A SIMULATION-BASED FRAMEWORK FOR THE ASSESSMENT OF SUPPLY CHAIN RESILIENCE

Edward Y. Hua[1], Kate S. Mintram[2], and Anastasia Anagnostou[2]

[1]Department of Simulation, Experimentation and Gaming, The MITRE Corporation, e-mail: ehua@mitre.org
[2]Modelling & Simulation Group, Department of Computer Science, Brunel University of London, e-mail: kate.mintram@brunel.ac.uk; anastasia.anagnostou@brunel.ac.uk

KEYWORDS

Many Objective Optimization, supply chain management, agent-based modelling, decision support.

ABSTRACT

Enhancing the resilience of a supply chain (SC) presents a critical and challenging problem. Many of the Key Performance Indicators (KPIs) that measure the operational effectiveness of different SC entities conflict with each other; such conflicts frequently arise between local optimization and global resilience across the SC. Moreover, the SC has hidden brittle points that adversaries could exploit, resulting in degradation of overall SC performance. We propose a framework for assessing the resilience of an SC exposed to exogeneous risks. The framework consists of an agent-based simulation model of a generalized SC, a simulation-based optimization algorithm, and a decision support capability. The project's continuing research will center on areas such as implementation of the framework to create a tool that enables the sponsor to make data-driven, informed decisions that buttress SC resilience to exogenous risks.

INTRODUCTION

Supply chain management (SCM) is one of the most consequential issues facing the business world today. A supply chain (SC) is a network of business entities engaged in tasks from production to consumption, involving forward and backward flows of products, information, and monetary exchange. SCM attempts to balance the production and consumption across a SC, and favors a global, holistic view in which business entities collaborate to optimize the whole rather than their own individual elements. For decades, companies have strived to make supply chain operations as efficient as possible. Global tension and uncertainty threatens to disrupt supply chain operations, forcing companies to rethink their approach to SCM. There is a trend that they have become more interested in making their operations more resilient and sustainable in the face of adverse events.

A supply chain consists of a large number of Key Performance Indicators (KPIs), which traditionally prioritize operational efficiency, such as inventory level, order fulfilment delay, production cost, profit, maintainability, security, etc. In recent years, more KPI considerations have been given to sustainability and environmental protection, resulting in additional metrics such as environmental impact, ethical sourcing, and social impact.

Developing a robust supply chain, where its stakeholders take a multitude of KPIs into consideration, is a challenging problem in several facets. Different supply chain stakeholders have diverse interests in mind; the concerns of a company (e.g., making a profit), for example, may put it at odds with those of a government agency (e.g., providing employment). Local efficiency of a supply chain element (e.g. a factory, warehouse, port, etc.) could also conflict with the desired global resilience of the supply chain, since efficiency aims to reduce excessive use of resources, while resilience necessitates preparing for unexpected events with more resources than the bare minimum. Moreover, much proprietary data about the end-to-end operations of the supply chain remains absent from the public domain, and is often not exchanged even between relevant stakeholders.

The term "supply chain resilience" carries different meanings in the research community. The Intergovernmental Panel on Climate Change (IPCC) defines it as "the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structure and functions" (Field et al. 2012). Alternatively, Fiskel has defined it as the capacity for an enterprise to survive, adapt, and grow in the face of turbulent change (Fiksel 2006). A key property of the resilience is an ability to return to "normal" after turbulent change, or to transition to a "better" state after lessons are learnt. Yet a better ability might be sustainability reflecting an enterprise's ability to be viable during its lifetime. Petit et al. present a theoretical basis for SC resilience that acknowledges changes engendering SC vulnerabilities and management control creating SC capabilities (Petit et al. 2019). This gives context for their qualitative Supply

