Development of an Agent-based Simulator for Digital Supply Chain Twins

Takahiro Ogura, Tazu Nomoto, Akihisa Tsujibe, Atsuki Kiuchi
Hitachi, Ltd. Research and Development Group, Production System Research Dept.
takahiro.ogura.cu@hitachi.com, tazu.nomoto.nk@hitachi.com, akihisa.tsujibe.fv@hitachi.com, atsuki.kiuchi.aj@hitachi.com

Takahiro Ogura
School of Knowledge Science, Japan Advanced Institute of Science and Technology (JAIST)
takahiro.ogura@jaist.ac.jp

Abstract
Digital supply chain twins (DSCTs) are attracting attention as a new management system that can be used in an environment in which the market changes rapidly due to sudden risks. To realize DSCTs, an SCM simulator that can accurately reproduce information flow in addition to the conventional physical objects and cash flow and fast, high-precision key performance indicator (KPI) evaluation are required. In this study, the information controller is defined as an agent, the agent has a dynamic decision-making function called a behavior, and a modeling method is proposed in which the behavior is composed of three elements: start condition, execution logic selection condition, and execution logic. As a result of applying this simulator to the information equipment business, the SC was confirmed to be reproduced with a deviation rate of 5% or less, a model was constructed in 3 hours, and a KPI evaluation was performed in 12 seconds at most.

Keywords
Supply chain management, Agent-based simulation, Cyber physical system, Digital twins, Collaborative planning

1. Introduction
Manufacturing companies that are expanding their businesses globally are placed in a business environment where the market changes rapidly due to sudden risks, such as terrorism, financial crises, disasters, and variations in global economic growth. In such an environment, digital supply chain twins (DSCTs) are attracting attention as a means to respond quickly to changes and realize inventory reduction and improvement in order fill rate, cash flow (CF), and return on equity (ROE) for each company that makes up the supply chain (SC) (Ivanov et al., 2019). In DSCTs, first, the SC is reproduced on a computer from the information collected by the Internet of Things (IoT), etc., and the key performance indicators (KPIs) of management, such as future inventories, order fill rate, CF, and ROE, are predicted based on the market forecast. Then, if the KPI does not meet the management target, a proposal to change the SC operation method, such as inventory arrangement, transaction conditions, or business process, is proposed. Furthermore, proposed changes in the operation method are reflected in the SC reproduced on the computer. Then, the change is confirmed from the predicted KPI whether the management target will be met, and the proposed changes to be adopted are determined. Finally, the actual SC operation is initiated with the proposed changes that have been determined to be adopted. All of the above operations are performed within few hours each time business conditions or market forecasts change.

To realize DSCTs, an SCM simulator that can reproduce the actual SC on a computer and predict high-precision KPIs is required. For this purpose, it is necessary to precisely reproduce the flow of “information” along with “physical objects” and “cash” that make up the SC. For example, when the assembly manufacturer determines the production plan at 16:00 every Monday, if more than certain amount of product inventory is available, the production plan gives priority to demand tracking so that the inventory does not increase further. In other cases, the production plan gives priority to the equipment operation rate, and if the assembly manufacturer changes the production plan, the parts supplier also reviews the shipment plan on the next business day. This is the routine flow of "information" in an actual business. When studying supply chain management (SCM), simulations have been used to derive and propose optimal SC operating conditions (Zahra et al. 2013). However, as mentioned above, the flow of complex "information," such as logic, cycles, and the timing of information updates, that changes dynamically according to the situation and to the collaboration between and within companies cannot be reproduced precisely. Therefore, in this study, an SCM simulator was developed that accurately reproduces the flow of "information" in addition to "physical objects" and "cash" and enables rapid high-precision KPI evaluation by changing these variables.

2. Literature Review

Many studies have been conducted on SCM simulations because of their ability to reproduce complex, large-scale, and time-series influenced propagation relationships. According to Alexandra et al. (2018), the simulation approach can be divided into three categories: discrete simulation that applies queuing theory, system dynamics, and agent-based simulations (ABSs). In the area of discrete simulation, a study that focused on the flow of "physical objects" and analyzed the impact of disasters was conducted. The study conducted by Carvalho et al. (2012), Schmitt et al. (2012), and Ivanov (2017, 2018) proposed a model that evaluated the difference between the degree of impact on the delivered lead time (LT) when SC disruption events, such as production and transport capacity loss, occur and the effect of a multiple capacity recovery scenario. This model showed that if a disruption occurs at the material manufacturer, its effect will last for a long time, and it is effective to increase safety inventories at the sales and distribution points. However, these studies do not consider the flow of "information." In addition, a study was conducted that focused on the flow of "physical objects" and "information" and showed the relationship between information sharing between companies and the bullwhip effect. The study conducted by Hau et al. (2000), Disney and Towill (2003), and Chatfield et al. (2004) showed that a longer delivery LT results in a greater effect and sharing final product demand information and introducing vendor management inventory (VMI) are effective in reducing that effect. However, these studies have constant information updates in terms of the logic, cycles, and timing and do not consider dynamic changes. In the area of system dynamics, the study conducted by Wilson (2007) proposed a model to evaluate the order fill rate and the degree of impact on inventory when transportation is stopped in a multistage SC focusing on the flow of "physical objects" and "information." This study showed that the suspension of transportation between sales and distribution bases has a greater impact than the suspension between assembly and material production bases, and it is effective to introduce VMI. However, these studies also have constant information updates in terms of logic, cycles, and timing and do not consider dynamic changes. In the area of ABSs, studies conducted by Prezhman et al. (2018, 2019) focused on the flow of "physical objects," "information," and "cash" and showed the effectiveness of automatic supplier selection by agents and automatic order allocation for multicompany purchasing. However, these studies had a fixed update cycle and timing and did not consider dynamic changes or plan collaboration between companies or within the same company. A study conducted by Xu et al. (2014) focused on the flow of "physical objects" and "information" and evaluated the impact of differences in the capacity recovery policy when the supply capacity of the topmost supplier was lost due to a fire, etc. on the on-time delivery rate in a three-stage SC. However, these studies had constantly updated logic, cycles, and timing and did not consider dynamic changes. In this manner, many studies on SCM simulations have been conducted, but in terms of the flow of "information," the planning logic, cycle, and timing of each plan, including the production plan, change dynamically according to the situation, and the flow of "information" that is carried out in an actual business, such as a collaboration between companies or within the same company, cannot be reproduced.

