Simulation–Based Optimisation Model as an Element of a Digital Twin Concept for Supply Chain Inventory Control

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Abstract. Supply chain management is a critical success factor for many manufacturing companies. During the pandemic period, the problem of meeting delivery on time according to customer needs has intensified in many companies around the world. Companies would like to keep inventories at a level that ensures smooth order fulfilment while minimising their own costs. Determining the optimal parameters is, however, a major challenge for Supply Chain inventory policy (SC). Combining simulation methods with optimisation techniques offers a methodology for obtaining an acceptable solution and, at the same time, provides a high degree of flexibility in the formulation of assumptions and the possibility of improving the decision-making process with respect to risk management. In this paper we present a simulation-based optimisation model to improve the quality of inventory management decisions in SC design and planning. Finally, we refer to the benefits of implementing the model in the concept of digital twins.

Keywords: Discrete Simulation, Supply Chain, Digital Twin

1 Introduction

Supply chain (SC) management is the management of the flow of goods and services and includes all processes that transform raw materials into final products delivered to consumers. Supply chains can be external if they include processes for the flow of raw materials from suppliers through manufacturers to the final external consumer. Supply chains can also be internal, in terms of the processes of material flow from supplier to customer within an organisation. One of the key components of internal SC is an inventory management due to the high share of warehouse costs in the total cost of a product, considering the entire supply chain [1]. Companies therefore strive to have inventory levels set at optimal values to ensure smooth order fulfilment and keep costs in an acceptable range. Finding optimal parameters values is, however, severely hampered by the high level of supply and demand uncertainty, the large number of decision variables, various internal and external constraints, and, above all, the high variability observed dynamically in the company itself and its environment. In the search for the

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optimum values of the decision variables, optimisation methods are particularly helpful. However, its use is limited in cases where the degree of complexity of the problem and computational requirements make it impossible to find a solution using analytical methods. The combination of simulation methods with optimisation techniques makes it possible to obtain results that are impossible to achieve applying each of these approaches separately [2]. Simulation helps to dispense with the restrictive simplifying assumptions in the model and allows the inclusion of any number of parameters to achieve the required level of accuracy in the representation of the system under study. An important advantage of simulation is also its flexibility in mapping any number and various types of uncertainty and randomness.

The industry 4.0 philosophy is making more and more companies focus on increasing automation through the application of the Internet of Things, sensors, advanced communication systems, and the Digital Twin concept (DT) [3]. The use of simulation models in the form of DT provides technology that can lead to better decisions that result in more efficient systems, also with regard to external and internal supply chains.

The purpose of this paper is to contribute to existing work by presenting a simulation-based optimisation model to enhance the quality of inventory management decisions in SC design and planning, taking into account uncertainty and risk analysis. The paper will also propose the concept of using the simulation model as a DT to simulate the near future of SC to predict potential delays and calibrate the ordering and renewal procedures parameters based on risk analysis.

2 Decision Support in Supply Chain Management

In recent years, many manufacturing companies have begun to see supply chain management as a critical success factor. Organisations that are able to deliver products to the customer in the right quality, time, and cost win the competitive battle. The problem of timely delivery according to customer needs has become apparent in a pandemic period [4][5]. Many of the risks associated with external supply chain conditions are beyond the control of companies, but they can mitigate risks in the operation of the internal supply chain, such as by properly managing the supply process based on the use of modern approaches to material inventory control.

The classic approach to inventory management uses a push approach, in which the flow of materials within an organisation is controlled by demand forecasts [6]. Inventory volumes are constant throughout the time covered by the forecast. The modern approach, the so-called pull approach, assumes that the flow of materials within the organisation is controlled by a signal received from the customer. The level of inventory in the company is held at a minimum and is replenished as demand arrives from the customer [6]. This approach is used in the concepts of Just-in-Time delivery and Lean Management, which have been increasingly used in organisations in recent years.

From the point of view of inventory management, the use of the pull approach compared to the classical approach brings many advantages, including [7] less storage, less use of warehouse space, reduction of material waste, reduction of costs. However, its use can also cause problems in the form of the risk of running out of stock, lack of

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control over the time frame, and more planning required to take into account risks from the environment. The pull approach requires the collection of information from customers and its processing in real time, and the adoption of a number of organisational solutions in the material flow process itself, as well as the use of a number of tools categorised as Industry 4.0 tools that increase the efficiency of information processing.

