mechanism employs digital twin technology based on information-physical synchronization to establish a high-fidelity digital twin resource service pool. This service pool, encrypted using hash algorithms, is stored on the blockchain. Through network broadcasting and consensus verification mechanisms, it is incorporated into the blockchain network to form a service blockchain. Asymmetric encryption technology ensures information security, providing reliable data support for trustworthy coordinated operations.

For trustworthy autonomous collaboration, the paper provides an automated collaboration mechanism based on blockchain smart contract tree, allowing reliable cooperation even among untrusting manufacturing entities. Smart contracts are self-executing agreements defined as computer programs that automatically execute, control, and document transaction relevant events and actions on a blockchain. By endowing operational objects with digital characteristics, smart contracts are programmed under predefined conditions and rules, deploying digital objects as shared resources within a distributed network on the blockchain. External events can automatically trigger the creation and execution of contracts, thereby altering the network state and value of digital objects on the blockchain [39]. Smart contracts possess several key features: firstly, once the terms and conditions are encoded, they can be executed automatically without human intervention; secondly, once deployed on the blockchain, the contract content becomes immutable, ensuring transparency and security; finally, smart contracts can adjust based on real-time external data, facilitating dynamic decision-making. Constructing a blockchain smart contract tree for SPLS enables automated and reliable dynamic collaboration among various nodes within a distributed production logistics network, effectively addressing complex personalized tasks. The smart contract tree includes the overall operation logic main contract and four underlying sub-contracts. The overall operation logic main contract controls the overall execution logic and manages the execution of sub-contracts. Each sub-contract is responsible for different functions, such as the system resource assessment contract evaluating system resource availability, the static operation plan contract selecting production resources and operation plans, the dynamic disturbance evaluation contract assessing system dynamics and triggering coordinated response strategies, and the dynamic correction plan contract formulating corrective plans [3].

The operational logic of this mechanism is divided into two stages: plan formulation and plan execution. In the plan formulation stage, order allocation agents (OAAs) process customer demands, decompose orders into production logistics orders, and integrate them into manufacturing task agents (MTAs). Guided by the system resource assessment contract and static operation plan contract, initial resource allocation and operation plans for personalized production tasks are formulated. In the plan execution stage, manufacturing system agents (MSAs) obtain initial resource allocations and operation plans assigned by the MTAs. The production system agents (PSAs) within the MSAs match with the MTAs. During production, distribution system agents (DSAs) receive and execute logistics distribution orders from the MTAs, delivering finished products to other PSAs. Upon production

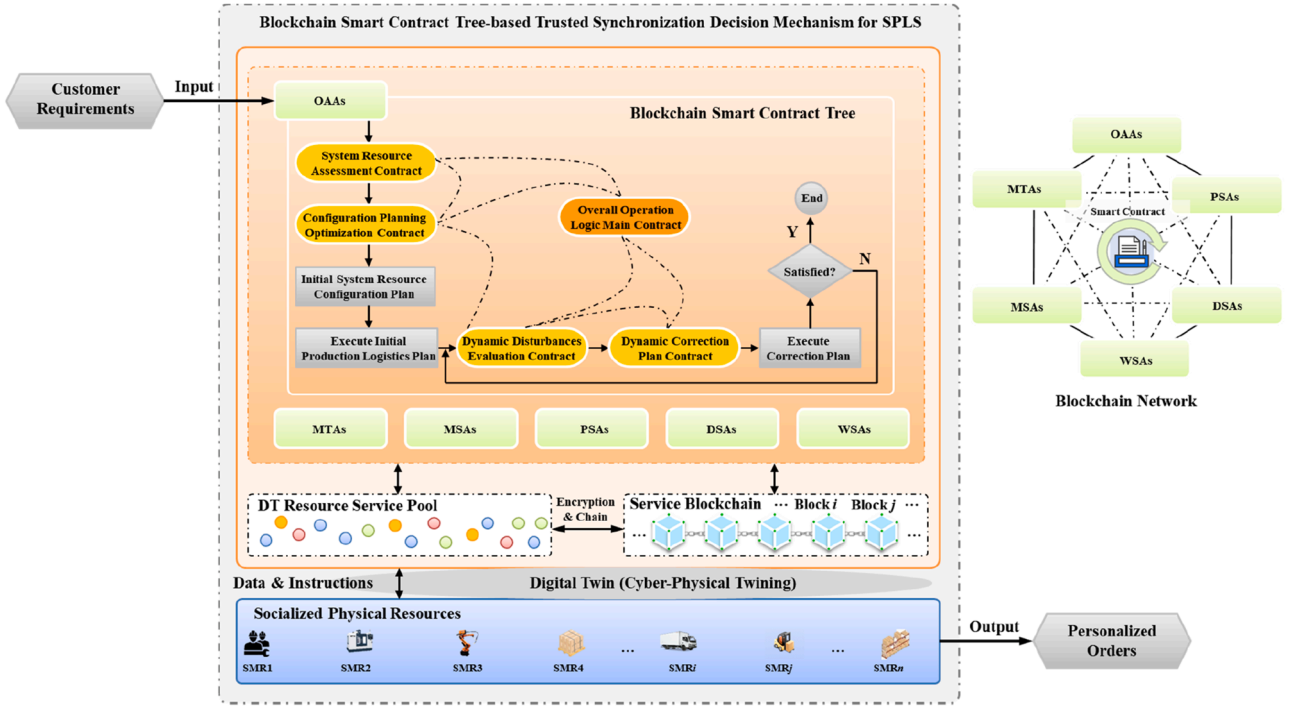


Fig. 4. Blockchain smart contract tree-based trusted synchronized decision mechanism for SPLS.

completion, DSAs transport finished products to designated warehousing system agents (WSAs) for storage. In case of dynamic disturbances, the dynamic disturbance evaluation contract automatically identifies and evaluates them, triggering coordinated response strategies, while the dynamic correction plan contract guides the formulation and output of optimal corrective plans to be executed by the physical resource layer. This iterative process ensures efficient delivery of customer orders.

Through the trusted synchronized decision-making mechanism based on blockchain smart contract tree, various entities within the SPLS system communicate using an efficient peer to peer (P2P) consensus protocol, achieving a loosely coupled coordination mode. This enhances adaptive interaction and collaboration among system components. This approach improves overall system reliability and response speed, while reducing operational complexity and management difficulty. In an open socialized manufacturing environment, the mechanism enables the SPLS system to operate efficiently and reliably, achieving horizontal coordination among production, distribution, and warehousing subsystems,

and ensuring dynamic adaptation in the "decision-execution" layer vertically. This horizontal and vertical coordination not only enhances the overall performance of the manufacturing system but also improves its adaptability and stability in the face of changes and uncertainties.

- Multi-scale synchronized response strategy

During the execution of production logistics, SPLS inevitably encounters various dynamic disturbances. SPLS consists of different decision-making subsystems, each capable of handling corresponding ranges of dynamic disturbances. Due to varying dynamic disturbances, the impact on system operations and the response costs differs. Therefore, the system needs to adopt specific coordinated response strategies based on the level of impact to minimize the mitigation or eliminate the impact of the disturbance on the system. This study proposes a multi-scale synchronized response strategy, which consists of four levels of synchronized response strategies (see Fig. 5).

Level 1: intra-subsystem synchronized response strategy. This

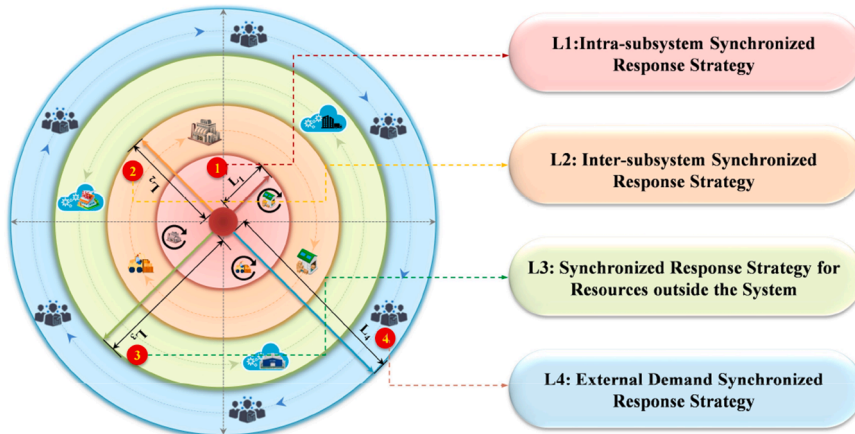


Fig. 5. Multi-scale synchronized response strategy under dynamic disturbances.

strategy applies to the internal coordination within the production, distribution, or warehousing subsystems. When the disturbance is minor and the impact is limited to a specific subsystem without affecting other subsystems, the affected subsystem should reschedule internally to eliminate the disturbance. For instance, if equipment in the production subsystem breaks down before starting, idle equipment can be immediately allocated to replace it, ensuring that the production schedule proceeds without affecting subsequent logistics distribution and warehousing plans.

