

SUPPLY CHAIN RESILIENCE OPTIMIZATION WITH AGENT-BASED MODELING (SCROAM): A NOVEL HYBRID FRAMEWORK

Anastasia Anagnostou¹, Kate Mintram¹, and Simon J E Taylor¹

¹Modelling and Simulation Group, Dept. of Computer Science, Brunel University, London, UK

ABSTRACT

Supply chains are vulnerable to an array of exogenous disruptions, including operational contingencies, natural disasters, terrorism, and political and geopolitical instability. In order to ensure resilience to these disruptions, supply chains can use mitigation strategies to minimize risk and maximize recovery. Modeling approaches can be utilized to determine the most appropriate mitigation strategies for a specific scenario; however, there is currently no recognized modeling framework which can be applied to all supply chain sectors. This paper describes the key disruption risks to supply chains; the resilience and optimization strategies and performance metrics employed by supply chains to mitigate these risks; and the applications of simulation modeling in supply chain management. We present a hybrid framework for using agent-based modeling, alongside early warning systems, many objective optimization and option awareness analysis, to manage exogenous risks for a non-specific supply chain.

1 INTRODUCTION

A supply chain is a network of facilities and distribution mechanisms that performs the functions of material procurement, material transformation to intermediates and final products, and distribution of these products to customers (Papageorgiou 2009). The ability of firms to produce and distribute their products can, however, be severely disrupted by devastating natural disasters, political turmoil, fuel crises, diseases and terrorism (Tukamuhabwa et al. 2015). The complex networks of autonomous components within a supply chain makes them inherently vulnerable to these disruptions, where disruption to one component results in a cascading effect on the rest of the supply chain. This is known as the ripple effect (Dolgui et al. 2018).

The impact of disruptions on supply chains depends on the vulnerability of its elements to disruption risks. Wagner and Bode (2006) investigated the relationship between supply chain vulnerability and supply chain risk. They conducted a large-scale survey aiming to understand the effect of supply chain design on supply chain risk exposure. They noted that most of the time these relationships seem obvious by intuition, nonetheless there is lack of empirical work to substantially quantify the impact of supply chain disruption risks and vulnerabilities relationships. It is therefore challenging to fully understand the mitigation and adaptation actions that companies should adopt in order to alleviate the impact of disruption.

There is a body of research attempting to support companies being more robust and resilient to supply chain disruption risks. Fiksel (2006) defines supply chain resilience as “the capacity for an enterprise to survive, adapt, and grow in the face of turbulent change.” To support companies to understand their capacities to overcome disruption, Pettit et al. (2019) propose a resilience assessment framework that attempts to identify resilience gaps by quantifying and linking capabilities and vulnerabilities within a supply chain. Arguably, selecting the appropriate resilience strategy for different disruption risks is not a trivial task for global supply chains. Further, localized risks and consequently localized mitigation actions may have different, and sometime conflicting, impacts on downstream and/or upstream elements of a supply chain.

Here, we propose a hybrid framework based on agent-based modeling to support supply chain management decision making with respect to resilience. Our work adds to the conceptualization of Fiksel

(2006) by acknowledging that actions of mitigation and adaptation can be anticipatory or reactive. The centric component of our hybrid framework is an agent-based model of a supply chain facilitating the simulation execution of different resilience strategies. The peripheral components of our hybrid framework are Early Warning Systems (EWSs), Many Objective Optimization Problem (MaOP) implementation (Li et al. 2015), and Option Awareness (OA) analysis (Pfaff et al. 2013). Section 5 gives an overview of these concepts and discusses how the combination of these components may help better decisioning making in supply chains with respect to the risk-benefit trade-off of different resilience strategies.

The paper is structured as follows. Section 2 identifies the key disruption risks to global supply chains. Section 3 discusses the resilience strategies that supply chains can adopt. Simulation modeling efforts for supply chain management are analyzed in Section 4. In Section 5, we present our novel hybrid conceptual framework for incorporating early warning systems, many objective optimization and agent-based simulation to support supply chain resilience analysis. The Section also demonstrates the application of our framework through a generic supply chain use case example and, finally, Section 6 concludes the paper.

