Modelling of disruption mitigation in supply chains

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Abstract: Disruptive events can severely impact supply chains. Resilience is a property of supply chains able to assess its robustness to disruption and the rapidity in recovering functionality. Supply chain resilience can be improved through several preventive or protective mitigation measures. However, to assess the effectiveness of such measures, to provide their economic justification, and to properly choose which measure to apply in specific instances asks for the capability of describing in a realistic and detailed manner how a supply chain responds to disruption scenarios. In this paper it is shown how a newly developed simulation model, especially conceived for detailed simulation of supply chains under disruption conditions can help decision maker to assess mitigation measures. After briefly describing the model, a reference supply chain is presented and service level simulations are carried out under several scenarios and mitigation measures combinations. Means to assess the cost-effectiveness of the mitigation efforts are also presented. Results show that supply chain performances are highly dependent on the type of implemented mitigation measure. Results also show that a trade-off has to be sought between revenue reduction owing to service level deterioration and implementation cost of mitigation measures.

Keywords: Supply chain, Resilience, Simulation model, Disruption mitigation, Service Level

1.Introduction

Resilience is the property of a system of sustaining the impact of a major disrupting event and rapidly recovering its functionality, thus accounting for both short-term and long-term effects of disruptions. It is generally agreed that resilience is the combined result of three major properties, namely absorptive, adaptive, and restorative capacities. Absorptive capacity represents the ability to withstand the immediate effect of the disruption limiting the functionality loss of the systems. Adaptive capacity is represented by the ability to rearrange the system to allow continued operation after disruption. Finally, Restorative capacity represents the system's capability of rapidly recovering from the disrupted state in order to return to the original functionality level. In the industrial production field, the resilience concept may be associated with single autonomous entities such as manufacturing plants. In this case, the disruption may imply either physical damage to the entity (i.e., a major accident or external causes such as natural hazards damaging production equipment), or an upstream or downstream perturbation (i.e. failure of a supplier interrupting the input material flow, or significant changes in market demand) impairing the normal operation of the business. The same applies to systems of networked entities, such as supply chains (SC) made up of interconnected nodes (Ivanov, 2021a). In this case, the disruption may be represented by a failure of upstream and downstream nodes or interruption of interconnections between nodes, where disruption in a node or connection may rapidly propagate to the entire system through a ripple effect (Dolgui and Ivanov, 2021). Recent examples are the attacks on shipping vessels in the Red Sea, the blockage of the Suez Canal, affecting the flow of goods, and the COVID-19 pandemic, causing both a shortage of supply owing to the lockdown of production plants and a surge in demand of sanitary items such as pulmonary ventilators and face masks (Alexopoulos *et al.*, 2022). A vast body of literature investigating determinants of SC resilience, developing quantitative models to assess SC resilience, and approaches to design robust and resilient supply chains has been produced by scholars over the past decades. Several reviews are available (Aldrighetti *et al.*, 2021; Aldrighetti *et al.*, 2024; Chen *et al.*, 2022; Han *et al.*, 2020; Govindan *et al.*, 2017; Hosseini *et al.*, 2019; Ivanov *et al.*, 2017; Joshi and Luong, 2022; Katsialiaki *et al.*, 2022; Ponomarov and Holcomb, 2009; Rahman *et al.*, 2022; Sudan *et al.*, 2023; Tukamuhabwa *et al.*, 2015). However, literature modelling mainly focuses on the optimal design of resilient SC resorting to mathematical programming approaches. This imposes some simplification in the modelling approach, preventing capturing the operational and structural details of SC in realistic settings, and does not allow for verification of the performance of the resulting SC configurations. Some commercial SC simulation software tools (i.e., Anylogistix) also allow some capabilities for the simulation of SC in disrupted conditions. In this respect, simulation approaches allow a more faithful representation of the SC and greater flexibility in modelling actual management practices, acting as a synergic tool when devising strategies to improve SC resilience Nevertheless, specific tools for detailed resilience assessment of SC are still lacking. In this paper, in order to contribute to a solution to this problem, we extend the capabilities of a newly developed SC resilience simulation model (Donati, 2023; Caputo *et al.*, 2023) to include disruption mitigation practices, and show how this tool can help in assessing performances of disrupted SC and compare the effectiveness of mitigation measures. The paper is organized as follows. First, the possible SC resilience mitigation measures are briefly discussed. The simulation model is briefly described. Then a reference supply chain acting as a case study example is presented. Afterward, the effectiveness of alternative disruption mitigation strategies, namely prepositioned safety stock and sourcing from alternative suppliers, and backup capacity in alternative manufacturing sites, when disruption is the interruption of transportation routes, is compared with reference to the considered application example. Means to assess the cost-effectiveness of mitigation measures are presented and, finally, a brief discussion of model limitation and perspective for future research complete the paper. It should be pointed out that this paper is not aimed at providing generalizable results on a specific research question, but rather to demonstrate the functionality of a general-purpose simulation model conceived to analyze SC resilience and compare the performances of alternative case-specific mitigation measures. In a numerical application example built over a sample SC, we show that different mitigation measures do not have the same effectiveness and that the resulting necessity of selecting the proper measures asks for a cost-effectiveness analysis enabled by the developed tool.

