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The Application of Supply Chain Digital Twin to Measure Optimal Inventory Policy

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Abstract: The present heterogeneous behaviour of the competitive market poses significant problems at regional as well as global scales in terms of inconsistent tracking, ripple effects, dashboard collaboration, and complex product portfolios along with stringent criteria. Meanwhile, it is also counterproductive to the visibility of the supply chain besides that adversely responsible for optimal inventory policies (OIP). Henceforth, this paper considers the supply chain digital twin (SCDT) for OIP within an integrated physical and digital world fusion vision. Consequently, the agent-based simulation method is applied to create administrative asset shells for small and medium-scale factories. The proposed model incorporates an OIP trade-off for retailers, wholesalers, customers, and factories. The results underlined the benefits and characterized OIP tactics that help estimate system performance. Finally, the managerial implications provide insides for predictive and reactive decisions to ensure the optimal supply chain running cost and customer satisfaction by utilizing the advantages of SCDT. Furthermore, this paper discusses the OIP optimization method and essential measures for developing the SCDT distribution strategy within the trade network.

Keywords: Supply Chain Digital Twin, Simulation, Inventory policy, Anylogic, Customer Satisfaction

1. INTRODUCTION

The recent development in supply chain (SC) management emphasizes the need for robust and agile inventory policies to trade-offs between the factories, wholesalers, and retailers to mitigate customer satisfaction (Nasr, 2022; Tao et al., 2022). However, Chen et al. (2021) state that the SC inventory policies can exhibit high variability, inter-arrival autocorrelation, time-dependency, unpredictability, and identification demand types (for instead direct or derived). Nevertheless, optimal inventory policies (OIP) measures are infancy stage, whereas some recent papers enhance the literature on OIP by incorporating digitalization and its applications. The SC's digitalization can lead companies to achieve flexibility and productivity (Choi et al., 2022).

Therefore, the digital paradigm (DP) has enabled virtual analysis due to the widespread adoption of digital technologies and represents the most significant shift in the data-driven approach (Choi et al., 2022; Maheshwari et al., 2021; Rahmanzadeh et al., 2022). Furthermore, the DP enables real-time controlling, monitoring, and data collection along with executions of cyber-physical systems (Sankaran et al., 2021). Henceforth, it has the potential to integrate the physical and virtual interface. In such a context, the supply chain digital twin (SCDT) concept represents an emerging research topic in manufacturing modelling, management, and control of the SC. Recent studies show that SCDT helps evaluate, predict, and optimize system behaviour in physical and virtual directions. In 2011, the concept of Industry 4.0 entered scientific parlance with the prospect of joining things and services into a global commercial network (Dolgui, 2019). Industry 4.0 characterizes the current automation and data exchange development trend (Chen et al., 2021). It is a new level of organizing production and value chain management over the whole life cycle of manufactured goods (Shafiee et al., 2021).

Moreover, the research objective of this paper is to provide OIP and the application of the SCDT in OIP measurement. The research implications show that the SCDT helps provide a better trade-off between the stakeholders of the SC. Additionally, SCDT imparted the customer waiting time by incorporating the deviations. The theoretical implications of the paper provide insights into implementing digital twin in SC. At the same time, the practical implications help determine the optimal inventory level at each point of SC.

Furthermore, section 2 respent the literature review by incorporating the state of the art of SCDT, inventory policies, and research gap. Section 3 provides the research methodology, problem descriptions, and model formulations. The results, analysis, and discussion are represented in section 4. Finally, section 5 describes the conclusion of this paper.

2. LITERATURE REVIEW

2.1 Supply Chain Digital Twin (SCDT)

The application of digital twins to optimise inventory operations and supply chain management functions is a bourgeoning practice. Most of the researchers have attempted to keep pace with this development initiating a fast-evolving research agenda. More precisely, it is a method of developing sustainable, intelligent manufacturing systems for attaining robust quality, reducing time, and customized products using real-time information throughout the product life cycle. Kamble et al. (2022) define the digital twin as a simulation approach that is a digital counterpart of the physical system that deals with different aspects of digital technology, optimizes the physical environment, and improves efficiency. In contrast, Ivanov et al. (2021) provide the conceptual

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background for the digital twin as a triad simulation, optimization, and data analytics technique. However, the SCDT model represents the network state for any given moment and allows for complete end-to-end SC visibility to improve resilience and test contingency plans.

