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Digital Twin-Based Prediction and Optimization for Dynamic Supply Chain Management

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Abstract: Manufacturing supply chains are becoming increasingly complex due to geopolitical issues, globalization, and market demand uncertainties. These challenges lead to logistics disruptions, inventory shortages, and interruptions in raw materials and spare parts production, resulting in delayed delivery, reduced market share, and lower customer satisfaction. Effective supply chain management is critical for improving operational efficiency and competitiveness. This paper proposes a supply chain digital twin methodology to enhance operational efficiency through real-time monitoring, analysis, and response to disruptions. This methodology defines a supply chain digital twin system architecture and outlines the operational process of digital twin applications. It introduces two key modules: a digital twin module for prediction and monitoring and an optimization module for determining the optimal movement of products. These modules are integrated to align digital simulations with real-world supply chain operations. The proposed approach is validated through a case study of an automobile body production company's supply chain, demonstrating its effectiveness in reducing inventory and logistics costs while providing countermeasures for abnormal situations.

Keywords: supply chain management; digital twin; optimization; metaheuristic; simulation

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1. Introduction

Technologies such as digital twin (DT) and optimization, which have been developed with the introduction of Industry 4.0, not only enable the automation of production lines but also create a manufacturing environment in which problems can be solved with minimal intervention by analyzing specific problems. These technologies considerably influence the entire supply chain (SC), including retailers, operational companies, and service providers [1]. In manufacturing, risks such as SC interruptions and disruptions in logistics and recovery schedules increase owing to interruptions in the production of raw materials and spare parts [2]. Combined with the growing complexity of SCs, globalization, external environmental changes, and market uncertainty, these disruptions result in demand fluctuations, inventory shortages, and delivery delays, leading to recurrent interruptions.

SC disruptions directly affect the overall performance of companies and have serious consequences, such as loss of market share, delays in delivery, decline in service level, and lower customer satisfaction [3]. The operational efficiency and competitiveness of companies and partners in SC must be improved to provide products that customers require in a timely and profitable manner [4]. Previous studies have attempted to minimize costs and maximize profit and customer service to increase the operational efficiency and competitiveness of SC by using operation research and optimization methodologies [5,6]. However, it is extremely complex to formally express these technologies because there are multiple objects within the SC, and interactions between them occur. Moreover, it is difficult to simultaneously consider multiple concepts such as uncertainty, risk, and time issues owing to production delays at intermediate manufacturers or accidents on the road [7–9]. Thus, these SC issues need to be considered simultaneously to support decision-makers.

Conversely, a simulation methodology can analyze various scenarios and select appropriate solutions by considering the complexity and dynamics to support decision-makers [8–10]. However, there are limitations in that the integrated analysis and unified management of the participants in the entire SC are difficult because of challenging requirements such as real-time management and dynamics [11]. Accordingly, there is an increasing need to implement DT technology for two key reasons: (1) to account for real-time changes by applying a metaheuristic algorithm capable of finding a feasible optimal solution within a reasonable timeframe [12] and (2) to monitor/analyze/predict real-time status by integrating the demand forecast data, delivery information, order plans, production plans, and logistics plans across SC members [13].

Therefore, this study proposes a DT-based prediction and optimization methodology to improve the operational efficiency of SC. To this end, this study designed a digital SC system architecture and built a simulation model for suppliers, manufacturers, and logistics operators who are members of SC. Furthermore, a metaheuristic-based algorithm for logistics optimization by hierarchy level was developed, and a process for operating the supply chain digital twin (SCDT) system was defined. Finally, the efficiency and validity of the proposed methodology were verified through a case study targeting the SC of an automobile body manufacturing company.

The remainder of this paper is organized as follows. Section 1 describes the background, purpose, and necessity of this study. Section 2 reviews existing studies on SC and supply chain management (SCM), which form the theoretical background, and introduces the definition of SCDT. Section 3 presents the architecture of the SCDT system and explains the modules that constitute the DT. In Section 4, the effectiveness of the proposed DT application is verified through a case study. Section 5 explains the significance and contributions of this study. Section 6 presents the conclusions and suggests future research directions.

2. Research Background

2.1. Supply Chain Management

SCM integrates various business processes such as demand planning and forecasting, procurement, manufacturing, assembly, distribution, resource management, and customer-centric process management [14]. SCM can be defined in various ways. Christopher defined SC as a network of organizations involved in various processes and activities that create value through products and services delivered to end consumers via upstream and downstream connections [15]. APICS defines an SC as a process that begins with raw materials and extends to the final consumption of finished products, linking suppliers and users, or as a value chain function that spans from product production to delivery to customers [16]. Chow et al. define an SC as a group of manufacturers, suppliers, distributors, retailers, transportation providers, information providers, and other logistics management service providers involved in providing goods to consumers [17].

In summary, an SC comprises supply, distribution, and final consumers. The main objective of SCM is not only to integrate the purchase, supply, and control of materials from a holistic system perspective across multiple functions and multiple Tiers of suppliers but also to harmonize conflicting goals, such as high customer service, low inventory management, and low unit cost to synchronize customer requirements with supplier material flows [18,19]. Several manufacturing companies have built distributed global SC, not only domestically but also overseas, to take advantage of economic labor and materials over several decades.

2.2. Operation Research for Supply Chain Management

The methodology for improving the operational efficiency and competitiveness of existing SC is primarily operational research. In other words, an optimization methodology was used to optimize the SC production plan and inventory to minimize costs and maximize profits. Graves et al. proposed a methodology that minimizes the total SC cost using the minimum spanning tree method when there are various constraints, such as the selection of suppliers, parts, and transportation methods along the SC [20]. Perea-Lopez et al. presented a predictive control methodology to determine the optimal decision variables to maximize the profits of SC for multiple products, factories producing multiple types of products, and multi-tiered distribution networks [21].

Jamshidi et al. employed a mixed genetic algorithm (memetic algorithm) based on the Taguchi method to minimize annual costs, considering not only SC cost factors such as transportation, holding, and order costs but also environmental impact factors, including volatile organic compounds generated by SC facilities and transportation [22]. Kaasgari et al. used a genetic algorithm and particle swarm optimization to manage the inventory of products with a defined lifetime by calculating and minimizing the overall costs, including fixed ordering, inventory holding, and product obsolescence costs and determined the retailer's replenishment cycle, order size, and production time [23]. Braido et al. reduced logistics costs by selecting a distribution center that reflected raw material, transportation, factory, and facility fixed costs through SC optimization based on the tabu search algorithm [24].

Existing studies have primarily used mathematical methods to analyze and optimize SC. However, it is difficult to analyze the SC process considering various aspects such as production delays, uncertainty, risk, and time issues due to road accidents [7–9]. Additionally, there is a risk of generating unrealistic results owing to the simplification and assumptions made across various factors when simulating real-world scenarios [25]. In other words, there are still limitations in deriving solutions for the future with many uncertainties, although there have been many efforts to efficiently analyze SC using existing methodologies.

2.3. Simulation for Supply Chain Management

Therefore, simulation-based methodologies have been proposed to overcome these limitations. Physical experiments are difficult to perform owing to technical and cost-related limitations. Simulation methodologies reflect the basic properties of an object and a real situation and construct and synchronize a model that simulates their characteristics and behavior. They also perform situation prediction, identification, result analysis, and decision support through what-if analysis [26,27]. Simulation-based methodologies have emerged as core technologies that support state-of-the-art manufacturing [28]. Simulation methodologies in terms of SCM can quantitatively evaluate the benefits and problems through a what-if analysis in a virtual environment [29].

Additionally, the constructed SC simulation model must be preceded by the construction of a manufacturing and logistics system model that includes business processes and information flow in addition to material flow [30]. The commonly used SC simulation methodologies include process-oriented simulation, object-oriented simulation, system dynamics-based simulation, Petri net-based simulation, High-Level Architecture (HLA)-based simulation, and discrete event simulation. Among these, discrete event simulation is the most widely used methodology for SCM [31]. Bhaskaran focused on stamping pipelines in an automobile SC and presented a methodology for analyzing the SC instability and inventory using simulations [32]. Bottani et al. presented a methodology for the quantitative evaluation of the influence of various SC components, such as reordering, inventory management policies, and demand information sharing, on total SC costs and the bullwhip effect through a discrete event simulation [33]. Carvalho et al. [34] presented a methodology for improving SC resilience to change using a simulation of the Portuguese automobile SC and evaluated how response strategies affect member performance. Rouzafzoon et al. presented a methodology to reduce inventory quantity by optimizing vehicle scheduling and delivery vehicle quantity through an agent-based simulation [35].

