

Article

A Dynamic Analysis for Mitigating Disaster Effects in Closed Loop Supply Chains

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Abstract: The increased level of complexity in the case of Closed Loop Supply Chains (CLSCs) turns them into vulnerable systems under a disaster event. The latter calls for a methodological approach that allows a dynamic study under alternative policies in mitigating the disaster effects with a focus on creating sustainable CLSCs. For this reason, we provide a System Dynamics (SD)-based analysis for disaster events on the operation of CLSCs. By “disaster event”, we mean three different categories taking shape on the basis of duration. Furthermore, three different demand patterns emerging due to the disaster event are examined. We assume that the disaster event affects the manufacturer, and we examine the system response under different mitigation policies. For each demand pattern two different mitigation policies at the manufacturer level are examined by considering the total CLSC profit and demand backlog as measures of policy performance. For each combination, extensive simulation experimentation reveals sustainable policy recommendations under alternative settings regarding the reduction in the manufacturer’s production.

Keywords: sustainable supply chain; system dynamics; supply chain management; disaster management; closed-loop supply chain



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1. Introduction

The industrial world is increasingly exposed to risk as a result of major natural and man-made disasters, necessitating a rethinking of how industrial companies and communities recover [1]. Experience has shown that policies designed to operate within a given range of conditions are frequently confronted with unexpected challenges when they are used outside of that range due to an unexpected disaster event [2]. Makridakis et al. [3] proposed to distinguish between known–known, known–unknown, and unknown–unknown risks when handling uncertainty in a given situation. For a SC, disaster is a risk source of unknown–unknowns [4].

By “disaster”, we refer to extreme phenomena affecting the normal function of SCs to a great degree [5,6]. These phenomena can include natural disasters, such as typhoons [7,8] and earthquakes [9–11], or the spread of a pandemic as is the case with the COVID-19 disease [6,12,13]. They can be divided into three categories based on their duration: small-scale, medium-scale and large-scale. There are plenty real-world examples for each category: Earthquakes [9–11] are small-scale phenomena, such as the earthquake that hit Taiwan in 1999 and caused a two-week global semiconductor shortage because Taiwan was the world’s third largest provider of computer accessories when the phenomenon occurred [11].

Natural disasters, such as typhoons, are medium-scale phenomena [7,8]. Zhang Yi et al. [14] analyzed the economic loss of four selected ports in China due to typhoon-induced wind disasters from 2007 to 2017. The overall economic loss was calculated as the sum of reputational loss, loss to the shippers, loss to the carrier and loss to the ports and was approximately equal to \$20 billion.

Finally, large-scale phenomena are outbreaks of diseases, epidemics and pandemics. For instance, disruptions caused by epidemics, such as the outbreak of mad cow disease in Europe (2001), which resulted in a shortage of leather goods, and the breakout of SARS in Asia (2003) that impacted information technology SCs, are large-scale phenomena [15]. Dixon et al. [16] mentioned that the trough of the economic downturn is expected to be around 19% at the end of the first quarter of 2020, with a 12% fall by the end of the second quarter. According to the CBO (2020), the Real GDP declined by 11% in the second quarter of this year, resulting in about 26 million fewer persons employed than in the fourth quarter of 2019.

A disaster effect may result in production disruptions with significant consequences on profitability. An important challenge is the identification of mitigation policies that should be implemented when production is disrupted due to disasters. In 2000, for example, Ericsson's sole microchip source was the Phillips Electronics semiconductor factory in Albuquerque, New Mexico. Due to a fire caused by a lightning strike in 2000, this factory was destroyed, resulting in a \$400 million loss for Ericsson [17].

On the contrary, Nokia, a competitor of Ericsson and a major customer of the same Philips Electronics plant, sensed this disruption following a multiple-supplier strategy and responsiveness and took immediate action by shifting its chip orders to other Philips factories and other Japanese and American suppliers. This quick response resulted in increasing Nokia's handset market share from 27% to 30% [18]. According to estimates, 315 disasters occurred around the world in 2018, resulting in 11,804 deaths, 68.5 million people affected and \$131.7 billion in economic damage [19].

Coordinated operations among supply chain actors and optimized emergency supply chain operations are critical to provide a speedy response to the presence of demand uncertainty, which remains one of the main challenges in disasters [20]. Ivanov and Dolgui [21] mentioned that the concerns that occurred particularly from the drastic increase or reduction in demand due to the COVID-19 pandemic cannot be handled within a narrow SC perspective but rather require a larger-scale analysis that goes beyond the current state-of-the-art in SC resilience.

In addition, Ivanov [22] presented the findings of a simulation study that opens up to some new research tendencies regarding the impact of COVID-19 on global SCs, specifically the consideration of different risk mitigation inventory levels as elements of pandemic plans. Umar and Wilson [23] adopted a multiple case study to examine the role of collaboration within food supply chains in two different South Asian regions in order to investigate how these capabilities influence the resilience of supply chains in rural communities that experience regular natural disasters.

Taking into consideration the relevant inventory policy suggestions by Ivanov [22] and the collaborative approach presented by Umar and Wilson [23], we provide an analysis based on System Dynamics (SD) that focuses on the development of effective policies in order to mitigate disaster effects for Closed-Loop Supply Chains (CLSCs).

In particular, we deal with a single manufacturer/multi-echelon CLSC with remanufacturing and recycling activities. The actors involved in the forward channel are the raw materials supplier, the parts producer, the manufacturer, the wholesaler and the retailer, while in the reverse channel it is the collector and the disassembly center that are involved. The reverse channel activities include the operations of disassembly, remanufacturing and recycling of used-product returns. Remanufacturing operations produce "as-good-as-new" parts for the manufacturer, while recycling operations supply the parts producer with recycled raw materials.

Moreover, we introduce dynamic feedback mechanisms, which control the rate of inflows and outflows for each echelon at both channels. We formulate a dynamic hypothesis about the effects of three (3) disaster scenarios on the manufacturer's production, which are applied to each of the three categories of disaster events mentioned above (small-scale, medium-scale, large-scale).

We study the consequent economic impact on the manufacturer's operations together with the side effects on the level of demand backlog. This study aims to fill the research gap by providing an SD model applicable to the disaster operations management in CLSCs. This dynamic analysis considers two different set of policies for mitigating the disaster effects. In the first case, the manufacturer follows alternative inventory management policies, regarding both the desired stock level and adjustment time in aligning the actual stock level with its desired value. In the second case, the manufacturer satisfies the wholesaler's demand by contracting with a third-party producer who is not affected by the disaster event.

The above-mentioned policies were tested under alternative settings regarding the reduction in the manufacturer's production due to the disaster event and also under the following demand patterns:

- Demand Pattern 1: Demand does not vary as a result of the phenomenon (for instance, food products during COVID-19 effect).
- Demand Pattern 2: Demand marks a sudden increase when disaster materializes. This increase is maintained for as long as the phenomenon last (disaster-period) and thereafter (post-disaster period) it returns to its pre-disaster level. An indicative example for this case is the sudden increase in demand for medical masks owing to the outbreak of COVID-19 [24].
- Demand Pattern 3: Demand marks a sudden decrease during the disaster period. During the post-disaster period, it increases to reach higher levels compared with pre-disaster conditions and after a certain amount of time, it returns to its pre-disaster level (for instance, the automotive industry during COVID-19 [24]).

In addition, we assume that the under study product is at the maturity stage of the product life cycle.

The rest of the paper is organized as follows: Section 2 provides a literature review of the basic elements of disaster management related to our study in order to identify the research gap and to justify the suitability of SD as an appropriate modeling approach. Section 3 presents a generic description of the CLSC under study and the formulation of effects due to a disaster event hitting the manufacturer. The mathematical representation of the SD model and mitigation policies are given in Section 4. Section 5 provides the settings of a numerical experimentation for each disaster scenario followed by a concluding discussion based on results gained by extensive simulation experimentation.

2. Literature Review

There are many approaches that deal with different supply chain management issues, with a focus on sustainable CLSC. Wen-Hui et al. [25] introduced measures of the implementation of remanufacturing supply chain management in a CLSC. Hosseini-Motlagh et al. [26] studied the sustainability of a real pharmaceutical CLSC through effective collection interruption management. Ullah et al. [27] introduced mathematical models to reveal the best remanufacturing strategy and also reusable packaging capacity for single and multi-retailer CLSCs under stochastic demand and return rates.