There is currently a discussion in the practitioners and researchers community about using digital twin modelling to manage the OIP in SC management (Tao et al., 2022; Nasr, 2022). The SCDT is gaining special attention due to its nature and advanced features to connect the physical and virtual world. Therefore the SCDT technology reconfigures the SC environment, and identifying a physical entity is the primary step to implementing the SCDT that helps to twin the entities virtually. The physical and virtual environment collaboration level is responsible for the physical-to-virtual connections. However, this connection is measured by metrology and synchronized by the twining approach. To achieve the OIP approach, four essential layers of SCDT are as follows-

1. Physical layer
2. Digital supply chain twin layer
3. Digital supply chain twin analysis layer
4. Digital supply chain twin application layer

Meanwhile, Kamble et al. (2022) endorse the lack of literature on the SCDT, whereas the digital twin concept has grown well in recent years. So we have evaluated the digital twin concept and their technologies to provide insides for the SC sector. To do so, We analyzed the key aspects of digital twins.

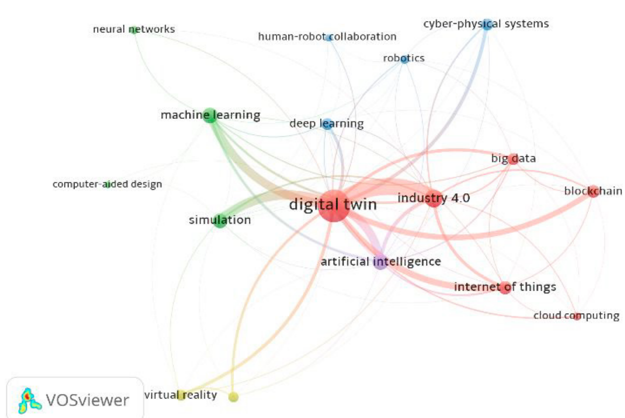

Figure 1 Key aspects of the digital twin

Figure 1 demonstrates the Vosviewer analysis of the digital twin's key aspects and provides the linkages between advanced technologies. The analysis shows that Industry 4.0, simulation, and machine learning have a solid link to making digital twin more impactful. However, cloud computing, the internet of things, big data analytics, blockchain, and artificial intelligence strengthen the Industry 4.0 concept. Whereas computer-aided design, virtual and augmented reality helps present the simulation concept. Finally, the machine learning concept is strongly connected with the neural network, human-robot collaboration, deep learning, and cyber-physical system (Coito et al., 2021). Therefore, with the help of advanced technology and its linkages, the digital twin can represent the replica of the system and update the information on a real-time basis (Kegenbekov and Jackson, 2021).

2.2 Inventory Policies

In the traditional SC model, wholesalers and retailers trade-off the factory and the customer (Maheshwari et al., 2021; Rahmanzadeh et al., 2021). Therefore, multiple echelons are generated a ripple effect due to the involvement of incompetent numerous channels and stakeholders (Shafiee et al., 2021). Thus, the lack of information and product flow is responsible for the retail stockout (Kamble et al., 2022). Instead, the retail stockout rate for fast-moving consumer products hovers around 8%, and stockout costs retailers about 4% of sales, translating into a 4% reduction in earnings per product (Tao et al., 2022). Therefore, an optimal inventory policy needs to incorporate the factory, wholesalers, retailers, and customers. More recently, some papers have considered that the holding cost per unit and per unit of time is a linearly increasing function of time (Venkitasubramony and Adil, 2021).

In contrast, the theory of stock management seeks to maintain adequate inventory levels to meet customer demand and obtain the highest possible profit (Maheshwari et al., 2021). It is necessary to develop mathematical models that allow the inventory systems' characteristics to be represented to deduce good properties on the strategies to follow in the stock control. In this way, the OIP applied to stock management can be determined. As in real-life inventory systems, the demand rate often depends on time, so it would be interesting to analyze better functions representing the demand rate. Thus, the researcher provides an adequate function to model the customer demand process. This adequate function considers the demand on time elapsed since the last replenishment and on the duration of the inventory cycle (Nasr, 2022).