Thus, simulation methodologies can improve the operational efficiency of SC by presenting optimized alternatives by implementing and analyzing various SC scenarios. However, there are limitations to managing the SC from an integrated perspective, such as logistics of various products and multiple SC objects by hierarchy, considering real-time, and it is also difficult to analyze how the actions of SC objects are related to the entire SC through integrated analysis among SC participants [33,34]. Therefore, to increase the operating efficiency of SC and become competitive, it is necessary to introduce DT technology to monitor, analyze, and predict the real-time status by integrating and analyzing hierarchical demand and delivery information, orders, production, and logistics plans.

2.4. Digital Twin

DT, first introduced in 2002, is an evolving concept that is increasingly emphasized in academia and industry [36,37]. It represents an advanced version of virtual simulation models that integrate real and cyber environments to simulate real-world components, reflecting information models and functional elements [37–39]. Söderberg et al. defined a DT as a model capable of real-time control and optimization through data, algorithms, and simulations [40], whereas Wang et al. highlighted its support for technologies such as machine learning and cloud services [41]. Compared with traditional simulation models, DT offers significant advantages, including real-time data integration, bidirectional communication between physical and digital systems, and adaptive behavior through machine learning algorithms. Unlike traditional models, which typically function in isolated and static environments, DT continuously updates in real-time based on live data, enabling dynamic diagnostics, predictive capabilities, and improved decision-making [42,43].

Owing to these additional advantages, DT is increasingly applied in areas other than manufacturing [44]. In SCM, DT provides an integrated view, enabling stakeholders to collaborate across stages through simulation, optimization, and data analysis [11,45]. Busse et al. described it as a long-term, interactive digital model of logistics systems [46], whereas Kalaboukas et al. emphasized its predictive flexibility in dynamic environments [47]. By applying DT to SCM, companies gain enhanced inventory visibility, demand detection, flexibility, and reduced risk and cost [48].

Several frameworks have been proposed for the SCDT. Ivanov introduced a risk analysis framework that lacked empirical validation [49]. Lee developed a system for production-logistics integration but focused on single-layer supplier-manufacturer relationships [50]. Blomkvist et al. demonstrated improved logistics visibility using a DT, confirming its value in asset analysis, diagnosis, and prediction [51]. Lee et al. proposed a framework for real-time logistics risk simulation, though its scope was limited to logistics and did not address broader SC flows [13]. Ivanov offered guidelines for managing disruptions through DT, but the lack of empirical case studies hindered confirmation of their effectiveness [52].

Research on SCDT remains in its early stages and is in progress in terms of concept definition and the application of frameworks and cases to specific situations. Recent studies highlight the potential of DT technologies to enhance SC resilience, efficiency, and flexibility. For example, DT has been applied to predictive logistics, disruption-mitigation strategies, and risk assessment, enabling SC to respond proactively to uncertainty and real-time challenges [53]. Moreover, bibliometric analyses have pinpointed key research areas, such as DT integration, design, and its role in optimizing SC performance, emphasizing its growing significance in contemporary SC systems [54].

However, despite these advancements, much of the existing literature continues to focus on isolated elements of the SC, such as single-layer supplier-manufacturer relationships or static simulation models, which overlook the dynamic, multi-tiered, and interconnected nature of modern SCs [55]. Additionally, lean SCM has emerged as a key area where DT can play a pivotal role. However, its application faces challenges in achieving real-time integration and scalability when combined with optimization methodologies [56]. Existing optimization techniques, such as heuristic and metaheuristic methods, often face challenges in balancing computational efficiency with solution quality in large, complex, and dynamic SC networks.

This study addresses these limitations by proposing a unified SCDT system that integrates suppliers, manufacturers, and logistics providers into a single, real-time digital framework. Unlike previous studies, the proposed approach combines a DT-based real-time simulation with a tabu search optimization algorithm to enable dynamic decision-making across the entire SC. By integrating real-time data, hierarchical optimization, and unified modeling, the proposed system addresses current challenges related to scalability, real-time performance, and the complexity of multi-tiered SCs.

3. Supply Chain Digital Twin

This section introduces a digital-twin-based prediction and optimization system for dynamic SCM. The architecture of the SCDT system is defined to implement the proposed system, and the information flow of the system is described based on the defined architecture. In addition, the function of each module comprising the system is explained, and the information required for each module and application sequence is introduced in detail.

3.1. Architecture of Supply Chain Digital Twin System

This subsection proposes the architecture of an SCDT system to improve operational efficiency. The existing SCM has three major limitations: (1) inability to consider real-time, (2) difficulty in integrated analysis among SC participants, and (3) inability to respond to volatility. This study aims to improve the operational efficiency of an SC to mitigate the abovementioned limitations by integrating and optimizing supplier, manufacturer, and logistics information through an SCDT system and monitoring and analyzing the entire process in real-time.

The proposed information flow between SC components is shown in Figure 1. A typical information process (AS-IS) in a traditional SC follows this sequence: the manufacturer plans orders, the supplier plans production, the transporter plans outbound logistics, and finally, production occurs. However, it is difficult to reflect demand fluctuations and logistics disruptions in real time, which limits the ability of SC to respond to abnormal situations. Therefore, the proposed SCDT system (TO-BE) integrates this information to collect and analyze information from SC members. This involves integrating and analyzing the information required from all aspects of the SC, not delivering it sequentially.

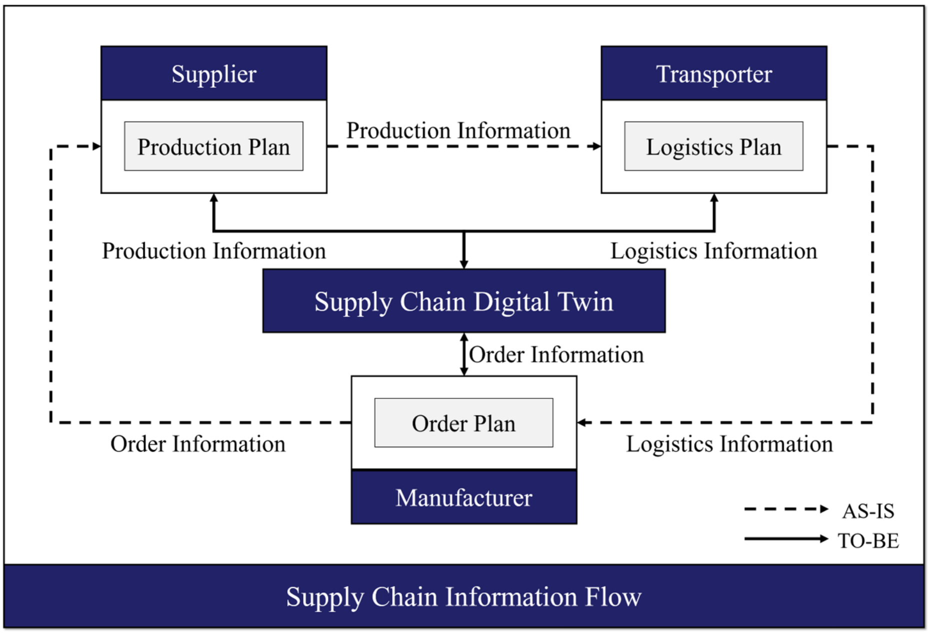


Figure 1. Information flow of supply chain.

The architecture of the proposed SCDT system is shown in Figure 2. First, the simulation model requires data from suppliers, secondary and primary manufacturers, and customers collected from an actual SC. These data are stored as a simulation modeling database for building simulation models and as a manufacturing planning database for running a DT. The simulation modeling database contains modeling information for building production and logistics simulations, whereas the manufacturing planning database contains production and logistics planning information.

The data from these SC members is transmitted through an interface to the SCDT application, while information from the simulation modeling database is integrated into the simulation logic to construct supplier, manufacturer, and logistics models. The manufacturing planning database contains the manufacturer's order plan, production plan, logistics plan, and time data, which are used as input for executing the DT. The SCDT application is driven based on this information.