Garai et al. [28] examined a CLSC for herbal medicines, while Garai and Sarkar [29] researched a CLSC for herbal medicines and biofuel by applying a minmax method based on a semi-autonomized multi-objective optimization algorithm from the economical point of view. By adopting a game-theoretical approach, Ma [30] examined different government subsidies for the management of CLSCs under demand disruption, in order to find the subsidies with the best economic and environmental benefit outputs. Sarkar et al. [31] proposed the conversion of a single food product supply chain into a two-stage supply chain in order to achieve zero waste through recycling. Although these contributions focus on sustainable CLSCs, the employed modelling and analysis approaches ignore issues related to disaster management.

In particular, disaster management in CLSCs has received increased attention over the last 15 years. It is remarkable that, although the topic is suitable for OR/MS research, the scientific community has not yet produced many articles dealing with operations manage-

ment issues in large-scale disasters; interesting reviews of this field are provided in Altay and Green [5], Galindo and Batta [32] and Farahani et al. [33]. In addition, Borja et al. [34] mentioned that the literature on the dynamic behavior of CLSCs remains limited.

Complex adaptive systems theory [35–37], chaos theory [38–40], catastrophe theory [41], catastrophe-risk approaches [42], disaster preparedness [43], along with non-linear dynamic approaches [40,44,45], provide methods for the dynamic analysis and optimization of CLSCs under disaster effects. However, models based on these methods usually lead to more complex approaches and to more restrictions on the number of state variables and cost structure than they can handle.

Systems thinking may provide a systematic and structured approach to disaster management due to its ability to consider the systemic settings within a larger system. In addition, this approach may consider the interdependent nature of the system [46]. System-oriented and holistic approaches have been identified as important in modeling the complex, deeply uncertain and dynamic elements of disaster management [5,34,47].

The SD methodology introduced by Forrester [48] provides a more flexible and simple modeling and simulation framework for making decisions in dynamic and complicated industrial management situations [23,45]. It is an appropriate approach to study disaster operations problems in a CLSC context, mainly due to the following two reasons: (i) it has the ability to integrate soft factors into an operations analysis; (ii) it can deal with increased complexity caused by causal influences among different involved actors, non-linear behavior and time delays [46,49,50].

Additionally, the benefits of using SD models include: (i) allowing for the study and evaluation of alternative scenarios, making their impact on the system's performance testable and (ii) being highly valued and well understood by managers, as they augment brainstorming and rely less on hard facts than other approaches [46]. This methodology provides an understanding of the changes occurring within a system by focusing on the interaction between physical flows, information flows, delays and policies that create the dynamics of the variables of interest.

Thereafter, the SD methodology searches for policies to improve system performance by considering the causal influences of relative decisions on the operational dynamics [51,52]. SD has been identified as promising for modeling complex and adaptive to nonlinear evolutionary change problems [47] and also as analysis tool to improve SC risk mitigation policies and recovery plans [53]. However, it is surprisingly underutilized in disaster operations management research [5,32,33] as shown in Table 1.

Table 1. Methodological approaches in dealing with disaster management in CLSCs.

Approaches	Reference
Complex Adaptive Systems Theory	[35–37]
Chaos Theory	[38–40]
Catastrophe Theory	[41]
Catastrophe-Risk Approaches	[42]
Disaster Preparedness	[43]
System Dynamics	-
Non-Linear Dynamic Approaches	[40,44,45]

Some studies demonstrated SC dynamics as endogenous outcomes of feedback structures established under various dynamic hypotheses: Ozbayrak et al. [54] and Pierrel et al. [55] dealt with the dynamic analysis of manufacturing SCs and automotive industry, respectively; Keilhacker and Minner [56] applied an SD approach to examine the individual company's reaction in the rare earth element (REEs) supply chain to China's introduction of export restrictions; Lai et al. [57] studied the system dynamics in just-in-time logistics; Mikatia [58] examined the dependence of lead time on batch size in a manufacturing model; and Suryani et al. [59] studied capacity expansion decisions for innovative products with short lifecycles for the cement industry.

Other studies investigated the performance of SC systems under different operational disruption settings: Wilson [60] investigated the effect of transportation disruptions for the case of a five-echelon supply chain; Chen et al. [61] examined the effects of disruptions considering pipeline inventory control and vendor-managed inventory control; Ankit [62] studied the effects of SC between any two players in a multi-player SC system; and Aguila and ElMaraghy [63] proposed an SD model to study SC behavior in the face of interruptions.

The model may be used to predict the impact of potential interruptions on several critical performance indicators throughout the SC design and planning stage; Diaz et al. [64] proposed an SD model that analyzes the issue of housing recovery in the aftermath of a disaster, from both a demand and a supply standpoint; Bashiri et al. [65] investigated the sustainability risks in the Indonesia–UK coffee supply chain by using SD; and Zhang et al. [66] proposed an SD model to examine the effects of supply disruption, production disruption and sales disruption on the inventory, order accumulation rate and profit level of suppliers, manufacturers and retailers for a fixed outage time in a SC.

The contributions are limited when focusing on integrating aspects of SC and aspects of reverse logistics using SD [67]. Indeed, the formulation of dynamic strategic capacity planning policies [68,69], the examination of the bullwhip effect [70], the impact of environmental legislation on the long-term dynamic behavior of closed-loop remanufacturing networks [52] and the ecological and economic dimensions of sustainability in closed-loop recycling networks [71] are some of the few fields that have received special attention.

These models include either remanufacturing or recycling options of product reuse, while the integration of both remanufacturing and recycling into a closed-loop model for long-term evolutionary analysis and decision-making was introduced by Gu and Gao [72]. However, there is a gap in the SD literature in providing a dynamic approach for modeling and mitigation policy-making under disaster effects that considers a holistic picture of CLSC networks with remanufacturing and recycling options [73]. The purpose of this paper is to fill this gap by identifying effective policies in mitigating of disaster events.

3. System and Problem Description

3.1. System Description

Figure 1 exhibits a very generic description of the CLSC under study. In particular, we deal with a single manufacturer/multi-echelon CLSC with remanufacturing and recycling activities. The forward supply chain comprises five echelons; *Raw materials supplier*, *Parts producer*, *Manufacturer*, *Wholesaler* and *Retailer*. The *Raw materials supplier* obtains materials from the *Supply market*. The *Parts producer* produces parts by using two inflows of materials; original raw materials by the *Raw materials supplier* and materials recovered by *recycling*.

Priority is given to supply with recycled materials. The *Manufacturer* produces end-products by assembling $n = 1, 2, \dots, N$ parts. The *Manufacturer* obtains these parts by using two inflows; original parts supplied by the *Parts producer* and parts obtained from a *remanufacturing* recovery process, which has priority over using original parts. The *Wholesaler* purchases end-products from the *Manufacturer*, while the *Retailer* purchases from the *Wholesaler* in order to satisfy the *Demand Backlog*. The latter is the level of all unsatisfied orders from *Demand Market*, which are backlogged in order to be satisfied in a subsequent time period.

The reverse channel includes the activities of collection (provided by the *Collector*), disassembly (provided by the *Disassembly center*), *remanufacturing*, *recycling* and *Disposal*. In particular, *used-products* are collected by the *Collector* for reuse and thereafter are transferred and sold to the *Disassembly center*. The re-manufacturability condition (quality) of parts obtained through the disassembly procedure is inspected to sort them in the remanufacturable stream. The condition of parts rejected for remanufacturing is inspected for recycling.