Here, an agent-based model (ABM) is considered an excellent modeling technique for reproducing a complex system on a computer with high precision. An ABM is a model in which agents that act autonomously according to a set of rules interact with each other and represent the entire complex system. An ABS evaluates the impact of rules and interactions of ABM agents on the entire complex system, and ABMs focusing on social science problems, such as congestion and stock price simulations, have been actively studied (Charles and Michael 2014). Therefore, in this study, through the use of ABM, we propose that the flow of "information" within actual businesses can be reproduced by "agents" that dynamically change the flow of "information," such as the planning logic, cycle, and timing of each plan, and high-precision KPI evaluation can be conducted by SCM simulation. In addition, since "physical objects," "cash," and "information" are defined as the basic components of the supply chain in the supply chain operations reference (SCOR) model, "physical objects," "cash," "information," and "agents" can be prepared as a template for each company type, e.g., factories, warehouses, and sales companies. Then, we propose that a KPI evaluation simulation model can be generated by changing the SC operation method in a short time by combining templates. As described above, in this study, "physical objects," "cash," "information," and "agents" that dynamically control "information" are considered the basic components, and an agent-based SCM simulator, which can reproduce SCM by defining templates that combine these components in advance for each company and enable high-precision KPI evaluation by changing the SC operation method in a short time, is developed. The effect of this simulator is shown through numerical experiments.

The structure of the subsequent sections of this paper is as follows. Section 3 describes the requirements and architecture of the agent-based SCM simulator to be developed. Section 4 describes the results and the KPI evaluation, and effective conditions using an intercompany collaboration model as an example are used to confirm the reproducibility of the SCM provided by this simulator using an information equipment business and the SC conditions given by the optimum conditions. Section 5 summarizes the conclusions.

3. Development of Agent-based SCM Simulator

3.1 Simulator Requirements

As described in Section 1, the SC is reproduced by the SCM simulator and the KPI for each operation method is evaluated in the DSCT. At each time, to appropriately select the SC operation method to be adopted, it is desirable that the deviation in the KPI value predicted on the computer and the result of actually operating the SC under the same conditions is small. Therefore, the target KPI evaluation deviation rate in this study was set to 5% or less, which is acceptable by management in practice. In this study, the deviation rate is calculated using the following formula (1). Here, T is the simulation period, S_t is the simulation result on day $t \in T$, and A_t is the actual value on day $t \in T$.

$$\text{Deviation Rate} = \sum_{t \in T} \frac{|(S_t - A_t)|}{A_t} \qquad (1)$$

When modeling and simulating using an ABM/ABS, it is necessary to define the agent behavior and interaction rules. AnyLogic is a widely used tool to achieve this goal. These tools are highly versatile for creating an ABM and can model various systems. On the other hand, it is necessary to sequentially program the agent behavior and interaction rules, and it is difficult to quickly evaluate the effect of restructuring the SC configuration and business processes. In corporate activities, demand tracking and changes in circumstances must be addressed quickly. Therefore, the requirement of the simulator in this study is to create an ABM within 7 hours and to calculate the KPI as an output within 1 minute with the aim of responding within 1 day after the change occurs in an SC that consists of approximately 3000 items, suppliers, factories, and markets, using an information equipment business as an example.

3.2 Architecture

To meet the requirements stated in the previous section, an agent-based SCM simulator was constructed with an architecture that models and simulates the entire business by combining parts according to the proposed changes in the SCM type and SC operation method of the business. The "components" equivalent to these parts need to be separated into elements that can be used in common by any business, but it will take time to construct a model if they are too detailed. Therefore, to ensure both versatility and ease of construction, the components have been separated into a size that can be supported by various supply chains, and then a "company template," in which the components are grouped according to the company types that make up the supply chain, "agent," and "behavior" have been defined, and a modeling method using these variables has been formulated. The details are given below.

(1) Components
When illustrating the SC, it is common to describe the flow of "physical objects," "cash," and "information" as a network flow, and the minimum components are nodes and arcs. Therefore, we hypothesized that the model of this simulator will be highly versatile if it is configured with a network flow consisting of nodes and arcs. Table 1 lists the nodes, and Table 2 lists the arcs. Nodes consist of events related to logistics (warehousing, storage, production, and delivery), events related to the flow of money (deposits, savings (account), and withdrawal), events related to flow of information (decision-making), and data generated as a result of decision making. The arcs are defined by a vector with a flow rate that connects these nodes.