2.Disruption mitigation measures in supply chains

Given the strategic and tactical relevance of SC resilience, several strategies, both proactive and reactive, have been devised to mitigate the effects of SC disruptions. The more relevant (Bret *et al.*, 2021; Govindan *et al.*, 2017; Guo *et al.*, 2023; Hosseini *et al.*, 2019; Ivanov, 2021b; Joshi and Luong, 2022; Kamalahmadi and Parast, 2017; Rahman *et al.*, 2022; Sudan *et al.*, 2023; Um and Han, 2020), being namely a) Pre-positioned safety stocks (either upstream, within or downstream the manufacturing nodes); b) Sourcing from alternative suppliers (including multiple, backup, or protected suppliers, and using geographically segregated suppliers to avoid simultaneous supplier failure caused by the same disrupting event); c) Use of alternative transporters or routes; d) Back up capacity in alternative production sites; e) Extra capacity at production site; f) Revenue management through dynamic pricing; g) Organizational measures to reduce recovery time of damaged nodes; h) Search for alternative markets and buyers; i) Make or buy decisions to externalize part of production processes; j) Substitution of input materials; k) Fortification against physical disruptions; l) Postponement and delayed differentiation of product; m) Flexible contracts. However, assessing the effectiveness of alternative measures and choosing the proper mix of mitigation measures in a specific SC instance is not easy. Furthermore, each mitigation measure implies added costs and response delays (Sawik, 2022; Kamalahmadi and Parast, 2017) which need to be balanced against the economic penalties and opportunity costs of a disrupted SC. Kamalahmadi and Parast (2017), for instance used two-stage Mixed Integer Programming to assess three types of redundancy practices (pre-positioning inventory, backup suppliers, and protected suppliers) in a firm's supply chain. Alikhani *et al.* (2023), use resource dependence theory and two-stage stochastic programming, for choosing resilience strategies in a SC design considering their synergistic effects under resource constraints. They include node fortification and safety stocks, direct shipping between nodes, alternative transport routes, and cyber safety measures, as well as penalties for lost sales. Chen *et al.* (2021), consider modification of product design to utilize alternative, and more costly, materials. Sawik (2022), considers prepositioned stock and backup suppliers. Hosseini and Barker (2016), adopt Bayesian networks to select suppliers while late deliveries are penalized on the basis of tardiness, while Hosseini *et al.* (2019), use decision trees and bi-objective mixed integer programming to optimally support supplier selection under geographical segregation and capacity extension as well as order allocation. Hosseini *et al.* (2019), consider backup suppliers. Torabi *et al.* (2015), explore the combination of multiple suppliers, backup suppliers, fortification, and prepositioned inventory. In case of disruption demand is satisfied by restoring I sequence to prepositioned inventory, then to backup suppliers, and finally through main suppliers after capacity recovery. Lucker and Seifert (2017), instead combine risk mitigation inventory, dual sourcing, and agility capacity to build up resilience in an SC. Aldrighetti *et al.* (2023), include backup suppliers, new capacity, and capacity extension and/or protection at existing nodes. While these studies provide valuable insights into disruption mitigation strategies, they often rely on simplified models or specific assumptions that may not fully capture the complexities of real-world supply chains. The present work aims to bridge this gap by developing a comprehensive simulation model that can be adapted to various supply chain structures and disruption scenarios.