2 DISRUPTION RISKS TO SUPPLY CHAINS

Modern supply chains are highly complex networks of entities, spreading in wide geographical areas, most of the times across the globe. At the same time, in recent years, we have observed several events that have disrupted supply chains with devastating impacts on economies. Further, due to globalization, the effects of local catastrophes reverberate across the world and have indirect impacts to entire global supply chains. Supply chain disruptive events can be either external, such as natural disasters, or internal, such as equipment malfunctions (Wagner and Bode 2006).

We attempted to categorize the disruption risk in four broad categories. The rationale behind this categorization is twofold, first to capture the nature of the risk in a localized manner and second to support incorporating the disruptions in our hybrid modeling framework. Table 1 summarizes the key disruptions to global supply chains and highlights some of the historical damages that each risk has caused to industries. The list is by no means exhaustive, nonetheless it is sufficiently inclusive to comprehensively model the hazards and the impact of different mitigation strategies in a generic manner that applies to different industries.

Whilst all supply chains will be vulnerable to some degree to the disruption risks described in Table 1, the level of risk is highly variable between industries. It is largely dependent on the nature of the product, the attendant length and complexity of the supply chain, and the resilience strategies in place to reduce the risk of disruption. An article by McKinsey & Company summarizes the expected net losses of thirteen different industries over a 10-year period and highlights the commercial aerospace industry as the most vulnerable, and the pharmaceutical industry as the least vulnerable (Foster et al. 2021). They attribute the differences to the least vulnerable industries having high inventory levels and low costs incurred in production.

The category of disruption risk also varies across different industries. The pharmaceutical industry, for example, is most vulnerable to cyberattacks and trade disputes, whereas the communication equipment industry is also vulnerable to geophysical events (Foster et al. 2021). In 2017, Merck reported that a cyberattack that occurred in June 2017 unfavorably affected revenue in the fourth quarter of 2017 by \$125 million and for 2017 and 2018 by \$260 million and \$150 million, respectively (Merck 2019). With this in mind we now give an overview of different supply chain resilience strategies.

3 SUPPLY CHAIN RESILIENCE STRATEGIES

Supply chain resilience is the capacity for an enterprise to survive, adapt, and grow in the face of turbulent change (Fiksel 2006). Supply chain resilience strategies can mitigate for the disruptions described above and allow supply chains to recover faster. They can be either proactive, reactive or both. Notably, as Pettit et al. (2019) suggest, supply chain resilience is a globally relevant construct, cutting across industries and cultures.

Table 1: The key disruption risks to supply chains.

Risk	Description	Exemplar case study
Operational contingencies	Equipment malfunctions and systematic failures, cybersecurity breaches, abrupt discontinuity of supply (e.g., supplier goes out of business), human-centered issues (e.g., strikes, fraud).	August 14th 2003 grid blackout in the Northeast region of the US (Kleindorfer and Saad 2005).
Natural hazards	Earthquakes, hurricanes, storms, extreme heat.	The Great East-Japan Earthquake of 2011 substantially reduced production throughout Japan. Tokui et al. (2017) estimated that the economic impacts of the supply chain disruptions as a result of the earthquake amounted to at least 0.35% of GDP.
Terrorism and political and geopolitical instability	A widespread occurrence of an infectious disease over a whole country or the world at a particular time.	The 2020 Covid-19 pandemic affected the entirety of the global food supply chain, from the field to the consumer (Aday and Aday 2020). As an example from the production side, it is estimated that pork production decreased by 25% in late April (Flynn 2020).
Foreign supply chain dependency	Sabotage and destructive competitive acts, and political instability in different countries at different times have increased globally and are having a greater effect on supply chains as they increase in outsourcing and global complexity (Kleindorfer and Saad 2005).	After the 9/11 terrorist attack, global supply chains were disrupted largely due to the reaction of the US government (Sheffi et al. 2003). Toyota and Ford were vulnerable to transportation disruptions because they were using a “Just-in-Time” inventory system, keeping raw materials and components on hand for only a few hours of operation (Khan and Zhang 2020). Ford had to shut down five of its US plants, partly because it could not get enough parts from suppliers in Canada. The result was a 13% drop in production in that quarter (Sheffi et al. 2003).
	The problem of foreign supply chain dependency is of particular concern to localized regions as a significant portion of their economy is dependent on supplies from overseas (Rosen et al. 2022).	Dependence of the US on the Asian supply chain. (Rosen et al. 2022) used a simulation modeling framework to show that Alabama’s state economy would decline by a little more than 3% when discontinuing supplies from China, which would reach up to an average of \$10.572bn per day towards the end of the year.