The SCDT application consists of DT and optimization modules. The DT module consists of a production simulation model and a logistics simulation model and performs real-time synchronization, forecasting, operation management, abnormal situation management, delivery verification, and visualization. The DT module supports the decision-making of SC stakeholders by analyzing and visualizing production simulation results, logistics simulation results, and optimization algorithm results. The production simulation model was controlled using a discrete-event simulation, and the logistics simulation model was controlled using a dynamic simulation. The optimization module performs SC optimization using the tabu search algorithm, which selects the next best factory location for each product based on forecast inventory and cost information.

The SCDT system acts as a central integration engine, where data are collected, updated, and synchronized in real-time from all SC participants, including suppliers, manufacturers, and logistics providers. The responsibility for feeding and updating the system is distributed across the respective stakeholders facilitated through automated data collection systems, such as IoT devices, ERP systems, and logistics tracking tools. The SCDT application ensures real-time synchronization and updating by interfacing these data sources via a standardized data interface. SC analysts typically manage the central monitoring and control of SCDT systems. SC analysts oversee data collection, interpretation, and performance monitoring by suppliers, manufacturers, and logistics providers. They ensured that the real-time data feed was accurately integrated into the SCDT system. This means that each company involved in the SC must have its own SC engineer, implying that collaboration among various SC entities can be achieved.

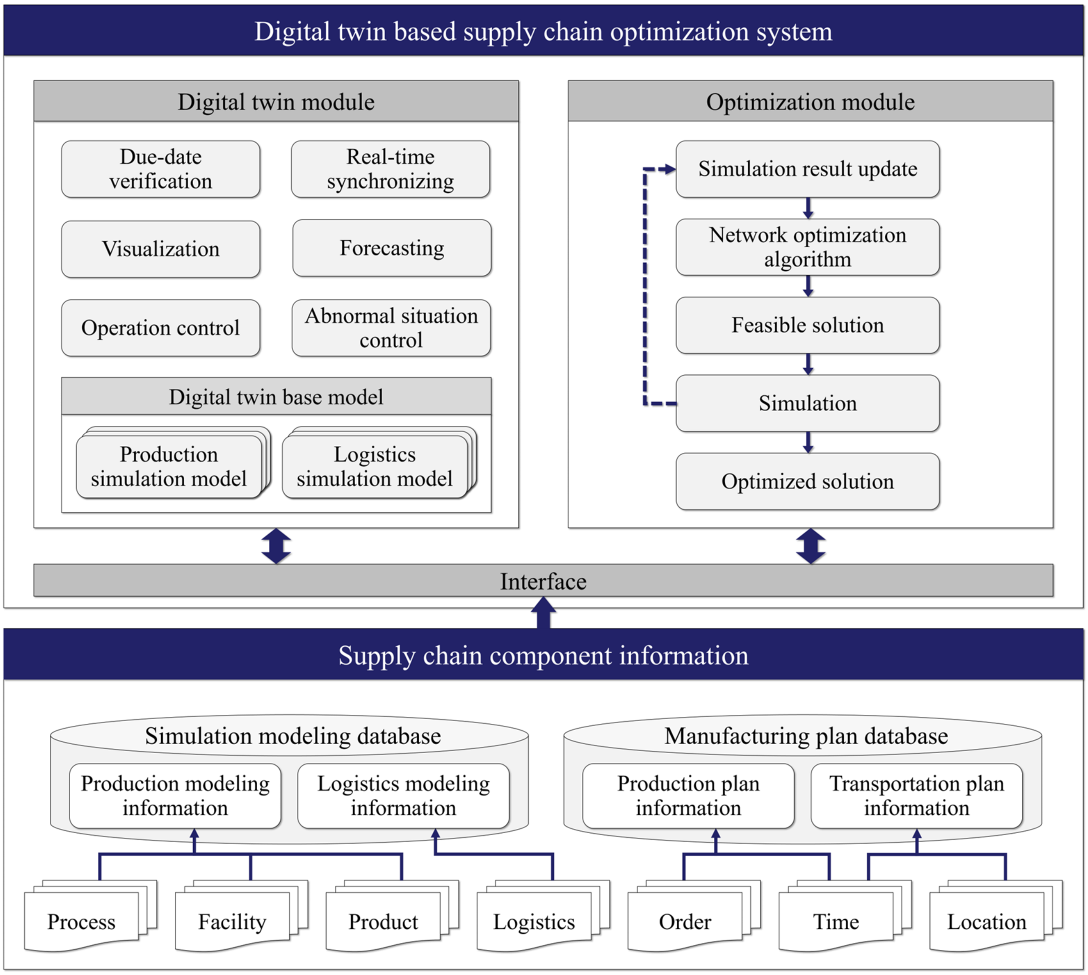


Figure 2. The architecture of the supply chain digital twin.

While developing simulation models for production and logistics, responsibility is shared among multiple roles to ensure both accuracy and seamless integration. Domain experts, such as SC engineers, production planners, and logistics managers, define the operational parameters, constraints, and real-world requirements of DT models. They ensure that the models accurately reflect the SC processes and dynamics. IT specialists, including simulation engineers and data integration experts, are tasked with building DT models and implementing the necessary data interfaces. They are responsible for transforming operational requirements into functional simulation models and ensuring seamless data flow between components. The integration of these models into the SCDT system is overseen by a dedicated integration team or system architect, which ensures the consistency, synchronization, and smooth operation of the entire system. This collaborative approach allows the SCDT system to deliver reliable insights and real-time decision support across all SC entities.

The sequence diagram of the proposed SCDT system is shown in Figure 3. When the application starts, the DT module requests information about the ordering plan by-product from the database (#1 process in Figure 3). The database delivers information regarding the products produced, production volumes, and delivery dates through the data interface to the DT module (#2 process in Figure 3). A production simulation model is executed for the supplier using the received information as the input, and the predicted production quantity, inventory quantity, and production completion time information for each product are derived (processes #3, #4, and #5 in Figure 3).

The predicted production quantity, inventory, and logistics cost information by factory location were sent to the optimization module through an interface (#6 process in Figure 3). The production location information by product is derived from the optimization module and sent to the interface (processes #7 and #8 in Figure 3). Then, the logistics simulation model between the supplier and intermediate manufacturer is executed based on the product-specific movement location information obtained from the optimization module, and the information on the estimated arrival time and travel distance for each product is stored in the DT module (processes #9 and #10 in Figure 3).

Subsequently, the production simulation model of the selected intermediate manufacturer was executed, and the forecast production quantity, inventory quantity, and production completion time for each product were derived (#11, #3, #4, and #5 in Figure 3). The predicted production quantity, inventory, and logistics cost information by factory location were sent to the optimization module through the interface, and the production-location information of the last manufacturer by-product was obtained by executing the optimization module. The product-specific movement location information generated by the optimization module is sent to the logistics simulation module, where the logistics simulation model between the intermediate and last manufacturers is executed. Because the production plan is validated through the SCDT application, this process is carried out for the planned production period, and delivery compliance is assessed based on the final arrival date.

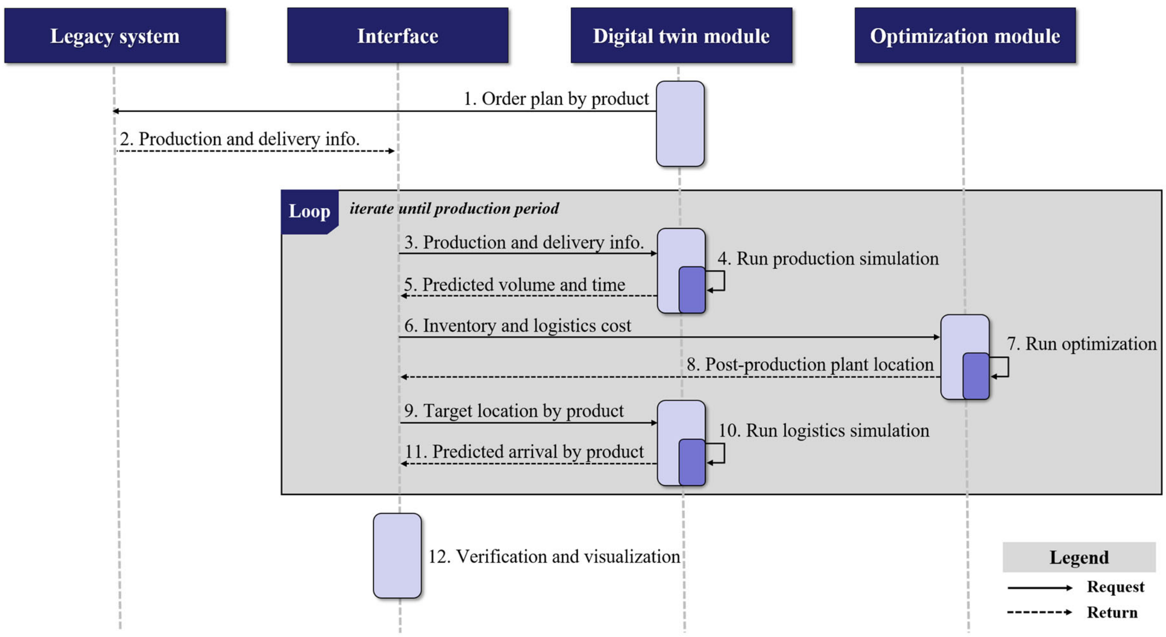


Figure 3. Sequence diagram of supply chain digital twin.