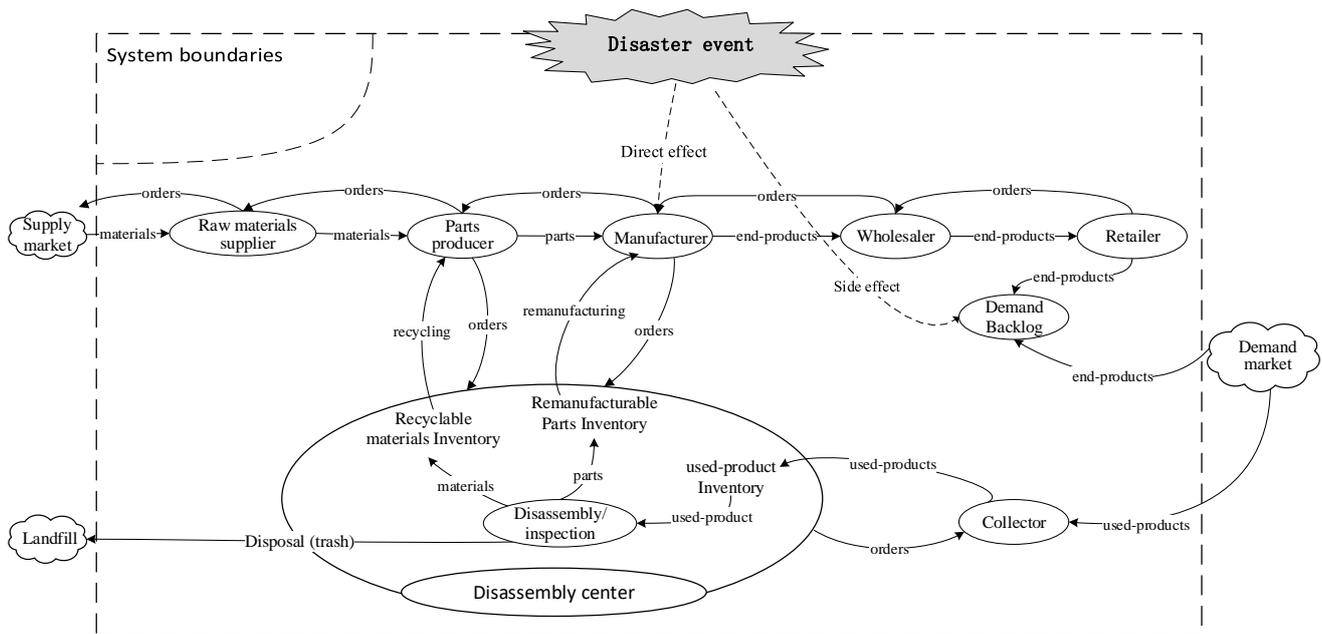


Figure 1. Generic Closed Loop Supply Chain and disaster event.

The parts accepted for recycling are sorted as recyclable materials, while those rejected are controllably disposed as trash (*Disposal*). The output of *remanufacturing* is “as-good-as-new parts” for the *Manufacturer*, while that of the recycling process is substitutes of virgin raw materials for the *Parts producer*. With regard to the buy/supply relationships among involved actors, we assume a single-supplier strategy in both channels, which means that a single *Parts producer* is the sole supplier for the *Manufacturer*, and the latter is the sole supplier for a single *Wholesaler*, etc.

3.2. Problem Description

The main point of this paper is the examination of the dynamic behavior of a CLSC system under disaster effects hitting the manufacturer and the investigation of the efficiency of adopted alternative mitigation policies. This examination also takes into consideration the side effects of each mitigation policy on the demand backlog level.

The modeling of the disaster effect on the production rate of the manufacturer is shown in Figure 2, which illustrates a likelihood pattern for the production rate at the pre-disaster, disaster recovery and post-disaster time periods; t^D is the unknown time of occurrence of a disaster event, while h^D is the unknown duration of disaster event, and h^{rec} is the recovery period during which each mitigation policy is implemented by the manufacturer. This approach is based on the disaster resilience triangle concept originally introduced by Bruneau [74] and thereafter extended by Zobel and Khansa [75].

During the disaster event period (h^D), two options are considered regarding the disruptions of the manufacturer’s production rate due to the disaster effect: a 50% reduction of the production rate and a 20% reduction of the production rate.

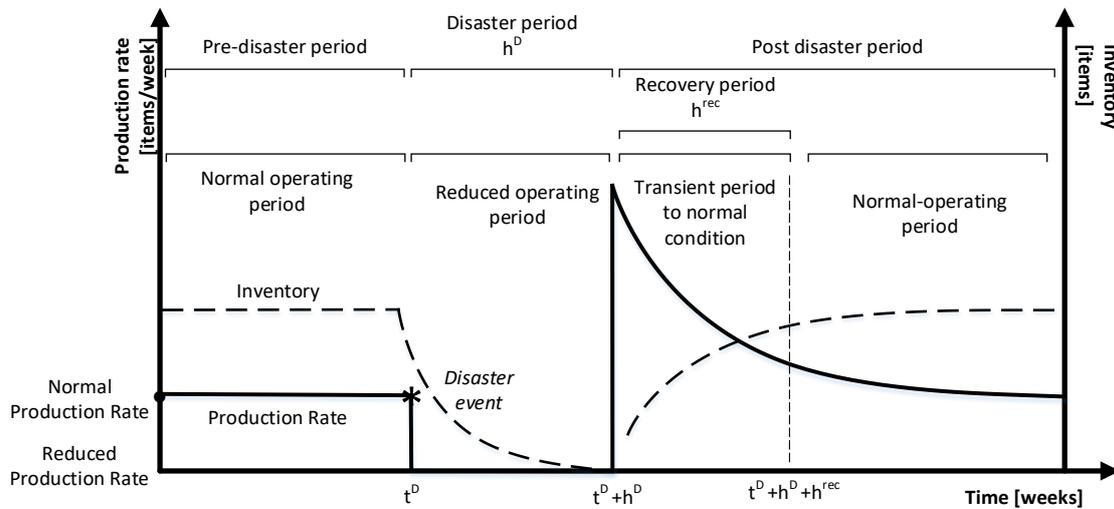


Figure 2. Likelihood pattern for the production rate and level of inventory under disaster effects at the manufacturer.

4. The SD Model

Stocks and flows, along with feedback loops, are the two central characteristics of the SD theory. Stocks are the accumulations of the inflows and the outflows within the chain. SD uses a particular diagramming notation for stocks and flows [76]. Stocks are symbolized by rectangles; inflows are symbolized by pipes pointing into (adding to) the stock, and outflows are symbolized by pipes pointing out of (subtracting from) the stock. Stocks are defined by the stock equations as the time integrals of the net flows.

Flows are defined by the rate equations as the time functions of stocks and system parameters. In SD models, the stock and flow perspectives represent time as unfolding continuously; events can happen at any time, and change can occur continuously. The stock–flow diagram is translated into a system of differential equations, which is then solved via simulation, generally currently supported by high graphical simulation programs, such as PowerSim[®], Vensim[®], i-think[®] and Stella[®] [77].

The SD model's full stock–flow diagram includes 30 stock variables, 58 rate variables, 151 auxiliary variables and over 45 balancing (negative) and reinforcing (positive) feedback loops. This section provides details regarding the mathematical modelling by keeping the analysis as generic as possible.

4.1. Generic Stock and Flow Structure

The generic stock–flow diagram is shown in Figure 3. The forward supply chain begins from the upper left corner. The *Raw Materials Supplier's Inventory (RMSI)* is increased by the *coming rate of new material* and is decreased by the *purchase rate of new material*, which is the flow of virgin (new) materials to the parts producer. The demand of the parts producer for materials (*total amount of the material*) is satisfied with priority over recycled materials defining the *recycling rate*, while the unsatisfied part of demand is fulfilled by the raw materials supplier (*purchase rate of new material*).

The *Parts Producer's Inventory (PPI)* is increased by the *part production rate* and is depleted by the *purchase rate of new part*. The manufacturer's demand for parts (*total amount of the part*) is satisfied with priority over remanufactured parts, thus, defining the *remanufacturing rate*. The unsatisfied part of demand is fulfilled by supplies from the parts producer (*purchase rate of new part*). The *production rate* increases the *Manufacturer's Inventory (MI)* in end-products, which is subsequently depleted by the *shipment to wholesaler* in order to satisfy as many of the wholesaler's orders as possible. The *Production rate* is subject to the availability of inventory in parts; either recycled or new.