3.1 Cooperation and Collaboration

Cooperation and collaboration amongst business entities is considered a promising resilience strategy, and studies have revealed a positive connection between communication, cooperation, integration, and supply chain resilience (Wieland and Wallenburg 2013). Collaboration encompasses information sharing, decision synchronization, resource sharing, collaborative communication, and goal alignment (Lohmer et al. 2020). (Li et al. 2017) investigated the value of information sharing in a generalized three-echelon supply chain using a systems dynamic approach. Three decision making rules based on different levels of information sharing were developed, and the authors concluded information sharing as a valuable resilience strategy.

Blockchain technology (BCT) is considered a promising new approach to increase collaboration and transparency between business entities. The widespread uptake of BCT within supply chains is looking likely; according to a study by KPMG in 2019, 48% of the 740 global technology leaders surveyed believe that BCT is likely or very likely to change their business in three years (KPMG 2019).

Blockchain refers to a ‘consecutive list of time-stamped records sequentially linked using cryptography. A peer-to-peer network of participating nodes contribute to the formation and validation of blockchain and manages distributed consensus by network majority’ (Chang and Chen 2020). Blockchains are immutable, transparent (single source of truth), disintermediate, irreversible, and have automation potential through smart contracts (Babich and Hilary 2020; Lohmer et al. 2020).

Lohmer et al. (2020) used an agent-based model to analyse the impact of blockchain technologies on supply chain resilience (measured as the total costs, recovery time, and the number of affected partners of the entire network). The authors identify three potential BCT application scenarios to support supply chain resilience: 1) unidirectional sharing of demand data in vertical collaboration; 2) an increased state of collaboration in the supply chain as information is shared bidirectionally between all entities using a consortium blockchain; 3) vertical information sharing and collaboration, as well as horizontal collaboration between entities on the same supply chain tier using a Proof-of-Authority consensus. The third scenario was simulated, and compared to the baseline model, they found using blockchain to share data in the supply chain can significantly reduce the number of partners affected by a disruption, the disruption costs, and the recovery time in the network.

3.2 Multi-sourcing

One of the most common strategies for building resilience is to expand the network of suppliers. According to a 2022 survey undertaken by Deloitte and the Chartered Institute of Procurement & Supply (Deloitte 2022), 70% of private and 63% of public sector respondents have increased their level of dual and multi-sourcing within their strategic spend category, and 38% have entered into new supply chain markets to reduce their risk of discontinuity of supply in the last 5 years.

Different types of multi-supplier networks can be built within a supply chain; for example, constant multi-sourcing among internal suppliers (controlled by a centralized headquarter), or contingent multi-sourcing among independent external suppliers (Seok et al. 2016). The former is more commonly used within supply chains because of the ease of collaboration and shared goals; however, (Seok et al. 2016) argue that under specific conditions, selective contingent collaboration can achieve more resilient and cost-effective performance when disruption occurs.

Another multi-sourcing strategy is spot-purchasing. This involves buyers make spot purchases at market price on the day that the commodity is needed, with no underlying contracts. It is considered a powerful tool for dealing with disruption risks (Namdar et al. 2018).

3.3 Physical Buffers

A company in a high-risk area may harden its physical assets to withstand disruption by striking a better balance between just-in-time and just-in-case inventory levels (Foster et al. 2021). This is usually in the form of inventory or capacity buffering. Inventory buffering incorporates additional inventory at different stages of the supply chain (e.g., in a warehouse), meaning resources can be immediately available in the

case of a disruption. This prevents companies having to go back to the network of suppliers to provide emergency stock. Capacity buffering adds additional operation setups to the supply chain (e.g., additional machines in case of failure) (Ergun et al. 2023).

Physical inventory and capacity buffers are well-suited to disruptive scenarios that are comparatively likely. But they are too expensive to justify for rare events (Ergun et al. 2023).