Table 1. List of Nodes

Node Type	Object	Symbol
Physical Objects	Receiving, Production, Transportation, Issuing	○
	Stock	▽
Cash	Deposit, Withdrawal, Payment	○
	Savings (Account)	▽
Information	Decision making (Agent)	
	Data	□

Table 2. List of Arcs

Arc	Symbol
Physical flow	⟶
Cash flow	⟶
Information flow: reference	•·······>
Information flow: update	---->

(2) Company template
The companies that make up the SC consist of suppliers, sales companies, factories, warehouses, and transport operators that handle "physical objects," financial institutions that handle "cash," and markets (customers). The basic role of these companies has been decided, and the flow of "physical objects," "cash," and "information" in each company is represented by a directed graph by combining the nodes shown in Table 1 and the arcs shown in Table 2, and this combination will be prepared as a company template. For example, the template for factories will be prepared as shown in Figure 1. When building a simulation model, the number of company templates that are selected and connected is equal to the number of companies that make up the SC.

(3) Agents
In actual business, the objects that control the flow "information" are the data objects, which correspond to input information and output information, and decision-making objects, which correspond to decision makers. The decision makers include the person in charge of planning, the person in charge who directs the movement of physical objects and money, and the person in charge who predicts the risk of fluctuations in demand and exchange rates. The decision-making factors of each person in charge include factors related to the flow of "physical objects," such as supply allocation and inventory allocation, and factors related to the flow of "cash," such as capital investment and collection of receivables, and these factors change dynamically with environmental changes and changes in the decision-making method. For example, when the production load exceeds the capacity of the equipment, outsourcing the excess work can be defined as a change in decision-making method of the production instructor due to the load. Unlike "physical objects" and "cash" objects, decision-making objects need to have dynamically changing output information according to the input information. In this simulator, the decision maker object is defined as an "agent" to distinguish it from other objects. The agent has a dynamic decision-making function called a "behavior" to facilitate the registration of the change pattern. The basic agent is deployed in the company template described above, and the user specifies the behavior of the agent when selecting the company template. For example, the factory template shown in Figure 1 is

deployed with a supply plan agent, a production plan agent, a procurement plan agent, a delivery instruction agent, and a production instruction agent, and the user selects the factory template and, at the same time, specifies the behavior of each agent.

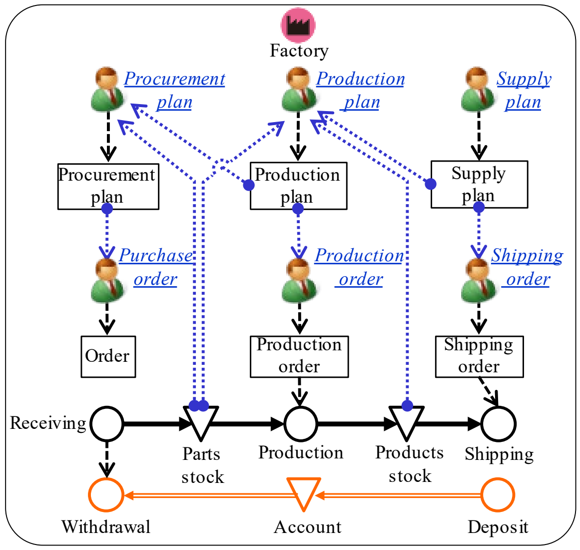

Figure 1. Factory Template

(4) Behavior

Using the example of the factory production plan agent, the "behavior" of the agent indicates the decision-making rules, such as determining the production plan every Monday at 16:00 and, if there is more than a certain amount of product inventory, developing a production plan that prioritizes demand tracking so that the inventory will not increase further and, in other cases, developing a production plan that prioritizes equipment utilization. Here, the components of "behavior" can be divided into three parts: "start conditions," "execution logic selection conditions," and "execution logic." In the above example, "every Monday at 16:00" is the start condition, "product inventory more than a certain amount" and "other cases" are the execution logic selection conditions corresponding to the "execution logic" of developing "a production plan that prioritizes demand tracking" and "a production plan that prioritizes equipment utilization." "Execution logic" can be externally defined in a dynamic link library (DLL) format using enterprise resource planning (ERP) software, such as SAP R3, S4 HANA, or Microsoft Dynamics, or supply chain planning (SCP) software, such as JDA or E2open. The execution logic from the legacy system of each company can converted into a library in advance, allowing the user to input the "behavior" in a selective manner and generate the model in a short time. The user can thus also use a new execution logic not present in the library in a short time because a program for the execution logic portion alone can be created or copied from the actual business system and added to the library as a new module in the simulator.

4. Confirmation of SCM Reproducibility and Evaluation of The Proposed SC Operation Method

We conducted numerical experiments to confirm the effectiveness of the agent-based SCM simulator proposed in this study. First, using the actual data for the electronic equipment business, we verified the reproducibility of the actual SCM using this simulator and verified if the KPI for the proposed changes in the SC operation method could be evaluated in a short time. Further, as an example of examining the optimum SC operation method, we evaluated the KPI and verified effective conditions in terms of the collaboration of business processes between companies using a random number of data generated by a computer. Each experimental condition and its result are given below.

4.1 Experiment 1: Verification of reproducibility and effectiveness in the electronic equipment business

The details of the experimental conditions are given as follows.

Items: We simulated a total 2,874 items for a business that manufactures electronic equipment products such as servers. Of these, in this study, the items were divided into three groups according to the standard deviation of demand, and the result of one representative item belonging to each group is reported.