Level 2: inter-subsystem synchronized response strategy. This strategy is suitable for coordination among the production, distribution, and warehousing subsystems. When the disturbance disturbances and internal adjustments within a single subsystem cannot resolve the issue, an inter-subsystem coordinated response strategy is required. Through dynamic collaboration and mutual adjustments between subsystems, the disturbance can be addressed. For example, an urgent new order may alter the completion time of production orders, subsequently affecting the delivery and warehousing plans for finished products. Therefore, production logistics tasks must be redefined and closely coordinated between the production and logistics subsystems.

Level 3: synchronized response strategy for resources outside the system. When the intensity of the disturbance is severe, exceeding the system's current resource capacity, and inter-subsystem coordination is insufficient, an external resource coordinated response strategy is adopted. By introducing external resources, the system's resource structure can be reconfigured to enhance response capabilities and reduce total costs. For instance, when faced with a large number of new orders that the internal system resources cannot meet, if the cost of renting external resources is lower than the cost of production delays, nearby manufacturers' production equipment can be dynamically rented to meet the demand.

Level 4: external demand synchronized response strategy. When the disturbance is extremely severe, and the costs incurred by the previous strategies exceed the system's tolerance, a customer demand coordinated response strategy is employed. This strategy involves reducing some customer orders or renegotiating delivery times to minimize the impact. For example, when a large number of urgent orders are added and the previous strategies cannot meet the demand and affect the execution of other orders, the system may choose to abandon some customer orders to reduce the overall operational load. By implementing the multi-scale coordinated response strategies, SPLS can efficiently and cost-effectively manage dynamic disturbances, ensuring the stability and reliability of the production logistics system.

4.3. CO-based collaboration optimization model for "production-distribution-warehousing"

(1) Problem model assumptions and parameter definitions

This study aims to explore the integrated decision-making problem for "production-logistics" focused on finished product assembly. Based on the constraints of multi-variety, small-batch customer order demands, and execution stage resource limitations, the challenge is how to effectively coordinate the production, distribution, and warehousing stages. The goal is to develop a globally coordinated and consistent finished product assembly plan, distribution plan, and warehousing plan, thereby minimizing the total operational cost of the finished product assembly "production-logistics" system. To ensure the problem is simplified while maintaining its generality, the model's assumptions are shown in Table 1.

The relevant symbols involved in the mathematical model proposed in this paper are shown in Table 2.

(2) CO-based collaboration decision model for "production-distribution-warehousing"

The collaborative optimization (CO) algorithm is a type of MDO algorithm. It addresses the coupling issues between different disciplines in large-scale complex systems through a two-level optimization

Table 1
Model assumptions.

No.	Problem assumption	No.	Problem assumption
1	All customer orders have been converted into corresponding information, including production orders and related information	2	Customer orders generally contain multiple types of products, which are allocated to corresponding assembly factories for production
3	Each type of product in a customer order corresponds to a production order	4	The total assembly system comprises multiple assembly factories capable of producing various products
5	Each assembly factory has limited production capacity, meaning the total number of products that can be produced daily is capped	6	Each production order can be divided into multiple different batches for production
7	For each assembly factory, the adjustment time and cost required for switching between different products are known	8	The actual completion time of each production order is determined by the completion time of the last batch in the order
9	Each production order has an expected delivery date, and delays will incur corresponding penalty costs	10	The geographical locations of the offline points of all assembly factories within the total assembly system are fixed and known
11	Delivery vehicles are not allowed to be overloaded and travel at a constant speed	12	Production orders are not allowed to be split for delivery
13	Each delivery route can be completed by one or more vehicles	14	Each vehicle is responsible for only one delivery route per trip
15	Delivery vehicles depart from the warehouse, complete the pickup tasks, and return to the warehouse	16	In the warehouse, the time taken for loading and unloading delivery vehicles is considered negligible
17	In the warehouse, the movement of finished products from the temporary storage area to the loading area is unidirectional	18	The transfer time for finished products from the temporary storage area to the loading area in the warehouse is fixed and known
19	The warehouse is equipped with a sufficient number of forklifts to ensure timely transfer of finished products	20	The number of pallets stored in the warehouse must not exceed its maximum capacity
21	Delivery can only proceed once all products of a customer order are fully ready in the loading area		

framework. This method decomposes complex system optimization problems into a system level and several parallel subsystems (or disciplines). The core of this approach is to break down complex objective functions into multiple simple sub-objectives and perform coordinated optimization.

In the context of the integrated decision-making problem for finished product assembly in "production-distribution-warehousing," the finished product assembly system is analogous to the system level in the CO algorithm. The main task is to coordinate decisions among production workshops, distribution fleets, and warehouses. Each subsystem must consider optimization objectives and resource constraints during task execution, aligning with the subsystem level in the CO framework. Due to the high compatibility and suitability between the two-level optimization structure of the CO algorithm (see Fig. 6) and the quantitative calculation requirements of the integrated "production-distribution-warehousing" decision-making, this study selects the CO algorithm to solve the coordination among subsystems.

• System-level optimization model

The primary task of the system level is to coordinate the optimization objectives among the production, distribution, and warehousing subsystems to minimize the overall operating cost of the "production-

Table 2
Model symbols.

Symbol	Description	Symbol	Description
i	Customer order number i , where $i \in \{1, 2, \dots, I\}$	q^v	Actual total load of vehicle v
j, l	Pickup and delivery network node (assembly factory) numbers j and l , where $j, l \in \{0, 1, 2, \dots, J\}$, and 0 represents the warehouse	$N_{i,s}$	Storage quantity of order i at storage location s
v	Vehicle number, $v \in \{1, 2, \dots, V\}$	$C_{i,j}$	Unit production cost of order i products at assembly factory j
s	Storage location number s , where $s \in \{1, 2, \dots, S\}$	$u_{i,j}$	Unit switching cost for order i products at assembly factory j
Q_i	Demand quantity of customer order i	C_v^f	Fixed departure cost of vehicle v
p_i	Demand quantity of production order i	C_w^e	Unit penalty cost for early arrival of vehicle v
k	Production batch of the order	C_v^e	Unit delivery cost of vehicle v
K_i	Total number of batches for production order i	C_s^f	Fixed usage cost of storage location s
$T_{i,j}$	Unit production time for order i products at assembly factory j	C_s^v	Variable usage cost of storage location s
α_{ij}	Production quantity of order i at assembly factory j	C_i^{del}	Unit penalty cost for delayed delivery of order i
$\alpha_{i,k}$	Quantity of order i in batch k	$t_{j,l}^{in}$	Delivery-to-warehouse time for production order i
A_j	Total production quantity at assembly factory j	t_j^{in}	Warehouse entry time for production order i
R_j	Production capacity limit of assembly factory j	T_{bm}	Transfer time from temporary storage area to loading area
T_i	Actual completion time of order i products	D_i^r	Required delivery time for order i
$tf_{i,j}$	Offline time for order i at assembly factory j	T_i^o	Allowed warehouse departure time for order i
$Tc_{i,j}$	Unit switching time for order i products at assembly factory j	$[S_0, E_0]$	Operating time window of the warehouse
q_j^v	Pickup quantity of vehicle v at assembly factory j	$x_{i,k,j}$	Binary variable: 1 if batch k of order i is produced at assembly factory j ; 0 otherwise
t_o^v	Arrival time of vehicle v at the warehouse	$\gamma_{i,j}$	Binary variable: 1 if production of order i at assembly factory j requires switching; 0 otherwise
$w_{a,i}^v$	Waiting time of vehicle v at assembly factory a	V_s	Capacity of storage location s
w_v	Rated load of vehicle v	$g_{j,i}^v$	Binary variable: 1 if order i is transported by vehicle v ; 0 otherwise
$\bar{v}$	Average speed of vehicle v	$\psi_{r,i}$	Binary variable: 1 if order i is transferred to the loading area after order r ; 0 otherwise
T_0^v	Departure time of vehicle v	ϕ_i	Binary variable: 1 if order is first stored in the temporary storage area after warehouse entry; 0 otherwise
at_j^v	Delivery time of vehicle v to assembly factory j	$q_{i,s}$	Binary variable: 1 if order i is stored in the loading area at storage location s ; 0 otherwise
st_i	Service time for assembly factory i	$\xi_{i,a,s}$	Binary variable: 1 if order i is stored in the temporary storage area; 0 otherwise
$[ET_j^c, LT_j^c]$	c -th time window of assembly factory j	$\xi_{t,s}$	Binary variable: 1 if storage location s is used at time t ; 0 otherwise
$d_{j,l}$	Distance between nodes j and l	$\gamma_{0,l}^v$	Binary variable: 1 if vehicle departs from node 0 and travels to node b ; 0 otherwise

Table 2 (continued)