3.4 Postponement

Postponement provides supply chains with flexibility during a crisis by deferring demand to a future period (Tukamuhabwa et al. 2015). Al-Hakimi et al. (2022) reveal that postponement positively and significantly affects supply chain resilience for small and medium enterprises (SMEs). (Avanzi et al. 2013) describe how exploiting postponement options enabled Mallefer, a Swiss manufacturer of cable extrusion equipment, to build resilience strategies against disruptions caused by economic difficulties and to gain a competitive advantage by creating volatility and later effectively responding to it (Tukamuhabwa et al. 2015).

3.5 Other

Additional resilience strategies identified in the literature include increased security, economical supply incentives, supplier relationship building, and demand forecasting (Lohmer et al. 2020).

4 SIMULATION MODELING IN SUPPLY CHAIN MANAGEMENT

The above has given an overview of resilience strategies in supply chains. However, most strategies still need some method to evaluate their potential effectiveness. Supply Chain Management (SCM) attempts to balance production and consumption across a supply chain that favors a global, holistic view in which business entities collaborate to optimize the whole rather than their own individual elements. As evidenced by some of the studies described above, simulation models provide a powerful tool for SCM and they are routinely used by companies to ensure resilience and optimize processes (Mustafee et al. 2021; Terzi and Cavalieri 2004). Terzi and Cavalieri (2004) in a review of 80 articles, ascertained that the general objectives that simulation is called to solve in SCM are (i) to enable companies to perform powerful what-if analyses leading them to better planning decisions; (ii) to permit the comparison of various operational alternatives without interrupting the real system and (iii) to permit time compression so that timely policy decisions can be made. The simulation techniques most frequently used in SCM are discrete-event simulation (DES), systems dynamic (SD) approaches and agent-based modeling (ABM). Generally speaking, SD is mostly used to model problems at a strategic level, whereas DES is used at an operational/tactical level (Tako and Robinson 2012). Tako and Robinson (2012) found that DES has been used more frequently to model supply chains than SD, with the exception of the bullwhip effect, which is mostly modeled using SD. ABMs, on the other hand, can capture much more complicated behavior, dependencies and interactions thus providing for deeper insight into the modeled system (Borshchev and Filippov 2004).

It is evident from the high number of industrial case studies that simulations are successfully used in practice for supply chain optimization (e.g., Maina and Mwangangi 2020; Persson 2003; Turner and Williams 2005). For example, AnyLogic (AnyLogic n.d.-b) describe how GlaxoSmithKline used DES to determine the optimal vaccine supply chain design from the standpoint of costs and service level. Similarly, Microsoft used an SCM simulation solution to achieve one set of planning, execution and improvement rules for managing all products and order fulfilment strategies. Microsoft reported that their inventory levels dropped by \$250 billion, leading to reduced markdowns and reduced excess and obsolescence of over \$100 million (AnyLogic n.d.-a).

Whilst ABMs often require a higher level of complexity, and thus computational demand, they provide a wider approach to SCM. Agents (in this case, supply chain entities) within the model are characterized by unique attributes and behaviors, who interact together, and with their environment so that the generated outcomes emerge from these behaviors and interactions. They can therefore be used to model the emergent effects of changes to attendant characteristics, e.g., due to disruptions, on supply chain key performance

indicators (KPIs). There is an array of ABMs in the literature developed for the optimization of specific supply chains (e.g., Jetly et al. 2014; Lohmer et al. 2020; Pourghahreman et al. 2018; Proselkov et al. 2024; Zhu et al. 2024).

Simulation modeling for SCM relies on KPIs which are employed to capture the influence of an action or event on the system response across the multiple tiers that comprise the supply chain (Munoz and Dunbar 2015). Two recent comprehensive literature reviews, (Karl et al. 2018; Singh et al. 2019), have summarized the KPIs suitable for assessing supply chain resilience performance (see Table 2).

Given that simulation modeling has been widely used in supply chain management, the question remains as to how it can be used to help analyze different resilience strategies. In the next section we present one possible conceptualization of this.

Table 2: Key performance indicators commonly used for supply chain management (summarized from Karl et al. 2018; Singh et al. 2019).