3.Case study description

In order to show the capabilities of SC resilience simulation tools in the assessment of mitigation measures, we refer to a reference supply chain inspired by Habibi *et al.* (2023). The original supply chain, relating to biomass, has been modified to reflect a more generic case of manufacturing goods. For the sake of brevity, the structure of the supply chain is extremely schematic, in fact, it includes a single type of finished product generated from a single type of raw material and a single connection for each pair of linked nodes. We utilize the simulation model succinctly described in the Appendix as well as in Donati (2023) and Caputo *et al.* (2023). The simulation model is implemented in a Matlab environment and is based on a discrete-event simulation paradigm. It consists of three overlapping layers representing nodes, paths, and transporters. Nodes represent manufacturing companies or warehouses, paths represent physical connections between nodes, and transporters are responsible for moving materials along these paths. The model simulates

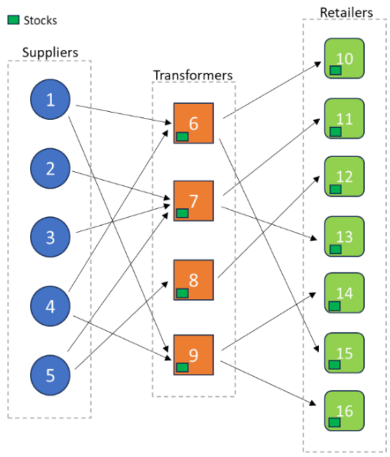

Figure 1. SC inspired by Habibi et al. (2023)

material flows, information flows (through orders), and the impact of disruptions on node functionality and path availability. The primary performance measure used is the Resilience Index (RI), which is the ratio of the integral of the total service level under disrupted conditions to the integral of the service level under normal conditions. The SC (Fig. 1) includes three tiers: the first is composed of suppliers, represented by warehouses; the second tier is composed of transformer (i.e., manufacturer) nodes; the third is made up of retailer warehouses.

Suppliers provide transformers with raw materials, while transformers, after the production process, supply retailers with finished products to fulfill final customers' demand. The main input data characterizing the case study entities are shown in Table 1.

Table 1. Input data characterizing nodes and product

	Nominal production capacity [unit/day]	Maximum inventory [unit]	Reorder level [unit]	Reorder lot [unit]
Suppliers		200	150	40
Transformers	6	200	150	40
Retailers		200	150	40
	Daily market demand (for each retailer) [unit/day]		**Promised delivery time [days]**	
Final product	Normal Distribution, $\mu = 2$ $\sigma = 3$		7	

The hypothesized disruptive events are the recent Houthi attacks in the Red Sea which are disrupting navigation routes, and the consequent use of the Suez Canal, since October 2023.

The attacks forced hundreds of vessels to divert their route circumnavigating Africa, resulting in increased time and costs (Nicola, 2023). It is assumed that the disruption affects the SC according to two different scenarios. In