SC configuration: Figure 2 shows the configuration of the SC. This business has adopted a build to order (BTO) business model, in which parts are ordered based on the demand forecast and assembled based on orders from the customers. Therefore, there is no factory product inventory.

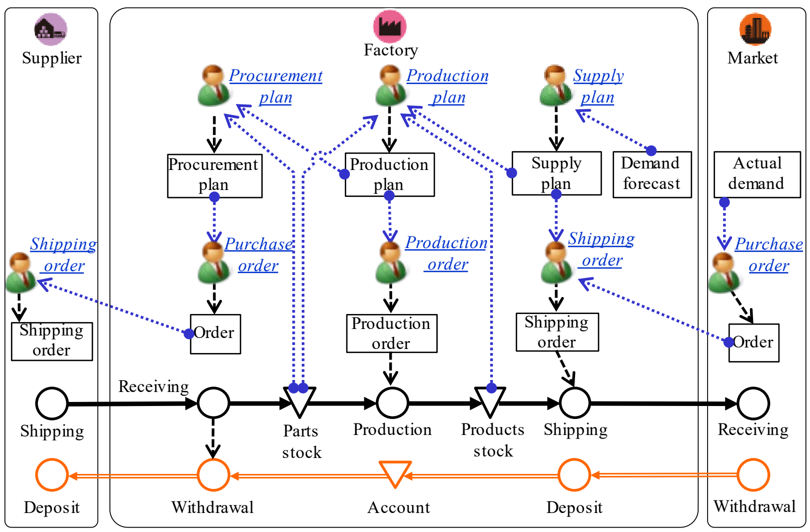

Figure 2. SC Configuration in Simulation of Electronic Equipment Business

Behavior: Table 3 shows the start conditions, execution logic selection conditions, and execution logic set as the behavior of each agent belonging to each company in Figure 2. The start conditions are as follows: all the plan agents start monthly, and the execution system agents, such as ordering agents, start daily.

Table 3. List of Behaviors in the Simulation of an Electronic Equipment Business

Company	Agent	Update condition	Condition for execution logic	Execution logic
Market	Purchase order	Every day at 9:00 AM	If ordering date is today, logic (1).	(1) Issue an order based on demand.
Factory	Shipping order	Every day at 9:25 AM	If new order is received, logic (2).	(2) Make a stock reservation based on the order from the market company. In case of a product stock shortage in product, the order will be treated as backorder.
	Supply plan	Every month on the 1st Mon. at 6:00 PM	If revised supply forecast exists, logic (3).	(3) Plan supply date and quantity based on the demand forecast.
	Production plan	Every month on the 1st Tue. at 6:00 PM	If revised supply forecast exists, logic (4).	(4) Plan production start date and quantity based on the supply plan.
	Procurement plan	Every month on the 1st Wed. at 6:00 PM	If revised production plan exists, logic (5).	(5) Plan a procurement date and quantity considering a parts safety stock based on the production plan.
	Production order	Every day at 9:45 AM	If production start date of production plan is today, logic (6).	(6) Issue production instruction based on the production plan.
	Purchase order	Twice a month on the 1st and 3rd Mon. at 9:50 AM	If procurement start date of procurement plan is today, logic (7).	(7) Issue a purchase order based on the procurement plan.
Supplier	Shipping order	Every day at 9:55 AM	If new order is received, logic (8).	(8) Make a stock reservation based on the order from the factory. The stock quantity at the supplier is infinity.

Demand and demand forecast: We used the demand and demand forecast data from April to September 2012.

Safety stock: As mentioned earlier, this business uses BTO to maintain a safety stock that absorbs fluctuations in demand in a factory's parts inventory. The "advance order days logic" that holds the required number of parts in advance for a specific number of days in the production plan of each product was used as the safety stock setting method. In this simulator, this setting was configured to calculate the safety stock by the factory procurement plan agent.

Lead time: The transportation LT between the market and the factory is 1 day, and the production LT at the factory is 1 day for all items. The LT between the factory and supplier of each item was set in the range of 30 to 40 days based on the contract information.

Calculation environment: We used a PC equipped with an Intel Core i7 6600U 2.6 GHz processor and 20 GB of memory.

Figure 3 shows the results of the simulation under the conditions mentioned above. Figures (a) to (c) show the results of one representative item belonging to each of the three groups classified by the size of standard deviation of demand, starting from (a) in ascending order of standard deviation. The figure shows the actual values (Actual) in the actual work and the result (Simulation) of reproducing the work with this simulator. As mentioned above, since the factory's products do not have inventory, the inventory in the figure shows the parts inventory of each item at the factory. The order fill rate is the

