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Revealing the hidden potentials of Internet of Things (IoT) - An integrated approach using agent-based modelling and system dynamics to assess sustainable supply chain performance

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ABSTRACT

The Internet of Things (IoT) brings new opportunities for creating intelligent and streamlined supply chains that have better environmental and cost performance as compared to conventional ones. In this paper, we quantify such improvements for a specific logistics chain case. To support the inventory of cost and emission data, we utilize system dynamics (SD) and agent-based modeling (AB) to define the structure of the two logistical systems, simulating and estimating differences in e.g., required storage levels, efficiency of transport, etc. In particular, we assess the difference in carbon emissions, cost, and market performance of a battery delivery chain in the delivery process between a two-tier IoT-supported supply chain (users are served by an IoT retailer directly connected to the producer) and a conventional three-tier supply chain (include an additional wholesaler to connect retailer and producer). The results demonstrate that IoT supply chains have significant advantages in minimizing average product storage and shipment fluctuations. IoT suppliers can estimate market demand to adjust production and transportation strategies for new orders. Consequently, the overall profitability of the IoT supply chain increases by more than 30%. Heating and lighting emissions in the storage process and direct emissions in transportation per functional unit (one unit of a Li-ion cell module) are reduced by 60%–70% under middle- and low-demand scenarios, and by at least 50% under high-demand scenario. However, the increasing use and higher loading rates of heavy trucks will weaken the advantages of IoT. Moreover, IoT products occupies a 10% lower market share compared to conventional ones under the same pricing strategy but achieves similar market share under the same value-added strategy.

1. Introduction

As current supply chain systems are becoming more and more complex, there is an increasing demand for integrating industry 4.0 technologies like IoT into supply chain and production management. Combined with operation approaches such as just-in-time (JIT) production, lean logistics, and vendor managed inventory, IoT has become one of the important contributors to sustainable supply system (Coe et al., 2008; Mastos et al., 2020; Ding et al., 2023a). Sustainable Supply Chain Management (SSCM) supported by IoT is regarded not only as an environmentally useful procedure but also as leverage that can improve the economic performance of supply chains, as well as manufacturers' competitiveness (Porter and Linde, 1995; Green et al., 2012). Scholars highlighted the necessity of focusing on sustainability by utilizing IoT to meet customers' requirements and organizations' goals as well as the aggressive changes in market dynamics (Manavalan and Jayakrishna, 2019). For instance, Ding et al. (2023b) reviewed and identified positive impacts of IoT capabilities on six different circular practices and estimated 20–30% carbon reduction potential on average. Ali and Shahram (2020) elaborated on improving IoT in hardware, software, communication and architecture and its positive effects on carbon emission reduction. Pan et al. (2020) showed that the implementation of smart logistics and inventory can significantly curb carbon emissions and have a sustained impact in the following years.

However, most of these studies discuss conceptual frameworks and theoretical evaluations rather than quantitative case studies. Such work

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is less persuasive to small and medium enterprises (SMEs) having them implementing IoT-enabled SSC. At the same time SMEs are encountering significant pressure to improve environmental and cost performance, but the adoption cost of innovative Industry 4.0 technology could be high (Awan et al., 2022). There is hence a need for quantitative case studies. While LCA and LCC are powerful tools for environmental impact and cost assessment, they do tend to use static systems as point of departure. In practice products and processes form inherently dynamic networks in which behavior changes over time (McAvoy et al., 2021). The use of systems thinking, and the group model building process can identify critical variables that traditional LCA/LCC may not consider, thereby strengthening the LCA/LCC approach (Mccabe and Halog, 2018; Laurenti et al., 2014). Therefore, an ex-ante assessment for dynamic industrial process through simulation can be supportive to reduce investment risks (Ding et al., 2023a).

A system dynamics (SD) model is an ex-ante simulation technique for evaluating the outcomes of decision-options (Guan et al., 2011; Tan et al., 2018). Compared with another dynamic modeling method - discrete event simulation (DES), SD is based on the continuity of time, and has advantages in demand forecasting, production and inventory planning, and describes bullwhip effects which can be considered more at a strategic level (Tako and Robinson, 2012). SD can explore the information-feedbacks in industrial systems and improve their organizational form (Kim et al., 2014). For example, Zhao et al. (2018) adopted an SD model to improve products efficiency by energy recovery and emulated simple resource pollution control in green supply chain. Tan et al. (2018) developed an SD model for simulating the sustainability performance of urban systems by considering four sub-factors – the economic, social, environmental and resource sector. The simulation results proved to help policy makers to formulate relevant strategies for a better sustainable development of cities.

Scholars also have been enhancing the capabilities of SD by linking Life Cycle Assessment (LCA) into SD modelling. The use of SD allows for the tracking of multiple elements while multiple variables are interacting or changing simultaneously. In this way, SD allows for better estimates of (future) structures of production-consumption systems on which Life cycle inventories (LCIs) for LCAs can be based. In the same way, Life cycle costing (LCC) can be supported by SD models. For instance, Pinto and Diemer (2020) used emission and resource extraction inventory data and impact assessment models from LCA and linked them to nodes in a stock and flow system from a top-down SD model. Cao et al. (2019) established a top-down SD model including production, transportation, storage and consumption to simulate the carbon emission reduction plan in the entire life cycle of a coal supply chain, and discussed the main sources and key influencing factors for associated carbon emissions. Their reality tests showed the validity of their model.

SD can further be combined with agent-based (AB) modelling to describe the complex and inter-dependent relationships between variables and agents. Such a hybrid SD/AB model can simulate the dynamic of supply chains effectively by defining the important interacting entities as agents. For instance, Wang et al. (2023) used a top-down SD model to explore the interaction of multiple factors (urban socio-economic development, low-carbon transportation, and environmental economic policies) for selecting an optimal policy scheme taking into account multiple agents – government, enterprises, and residents. The model was validated by comparing the simulation results with historical data from 2005 to 2018 though factors like urban space planning, market mechanisms are not considered.

Therefore, the combined SD and AB approaches can help to create the chain structure and life cycle inventory data (LCI) in line with LCA and LCC. This combined model can not only describe the overall dynamic process of the system, but also reflects the interaction between agents and the external environment. It can better simulate the performance of IoT-enabled smart supply chains (real-time order forecasting, cargo tracking, and production arrangement) in a dynamic market (Ding et al., 2023a).

There are several conceptual papers suggesting IoT can improve environmental performance and economic value creation and hence contribute to sustainable business (Ranta et al., 2018; Whalen, 2019; Ding et al., 2023a). However, in earlier work we showed that there are still limited case studies that systematically analyze the impact of IoT on cost and emissions reductions (Ding et al., 2023b). Studies that analyze the impact of IoT with AB and SD approaches are virtually absent (Rajeev et al., 2017; Rebs et al., 2019). Therefore, this article introduces two typical supply chain structures (IoT enabled and non-IoT enabled) and applies a combined SD and AB approach to compare supply chain structures and measure their performance in terms of profitability (through LCC), carbon emissions (through LCA) for a Li-ion battery case, next to estimating their market penetration.

This study aims to answer the following research questions:

- RQ 1 How can the capabilities of IoT enabled SSC be simulated?
- RQ 2 What are the economic and environmental gains of the IoT-enabled SSC in comparison with its conventional competitors under a Li-ion battery case (assessed with LCA and LCC)?
- RQ 3 Which factors are decisive for shaping the performance of IoT-enabled SSC?

The paper proceeds as follows: Section 2 introduces the research goals and scopes in the model. Section 3 defines the key elements and describes the approach mathematically how IoT-enabled and conventional supply system operates and how to calculate their total net income and emissions, respectively. Section 4 gives the parameter settings. Section 5 presents and discusses the results with sensitive analysis and model validation. Section 6 highlights the contribution and novelty of the research to academic and industrial fields. Finally, section 7 reflects on the key findings, lists the limitations and proposes the future steps.

2. Goal and scope

2.1. Goal and model framework

In order to show the simulation results and obtain general conclusions. We select Li-ion battery cells (Audi A6 PHEV) as the research case, and each cell module is regarded as 1 functional unit to compare 2 supply chains performance (Lehnert, 2017). A combined SD-AB model is established to understand how these different supply chains operate in terms of product flow and storage per step in the chain, and also allow to assess market shares.

The model generally operates as follows. The Li-ion cell modules from the producing factories are being sold to users (e.g., electric vehicles users) who are sensitive to price changes as well as to the word of mouth (initially there are no users of the product) (Koberg and Longoni, 2019). They both shape the impression of potential (future) users of the products. Therefore, the demands of potential users drive the production arrangement of Li-ion modules of the alternative two supply chains. The conventional supply chain includes manufacturers, wholesalers and retailers while the IoT-enabled supply chain includes only manufacturers and retailers, as shown in Fig. 1. In addition, users of either IoT supply chain products and conventional products may switch to the alternative supply chain products when their in-used products are scrapped, which is mainly based on the purchased product quality. The constructed market is part of a standard SD approach, namely based on Bass diffusion model (Silva et al., 2020).

The linkage between market and supply chains is realized in the following way. The SD model exposes the demand of potential users to the retailer, and the retailer supply the demand and at the meantime ask upstream supply nodes (wholesalers and manufacturers) to add up its inventory in preparation for next demands. By simulating the behavior of different nodes of the two supply chains, the model can depict the logical ways of demand forecasting, order shipment and inventory management of the two supply chains.

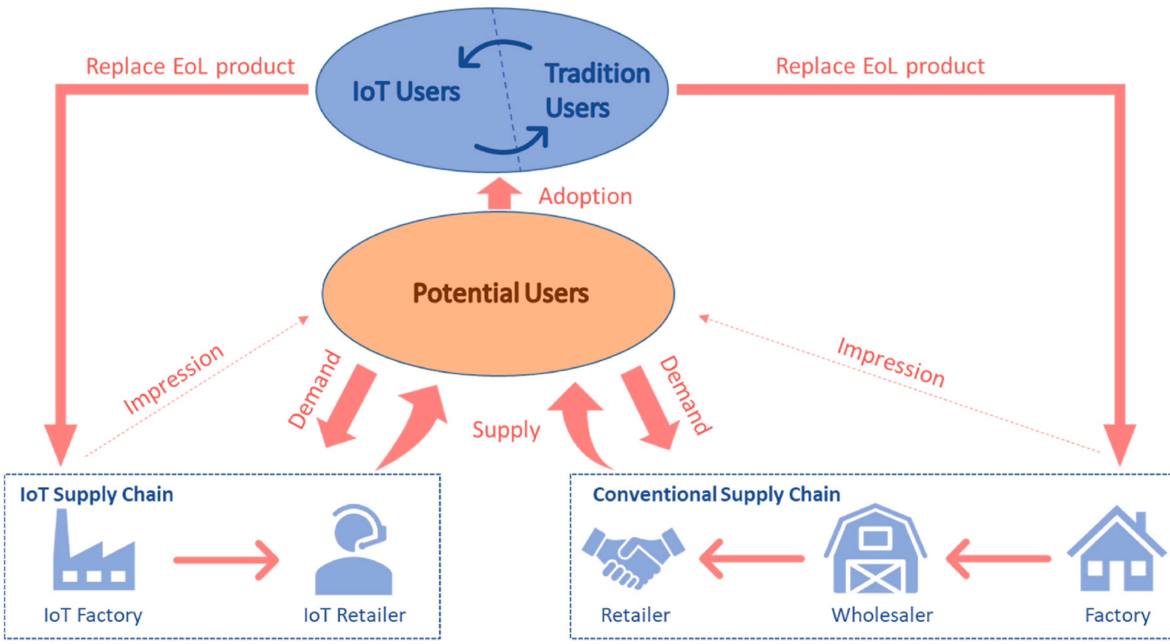

Fig. 1. The market competition mechanism of two types of supply chains.