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Chain Resilience Assessment and Management (SCRAM) tool.
Our work is based on the SC resilience as defined by IPCC. The majority of research in the published literature focuses on the "absorb" and "recover" aspects of that resilience definition. Little attention, however, has been paid to the "accommodate" aspect. Our project aims to explore the use of simulation-based modeling as a viable tool to investigate the accommodation of disruptive events to sustain robust SC operations.
SCM study is often formulated as an optimization problem, with multi-objective optimization being a popular solver by researchers. However, such an approach can only solve problems where the number of objective functions is no more than four. Studying the SC resilience requires a more holistic perspective, taking into consideration many more objective functions (i.e., KPIs) than multi-objective optimization can handle.
In this paper, we propose to develop a simulation-centered framework to support decision making with respect to supply chain resilience assessment. SC simulation can uncover complex, dynamic behaviors in supply chain operations, and can explore "what-if" scenarios across a range of KPIs and parameters (Mustafee et al. 2022). In addition to leveraging this strength, the proposed framework will help establish the requirements for decision-support tools to provide actionable options for the stakeholders, empowered by a deeper understanding of a supply chain's sources of fragility, both to mitigate vulnerabilities and to enhance overall resilience. Our work adds to the conceptualization of (Fiksel 2006) by acknowledging that actions of resistance and adaptation can be anticipatory or reactive. Finally, as part of the future work, the framework will also feature a capability based on the principles of Option Awareness (Pfaff et al. 2013) to facilitate SC stakeholder decision making.
The remainder of this paper is organized as follows. The Related Work section discusses the current optimization formulation's limitation in solving problems with a larger number of objective functions, and discusses the premises of our proposed framework. This is followed by a presentation of our proposed framework to assess the supply chain resilience. The Future Work section discusses a decision-support capability, which we plan to incorporate into the proposed framework. The Conclusion section summarizes the key contributions of the paper.

RELATED WORK

The challenge of assessing supply chain resilience is multi-pronged. Not only do we need to consider a diverse multitude of KPIs that are both operational (e.g., inventory levels, order fulfilment delays, production costs, profit, maintainability, security, etc.) and sustainability-relevant (e.g., environmental impact, ethical sourcing, social impact), which may often conflict with each other, but conflict also arises between the local optimization at a SC element and global resilience. Optimization problems on various components of the manufacturing process have received a great deal of attention (e.g. ant colony optimization, fuzzy logic, evolutionary algorithms, and combinatorial optimization techniques). However, these are limited to solving a few objective functions, often no more than four.
Researchers at Brunel University London have developed a novel class of optimization algorithms, known as the Many-Objective Optimization (MaOP) (Yang et al. 2013; Li, Yang, and Liu 2015). MaOP is based on evolutionary optimization approaches that allow a Pareto front to be rapidly approximated. This then forms the basis for more detail optimization and the creation of a solution space over many objectives, acting as a decision support system for decision-makers (Santos et al. 2022). So far, MaOP has been applied in a conventional decision- science manner, i.e., an objective function is created and applied to available historical datasets. While useful, this approach suffers from three problems: (1) if historical data is not available or is of poor quality, it is difficult to apply these techniques; (2) historical data does not often capture system structure or dynamics (i.e., resource bottlenecks, machine breakdown, etc.); and (3) it is difficult to perform predictive or analysis, as historical data might not be an appropriate basis for what could happen in the future if there are changes to the supply chain (i.e., what-if scenarios).
Modeling & Simulation (M&S) techniques are used to build dynamic models of systems. Different techniques exist that enable the modeling of systems in the most appropriate manner (e.g., discrete-event simulation, agent-based simulation, system dynamics and hybrid combinations). Models built from these techniques use stochastic distributions derived from existing data or expert opinion. Simulating these models, therefore, allows existing problems to be explored in such a way that captures the impact of system structures and avoids data paucity issues, as data is effectively derived from a model's distributions. M&S approaches are extremely useful in predictive/prescriptive analytics, as different future scenarios can be easily created. Optimization in M&S is mostly "many" in nature.
Marrying M&S with MaOP is an attractive approach which we explore in this paper to study supply chain resilience assessment. M&S avoids data paucity and can be used for future analysis, while MaOP enables far more KPIs to be considered. Initial work at Brunel has been investigating how both areas can be combined. Essentially, the objective function in MaOP is augmented with a M&S model; that is, the objective function still exists, but is evaluated by running a M&S model rather than just a dataset, i.e., the model effectively creates the dataset. Use of such synthetic data to drive a simulation is increasingly becoming an acceptable approach in the research community as well as in practice, especially when the real-life data is hard to obtain. In our proposed

framework, both synthetic data and real-life data can be accepted to drive the simulation run.