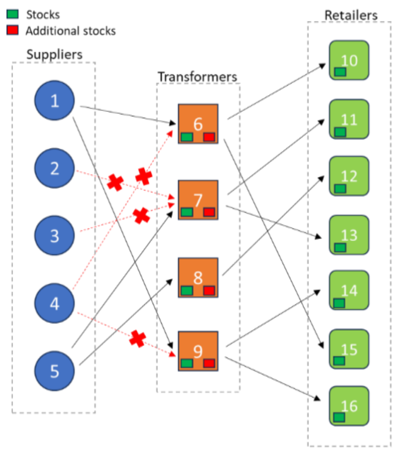

Figure 2. Scenario A Case 1A

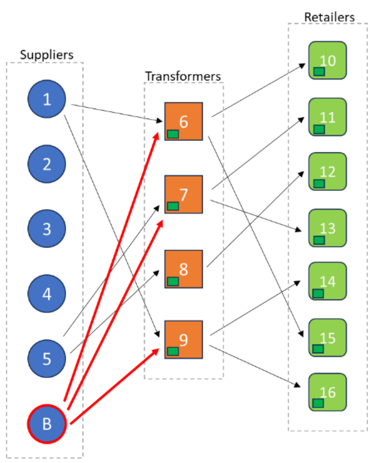

Figure 3. Scenario A Case 2B

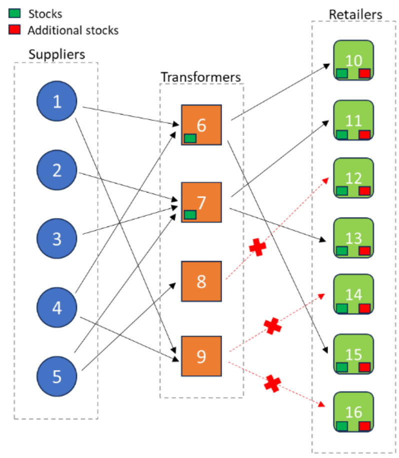

Figure 4. Scenario B Case 1B

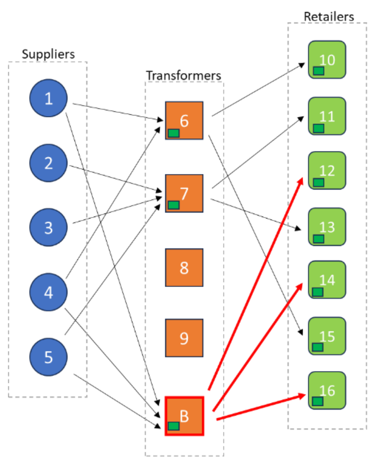

Figure 5 Scenario B Case 2B

scenario A the connecting arcs upstream of the transformer nodes are interrupted, while in scenario B the downstream arcs, are indicated by red crosses in the figures. For brevity, we only consider interruptions of the paths which, in this case, generate the complete interruption of multiple nodes as no alternative paths exist. In fact, it is assumed that the customers of the affected nodes are not able to bear the increased transport costs resulting from the circumnavigation of Africa, excluding this option a priori. The interruption lasts from simulation day 100 to day 200. In Scenario A three suppliers (ID 2, 3, and 4), located in the Far East, are affected by the blocking of corresponding paths, used to reach transformer nodes located in Europe. In Scenario B, instead, 2 transformer nodes (ID 8 and 9) are located in the Far East and need the interrupted paths to reach their European retailer customers.

Both scenarios A and B were simulated in different conditions, labeled 0, 1, 2. The reference case "0" does not consider any specific mitigation measures. Case 1 includes extra inventory as a mitigation measure (stock reorder level is increased from 150 to 250 units and the maximum inventory volume from 200 to 300 units). In particular, simulation 1A includes extra inventory in transformer nodes, while 1B involves additional inventory in retailer nodes. Case 2 includes backups, in particular the activation of a backup supplier node in case 2A, or the activation of a backup transformer node in case 2B. The backup node has the same capacity as any of the failed nodes. Therefore, lost capacity is only partially compensated, as it is likely that the available backup capacity may be lower than that used under ordinary conditions. In each scenario, the backup node is activated from day 130, until the disturbance ceases. This delay simulates the time necessary for identifying and reaching an agreement with a new supplier. Figures 2 to 5 depict the scenario and adopted mitigation measures.

4.Results and Discussion

Plots in Figures 6 and 7 show the weekly moving average of service level (SL) trends, over multiple replications, in each considered Scenario/Improvement Measure combination. The RI index (Eq. 1 in the Appendix), has the denominator calculated in the case without disruption and mitigation measures. This trend serves as a reference and is the same in any combination (represented in grey in the figures). For the sake of scenario comparison, the integration time interval, equal for each combination, starts at the smallest date, among all the cases being compared, in which the SL value is lower than the scenario without disruption and remains lower continuously throughout the disrupted period.

The end of the integration period, instead, is defined as the maximum day, among all cases, in which the trend under analysis is continuously lower than the reference