In terms of organisational solutions companies must:

- use a set of permanent suppliers based on selection criteria that primarily take into account the quality and reliability (timeliness) of deliveries,
- develop spatial arrangement of workstations and tools (equipment) that optimise flow efficiency,
- introduce automation of logistics processes,
- apply system/methods of process integration inside and outside the company,
- introduce a system for detecting and fixing problems inside the process,
- apply risk assessment in the process flow and from the environment.

The basic tools classified as Industry 4.0 tools that are applicable to inventory management are the following [8]:

- Internet of Things (IoT) [9][10] that refers to the transmission and exchange between two or more objects different information through the Internet,
- strongly correlated to IoT, the OPC – UA (Open Platform Communications - Unified Architecture),
- Big Data, which helps to link (put in relation) large amounts of heterogeneous data in order to discover links between different phenomena and predict future ones,
- cloud computing identified as the provision of services from a supplier to the end customer through the use of an Internet network.

Simulation methods are widely used in supply chain inventory management to help optimise material flow processes or the spatial distribution of inventory. Discrete event simulation (DES), agent-based simulation, Monte Carlo simulation, and system dynamics (SD) are being applied [11], but of these, the most widely used approach is DES and SD [12]. When comparing the use of DES and SD models in logistics, the clear advantage of DES is seen in modelling supply chain processes. According to [12] DES is primarily used to address issues such as supply chain structure, supply chain integration, replenishment control policy, supply chain optimisation, cost reduction, system performance, inventory planning and management, demand planning and forecasting, production planning and scheduling.

3 Case Study

3.1 Problem Definition

This article deals with the delivery process of five products offered by the company. In addition to these five products, the company supplies customers with almost 200 other types of products, which the company manufactures on its own in Poland by importing

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materials from various countries. In the case of the five types of products under consideration, due to the high production costs in the country, the company decided to import them directly from the Chinese market. The process starts with the arrival of customer demand (Fig.1). Once a demand request is received from a customer, the process of completing the accepted request begins. If there are enough products of a given type in the stock, the request is processed immediately. If there is an insufficient inventory level, the request waits for the stock level to be renewed. The inventory level is monitored on an ongoing basis. When the number of products in the stock falls to a certain minimum level (or below), an order is placed with a supplier in China. The production process at the Chinese manufacturer takes about 6 weeks (42 days) regardless of the quantity and type of products ordered. Finished products are imported by sea or air. The expected delivery time by air transport is 2 weeks, while the expected delivery time by sea is about 8 weeks. Due to the long distance and many stochastic factors that affect the timeliness of delivery, the risk of delay is quite significant. Once the order is received, there is a quality control that takes about a week. After this time, the product is ready for sale and is put into the stock. The general structure of the considered supply chain is given in Fig.1.

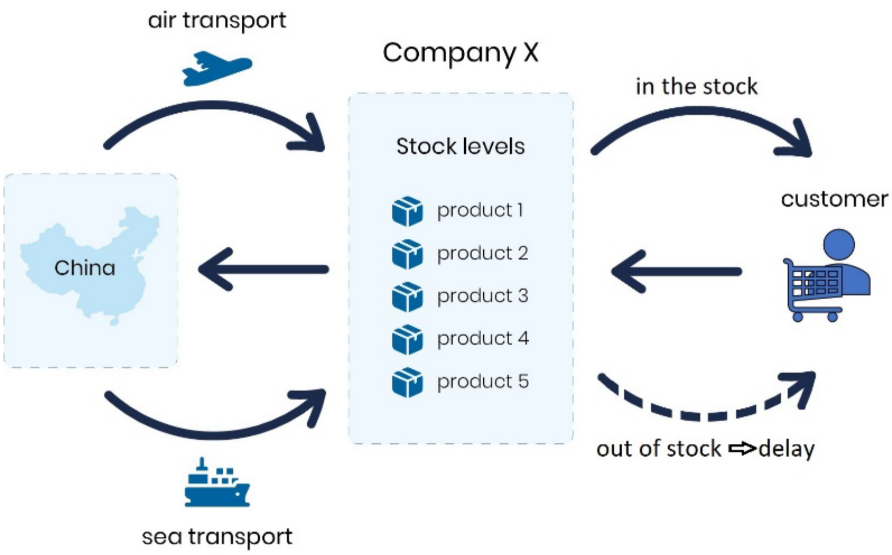

Fig. 1. General structure of the considered supply chain.