As such, a supply chain can be thought of as a complex adaptive system (CAS), yet one with deep uncertainty (i.e., the system contains inadequate or incomplete information). In analysing such a system, which is often socio-technical in nature, (Tolk 2022) recognizes the need to integrate the search for a robust solution (i.e., optimization) by performing exploration modelling and analysis (i.e., simulation). Output of such simulation-based optimization should also be presented to the decision makers in an understandable and actionable manner, allowing them to make well-informed decisions.

FRAMEWORK DEVELOPMENT

Conceptualizing Resilience

We have developed a graphical four-layered model of a generalized supply chain to guide our framework development, as is shown in Figure 1. The top layer presents the types of stakeholders along the value chain of the product SC. The second layer shows the functions each stakeholder performs along the product supply chain. Each of the functions is enabled by the assets and services depicted in the third layer. The fourth row captures the stakeholder entities that own these assets and services. Ultimately, these entities are under the control of their national government.

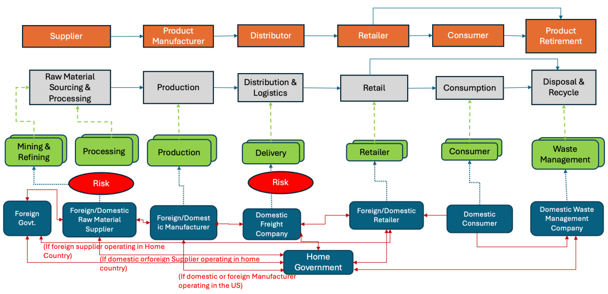

Figure 1: A Generalized SC Model

In addition, depending on the scenario we wish to study, we can place a suitable risk at a location in the model that will create an adverse impact on the operations too. Note that in this study, we assume perfect supply-chain operations internally (e.g., no labor strikes, no financial accounting irregularities, no machinery failures, etc.), and only consider exogenous risks, i.e., those that are external to the supply chain operations, such as political instability, geopolitical tension, climate change, natural disasters, etc. We have identified a number of exogenous risks using the System of Trust (SoT) tool, a data-driven analysis platform developed at MITRE that catalogs hundreds of risks and classifies them into different types to facilitate SC security risk assessment. A sample of the risks that pertain to our work is shown in Table 1.

The graphical model presented in Figure 1 is sufficiently high-level, but can be expanded to include more details of particular elements of the supply chain. Each SC element has one or more resilience-related vulnerabilities, or resilience risks (RRs). SC operations may be further influenced by business climate, government directives, external logistics and resources, and other risks (e.g., climate, geopolitical, pandemic, etc.). Each element can be detailed as part of the graphical model. In addition, other elements such as regions and places are also being considered. For example, a region is a geographic area that may be subject to RRs; a place is within a region that may have its own RRs. A region might have a seasonally related RR (e.g., torrential rain) and a place might have a significant RR (e.g., a port with a high level of corruption). Regions and places therefore can help to represent RRs in more detail. Routes are also elements. A route can start and end at a place and go through several regions. In this way, transportation resilience between SC elements can be represented in more detail and solutions may be planned to mitigate these.