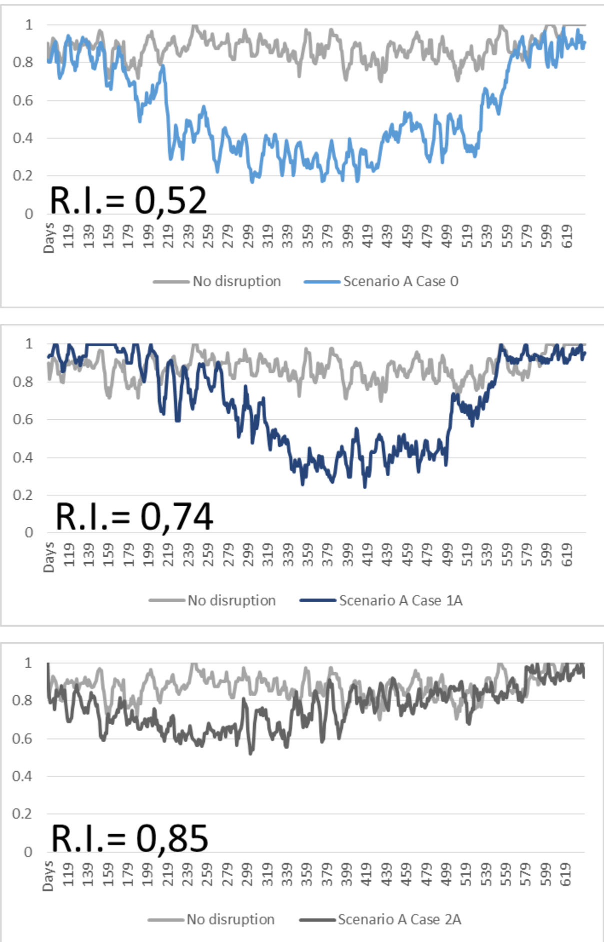

Figure 6. Service level trend in Scenario A cases

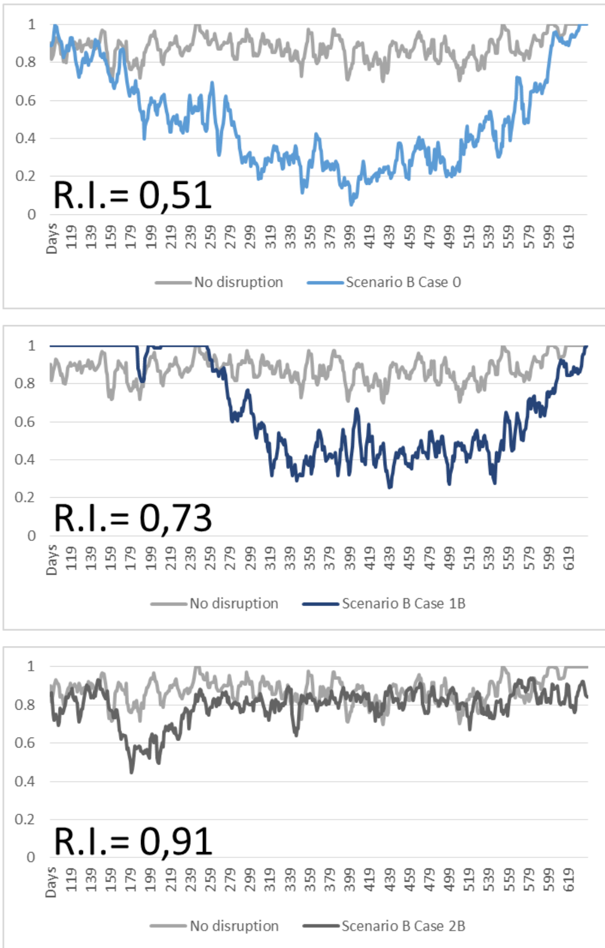

Figure 7. Service level trend in Scenario B cases

trend. The resulting integration interval is from day 147 to 638. In both scenarios, the case where the service level deviates most from undisturbed conditions is case 0, i.e., in the absence of improvement measures, as expected. Obviously, even the resilience index is lower in this case, as shown in Figures 6 and 7. Increasing inventories, both in 1A and 1B versions, improve performances even before the occurrence of the disruptive event, in which a higher service level than the reference case is noted. Furthermore, the extra stocks delay disruption effects in both cases 1A and 1B, although for a limited duration until extra stock exhaustion. Cases 2A and 2B, relating to the additional backup node, have opposite behavior. In this case, the delay in activating the back-up node generates a performance loss in the interval where both the disturbed nodes and the back-up node are absent. It can be noticed that after an initial drop in performance, the system recovers a level comparable to the initial one in a shorter time as compared to the use of extra stock. In this simplified example, backup nodes perform better than extra stock irrespective of the position of interrupted routes. The results of the simulations are consistent with the behavior expected from the supply chain in the considered conditions. While the above results are not intended to be generalizable, they serve as an example demonstrate that alternative disruption mitigation measures have different level of implied performances, so that, a cost-effectiveness analysis is required to identify the best manner to improve SC resilience in any specific instances. This kind of analysis asks for dedicated analysis and simulation models such as the one referenced here.