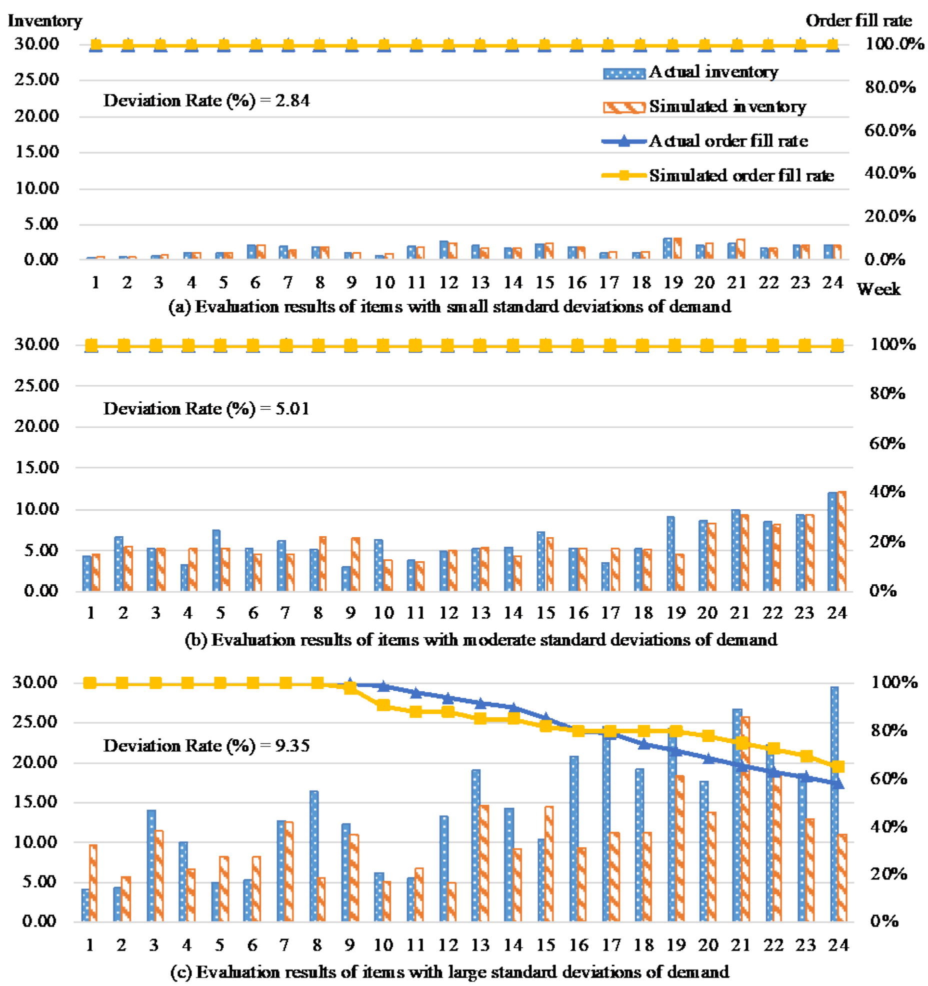

Figure 3. Simulation Results for an Electronic Equipment Business

cumulative value of the ratio of the quantity that can be delivered immediately for the demand of the customer (market). The results in Figures 3 (a) to 3 (c) indicate the deviation rate when using the simulator proposed in this study. The deviation rate is 2.84% in (a) and 5.01% in (b), and the order fill rates are exactly the same, indicating that the target deviation rate of 5% or less has almost been achieved. In (c), where the deviation rate is 9.35%, which is below the target value, there are periods such as weeks 21 to 23 in which the trends are similar, but there are weeks like week 8 and weeks 16 to 18 in which the deviation from the simulation result is significant. There are various possible reasons for these trends, but for example, the most likely reason is deviation from the prescribed work, such as placing more orders than usual anticipating that more demand will come in the future because the order fill rate decreased in the 8th week. On the other hand, the order fill rate and average inventory have achieved better results in the simulation than those of the actual business. This result suggests that a high order fill rate can be maintained with a small inventory if the results calculated by this simulator are used in the actual business.

Next, the KPIs of the proposed changes in the SC operation method in the actual work targeted in this experiment are evaluated. Based on the results of the previous simulation, we proposed the SC operation method to flexibly change factory part inventory levels according to demand. Specifically, in the factory procurement plan agent, “Start when the factory part inventory becomes half or 1.5 times the safety stock amount” was added to the start condition to redevelop the procurement plan. Other agents operate with the settings given in Table 3. Hereinafter, this model is referred to as the proposed reformed SC operation model (Reformed proposal). Table 4 gives the simulation results of the proposed reformed SC operation model, the actual values (Actual), and the results of reproducing the work (Simulation). Table 4 indicates that a high order fill rate with the simulation and actual results. In addition, the proposed reformed SC operation model shows that a greater deviation can be achieved with a small amount of inventory after comparing the results of the proposed reformed SC operation model in demand yields more effective results compared to the other cases. This finding suggests that the proposed reformed SC operation model can quickly detect the deviation in inventory amounts from the demand forecast and orders can be placed with the supplier to minimize any decrease in the order fill rate.

Table 4. Comparison of Simulation Results

		Standard deviations of demand		
		Small	Moderate	Large
Actual	Order fill rate	100.00%	100.00%	58.21%
	Average inventory	1.67	6.27	14.91
Simulation	Order fill rate	100.00%	100.00%	65.00%
	Average inventory	2.00	5.99	11.12
Simulation (Reformed proposal)	Order fill rate	100.00%	100.00%	94.44%
	Average inventory	1.43	5.43	7.36

In the numerical experiment performed in this section, we confirmed that the time required to build all the ABMs by reproducing the current situation to the evaluating the reformed SC plan was 3 hours, and the maximum calculation time per simulation was 12 seconds; hence, the target ABM creation time of 7 hours and the KPI calculation time of 1 minute were achieved. The results above indicate that this simulator can accurately reproduce the SCM of the actual business, and the KPI for the proposed changes in the SC operation method can also be evaluated quickly.

4.2 Experiment 2: Verification of Case of Evaluation of Collaboration Between Companies

As an example of studying the optimum SC operation method, we verified the KPI evaluation using collaboration between businesses and verified the demand characteristics of items for which collaboration is effective. Considering the demand characteristic item as a magnitude of the variation, we used random number data generated by a computer to perform a sensitivity analysis of the impact of variation on the KPI. The details of the experimental conditions are given as follows.