3.2. Configuration Modules

This subsection presents the DT and optimization modules that form the SCDT system based on a previously defined architecture. It details the information required by each module, the information generated by each model, and the specific role of each module within the system.

3.2.1. Digital Twin Module

The DT module comprises a production simulation model and a logistics simulation model. The production simulation model is developed based on data such as product-specific facility process time, facility-specific setup time, facility-specific management indicators, and Bill of Materials (BOM) information from actual manufacturers and suppliers, as shown in Figure 4a. This model is implemented using libraries configured with the simulation engine and development language embedded within the simulation tool. The logistics simulation was implemented and modeled using the Open API with the location coordinates of each factory, as shown in Figure 4b.

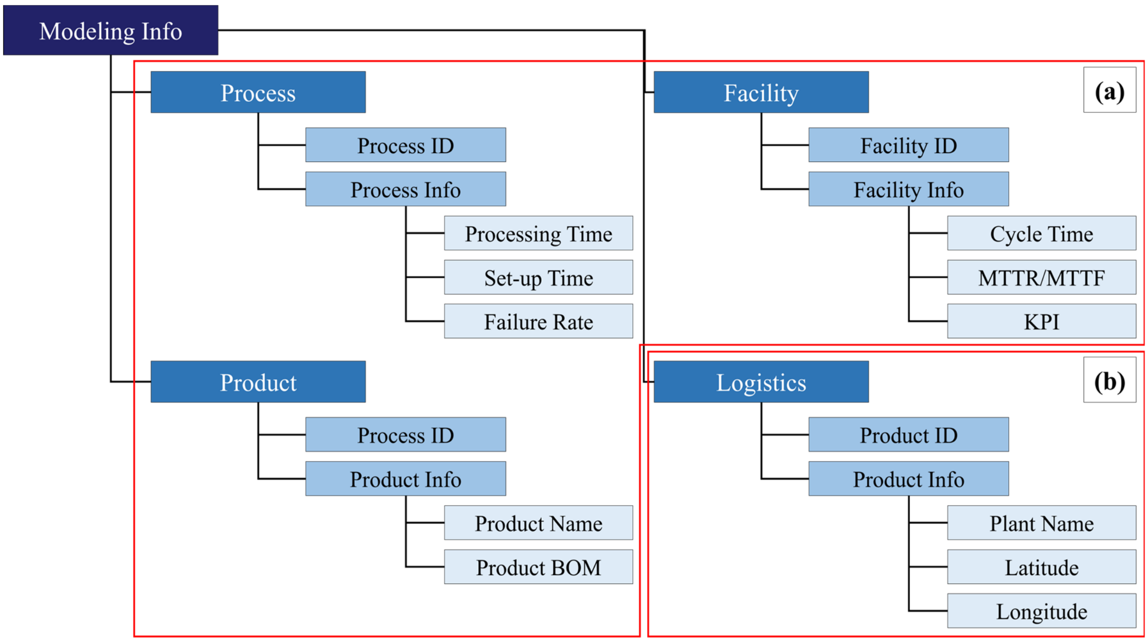


Figure 4. Information model of digital twin module: (**a**) information model of production simulation; (**b**) information model of logistics simulation.

For the production and logistics simulations, the order volume by product, current production plant location, future production plant location, and product production completion time were input, as shown in Table 1. Additionally, the algorithm outputs the predicted production volume, production completion time, product arrival time, and travel distance for each product. The production simulation model calculates the predicted production volume based on the input information and evaluates the production feasibility, whereas the logistics simulation model calculates the travel distance and travel time for each production location. This enables the pre-validation and calculation of the prediction results.

When a DT application is executed, the DT module receives information from the interface and synchronizes it with the simulation model in real-time. It then receives the prediction result information from the simulation model and exports the information to the optimization module through the data interface. Subsequently, the logistics simulation model is executed by receiving the resulting information of the optimization module from the data interface.

Furthermore, based on the demand forecast information, it executes and operates the SCDT and visualizes and analyzes the resulting information, such as the order request time, production completion time, product arrival time, order volume by product, and movement location by product. Thus, it supports the decision-making of SC stakeholders by requesting production plan revisions when the demand forecast information changes and verifying whether products can meet the delivery dates.

Table 1. Input and output of simulation module.

Category	Input Data	Output Data
Production Operations	Real-time order volume	Predicted production volume Production finish datetime
Logistics Simulation	Pre-/post- production plant location Production finish datetime	Product arrival datetime Travel distance

3.2.2. Operation Module

The SC optimization module performed SC optimization based on the production and inventory forecast results of the simulation. The SC optimization algorithm is built upon the tabu search algorithm, a metaheuristic approach designed to solve optimization problems, irrespective of their specific form. It retains tabu information about the local optimum to avoid converging to it, enabling the search for an optimal solution by steering clear of local optima.

The selection of the tabu search algorithm in this study is driven by its proven effectiveness in addressing combinatorial optimization problems, especially in dynamic and high-dimensional environments such as SCs. A tabu search efficiently explores the solution space by avoiding local optima through its adaptive memory mechanism. This makes it suitable for real-time decision-making scenarios in which quick and near-optimal solutions are required. It means that it is possible to derive efficient solutions with relatively low computational effort, thereby enabling real-time decision-making that can overcome the limitations of low responsiveness by leveraging adaptive memory [57].

Additionally, tabu search provides flexibility to incorporate constraints such as production availability and product-specific limitations, which are critical factors in SC optimization. Its ability to balance computational efficiency with solution quality makes it a practical choice for addressing the complexities of multilayered SC networks. The optimization module is applied in the part shown in Figure 5 when determining the optimal product production location, and the optimal production location is determined based on constraints and considerations as the product moves from the supplier to the second-tier manufacturer and from the second-tier manufacturer to the first-tier manufacturer.

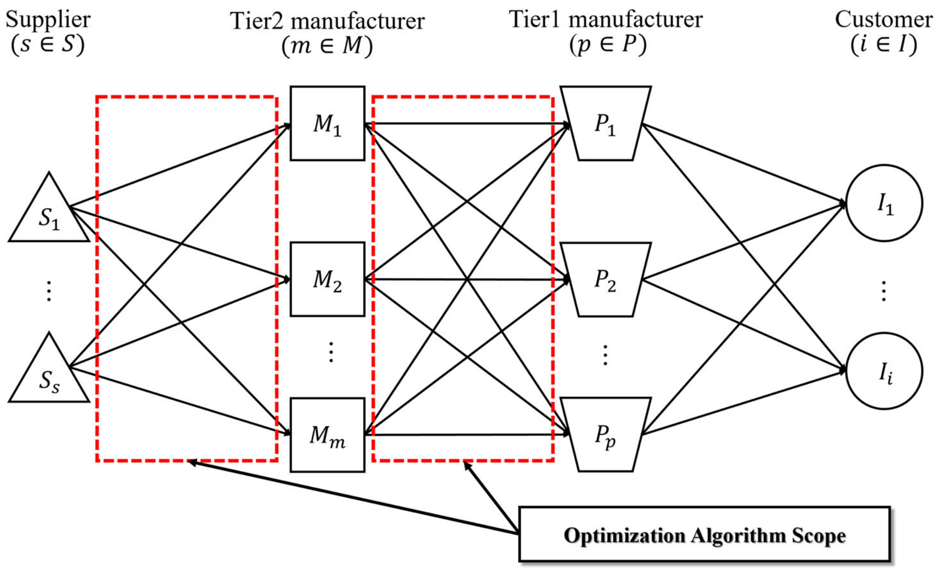


Figure 5. Application scope of optimization module.