Table 1: Examples of Exogenous Risks

Exogenous Risk	Affected SC Entity
Supplier operational location in countries with problematic national governance	Product Manufacturer
Supplier operational locations in country or countries of concern	Product Manufacturer
Supplier's sub-suppliers are in country o countries of concern	Supplier, Product Manufacturer
Manufacturing/R&D occurs in country or countries of concern	Product Manufacturer
Supplier operational locations in countries with prevalence of national corruption	Supplier, Product Manufacturer
Supplier facilities are located in areas prone to natural disasters	Supplier
Supplier facilities are located in areas prone to political instability	Supplier
Supplier facilities are located in areas prone to geopolitical instability	Supplier
Supplier facilities have a high geographic concentration	Supplier

SC Resilience Assessment Framework

The proposed resilience-assessment framework leverages a data-driven approach to assess vulnerabilities, mitigate risks and buttress supply chain resilience. It can be represented in three layers, as shown in Figure 2. At the base of the framework sits the agent-based simulation (ABS). It simulates the elements of the supply chain as well as the interactions between them. The output of the ABS is used as input into an optimization formulation, in which we define the concerns of the supply-chain stakeholders as objective functions that correspond to the KPIs. We use MaOP as a viable optimization formulation, although it is possible to choose another optimization method, as long as it can produce the results for the objective functions. The solutions of the optimization are then fed into to a decision support capability. The decision support capability gives the stakeholder or a decision maker the tool to holistically assess the resilience outlook of the supply chain; it allows the decision maker to uncover brittle points in the supply chain that are most vulnerable to the exogenous risk; in addition, it can suggest courses of action to mitigate such risks and improve the supply chain resilience. The output of the Decision Support layer can also be used to inform and refine the ABS; this feedback could also enable the stakeholders to perform what-if analysis with this framework.

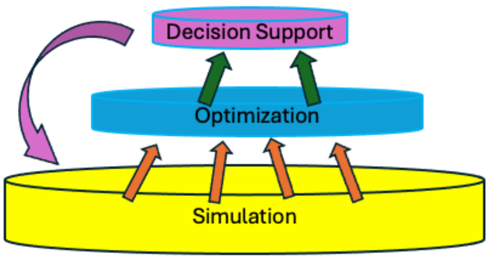

Figure 2: Framework for SC Resilience Assessment

Supply Chain Conceptual Model

We follow the methodology by Robinson to develop a conceptual model of a supply chain (Robinson 2008). A conceptual model can be constructed with the following pieces: 1) general and modelling objectives; 2) model input/output; 3) model scope; 4) model level of detail; and 5) simplification and assumptions. Due to the space constraints of this paper, we cannot include all these pieces of information. We selectively present a few of these pieces to demonstrate what we have accomplished so far.

While we keep in mind that our framework is agnostic to any particular industry and domain, to develop the SC conceptual model, we choose a pharmaceutical supply chain (PSC) as an illustrative example.

General and Modelling Objectives

General objectives provide an overall guidance on what the conceptual model aims to achieve. The PSC modelling has two general objectives: 1) Discover the interactions between the inputs and outputs of the PSC, and 2) identify the regulatory framework, incentive structures, and monitoring requirements that determine the adequacy of PSC. The PSC consists of the following seven SC elements: Active Pharmaceutical Ingredient (API) Supplier, Drug Manufacturer, Wholesaler, Pharmacy Benefits Manager (an entity that negotiates the drug price between the Wholesaler and Pharmacy), Pharmacy, Patient, and Waste Disposal. Each of these PSC elements has a defined modelling objective. For example, the Drug Manufacturer needs to have enough API material to sustain drug production during a SC disruption.

The modelling objectives are directly related to the implementation of the conceptual model. In the case of PSC, it has its own defined modelling objectives: 1) Explore the regulatory framework, incentive structure, and monitoring requirements that determine the PSC resilience; and 2) resolve any PSC disruption as quickly as possible. Clear statements of these modelling objectives can help the modeler focus on including only the necessary agents to prevent over-complexity of the simulation model.