5.Economic assessment of mitigation measures

Mitigation measures discussed in Section 2 may be characterized by both fixed and variable costs, while the costs may be borne prior to the disruption and regardless of the disruption occurrence, in case of proactive measures, as well as following the disruption in case the measures are exploited. The table in Appendix II shows the possible cost structure of several mitigation measures as modelled in the literature (Aldrighetti *et al.*, 2021; Aldrighetti *et al.*, 2023; Alikhani *et al.*, 2023; Chen *et al.*, 2021; Hosseini *et al.*, 2019; Kamalahmadi *et al.*, 2017; Lucker and Seifert, 2017; Sawik, 2022; Torabi *et al.*, 2015). The net expected value of a mitigation measure (NEVMM) may be stated as:

$$\mathrm{NEVMM} = -\mathrm{FC} + \sum_{s=1}^{S} \mathrm{ps}_i (\mathrm{EB}_i - \mathrm{VC}_i) \tag{1}$$

where FC is the fixed cost of measure implementation which is borne prior to disruption occurrence, and EB_i is the economic benefit deriving from the implemented measure in case of occurrence of *i*-th disruption, having a probability of occurrence psi. VC_i are the variable costs consequent to the implemented measure in case the *i*-th disruption occurs. S is the set of considered disruptions and s = 1..S is the disruption identification index. We assume that the disruption may determine both an economic penalty (EP) due to late deliveries and lost sales in case delivery tardiness is greater than a maximum customer waiting time. The benefit from mitigation measures derives from the reduction in the above penalty when measures are implemented vs the case when no mitigation measure is applied.

$$\mathrm{EB}_i = \mathrm{EP}_i\big|_{\text{no mitigation}} - \mathrm{EP}_i\big|_{\text{with mitigation}} \tag{2}$$

$$\mathrm{EP}_i = \sum_{j=1}^{N} \mathrm{d}_j \mathrm{pgr} + \sum_{k=1}^{M} \mathrm{pmv}_k \tag{3}$$

being d_j the delivery delay for a *j*-th customer order, N the set of the order delivered late, pgr the daily economic penalty for late delivery, pmv_k the economic penalty for lost sale (i.e., according to the situation a constant, or a percentage of the order value or its contribution margin), *k* the index identifying cancelled order, and M the set of cancelled orders due to excessive delay. N, M, d_j, EP_i, and EB_i are computed based on the simulation results in each considered disruption scenario.

6.Conclusions

The use of a new framework for SC simulation and resilience assessment has been demonstrated by comparing the effectiveness of several measures useful to mitigate disruption effects. While the developed model is descriptive instead of prescriptive, in that it does not allow performance optimization, it allows us a more realistic description of the SC structure and working logic as compared to analytic optimization models or commercial simulation tools. The proposed simulation model distinguishes itself by offering a more granular and adaptable framework for simulating supply chain disruptions than traditional approaches. Unlike many existing models that rely on simplified representations or specific assumptions, this model allows for a detailed representation of the supply chain's operational and structural complexities, including various types of disruptions, the dynamic recovery of nodes and paths, and the implementation of diverse mitigation strategies. In the future the model will be extended to include the computation of several alternative performance measures describing other aspects of the SC resilience and the computation of cost of mitigation measures will be implemented in order to allow cost-benefit analyses and comparison for different SC structures and disruption scenarios. Based on the results obtained in the considered case study, although not generalizable, it appears that the proposed model is useful for assessing the consequences of a disruptive event on the performance of a supply chain, and for calculating a resilience index resorting to a realistic and detailed simulation of disruptions propagation which takes into account the structure and inner working logic of the system. This helps to compare, on a consistent basis, the effectiveness of any improvement measures.