2.3 Research Gap

The literature on inventory management has confirmed the effect of inventory inaccuracy on ordering policies. Tao et al. (2022) state that inventory inaccuracy leads to conflicting vendor-customer relations, ineffective decision making, higher lead time, stock out, lack of visibility in SC responsible for customer dissatisfaction, and enhancement in incremental costs.

Venkitasubramony and Adil (2021) modelled the effect of inaccuracy in product flow using queuing theory and incorporated the block-stacking layout. Tao et al. (2022) formulated the competitive SC model subjected to inventory inaccuracy. Meanwhile, Ivanov et al. (2021) comprehensively addressed the OIP issues and provided the researcher's perspectives on multidisciplinary analysis. Moreover, the research implications suggested that the role of innovative technologies such as the internet of things, augmented reality, virtual reality, SCDT, Blockchain, artificial intelligence, and machine learning should be explored practically and strategically.

Furthermore, Kamble et al. (2022) provide a systematic literature review of 98 research papers covering the different dimensión of the SC. The research finding suggests that SCDT can mitigate the sustainable performance objectives.

The literature analysis provides an enriching theoretical background of SCDT but consistent lack practical implications. Therefore, we offer the practical sense of SCDT in the proposed OIP model because the current state of the art indicates the importance of OIP to mitigate disruptions and competitive market conditions.

3. METHODOLOGY, PROBLEM DESCRIPTION AND MODEL FORMULATION

3.1 METHODOLOGY

In this paper, we have followed the research approach suggested by Borshchev and Grigoryev (2014). Experimental optimization-based simulation helps build the virtual replica of the SC and create a digital twin. The agent-based simulation methods incorporate the customer, retailers, wholesaler, and factory to create the digital twin. The idea behind creating a digital twin is to manage the supply chains, thus making them more reliable at each node of SC. Therefore, simulation and optimization are two essential methods used primarily as strategic planning tools. However, the quality of decisions when risks occur depends drastically on the timely availability of relevant data since decisions should often be made immediately.

We used the Anylogic tool to produce the replica of the existing system using the JAVA enable programming editor.

3.2 PROBLEM DESCRIPTION

Modelling the OIP is a critical challenge in inventory management, where an accurate characterization of the demand process often involves accounting for a wide range of statistical descriptors. Chen et al. (2021) suggested that incorporating the hierarchical process and multiple echelon involvement decreases SC's visibility, enhancing the computational complexity. In recent years, frequent product distribution and customer dissatisfaction negatively impacted OIP and SC performance.

3.3 MODEL FORMULATION

This paper has formulated the typical SC model incorporating four essential components, i.e., factory, wholesalers, retailers, and customers. We incorporate the demand size distribution variable as demand size probability as a demand generator between the SC components for model synchronization. The assumptions for model formulations are the followings-

1. The arrival rate of the customer is within an exponential interarrival period mean of 0.1 days with single product demand. In contrast, the demand size follows discrete random variables 1 to 5 with probabilities of 0.2, 0.4, 0.2, 0.1 and 0.1, respectively.
2. If the inventory level is significant as the customer demand at the retailer's end, demand is immediately satisfied.
3. The exceeded demand transfers to the wholesalers as regular demand or backlogged at the retailer's end.

3.3.1 Model for the retailer's inventory policy

Suppose that at the beginning of each day, retailers review the demand inventory level and ordered Q_R items to the wholesaler with the ordering cost of $S_R + i_R Q_R$ where the term $S_R$and i_R setup and incremental cost, respectively. Here, $I_R$is the initial inventory level at the beginning of the day

So, the inventory policy for the retailer is given by the following expressions-

$$Q_R = \begin{cases} K_R - I_R \; if \; I_R < k_R \\ 0 \qquad if \; I_R \geq k_R \end{cases}$$