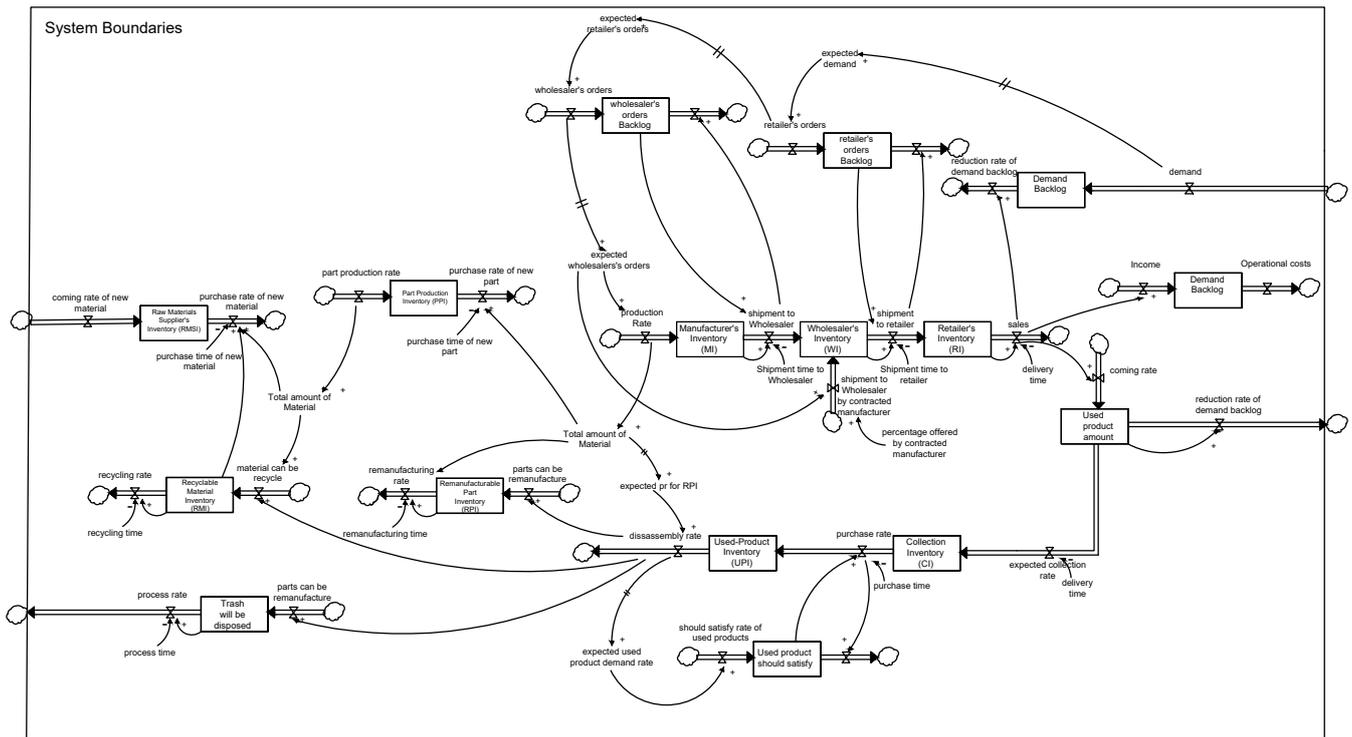


Figure 3. Generic stock and flow diagram of the CLSC under study.

The shipments to the wholesaler take shipment time (*shipment time to wholesaler*) and deplete the wholesaler's orders (*wholesaler's orders backlog*). The shipment to the wholesaler increases the *Wholesaler's Inventory (WI)*. The *Wholesaler's Inventory* is depleted by the *shipment to retailer*, which also takes shipment time (*shipment time to retailer*). The *shipment to retailer* depletes the retailer's unfulfilled orders (*retailer's orders backlog*) and increases the *Retailer's Inventory (RI)*. The latter is decreased by *sales*, which take *delivery time* to satisfy the demand for end-products (*demand*). All unsatisfied market demand is backlogged and satisfied in a subsequent time period (*demand backlog*). The same stands for orders placed by the retailer and directed to the wholesaler (*retailer's orders backlog*), as well as for orders placed by the wholesaler and directed to the manufacturer (*wholesaler's orders backlog*). Following a time delay (the *usage period* of a product), *sales* turn into used-products (*coming rate 1*).

The reverse channel starts with the collection activities. The stock of used-products at the collector (*Collection Inventory (CI)*) is increased by the *expected collecting rate*. The values of this rate are practically the forecasted values of the disassembly center's demand for used-products. The *Collection Inventory* is depleted by supplies to the disassembly center (*purchase rate*), which also deplete the unsatisfied demand of the disassembly center (*used-product should satisfy*); the demand of the disassembly center for used-products is expressed by *should satisfy rate of used-product*, while the unsatisfied demand is backlogged and satisfied in a subsequent time period.

The purchase rate increases the *Used-product inventory (UPI)* at the disassembly center, which is depleted by the *disassembly rate*. The parts obtained through the disassembly operation (*disassembly rate*) are sorted into three streams. In particular, the output of the disassembly sorts the used-products (after inspection) with priority into remanufacturable parts. These parts (*parts that can be remanufactured*) increase the level of *Remanufacturable Part Inventory*. Parts rejected for remanufacturing are sorted as recyclable materials (*material that can be recycled*), which increase the level of *Recyclable Material Inventory (RMI)*. Parts rejected for recycling are disposed as trash (*remanent trash will be disposed*). Finally, the

remanufacturing rate delivers remanufactured parts to the manufacturer, while the recycling rate delivers recycled materials to the parts producer.

4.2. Mitigation Policies at the Manufacturer Level

Figure 4 represents the stock and flow structure of CLSC from production of the end-products to market demand satisfaction together with the implemented policies for mitigating the disaster effects. In particular, MP1 refers to the various mitigation policies regarding the serviceable inventory at the manufacturer level (*Manufacturer's Inventory (MI)*). Their implementation is achieved through the alternation of the values for the *adjusted time of MI* and the *cover time of MI* parameters (base stock expressed in time units), which refer to the time for achieving the desired value for MI and to the level of the desired value for MI (*Desired MI* see Equation (14)), respectively.

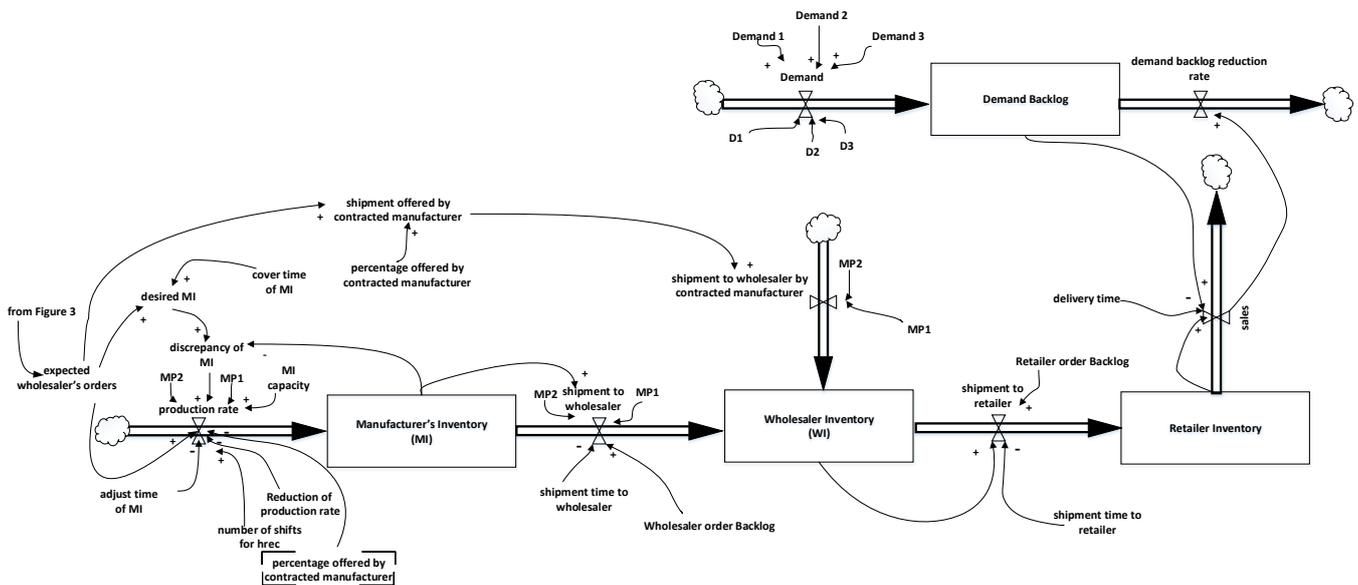


Figure 4. Stock and flow structure of MP1–MP2.

In the case of MP2, the manufacturer enters into a contract with a third-party manufacturer who will fulfill a percentage (*percentage offered by the contracted manufacturer*) of the *expected wholesaler's orders* placed by the wholesaler only during the disaster period and recovery period. Parameters MP1 and MP2 shown in Figure 4 take dual values (0/1), activating ($MP_i = 1$) or deactivating ($MP_i = 0$) the corresponding MP_i . The sets of control parameters that fully describe MP1 and MP2 are the following:

- MP1: [MP_1 , cover time of MI, cover time of MI due to event, adjust time of MI, adjust time of MI due to event, h^{rec}].
- MP2: [MP_2 , cover time of MI, cover time of MI due to event, adjust time of MI, adjust time of MI due to event percentage offered by contracted manufacturer, h^{rec}].

The mathematical representation for MP_1 and MP_2 is given by the following equations; where equations are differentiated, the values of parameters MP_i are given to indicate the active mechanism.