SC configuration: Considering a linear SC configuration of suppliers → factories → sales companies → market, the transportation LT was 1 day, and the production LT was 10 days for all (Figure 4).

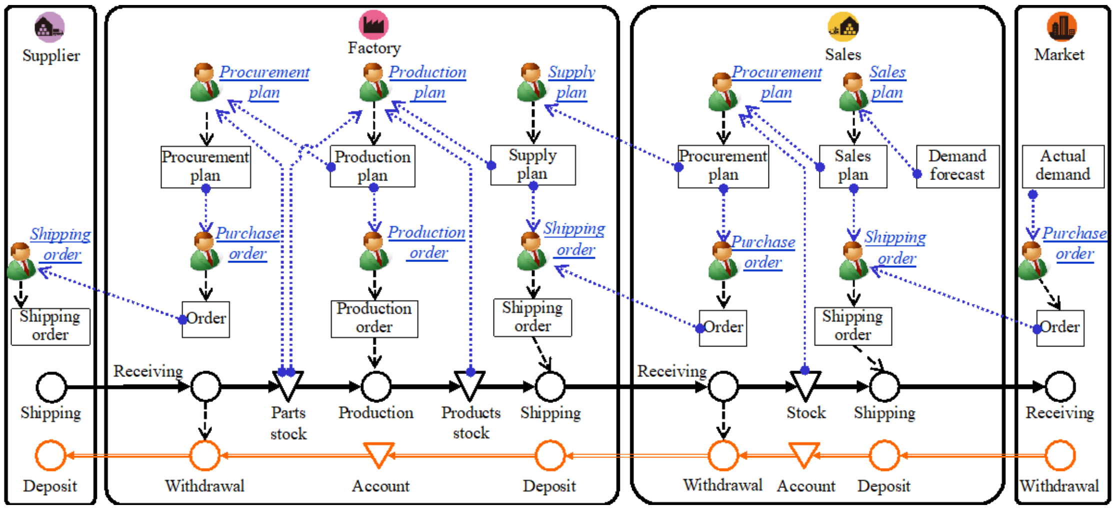

Figure 4. Simulation Model Used to Verify the Case of Evaluation of Collaboration Between Companies

Items: The number of items was set to 1, and the number of parts required to produce one unit of the item was set to 1.

Behavior: Table 5 shows the start conditions, execution logic selection conditions, and execution logic set in the model that has intracompany collaboration as the behavior of the agents in each company, as shown in Figure 4.

Demand: Based on normal random numbers, the demand for each day (considering the simulation period was 1 year) was generated with an average of 200 and a standard deviation of 10 to 100 (interval 10). Additionally, the numerical experiment was conducted by changing the seed value to a random number 100 times for each pattern.

Table 5. List of Behaviors in the Intracompany Collaboration Model (Experiment 2)

Company	Agent	Update condition	Condition for execution logic	Execution logic
Market	Purchase order	Every day at 9:00 AM	If ordering date is today, logic (1).	(1) Issue an order based on demand.
Sales	Shipping order	Every day at 9:25 AM	If new order is received, logic (2).	(2) Make a stock reservation based on the order from the market company. In case of a product stock shortage, the order will be treated as backorder.
	Sales plan	Every month on the 1st Mon. at 6:00 PM	If demand forecast exits, logic (3).	(3) Plan sales date and quantity based on demand forecast.
	Procurement plan	Every month on the 1st Tue. at 6:00 PM	If revised sales forecast exists, logic (4).	(4) Plan procurement date and quantity considering a safety stock based on the sales plan.
	Purchase order	Every day at 9:30 AM	If procurement start date of procurement plan is today, logic (5).	(5) Issue a purchase order based on the procurement plan.
Factory	Shipping order	Every day at 9:40 AM	If new order is received, logic (6).	(6) Make a stock reservation based on the order from the sales company. In case of a product stock shortage, the order will be treated as backorder.
	Supply plan	Every month on the 1st Wed. at 6:00 PM	If revised supply forecast exists, logic (7).	(7) Plan supply date and quantity based on the demand forecast.
	Production plan	Every month on the 1st Thu. at 6:00 PM	If revised supply forecast exists, logic (8).	(8) Plan production start date and quantity considering a product safety stock based on the supply plan.
	Procurement plan	Every month on the 1st Fri. at 6:00 PM	If revised production plan exists, logic (9).	(9) Plan a procurement date and quantity considering a parts safety stock based on the production plan.
	Production order	Every day at 9:35 AM	If production start date of production plan is today, logic (10).	(10) Issue production instruction based on the production plan.
	Purchase order	Every day at 9:45 AM	If procurement start date of procurement plan is today, logic (11).	(11) Issue a purchase order based on the procurement plan.
Supplier	Shipping order	Every day at 9:50 AM	If new order is received, logic (12).	(12) Make a stock reservation based on the order from the factory. The stock quantity at the supplier is infinity.

Demand forecast: The demand forecast used by the sales company was 200 per day.