Symbol	Description	Symbol	Description
$F(Z)$	Total operational cost of the "production-distribution-warehousing" system	J_{21}^*	Consistency constraint between the coupling variable of delivery time and the system design variable in the distribution subsystem
Z_{pro}	Total cost of the production subsystem	J_{22}^*	Consistency constraint between the coupling variable of delivery batch size and the system design variable in the distribution subsystem
Z_{dis}	Total cost of the distribution subsystem	J_{31}^*	Consistency constraint between the coupling variable of storage time and the system design variable in the warehousing subsystem
Z_{war}	Total cost of the warehousing subsystem	J_{32}^*	Consistency constraint between the coupling variable of storage batch size and the system design variable in the warehousing subsystem
T_{ij}^U	Expected offline time designed for the production subsystem at the system level	f_{p1}	Cost of assembling products
Symbol	Description	Symbol	Description
A_{ij}^U	Expected number of products offline designed for the production subsystem at the system level	f_{p2}	Cost of switching products
$T_{i,s}^U$	Expected delivery time designed for the distribution subsystem at the system level	f_{p3}	Penalty cost for production delays
Q_v^U	Expected delivery quantity designed for the distribution subsystem at the system level	f_{d1}	Fixed usage cost of delivery vehicles
$T_{i,s}^U$	Expected storage time designed for the warehousing subsystem at the system level	f_{d2}	Variable travel cost of delivery vehicles
$Q_{i,s}^U$	Expected storage quantity designed for the warehousing subsystem at the system level	f_{d3}	Penalty cost for pickup time losses
e	Relaxation factor	f_{w1}	Fixed cost of using storage locations
J_{11}^*	Consistency constraint between the coupling variable of production time and the system design variable in the production subsystem	f_{w2}	Variable cost of using storage locations
J_{11}^*	Consistency constraint between the coupling variable of production batch size and the system design variable in the production subsystem	f_{w3}	Penalty cost for customer order delivery time losses

distribution-warehousing" system for finished product assembly. To achieve this goal, the objective function and consistency constraints of the system-level optimization model are as follows:

$$\text{Min } F(Z) = Z_{pro} + Z_{dis} + Z_{war} \quad (\text{S.1})$$

$$J_{11}^* = (tf_{i,j} - T_{ij}^U)^2 \leq e \quad (\text{S.2})$$

$$J_{12}^* = (\alpha_{i,j} - A_{ij}^U)^2 \leq e \quad (\text{S.3})$$

$$J_{21}^* = (t_{j,i}^{in} - T_{i,s}^U)^2 \leq e \quad (\text{S.4})$$

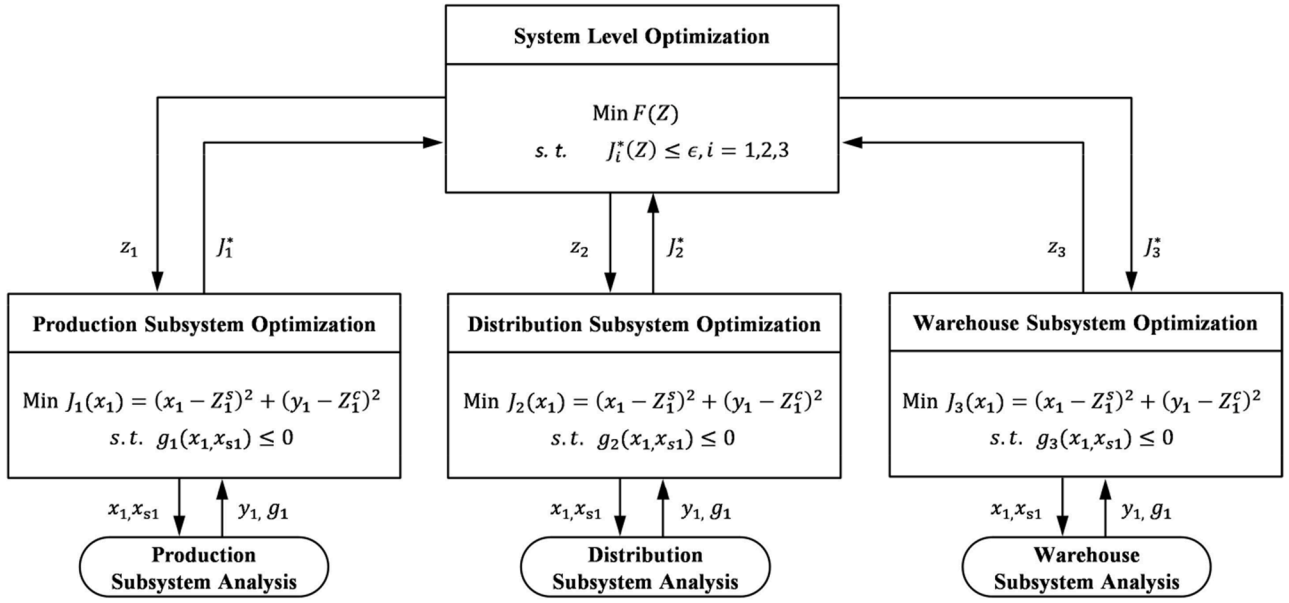


Fig. 6. CO Framework.

$$J_{22}^* = (q^v - Q_v^U)^2 \leq \epsilon \quad (\text{S.5})$$

$$J_{31}^* = (t_j^{\text{in}} - T_{i,s}^U)^2 \leq \epsilon \quad (\text{S.6})$$

$$J_{32}^* = (N_{i,s} - Q_{i,s}^U)^2 \leq \epsilon \quad (\text{S.7})$$

Equation (S.1) represents the system-level objective function designed to minimize the total operating cost of the entire "production-distribution-warehousing" system. Equations (S.2) and (S.3) represents the difference between the production offline time and batch size of the production subsystem and the system-level design variables, designed to be close to a relaxation factor. Equations (S.4) and (S.5) represents the difference between the warehouse arrival time and delivery batch size of the distribution subsystem and the system-level set variables, designed to be close to a relaxation factor. Equations (S.6) and (S.7) represents the difference between the storage time and storage batch size of the warehousing subsystem and the system design variables, designed to be close to a relaxation factor to achieve better consistency between subsystem and system-level objectives.

• Production scheduling model

The objective of the production subsystem-level mathematical model is to plan the production batch size, time, and sequence of each order under multiple constraints, such as ensuring production capacity is not exceeded and meeting delivery deadlines as much as possible. It aims to minimize the deviation between the production subsystem design variables and the system expectations. The production subsystem mathematical model includes the following:

$$\min J_1 = (tf_{ij} - T_{ij}^U)^2 + (\alpha_{ij} - A_{ij}^U)^2 \quad (\text{P.1})$$

$$Z_{pro} = f_{p1} + f_{p2} + f_{p3} \quad (\text{P.2})$$

$$f_{p1} = \sum_{i=1}^I \sum_{j=1}^J C_{ij} \cdot \alpha_{ij} \quad (\text{P.3})$$

$$f_{p2} = \sum_{i=1}^I \sum_{j=1}^J u_{ij} \cdot Tc_{ij} \cdot \gamma_{ij} \quad (\text{P.4})$$

$$f_{p3} = \sum_{i=1}^I C_i^{\text{del}} \cdot \max\{T_i - D_i^r, 0\} \quad (\text{P.5})$$

$$\sum_{k=1}^{K_i} x_{i,k,j} = 1, i \in \{1, 2, \dots, I\}, j \in \{1, 2, \dots, J\} \quad (\text{P.6})$$

$$\sum_{j=1}^J x_{i,k,j} = 1, i \in \{1, 2, \dots, I\}, k \in \{1, 2, \dots, K_i\} \quad (\text{P.7})$$

$$\sum_{k=1}^{K_i} \alpha_{i,k} = p_i, i \in \{1, 2, \dots, I\} \quad (\text{P.8})$$

$$\alpha_{ij} = \alpha_{i,k} \cdot x_{i,k,j}, i \in \{1, 2, \dots, n\}, j \in \{1, 2, \dots, J\}, k \in \{1, 2, \dots, K_i\} \quad (\text{P.9})$$

$$\sum_{j=1}^J \alpha_{ij} = p_i, i \in \{1, 2, \dots, I\} \quad (\text{P.10})$$

$$\sum_{i=1}^I \alpha_{ij} = A_j \leq R_j, j \in \{1, 2, \dots, J\} \quad (\text{P.11})$$

$$T_i = \max_{j=1}^J (tf_{ij} + T_{ij} \cdot \alpha_{ij} + u_{ij} \cdot \gamma_{ij}), i \in \{1, 2, \dots, I\} \quad (\text{P.12})$$

Equation (P.1) represents the optimization objective of the production subsystem level model, i.e., to minimize the deviation between the production subsystem's optimization results and the system expectations. Equation (P.2) represents the total cost of the production subsystem. Equation (P.3) represents the cost of assembling products. Equation (P.4) represents the cost of switching products. Equation (P.5) represents the penalty cost for production delays. Equations (P.6) and (P.7) ensure that each batch of an order is processed on a specified assembly factory. Equation (P.8) ensures that the total production quantity for each order meets the product demand. Equation (P.9) represents the production quantity on each assembly factory. Equation (P.10) indicates that the total production quantity on assembly factories equals the order's product demand. Equation (P.11) ensures that each assembly

factory's production capacity is not exceeded. Equation (P.12) represents the offline completion time for each production order.