Simplifications and Assumptions

Table 2 presents the simplifications and assumptions for the elements in the PSC conceptual model. They help make the ABS development more manageable, and reduce simulation runtime. At the present, we keep the PSC model relatively simple. This is because building the simulation model is only part of the proposed framework; our project objective is to test the integration of the underling ABS and the MaOP optimization formulation, with the future plan of incorporating an additional decision support capability). Once this framework proves successful, we can increase simulation complexity to handle more sophisticated use cases for study.

Table 2: Simplifications and Assumptions

PSC Element	Simplifications	Assumptions
(Raw Material Mining and Processing)		Assuming it is also available; not included in the model due to low visibility
API Supplier	To model only one API Supplier	There is sufficient work force to produce the requested API amount
Drug Manufacturer	Constant production rate	There is sufficient work force to produce the requested amount of drug
Wholesaler	A finite capacity of drug storage	
PBM	To model only one PBM	PBM can negotiate to lower drug price by a certain percentage, if the amount of drugs at Wholesaler exceeds a certain threshold
Pharmacy	To model only one Pharmacy	
Patient	To model multiple Patients being serviced by the Pharmacy; each Patient buys the same amount of drug	During disruption, a Patient may choose to buy 2X amount of drug needed from Pharmacy
Waste Disposal	There exists one Waste Disposal Company	Accepts expired (unsold) drug from the Drug Manufacturer, Wholesaler, and Pharmacy
Whole Supply Chain		Only one type of drug is considered in the model

Modelling Inputs and Outputs

The inputs and outputs of modelled SC agents define the intervening processes and states in the simulation. These are quantitative variables, each with a definitive unit of measure. Any simulated SC disruption will impact one or multiple inputs, and the extent of the effect can be quantified by measuring changes in the outputs. Table 3 presents some example inputs and outputs for each of the seven entities of the PSC model. Among the seven, the Patient does not have an output. This is because the Patient's consumption of the drug is assumed to mark the end of the drug's lifecycle, and to exit from the supply chain circulation.

Table 3: Inputs and Outputs of the PSC Model

SC Element	Input	Output
API Supplier	API production rate of the API Supplier	
	Delivery rate of API to Drug Manufacturer by the API Supplier	
Drug Manufacturer	Drug production rate of the Manufacturer	Time series of the amount of drugs the Manufacturer has produced
Wholesaler	Time series of amount of drugs ordered by Wholesaler	Time series of the amount of drugs it bought and received from the Drug Manufacturer
		Time series of the amount of drugs it sold to Pharmacy over the entire run
PBM	Pricing information from the Wholesaler; demand information from Pharmacy	Time series of the PBM's negotiated drug price
Pharmacy	Time series of amount of drugs ordered by Pharmacy	Time series of amount of drugs received at Pharmacy
	Drug storage capacity at Pharmacy	Time series of the time it takes from order to receipt of drug at the Pharmacy
Patient	Time series of amount of drugs purchased	
Pharma Waste Disposal	Time series of amount of drugs sent for disposal	Time Series of amount of disposed drugs received by the Pharmaceutical Waste Disposal

Modelling Scope and Level of Detail

Clearly stated modelling objectives, as previously discussed, can inform the appropriate scope and level of detail of the simulation. Defining a proper scope to model the supply chain allows us to focus on attuning the simulation to the use case being studied. Table *4*Table 4 presents the scope of the supply chain model. Table 5 Table *5*presents the modelling level of detail for the simulated agents. Taken together, the scope and level of detail allow the modeler to implement the simulation at an appropriate abstract level, one that does not result in excessive computational complexity and leads to more efficient execution during runtime.