Safety stock: The safety stock of the sales company and factories was calculated using a formula (2). σ is the standard deviation of the order quantity received by the company, α is the safety stock coefficient, and procurement LT is the procurement lead time. The value of the safety stock coefficient was 1.65, which achieves the target order fill rate of 95%.

$$Safety\ Stock = \alpha \times \sigma \times \sqrt{Procurement\ LT} \qquad (2)$$

4.2.1 Model for a Business with Intracompany Collaboration only

All the plan agents, such as the production plan agent in Figure 4, start monthly. The execution system agents, such as the order agents, start every day, and plan and execution agents collaborate only within each company. Using the example of a sales company, the delivery instructions (inventory allocation) are given first, and then the sales plan is updated. Then, after developing a procurement plan based on that information, an order is issued (hereinafter referred to as the intracompany collaboration model).

4.2.2 Model for a Business with Intercompany Collaboration

Table 6 shows the start conditions of the agents that are added to the intracompany collaboration model described in the previous section. "Start when the inventory of your own company becomes half or 1.5 times the safety stock amount" was added in the start condition of the procurement plan agent of the sales company, and this setting was changed to redevelop the procurement plan. In the case where the agent started under this condition as a trigger, this setting was added so that the next agent will redevelop the plan the moment the previous agent completes the information output in the factory supply, production plan, or procurement plans. The execution agent was the same as in the previous section and was not changed so that this agent would perform the order reception, ordering, and production instruction work regardless of the trigger (hereinafter referred to as the intercompany collaboration model).

Table 6. List of Behaviors in the Intracompany Collaboration Model (Experiment 2)

Company	Agent	Update condition
Sales	Procurement plan	Every month on the 1st Tue. at 6:00 PM. + Condition (A): When the product stock level is less than half of the safety stock. + Condition (B): When the stock level is more than 1.5 times of the safety stock.
Factory	Supply plan	Every month on the 1st Wed. at 6:00 PM. + Condition (C): When the procurement plan agent in the sales company worked by condition (A) or (B).
	Production plan	Every month on the 1st Thu. at 6:00 PM. + Condition (D): When the supply plan agent in the factory worked by condition (C).
	Procurement plan	Every month on the 1st Fri. at 6:00 PM. + Condition (E): When the procurement plan agent in the factory worked by condition (D).

4.2.3 Results of Experiment 2

Figure 5 shows the experimental results of the intra- and intercompany collaboration models and indicates the order fill rate and the average inventory of the entire SC for each standard deviation of demand. This simulation result indicates that when a intercompany collaboration model is used, it is possible to achieve a high order fill rate with a smaller amount of inventory than in the intracompany collaboration model for all standard deviations. The result also suggests that the difference in the average inventory between an intracompany collaboration model and an intercompany collaboration model tends to increase with an increase in the standard deviation of the demand. This result indicates that the larger the standard deviation of demand, the greater the effect of the intercompany collaboration. As described above, this simulator enables the study of the optimum SC operation method according to the demand characteristics of the product.

5. Conclusion

In this study, to realize DSCTs, an SCM simulator that accurately reproduces the flow of "information" in addition to