Non-financial KPIs	Capacity utilization; stock level; quality of delivered goods; order lead time; delivery lead time; manufacturing lead time; on-time delivery of goods; supplier delivery efficiency; supplier rejection rate; consumer satisfaction; damage return rate; Lead time ratio; customer loyalty; product development cycle time; order-to-delivery cycle time; demand forecasts; energy consumption; peak demand; timely information about the event; real-time strategic decision; knowledge of operating assets; speed of recovery; loss per unit of time; culture of quality; effective communication; leadership and innovation; change in the configuration of the new product; increased inventory level; technological threats; lead time reduction; time to re-route requirements.
Financial KPIs	Cost efficiency; total cost; turnover; market share; net profit; inventory holding costs.

5 A HYBRID FRAMEWORK FOR SUPPLY CHAIN RESILIENCE OPTIMIZATION: AN AGENT-BASED MODELING APPROACH

Arguably a resilient supply chain is one that has disaster recovery or mitigation strategies already in place, or at least in preparation when signs of a potential disruption are being identified. A strategy might have different possible implementations. Simulation can be used to evaluate and rank these possible implementations in terms of supply chain KPIs. However, the number of KPIs and possible implementations may need some form of optimization to generate the most desirable set of outcomes. These then need to be presented to decision makers in a manner that enables them to choose the best implementation to recovery from the disaster. Simulation has already been identified as a useful tool in SCM. However, it needs to be contextualized. Ideally some form of EWS needs to be used to enable decision makers to identify potential hazards or disasters. According to the United Nations Office for Disaster Risk Reduction ([UNDRR](#)), EWS is “*An integrated system of hazard monitoring, forecasting and prediction, disaster risk assessment, communication and preparedness activities systems and processes that enables individuals, communities, governments, businesses and others to take timely action to reduce disaster risks in advance of hazardous events.*” When designing for resilient systems, it is very important to account for forewarnings about imminent hazards so risk mitigation strategies can be put in action in a timely manner in order to minimize their consequences. Further, the number of KPIs needed to be considered suggests some form of optimization based on approaches to MaOP that uses evolutionary computing techniques to consider a wider range of KPIs than traditional optimization techniques. Typically,

when an optimization problem has more than three objectives it is considered a MaOP and it is implemented using Pareto-based algorithms with modified Pareto dominance relation (Li et al. 2015). Given the extensive range of KPIs that exist in supply chains, optimization may lead to a wide range of potential strategy implementations. Some way of presenting these to a decision maker is therefore needed that considers their perception of the relative desirability of these available options. One such tool is option awareness, that is defined as *“the perception and comprehension of the relative desirability of the available options, as well as the underlying factors, trade-offs, and tipping points that explain that desirability”* (Pfaff et al. 2013). Such a tool, therefore, that considers the decision maker’s perceptual and cognitive abilities can support timely and better-informed decisions, especially in time of crises.

Here, we present our Supply Chain Resilience Optimization with Agent-based Modeling (SCROAM) framework. SCROAM is a hybrid framework for supply chain resilience optimization, using ABM as the primary tool. We chose ABM as the modeling paradigm for the supply chain simulation because we consider that it has an advantage over DES and SD in terms of topology flexibility, ability to model interactions between entities and ability to observe emergent phenomena. Supply chains are primarily networks of entities that are involved in the production and delivery of goods and services, and therefore, an agent-based simulation with network topology seems a natural choice. Also, in the context of resilient systems, it is important to model the communication between supply chain entities (e.g., through interactions between agents) in order to study resilience strategies related to cooperation and collaboration. Finally, ABM can reveal behaviors that emerge only when the entities interact in a wider whole (e.g., in a global supply chain network) and, therefore, can support better understanding of the wider impacts of hazardous events and the application of different resilience strategies. The hybrid framework integrates multiple toolsets to allow any supply chain to manage exogenous disruption risks and it is sufficiently generic so it can be integrated within any SCM system, with the aim to provide decision makers with the most efficient and effective mitigation options in the event of a disruption.