3.2 Methods

Discrete event simulation (DES) was used to simulate the supply chain from the moment of the arrival of the customer's request to the moment of the completion of customer service. Arena ® by Rockwell Automation software was used to build the simulation model. The simulation is carried out over a period of one year and starts with the set of initial inventory values. The goal of the simulation is to mimic the sales and

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ordering process of five types of products imported from China, taking into account the random values of parameters that affect the delivery and the dynamics of the process. One of the key decisions reproduced in the model is the choice of the mode of transportation: by air or by sea. The decision made has a direct impact on the costs incurred by the company and on the average customer's waiting time. The verified simulation model was then used in a two-stage optimisation, the aim of which was to find such values of input parameters at which the company incurs low order processing costs and at the same time the customers waiting time is acceptable. In the first stage of optimisation, a series of simulation experiments was conducted to identify sets of values of boundary parameters in the vicinity of which a suboptimal solution might be found. The identified sets of input parameters were then entered into the OptQuest tool, which automatically searches for optimal solutions within the Arena simulation model, based on the set of baseline scenarios developed in the first phase of optimisation. The general scheme of simulation-based optimisation is shown in Fig. 2.

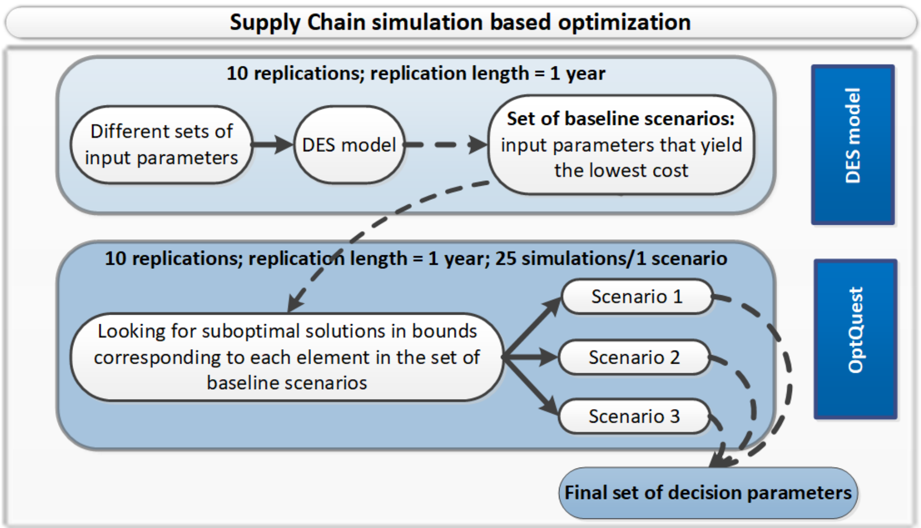

Fig. 2. Conceptual model of simulation-based optimisation.

3.3 Data and Input Parameters

The basic groups of input parameters, which were elaborated on the basis of real data, are shown in Tab.1. Each of the five types of products has different characteristics. The most frequent demand requests are received for Product 4 and the fewest for Product 5. Within a single order, customers request the most units of Product 4 (from 1 to 235 with varying probability), while the lowest orders are for Product 1 (from 1 to 25 with varying probability). The price of individual products varies. Thus, the most expensive is Product 1 (€182/piece) and the cheapest is Product 5 (€27/piece). Transportation costs by air and sea are the highest for Product 3, while the lowest for Product 5. Differences between products are visualised in Fig. 3.

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Table 1. Values of input parameters.

Parameter	Distribution	Prod.1	Prod.2	Prod.3	Prod.4	Prod.5
Arrival rate [days]	Poisson	67	48	52	22	72
Initial stock [units]		200	350	150	250	300
Demand volume [units]	Discrete	1–25	1–200	1–75	1–235	1–75
Cost of air transport [€/unit]		6	4.05	6.6	4.2	2.25
Cost of sea transport [€/unit]		2	1.35	2.2	1.4	0.75
Unit price [€]		182	78	96	35	27