The total cost of the SC, which is to be minimized through the optimization module, comprises inventory and logistics costs, as shown in Equation (1). The indices, variables, and parameters used in the objective function are listed in Table 2. The factors determined by tabu search are variables determined after the algorithm is performed according to the indices, and the parameters are the unit costs required to calculate the inventory and logistics costs.

$$\min\left(\sum_s\sum_m q_{sm}d_{sm}+\sum_m\sum_p w_{mp}e_{mp}+\sum_p\sum_i r_{pi}f_{pi}+\sum_s j_s Q_S+\sum_m k_m Q_m+\sum_p l_p Q_p\right) \quad (1)$$

Table 2. Notations for the objective function.

Indices	
s	Index for suppliers ($s \in S$)
m	Index for Tier2-manufacturers ($m \in M$)
p	Index for Tier1-manufacturers ($p \in P$)
i	Index for customers ($i \in I$)
Parameters	
q_{sm}	Unit transportation cost for the material from supplier s to Tier2-manufacturers m
w_{mp}	Unit transportation cost for the material from Tier2-manufacturers m to Tier1-manufacturers p
r_{pi}	Unit transportation cost for the material from Tier1-manufacturers p to customer i
j_s	Inventory maintenance cost per unit for supplier s
k_m	Inventory maintenance cost per unit for Tier2 manufacturer m
l_p	Inventory maintenance cost per unit for Tier1 manufacturer p
Variables	
d_{sm}	Quantity of material shipped from supplier s to mid-plant m
e_{mp}	Quantity of material shipped from Tier2-manufacturers m to Tier1-manufacturers p
f_{pi}	Quantity of product shipped from Tier1-manufacturer p to customer i
Q	Quantity of inventory for supplier, Tier2/Tier1 manufacturer

The purpose of the optimization algorithm is to ensure that a product is moved to a post-processing location that minimizes logistics and inventory costs. The algorithm must also consider the availability of the product at each production location and the availability of subproducts based on the BOM of the product. The conventional tabu search algorithm involves the following steps: (1) generate a random initial feasible solution and calculate its cost; (2) generate a trial solution from the feasible solution; (3) compare the costs of the feasible solution and the trial solution; (4) update the feasible solution; (5) update the tabu queue of the feasible solution information; (6) if the iteration limit has been reached; and (7) select the best solution if it is met. If not, repeat steps (2) until the limit is met and select the best solution.

A flowchart of the proposed TS-based optimization algorithm is shown in Figure 6. As an SC consists of suppliers, Tier2 manufacturers, Tier1 manufacturers, and customers, it is difficult to consider them as the same layer. Thus, it is difficult to determine an optimal solution by changing the conditions in the layer, as in a typical tabu search algorithm. Therefore, all feasible solutions that allow the product to move from the supplier to the Tier2 manufacturer and from the Tier2 manufacturer to the Tier1 manufacturer are entered into a tabu queue.

Here, a feasible solution is that the entities in the SC do not produce all products; rather, each entity can produce only certain products, and if one entity does not produce a product, the other entity does. A feasible solution and a trial solution were generated using a tabu queue, and the costs of these two solutions were compared. After updating the solution to a feasible solution at a higher cost, all the feasible solutions in the tabu queue are compared by changing the products that can be produced in the same layer, and the best solution is selected.

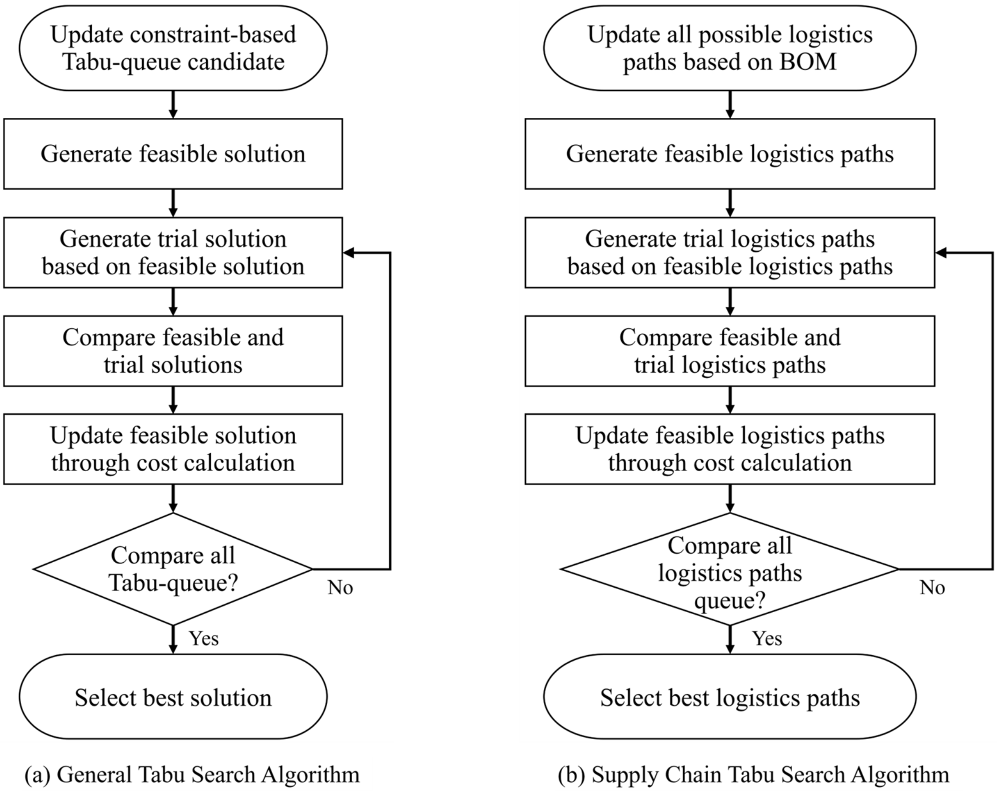


Figure 6. Flowchart of the tabu search algorithm.

4. Case Study

This section describes the implementation of a prototype of the proposed SCDT system and case studies on real factories that target supplier S and OEM G in the Republic of Korea. In the case studies, normal and abnormal situations were applied. Each case study provided a concrete example of the role of the proposed SCDT system.

4.1. Implementation Scope

This study simulated the SC of an automobile body production plant and implemented SCDT for a 2-3-3 company SC consisting of suppliers, Tier2 manufacturers, Tier1 manufacturers, and an inter-manufacturer logistics chain, as shown in Figure 7a. SCDT has two main applications. First, if the SC is stable, the DT is applied at the time of initial planning. Next, if an abnormal situation occurs in the SC, such as plan changes during operation or traffic jams, a DT is applied to response measures, such as a new production plan, or to find a logistics route that minimizes delays. The scope of the analysis was from the time the product was ordered by the Tier1 manufacturer to the time the production was completed. Order and production planning information, logistics costs, and inventory costs were used to conduct the simulation analysis. The products that can be produced in each factory are different. The products were those of Company S, an automobile body production factory, and consisted of three products: A, B, and C. They were organized into two BOM levels, as shown in Figure 7b.

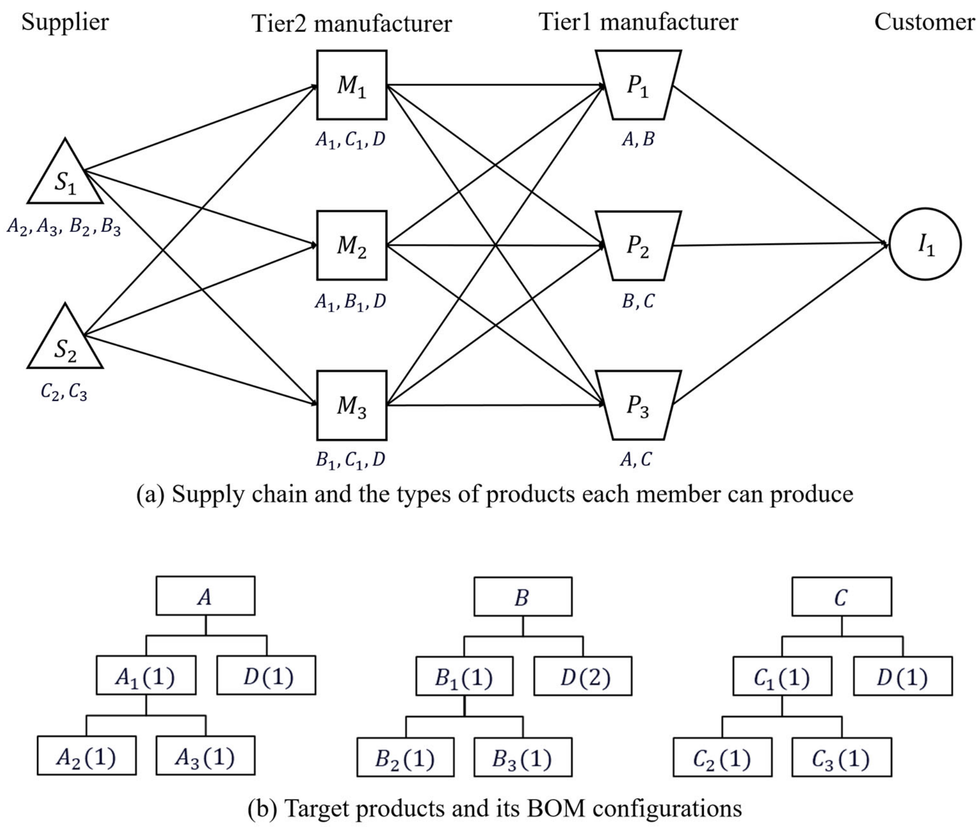


Figure 7. Network and product BOM of target supply chain.