Table 4: Modelling Scope

Model Scope			
Model Type	**Component**	**Include/Exclude in Conceptual Model**	**Justification**
Entities	(Raw Material Mining/Processing)	Exclude	Assuming always available; low visibility
	API Supplier	Include	To model the API production rate
	Drug Manufacturer	Include	To model the drug production rate and whether the Manufacturer has enough API for production
	Wholesaler	Include	To model distribution and logistics between Drug Manufacturer and Pharmacy
	Price Negotiator	Include	Sets the drug price for both Drug Manufacturer and Pharmacy
	Pharmacy	Include	The capacity of the Pharmacy to receive drug from the Wholesaler and to sell to the Patients
	Patient	Include	To model the consumption of the drug
	Waste Disposal	Include	
Activities	API Production	Exclude	Assuming always available; low visibility
	Drug Production	Include	To model the available supply of drug
	Wholesaler	Include	To model how much drug can be sold and shipped to Pharmacy
	Pharmacy	Include	To model the rate of selling the drug to Patients
	Patient Consumption of Drug	Exclude	Not relevant to the modeling objectives
	Unsold Drug Disposal	Exclude	Can be computed by defining a countable variable in Pharmacy
Queues	API Supplier-to-Drug Manufacturer	Include	To model the time it takes and unit amount of API from the API Supplier to Drug Manufacturer
	Drug Manufacturer-to-Wholesaler	Include	To model the time it takes to ship the drug from Drug Manufacturer to Wholesaler
	Whohlesaler-to-Pharmacy	Include	To model thetime it takes to ship the drug from Wholesaler to Pharmacy
	Pharmacy-to-Patient	Exclude	Can assume the sale to the Patient is instantaneous
Resources	Home Government	Include	To model the negotiation and resolution of conflict
	Foreign Govrnment	Include	To model the negotiation and resolution of conflict

Table 5: Modelling Level of Detail

Level of Detail			
		Attribute	**Value**
Entities	API Supplier	Quantity (no. of API Suppliers)	1
		API arrival pattern (pounds)	Constant / Poisson
	Drug Manufacturer	Quantity (no. of Drug Manufacturers)	1
	Wholesaler	Quantity (no. of Wholesalers)	1
		Storage capacity (pounds)	Constant
	Price Negotiator	Quantity (no. of PBMs)	1
		Negotiated Drug Price ($)	Variable
	Pharmacy	Quantity (no. of Pharmacies)	1
		Drug storage capacity (pounds)	Constant
	Patient	Quantity (no. of Patients)	50
	Waste Disposal	Quantity (no. of Waste Management Companies)	1
Activities	API Production	API production rate (pounds/week)	Constant
	Drug Production	Drug production rate (pounds/week)	Constant
	Pharmacy	Selling rate (pounds/week)	Variable
	Patient Consumption of Drug	Amoung of drug per purchase (pounds/week)	Constant
Queues	API Supplier-to-Drug Manufacturer	API arrival rate	Constant
	Drug Manufacturer-to-Wholesaler	Drug arrival rate	Constant
	Whohlesaler-to-Pharmacy	Drug arrival rate	Constant
Resources	Home Government	Where resource required	API disruption
	Foreign Govrnment	Where resource required	API disruption

Process Flow Diagrams

We have adopted a generic modelling approach where each supply chain element is modelled as an archetypal component (i.e., an agent) with input and output links (i.e., interactions). The generic component's logic includes the operational functions of each entity, as well as properties that support risk modelling. The links represent upstream and downstream flows of material/goods, information and money, as well as multimodal transportation routes. As an example, we present here the algorithms of the first two upstream elements in a SC, i.e., *Supplier* and *Manufacturer*.

Figures 3 and 4 depict the process flow diagrams of the algorithm for the *supplier* and *manufacturer* elements, respectively. Both algorithms execute at each time step of the simulation, and they exchange information as appropriate. *Supplier* is the first upstream element.