4.3. Stock Equations

$$MI(t) = MI(t = 0) + \int_0^t [\text{production rate}(t) - \text{shipment to wholesaler}(t)] dt \quad (1)$$

$$WI(t) = WI(t = 0) + \int_0^t \left[\text{shipment to wholesaler}(t) + \text{shipment to wholesaler by the contracted manufacturer}(t) - \text{shipment to retailer}(t) \right] dt \quad (2)$$

$$\text{Retailer Inventory}(t) = \text{Retailer inventory}(t = 0) + \int_0^t [\text{shipment to retailer}(t) - \text{sales}(t)] dt \quad (3)$$

$$\text{Demand Backlog}(t) = \text{Demand Backlog}(t = 0) + \int_0^t [\text{Demand}(t) - \text{demand backlog reduction rate}(t)] dt \quad (4)$$

4.4. Flow Equation

$$\text{production rate}(t) = \begin{cases} \text{MI capacity,} \\ \min \left(\text{expected wholesaler's orders}(t) + \frac{\text{discrepancy of MI}(t)}{\text{adjusted time of MI}} \right) \text{ for } t < t^D \text{ and } t > t^D + h^D + h^{rec} \\ \min \left[\text{MI capacity} * \text{reduction of the production rate, } (100 - \text{percentage offered by the contracted manufacturer}(t)) * \right. \\ \left. * \left(\text{expected wholesaler's orders}(t) + \frac{\text{discrepancy of MI}(t)}{\text{adjusted time of MI}} \right) \right] \text{ for } t^D \leq t \leq t^D + h^D + h^{rec} \end{cases} \quad (5)$$

$$\text{shipment to wholesaler}(t) = \begin{cases} \left(\frac{\min(\text{MI}(t), \text{wholesaler's orders backlog}(t))}{\text{shipment time to wholesaler}} \right) & \text{for } MP_1 = 1 \\ \left(\frac{\min(\text{MI}(t), \text{wholesaler's orders backlog}(t))}{\text{shipment time to wholesaler}} \right) & \text{for } t < t^D \text{ and } t > t^D + h^D + h^{rec} \\ \left(\frac{\min(\text{MI}(t), \text{wholesaler's orders backlog}(t))}{\text{shipment time to wholesaler}} - \text{shipment to wholesaler by contracted manufacturer}(t) \right) & \text{for } MP_2 = 1 \\ & \text{for } t^D \leq t \leq t^D + h^D + h^{rec} \end{cases} \quad (6)$$

$$\text{shipment to wholesaler by contracted manufacturer}(t) = \begin{cases} 0 & \text{for } MP_1 = 1 \\ \begin{cases} 0 & \text{for } t < t^D \text{ and } t > t^D + h^D + h^{rec} \\ \text{expected wholesalers orders} * \text{percentage offered by contracted manufacturer} & \text{for } t^D \leq t \leq t^D + h^D + h^{rec} \end{cases} & \text{for } MP_2 = 1 \end{cases} \quad (7)$$

$$\text{shipment to retailer}(t) = \frac{\min(WI(t), \text{retailer's orders backlog}(t))}{\text{shipment time to retailer}} \quad (8)$$

$$\text{sales}(t) = \frac{\min(\text{Retailer Inventory}(t), \text{Demand Backlog}(t))}{\text{delivery time}} \quad (9)$$

4.5. Auxiliary Equations

$$\text{percentage offered by contracted manufacturer}(t) = \begin{cases} 0 & \text{for } MP_1 = 1 \\ \text{percentage offered by the contracted manufacturer}(t) & \text{for } MP_2 = 1 \end{cases} \quad [\%] \quad (10)$$

$$\text{discrepancy of MI}(t) = \text{desired MI}(t) - \text{MI}(t) \quad (11)$$

$$\text{desired MI}(t) = \text{cover time of MI} * \text{expected wholesaler's orders}(t) \quad (12)$$

$$\text{adjust time of MI} = \begin{cases} \text{initial adjust time of MI} & \text{for } t < t^D \text{ and } t > t^D + h^D \\ \text{adjust time of MI due to } MP_i & \text{for } t^D \leq t \leq t^D + h^D + h^{rec} \end{cases} \quad (13)$$

$$\text{cover time of MI} = \begin{cases} \text{initial cover time of MI} & \text{for } t < t^D \text{ and } t > t^D + h^D \\ \text{cover time of MI due to } MP_i & \text{for } t^D \leq t \leq t^D + h^D + h^{rec} \end{cases} \quad (14)$$

$$\text{expected wholesalers' orders} = \text{DELAYMTR}(\text{wholesaler orders}; T_m; 1; \text{wholesaler orders}) \quad (15)$$

Equations (1)–(4) represent the stock equations for *MI*, *WI*, *Retailer Inventory* and *Demand Backlog* in end-products. The inflow to *MI* is the *production rate* (see Equation (5)), and the outflow from *MI* is the *shipment to wholesaler*, which is defined by Equation (6). At

the same time, *shipment to wholesaler* constitutes the inflow to *WI*. The second inflow to *WI* is the *shipment to wholesaler by contracted manufacturer* (see Equation (7)). The outflow from *WI* (*shipment to retailer*) is defined by Equation (8). The inflow to *Retailer Inventory* is the same with the outflow of *WI* (*shipment to retailer*), while the outflow from *Retailer Inventory* is *sales*, which is defined by Equation (9). The inflow to *Demand Backlog* (*demand*) is determined under alternative demand patterns, while the outflow from *Demand Backlog* (*demand backlog reduction rate*) is equal to *sales*.

In Equation (5), the *production rate* is defined for the normal operating period, the disaster period and the recovery period h^{rec} as the combination of the *expected wholesaler's orders* with an adjustment that brings the *MI* in line with its desired value (*desired MI*). The *production rate* is subject to the availability of actual stock in parts. The *percentage offered by contracted manufacturer* in Equation (5) is defined by Equation (10) under MP_2 , while the *expected wholesaler's orders* is a forecasted value for *wholesaler's orders* (see Figure 3 and Equation (15)) calculated from a first-order exponential smoothing. The adjustment of *MI* is based on a proportional rule that controls the discrepancy (*discrepancy of MI*) between *desired MI* and actual *MI* (Equation (11)).

The adjustment time (*adjust time of MI*) represents how quickly the manufacturer decides to close the gap between the desired and the actual inventory level. It expresses the incorporated mitigation policies during the disaster period and the recovery period h^{rec} . Especially during the disaster period and during the recovery period h^{rec} , the value of adjust time of *MI* is decreased so as for the system to be able to respond to the changes caused by the disaster event (see Equation (13)). *Cover time of MI* (see Equation (14)) is the base stock expressed in time units.

4.6. Profit Equations

Profit equations are provided through profit per period (*Profit*) and *Total Profit* as the sum of *Profit* (profit per simulation time-step) over the simulation horizon. The *Profit* is captured by monetary flows created by physical flows per period (*Profit calculation* in Figure 3).

$$\text{Profit}(t) = \text{Sales}(t) * \text{Price} - \text{Operational Costs}(t) \quad [\text{€}/\text{tu}] \quad (16)$$

$$\text{Total Profit}(t) = \text{Total Profit}(t = 0) + \int_0^t [\text{Sales}(t) * \text{price} - \text{Operational Costs}(t)] dt \quad [\text{€}] \quad (17)$$

Sales and *Price* refer to market demand. *Operational Costs* include: (i) the production, inventory holding and transportation costs in the forward channel, i.e., the sum of operational costs for the raw materials supplier (*RMScost*), the parts producer (*PPcost*), the manufacturer (*Mcost*), the wholesaler (*Wcost*) and the retailer (*Rcost*); (ii) the collection, disassembly, remanufacturing, recycling, transportation, holding and disposal costs in the reverse channel, i.e., the sum of operational costs for the collector, the disassembly center, the remanufacturer and the recycler; and (iii) the cost of supplies by a contracted third-party manufacturer in the case of MP_2 . The detailed income/cost equations are based on standard calculations.

5. Numerical Experimentation and Discussion

By utilizing the SD model, we conducted a simulation experimentation in order to examine the system response to the effect of a disaster event. Our target was to search for sustainable mitigation policies that allow the manufacturer to return as soon as possible to normal condition operations through transitional dynamics. During this experiment, we considered the total CLSC profit and demand backlog as measures of policy performance. Throughout investigation, the output results are presented as ratios to the corresponding values obtained by the simulation run of the basic scenario (namely, *Profit index*, *Total profit index*, *Demand Backlog index*). The basic scenario (BS) refers to a CLSC operation under normal conditions (disaster-free model).

5.1. Validation of the SD Model

Structure and behavior validity are the basic criteria for the validation of an SD model. These are detected following certain procedures and tests suggested by the SD literature [46,78,79].