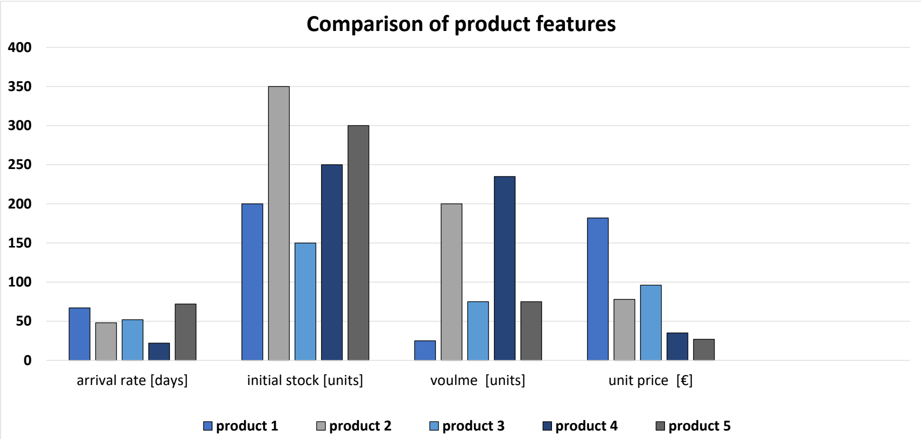

Fig. 3. Differentiating characteristics of the products considered in the model.

3.4 Assumptions

Several assumptions were formulated in the simulation model:

- The cost of transporting one unit of the product does not change and is independent of the number of ordered products of a given type.
- In the case of parallel execution of an order for several types of products, the transportation cost per one unit always remains the same.
- The production time of the products with the Chinese manufacturer does not depend on the number of ordered products.
- For the purpose of the simulation, it was assumed that the delivery time by sea transport is in the range of 8 – 12 weeks, while by air it takes 1.5 – 2.5 weeks.
- Inventory holding costs are not included in the simulation model.
- Lost sales are not included in the simulation model. All customer orders are processed from the time they are placed to delivery.
- The simulation ends after 365 days, and pending orders are not included in the final statistics.

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Assumptions relating to the initial conditions of the simulation are also formulated. At the start of the simulation:

- the company is not fulfilling any previous demand requests from customers;
- no transportation is being carried out;
- there is a certain amount of each product in the warehouses.

3.5 Simulation Phase

Course of Simulation. In the simulation model, two types of entities are defined: demand generated by customers and orders placed by the company with a Chinese supplier.

The demand requests from customers arrive according to a Poisson distribution (Tab.1) independently for five types of products. If products are in the stock when demand from customers arrives, they are released to customers without undue delay, and the stock is reduced accordingly. If the products are out of the stock (customer demand cannot be met in full), the customer waits for the stock to be renewed.

Stocks are continuously monitored. If the quantity of a product of a given type falls to a minimum level and, at the same time, an order has not been previously placed with the supplier for this product (no delivery is currently "on the way"), an order is placed with the supplier. The delivery process then begins. When the products are delivered to the company, the stock of the warehouse is increased, and demand requests from customers waiting in the queue are immediately fulfilled.

Mode of Transport. During the simulation, customer waiting times are continuously monitored. The decision to choose the mode of transportation (ship or plane) is made by comparing the current waiting time $QueueTime_i$ (i denotes customer, $i = 1, 2, \ldots$) of the customer who waits the longest in the queue with a critical value of the decision parameter *MaxWaitT* (Eq.1). The critical value reflects the company's preference for an acceptable maximum customer waiting time for a product.

$$QueueTime_i \geq MaxWaitT \tag{1}$$

When $QueueTime_i$ is greater than *MaxWaitT,* transport by air is selected, otherwise the sea route is chosen. Parameter *MaxWaitT* is a decision variable that can be freely defined by the company and reflects customers' expectations regarding the quality of the service. Parameter $QueueTime_i$, on the other hand, is the current reading obtained during simulation. This parameter is continuously monitored and directly affects the choice of transport route.

Total Cost and Maximum Cost. During the simulation, the so-called cost of the frozen capital (in short, *TotalCost)* is calculated on the ongoing basis. This is the amount of money the company has to spend on fulfilling orders from the moment the order is placed with the supplier until the product is sold to the customer. The value of the *TotalCost* parameter changes over time. At the end of the simulation, the average value of

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this parameter is calculated for each replication (averaging over time). *TotalCost* consists of three components:

- $SCCost_{jk}$ (Eq.2): The total cost of the supply chain is calculated when a decision is made on the type of transport (air or sea) for the order *j* of the product *k*. The value of this element always adds to the current value of *TotalCost*.
- $PPCost_{jk}$ (Eq.3): The product purchase cost is calculated at the time the order *j* for the product *k* is placed with the supplier. It always increases the current value of *TotalCost*.
- $PSRev_{ik}$ (Eq.4): The product sale revenue relates to the sale of the product *k* to the customer *i*. It is calculated when the products are delivered to the customer. The value of this element always reduces the current value of *TotalCost.*

$$SCCost_{jk} = OrderVol_{jk} \cdot TransCost_k \tag{2}$$

$$PPCost_{jk} = OrderVol_{jk} \cdot UnitPrice_k \tag{3}$$

$$PSRev_{ik} = DemandVol_{ik} \cdot UnitPrice_k \tag{4}$$

where *i* denotes *Customer* ($i = 1, 2, \ldots$), *j* denotes *Order* ($j = 1,2,\ldots$), and *k* denotes product type ($k = 1\ldots5$).
$OrderVol_{jk}$: number of products of type *k* ordered from the supplier under the order *j*;
$TransCost_k$: the cost of transporting product *k* by sea or air, respectively (Tab.1);
$UnitPrice_k$: the cost of purchasing one unit of product *k* from the manufacturer;
$DemandVol_{ik}$: the number of products of type *k* requested by the customer *i;*

In addition, at the end of the simulation the *MaxCost* parameter is also determined (Eq.5). It informs what the highest amount of money the company had to spend at a certain point during the simulation to fulfil the order with the supplier.

$$MaxCost = max(TotalCost_t)_{t \in T} \tag{5}$$

where *t* denotes the simulation time advancing in steps at specific moments determined by events, from moment zero to the end *T* of replication.

Decision variables. The simulation model operates on 11 decision variables. These are:

- *ReorderPoint*: Minimum stock levels (5 variables) set separately for each product type. It defines the minimum level of the stock in the warehouse, below which the company places an order with the supplier to deliver the next batch of products.
- *OrderVolume*: The size of the order placed with the supplier (5 variables), set separately for each product type.
- *MaxWaitT*: The maximum acceptable waiting time for a customer (one variable).

Output variables. At the end of each simulation experiment, the following output variables are observed: the average cost of frozen capital (*TotalCost*), the maximum value of frozen capital (*MaxCost*), the average customer waiting time, the average number of

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customers waiting for products, and the number of times there were no products in stock when a new demand request from a customer arrived.

3.6 Verification and Validation

Each simulation experiment consists of 10 replications. The duration of one replication was 365 days. The simulation is run with the preset initial stock levels and with a one-month warm-up period. Key experts from the Company actively participated in the process of formulating assumptions for the model. The model was subjected to extensive verification and validation. As part of the verification, tests were conducted to verify internal consistency. These were visualisation tests, degeneration tests, extreme conditions tests, and many others. For validation purposes, two parameters were compared: the number of completed deliveries and the total volume of all deliveries. The results, shown in Tab.2, confirm the credibility of the model.

Table 2. Validation of the simulation model (10 replications).

Parameter	Real system	Simulation	Half-width
Number of orders	19	20.1	6.9
Total volume ordered	5030	5106	1525.4
Product 1	270	206	
Product 2	1155	1250	
Product 3	675	850	
Product 4	2550	2500	
Product 5	380	300	

4 Results

4.1 Simulation-Based Optimisation Scenarios

Due to the large number of decision variables (11 variables; see Section 3.5), the optimisation was carried out in two phases. In the first phase, a series of simulation experiments were performed to determine potential sets of input parameters for further analysis using the OptQuest optimiser (Tab.3). The objective function is to minimise the average value of the cost of the frozen capital (*TotalCost*). Three additional parameters are also taken into account: *MaxCost* (see Section 3.5), average customer waiting time *QueueTime* and average queue length of waiting customers *QueueLength.* In all experiments, the values of 10 decision variables (*ReorderPoint* and *OrderVolume*) are fixed, while the optimisation algorithm selects the value of the *MaxWaitT* variable moving with a step of 1, from the starting value of 1 to 70. Each experiment was performed with the same simulation parameters as in the base scenario. In Scenario 1, the baseline values of 10 decision variables are established. In Scenario 2, an equally low *ReorderPoint* for all products was introduced and, at the same time, *OrderVolume* values were raised slightly. In Scenario 3, the values of the 10 decision variables were set taking into account the characteristics of the products (see Tab. 1).

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Table 3. Simulation–based optimisation scenarios.