2.2. Selection on impact indicators

The total net profits represent the cost performance of two supply chains. It is numerically expressed as the sum of the net profits of all nodes in each supply chain. That is, the difference between the selling price of each node and the purchase price as well as other costs (including transportation costs, inventory costs).

We focus on the CO2 emissions caused by supply chain activities, where heating, electricity and transportation contribute to the majority of differences between the two different supply chains. The inventory data from an LCI database are attached to supply chain processes (determined by the storage and flow of products) in our SD-AB model. We use the Ecoinvent 3.8 (most extensive LCI databases available) to estimate emissions per step in the logistics chain of Li-ion battery cells. The use of medium voltage electricity, lorry transport for freight and heat using natural gas are the processes taken from Ecoinvent 3.8 to calculate emissions of greenhouse gases. We use the 100-year Global warming potential (GWP 100) to characterise greenhouse gas emissions and obtain their related contribution to climate change impacts. GWP is an indicator of the overall effect of the process related to the heat radiation absorption of the atmosphere due to emissions of greenhouse gases (CO2-eq) of the system under assessment over a 100-year time horizon.

The market performance can be directly expressed as the number of current users of product from a certain supply chain. The expansion of these groups come from the existing product demands of potential users and the demands of End-of-Life (EoL) product users for substitutes.

The GWP 100 and net profits of two supply chains are compared both on a functional unit level and full market level, providing our LCA and LCC results respectively.

Tarancón and Río (2007) created a sensitivity analysis method considering both technology-production factor and final demand factor to be structural factors that affecting sectoral carbon emissions. The technology-production factor can be regarded as a supply-side factor, which depends on the inputs in the production and logistics process required to deliver a unit of product. While the final demand factor depends on the sales of the final demand sector. In the structure model of this paper, potential users and End-of-life product users can be regarded as two final demand sectors. While transportation, as a process connecting different nodes, can directly affect the supplying dynamics. Therefore, we choose contact rate, product lifetime and truck load capacity as representative factors to explore how they may influence IoT's contribution in reduction of carbon emissions and costs. They affect supply chain dynamics from two different sources of market demand (potential users and End-of-life product users) and one major supply factor (shipment rates), respectively.

3. Mathematical description and inventory data

3.1. Definition of key elements

Kibira et al. (2009) built a comprehensive conceptual framework for the SD model of SSCM for integrating economic and environmental domains in manufacturing system. They identified key elements under this system – storage, manufacturers, retailers, consumers and market, and proposed possible stocks (user and product) and flows (product, user and information) for model building. This supply chain produces final products which get stored as serviceable inventory so as to remain financially viable.

3.1.1. Storage

The flow of stored product along the supply chain to the end consumer represents the manufacturing activity. The storages are modeled as multiple stocks based on location along the supply chain including manufacturers' storages, retailer storages, products in use.

3.1.2. Manufacturers

The manufacturers are the beginning nodes of final products flowing to the end users in the manufacturing system. Their production rates are influenced mainly by the market demands under a certain availability of energy, labor, and materials (Amini et al., 2012).

3.1.3. Retailers

This category represents the organizations and people involved in ensuring that the products reach the end users. They are the connection nodes between market and manufacturing system. Where manufacturers and retailers are difficult to connect directly due to geographical distance or delivery uncertainties, wholesalers play a role as a transit center for large quantities of goods (Rawwas and Iyer, 2013).

3.1.4. Consumers and market

The market studied resembles a complex adaptive system driven by social network consumer interactions (Miller and Page, 2009; North and Macal, 2007). Consumers have three fundamental properties: Autonomy, Interactivity, and Bounded rationality (Amini et al., 2012). Autonomy suggests the influence of customers attitude towards product price and quality; Interactivity suggests the influence of product positive and negative word-of-mouth among consumers; Bounded rationality suggests the effectiveness of advertisement.

Although this framework is not subjected to confirmatory factor analysis and defines no agents, it provides a feasible enterprise-level substructure for modeling supply chain and management activities (Rebs et al., 2019; Zhang et al., 2013). We use these key elements and integrate IoT capabilities – tracking, monitoring and optimization to construct a SD framework where an IoT-enabled and a conventional supply chain compete in a market (Ding et al., 2023b). A conceptual diagram in Fig. 2 shows agents, stocks and flows in this framework. Stocks refer to user stocks in the market and product stocks (storage) of each supply nodes, and flows refer to product flows (from manufacturer via retailer to users), user flows (from potential users to users) and information flows (Shipment requested to upstream nodes to add up local products storage).

We then define the important stakeholders that directly affect the operation of supply chains as agents: Manufacturers (including conventional manufacturers and IoT manufacturers, they have their own shipment fleets), Wholesalers (only in conventional supply chains), Retailers (including conventional retailers and IoT retailers). The other stakeholders (such as energy supplying companies, logistics companies, etc.) are excluded as they are not considered to be substantial enough or sufficiently explicit when comparing the performance of supply, see e.g., Rahman et al. (2022) for more details.

3.2. Market demand

The market part of the model defines the users' demand for the product, which becomes the driving force of this market competition model. The demand D_t for products is driven by three forces, the adoption rate of potential users, the discard rate of end of their life products, and the rate of consumer switching the manufacturer because of dissatisfaction resulting in (1).

$$D_t = Adop_t + Disc_t + Tran_{iot} \quad (1)$$

D_t represents the user's demand for conventional factory products. $Adop_t$ represents the adoption rate from potential users. $Disc_t$ represents the discard rate of conventional sold products. $Tran_{iot}$ represents the shift flow from IoT products users. Similarly, for product from IoT factories, its demand can be represented by the following (2).

$$D_{iot} = Adop_{iot} + Disc_{iot} + Tran_t \quad (2)$$

The adoption rate of potential users can be further expressed in the following (3) and (4). It is divided into two parts. The first part reflect that potential consumers generate new demand through advertisement (Goldenberg et al., 2007). The second channel reflects that demand is generated through product recommendations from current users (Amini et al., 2012). PU represents the current amount of all potential users who might be interested in this kind of product but do not have one. Ad_t and Ad_{iot} represents the advertisement effect of products from conventional factory and IoT factory respectively. U_t and U_{iot} represent current users of product from conventional and IoT production, respectively. C represents contact rate, which means the number of potential user one user will contact per unit time (every day). S_t and S_{iot} represents the satisfactory rate of conventional product users and IoT product users. f is used to define the market fluctuation.

$$Adop_t = \left(Ad_t + C * S_t \frac{U_t}{PU + U_t + U_{iot}}\right) * f * PU \quad (3)$$

$$Adop_{iot} = \left(Ad_{iot} + C * S_{iot} \frac{U_{iot}}{PU + U_t + U_{iot}}\right) * f * PU \quad (4)$$

In the consumer value theory that affects purchase behavior, functional value (which includes product reliability, convenience, and price) is considered to be the most important aspect (Moon et al., 2021). Tversky and Shafir (1992) demonstrated that consumer purchase delays have a significant impact on purchasing decisions, which is in line with standard economic theory of time preference (Nordhaus, 2013). Therefore, user's satisfaction with the product mainly includes three aspects, quality, price and delay. Therefore, S_t and S_{iot} can be further expressed by (5) and (6).

$$S_t = w_q Q_t + w_p \frac{P_{iot}}{P_t + P_{iot}} + w_d \frac{Supply_t}{D_t} \quad (5)$$

$$S_{iot} = w_q Q_{iot} + w_p \frac{P_t}{P_t + P_{iot}} + w_d \frac{Supply_{iot}}{D_{iot}} \quad (6)$$

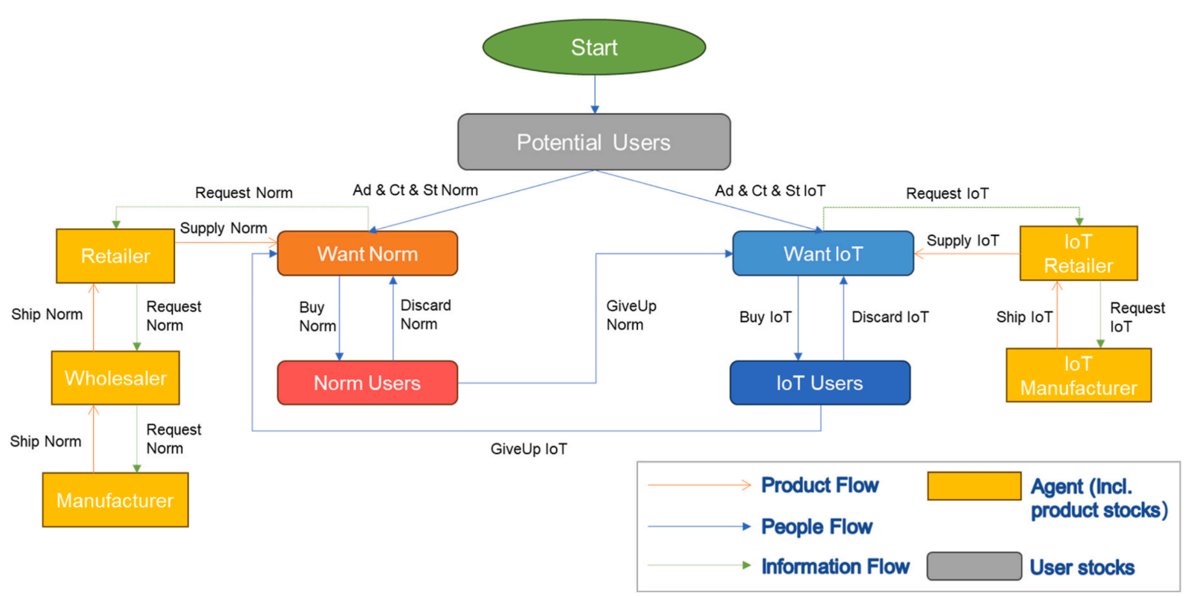

Fig. 2. Stocks and flows of SD-AB model.

Q_t and Q_{iot} respectively represent the qualified rate of products produced by conventional factories and IoT factories, and represent the quality and reliability of products. P represents the final retail price of the products. $Supply_t = \min(D_t, I_t^r)$ and $Supply_{iot} = \min(D_{iot}, I_{iot}^r)$ represent actual supply amount products from the conventional- and IoT factory, where I_t^r and I_{iot}^r represent the inventory level of retailer from conventional factories and IoT factories. That is, when the user's demand is less than the retailer's inventory level, it can be shipped immediately. When the demand is greater than the inventory level (that is, the demand exceeds supply), users need to wait for the manufacturer to replenish new goods, then delay decreases purchase preference. w_q, w_p and w_d represent the weights of quality, price and delay dimensions.