- Vehicle scheduling model

The objective of the distribution subsystem-level mathematical model is to plan the departure time, delivery route, and delivery volume of different vehicles reasonably under the constraints of vehicle load limits and delivery time, minimizing the deviation between the distribution subsystem's design variables and the system expectations. The distribution subsystem mathematical model includes the following:

$$\min J_2 = (t_{j,i}^{\text{in}} - T_{is}^U)^2 + (q^v - Q_v^U)^2 \quad (\text{D.1})$$

$$Z_{\text{dis}} = f_{d_1} + f_{d_2} + f_{d_3} \quad (\text{D.2})$$

$$f_{d_1} = \sum_{v=1}^V \sum_{l=1}^J C_v^f \cdot y_{o,l}^v \quad (\text{D.3})$$

$$f_{d_2} = \sum_{v=1}^V \sum_{j=1}^J \sum_{l=1}^J C_v^c \cdot (d_{j,l} / \bar{v}) \cdot y_{j,l}^v \quad (\text{D.4})$$

$$f_{d_3} = \sum_{v=1}^V \sum_{j=1}^J C_v^w \cdot \max(ET_j^c - at_j^v, 0) + \sum_{v=1}^V \sum_{j=1}^J C_v^d \cdot \max(at_j^v - LT_j^c, 0) \quad (\text{D.5})$$

$$\sum_{j=1}^J \sum_{l=1}^J q_j^v \cdot y_{j,l}^v = q^v \leq w_v, v \in \{1, 2, \dots, V\} \quad (\text{D.6})$$

$$\sum_{l=1}^J y_{o,l}^v = \sum_{j=1}^J x_{j,0}^v \leq 1, v \in \{1, 2, \dots, V\} \quad (\text{D.7})$$

$$\sum_{v=1}^V \sum_{l=1}^J x_{j,l}^v \geq 1, j \in \{1, 2, \dots, J\} \quad (\text{D.8})$$

$$\sum_{i=1}^I p_i = \sum_{v=1}^V q_j^v, j \in \{1, 2, \dots, J\} \quad (\text{D.9})$$

$$\sum_{v=1}^V g_{j,i}^v = 1, j \in \{1, 2, \dots, J\}, i \in \{1, 2, \dots, I\} \quad (\text{D.10})$$

$$at_j^v + wt_{j,i}^v + st_i + (d_{j,i} / \bar{v}) = t_o^v \quad (\text{D.11})$$

$$T_0^v + \sum_{j=0}^J \sum_{l=0}^J y_{j,l}^v \cdot [wt_{j,i}^v + st_i + (d_{j,i} / \bar{v})] = t_o^v \leq E_0, v \in \{1, 2, \dots, V\} \quad (\text{D.12})$$

Equation (D.1) represents the optimization objective of the distribution subsystem level model, i.e., to minimize the deviation between the distribution subsystem's optimization results and the system expectations. Equation (D.2) represents the total cost of the distribution subsystem. Equation (D.3) represents the fixed usage cost of delivery vehicles. Equation (D.4) represents the variable travel cost of delivery vehicles. Equation (D.5) represents the penalty cost for pickup time losses. Equation (D.6) ensures that each vehicle's delivery volume does not exceed its rated load capacity. Equation (D.7) ensures that vehicles depart from the warehouse, complete their assigned tasks, and return to the warehouse. Equations (D.8) and (D.9) ensure that finished product offline points can be visited multiple times by pickup vehicles, and their pickup demands are fully met. Equation (D.10) ensures that production orders cannot be split for delivery and must be processed as a whole. Equation (D.11) calculates the time vehicle v arrives at assembly factory b , which includes the arrival time at assembly factory a , waiting time at a , service time at a , and travel time from factory a to factory b . Equation (D.12) ensures that all delivery activities are conducted within the

specified warehouse operating time window.

- Storage location planning model

The objective of the warehousing subsystem-level mathematical model is to plan the storage batch size, storage time, and sequence of each order reasonably under the constraints of storage capacity and delivery time, and to allocate the most suitable storage location, minimizing the deviation between the warehousing subsystem's design variables and the system expectations. The warehousing subsystem mathematical model includes the following:

$$\min J_3 = (t_j^{\text{in}} - T_{i,s}^U)^2 + (N_{i,s} - Q_{i,s}^U)^2 \quad (\text{W.1})$$

$$Z_{\text{war}} = f_{w_1} + f_{w_2} + f_{w_3} \quad (\text{W.2})$$

$$f_{w_1} = \sum_{s=1}^S C_s^f \cdot \xi_{t,s} \quad (\text{W.3})$$

$$f_{w_2} = \sum_{j=1}^J \sum_{i=1}^I (T_i^o - t_{j,i}^{\text{in}}) \cdot N_{i,s} \cdot C_s^c \quad (\text{W.4})$$

$$f_{w_3} = \sum_{i=1}^I C_i^{\text{del}} \cdot \max(T_i^o - D_i^r, 0) \quad (\text{W.5})$$

$$\sum_{i=1}^I \xi_{i,a,s} \leq 2, s \in \{1, 2, \dots, S\} \quad (\text{W.6})$$

$$\sum_{i=1}^n \sum_{s=1}^S \xi_{i,a,s} \leq 1, i \in \{1, 2, \dots, I\} \quad (\text{W.7})$$

$$\sum_{i=1}^I q_{i,s} \leq 1, s \in \{1, 2, \dots, S\} \quad (\text{W.8})$$

$$\sum_{s=1}^S q_{i,s} \leq 1, i \in \{1, 2, \dots, I\} \quad (\text{W.9})$$

$$\sum_{i=1}^I \sum_{j=1}^J \xi_{i,a,s} p_i^j \leq V_s, s \in \{1, 2, \dots, S\} \quad (\text{W.10})$$

$$\sum_{i=1}^I \theta_{i,s} \cdot Q_i \leq V_s, s \in \{1, 2, \dots, S\} \quad (\text{W.11})$$

$$t_{j,i}^{\text{in}} = \sum_{v=1}^V t_o^v \cdot g_{j,i}^v \quad (\text{W.12})$$

$$t_j^{\text{in}} = \max(t_{j,i}^{\text{in}} | j = 1, 2, \dots, J) \quad (\text{W.13})$$

$$\sum_{i=1}^I q_{i,s} \cdot \xi_{i,a,s} = 0 \quad (\text{W.14})$$

$$T_i^o = t_j^{\text{in}}, \text{ if } \phi_i = 0 \quad (\text{W.15})$$

$$T_i^o = \sum_{j=1}^I \psi_{r,i} \cdot (t_j^{\text{in}} + T_{bm}), \text{ if } \phi_i = 1 \quad (\text{W.16})$$

Equation (W.1) represents the optimisation objective of the storage subsystem level model, i.e., to minimize the deviation between the warehousing subsystem's optimization results and the system expectations. Equation (W.2) represents the total cost of the warehousing subsystem. Equation (W.3) represents the fixed cost of using storage

locations. Equation (W.4) represents the variable cost of using storage locations. Equation (W.5) represents the penalty cost for customer order delivery time losses. Equation (W.6) ensures that a temporary storage location can store at most two customer orders. Equation (W.7) ensures that products of the same production order can only be stored in temporary storage locations. Equations (W.8), (W.9), and (W.10) ensure that a loading area storage location can only store one customer order, and a customer order can only be stored in one loading area storage location. Equation (W.11) ensures that the storage quantity does not exceed the design capacity of the warehouse storage locations. Equations (W.12) and (W.13) represent the arrival times of production and customer orders at the warehouse. Equation (W.14) ensures that the same customer order is stored in the same area. Equations (W.15) and (W.16) calculate the time when customer orders meet delivery requirements to ensure customer service quality and timely delivery.