The development environment for the prototype implementation of the SCDT system is presented in Table 3. For the production simulation model of the DT module, the simulation software Plant Simulation 15.2 from Siemens was used as the simulation engine. The open API of the SK T-map of the Republic of Korea is used as the logistics simulation model. For the optimization module, the SC optimization algorithm was implemented using the Python 3.8 library. The interface function was implemented using C# Windows Form and C# library.

Table 3. Development environment of prototype.

Digital Twin Module Development Environment	
OS	Windows 11
Processor	Intel(R) Core(TM) i7-70750H CPU @ 2.60 GHz (manufactured by Intel, based in Santa Clara, CA, USA)
IDE	Visual Studio 2019
Programming Language	C#, Javascript
Network Protocol	TIP/IP
Simulation Engine	Plant Simulation 15.2, SKT T-Map API
Optimization Module Development Environment	
OS	Windows 11
Processor	Intel(R) Core(TM) i7-70750H CPU @ 2.60 GHz
IDE	Spyder 4.1.5
Programming Language	Python 3.8
Network Protocol	TCP/IP

4.2. Implementation Result

The SCDT application consists of (a) a DT application interface, (b) a production simulation model, (c) an SC optimization module, and (d) a logistics simulation model, as shown in Figure 8. First, the DT application interface plays the role of visualizing the production simulation results, such as production completion time and production quantity, logistics simulation results, such as product arrival time at the production plant, and SC optimization results, such as post-processing location by-product in a dashboard. Furthermore, it integrates the production completion time and logistics time at each factory based on the results, visualizes them in a Gantt chart, and serves as a data interface for information exchange. The production simulation model simulates the production plants of suppliers, Tier2 manufacturers, and Tier1 manufacturers to predict production volumes, inventory levels, and production completion times. The SC optimization module minimizes the inventory and logistics costs for each product's next production plant location based on the predicted production and inventory levels from the simulation model. The logistics simulation model forecasts optimal routes and estimated arrival times between suppliers and Tier2 manufacturers, as well as between Tier2 manufacturers and Tier1 manufacturers, using the results optimized by the SC optimization module.

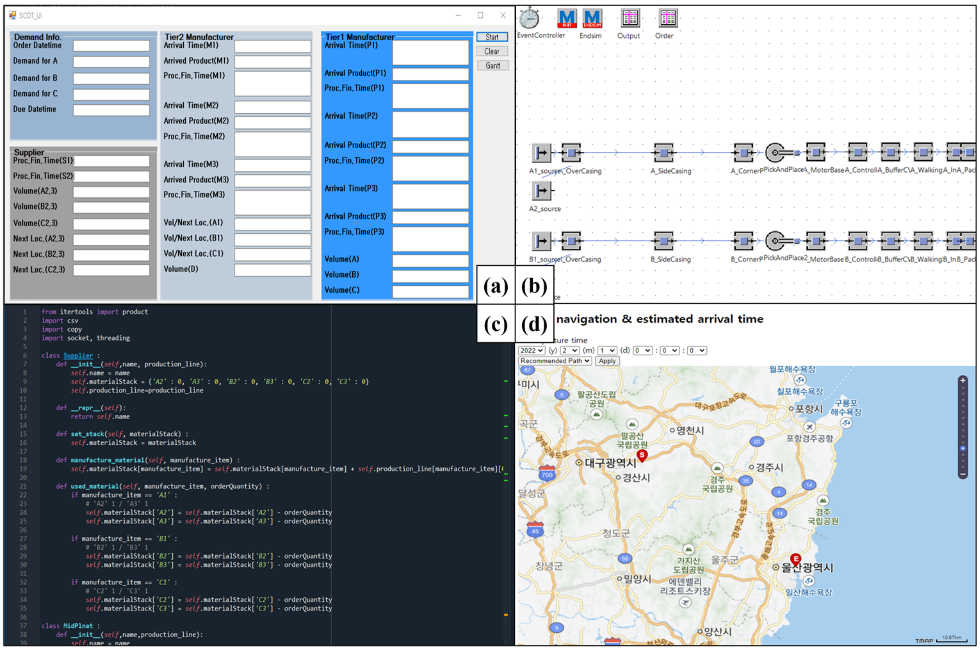


Figure 8. Supply chain digital twin application: (**a**) a digital twin application interface; (**b**) a production simulation model; (**c**) a supply chain optimization module; (**d**) a logistics simulation model (S: start location, E: end location).

4.3. Case Study Result

4.3.1. Scenario 1, Normal Situation

The effectiveness of the SCDT was evaluated using the conventional method and production planning data according to a normal scenario. The uptime, average production, and existing inventory for suppliers, Tier2 and Tier1 manufacturers are presented in Tables 4–6. Transportation was planned based on the time when production was completed, and transportation time was based on the location of the next factory.

Table 4. Performance of suppliers.

Supplier		**S1**	**S2**	**-**
Avg. Production (ea)	A-2, A-3	206	-	-
	B-2, B-3	218	-	-
	C-2, C-3	-	256	-
Avg. Operating Time (h)		12	12	12

Table 5. Performance of Tier2 manufacturers.

Tier2 Manufacturer		**M1**	**M2**	**M3**
Avg. Production (ea)	A-1	186	195	-
	B-1	-	192	215
	C-1	228	-	226
Avg. Operating Time (h)		12	12	12

Table 6. Performance of Tier1 manufacturers.

Tier1 Manufacturer		**P1**	**P2**	**P3**
Avg. Production (ea)	A	215	-	201
	B	205	212	-
	C	-	215	224
Avg. Operating Time (h)		12	12	12

Conventional SC operates based on fixed production plans, locations, and transportation routes, such as product A following S1-M2-P3, product B using S1-M3-P1, and product C using S2-M1-P2. This rigid structure limits flexibility and risk management in abnormal situations. To address this, optimizing production locations and routes with consideration of inventory and logistics costs allows for adaptive responses. The application of SCDT under normal conditions demonstrated significant improvements, reducing overall inventory costs by 8.97%, logistics costs by 1.3%, and total costs by 8.82% as shown in Table 7. While inventory cost reductions were primarily observed at Tier 2 manufacturers, SCDT also optimized production networks and logistics routes, enhancing the efficiency of the SC.

Table 7. As-is/To-be comparison of supply chain digital twin application.

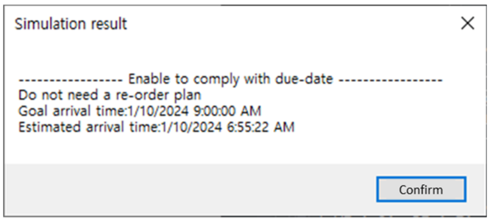
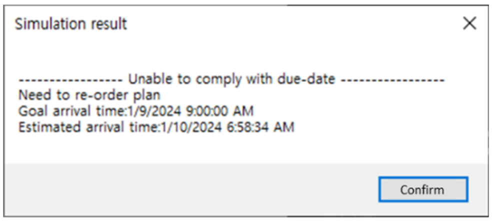
Cost	**As-Is (USD *)**	**To-Be (USD)**	**Comparison**	**Result**
Inventory Cost	5830.8	5307.7	−523.1	−8.97%
Supplier Tier2 Tier1	3692.3 1200.0 938.5	3692.3 676.9 938.5	0.0 −523.1 0.0	0.00% −43.59% 0.00%
Logistics Cost	121.4	119.8	−1.6	−1.30%
Supplier-Tier2 Tier2-Tier1	48.6 72.8	49.8 70.0	1.2 −2.8	+2.42% −3.78%
Total Cost	5952.2	5427.5	−524.7	−8.82%

* Currency: based on USD.