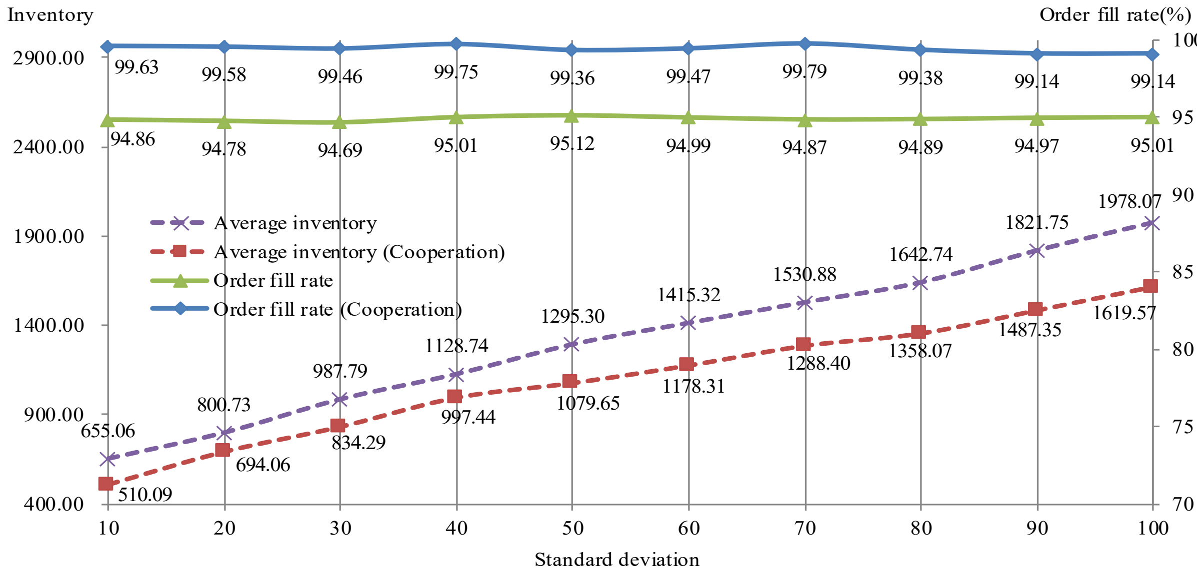

Figure 5. Simulation results for the Intercompany Collaboration Model

"physical objects" and "cash" and enables high-precision KPI evaluation by quickly changing the variables was developed. The "information" controller in the SCM was defined as an agent, and the agent was provided with a dynamic decision-making function called "behavior," and a method of modeling was proposed in which the "behavior" was composed of three elements: "start conditions," "execution logic selection condition," and "execution logic." As a result, it was possible to precisely reproduce the flow of "information" of an actual business that dynamically changes, including the production plan, the instruction designing logic, the cycle, and the timing according to the situation, and the plan collaboration between companies and within the company was possible. Then, through numerical experiments conducted using an electronic equipment product as an example, the rate of deviation between the predicted and actual KPI values was shown to be reproduced with an accuracy of 5% or less for items that performed the tasks according to the rules. Considering "company template," "agent," and "behavior" as the three basic elements of the SC and by providing these as selection choices, it is possible to quickly construct and change the SC model. In a numerical experiment using an electronic equipment product as an example, it was confirmed that the time required to construct the SCM model was 3 hours and the maximum KPI calculation time per simulation was 12 seconds, which meets the prescribed requirements. Further, as an example of examining the optimum SC operation method, we evaluated the KPI and verified effective conditions using an intercompany collaboration model built using random number data generated by a computer. With intercompany collaboration, it is possible to achieve a high order fill rate with a smaller amount of inventory, and a greater variation in the demand resulted in a greater effect; it is possible to support the selection of proposed changes in the optimum SC operation method according to the variation in demand.

In the future, to further refine the DSCT model, we will develop technology to automatically learn the SCM model from the actual data collected by the IoT, etc., and technology to automatically search the SC operation method to be adopted in response to changes in the situation based on a simulation.

References

Alexandre, D., Dmitry, I., and Boris, S., Ripple effect in the supply chain: an analysis and recent literature, *International Journal of Production Research.*, Vol. 56, No. 1-2, pp. 414-430, 2018.

Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., and Cruz-Machado, V., Supply chain redesign for resilience using simulation, *Computers & Industrial Engineering*, Vol. 62, Issue 1, pp. 329–341, 2012.

Charles, M., and Michael, N., Introductory tutorial: Agent-based modeling and simulation, *Proceedings of 2014 Winter Simulation Conference,* pp. 6-20, 2014

Chatfield, D. C., Kim, J. G., Harrison, T. P., and Hayya, J. C., The bullwhip effect—impact of stochastic lead time, information quality, and information sharing: A Simulation Study, *Production and operations management*, Vol. 13, Issue 4, pp. 340-353, 2004.

Disney, S. M., and Towill, D. R., Vendor-managed inventory and bullwhip reduction in a two-level supply chain, *International Journal of Operations & Production Management*, Vol. 23 No. 6, pp. 625-651, 2003.

Hau, L. L., Kut, C. S., and Christopher, S. T., The value of information sharing in a two-level supply chain, *Management Science*, Vol. 46, No. 5, pp. 597-743, 2000.

Ivanov, D., Simulation-based ripple effect modelling in the supply chain, *International Journal of Production Research*, Vol. 55, Issue 7, pp. 2083–2101, 2017.

Ivanov, D., Revealing interfaces of supply chain resilience and sustainability: a simulation study, *International Journal of Production Research*, Vol. 56, Issue 10, pp. 3507-3523, 2018.

Ivanov, D., Alexandre, D., Ajay, D., and Boris, S., Digital Supply Chain Twins, Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility, *Handbook of Ripple Effects in the Supply Chain*, pp. 309-332, 2019.

Pezhman, G., Farshad G. T., and Cathal, H., A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain, *European Journal of Operational Research*, Vol. 269, Issue 1, pp. 286-301, 2018.

Pezhman, G., Chao, W., Ming, K. L., and Gathal, H., Intelligent sustainable supplier selection using multi-agent technology: theory and application for Industry 4.0 supply chains, *Computers & Industrial Engineering*, Vol. 127, pp. 588-600, 2019.

Schmitt, A. J., and Singh, M., A quantitative analysis of disruption risk in a multi-echelon supply chain, *International Journal of Production Economics*, Vol. 139, Issue 1, pp. 23–32, 2012.

Xu, M., Wang, X., and Zhao, L., Predicted supply chain resilience based on structural evolution against random supply disruptions, *International Journal of Systems Science: Operations & Logistics,* Vol. 1, Issue 2, pp. 105–117, 2014.

Wilson, M. C., The impact of transportation disruptions on supply chain performance, *Transportation Research Part E: Logistics and Transportation Review*, Volo. 43, Issue 4, pp. 295–320, 2007.

Zahra, L., Muriati, M., Shahnorbanun, S., and Ali, T. Z., Information sharing in supply chain management, *Procedia Technology*, Vol. 11, pp. 298-304, 2013.

Biographies

Takahiro Ogura received B.S. and M.S. degrees in Industrial and Management System Engineering from Waseda University in 2003 and 2005. He serves in Production Systems Research Department, R&D Group, Hitachi, Ltd. Also he is a PhD student in School of Knowledge Science, Japan Advanced Institute of Science and Technology.

Atsuki Kiuchi received B.S. and M.S. degrees in Information and Tele-communication Engineering from Tokai University in 2013 and 2015. He serves in Production Systems Research Department, R&D Group, Hitachi, Ltd.

Akihisa Tsujibe received B.S. and M.S. degrees in Computer Science and Systems Engineering from Kobe University in 2009 and 2011. He serves in Production Systems Research Department, R&D Group, Hitachi, Ltd.

Tazu Nomoto received B.S. degree in Home Economics Science from Japan Women's University in 1991 and M.S. degree in Systems Management from University of Tsukuba in 1999. She serves in Production Systems Research Department, R&D Group, Hitachi, Ltd.