Figure 1 shows all of the component of SCROAM in a high level. The central component of SCROAM is the simulation of an ABM. As well as agent-based simulation, the framework entails three additional tools: an EWS, an MaOP implementation, and option awareness analysis (OAA). These are shown in the grey-shaded boxes in Figure 1. Apart from the main components, SCROAM consists of two more auxiliary

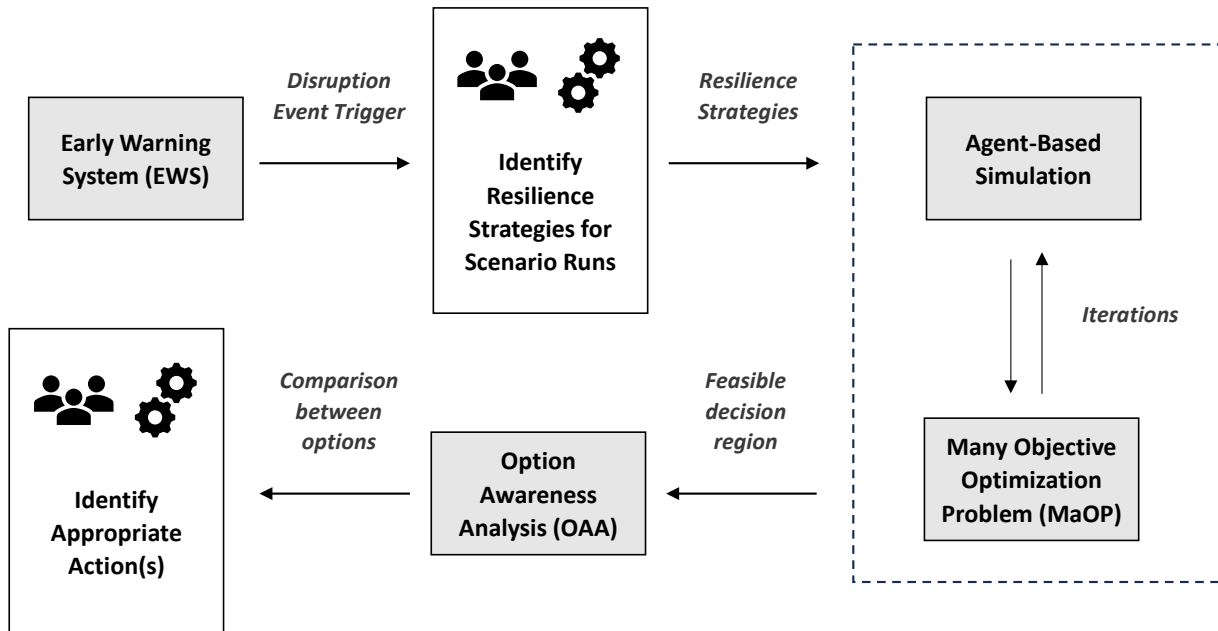


Figure 1: Components of the SCROAM hybrid framework.

modules to support users to identify resilience strategies and appropriate actions, respectively. The role of each component and the flow of actions are described below.

The first component of the flow is an EWS. EWSs are used for the early identification of hazards and are commonly used to alert governments, businesses and local communities about natural disasters (volcanoes and earthquakes), climate change related events (United Nations, n.d.), and infectious disease outbreaks (Meckawy et al. 2022). The integration of an EWS would allow supply chains to act contingently before an event happens so that resilience strategies can be put in place prior to the disruption taking place. To achieve this, after EWS triggers a disruption event in the system, all potential resilience strategies for the particular hazard are identified. This step can be conducted either by supply chain experts or by an automated scenario management tool.

After the appropriate resilience strategies have been chosen (refer to Section 2), the agent-based model can simulate the selected mitigation scenarios. Nonetheless, the complexity of global supply chains indicates a large number of KPIs and often these KPIs are conflicting either within or across supply chain elements. SCROAM therefore adopts a simulation optimization approach. To account for the many KPIs, MaOP algorithms are integrated within the agent-based model in order to obtain simultaneous optimization solutions which provide the best trade-off between conflicting objectives. The agent-based simulation and the MaOP algorithms implementation are executed iteratively, where the simulation produces the range of KPI values and the optimization evaluates that the outcomes are within the feasible region. The iterations stop when the set objectives are met. MaOP allows the objectives (i.e., the acceptable KPIs values) of the different attendants within the supply chain to be considered. The simulation optimization components are contained in the dashed box in Figure 1. The MaOP algorithms use a sub-set of chosen KPIs (see Table 2) to calculate the multiple options in the feasible decision region. These then are exported to the OAA component for further analysis.