Let inventory level at the retailers at the time (t) = $I_R(t)$

Favourable inventory level at retailer's $I_R^+ = max\{-I_R(t), 0\}$

Backlog inventory level at retailer's $I_R^- = max\{-I_R(t), 0\}$

Therefore, the average ordering cost will be =

$$\bar{Q}_R = \frac{\sum_{i=1}^{n} Q_R(i)}{n}$$

where i=1, 2..n days with time intervals [i-1, i]. The quantities of the items for period n-days expressed by

$$\bar{I}_R^+ = \frac{\int_0^n I_R^+(t)dt}{n}$$

Whereas the backlog quantities can be expressed by

$$\bar{I}_R^- = \frac{\int_0^n I_R^-(t)dt}{n}$$

Finally, the retailer's average total cost per day is calculated by

$$\bar{\alpha}_R = \bar{Q}_R + \bar{H}_R + \bar{K}_R \qquad (1)$$

Where $\bar{H}_R = h_R \bar{I}_R^+$, and $\bar{K}_R = \rho_R \bar{I}_R^-$ are average holding and backlog costs per day, respectively.

3.3.2 Model for wholesaler's inventory policy

The wholesaler operates on a stationary inventory policy to order the items to the factory, followed by the expression-

$$Q_W = \begin{cases} K_W - I_W^N \; if \; I_W^N < k_W \\ 0 \qquad if \; I_W^N \geq k_W \end{cases}$$

Finally, the wholesaler's average total cost per day is calculated by

$$\bar{\alpha}_W = \bar{Q}_W + \bar{H}_W + \bar{K}_W \qquad (2)$$

3.3.3 Model for factory's inventory policy

The factory operates on a stationary inventory policy to order the items to the factory, followed by the expression-

$$P_F = \begin{cases} K_F - I_F^N \; if \; I_W^N < k_F \\ 0 \qquad if \; I_W^N \geq k_F \end{cases}$$

Here, the value of 2x is the time to setup the production line and x is the time to produce each item if $P_F = 0$. Furthermore, the time required for the production of the items follows the correlation $2x + xP_F$ Days. The OIP at the factory follows two sequences. First, they checked the inventory level at the beginning of the day and shipped the wholesaler's demand in a first-in-first-out (FIFO) manner. However, $LT_F$is the random lead time that is uniformly distributed on the time interval $[x, 2x]$ days. We assume that the probability of LT_W being initially 2x days is zero by defining a continuous random variable. Hence, the new inventory level is $I_F^N = (IL)_{present} - items\ shipped.$ The production cost incurs setup and incremental costs.

Finally, the factory average cost per day to maintain optimal inventory level is calculated by (t)= 0, 1,…,n-1.

$$\bar{\alpha}_F = \bar{P}_F + \bar{H}_F + \bar{K}_F \tag{3}$$

3.4 Simulation model architecture

Simulation model parameter standards for SC processes involve backlog cost and holding cost per item per day. However, we also incorporate the ordering cost per item and order setup cost.

The run time of the simulation model is $n = 365$ days. We fixed the average total cost per day for the whole scenario is statistically updated once a day, whereas the average time for the customer to get an order is $\bar{T}$.

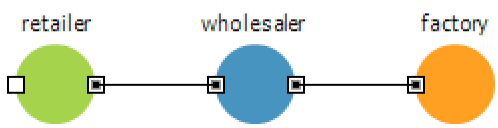

Figure 2. SC model structure

The problem formulation follows the fixed SC configuration with a single hierarchical process shown in figure 2. Therefore, an Anylogic configures the database and graphical connections. The SCDT helps to provide a replica of the physical system to integrate the information and material flow in terms of demand, order, and shipment. Thus, we generate the three Java classes wizard. However, we define the FIFO policy and keep them in a collection in such a way to create LinkedList and trigger the order, shipment status and equations.