4.4. CO-based global coordination optimization process for “production-distribution-warehousing”

The CO-based global coordination optimization process framework for “production-distribution-warehousing” (see Fig. 7) is outlined as follows:

- (1) Initial design variable setting. The system-level optimization model allocates initial design variables $T_{i,j}^U$ and $A_{i,j}^U$ for the production subsystem; $T_{i,s}^U$ and Q_v^U for the distribution subsystem; and $T_{i,s}^U$ and $Q_{i,s}^U$ for the warehousing subsystem, establishing the optimization starting point.
- (2) Local optimization of subsystems. Each subsystem—production, distribution, and warehousing—conducts local optimization based on the system-level initial design variables, yielding optimal solutions $tf_{i,j}$ and $\alpha_{i,j}$, $t_{j,i}^n$ and q^v , t_j^{in} and $N_{i,s}$.
- (3) Feedback of subsystem optimization results and global cost calculation. Each subsystem reports its optimal solutions back to the system level, where the system-level model calculates the current global optimal total cost $F(Z)$ based on these solutions.
- (4) Consistency constraint verification and iterative optimization. The optimal solutions for the design variables are checked against the system-level relaxation factor ϵ for consistency. If satisfied, the optimization results $F(Z)$ are outputted and the process concludes; otherwise, new design variables are generated at the system level, repeating the local optimization and feedback steps. Through iteration, the optimal solutions of subsystems gradually align with the system-level objectives until the consistency

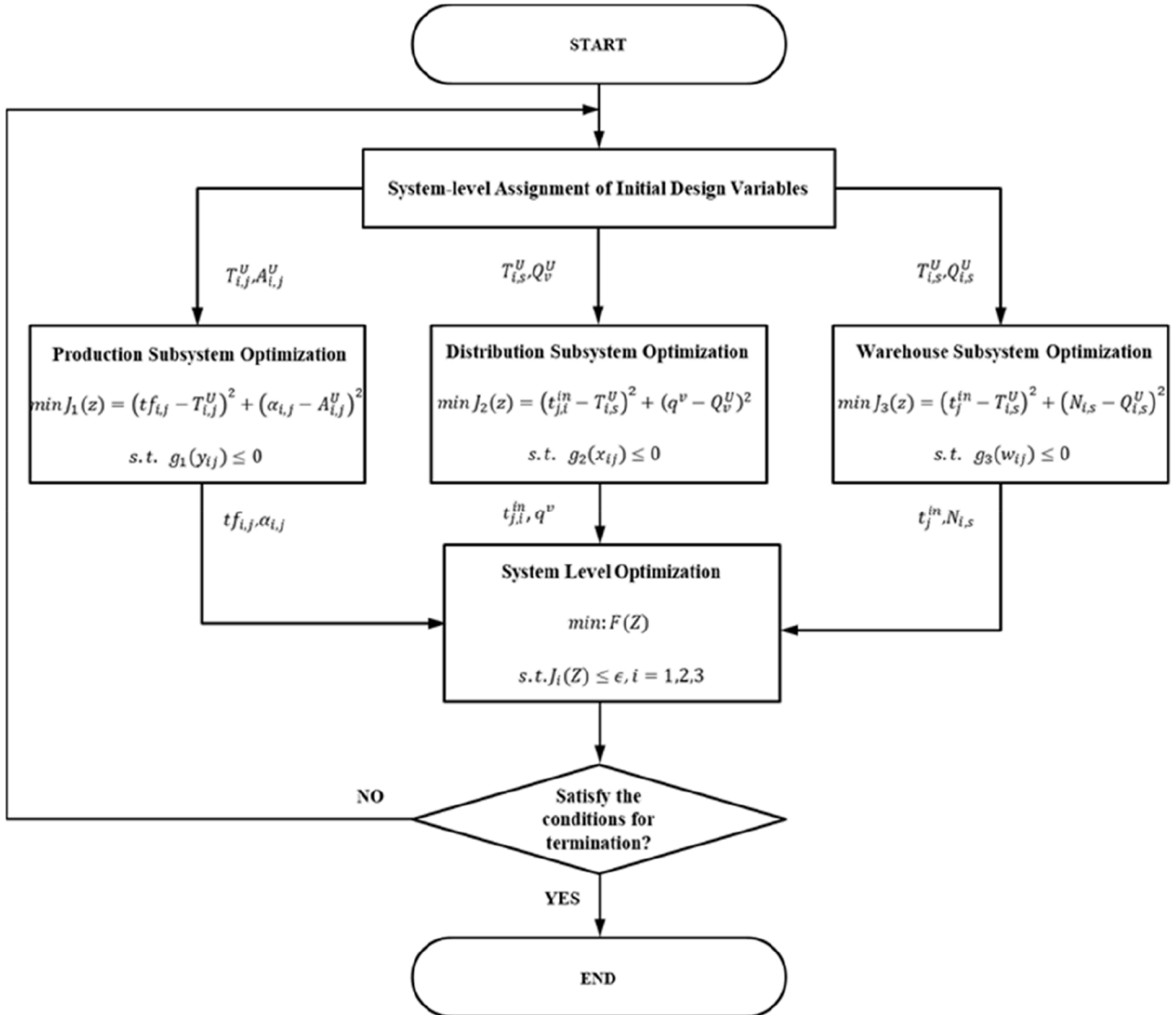


Fig. 7. CO-based global coordination process for “production-distribution-warehousing”.

constraints are met or a predetermined number of iterations is reached, ultimately providing a globally optimal result.

This collaborative iterative method ensures the formation of an optimal system design scheme that meets global optimization goals while accommodating the specific needs of each discipline, thereby enhancing the overall coordination and optimization efficiency.

5. Case study

This study focuses on the production logistics operations problem within the air conditioner manufacturing industry chain in the Greater Bay Area, utilizing the CO algorithm to address the "production-distribution-warehousing" synchronized decision problem. The information system developed based on the BCDT trusted synchronized control (TSC) method has already been successfully applied within manufacturing and logistics enterprises. This study, grounded in the actual operational data of manufacturing enterprises, employs numerical simulation and result analysis to validate the feasibility and effectiveness of the proposed model and mechanism in the dynamic demand environment.

5.1. Case description

This study focuses on social production logistics systems composed of assembly factories, distribution fleet, and storage warehouses. Different assembly factories are used to assemble air conditioner products of various specifications. The production-logistics operation process of the air conditioners resembles the social production logistics process described in Section 2. Additionally, to meet the increasingly diverse and small-batch product demands of customers, the company implements a make to order (MTO) production organization method. Through this method, the enterprise can significantly reduce raw material and finished product inventory, thereby effectively lowering production costs and enhancing market competitiveness.

However, due to the high complexity of the mixed-flow assembly process of air conditioners and the seasonal fluctuations in air conditioner product demand, the production logistics operations process of the manufacturing enterprise is inevitably affected by internal and external dynamic disturbances such as orders, resources, services, and processes, leading to a series of operational issues. To address these issues, this study makes reasonable assumptions and simplifications of the operational problems, forming a broadly representative general case. This paper focuses on the multi-stage collaborative optimization decision problem of finished products' "production-distribution-warehousing" under dynamic new demand and applies the proposed TSC method to the case enterprise to verify the feasibility and effectiveness of the proposed method.

To ensure the security of commercially sensitive information, this study desensitized the relevant data. Below are the basic desensitized data for this case. Table 3 shows the basic information of production orders for a certain day. Table 4 provides information on the production

Table 3
Basic production order information.

Order number	Product type	Quantity	Delivery time (min)	Delay Penalty (\$/min)
O1	A	20	390	40
O2	A	20	426	40
O3	A	30	360	30
O4	B	40	550	30
O5	B	20	588	30
O6	B	50	490	30
O7	C	30	350	50
O8	C	30	600	50
O9	D	40	650	25
O10	B	40	515	25

Table 4
Product production assembly information.

Metric	Social factory	A	B	C	D
Unit assembly time (min)	SF1	3.5	2	2.4	–
	SF2	–	2.5	3.0	2.4
	SF3	2.0	3.5	4.8	4.5
	SF4	–	5	4	5.1
Unit assembly cost (\$)	SF1	36	20	31	–
	SF2	–	11	19	21
	SF3	32	12	23	15
	SF4	26	32	40	29

Table 5
Switching costs and times between different product types.

Social Factory	Unit switching cost (\$)	Product type	A	B	C	D
SF1	15	A	0	5	2	–
		B	5	0	2	–
		C	3	3	0	–
		D	–	–	–	–
SF2	10	A	–	–	–	–
		B	–	0	3	5
		C	–	3	0	5
		D	–	9	9	0
SF3	8	A	0	6	3	3
		B	6	0	6	3
		C	3	6	0	3
		D	3	3	3	0
SF4	5	A	–	5	2	–
		B	6	2	9	–
		C	5	5	0	–
		D	–	–	–	–

Table 6
Distance information between assembly factories and warehouse (km).

Node number	W0	SF1	SF2	SF3	SF4
W0	0	0.37	0.52	0.22	0.32
SF1	0.37	0	0.81	0.52	0.22
SF2	0.52	0.81	0	0.59	0.80
SF3	0.22	0.52	0.59	0	0.37
SF4	0.32	0.22	0.80	0.37	0

Table 7
Basic information of distribution vehicles.

Vehicle type	Rated load capacity (t)	Quantity (unit)	Driving speed (km/h)	Fixed departure cost (\$/time)	Unit distance delivery cost (\$/km)
1T	15	5	10	150	2
2T	30	5	10	200	3
3T	45	5	10	260	5

Table 8
Service information related to assembly factories.

Factory number	SF1	SF2	SF3	SF4
Service time (min)	5	5	5	5
Early arrival penalty (\$/min)	0.4	0.4	0.4	0.4
Late arrival penalty (\$/min)	0.8	0.8	0.8	0.8

assembly of different products at the assembly factories. Table 5 details the cost and time required for switching between different products. Table 6 shows the distances between each assembly factory and warehouse, where W0 represents the finished product warehouse, and SF1 to SF4 represent four social assembly factories. Table 7 provides basic information on the distribution vehicles. Table 8 lists the service

Table 9

Basic information of finished product warehouse locations.

Location type	Location name	Area	Capacity (pallet)	Transfer time (min)
Long location	A1-A3	Loading area	80	0
Short location	B1-B7	Staging area	20	15

Table 10

Other basic information.