The above-mentioned tests were conducted as follows: First, we checked the dimensional consistency of the model. Then, we conducted extreme condition tests to assess whether or not the model behaved realistically even under extreme situations. For example, we verified that if no used products were collected, only raw materials were used for production, or that, in the absence of demand, production ceased. Integration error tests were subsequently conducted. The model employs the Euler integration method with an integrating time-step equal to 1 week. The results of the tests indicated no integrating errors. Structural validation tests were executed, which confirmed the sensitivity of the model structure to specific parameters.

Due to the absence of real data and published research for a point-by-point match between model behavior and real behavior, the behavior validation of the SD model was tested by comparing the simulation results obtained by running the disaster-free model with those provided by the literature. In particular, Figure 5 shows that the accumulated level of inventory at the manufacturer (MI , see Equation (1) and Figure 4) exhibited similar dynamic behavior compared to that provided by Yadav et al. [80]. The comparative study of simulation results with those given by Gu and Gao [72], resulted in similar dynamic behavior regarding the crucial rate variables, namely, the *production rate* (see Equation (5)), *part production rate* and *disassembly rate* (see Section 4.1 and Figure 3).

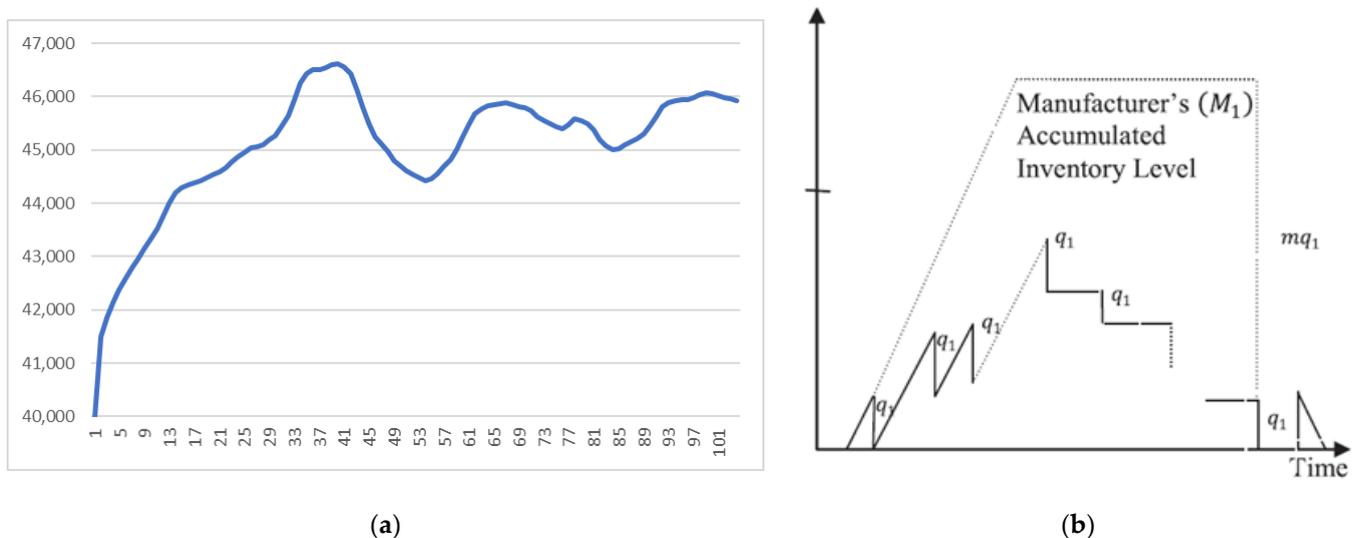


Figure 5. Dynamic behavior of Inventory level at the manufacturer. (a) This study (MI , disaster-free model); (b) Yadav et al. [80]. Copyright Year: 2022, Copyright Owner's Name: Elsevier.

5.2. Settings

The SD model was executed for a simulation horizon of 24 months with time-step equal to 1 week. The *Demand* at normal operation conditions for end-products followed a normal distribution function [$Demand \sim N(10,000 \text{ items/week}, 1,000 \text{ items/week})$]. We assumed that normal operation conditions belongs to the maturity stage of product life cycle, while the CLSC refers to products that are included in the group of furnishings and household equipment (major household appliances whether electric or not and small electric household appliances). The time of disaster occurrence was equal to $t^D = 12$ [week], while the duration of the *disaster period* (h^D) was examined under three sets of value: 2 weeks (small-scale); 6 weeks (medium-scale); 10 weeks (large-scale). The alternative demand patterns (Demand Pattern 1, Demand Pattern 2 and Demand Pattern 3) due to the disaster event (see explanation in Section 1) are given in Figures 6–8.

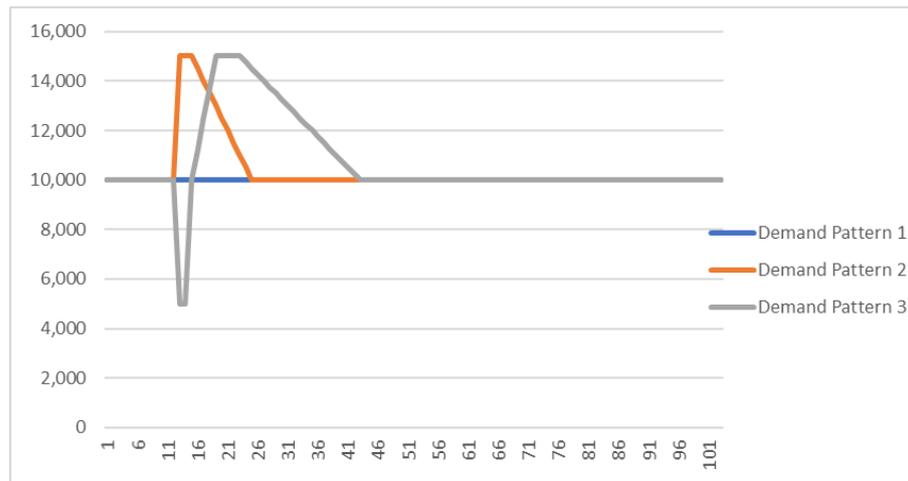


Figure 6. Demand patterns ($t^D = 12$ weeks $h^D = 2$ weeks).

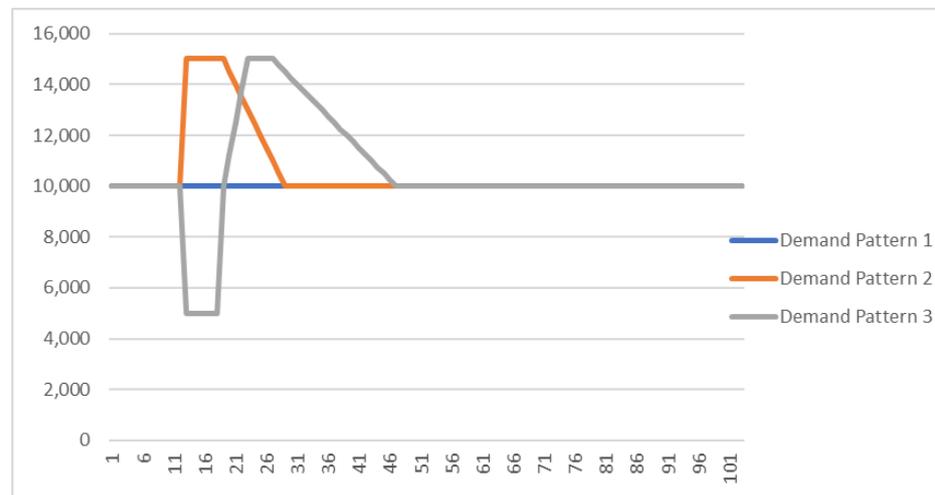


Figure 7. Demand patterns ($t^D = 12$ weeks, $h^D = 6$ weeks).