4.3.2. Scenario 2, Due Date Abnormal Situation

Product delivery dates are likely to change as customer order volume changes. In other words, it is necessary to make quick decisions if the order volume is decreased or increased. Thus, situations in which the customer's product order volume and delivery date change should be predicted. The SCDT was executed based on the situation in which the delivery schedule was changed from the existing delivery schedule of 2024-01-10T09:00:00 to 2024-01-09T09:00:00 owing to the decreased customer order volume, as suggested above. By executing the SCDT based on the existing schedule, the delivery date can be met, as shown in Table 8 (a). However, when the SCDT was executed based on the changed delivery schedule, as the order volume decreased, the estimated arrival schedule fell behind the target arrival schedule, as shown in Table 8 (b). Consequently, a message stating that the delivery date could not be met, and a request to revise the order plan were sent to the SC manager. In other words, if a customer's product order decreases or increases, the SCDT provides an opportunity to view the expected delivery schedule and modify the ordering plan accordingly. This indicates that it is possible to manage more efficiently by reducing the risk of misleadingly assuming that a customer's product order will arrive sooner than it will when the customer's order volume decreases. This suggests that product delivery dates are predicted by the product SC when customer order volume increases.

Table 8. Response results of due-date abnormalities.

<table>
<tr><th></th><th>Existing Due-Date (a)</th><th>Changed Due-Date (b)</th></tr>
<tr><td>Due-date</td><td>2024-01-10T09:00:00</td><td>2024-01-09T09:00:00</td></tr>
<tr><td>Analyzed result</td><td>
</td><td>
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</table>

4.3.3. Scenario 3, Production Abnormal Situation

The manufacturing SC comprises several members, as described above. They include multiple suppliers and manufacturers, and there is a possibility that one or more may stop production for reasons such as equipment failure or material shortages. Therefore, in this scenario, SCDT is executed based on the abnormal situation of a manufacturer's production disruption. We assume that a Tier2 manufacturer, Factory M1, stops production because of equipment failure. In this situation, the optimization algorithm searches for factories other than M1 that can produce a product and derive an optimal solution. Under normal circumstances, products A-2 and A-3 are transferred to factory M1, products B-2 and B-3 are moved to factory M2, and products C-2 and C-3 are moved to factory M3, as shown in Figure 9a. However, when the optimization algorithm accounts for the discontinuation of production at M1, products A-2 and A-3, along with products B-2 and B-3, moved to M2, and products C-2 and C-3 moved to M3, as shown in Figure 9b. In other words, the algorithm enables the determination of whether a deadline can be met in the event of an abnormal situation, such as a production disruption. If the deadline cannot be met, adjustments can be made by either altering the delivery deadline or extending the operating hours of other manufacturers within the SC.

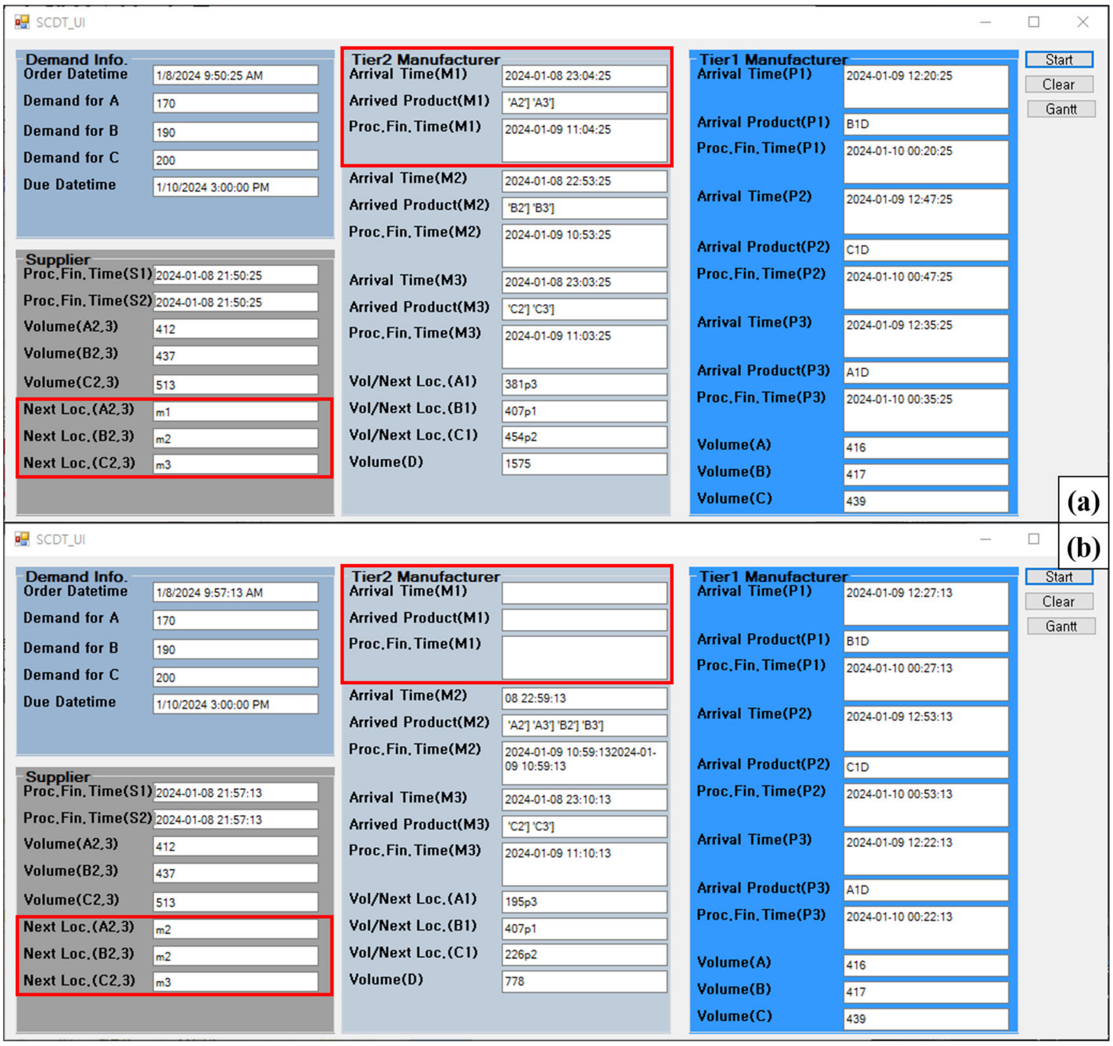

Figure 9. Response results of production interruption abnormalities: (**a**) normal production allocation; (**b**) reallocation under production disruption.

4.3.4. Scenario 4, Traffic Abnormal Situation

Product logistics is broadly divided into in-plant and out-of-plant logistics. Out-of-plant logistics requires transportation from factory to factory, which requires local logistics transportation equipment such as planes, trains, and vehicles. This indicates that some routes or roads need to be followed and that when traveling on those routes, collisions and deviations may occur, or traffic jams, such as those caused by construction, may occur. Therefore, in this scenario, a vehicle traveling on an existing planned roadway encounters a traffic jam. The average processing time for an accident on the road is approximately 40 min, indicating that traveling along an existing route requires approximately 40 min more time [58]. Accordingly, when the alternate route search is performed through the SCDT, the results of the alternate route search are displayed as the blue route instead of the red route in Figure 10, reflecting road conditions where there is an accident or congestion. Consequently, a trip using the existing transportation route would require 108 min, whereas a trip using the discovered alternative route would require 87 min. This indicates a time saving of 21 min and a 19.44% reduction in travel time when the alternate route is used. In other words, the SCDT can reflect the current traffic situation in real-time to find the best route and ensure optimal movement of outbound logistics between members of the SC.

Start location
End location

Logistics Time	
As-is	108 min
To-be	87 min
Comparison	−21 min
Result	−19.44%

Figure 10. Response results of road congestion abnormalities.