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Appendix A. MODEL DESCRIPTION

This Section succinctly describes the overall simulation model framework. Further details are in Caputo *et al.* (2023), and Donati (2023). The model is capable of representing the physical structure and relational dynamics among entities in the supply chain as well as their internal operations. Any complexity level of SC in terms of number of nodes, topology, materials variety, disruption scenarios, and time trend of functionality recovery of entities can be accounted for. The simulation framework, built in Matlab environment, includes three overlapping layers representing respectively nodes, paths, and transporters (Fig. A1). Nodes have a predefined geographical location and represent manufacturing companies or warehouses. Manufacturers procure necessary raw materials, produce, and supply downstream the products while warehouses serve as intermediate storage for materials. Both can act as customers for upstream nodes and as suppliers for downstream nodes. Final customers are served by warehouses pertinent by geographical area. Randomly generated customer orders are issued to the specific area retailer. In the event of a failure of a retailer node, orders will be redirected to adjacent nodes capable of providing the requested product, if available. Paths are physical connections (road, maritime, railway, air routes) utilized by transporters to move materials between an origin node and a destination node. Paths can be shared by a specified subset of different transporters and may not be utilized by others. Nodes involved in the interruption of a path might be able to use alternative connections, if available, which may be characterized by higher travel times. Transporters are responsible for moving materials from the supplier node to the destination node along the paths. They are not assigned a specific geographical location and their capacity, subject to disruption, is that of the utilized vehicles. In case a path is interrupted, all transporters using that path will be unable to transport materials unless an alternative path is found, until the path is restored. The model simulates flows for all the materials that make up the Bill of Materials (BOM) of the finished products considered by the supply chain. Material flows allow for the variation of node inventories. Information flows are simulated through the exchange of various types of orders, representing requests for material supply or their transportation. The model adopts the paradigm of discrete event simulation. According to the user-defined disruption scenario, the analyst can specify a time trend of capacity loss (i.e. residual functionality) for each node or transporter, as well as the interruption of selected paths. The adopted resilience performance measure (Resilience Index RI) is the ratio of the integral of the total service level under perturbated conditions (SLP) to the integral of the service level under normal conditions (SL) over the same time interval. The two trends result from the averages of two separate sets of simulations (with and without perturbation).

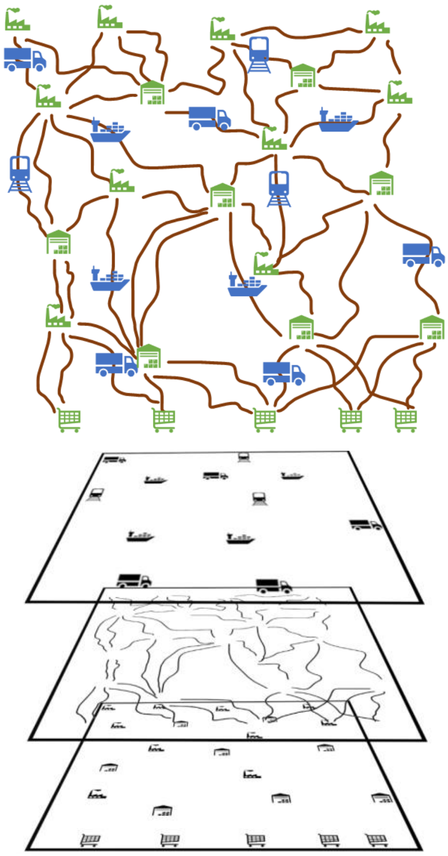

Figure A1. The simulation framework

$$\text{Resilience Index} = \frac{\int_{t_0}^{t_h} \text{SLP}(t)dt}{\int_{t_0}^{t_h} \text{SL}(t)dt} \quad \text{(A1)}$$

Normalization of service level respect for the unperturbed situation is required because the original service level without disruption may be lower than unity, otherwise, the perturbed service level could be underestimated. In turn, the Service Level is calculated daily as follows

$$\text{SL} = \frac{\text{OSR}(t)}{\text{OT}(t)} \quad \text{(A2)}$$

both in normal or perturbated conditions as the ratio of the number of orders fulfilled without delay until day t (OSR) to the number of orders whose expected delivery date is on day t (OT). The SC is thus simulated twice, either in unperturbed or disrupted conditions. In turn, each of the two sub-phases involves iteratively the execution of 9 simulation processes, for each simulated day, and each node, each one correlated with a specific type of entity (Figure A2). In step 1 the daily value of entity functionality is updated according to the user-defined temporal profile of capacity. In step 2 new customer orders are randomly generated according to user-defined probability distributions and sent to retailers. In step 3 manufacturer nodes collect new orders. In case existing inventory allows order fulfillment a transportation order is issued to a transporter and the inventory level is updated as soon as transportation is started.