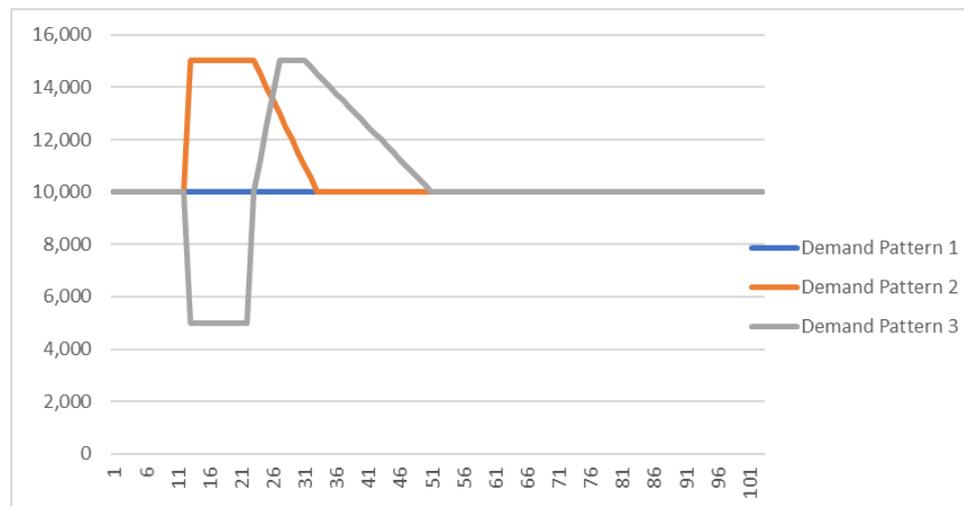


Figure 8. Demand patterns ($t^D = 12$ weeks, $h^D = 10$ weeks).

The sale price of end-product is equal to 200 €/end-product.

The alternative mitigation policies are expressed by the following sets of control parameters:

- MP1: [MP_1 , cover time of MI, cover time of MI due to event, adjust time of MI, adjust time of MI due to event, h^{rec}].
- MP2: [MP_2 , cover time of MI, cover time of MI due to event, time of MI, adjust time of MI due to event, percentage offered by contracted manufacturer, h^{rec}].

Finally, the settings for the basic scenario are as follows:

- BS: [Demand $\sim N(10,000$ items/week, 1000 items/week, stock management: cover time of MI = 4 weeks; adjust time of MI = 6 weeks].

5.3. Recommendations for Mitigating Disaster Effects

We concentrate on the efficiency of two mitigation policies for the manufacturer in responding to the demand market. Specifically, we examine the dynamic response of the system for three categories of disaster event, three sets of demand patterns and under two possible mitigation policies in combination with: (i) four sets of values for the *cover time of MI due to event* (2, 4, 6 and 8 weeks); (ii) five sets of value for the *adjustadjusted time of MI due to event* (1, 2, 3, 4 and 6 weeks); (iii) two sets of value for the *reduction of production rate* (20% and 50%); and (iv) three sets of value for the h^{rec} (4, 8 and 12 weeks).

All possible combinations ($3 \times 3 \times 2 \times 4 \times 5 \times 2 \times 3 = 2160$) represent a broad area of response scenarios for mitigating the effects of disaster event. For each combination, 20 repetitive simulation runs were conducted to test for alternative generators of random numbers (used in definition of *Demand*), thus, giving a total of $2160 \times 20 = 43,200$ runs. In each run, the values of stock variables and of smoothing functions were first initialized by considering an initialization horizon of 260 weeks in order to capture the system's behavior outside its transient region.

Thereafter, a simulation horizon of 24 months, starting at $t = 0$ and using time-step equal to 1 week, represents the real-time experimentation for each combination. Throughout investigation, the CLSC profitability (profit per week (*Profit*)—see Equation (15), *Total profit*—see Equation (16) and Demand Backlog level—see Equation (4), (as the mean values of 20 repetitive runs) are considered as the output of the relative combinations for each category of disaster event and each demand pattern. The output results are presented as ratios to the corresponding values obtained by the simulation run of the basic scenario (i.e., *Profit index*, *Total profit index* and *Demand Backlog index*). The basic scenario (BS) refers to a CLSC operation under normal conditions (disaster-free model).

5.3.1. Profitability of the CLSC System

Table 2 displays the best and worst mitigation policies in each set of values for disaster event under each combination of *reduction of production rate* and *demand pattern*. Note that the results refer to the period from the appearance of the disaster event to the end of the simulation period. The lower/upper limits of the *Total profit index* express the detected minimum/maximum values. Depending on the combination, we found that the best policy recommendations are either MP1 or MP2 combined with specific values of *cover time of MI due to event*, *adjust time of MI due to event* and h^{rec} .

Taking all the above into consideration, we observe that, from an economic perspective, it is preferable to preserve a low security stock (defined by *cover time of MI due to event*) upon materialization of the disaster event, throughout its duration and during the recovery period (h^{rec}). In addition, it is preferable for the duration of h^{rec} to be long (8 or 12 weeks). For example, in the case of $h^D = 6$ weeks and *reduction of production rate* = 20%, from Table 2, we found that the best policy recommendations were: MP2, $h^{rec} = 12$ weeks, *adjust time due to event* = 2 weeks and *cover time due to the event* = 2 weeks for all demand patterns.

Table 2. Best/worst mitigation policies according to the Total Profit Index.

h^D (Weeks)	Reduction of Production Rate	Demand Pattern	Best/Worst Cases	MP *	J_t^{rec} (Weeks)	Adjust Time due to Event (Weeks)	Cover Time due to Event (Weeks)	Total Profit Index [$\frac{\text{Total profit}_t}{\text{Total profit}_t^{(BS)}} * 100$]			
								Lower	Upper	Equilibrium State	
2	0%	1	Basic Scenario (BS)					100	100	100	
	20%	1	Best	MP2	12	1	2	100	106.58	100.88	
			Worst	MP2	12	2	8	80.41	99.93	95.90	
	20%	2	Best	MP2	12	4	2	99.81	142.83	105.60	
			Worst	MP2	12	2	8	95.67	119.84	103.60	
	20%	3	Best	MP2	12	2	2	82.59	160.12	137.00	
			Worst	MP1	12	4	8	73.29	154.10	134.00	
	50%	1	Best	MP1	12	2	2	100	109.66	100	
			Worst	MP2	12	4	8	85.73	99.30	96.60	
	50%	2	Best	MP1	12	4	2	99.87	145.95	106.80	
			Worst	MP1	12	3	6	96.61	130.04	105.45	
	50%	3	Best	MP1	12	3	2	85.49	162.30	137.40	
			Worst	MP1	8	6	8	76.92	148.91	123.90	
	6	20%	1	Best	MP2	12	2	2	98.93	108.97	99.00
Worst				MP2	12	2	8	82.13	97.99	94.58	
20%		2	Best	MP2	12	2	2	99.26	156.45	108.20	
			Worst	MP1	12	4	8	95.90	132.55	107.50	
20%		3	Best	MP2	12	2	2	65.08	151.73	133.86	
			Worst	MP1	12	4	8	45.07	145.35	131.60	
50%		1	Best	MP1	8	4	2	100.33	114.48	100.53	
			Worst	MP2	12	1	8	91.84	99.17	97.79	
50%		2	Best	MP1	12	3	2	101.13	163.40	109.82	
			Worst	MP2	8	3	6	97.82	147.99	107.97	
50%		3	Best	MP1	12	4	2	67.64	155.12	135.10	
			Worst	MP1	12	3	8	53.80	147.33	132.97	
10		20%	1	Best	MP2	8	6	2	98.11	110.12	98.15
				Worst	MP2	8	3	8	83.04	98.43	95.35
	20%	2	Best	MP2	12	1	2	100.13	166.10	111.00	
			Worst	MP1	12	4	8	96.17	143.76	110.90	
	20%	3	Best	MP1	12	3	2	50.33	144.16	131.52	
			Worst	MP2	12	2	8	30.72	135.70	125.90	
	50%	1	Best	MP1	12	4	2	99.94	119.43	100.90	
			Worst	MP1	4	6	8	93.41	102.90	99.13	
	50%	2	Best	MP1	8	2	2	100.88	178.86	113.40	
			Worst	MP1	8	4	8	97.66	158.60	112.70	
	50%	3	Best	MP1	12	4	2	58.92	148.35	133.80	
			Worst	MP1	12	2	8	42.75	137.77	127.70	

* MP1: mitigation policies regarding the serviceable inventory at the manufacturer level (see Section 4.2); MP2: a contract with a third-party manufacturer who will fulfill a percentage of expected wholesaler’s orders (see Section 4.2).

It is necessary to combine this safety stock with the time parameters regarding system control at *MI* level, because—as it appears from the results—a wrong combination may have undesirable consequences on the Total Profit. Another very important observation is that cooperation with a third party (MP2) is recommended in cases where the duration of the disaster event (h^D) or the *reduction of production rate* fluctuate among small values. In the opposite cases, MP1 with the appropriate adjustments to the rest of the parameters is preferable. Finally, we observe that, if the best mitigation policies are implemented,

the system returns to the same or an even better condition compared with the one in the pre-disaster period.