Cost type	Cost
Fixed cost for long location (\$/time)	100
Fixed cost for short location (\$/time)	200
Variable cost for long location (\$/min)	0.5
Variable cost for short location (\$/min)	1
Penalty cost for delayed shipment (\$/min)	5

information related to the assembly factories. Table 9 details the basic information of the storage locations in the finished product warehouse. Table 10 includes other basic information involved in the production logistics operation process.

5.2. Results analysis

• Static initial decision results analysis

Based on the provided operational data, this study uses Matlab R2022b for programming and simulation. The simulation experiments are conducted on a computer equipped with an Intel (R) Core (TM) i9-13900HX 2.20 GHz processor and 16GB RAM, running a 64-bit Windows 11 operating system. Before the production logistics execution begins, this study collects all static data of the finished product "production-distribution-warehousing" system through the synchronized decision information architecture. These data are used to construct accurate digital twin models in the twin service layer. Based on the known production order information and available resources, the twin service layer employs an embedded CO algorithm. Following the global coordination optimization process based on CO described in Section 4.4, coordination optimization is conducted on the basic static models established for each independent decision subsystem. Through multiple iterations, the design variables of each subsystem are gradually adjusted, ultimately achieving the global optimal solution that minimizes the total operational cost of the system. This results in the

formulation of an initial scheduling plan for the production, distribution, and warehousing of finished products.

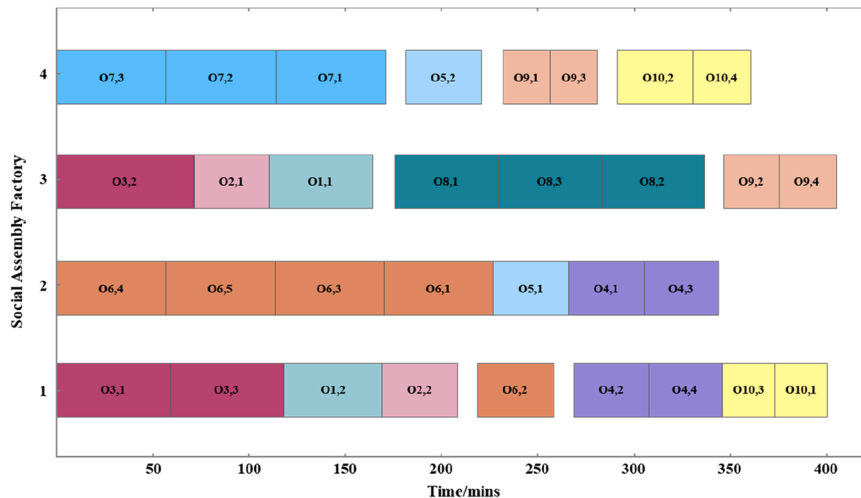
This study uses a genetic algorithm to locally solve the production, distribution, and warehousing subsystems, with the algorithm parameters set as follows: population size of 100, maximum number of iterations of 500, crossover probability $P_c=0.7$, and mutation probability $P_m=0.05$. The results show the initial production scheduling Gantt chart for finished products (see Fig. 8), with the shortest completion time for production orders being 406.7 min. The initial vehicle scheduling results for finished product distribution are shown in Table 11, and the initial storage location planning Gantt chart for finished product warehousing is shown in Fig. 9.

After the initial collaborative scheduling of the production, distribution, and warehousing subsystems through the CO algorithm, the cost of the production subsystem is 8890.8, the cost of the distribution subsystem is 3988, and the cost of the warehousing subsystem is 5818.5, resulting in a total system operation cost of 18,697.3. Specifically, in the production subsystem, the assembly cost is 8070.8, the switching cost is 820, and there is no penalty cost for delayed delivery. In the distribution subsystem, the fixed usage cost of distribution vehicles is 2350, the variable driving cost of distribution vehicles is 1623, and the penalty cost for pickup time loss is 15. In the warehousing subsystem, the fixed cost of storage location usage is 3800.5, the variable cost of storage location usage is 2018, and there is no penalty cost for shipping time

Table 11

Vehicle scheduling for finished goods distribution.

No.	Vehicle type	Pick-up path	Distribution quantity	Departure moment
1	2T	W0-SF1-SF2-SF4-SF3-W0	30	0
2	1T	W0-SF3-SF1-W0	15	50
3	2T	W0-SF1-SF4-SF3-SF2-W0	29	100
4	2T	W0-SF2-SF1-SF4-W0	27	185
5	2T	W0-SF2-SF4-W0	26	250
6	2T	W0-SF4-SF2-SF3-SF1-W0	30	320
7	2T	W0-SF4-SF2-W0	30	355
8	2T	W0-SF4-SF1-W0	20	390
9	3T	W0-SF3-SF4-SF2-W0	38	440
10	3T	W0-SF2-SF3-SF1-SF4-W0	40	430
11	3T	W0-SF1-SF4-SF2-W0	35	455

**Fig. 8.** Initial production scheduling Gantt chart for finished assembly.

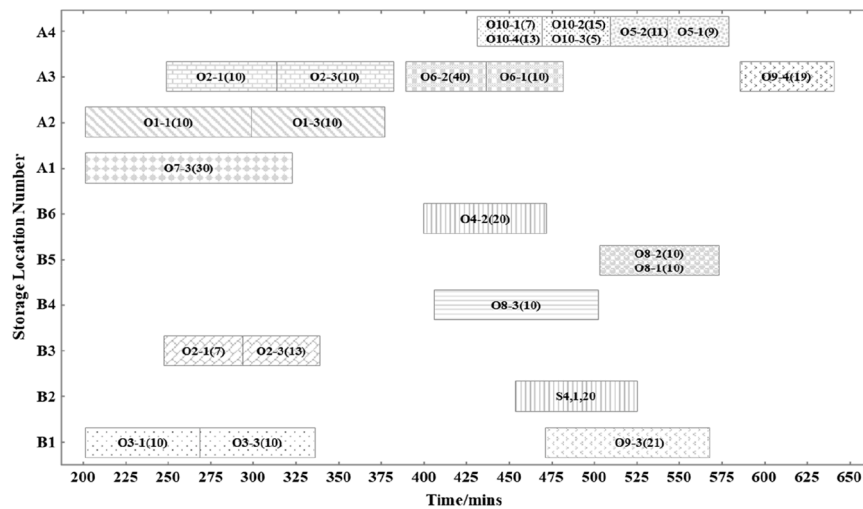


Fig. 9. Gantt chart of initial storage location planning.

loss.

• Dynamic correction decision results analysis

In a diversified, small-batch personalized production mode, the finished product production logistics process inevitably suffers from various dynamic factors such as orders, resources, services, and processes. This study focuses on the most representative dynamic factor in the production logistics system—new customer orders. The objective is to analyze the impact of this dynamic factor on the finished product production logistics process and verify the feasibility and effectiveness of the proposed TSC method. Assuming that a customer production order is temporarily added after the start of the finished product assembly "production-logistics" system, the basic information is shown in Table 12. Since this new demand affects not only the production subsystem but also the distribution and warehousing subsystems, this type of dynamic disturbance is classified as secondary dynamic. This study uses a level 2 synchronized strategy based on the TSC method to reschedule the "production-distribution-warehousing" plan and applies the optimal rescheduling plan to the physical resource layer.

The re-planning decision results of each subsystem based on the TSC method are as follows: the production re-scheduling Gantt chart for finished products is shown in Fig. 10; the vehicle re-scheduling results for finished product distribution are shown in Table 13; and the storage location reallocation results for finished product warehousing are shown in Fig. 11. To verify the effectiveness of the TSC method, this study uses the existing control (i.e., non-trusted synchronized control, NTSC) method as a benchmark for comparison. The basic logic of the NTSC method is that the enterprise, based on traditional manual experience, does not change the original scheduling plan but waits for all scheduled orders to be completed before arranging new orders. NTSC is chosen as the benchmark because it represents a traditional control strategy that does not take into account the trust relationship between multiple parties. The cost comparison results obtained by the NTSC and TSC methods are shown in Table 14.

Under the NTSC method, the total cost of the production subsystem is 15,420, the total cost of the distribution subsystem is 4377, and the total cost of the warehousing subsystem is 9620, totaling 29,417. In contrast, under the TSC method, the total cost of the production subsystem drops

to 9433, a reduction of 38.8 %; the total cost of the distribution subsystem drops to 3531, a reduction of 19.3 %; and the total cost of the warehousing subsystem drops to 6082, a reduction of 36.8 %. The above analysis shows that under the NTSC method, production logistics resources are not fully utilized, making it difficult to deliver newly added production orders on time, significantly increasing the delay penalty cost for the entire system.