3.5 Numerical Example

The SC operates 24 hours a day for 365 days, consists of setup costs for the retailers, wholesalers, and factory are $S_R = \$60$, $S_W = \$80$ and $S_F = \$100$, respectively. Whereas the incremental cost at retailers, wholesalers, and factory are $i_R = \$6$, $i_W = \$8$ and $i_F = \$10$. Meanwhile, the holding cost, shortage cost at the retailer's end is $h_R = \$1$ and $\rho_R = \$\,10$ per item per day, respectively, with an initial inventory level $I_R(0) = 120$. The holding cost and shortage cost at the wholesaler's end is $h_W = \$2.5$ and $\rho_W = \$\,12$ per item per day, respectively, with an initial inventory level of $I_W(0) = 160$. The holding cost, shortage cost at the factory's end is is $h_F = \$1.5$ and $\rho_F = \$\,8$ per item per day, respectively, with an initial inventory level $I_F(0) = 140$.

4. RESULTS, ANALYSIS AND DISCUSSION

4.1 Results

We have formulated the SCDT for the single echelon SC using Anylogic software. The simulation results show that better visibility between the stakeholders improves the SC performance. Section 4 formulated the inventory strategy at the factory, retailers, and wholesalers' end. However, the demand pattern fluctuates every month due to the stochastic demand of customers. Thus, simulation results reflect the fluctuation of inventory retailers to factory in terms of quantity to be ordered.

Meanwhile, the average waiting time is 0.39% of the total lead time under the static condition, as shown in figure 3. Since we consider the daily demand pattern, there is a sudden increase in demand at the beginning of the graph; then, it is normalized to 0.39%.

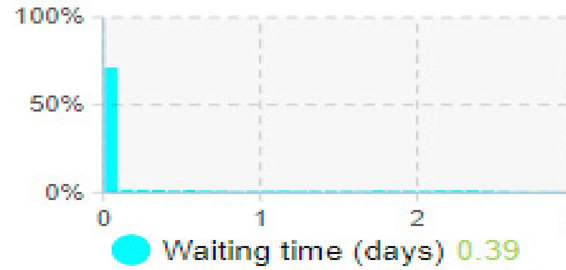

Figure 3. Customer waiting time (in days)

Furthermore, figure 4 shows the demand size probability. The demand size is a discrete random variable that holds 0.2, 0.4, 0.2, 0.1, and 0.1 probabilities.

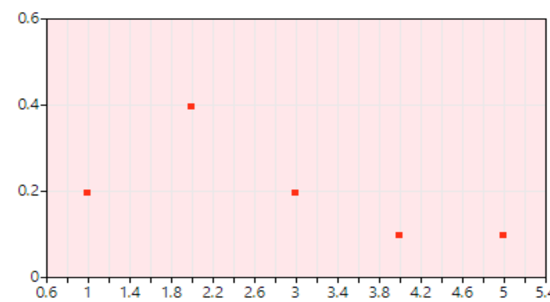

Figure 4. Demand size probability

Moreover, figure 5 represents the inventory level of items at each stage of SC. The mean inventory level at the retailers varies between 50 to 100 products per day. However, the mean inventor level at the wholesalers varies between 150 to 160 products per day. To incorporate the demands, factory produce shipped 150 to 170 products per day. The simulation results show the sudden fluctuation in demand of wholesalers at the end of the month. At the same time, the factory failed to mitigate the demand during that particular time. Therefore, it is recommended that the factory produce 160 to 180 products at the end of each month; however, the manager needs to limit the production to the second half of each month.

Figure 6 shows the trade-off between the different stakeholders of SC. The retailers ordering cost \$87.1, 54% of the wholesalers ordering cost. The holding cost is \$25.12. However, the ordering cost of the wholesaler is \$11.24, and the investment in holding cost is \$86.7. The simulation results show that the shortage cost imposed \$217.86 on the wholesaler. Furthermore, the factory's holding and shortage costs are \$65.49 and \$102.65. The analysis shows that shortage cost imposed a more negative effect on wholesalers' inventory policy than on retailers and factories because the probability of loss is higher due to investment in warehouse operations and stock-keeping units. The analysis also highlighted that customers do not wait for items and opt for alternatives, so lead time should be minimized.