Scenario		Decision variables		
		ReorderPoint [units]	*OrderVolume* [units]	*MaxWaitT* [days]
Sc1	Prod.1	15	100	1 – 70
	Prod.2	200	350	
	Prod.3	100	250	
	Prod.4	400	150	
	Prod.5	10	200	
Sc2	Prod.1	50	200	1 – 70
	Prod.2	50	400	
	Prod.3	50	150	
	Prod.4	50	400	
	Prod.5	50	300	
Sc3	Prod.1	100	200	1 – 70
	Prod.2	150	600	
	Prod.3	150	200	
	Prod.4	300	600	
	Prod.5	100	350	

4.2 Discussion

The optimisation results are shown in the Tab. 4.

Table 4. Scenario results: only the selection of results of the *MaxWaitT* parameter is displayed.

Scenario	*MaxWaitT*	Average *TotalCost*	*MaxCost*	Average Queue Waiting Time	Average Queue Length
Sc1	1	116.9	216.7	16.4	56.1
	30	112.5	215.3	19.4	76.9
	50	108.6	214.8	23.7	89.2
	70	104.5	215.4	32.7	116.4
Sc2	1	101.7	132.9	40.8	126.7
	10	101.7	132.9	40.9	126.8
	20	102.0	132.2	41.3	129.1
	30	101.9	131.5	41.3	129.1
Sc3	1	147.1	190.0	28.1	61.6
	30	143.8	185.2	37.2	80.7

The best results were obtained in Scenario 1. Although Scenario 2 provides a lower value of the objective function and a lower value of *MaxCost*, this is at the expense of high values of the parameters that describe the queue of waiting customers. This Scenario turns out to be immune to changes in the *MaxWaitT* parameter. The values of the variables relating to the cost, as well as the parameters describing the queues, change very little as the *MaxWaitT* parameter increases. Only setting *MaxWaitT* to 20 causes a noticeable change in values of the observed parameters. Scenario 3, on the other hand, turned out to be unfavourable in terms of all parameters. Figures 4 and 5 show the optimisation results for all *MaxWaitT* values obtained in the best Scenario 1.

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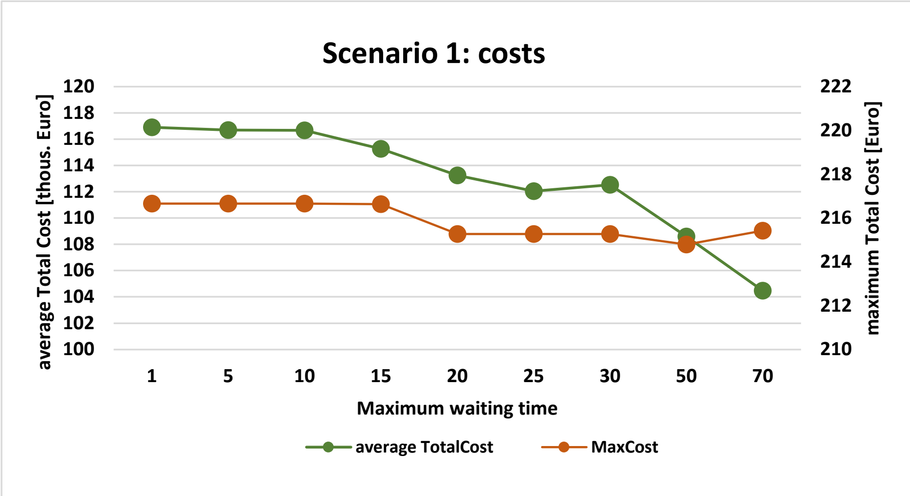

Fig. 4. Results of simulation-based optimisation according to Scenario 1: cost parameters.