In addition, the discard rate can also be represented by two variables, the product qualification rate and the product life cycle. The transfer rate represents dissatisfaction with the current product, which is directly related to product quality. LT represents life time of all products that belong to the same type. These relations are depicted in following equations (7)–(10).

$$Disc_t = \frac{Q_t * U_t}{LT} \tag{7}$$

$$Disc_{iot} = \frac{Q_{iot} * U_{iot}}{LT} \tag{8}$$

$$Tran_t = \frac{(1 - Q_t) * U_t}{LT} \tag{9}$$

$$Tran_{iot} = \frac{(1 - Q_{iot}) * U_{iot}}{LT} \tag{10}$$

Therefore, the real-time number of product users U_t and U_{iot} can be expressed as the following (11)–(12), that is, the accumulated value of actual supplied demand minus the discard rate and its own transfer rate. N_t and N_{iot} represent the number of shipments from two kinds of retailers.

$$U_t = \sum_{n=1}^{N_t} \min\left(D_t, I_t^r\right) - Disc_t - Tran_t \tag{11}$$

$$U_{iot} = \sum_{n=1}^{N_{iot}} \min\left(D_{iot}, I_{iot}^r\right) - Disc_{iot} - Tran_{iot} \tag{12}$$

3.3. Structure of logistics chains

3.3.1. Conventional logistics chain from producer via wholesaler and retailer to user

The conventional supply chain is modeled by active agents (retailers, wholesalers, and manufacturers), and consists of three steps. First products go from manufacturer to wholesaler, then they flow to the retailer, and are finally delivered to the consumers. That is, user demands are fed back to the retailer. When the retailer's supply capacity is insufficient, wholesalers will supply retailers in bulk and apply for shipments from manufacturers to maintain a stable inventory level. Therefore, it is a supply chain driven by demands. Each agent has a specific (manufacturing, inventory and delivery) strategy (Belle et al., 2021). Being part of such a supply chain requires a certain degree of demand forecasting. As demand suddenly changes and information transfers upstream tier by tier in the supply chain, this information will be distorted, which is called 'Bullwhip Effect' (Rabe et al., 2006).

For retailers, the operating mechanism is as follows: First check the quantity of demand and select the smaller value of demand and current inventory to supply, then estimate the order O_t^r to the wholesaler to replenish the inventory, it is improved on a (Q, R) strategy – a fixed order quantity and fixed order point strategy under continuity check (Braglia et al., 2019; Pérez and Geunes, 2014; Xu et al., 2020), but the order quantity O_t^r does not remain unchanged, but obeys the rules shown in the following (13).

$$O_t^r = \begin{cases} \min\left(S_r - I_t^r, S_r - \left(I_t^r + EP_t^r - D_t\right)\right) & \left(I_t^r + EP_t^r - D_t < s_r\right) \\ 0 & \left(I_t^r + EP_t^r - D_t \geq s_r\right) \end{cases} \tag{13}$$

Where s_r and S_r represent the lower limit and upper limit of retailers' inventory respectively. When the current inventory I_t^r plus the expected amount of goods EP_t^r transferred from the wholesaler minus the actual demand is still less than the lower limit of inventory control line, the amount of the expected goods EP_t^r needs to be increased, but the value after the increase cannot be higher than the upper limit of inventory control line. The full conceptual diagram to describe the conventional retailer's behavior and interaction with other agents and market environment is shown in Appendix A1.

$$EP_t^r = \begin{cases} O_t^r & \left(O_t^r > 0\right) \\ 0 & \left(O_t^r = 0\right) \end{cases} \tag{14}$$

For wholesalers, they act as middlemen, as some producers are unwilling to sell in small batches in consideration of transportation management costs, while retailers are limited by financial conditions, unable to buy in large quantities, and are limited by manpower. Wholesalers can not only make bulk purchases from producers, but also divide the supply into small units and resell them to retailers. Therefore, they often have much higher upper and lower inventory limits S_w and s_w than retailers. In addition, it is basically the same as the retailer's ordering mechanism, but the demand D_t should be replaced with a backlog of retailers' orders BK_t^r, which is represented by (15).

$$BK_t^r = \sum_{n=1}^{N_t^{'}} O_r - SH_w \tag{15}$$

The backlog of retailers' order BK_t^r is expressed as all orders from retailers minus the supplied amount SH_w from wholesalers. $N_t^{'}$ represents the number of orders from conventional retailers. The full conceptual diagram to describe the wholesaler's behavior and interaction with upstream and downstream agents is shown in Appendix A2.

The conventional factory is normally facing complexity challenges in planning, which come from data integrity concerns, product mix exacerbated by increasing product customization needs, estimation of production volumes, control principles that minimizes work-in-process inventory, etc. (Vollmann et al., 2005) Because of limited real-time feedback of its own inventory, there remains less space to adjust the manufacturing speed. Therefore, its actual manufacturing rate Man_t depends on the rough inventory level and the number of backlogs. As shown in (16).

$$Man_t = \begin{cases} 0 & \left(I_t^m - BK_t^w > Sd\right) \\ MR & \left(I_t^m - BK_t^w \leq Sd\right) \end{cases} \tag{16}$$

Among them, when the manufacturer's inventory I_t^m can still meet the wholesaler's backlog of orders BK_t^w, production will not be started. If the supply quantity of the backlog of orders cannot be met, production will be started with full capacity MR. Sd represents the criterion for judging whether to start or not, usually it equals 0. The full conceptual diagram to describe the conventional manufacturer's production plan and interaction with wholesaler is shown in Appendix A3.

3.3.2. IoT supported logistics from producer via IoT retailer to user

The supply chain system supported by the IoT technology has some other characteristics. Due to the visibility of product information and management of big data, inventory can adopt more radical inventory and producing strategies by increasing responsiveness, coordination, accuracy of demand forecasts, accelerating changes and decreases in inventory levels, lead times and uncertainty (Calatayud et al., 2019; Anitha et al., 2021), such as zero inventory (Lyu et al., 2020;

Mashayekhy et al., 2022). As a result, wholesaler diminish. Exemplarily, researchers from the ING Economics Department concluded that Dutch wholesalers are no longer 'indispensable' and that various developments are affecting the wholesaler's existence, especially the growing digitization (Tjin, 2019). Therefore, the second structure considers a direct link between manufacturers and retailers. That is, user needs are fed back to retailers. When the retailer's supply capacity is insufficient, it will directly request the manufacturer for shipment to meet stable supply capacity. Consistent with the conventional supply chain, this is also a demand-driven supply chain.

For IoT retailers, the operating mechanism is as follows: First check the quantity of demand and select the smaller value of demand and current inventory to supply, then calculate the order O^r_{iot} to the IoT manufactures to replenish the inventory, it indicates the potential shortage quantity, that is the possible shortage quantity when the next demand comes after the current inventory meets this demand. The initial value of EP^r_{iot} is 0, O_{iotr} obeys the rule shown in the following (17).

$$O^r_{iot} = \begin{cases} \min\left(S_r, D_{iot} - \left(I^r_{iot} + EP^r_{iot} - D_{iot}\right)\right) & \left(I^r_{iot} + EP^r_{iot} - D_{iot} < D_{iot}\right) \\ 0 & \left(I^r_{iot} + EP^r_{iot} - D_{iot} \geq D_{iot}\right) \end{cases} \tag{17}$$

Where S_r represent the upper limit of IoT retailer inventory. When the current inventory I^r_{iot} plus the expected amount of goods EP^r_{iot} transferred from the manufacturers minus the actual demand D_{iot} cannot meet the next order size, which is expected to be the same, the amount of the expected goods is increased. This value after the increase cannot be higher than the upper limit of inventory control line S_r. Compared with the conventional supply chain, the condition parameter D_{iot} is dynamic rather than stable. It depicts the IoT capabilities in monitoring used products, tracking on-way products to optimize demand estimation (Mashayekhy et al., 2022). EP^r_{iot} obeys the following (18).

$$EP^r_{iot} = \begin{cases} O^r_{iot} & \left(O^r_{iot} > 0\right) \\ 0 & \left(O^r_{iot} = 0\right) \end{cases} \tag{18}$$

However, the one-sided pursuit of zero inventory in the supply chain will transfer inventory pressure to the transportation sector, resulting in an increase in the number of shipments and costs (Chakrabortya and Chatterjee, 2016). Given that the current main transportation methods consume petrol and diesel etc., this will in turn lead to a surge in carbon emissions. Therefore, whether to forward the order to the manufacturer also needs to consider the size of potential shortage quantity O^r_{iot}. When it is greater than the minimum order quantity *mo*, the order can be sent to the IoT manufacturer. The full conceptual diagram to describe the IoT retailer's behavior and interaction with IoT manufacturer and market environment is shown in Appendix A4.

For the IoT manufacturer, its supply mechanism is similar to that of conventional manufacturers the actual manufacturing rate Man_{iot} depends on the inventory level and the number of backlogs. As shown in (19).

$$Man_{iot} = \begin{cases} 0 & \left(I^m_{iot} - BK^r_{iot} > Sd\right) \\ MR & \left(-\left(I^m_{iot} - BK^r_{iot}\right) > MR\right) \\ -\left(I^m_{iot} - BK^r_{iot}\right) & \left(-\left(I^m_{iot} - BK^r_{iot}\right) \leq MR\right) \end{cases} \tag{19}$$

Among them, when the IoT manufacturer's inventory I^m_{iot} can still meet the IoT retailer's backlog orders BK^r_{iot}, production will not be started. If backlog of orders is even larger than full manufacturing capacity *MR*, production will be continued with full speed. But if the number of backlog orders is smaller than *MR*, then only produce goods according to the out-of-stock quantity. The full conceptual diagram to describe the IoT manufacturer's scheduling in production, storage and shipment is shown in Appendix A5.

3.4. Inventory data per process in the two alternative logistics chains

3.4.1. Carbon emissions

Oluyisola et al. (2020) recommended that environmental KPIs should be developed to better measure how waste generation, resource use and emissions of manufacturing and transport can be reduced in IoT supported smart and sustainable supply chains. One of the most commonly used indicators is the amount of CO2 emissions.

In modern logistics supply activities, carbon emissions are mostly generated from three processes, i.e., production, storage and transportation. Energy consumption and carbon emissions in the production process are determined by production volume and production processes. The carbon emissions in storage are positively correlated with the warehouse storage level and stored time, and the carbon emissions during transportation are related to the number of trucks delivered and their distances. Both inventory and transportation emissions are strongly influenced by order strategy. For example, Chen et al. (2013) found that for specific situations though the order quantity increases the cost of the company, carbon emissions drop due to the decrease in the number of shipments. In the supply chain system, the IoT technology mainly affects carbon emissions by influencing the inventory and shipment strategies (Kluczek et al., 2021). Carbon emission from the production process depend deeply on the specific product type and manufacturing route, but it is basically positively related to the manufactured number.

Therefore, the final carbon emissions embedded in transportation and inventory of IoT - EM_{iot} and conventional supply chains EM_t should be represented by the following equations (20) and (21).

$$EM_t = \left(I^r_t + I^w_t + I^m_t\right)\gamma\varepsilon + \left(SN^r_t d^r_t + SN^w_t d^w_t + SN^m_t d^m_t\right)\rho + H^r_t + H^w_t + H^m_t \tag{20}$$

$$EM_{iot} = \left(I^r_{iot} + I^m_{iot}\right)\gamma\varepsilon + \left(SN^r_{iot} d^r_{iot} + SN^m_{iot} d^m_{iot}\right)\rho + H^r_{iot} + H^m_{iot} \tag{21}$$

Where γ represents the energy consumption per unit of inventory, ε represents energy consumption carbon emission coefficient, *SN* represents the number of delivery vehicles, *d* represents the distance of delivery (or delivery time instead), ρ represents the vehicle carbon emission coefficient and *H* represents the emissions caused by heating.