The TSC method has demonstrated a timely and effective response to new dynamic demands compared to the NTSC method. Despite changes in the initial scheduling plans of production, distribution, and warehousing subsystems, the TSC method ensures that these subsystems can complete assembly, distribution, and warehousing tasks within designated timelines, effectively mitigating the negative impacts of dynamic disturbances. As a result, the total system cost using the TSC method is significantly lower than that of the NTSC method, with total costs reduced from 29,417 to 19,046—a decrease of 35.3 %. This indicates that the proposed TSC method not only lowers operational costs across production, distribution, and warehousing subsystems but also significantly enhances the overall operational efficiency of the production logistics system. This may be mainly due to the fact that the TSC method enhances the trust among system segments through blockchain and digital twin technologies, enables more efficient information exchange and resource sharing, and provides a trusted synchronized response to specific dynamics disturbances (e.g., dynamic customer demands), thus realizing the global optimization of the production logistics system.

5.3. Sensitivity analysis

This study focuses on one key factor affecting the social production logistics systems—new customer demand. The quantity change of new demand reflects different levels of system dynamics and significantly impacts the system's resource requirements. When dynamic demand increases excessively, it may disrupt the normal operation of the system, causing order delays and corresponding penalties, thereby increasing the overall operation cost. Therefore, it is crucial to study the impact of new demand quantity on the production logistics system. This paper hypothesizes different additional demand quantities ($D = 10, 20, 30, 40, 50$) to analyze the performance of the production logistics system using both the TSC and NTSC methods. The specific indicators include production subsystem cost, distribution subsystem cost, warehousing subsystem cost, order delay penalty cost, total system operation cost, optimization cost, and cost optimization ratio. The optimization cost refers to the total operation cost saved by using the TSC method compared to the NTSC method, and the cost optimization ratio is the ratio of the optimization cost to the total cost of the NTSC method.

Table 12

New customer production order information.

Order No.	New moment	Product type	Order quantity	Shipment time
O11	30	C	20	550

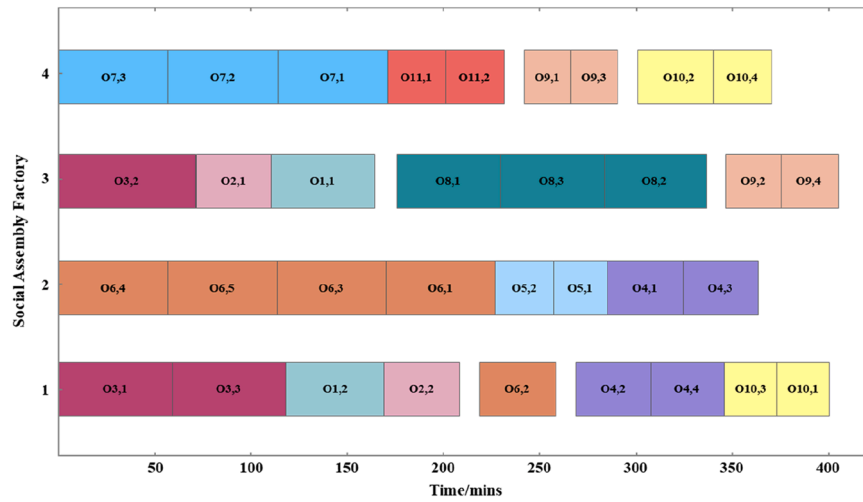


Fig. 10. Gantt chart of finished product assembly production rescheduling result based on CO.

Table 13
Vehicle Rescheduling Result Based on CO.

No.	Vehicle type	Pick-up path	Distribution quantity	Departure moment
1	2T	W0-SF3-SF4-SF2-W0	20	0
2	2T	W0-SF1-SF2-SF4-SF3-W0	28	60
3	1T	W0-SF2-SF1-SF3-W0	15	140
4	2T	W0-SF1-SF4-SF3-SF2-W0	30	285
5	2T	W0-SF2-SF1-SF4-SF3-W0	27	305
6	3T	W0-SF3-SF4-SF1-W0	37	328
7	2T	W0-SF4-SF2-SF3-SF1-W0	28	330
8	2T	W0-SF4-SF2-SF1-W0	30	365
9	3T	W0-SF4-SF3-SF1-SF2-W0	40	410
10	2T	W0-SF4-SF1-SF3-W0	25	421
11	2T	W0-SF1-SF3-SF2-W0	20	429
12	3T	W0-SF1-SF2-SF4-SF3-W0	40	450

Based on the results of the simulation experiments under different quantities of new demands (see Table 15 and Fig. 12), we come up with the following key findings and propose the corresponding key management insights.

(1) **Key finding I:** Significant advantages of the TSC method in resource allocation and cost control. Regardless of the scale of new demand, the four key costs associated with the TSC method (total production cost, total distribution cost, total warehousing cost, delay penalty cost, and total system cost) are lower than those associated with the NTSC method. This indicates that the TSC method demonstrates significant advantages in resource allocation and cost control. Furthermore, regardless of the method used, both the total production cost and total system cost are positively correlated with the amount of new demand. This reflects that as production demand increases, the demand for human and material resources also rises, clearly demonstrating the direct correlation between resource input and output demand in production activities.

Based on the above findings, the following management insights can be drawn: (i) Enterprise managers should prioritize the TSC method for

resource allocation and cost control, leveraging advanced decision-making mechanisms to optimize resource use and reduce operational costs. (ii) It is crucial for managers to understand the relationship between resource input and output demand, planning and scheduling resources to accommodate varying levels of new demand. (iii) Continuous optimization of resource allocation strategies is essential, especially during peak demand periods, to ensure efficient resource utilization and cost reduction.

(2) **Key finding II:** Trends in distribution costs and delay penalty costs under dynamic demand for the TSC method. With the increase in the number of new orders, the total distribution cost and delay penalty cost using the TSC method initially rise and then fall, with a turning point at $D = 40$. In contrast, these costs continue to rise under the NTSC method. This difference is primarily because, with the increase in dynamic demand, the system's available resources and optimization space are limited, making it difficult to complete some orders within the scheduled time, resulting in penalty costs for delays. However, when the order demand reaches $D = 40$, the TSC method effectively meets all order demands by implementing a level 3 synchronized response strategy and promptly introducing external resources, such as activating backup assembly factories, significantly reducing high costs due to delays.

Based on the above findings, the following management insights can be drawn: (i) During peak demand periods, Enterprise managers should adopt the TSC method, flexibly mobilizing internal and external resources to ensure timely order completion and minimize penalty costs. (ii) Establishing a reliable emergency response mechanism, including external resources like backup assembly plants, is crucial for addressing unexpected demand fluctuations. (iii) Additionally, dynamically adjusting delivery routes and schedules can further reduce distribution costs, especially amid significant demand variability.

(3) **Key finding III:** Trend of cost optimization rate with new demand volume. The cost optimization and cost optimization ratio (ranging between 39 % and 57 %) show an initial rise, followed by a decline and then a rise again with the change in new demand quantity. When the new demand quantity is relatively low (e.g., $D = 10, 20$), the system responds to demand changes through effective synchronized decisions, maintaining low-cost growth. However, as demand further increases, the available resources and optimization space of the system become limited, leading to an increase in synchronized costs, thereby narrowing the cost difference with the NTSC method. When the demand quantity exceeds $D = 40$, by introducing more external resources, the TSC method can effectively reduce the total cost. This indicates that although the initial limitation of resources may inhibit the cost optimization effect, timely resource supplementation and strategy

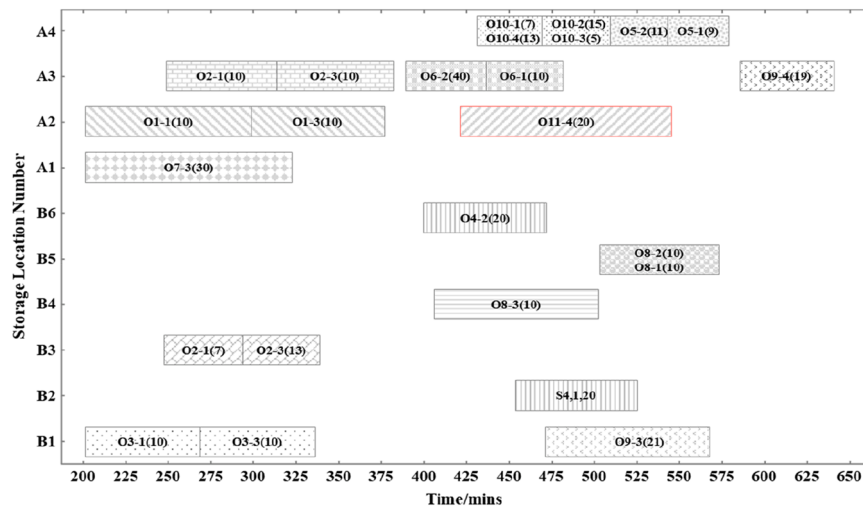


Fig. 11. Gantt chart of storage location reassignment results based on CO.

Table 14

Comparison of rescheduling costs under different control methods.