5.3.2. Demand Backlog and Manufacturer Inventory

In order to examine the burden observed on the system due to the disaster event as far as order fulfillment is concerned, we have created the DBMI indicator where we calculate the quotient between *Demand Backlog* (see Equation (4)) and the *Manufacturer Inventory* (see Equation (1)) in proportion to the corresponding BS (see Equation (18)).

$$DBMI_{index} = \frac{\frac{Demand\ Backlog_t}{MI_t}}{\left(\frac{Demand\ Backlog_t}{MI_t}\right)^{BS}} \tag{18}$$

If this particular indicator takes values larger than 1, this means that there is extra delay in demand fulfillment, while there is faster demand fulfillment due to the mitigation policies implemented if it takes smaller values than 1. Table 3 displays the best mitigation policies for each category of disaster events for each combination of *reduction of production rate* and for each demand pattern.

Table 3. Best mitigation policies according to DBMI_{index}.

<i>h^D</i> (Week)	Reduction of Production Rate	Demand Pattern	MP	<i>h^{rec}</i> [Weeks]	Adjust Time Due to Event (Week)	Cover Time Due to Event (Week)	DBMI _{index}	
							Max	Equilibrium State (Value/Time (Week) ¹)
2	0%	1	Basic Scenario (BS)			1	-	
	20%	1	MP2	12	All values	6 or 8	1.01	0.91/7
	20%	2	MP2	8 or 12	All values	6 or 8	1.52	0.93/36
	20%	3	MP1 or MP2	4	All values	6 or 8	1.54	1.02/60
	50%	1	MP1	12	All values	6 or 8	1.35	0.84/20
	50%	2	MP1 or MP2	All values	All values	4 or 6 or 8	2.05	1.06/50
	50%	3	MP1 or MP2	4	All values	6 or 8	2.05	1.11/74
6	20%	1	MP1	12	All values	8	1.07	0.72/20
	20%	2	MP1 or MP2	All values	All values	4 or 6 or 8	2.09	1.06/45
	20%	3	MP1 or MP2	4	1	8	1.23	0.96/50
	50%	1	MP1	12	All values	6 or 8	2.80	1.09/45
	50%	2	MP1 or MP2	All values	All values	4 or 6 or 8	5.50	1.11/80
	50%	3	MP2	4	All values	6 or 8	2.40	1.11/70
10	20%	1	MP1	12	All values	8	1.14	0.72/25
	20%	2	MP1 or MP2	All values	All values	4 or 6 or 8	4.85	1.12/70
	20%	3	MP1 or MP2	4	1	8	1.48	1.06/80
	50%	1	MP1 or MP2	All values	All values	4 or 6 or 8	7.41	1.09/45
	50%	2	MP1 or MP2	All values	All values	4 or 6 or 8	11.09	1.14/75
	50%	3	MP1 or MP2	4	1 or 2 or 3 or 4	6 or 8	3.67	1.12/70

¹ in number of weeks (*t* - *t^D*).

The equilibrium state refers to the values that makes the system reach that state after the disaster event. The time refers to the time needed for the system to enter again into an equilibrium state after the disaster event. Representative values are shown in Figure 9 for the best results in terms of DBMI_{index} for the case of medium scale (*h^D* = 6 weeks) disaster events and 20% *reduction of production rate*, for the three demand patterns described above. From the results, we found that the system entered into different equilibrium state for each demand pattern compared to BS (in all cases equilibrium state is differential to 1).

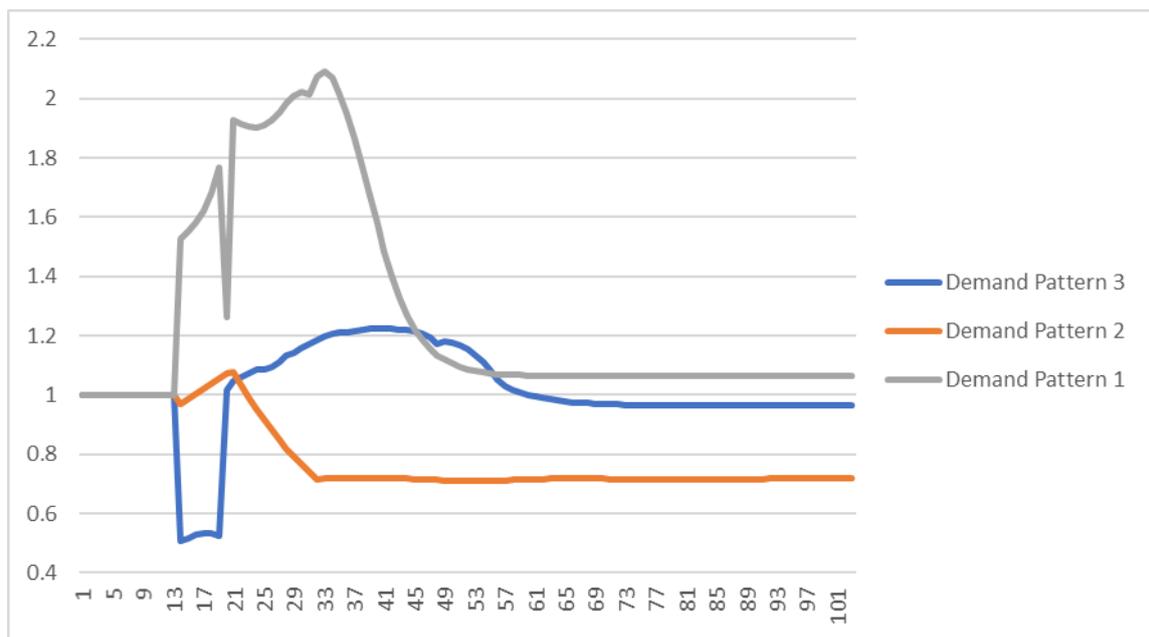


Figure 9. $DBMI_{index}$ for medium scale ($h^D = 6$ weeks) disaster event and reduction of production rate 20%.

Taking all the above results into consideration, we conclude that, in most cases, the best mitigation policy, based on $DBMI_{index}$, is independent from *adjust time of MI due to event*. As far as the safety stock is concerned, it reaches high levels in this case. For example, in the case of $h^D = 6$ weeks and *reduction of production rate = 50%*, from Table 3, we found that the best policy recommendations were: MP2, $h^{rec} = 4$ weeks, *cover time due to event = 6 weeks or 8 weeks* and is independent from *adjust time of MI due to event* for Demand Pattern 3. In most cases, MP2 is recognized as the best mitigation policy. Nevertheless, there are cases where MP1 is preferable, mainly when Demand Pattern 1 applies (for example when $h^D = 2$ weeks, *reduction of production rate = 50%* for Demand Pattern 1 MP1 is preferable). Finally, as far as h^{rec} is concerned, there are cases where the best policy is indicated for short time lapses, for long time lapses or is independent from time lapse.

6. Summary, Limitations and Future Research

This paper presents the development of an SD model for a single manufacturer/multi-echelon CLSC with remanufacturing and recycling activities in order to manage the effects of disaster events. In particular, the SD model examines three categories of disaster events under three demand patterns. The system reactions to two different mitigation policies, as well as to different values of time variables of the system control at the manufacturer level are examined.

It can be concluded from the results that the choice of the best policy for the creation of a sustainable CLSC varies depending on the level of focus (economic level, inventory level). For example, if we wish to create an economically sustainable CLSC, we would have to preserve a low security stock in the implementation of the mitigation policy. On the other hand, if we opt for sustainability in demand fulfillment from the manufacturer's stock, then a high security stock must be preserved.

This study is limited to the examination of a single manufacturer/multi-echelon CLSC with remanufacturing and recycling activities with single actors involved in the forward and reverse channel. Remanufacturing operations produce "as-good-as-new" parts for the manufacturer, while recycling operations supply the parts producer with recycled raw materials. The CLSC under study represents the supply chain of furnishings and household equipment (major household appliances whether electric or not and small electric household appliances).

The disaster event affects only the manufacturer, while the remaining actors of CLSC operate in normal conditions. The results presented in this paper certainly do not exhaust the possibility of investigating all the aspects of disaster management policies to the CLSCs. One differentiation is to include the possibility that some of the orders are not satisfied [81]. Another possible extension could be the study of disaster management under different remanufacturing settings, assuming, for example, that the remanufacturing process may produce not only as-good-as-new products but also B-class products directed to secondary markets [24]. Further possible extensions include the control of the system response to contingency that the disaster event effects as well as other partners of CLSC apart from the manufacturer [82].

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