5. Discussion

The case study demonstrates how SCDT can be used to construct and synchronize models that simulate the characteristics and behavior of targets, reflect their basic characteristics and real-world situations, and optimize products for each stakeholder.

First, the effects of reduced inventory and inventory costs can be verified in terms of production. In response to the production disruption of an existing production plant, the location of alternative production was searched through an abnormal situation response, and simulations were conducted to confirm that the product could be produced at the changed production location. In terms of logistics, an alternative route was explored for the anomaly of changing road conditions; it was observed that it took less time than the original route, confirming that transportation was possible through the alternative route within a set time of 100 min. Finally, in the end, the manufacturer's side, predicting the situation and analyzing the results allowed them to analyze the delivery schedule, which allowed them to deliver the product on time. This SCDT will reduce the overall lead time and inventory, which will lead to positive results, such as improved inventory turnover, increased shipments, and increased sales. Instead of deriving countermeasures based on the expertise of the existing SC officials, workers, and drivers, a DT system can be used to derive countermeasures for abnormal situations without human intervention.

However, the results of assigning members of production and logistics in SCDT can be derived using algorithms other than the tabu search proposed above. Accordingly, 0-1 integer planning can be applied to discrete allocation problems. Although the application of linear programming to large-scale problems is challenging, the case study in this paper has a rather small scope, i.e., 2-3-3 networks. In other words, to verify the feasibility of the tabu search proposed in this study, the allocation results of production and logistics members and the inventory and logistics costs derived using the 0-1 integer planning method are shown in Table 9. This result is the same as that produced by the tabu search method proposed earlier. This indicates that the methods available in the optimization module of the SCDT system proposed in this study are not limited to tabu search. In other words, if the methodology is for combinatorial optimization, other methods can be applied, and different algorithms may need to be applied in situations that differ from those presented in the case study.

The 0-1 integer planning method applied earlier identifies the optimal discrete solution given the constraints on the decision variables and the objective function, exploring all possible combinations of solutions. However, this approach may not be efficient for large problems. The tabu search proposed in this paper explores neighboring solutions of the current solution, avoiding local optima and identifying the global optimum. Because it does not explore all possible combinations of solutions, it is suitable for large-scale problems, such as SC problems. The case study presented, and a comparison of the results with those of a relatively simple 0-1 integer planning method confirmed the feasibility of the proposed algorithm. This suggests the need for further discussion of its application to large-scale SC.

Table 9. Results of 0-1 linear programming.

Product	Supply Chain	Inventory Cost				Logistics Cost			Total Cost (A + B)
		Supplier (a)	Tier2 (b)	Tier1 (c)	Subtotals (A = a + b + c)	Supplier–Tier2 (d)	Tier2–Tier1 (e)	Subtotals (B = d + e)	
A	s1-m1-p3	1107.7	246.2	476.9	1830.8	18.9	22.8	41.6	1872.4
B	s1-m2-p1	861.5	30.8	230.8	1123.1	11.0	20.2	31.3	1154.3
C	s2-m3-p2	1723.1	400.0	230.8	2353.8	19.9	27.1	46.9	2400.8
Total Cost		3692.3	676.9	938.5	5307.7	49.8	70.0	119.8	5427.5

Currency: Based on USD.

Unit inventory and logistics costs were determined based on the parameters outlined in Table 2, Section 3 of this paper. In other words, there is a blind spot regarding the minimization of the objective function, that is, whether the unit cost is heavily weighted toward the production or logistics side. Table 10 presents the results of executing the SCDT by changing the unit inventory cost applied in the case study. Specifically, the unit inventory cost was reduced by 95%, based on the assumption that the inventory cost was nearly negligible. This significant reduction highlights the sensitivity of SC configuration to cost parameters.

Table 10. Results of tabu search algorithm considering modified unit inventory cost.

Product	Supply Chain	Inventory Cost				Logistics Cost			Total Cost (A + B)
		Supplier (a)	Tier2 (b)	Tier1 (c)	Subtotals (A = a + b + c)	Supplier–Tier2 (d)	Tier2–Tier1 (e)	Subtotals (B = d + e)	
A	s1-m2-p3	55.4	19.2	23.8	98.5	11.0	19.7	30.8	129.2
B	s1-m2-p1	43.1	1.5	11.5	56.2	11.0	20.2	31.3	87.4
C	s2-m3-p2	86.2	20.0	11.5	117.7	19.9	27.1	46.9	164.6
Total Cost		184.6	40.8	46.9	272.3	42.0	67.0.	109.0	381.3

Currency: Based on USD.

The production members within the SC were altered for Product A, whereas Products B and C remained unaffected. The SC configuration was determined based on the unit inventory cost in the case study. For Product A, the configuration s1-m1-p3 was identified; for Product B, s1-m2-p1; and for Product C, s2-m3-p2. This analysis reveals that a reduction in the unit inventory cost led to a shift in the SC members for Product A to s1-m2-p3, whereas those for Products B and C remained unchanged.

Therefore, a discussion is necessary to identify the aspects to consider when reflecting on inventory and logistics cost parameters. In other words, the SC comprises various entities, such as manufacturers and distributors, highlighting the need for integrated analytics. This underscores the importance of further research on SCDT to optimize the SC. As the composition of key performance indicators for an optimized SC becomes more diverse, this study proposes an SCDT system that integrates discrete event simulation, dynamic simulation, and mathematical optimization methodologies, addressing both production and logistics aspects.

6. Conclusions

Owing to the complexity of SCs, globalization, external changes, and market demand uncertainty, the manufacturing industry faces demand fluctuations, inventory shortages, and delivery delays. SC disruptions lead to market share losses, delayed deliveries, and reduced customer satisfaction. Therefore, effective SCM is crucial for enhancing operational efficiency and competitiveness. Although heuristic and metaheuristic methods have been explored for SCM, they struggle to address uncertainty, risk, and temporal issues simultaneously. Simulation methodologies have been proposed, but are limited to handling real-time integration and comprehensive SC analysis. The DT methodology has emerged to overcome these challenges. However, research on SCDT is nascent, with few studies encompassing all SC participants.

Therefore, this paper proposes an SCDT methodology that can improve the operational efficiency of all members through SC monitoring, analysis, prediction, and abnormal situation responses. The architecture of the SCDT system and the process of operating the DT application were defined. To reflect the actual operation of the SC, a simulation model for prediction, an optimization module for calculating the optimal movement location for each product, and a DT application that integrates them were constructed. Finally, the effectiveness of the proposed system was demonstrated by applying SCDT implemented based on the SC of an automobile body production company and analyzing inventory quantity and cost. The findings of this study confirm that the DT system can derive countermeasures and support decision-making for abnormal situations, such as delivery date changes and factory production disruptions, instead of making judgments based on the manager's experience.

However, there are still numerous challenges that need to be resolved. This study validates the proposed SCDT system through a case study involving a small SC and a limited number of products. Although this approach effectively demonstrates the feasibility and foundational capabilities of the system, it has limitations in addressing larger and more complex SC networks. As the scale of the SC increases, the computational time of the optimization algorithm also increases, limiting the ability to perform real-time decision-making that overcomes low responsiveness. This may create challenges in supporting swift and accurate decisions in complex scenarios. To address these challenges, future research should focus on validating the scalability and adaptability of the system across diverse and dynamic SC scenarios, including multiple industries and larger networks. Additionally, integrating stochastic elements, such as random machine downtimes and variable production demands, better reflects real-world uncertainties and improves system robustness.

Next, the tabu search algorithm was selected because of its effectiveness in handling combinatorial optimization problems, particularly in dynamic and high-dimensional environments, like SCs. Its adaptive memory mechanism helps to avoid local optima, and its flexibility allows for the incorporation of real-world constraints, such as production availability and product-specific limitations. Moreover, tabu search balances computational efficiency with solution quality, making it suitable for real-time decision-making. However, it is important to acknowledge the need for benchmarking algorithms against alternative methods. Future research will involve a comparative analysis with other optimization techniques, such as genetic algorithms and machine learning-based approaches, to provide a comprehensive evaluation of the system's performance and identify opportunities for improvement.

As a last remark, this study optimizes SC operations based on the inventory and logistics costs derived from a single case study. However, these costs may vary depending on the SC situation, and additional economic indicators could offer a more comprehensive evaluation of the system's impact. Future research will explore suitable cost-weighting methods to minimize total production and logistics costs. Incorporating additional economic metrics such as energy consumption and carbon emissions enables a more comprehensive assessment of the system's contribution to sustainable SCM.

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