The OAA component supports supply chain experts to make informed decisions. Model solutions are traditionally analyzed by a human operator who makes decisions based on ‘Situational Awareness’. The three stages of situational awareness involve (1) perceiving information about the environment; (2) comprehending the meaning of this information; and (3) projecting the state of the environment into the future (Klein et al. 2011a). Option Awareness extends the perception, comprehension and projection of this decision space by providing decision makers with a computer supported visualization of their landscape of options and projected outcomes (Drury et al. 2009; Klein et al. 2011b). Pfaff et al. (2010) demonstrated that under circumstances of deep uncertainty these decision space visualizations not only enabled decision makers more often to identify robust options, but to make decisions faster and with more confidence than unaided decision makers (Klein et al. 2011a). We therefore suggest OAA software as the final tool in our SCROAM hybrid framework to allow for optimal decision making that often takes place under extremely stressful conditions of an imminent crisis. The mitigation actions are identified and acted upon by supply chain experts manually or with the aid of automated suggestion tools.

5.1 Modeling Approach

We adopted a generic modeling approach where each supply chain element is modeled as an archetypal component (agent) with input and output links (interactions). The generic component’s logic includes the operational functions of each entity as well as properties that support risk modeling. The links represent upstream and downstream flow of material/goods, information and money, as well as multimodal transportation routes.

In our approach, we consider the geography of a supply chain as a way to model exogeneous risks in each supply chain element. We divide the environment in regions and places; each supply chain element is located in a place; and each place is located in a region. Hazards are related to places and regions. The supply chain elements that are situated in that place inherit the relevant risks. The links between elements may cross multiple regions with their respective risks.

5.2 Exemplar Generic Supply Chain Use Case

To demonstrate the application of SCROAM, we present a hypothetical example of a generic supply case use case. Let's assume the following supply chain for Good A (GA) (see Figure 2). There are three manufacturers (MA, MB, and MC) that produce GA. The raw materials are supplied by two suppliers (SA and SB). SA supplies MA and MB, and SB supplies MA and MC. The manufacturers provide GA to four retailers (RA, RB, RC, and RD) through three distribution centers (DA, DB, and DC). MA uses DA; MB uses DB and DC; and MC uses DC. Finally, RA gets GA through DA and DB; RB through DB and DC; RC through DC; and RD through DB.

The following scenario might happen. There is a natural disaster in the place that DC is located and affects its capability to receive and deliver GA. This hazard has a direct effect on MB and MC, as well as on RB and RC. The risks of major disruptions however are different for the above four entities. MB uses two distributors, DB and DC, while MC uses only DC. Similarly, RC receives GA only from DC and therefore, there is a high risk for major disruption. Different entities therefore would benefit from different mitigation strategies.

SCROAM can be used in the above scenario to support timely actions. The EWS sends a notification that a natural disaster is imminent in the place that DC is located. The affected entities may choose the following mitigation strategies: MB may postpone to fulfil the orders received from DC, it can still distribute GA through DB; MC may choose to expand its distribution network and start collaboration with DA and/or DB; RB may choose to increase the GA stock; and RC may expand its network to get GA from DA and/or DB. These mitigation actions are fed into the ABS to observe the wider impact. There are several KPIs that need to be estimated, such as *inventory holding cost*, *delivery lead times*, *delivery costs*, *customer satisfaction*, *speed of recovery*, among others. These KPIs need to be optimized, therefore the MaOP implementation runs iteratively with the ABS to meet the objectives of maximizing customer satisfaction and speed of recovery while minimizing inventory holding cost, delivery lead times, delivery costs, etc. SCROAM's simulation optimization produces a set of solutions that are superior in the solutions space. These solutions then are presented to the decision makers using the visualization and reasoning capabilities of the OAA component.