Figure 5. Inventory level of items at each stage of SC

Figure 6. Mean daily cost at each stage of SC

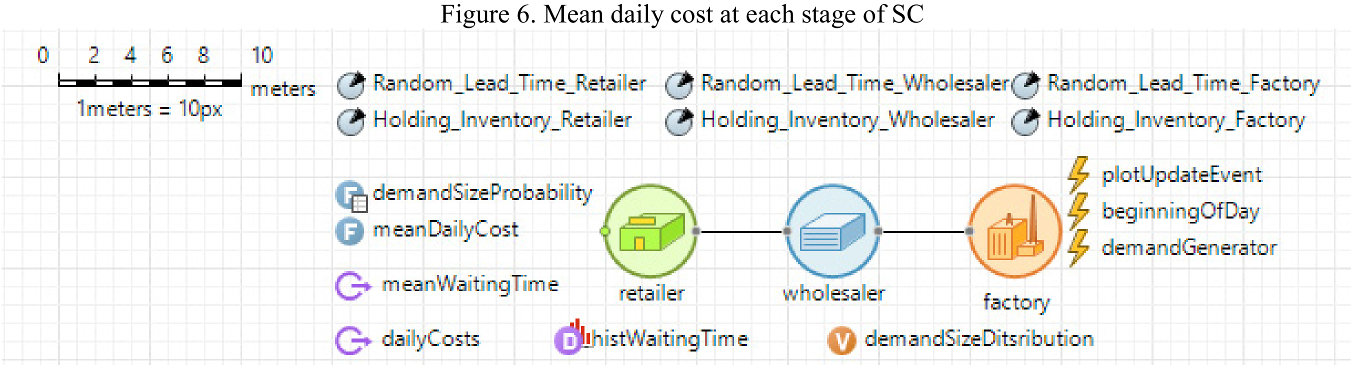

Figure 7. Anylogic model of the proposed SC model

4.2 Discussions

Figure 7 represents the proposed SC model for OIP and shows the parameters and variables to prepare the SCDT of the existing system. The implication of this paper has two folds. First, the paper describes the functionality and theoretical background of the SCDT by explaining the different aspects of SC, incorporating the retailers, wholesalers, and factory perspectives to mitigate the customer demand. However, this paper conceptualizes SCDT as a system of systems. In introducing SCDT, we present three essential features of SC, i.e. complete synchronization, dynamic data execution, virtual modelling, and SCDT challenges that will help practitioners and academicians provide resilient solutions for future SC management.

Secondly, we explain the role and possibilities of SCDT to characterize the OIP for the SC and provide the computational approach to measure the system's performance as a whole. The analysis fitted the realistic descriptor of customer expectations and demanded that the time-dependency function be captured. The analysis shows that most customers believe in zero or less lead time, which means customers do not wait for the products. Therefore, this paper emphasizes the vision of greater visibility and information sharing between the different SC nodes to minimize the lead time.

Numerical results enumerated that optimality of holding cost and order setup cost is highly important for the OIP. Therefore, policymakers should consider these during the SCDT model formulation.

5. CONCLUSION

The recent qualitative research implications represent that companies are generally reluctant to adopt digital technologies due to a high degree of heterogeneity and prior perceptions. In this paper, we demonstrate the advantage of SCDT in OIP quantitively.

The objective is to share the strategy to increase the visibility of the processes by measuring inventory policies among the various stakeholders of the supply chain processes. The proposed methodological tool uses demand size probability to generate the demands, and dynamic simulation techniques generate a what-if multi-scenario. Whereas this paper suggests the scheme to allow inventory monitoring analogous digitally. Finally, with this paper, we aim to demonstrate the inventory levels at each stage of the supply chain. The mathematical

model present a new paradigm for measuring OIP using SCDT and investigated the different perspectives of SC strategies. We characterized the SCDT to maintain the OIP. Additionally, implement the SCDT to achieve, validate and analyze the innovation of the virtual replica. Therefore, we integrate the SC environment through digital twin technology.
The proposed simulation model analyzes the holding, setup, and backlog cost at the retailer's, wholesaler's and factory's end and evaluates its effect on the customer end with the help of a numerical study. The proposed framework will guide future practitioners and researchers.

Since SCDT is a new paradigm, more research and studies are necessary to explain how SCDT can be implemented tactically and strategically in OIP. The design of crowdsourcing platforms, physical assets measurement under the disruption and stochastic demand will be the interesting future research agenda.

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