3.4.2. Income and cost

For most companies, one of the critical indicators is the level of profit, which is expressed in the form of sales revenue minus all costs. In this model, revenue comes from the amounts of products sold. Costs are composed of multiple parts, including product costs (considering labour costs, raw materials, energy consumption, etc.), inventory costs (including one-time inputs and energy consumption, etc.), transportation costs. For example, for a retailer in a conventional supply chain, its profit is represented by (22)

$$M^r_t = \min\left(D_t, I^r_t\right)P^r_t - IC_r I^r_t - SN^r_t SC_r - O^r_t P^w_t \tag{22}$$

Among them, M^r_t represents the profit level of the retailer, P^r_t represents the retailer's selling price, IC_r represents the unit inventory cost, SC_r represents the cost of delivery per vehicle, and P^w_t represents the purchase price from wholesaler. Wholesalers and manufacturers share similar profit mechanism.

4. Parameter settings in SD-AB model

Lighting is one of the significant factors for electricity consuming of inventory. T5 energy-saving lamps are currently widely used in warehouses (Jacobson et al., 2021), which have a light effect of about 100 lm/W, according to the minimum illumination requirement of 300 lux (Chen et al., 2017), each kilowatt T5 lamp can illuminate 346.79 m2 space. Therefore, one unit of Li-ion module demands 0.00865 kWh medium voltage electricity and 0.978 MJ heating as energy inputs. They contribute to 0.0086 kg and 0.036 kg CO2-eq emissions in China based on Ecoinvent 3.8 database, respectively. The functional unit for warehouse storage is 1 m2. The warehouse shelf for product storage has four floors, each shelf (contains 4 cell modules) occupies a storage area of 0.5 m2, and the shelf cover 50% of the total floor area considering the hallway space. Therefore 1 m2 of warehouse can store 4 cell modules.

As for transportation, Ecoinvent 3.8 provides detailed transportation embedded emissions dataset, carbon emissions for trucks (Unspecified, global) per ton kilometre is 0.13 kg. Considering the weight and sake of the battery shipment (Aujla and Kumar, 2018), each lorry can transport up to 200 units of modules at one time. Datasets from EKOL Logistics and UPS for parcel shipments in Turkey showed that the average truck load is 65% and 45%, respectively (Satır et al., 2018). Therefore, we set default minimum order quantity *mo* as half of trucks load capacity. For shipment the functional unit is 1 ton kilometre.

Other parameter settings are listed in the following Table 1. In some cases, we use the same values for IoT and conventional supply chain to control extraneous variables and get consistency analysis results. The model is realized in Anylogic 8.7.11, see Appendix B.

5. Results and interpretation

5.1. Differences in cost performance

The difference between conventional- and IoT supply chain in market competition is reflected in many aspects such as net profit. As shown in Fig. 3, the overall profit of the IoT supply chain is higher than that of the conventional ones, exceeding the latter by 31%. Since the IoT supply chain has only two nodes (manufacturers and the retailers), each node can acquire a higher relative profit level compared with the conventional structure. As for the profits per unit, IoT has 34% higher value than conventional competitors, see Fig. 4.

When setting up same value-added of product in each node of 2 supply chains, the IoT supply chain will own price advantage of its product (8$ compared with 10$) due to less value-added processes. In this case IoT supply chain still maintains 14% higher total profit and 4% higher profit per unit compared with conventional ones, see Appendix C1 and C2. In essence, IoT allows for a drastic reduction in product stocks at production and retail and cuts out the wholesale step, leading to large reductions in costs.

Table 1
Parameters setting for simulation experiment.

Parameters (Units)	Value	Resources
Potential users	100000	Example model (Anylogic company, 2008)
Fraction/IoT Fraction	0.4	Amini et al. (2012)
Contact rate/IoT Contact rate	25	Goldenberg et al. (2007)
Ad Effectiveness/IoT Ad Effectiveness	0.011	Example model (Anylogic company, 2008)
Product lifetime/IoT Product lifetime (Model time)	60	Above
Price of Norm factory/IoT factory (US dollars)	5	Kumar and Swaminathan (2003)
Price of wholesaler (US dollars)	8	Above
Price of retailer/IoT retailer (US dollars)	10	Above
Cost of inventory per unit (US dollars)	0.2	Above
Cost of shipment per truck from manufacturer to wholesaler/IoT retailer (US dollars)	0.75	Example model (Anylogic company, 2008)
Cost of shipment per truck from Wholesaler to Retailer (US dollars)	0.3	Above
Cost of shipment per truck from retailer/IoT retailer to consumer (US dollars)	0.1	Above
Distance retailers/IoT retailers → users (km)	20	Above
Distance wholesalers → retailers (km)	100	Above
Distance manufacturers → wholesalers (km)	600	Above
Distance IoT manufacturers → retailers (km)	600	Above
Weight of durable product quality, price and delivery convenience	0.31,0.37,0.32	Pushpavathani and Kumaradeepan (2013)
Market fluctuation	triangular (0.3,0.65,1)	Fairchild et al. (2016)

Note: Example model – "Supply Chain and Market Diffusion" in Anylogic 8.7.11 (The market part of the model is done using SD. The product is delivered by a single supply chain that is modeled by several active components (Retailer, Wholesaler and Factory).

5.2. Differences in carbon emissions

In addition to the aspects mentioned above, these two supply chains reveal different carbon emissions impacts. Since both supply chains produce similar products, and there is no significant difference in manufacturing technology, it can be assumed that the emission difference in the production phase negligible. The proportion and main difference of emissions in each phase – storage (InvH and InvE) and transportation (Ship) are shown in Fig. 5.

The IoT supply chain only produces 36% of the total CO2 emissions of its competitors during the model time. The IoT supply chain causes 3.52 kg carbon emissions per unit of product while the conventional one produces 7.75 kg carbon emissions per unit of product. Optimized IoT-enabled supply strategies can significantly reduce the retention time of products in warehouse, therefore reduce carbon emissions by electricity and heating, and even minimize unnecessary transportation frequency. Therefore, the IoT supply chain has pretty lower carbon emissions per unit of product.

In both cases shipment contributes to the lion's share of emissions, accounting in each case for over 75% of the total emissions. The IoT supply chain shows a better performance in minimizing shipment emissions. Compared with the conventional case there is a decrease of 55% of CO2-eq per product.

The largest contributor of storage emissions in both supply chains is heating. Due to optimized inventory strategies based on the IoT technology, it causes less emissions than conventional ones, only 46% on average (45% in heating and 51% in electricity). The inventory level in IoT supply chain remains relative steady over time, though has a slight growth with demand expansion. However, the conventional supply chain depicts a typical order point graph dynamic, the overall storage level is over 2 times higher than IoT supply chain, and reveals a step-by-step decline characteristic followed by an increase.

5.3. Differences in market share

The simulation also depicts the dynamics of market shares in both supply chains during the simulated period, see Fig. 6. The conventional supply chain occupies 11% more market share than the IoT supply chain in the end. Although this gap is not so obvious within model time slot.

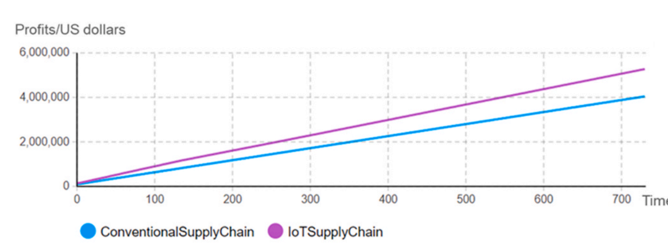

Fig. 3. Dynamics of total net profits in two supply chains (Same Price).

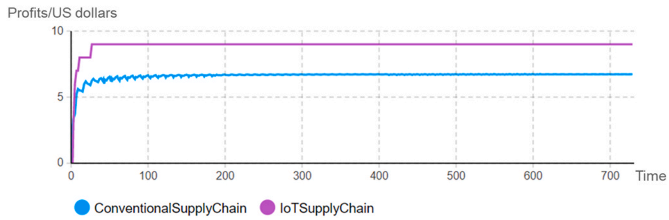

Fig. 4. Dynamics of net profits per functional unit in two supply chains (Same Price).

This is because the conventional supply chain maintains a large amount of stock through the wholesaler, who can supply the stored products to consumers faster than the IoT supply chain. While the latter usually needs to supply through the manufacturer when the retailer's stock is not sufficient. It reduces the satisfaction of potential users who prefer orders to be delivered as quickly as possible.

However, when setting up same value-added of product in each node of 2 supply chains, (8$ for IoT product compared with 10$ for conventional product). IoT products could acquire a higher market share and finally reach the level of conventional competitors, see Fig. 7. Here the strength of price makes up the weakness of IoT supply chain in instant delivery of products.

5.4. Sensitivity scenario analysis in carbon emission

To further verify the robustness of the model to evaluate the response of the coupled system to parameter changes and answer the third question: which factors are critical to influence the relative advantages of IoT supply chain. A sensitivity analysis is performed in this paper.

Since market demand mainly drives the operation of the supply chain in this model, we hence select two parameters – contact rate and product lifetime – as examples for conducting a sensitivity experimental analysis.

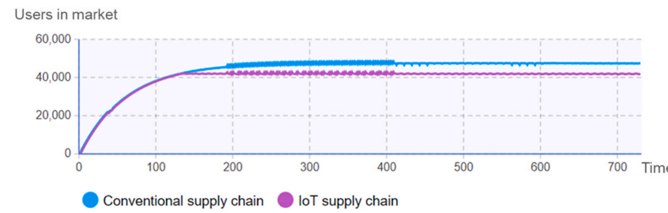

Fig. 6. Dynamics of market scale in two supply chains (Same Price).

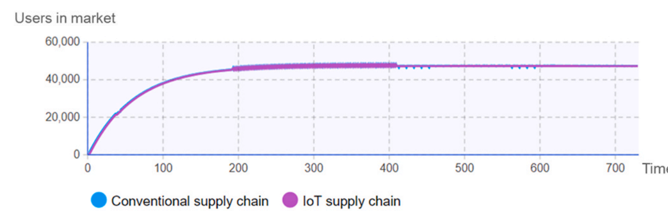

Fig. 7. Dynamics of market scale in two supply chains (Same Value-Added).