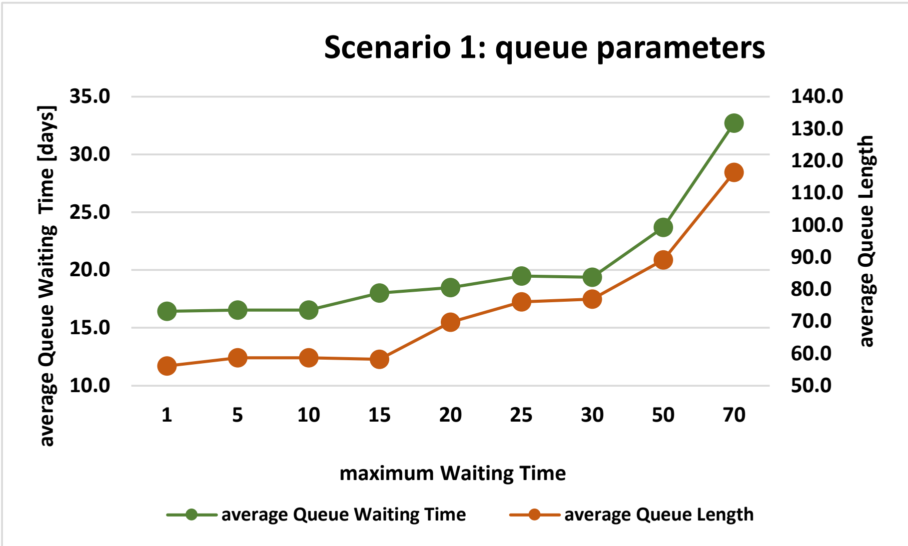

Fig. 5. Results of simulation-based optimisation according to Scenario 1: queue parameters.

The objective function reaches the lowest level for high values of *MaxWaitT* parameter. Analysis of the values of parameters that describe the queue allows us to select the *MaxWaitT* parameter = 50 days. At this value of the *MaxWaitT* variable, both cost parameters are low, while the parameters that describe the queue increase only slightly.

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4.3 The Concept of Digital Twin in SC Inventory Control

In the case study presented in the paper, the physical process of SC inventory planning and control is represented by a simulation model supported by optimisation tools. In a stable environment, the results of the applied approach that combines simulation with optimization, help to choose a solution that keeps costs at an acceptable level and at the same time provides the desired quality of services. However, the dynamic environment in which companies operate means that planned procedures in the near future may no longer be optimal. It is possible to use a cyclical (e.g. monthly) review of parameters and run the simulation again, but more and more companies are considering the use of digital twins (DT) to optimise warehouse design and operational performance [5][13][14]. DT is a virtual/ digital replica of physical entities such as devices, people, processes, or systems that help businesses make model-driven decisions, [13][14]. The key concept of DT is the coexistence of three elements: a physical system, a virtual model, and a two-way connectivity that allows data to flow from real to virtual space, and information flow from virtual space to real system.

In the case study presented above, once DT is integrated with the physical system, real-system information on customer requests can be fed into the simulation model on an ongoing basis. The optimisation module finds the optimal solution with changed values of the input parameters, and new decisions and adjustments are transferred back to the physical system. As a result, new values of decision variables are determined, which are immediately implemented in SC inventory management procedures.

A simulation experiment was performed to illustrate the intercommunication between the real system and DT (see Figures 6 and 7). After performing the optimisation described in Section 4.1, it was decided that the *MaxWaitT* decision variable should be 50 days. However, it was noticed that there was a slight increase in the arrival rate for Product 3, and the re-estimation of the inter-arrival rate for this product was performed. It turned out that after adjusting the value of the Arrival Rate parameter from 52 to 48 days, the value of the *MaxWaitT* decision variable should also change. Figures 6 and 7 compare the results of the two simulation-based optimisations. The values of the objective function in both optimisations change very similarly; that is, the lowest values of the *TotalCost* parameter are obtained at high values of *MaxWaitT.* However, the analysis of the parameters that describe the queue shows a deterioration in the customer waiting time and the length of the queue when the value of the parameter *MaxWaitT* is set to 50. A better choice would be to keep the *MaxWaitT* value less than 50 days.

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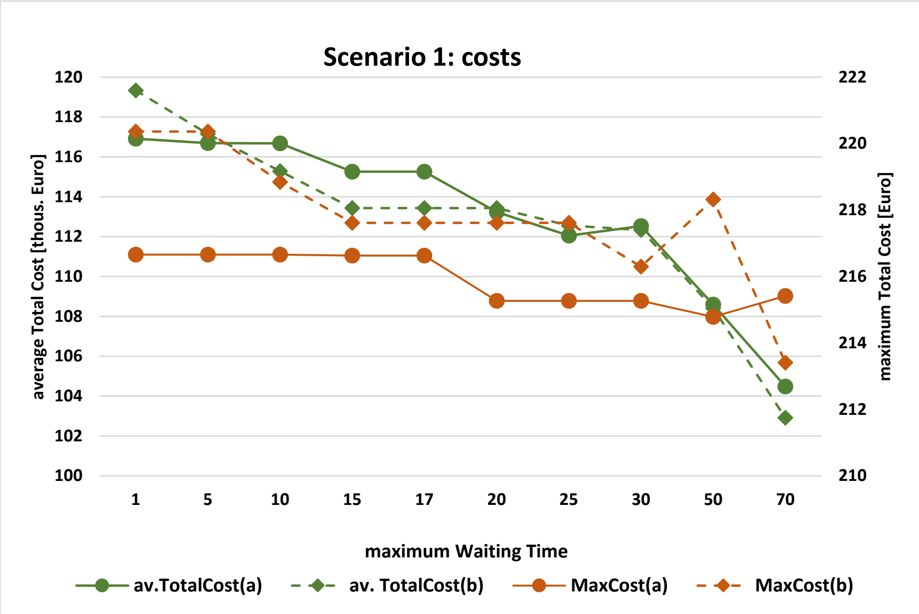