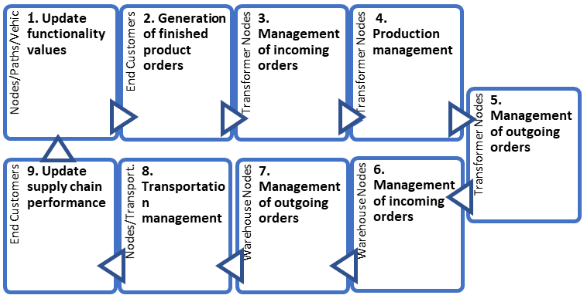

Figure A2. Scheme of daily simulation routine

Otherwise, a check is made on released processing orders. In case the amount is enough for future order fulfillment the requested amount is reserved, otherwise a new internal production order is issued. Internal production orders are completed (Step 4) as soon as the required cumulative work hours, resulting from the order quantity, have been allocated to that order on the basis of daily available capacity, provided that a minimum process lead time (user-defined and deriving from process constraints) from the start of order processing has expired. This determines the order fulfillment date and finished goods inventory update. Processing of a manufacturing lot determines raw materials consumption which can trigger replenishment orders towards upstream suppliers on a reorder level policy (Step 5). Separated orders to respond to external customers or to replenish internal inventory are thus included. Step 6 manages incoming orders by warehouses. Each node scans in FIFO sequence its list of incoming orders, checks the availability of inventory for each order fulfillment, and eventually moves the order from the incoming orders list to the transportation orders list, reducing the inventory of the ordered amount. If the inventory is insufficient, the node waits for materials replenishment, managed by process #7 and the unfulfilled incoming order remains in the list to be checked the subsequent day. In process 8 transporters take charge of orders awaiting transport from shipping suppliers and deliver them to receiving customer nodes, updating the related parameters for each involved actor. The process reviews the lists of orders awaiting transport on each node. For each shipping node list, it generates a list of paths, ordered in ascending order based on distance (i.e. travel time) connecting the shipping and receiving nodes. For each candidate path it identifies qualified transporters with available vehicles and a sufficient cargo volume and randomly selects one. After transportation completion (i.e. when the current date equals the planned delivery date) the vehicle is released the transportation order is deleted, the customer's inventory is increased, and the outgoing order from the supplier is eliminated. Finally, in Step 9, on the basis of the fulfilled order, the SC performance measure is updated daily.

Appendix B. MITIGATION MEASURES COST MODELLING APPROACHES

Mitigation measure	Fixed costs (pre disruption)	Variable cost (post disruption)	Activation delay	Notes
Pre-positioned safety stocks (either upstream, within, or downstream of the manufacturing nodes)	Prepositioned stock purchase and holding cost + warehouse installation fixed cost	Delivery cost	None	▪ The measure is operative until stock exhaustion
Sourcing from multiple suppliers	Contracted capacity cost	Purchase cost (proportional to purchased quantity) + delivery cost	None	▪ Possible increase of non-conformity cost and increase of unit purchase cost to a single supplier
Sourcing from backup suppliers	Contract activation cost	Purchase cost (proportional to purchased quantity) + delivery cost	Fixed delay to activate the alternative supply mode plus augmented delivery lead time	▪ Supply capacity may have an upper bound ▪ Higher unit purchase cost
Sourcing from protected suppliers	Contract activation cost + Capacity protection cost (proportional to the amount of protected capacity)	Purchase cost (proportional to bought quantity) + delivery cost	Fixed delay to activate the alternative supply mode plus augmented delivery lead time	▪ Higher unit purchase cost ▪ Finite protected capacity
Back up capacity in alternative production sites	Fixed cost of additional capacity (proportional to the amount of additional installed capacity)		Fixed delay to activate the alternative supply mode plus augmented delivery lead time	▪ Finite backup capacity
Extra capacity at the production site	Fixed cost of additional capacity (proportional to the amount of additional installed capacity)		None	▪ Finite backup capacity
Alternative transporters or routes	Contract activation cost	Transportation cost	Possible delays due to capacity saturation of alternative providers and longer routes	▪ Transportation costs dependent on logistic suppliers and alternative route