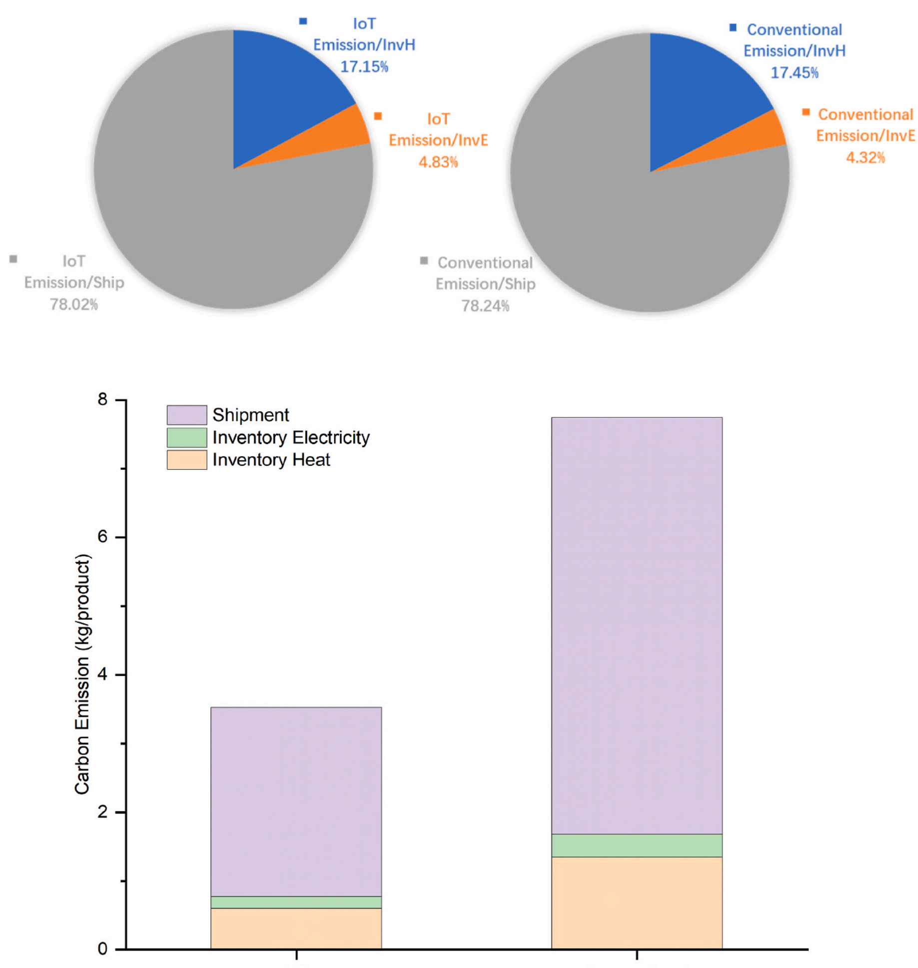

Fig. 5. Carbon emissions per product of the two supply chains.

They represent the disturbances of the demand of potential users to products and the demand of users to alternative products, respectively. Besides, as an important factor affecting the flow of products in the supply chain, the loading of trucks may not only affect the overall supply-demand relationship in the market, but also affect the performance of each supply chain nodes. Therefore, in order to avoid the impact of experimental randomness. We conduct 5 simulation experiments for each scenario and took the average values. As shown in Table 2.

The benchmark experiment shows a general market scenario, that is, a market with relatively balanced supply and demand, which represents most actual market performance. Based on the parameter setting of Contact rate = 25 in benchmark experiment, Run 1 increases this parameter value and therefore indirectly raise the demands from the potential users. It gradually forms a seller's market in which factories are operating at almost full capacity. While Run 0 performs in contrast way and represents a relative buyers' market. In these scenarios, IoT can still achieve robust estimations of market reactions resulting in comparably stable strategies for transportation and inventory optimization. Therefore, as demand increases, the carbon footprint ratio of the IoT supply chain drops slightly, but converges to a steady 40–45% of the conventional supply chain emissions.

A similar situation occurs in Run 3 and Run 4 scenarios. With the extension of product lifetime, the demand for replacing used products drops significantly. It gradually formed a buyer's market in which factories are operating far from full capacity. In this case, a low-frequency shipment situation results in the conventional supply chain with low inventory dynamics, thus contributing to larger proportion of unnecessary emissions and expanding the gap with the high-frequency and low-amount shipment model in IoT supply chain. We find that with an increase in product lifetime, the IoT supply chain carbon footprint would finally drop to only 30% of the carbon footprint of conventional supply chain.

However, the Run 4 and 5 results show that changing the load capacity of trucking impact larger on IoT's potential in reducing shipment emissions, since it accounts for more than 75% of total emissions. With the increase of truck load capacity (from 50 units to 1500 units), the total emission reduction of IoT weakens from 64% to 30% in heavy truck scenario, see Fig. 8.

In all, changes in total demand could influence the total carbon emissions of the two supply chains but impact limited on IoT's relative strength in decreasing carbon emissions. Compared with the conventional supply chain, the IoT supply chain has carbon emission reduction advantages under all proposed scenarios.

5.5. Model validation

This study conducts a unit check, reality test and extreme conditions test to examine whether the constructed AB-SD model is in consistent with reality. These three types of tests verify the validity of the developed model.

1. Unit check test

Battery supply chains contain various types of variables, including social, economic and environmental variables. The Unit check test is conducted by the Anylogic software automatically. The unit check results demonstrate that dimensions of variables are consistent and the structure of SD model is reasonable.

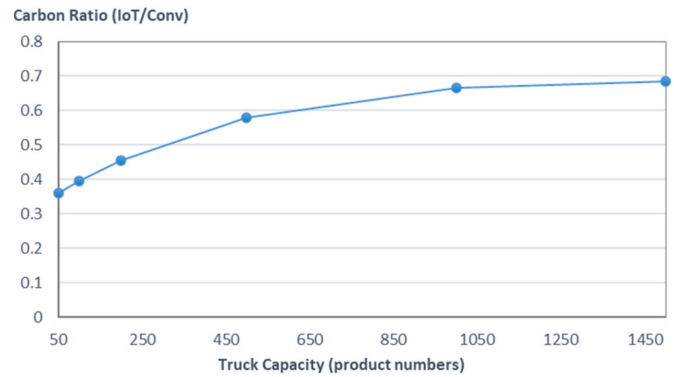

Fig. 8. Carbon ratio with two supply chains in different truck capacity.

2. Reality test

A Reality test examines the consistency of model with reality. It implies adjusting important variables, and observing whether the changing trend of other variables associated with it conforms with realistic situation. The SD model in this study is a pull supply chain for li-ion batteries. Demand is the essential variable to connect the three subsystems – potential users, users and supply chains. Variables related to the demand should change with the dynamic of demand. For instance, if demand increases (when the production rate has not reached full capacity), the number of produced products as well as total CO2 emissions by each supply chain should also increase.

The results of the reality tests are shown in Table 3. The table shows that the change of demand affects the battery supply chains and the dynamics are consistent. Hence, the SD model established in this study passes the reality test.

3 .Extreme conditions test

Supposing that the number of initial potential users is 0, most related variables should be set as 0. These variables include total user, CO2 emissions in storage and transportation processes by IoT supply chain. Only conventional supply chain has steady storage emission because of

Table 3
Reality test results.

Variable	Produced number (IoT)	Produced number (Conventional)	IoT Emission (kg)	Conventional Emission (kg)
Demand	100241	163200	63482	196207
Demand increased by 100%	191900	324800	109036	281051

Table 2
Sensitivity analysis in 6 scenarios (CO2-eq emission per product).

Scenario	Baseline	Run 0 (Contact rate = 5	Run 1 (Contact rate = 50	Run 2 (Product lifetime = 30	Run 3 (Product lifetime = 200)	Run 4 (Truck capacity = 100)	Run 5 (Truck capacity = 500)
Emission Conv	7.75	7.74	7.74	7.74	4.64	2.06	2.02
Emission IoT	3.52	3.57	3.40	3.58	2.12	0.93	0.92
Ratio IoT/ Conv	45.49%	46.09%	43.88%	46.27%	45.28%	39.63%	57.84%

its minimum storage strategy. Results of extreme conditions test are shown in Fig. 9. SD model developed in this study passes extreme conditions test.

6. Discussion

We consider the recent progress of supply chain structures and IoT studies in the literature to simulate the IoT capabilities in typical supply chain operations (Ding et al., 2023b). Assessing publications, most of them are qualitative theory studies focusing on the IoT-enabled efficiency improvements of manufacturing systems under certain enterprises or technical improvement potentials of IoT-enabled algorithms (Fisher et al., 2020; Prajapati et al., 2022). Few studies have conducted specific quantitative case study simulations on specific factories or workshops (Ekren et al., 2021). In comparison, this research leaves the workshop level and focuses on a muti-business level. It is the first to use a simulation approach to quantitatively investigate IoT-enabled supply chain level (muti-business level) problems. Our hybrid SD-AB model is hence specifically designed as a pre-LCA tool to explore the differences between a two-tier IoT-enabled supply chain and a three-tier conventional supply chain. We focus on profits, carbon emissions, and market penetration, which are key concerns of most enterprises.

The simulation reveals the strengths of IoT in minimizing emissions and costs (e.g., storage, shipment, and electricity) in supply chains, as well as drawbacks in market penetration. Sensitivity experiments further identify potential factors that affect IoT performance (e.g., demand amount, load capacity) and indicate the selection dilemma that IoT faces in some scenarios (when conventional competitors adopt higher load capacity). Most prominently these are the challenge to keep a balance between transportation frequency, average storage levels, and delivery times (influencing user satisfaction) to achieve higher profits, market penetration, and lower emissions, which requires higher information processing ability and better algorithms of IoT systems.

This simulation does not only bring new overall perspectives from whole supply chains for scholars but also helps to reduce the physical verification costs of IoT technology for most supply chain participants. Therefore, this research highlights opportunities, also to small and medium-sized enterprises being interested in IoT technology but have insufficient funds or poor trial-and-error capabilities. It helps them to better evaluate the necessity of investing or adopting IoT based on their own situations. Besides, the research also promotes IoT developers' (designers) awareness of potential challenges of IoT technology in supply chain applications so that they can iterate their own IoT products as the market wish.

7. Conclusions

This study set up a SD-AB model to explore the impact of IoT technology for a battery supply chain (from production to users) and assessing environmental and cost implications using the approaches of LCA and LCC. Compared with the conventional three-tier supply chain, the use of IoT (enabling real time monitoring, tracking and information feedback) allows for a two-tier supply chain resulting in less required warehouse space and less waste. The main conclusions of this study are as follows.

As for the economic and environmental gains, IoT supply chains have significant advantages in reducing average inventory and shipments fluctuation through real-time and accurate information sharing with different nodes, thus increasing the total net profits by at least 30% under the same selling price with conventional ones, and reducing carbon emissions by around 50% under balanced demand-supply scenarios. It contributes significantly to reducing shipment emissions, followed by emissions related to heat storage rooms.

However, IoT supply chain will be less able to fulfil demands in time due to the low storage strategy of its retailers when there is a huge market fluctuation. In contrast, conventional supply chain can satisfy users with no delivery delay with its higher safety storage level. Therefore, under the same product pricing, potential users are more inclined to purchase products from conventional supply chains, the IoT supply chain can obtain an equivalent market share only in lower pricing strategy.