Fig. 6. Results of simulation-based optimisation according to Scenario 1 (cost parameters) in response to revised data describing the arrival rate of product 3; (a) baseline arrival rate = 52 days, (b) corrected arrival rate = 48 days.

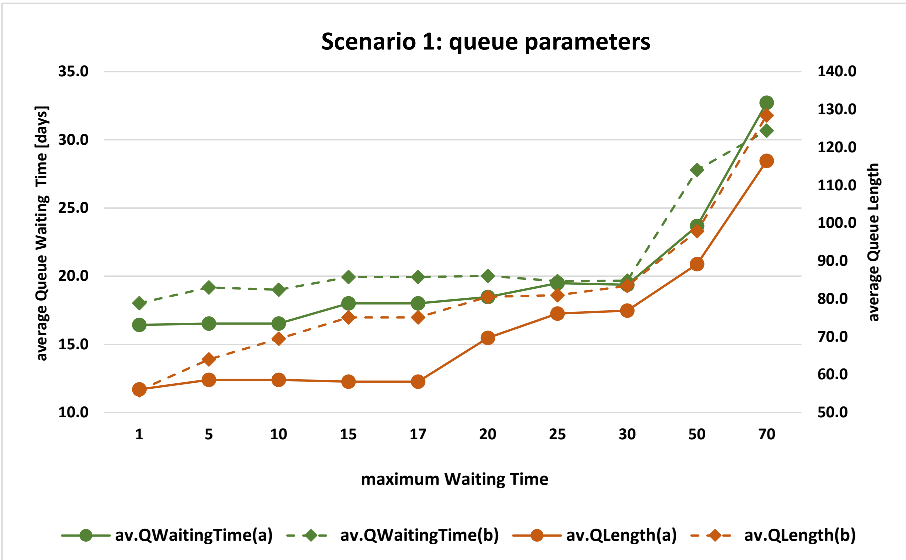

Fig. 7. Results of simulation-based optimisation according to Scenario 1 (queue parameters) in response to revised data describing the arrival rate of product 3; (a) baseline arrival rate = 52 days, (b) corrected arrival rate = 48 days.

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5 Conclusions

In this paper, we discuss the simulation-based optimisation approach to support management decisions in SC inventory control. A simulation model built according to the DES paradigm was used to map the supply chain process in the part of it that deals with inventory supply control. The simulation results were then fed into the optimisation module to obtain acceptable values for the decision variables chosen both for minimising the objective function (average cost of frozen capital) and for maintaining an acceptable level of customer service quality (expressed by parameters describing the queue of customers waiting for orders to be fulfilled).

The developed algorithm proved to be useful and fulfilled its purpose as a component of the decision support system in SC inventory control. The combination of simulation and optimization can significantly improve the quality of SC managers' decisions, especially when the complexity of the problem, the need to consider many variables, and the accumulation of factors of a random nature make it impossible to obtain an acceptable solution by analytical methods. In addition, the use of a two-phase algorithm, discussed in the article in par. 4.1, reduces the time of performing calculations by preliminarily indicating the ranges for potential optimization. The duration of one full simulation run is less than a minute. Searching for the optimal solution within a predefined range therefore significantly reduces the duration of the entire study compared to full optimization process. From the company's point of view, any set of parameters that meets predefined quality requirements is satisfactory. Nevertheless, further research work will be aimed at an even more precise selection, through simulation experiments, of decision parameter ranges for further optimization.

The article also discusses the concept of using a simulation-based optimisation model as an element of DT and thus obtaining a significant impact on the efficiency of the supply chain.

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