6 CONCLUSIONS

The research review presented in this paper describes the key disruption risks threatening the resilience of supply chains, including case studies of historical examples. It then goes on to describe supply chain

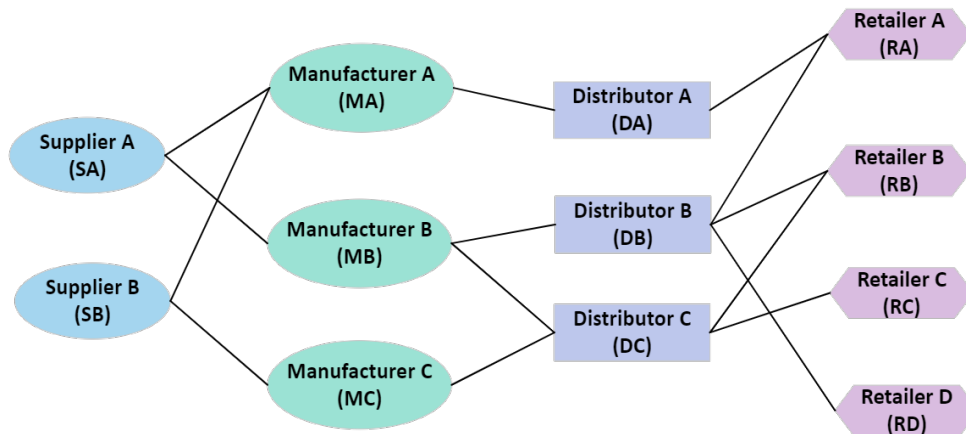


Figure 2: Example generic supply chain.

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resilience strategies that can aid in mitigating these disruptions, and explore the role of simulation modeling and key performance metrics as a tool for supply chain resilience optimization.

In this paper, we have presented a generic framework for rapid and effective supply chain management in response to exogenous disruption risks. Our hybrid SCROAM framework integrates early warning systems, agent-based modeling, many-objective optimization, and option awareness analysis tools to provide decision makers with a robust strategy to optimize resilience using specific KPIs. The application of SCROAM is demonstrated through a generic supply chain example. Further research will begin to bring this framework into fruition via the development of the computational approaches described.

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AUTHOR BIOGRAPHIES

ANASTASIA ANAGNOSTOU is a Senior Lecturer in the Department of Computer Science at Brunel University London and the co-lead of the Modelling & Simulation Group. Her main research interests lie in the areas of Advanced Computing Infrastructures for M&S, Open Science and M&S for Global Challenges primarily in Industry and the Healthcare sector.. She was Conference Co-Chair for the 10th OR Society Simulation Workshop (SW21). At the Winter Simulation Conference (WSC), she served as Chair of the PhD Colloquium Committee in 2018 and was Track Co-Chair for the Healthcare, Introductory Tutorials and Hybrid Simulation Tracks. She is also Program Chair for WSC 2025. She ACM SIGSIM Vice Chair and Associate Editor of the Journal of Simulation. Her email address is anastasia.anagnostou@brunel.ac.uk and her ORCID iD is <https://orcid.org/0000-0003-3397-8307>.

KATE MINTRAM is an Associate Lecturer in the Department of Computer Science at Brunel University London and is a member of the Modelling & Simulation Group. Her main research interest is using simulation modelling to address complex biological problems. She has developed population dynamics models for chemical risk assessments, climate change, understanding genetic viral resistance, and more recently has focussed on agent-based modelling for pandemic crisis management. Her email address is kate.mintram@brunel.ac.uk and her ORCID iD is <https://orcid.org/0000-0001-7180-9200>.

SIMON J E TAYLOR is a Full Professor at Brunel University London. He is also Co-Director of the Modelling & Simulation Group at the same University. His research has impacted over 3 million students and 300 universities in Africa, over 30 SMEs and several large enterprises including the Ford Motor Company and Sellafield. He co-founded the Journal of Simulation and the UK Simulation Workshop series and continues to be an editor at the Journal. He is a former chair and a member of ACM SIGSIM's Steering Committee. He is a member of the Computer Simulation Archive Advisory Committee and Executive Chair of the Simulation Exploration Experience. He continues to be interested in new technologies and simulation, international development and Open Science. His email address is simon.taylor@brunel.ac.uk and his website is <https://www.brunel.ac.uk/people/simon-taylor>.