The demand-supply relationship is an important factor shaping the performance of IoT-enabled SSC. Especially in low demand scenarios, the accurate scheduling of orders and storage becomes quite important. In conventional supply chains low demand scenarios easily lead to a relative high level of storage. At the meantime, the more accurate scheduling for a "zero inventory" enabled by IoT will lead to a reduction of carbon emissions of even 70%. Moreover, the frequency of shipment also plays an important role. By increasing the loading capacity or loading rate, the number of shipment turnovers (or the total transportation mileage) between various supply chain nodes can be decreased. The IoT supply chain is not significantly impacted by a higher

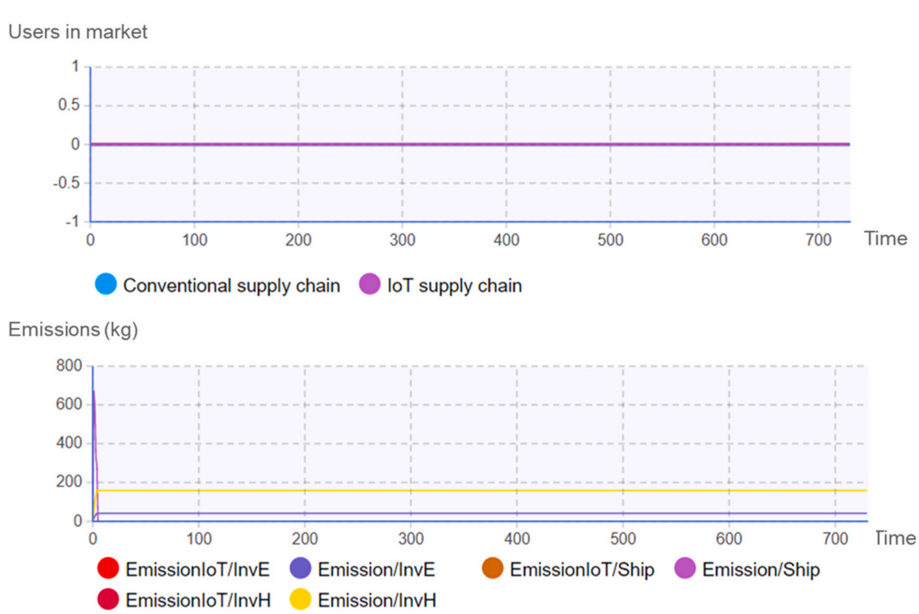

Fig. 9. Results of extreme conditions test.

loading rate, as trucks only restock storage and deliver products in proportion to demand. While the conventional supply chain can achieve safety storage target with less delivery frequency, thereby narrowing the total emissions gap between the two supply chains, particularly considering that shipment generally accounts for more than 75% of the total emissions.

This research also has some limitations. Firstly, this paper focuses on product flows which are part of supply chains between production and use. It does not consider the IoT's role in recycling or remanufacturing processes, which is an important part of circular economy. Secondly, labour market issues may have been insufficiently covered. A highly automated IoT supply chain requires a structured data management process between supply nodes using uniform data standards, and applying agreements on data ownership issues. Such IoT systems may hence reduce the demand for low-qualified labor and enhance the demand for highly qualified labor. Thirdly, we did not quantify the environmental and cost implications of creating the IoT infrastructure. While the cost and emission reductions due to more efficient transport and storage as covered in our paper are highly dominant, a more comprehensive LCA and LCC is desirable.

CRediT authorship contribution statement

Suiting Ding: Conceptualization, Data curation, Methodology, Software, Writing –– original draft, Visualization, Validation. **Hauke Ward:** Writing – review & editing, Funding acquisition, Supervision. **Stefano Cucurachi:** Data curation, Writing – review & editing. **Arnold Tukker:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendixes