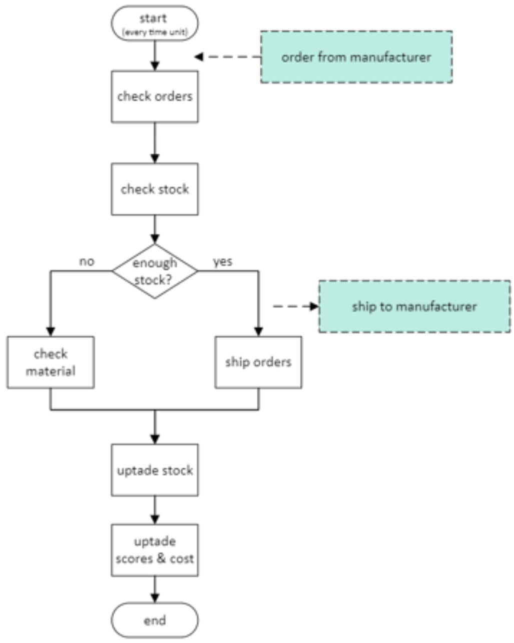

Figure 3: Supplier SC Element Algorithm

As shown in the process flow diagram in Figure 3, the Supplier's demand comes from the Manufacturer element in the form of orders. If there is enough stock, the Supplier ships the material to the Manufacturer. If not, the Supplier replenishes its stock. Risk and environmental scores as well as costs are calculated at the end of each time step.

Figure 4 shows the algorithm for the Manufacturer element. The Manufacturer's demand comes from the Distributor element (e.g., the Wholesaler in the PSC model) in the form of orders. If there is enough stock, the Manufacturer ships the products to the Distributor. If not, the Manufacturer checks the Bill of Material (BOM) and manufactured products, or order additional materials (place order to the Supplier), or both, accordingly. Products and materials stocks are thereby updated. Risk and environmental scores, as well as incurred costs, are calculated at the end of each time step. Note that both SC element algorithms also consider safety stock. Safety stock strategies can be parametrized and tested in different resilience scenarios. Disruptive events can be simulated to impact any of the attributes in Table 5.

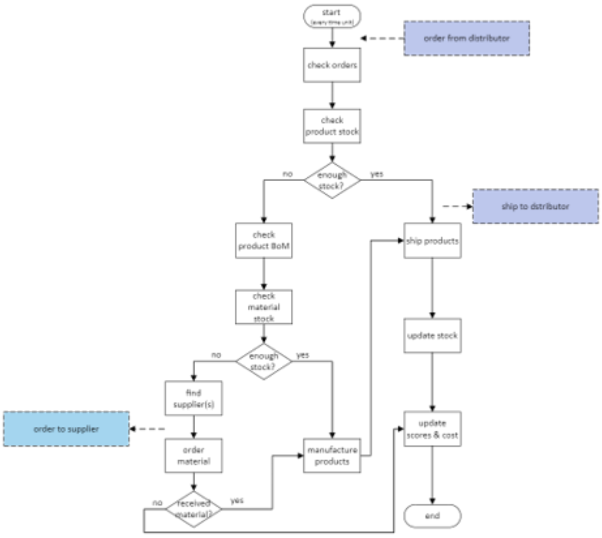

Figure 4: Manufacturer SC Element Algorithm

Sample Key Performance Indicators

Performance metrics capture the influence of an a KPI or event on the system response across the multiple tiers that comprise the supply chain (Munoz & Dunbar, 2015). The use of MaOP in the framework enables us to take into consideration a greater number of KPIs that impact SC resilience assessment. We have identified a number of KPIs that are classified into three categories: operational, risk, and sustainability, as shown in Table *6*Table *6*. The operational and sustainability KPIs are publicly available in the open domain, and the risk KPIs are obtained from the System of Trust; all of them can be numerically quantified. Note that these 15 KPIs represent a sample of relevant KPIs. The KPIs are linked to the outputs of relevant SC elements in the ABS, so that changes in these metrics can directly be quantified as a function of the disruption(s). Depending on the particular supply chain under study and its assessment objectives, the list of KPIs can be tailored to suit the general and modelling objectives.

Optimisation and Simulation Modelling

The MaOP algorithms are incorporated into the simulation model, and executed iteratively, to calculate simultaneous optimization solutions for a multitude of KPIs, which may be conflicting with each other and are defined by different entities of the SC (Table 6). As a result, the simulation produces a range of KPI values, and the MaOP evaluates that the outcomes (i.e. the objectives of each entity) are acceptable. When the objectives are met, the iterations stop (Anagnostou et al. 2024).