Cost type (\$)	NTSC	TSC
Assembly cost of production in final assembly workshop	9320	8653
Assembly shop production switching cost	1080	780
Finished product delay off-line penalty cost	5020	0
Distribution vehicle fixed use cost	2410	2116
Distribution vehicle variable travelling cost	1678	1385
Pick-up time loss penalty cost	289	30
Storage space fixed usage cost	5410	3423
Storage space variable usage cost	3560	2659
Order delivery delay penalty cost	650	0
Total system cost	29,417	19,046

Table 15

System performance under different additional demand quantities.

Cost Indicator (\$)	Method	D = 10	D = 20	D = 30	D = 40	D = 50
Production total cost	TSC	8420	8620	8715	11,475	12,950
	NTSC	12,420	17,420	19,245	23,578	26,680
Distribution total cost	TSC	3567	3567	4350	4600	4130
	NTSC	4200	4200	4600	4600	5000
Warehousing total cost	TSC	4250	4255	5052	5068	4528
	NTSC	4550	4560	5060	5078	5580
Delay penalty cost	TSC	0	0	1025	4825	0
	NTSC	5525	8256	9532	10,862	12,530
Total system cost	TSC	16,237	16,442	19,142	25,968	21,608
	NTSC	26,695	34,436	38,437	44,118	49,790
Optimization cost		10,458	17,994	19,295	18,150	28,182
Cost optimization ratio		39 %	52 %	50 %	41 %	57 %

adjustment can significantly enhance the cost-effectiveness of the synchronized strategy, especially in response to larger-scale demands.

Based on the above findings, the following management insights can be drawn: (i) When demand is low, Enterprise managers should fully utilize existing resources to sustain low-cost growth. As demand rises to a critical threshold, timely supplementation of external resources is necessary to maintain cost optimization. (ii) Enterprise managers should dynamically adjust resource allocation and optimization strategies based on demand fluctuations to achieve optimal cost-effectiveness at varying demand levels. (iii) Real-time data analysis can enhance demand forecasting accuracy, enabling proactive resource management and strategy adjustments to prepare for potential demand surges.

The experimental results underscore the significant impact of dynamic demand fluctuations on the operational costs of production logistics systems. As demand varies, operational costs tend to rise due to

the additional expenses associated with production adjustments, inventory control, and logistics management required to address sudden demand changes. Therefore, in dynamic operational environments, managers should actively adopt advanced synchronization control methods like TSC, which utilizes intelligent information-sharing architectures and embedded multi-disciplinary optimization algorithms to tackle relevant challenges. The TSC method not only facilitates effective prediction and response to potential dynamic disturbances but also promotes the flexible allocation of resources, balancing short-term and long-term benefits to optimize operations and reduce costs. Ultimately, the method helps maintain core competitiveness in a highly competitive market environment.

This research highlights the TSC method's advantages across varying new demand levels and provides essential insights for enterprise managers, enabling them to better navigate dynamic demand changes and enhance the overall efficiency and economic viability of their production logistics systems.

6. Conclusions

This study proposes a trusted synchronized control method for social production logistics systems, leveraging the integration of blockchain and digital twin technologies. This method relies on blockchain and digital twin technologies to reliably obtain real-time operational data from social production logistics systems and supports achieving predetermined production logistics decision goals in dynamically changing environments, effectively enhancing the system's anti-disruption capabilities. Through numerical simulation experiments of application cases, the feasibility and effectiveness of this control method in the dynamic demand environment are verified, providing a practical implementation framework and method for synchronized production and logistics operations and autonomous decision control, thereby offering new perspectives and strategies for manufacturing management practices. This study makes the following three main contributions to current literature and practice:

- By deeply analyzing the application of blockchain and digital twin technologies in real-time production system management, this study innovatively extends the traditional digital twin architecture. We propose a trusted synchronized decision framework that combines these two technologies, ensuring data security and transparency while enhancing the system's real-time monitoring and control capabilities.
- In the face of various dynamic disturbances in an open manufacturing environment, this study designs a trusted

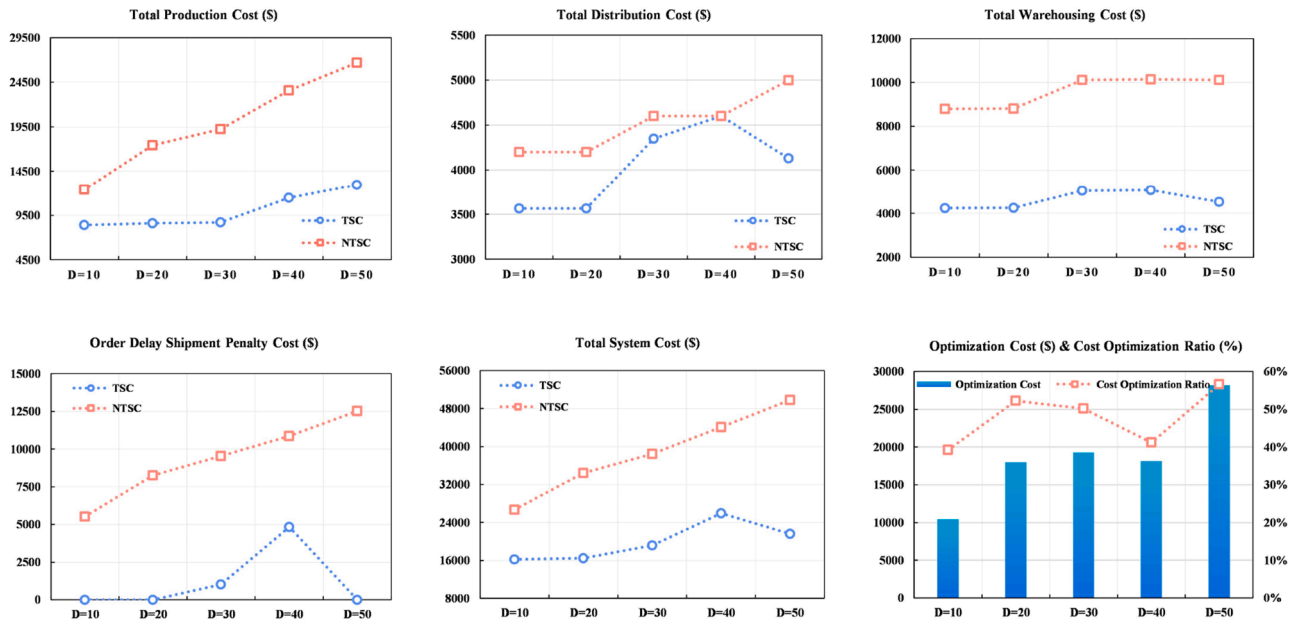


Fig. 12. System efficiency results under different dynamic demands. (a) Total production cost under different dynamic demands; (b) total distribution cost under different dynamic demands; (c) total warehousing cost under different dynamic demands; (d) order delay shipment penalty cost under different dynamic demands; (e) total system cost under different dynamic demands; (f) optimization cost and cost optimization ratio under different dynamic demands.

synchronized decision-making mechanism based on blockchain smart contract trees. This mechanism utilizes the immutability and decentralization features of blockchain to achieve fast and reliable decision-making in complex systems, and enhances the ability of the production logistics system to resist disturbances in the execution process.

- Through actual case studies, this paper applies the proposed framework and mechanism, and the model was solved using the collaborative optimization algorithm. The feasibility and effectiveness of the proposed synchronized control method are quantitatively verified, providing an effective implementation framework for synchronized production logistics operations and autonomous decision control, thereby offering new perspectives and strategies for manufacturing management practices.

Although this study has preliminarily verified its effectiveness in specific dynamic disturbance scenarios (such as new customer orders), future research should further explore the adaptability and effectiveness of this decision framework under more complex dynamic situations, such as equipment failures or delayed release of storage locations, to more broadly adapt to different types of production logistics challenges. Additionally, the application of real-time big data analysis technology to the synchronized decision-making of social production logistics systems is another direction worth exploring in depth. This study demonstrates the potential of a trusted synchronized control method based on blockchain and digital twin, which provides innovative strategies for production operation management practices and lays a solid foundation for achieving optimal operation of production logistics systems.

CRedit authorship contribution statement

Zhongfei Zhang: Writing – review & editing, Writing – original

draft. Ting Qu: Supervision, Conceptualization. George Q. Huang: Supervision, Conceptualization. Yongheng Zhang: Methodology. Kuo Zhao: Data curation. Jun Zhang: Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A

Table A.1 specifically show the relevant acronyms for this article.

Table A.1
List of key acronyms.

Acronym	Description
ATC	analytical target cascading
ALC	augmented Lagrangian coordination
BC	blockchain
CO	collaborative optimization
DT	digital twin
DSAs	distribution system agents
ERP	enterprise resource planning
IoT	internet of things
MDO	multidisciplinary design optimization
MTAs	manufacturing task agents
MSAs	manufacturing system agents
MTO	make to order
MES	manufacturing execution system
NTSC	non-trusted synchronized control
OAs	order allocation agents
PSAs	production system agents
P2P	peer to peer
SPLS	social production logistics systems
SocialM	social manufacturing
SOs	smart objects
TMS	transportation management system
TSC	trusted synchronized control
WSAs	warehousing system agents
WMS	warehouse management system

Data availability

The authors do not have permission to share data.

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