Appendix A

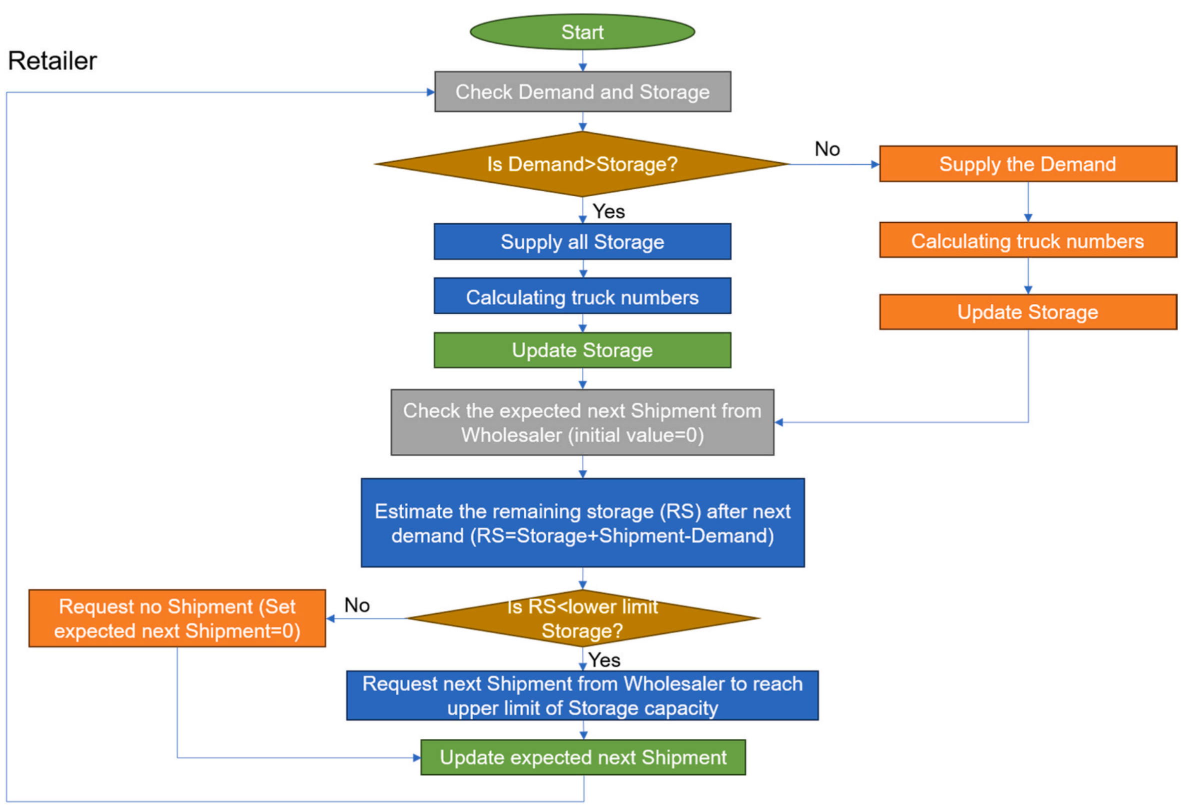

Fig. A1. Conceptual diagram of Retailer as an agent

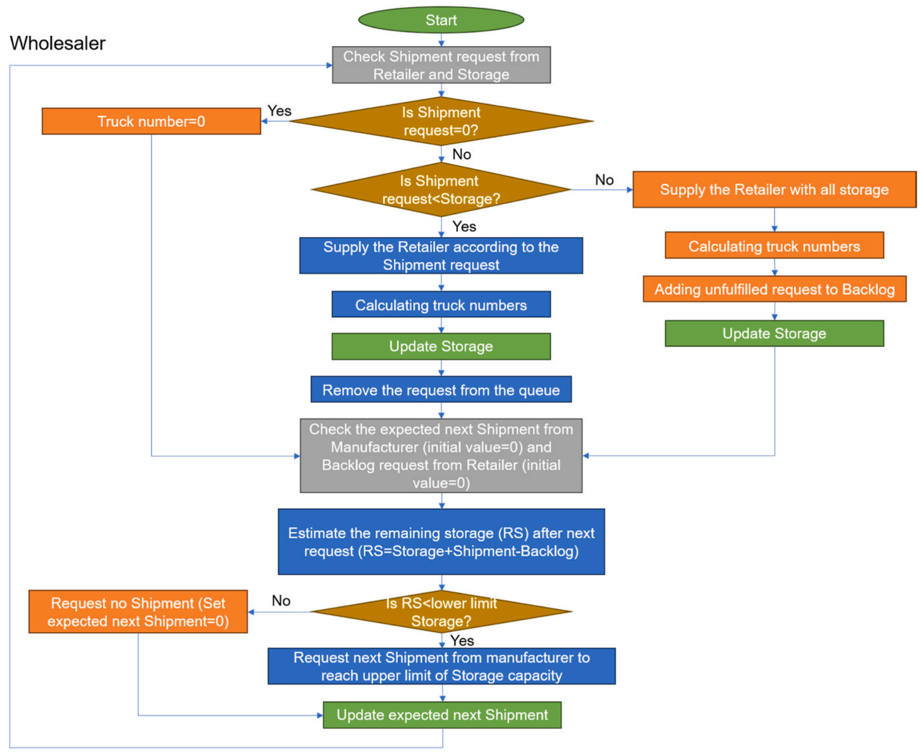

Fig. A2. Conceptual diagram of Wholesaler as an agent

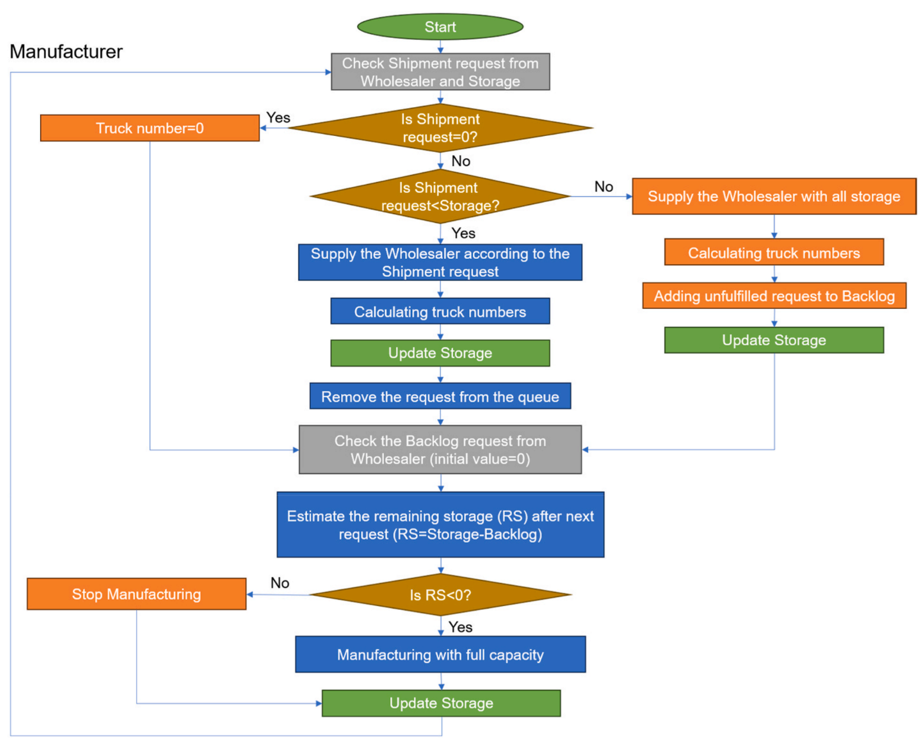

Fig. A3. Conceptual diagram of Manufacturer as an agent

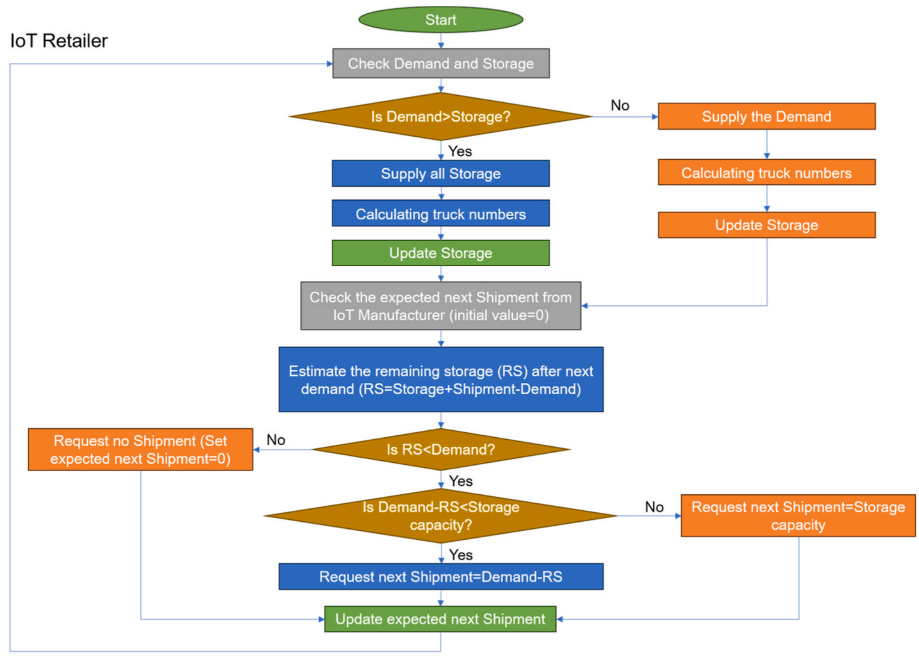

Fig. A4. Conceptual diagram of IoT Retailer as an agent

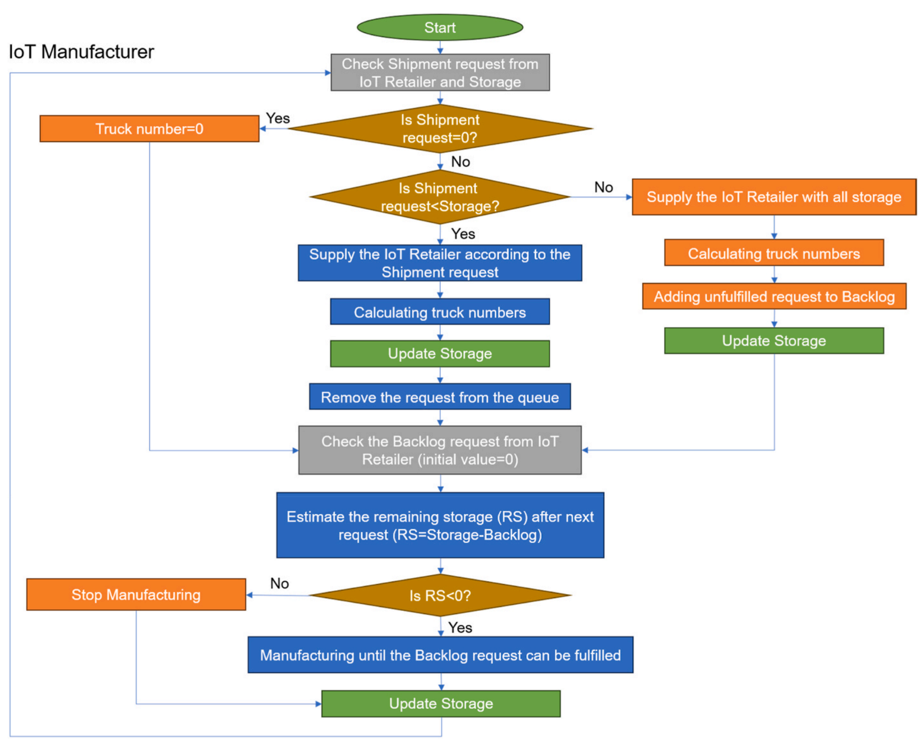

Fig. A5. Conceptual diagram of IoT Manufacturer as an agent

Appendix B

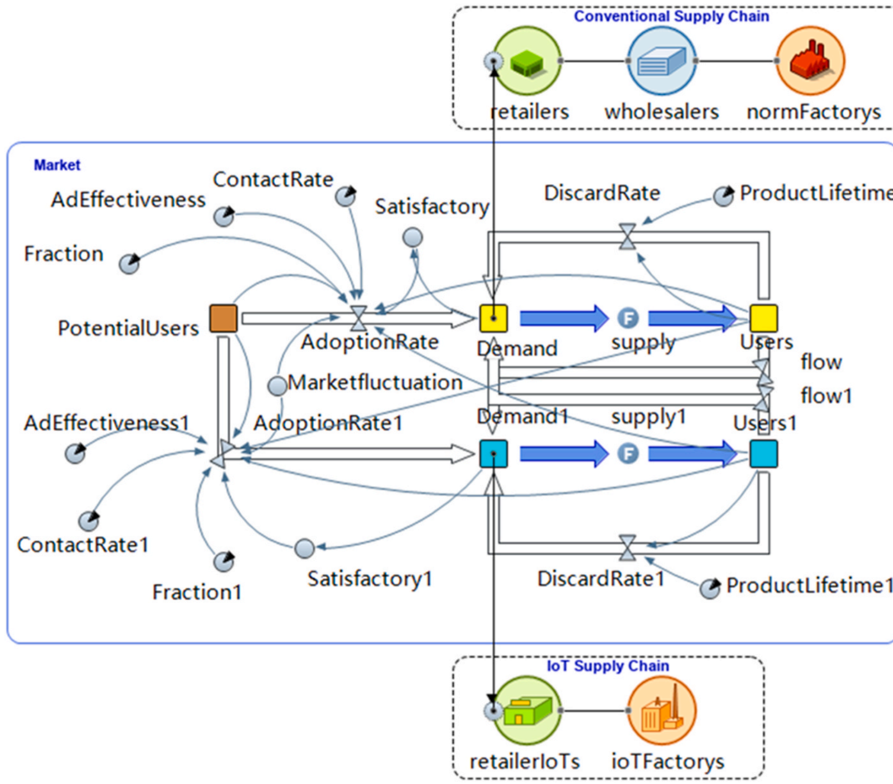

Fig. B. Main SD-AB structure of two supply chains in Anylogic 8.7.11

Appendix C

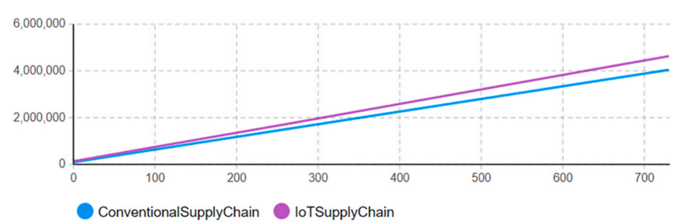

Fig. C1. Dynamics of total net profits in two supply chains (Same value-added)

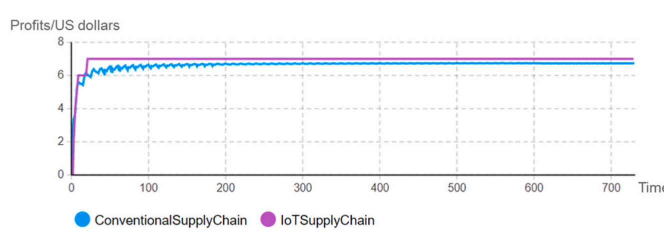

Fig. C2. Dynamics of net profits per functional unit in two supply chains (Same value-added)

References

Ali, E., Shahram, B., 2020. Green Internet of Things (GIoT): vision, applications and research challenges. Sustainable Computing: Informatics and Systems 28, 100448. https://doi.org/10.1016/j.suscom.2020.100448.

Amini, M., Wakolbinger, T., Racer, M., Nejad, M.G., 2012. Alternative supply chain production–sales policies for new product diffusion: an agent-based modeling and simulation approach. Eur. J. Oper. Res. 216 (2), 301–311. https://doi.org/10.1016/j.ejor.2011.07.040.

Anitha, K., Reddy, K.P., Krishnamoorthy, N., Jaiswal, S., 2021. IoT's in enabling the supply chain visibility and connectivity and optimization of performance. Mater. Today: Proc. https://doi.org/10.1016/j.matpr.2020.12.343.

Anylogic company, 2008. How to build a combined agent based/system dynamics model in AnyLogic. In: System Dynamics Conference 2008.

Aujla, G.S., Kumar, N., 2018. MEnSuS: an efficient scheme for energy management with sustainability of cloud data centers in edge–cloud environment. Future Generat. Comput. Syst. 86, 1279–1300. https://doi.org/10.1016/j.future.2017.09.066.

Awan, U., Gölgeci, I., Makhmadshoev, D., Mishra, N., 2022. Industry 4.0 and circular economy in an era of global value chains: what have we learned and what is still to be explored? J. Clean. Prod. 371, 13362 https://doi.org/10.1016/j.jclepro.2022.133621.

Braglia, M., Castellano, D., Marrazzini, L., Song, D., 2019. A continuous review, (Q, AuthorAnonymous, r) inventory model for a deteriorating item with random demand and positive lead time. Comput. Oper. Res. 109, 102–121. https://doi.org/10.1016/j.cor.2019.04.019.

Belle, V.J., Guns, T., Verbeke, W., 2021. Using shared sell-through data to forecast wholesaler demand in multi-echelon supply chains. Eur. J. Oper. Res. 288 (2), 466–479. https://doi.org/10.1016/j.ejor.2020.05.059.

Calatayud, A., Mangan, J., Christopher, M., 2019. The self-thinking supply chain. Supply Chain Manag. 24 (1), 22–38. https://doi.org/10.1108/SCM-03-2018-0136.

Cao, Y., Zhao, Y.H., Wen, L., Li, Y., li, H., Wang, S., Liu, Y., Shi, Q.L., Weng, J.F., 2019. System dynamics simulation for CO2 emission mitigation in green electric-coal supply chain. J. Clean. Prod. 232, 759–773. https://doi.org/10.1016/j.jclepro.2019.06.029.

Chakrabortya, A., Chatterjee, A.K., 2016. A surcharge pricing scheme for supply chain coordination under JIT environment. Eur. J. Oper. Res. 253 (1), 14–24. https://doi.org/10.1016/j.ejor.2016.02.001.

Chen, S., Zhang, J.X., Kim, J., 2017. Life cycle analysis of greenhouse gas emissions for fluorescent lamps in mainland China. Sci. Total Environ. 575, 467–473. https://doi.org/10.1016/j.scitotenv.2016.07.058.

Chen, X., Benjaafar, S., Elomri, A., 2013. The carbon-constrained EOQ. Eur. J. Oper. Res. 41, 172–179. https://doi.org/10.1016/j.orl.2012.12.003.

Coe, N., Dicken, P., Hess, M., 2008. Introduction: global production networks—debates and challenges. J. Econ. Geogr. 8 (3), 267–269. https://doi.org/10.1093/jeg/lbn006.

Ding, S., Ward, H., Tukker, A., 2023a. How Internet of Things can influence the sustainability performance of logistics industries – a Chinese case study. Cleaner Logistics and Supply Chain 6, 100094. https://doi.org/10.1016/j.clscn.2023.100094.

Ding, S., Tukker, A., Ward, H., 2023b. Opportunities and risks of Internet of Things (IoT) technologies for circular business models: a literature review. J. Environ. Manag. 336, 117662 https://doi.org/10.1016/j.jenvman.2023.117662.

Ekren, B.Y., Mangla, S.K., Turhanlar, E.E., Kazancoglu, Y., Li, G., 2021. Lateral inventory share-based models for IoT-enabled E-commerce sustainable food supply networks. Comput. Oper. Res. 130, 105237 https://doi.org/10.1016/j.cor.2021.105237.