At the completion of the simulation run, the optimized outputs are fed into a decision support capability, which provides data-driven analysis and allows the stakeholder to make informed decisions about mitigating the negative impact on SC operations due to some exogeneous risks. This is discussed in the next section.

Table 6: Sample KPIs

Operational	Risk	Sustainability
Inventory-to-Sales Ratio	Supplier facilities are located in areas prone to natural disasters	Recycling Rate
Carrying Cost of Inventory	Supplier facilities are located in areas prone to political instability	Greenhouse Gas Emissions and Carbon Footprint
On-Time Delivery and Accurate ETAs	Supplier facilities are located in areas prone to geopolitical instability	Energy Consumption
Days Sales of Inventory	Financial interests of supplier are located in a country of concern	Total Water Consumed
Perfect Order Delivery Rate	Financial interests of supplier are located in a country of concern	Amount of Recycled Water Consumed

FUTURE WORK

We plan to implement a robust decision support capability to be integrated in the proposed framework, i.e., the top layer in Figure 2. This capability is built on the principles of Option Awareness, or OA (Pfaff et al. 2013). A high-quality decision-making process requires two types of information input: situation awareness (SA) is the knowledge of what is going on; and option awareness (OA) is the knowledge of what to do about it. OA is the knowledge of the decision space, and it consists of three levels. Level 1 is the Comparison level, which aims to answer the question: what is the relative desirability of the available options over plausible futures? Level 2 is the Discrimination level, which probes the factors, trade-offs, and tipping points that influence the desirability of each of the options. Level 3 is the Enhancement level, which uses the knowledge from the Discrimination and Comparison to explore the possibility of finding even better options.

MITRE researchers have developed a tool called Multicriteria Option Comparison Application (MOCA), based on the OA principles. Researchers can apply this tool to a wide arrange of domains and challenges, allowing them to make informed decisions in adopting the best investment options.

CONCLUSION

Companies that operate supply chains globally must consider not only maintaining the efficiency of their operations, but also their abilities to absorb, recover, and accommodate the negative impact caused by exogenous risks that can lead to operational disruptions or environmental detriments.

In this paper, we proposed a framework to assess supply chain resilience by bringing together agent-based simulation, many-objective optimization, and decision-support capability used by the SC stakeholders. We presented a conceptual model for the ABS, and discussed the premises of leveraging MaOP to construct a comprehensive resilience outlook with a multitude of KPIs, which would the stakeholders to take a holistic approach in evaluating the supply chain resilience. As part of the future work, we are exploring the use of option awareness to support the development and integration of a decision-support capability. This capability, integrated with the ABS and optimization formulation, can enable stakeholders to make informed decisions about the best investment options to buttress the supply chain resilience.

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AUTHOR BIOGRAPHIES

EDWARD Y. HUA is a Lead Modeling & Simulation Engineer at the MITRE Corporation. He received his Ph.D. degree from Cornell University's Electrical and Computer Engineering. He is a member of ACM SIGSIM and INFORMS. His research interests include digital twins, simulation and AI, and wireless networks. His email address is ehua@mitre.org, and his ORCID is https://orcid.org/0000-0002-6294-3122.

KATE S. MINTRAM is an Associate Lecturer in the Department of Computer Science at Brunel University London. Her main research interest is using simulation modelling to address complex biological problems, including chemical risk assessments, epidemiology, climate change and SCM. Her email address is kate.mintram@brunel.ac.uk and her ORCID is https://orcid.org/0000-0001-7180-9200.

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 also serves as Program Chair for the Winter Simulation Conference 2025. She is ACM SIGSIM Vice Chair and Associate Editor of the Journal of Simulation. Her email address is anastasia.anagnostou@brunel.ac.uk, and her ORCID is https://orcid.org/0000-0003-3397-8307.

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