Fairchild, K. Wm, Misra, L., Shi, Y., 2016. Using triangular distribution for business and finance simulations in excel. J. Financ. Educ. 42 (3–4), 313–336. http://www.jstor.org/stable/90001156.

Fisher, O.J., Watson, N.J., Escrig, J.E., et al., 2020. Considerations, challenges and opportunities when developing data-driven models for process manufacturing systems. Comput. Chem. Eng. 140, 106881 https://doi.org/10.1016/j.compchemeng.2020.106881.

Goldenberg, J., Libai, B., Moldovan, S., Muller, E., 2007. The NPV of bad news. Int. J. Res. Market. 24 (3), 186–200. https://doi.org/10.1016/j.ijresmar.2007.02.003.

Green, K.W., Zelbst, P.J., Meacham, J., Bhadauria, V.S., 2012. Green supply chain management practices: impact on performance. Supply Chain Manag.: Int. J. 17 (3), 290–305. https://doi.org/10.1108/13598541211227126.

Guan, D., Gao, W., Su, W., Li, H., Hokao, K., 2011. Modeling and dynamic assessment of urban economy-resource-environment system with a coupled system dynamics geographic information system model. Ecol. Indicat. 11 (5), 1333–1344. https://doi.org/10.1016/j.ecolind.2011.02.007.

Jacobson, H., Carlson, A., Lindahl, M., 2021. Legal, environmental and economic issues with functional sales – a case of indoor lighting. J. Clean. Prod. 298, 126713 https://doi.org/10.1016/j.jclepro.2021.126713.

Kibira, D., Jain, S., McLean, C.R., 2009. A system dynamics modeling framework for sustainable manufacturing. In: Proceedings of the 27th Annual System Dynamics Society Conference.

Kim, K.S., Cho, Y.J., Jeong, S.J., 2014. Simulation of CO2 emission reduction potential of the iron and steel industry using a system dynamics model. Int. J. Precis. Eng. Manuf. 15 (2), 361–373. https://doi.org/10.1007/s12541-014-0346-5.

Kluczek, A., Gladysz, B., Ejsmont, K., 2021. Application of lifecycle measures for an integrated method of environmental sustainability assessment of radio frequency identification and wireless sensor networks. Energies 14, 2794. https://doi.org/10.3390/en14102794.

Koberg, E., Longoni, A., 2019. A systematic review of sustainable supply chain management in global supply chains. J. Clean. Prod. 207, 1084–1098. https://doi.org/10.1016/j.jclepro.2018.10.033.

Kumar, S., Swaminathan, J.M., 2003. Diffusion of innovations under supply constraints. Oper. Res. 51 (6), 866–879. https://doi.org/10.1287/opre.51.6.866.24918.

Laurenti, R., Lazarevic, D., Poulikidou, S., Montrucchio, V., Bistagnino, L., Frostell, B., 2014. Group Model-Building to identify potential sources of environmental impacts outside the scope of LCA studies. J. Clean. Prod. 72, 96–109. https://doi.org/10.1016/j.jclepro.2014.03.001.

Lehnert, S., 2017. I/EE-382 Lithium-Ion Battery for Audi A6 PHEV. Technical Report.

Lyu, Z., Lin, P., Guo, D., Huang, G.Q., 2020. Towards zero-warehousing smart manufacturing from zero-inventory just-in-time production. Robot. Comput. Integrated Manuf. 64, 101932 https://doi.org/10.1016/j.rcim.2020.101932.

Manavalan, E., Jayakrishna, K., 2019. A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. Comput. Ind. Eng. 127, 925–953. https://doi.org/10.1016/j.cie.2018.11.030.

Mashayekhy, Y., Babaei, A., Yuan, X.-M., Xue, A., 2022. Impact of Internet of Things (IoT) on inventory management: a literature. Survey. Logistics 6 (2), 33. https://doi.org/10.3390/logistics6020033.

Mastos, T.D., Nizamis, A., Vafeiadis, T., et al., 2020. Industry 4.0 sustainable supply chains: an application of an IoT enabled scrap metal management solution. J. Clean. Prod. 269, 122377 https://doi.org/10.1016/j.jclepro.2020.122377.

McAvoy, S., Grant, T., Smith, C., Bontinck, P., 2021. Combining life cycle assessment and system dynamics to improve impact assessment: a systematic review. J. Clean. Prod. 315, 128060 https://doi.org/10.1016/j.jclepro.2021.128060.

McCabe, A., Halog, A., 2018. Exploring the potential of participatory systems thinking techniques in progressing SLCA. Int. J. Life Cycle Assess. 23, 739–750. https://doi.org/10.1007/s11367-016-1143-4.

Miller, J.H., Page, S., 2009. Complex adaptive systems. In: Complex Adaptive Systems. Princeton university press.

Moon, D., Amasawa, E., Hirao, M., 2021. Transition pathway of consumer perception toward a sharing economy: analysis of consumption value for behavioral transition to laundromats. Sustain. Prod. Consum. 28, 1708–1723. https://doi.org/10.1016/j.spc.2021.09.009.

Nordhaus, W.D., 2013. The Climate Casino: Risk, Uncertainty, and Economics for a Warming World. Yale University Press, New Haven, CT.

North, M.J., Macal, C.M., 2007. Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation. Oxford University Press.

Oluyisola, O.E., Sgarbossa, F., Strandhagen, J.O., 2020. Smart production planning and control: concept, use-cases and sustainability implications. Sustainability 12 (9), 3791. https://doi.org/10.3390/su12093791.

Pan, X., Li, M., Wang, M., Zong, T., Song, M., 2020. The effects of a Smart Logistics policy on carbon emissions in China: a difference-in-differences analysis. Transport. Res. E Logist. Transport. Rev. 137, 101939 https://doi.org/10.1016/j.tre.2020.101939.

Pérez, C., Geunes, J., 2014. A (Q,R) inventory replenishment model with two delivery modes. Eur. J. Oper. Res. 237 (2), 528–545. https://doi.org/10.1016/j.ejor.2014.02.049.

Pinto, J.T.M., Diemer, A., 2020. Supply chain integration strategies and circularity in the European steel industry. Resour. Conserv. Recycl. 153, 104517 https://doi.org/10.1016/j.resconrec.2019.104517.

Porter, M.E., Linde, C., 1995. Green and competitive: ending the stalemate. Harv. Bus. Rev. 73 (5), 120–134.

Prajapati, D., Chan, F.T.S., Chelladurai, H., Lakshay, L., Pratap, S., 2022. An Internet of Things embedded sustainable supply chain management of B2B E-commerce. Sustainability 14, 5066. https://doi.org/10.3390/su14095066.

Pushpavathani, K., Kumaradeepan, V., 2013. Consumer's preference and consumer buyng behaviour of foot ware industry in vavuniya district, Sri Lanka. TRANS. Asian. J. Market. Manag. Res 2 (3–4), 56–69.

Rabe, M., Jäkel, F.-W., Weinaug, H., 2006. Supply chair demonstrator based on federated models and HLA application. SimVi 329–338.

Rahman, M.M., Nguyen, R., Lu, L., 2022. Multi-level impacts of climate change and supply disruption events on a potato supply chain: an agent-based modeling approach. Agric. Syst. 201, 103469 https://doi.org/10.1016/j.agsy.2022.103469.

Rajeev, A., Pati, R.K., Padhi, S.S., Govindan, K., 2017. Evolution of sustainability in supply chain management: a literature review. J. Clean. Prod. 162, 299–314. https://doi.org/10.1016/j.jclepro.2017.05.026.

Ranta, V., Aarikka-Stenroos, L., Mäkinen, S.J., 2018. Creating value in the circular economy: a structured multiple-case analysis of business models. J. Clean. Prod. 201, 988–1000. https://doi.org/10.1016/j.jclepro.2018.08.072.

Rawwas, M., Iyer, K., 2013. How do small firms possibly survive? A comparison study of marketing skills and logistics infrastructure of small and large wholesalers. Int. Bus. Rev. 22 (4), 687–698. https://doi.org/10.1016/j.ibusrev.2012.10.003.

Rebs, T., Brandenburg, M., Seuring, S., 2019. System dynamics modeling for sustainable supply chain management: a literature review and systems thinking approach. J. Clean. Prod. 208, 1265–1280. https://doi.org/10.1016/j.jclepro.2018.10.100.

Satır, B., Erenay, F.S., Bookbinder, J.H., 2018. Shipment consolidation with two demand classes: rationing the dispatch capacity. Eur. J. Oper. Res. 270 (1), 171–184. https://doi.org/10.1016/j.ejor.2018.03.016.

Silva, H., Uturbey, W., Lopes, B.M., 2020. Market diffusion of household PV systems: insights using the Bass model and solar water heaters market data. Energy. Sustain. Dev. 55, 210–220. https://doi.org/10.1016/j.esd.2020.02.004.

Tako, A., Robinson, S., 2012. The application of discrete event simulation and system dynamics in the logistics and supply chain context. Decis. Support Syst. 52 (4), 802–815. https://doi.org/10.1016/j.dss.2011.11.015.

Tan, Y.T., Jiao, L.D., Shuai, C.Y., Shen, L.Y., 2018. A system dynamics model for simulating urban sustainability performance: a China case study. J. Clean. Prod. 199, 1107–1115. https://doi.org/10.1016/j.jclepro.2018.07.154.

Tarancón, M.Á., Río, P., 2007. CO2 emissions and intersectoral linkages. The case of Spain. Energy Pol. 35 (2), 1100–1116. https://doi.org/10.1016/j.enpol.2006.01.018.

Tjin, A.T., 2019. Internationalization Monitor/2019-III(Wholesale). Den Haag.

Tversky, A., Shafir, E., 1992. Choice under conflict: the dynamics of deferred decision. Psychol. Sci. 3 (6), 358–361. https://doi.org/10.1111/j.1467-9280.1992.tb00047.x.

Vollmann, T.E., Berry, W.L., Whybark, D.C., Jacobs, F.R., 2005. Manufacturing planning and control for supply chain management. In: The Mcgraw-Hill/Irwin Series in Operations Decision Sciences, fifth ed. McGraw-Hill, New York, USA.

Wang, H., Shi, W., He, W., Xue, H., Zeng, W., 2023. Simulation of urban transport carbon dioxide emission reduction environment economic policy in China: an integrated approach using agent-based modelling and system dynamics. J. Clean. Prod. 392, 136221 https://doi.org/10.1016/j.jclepro.2023.136221.

Whalen, K.A., 2019. Three circular business models that extend product value and their contribution to resource efficiency. J. Clean. Prod. 226, 1128–1137. https://doi.org/10.1016/j.jclepro.2019.03.128.

Xu, C., Liu, X., Wu, C., Yuan, B., 2020. Optimal inventory control strategies for deteriorating items with a general time-varying demand under carbon emission regulations. Energies 13 (4), 999. https://doi.org/10.3390/en13040999.
Zhang, H., Calvo-Amodio, J., Haapala, K.R., 2013. A conceptual model for assisting sustainable manufacturing through system dynamics. J. Manuf. Syst. 32 (4), 543–549. https://doi.org/10.1016/j.jmsy.2013.05.007.
Zhao, Y.H., Cao, Y., Li, H., Wang, S., Liu, Y., Li, Y., Zhang, Y.F., 2018. Bullwhip effect mitigation of green supply chain optimization in electronics industry. J. Clean. Prod. 180, 888–912. https://doi.org/10.1016/j.jclepro.2018.01.134.