Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

EVALUATING THE EFFECTIVENESS OF COUNTERMEASURES IN ICT SUPPLY CHAINS THROUGH ELICITATION-INFORMED SIMULATION

Rong Lei
Samar Saleh
Weihong "Grace" Guo
Elsayed A. Elsayed

Department of Industrial and Systems Engineering
Rutgers University
96 Frelinghuysen Road
Piscataway, NJ 08854, USA

Fred S. Roberts

CCICADA Center and Department of Mathematics
Rutgers University
96 Frelinghuysen Road
Piscataway, NJ 08854, USA

Paul Kantor

Paul B Kantor, Consultant
2305 Keyes Ave
Madison, WI 53777, USA

ABSTRACT

Counterfeiting, the production of imitation goods, is a critical threat in the Information and Communication Technology (ICT) manufacturing supply chain (SC). Countermeasures (CMs) are strategies to mitigate disruptions and enhance a SC. We present a novel hybrid approach for assessing and selecting CMs in ICT SCs. Our model incorporates insights from subject matter experts (SME), via Delphi elicitation, into the simulation. This technique is used to study SC resilience against disruptions caused by counterfeiting. ICT is an integral part of our daily lives and life-supporting systems, making resilience against such threats vital. Using performance criteria including system service levels, delivery time, and product quality, our findings show the importance of integrating expert knowledge in simulation and the effectiveness of certain CMs.

1 INTRODUCTION

The Information and Communication Technology (ICT) supply chain (SC) is the network of organizations and activities involved in manufacturing and distributing ICT products. Individuals, governments, and companies buy these products, ranging from cell phones to software collecting and sharing confidential data. ICT SC resilience is crucial as SC disruption can harm economies and safety and its strength is determined by the weakest link. President Biden signed Executive Order 14017 in 2021 to develop sturdy SCs of six critical industries, including ICT, to ensure economic and national security. SC resilience (SCRES) is the ability of a SC to anticipate, respond to, and recover from disruptions by retaining operations continuity and structure and function control (Ponomarov and Holcomb 2009) and it is threatened by various factors, including natural disasters, counterfeiting, and geopolitical tensions. Knowing that prepared enterprises have a faster recovery and better shareholder returns, there is massive research and investment in SCRES. Work in this area can be categorized into simulation and non-simulation approaches. Simulation-based ICT supply chain analysis uses real data and fewer assumptions than non-simulation methods, which often make heavy assumptions and are only relevant under stringent conditions. This makes simulations a more robust and flexible method for decision-making in ICT supply chain management.

Simulating ICT SCRES has several advantages by enabling the development of virtual models that replicate behavior of actual systems. Simulation can be done with fixed parameters or dynamic inputs. Fixed parameter simulation uses fixed values for parameters such as demand and lead time to reveal ICT SC behavior in different settings and identify vulnerabilities and evaluate countermeasures (CMs). However, as it relies on fixed assumptions, it fails to capture real-time changes in the SC. The dynamic input simulation of ICT SC behavior, on the other hand, incorporates real-time data and empirical distributions and accounts for SC dynamics such as changing demand or emerging hazards, making it suitable for gauging resilience in unpredictable contexts. However, simulation with dynamic input requires precise data, sophisticated modeling, and computational resources which may present implementation and confidentiality challenges. Beside benefits, limitations, and research gaps persist. Research in ICT SC resilience simulation has unfilled lacuna. A lack of consensus on performance metrics selection can lead to inconsistent findings and impede the comparability of studies. Another gap is the lack of data that could help in modeling SC dynamic behavior and uncertainties, due to the data being unavailable or inaccessible.

This research aims to investigate the impact of natural and external factors, as well as proposed CMs, on ICT SC resilience. Elicitation, an independent step in Figure 1, gathers experts' knowledge, resolving data privacy concerns for organizations reluctant to disclose data but willing to contribute to information aggregation. A mapping methodology is proposed to integrate elicitation data as input empirical distributions. Simulation then determines the effective CM with the best SC performance metrics. The study procedures are outlined in Figure 1. The paper also explores the application of these techniques to address counterfeit goods in ICT SCs. The remainder of the paper is structured as follows. Section 2 offers a review of ICT SC resilience with a focus on studying SCRES using simulation and elicitation in simulation. Section 3 describes this study's SC network and the integration of elicitation into simulation. Section 4 presents a case study. Finally, Section 5 summarizes the findings and the possible directions for future research.

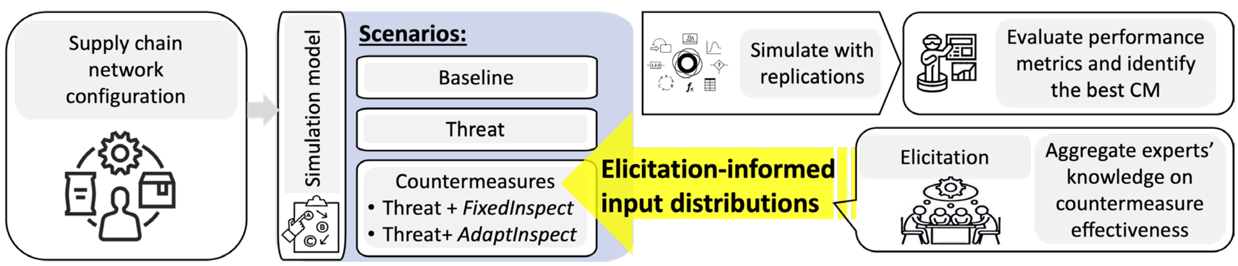

Figure 1: Concept map illustrating the key steps followed in this study.

2 LITERATURE REVIEW

2.1 ICT Supply Chain Resilience

While SCs are widely analyzed, studies on making ICT SCs resilient are conspicuously lacking. Studies often discuss using ICT in building robust SCs (Mensah and Merkuryev 2013; Mensah et al. 2015; Rahman et al. 2022) but not fortifying the ICT SC itself. Some are applicable but not particular to ICT SCs (Mensah and Merkuryev 2014). Chen et al. (2019) examined Taiwanese ICT SC disturbances and proposed a post-disruption management process to improve SCRES. After the COVID-19 pandemic, ICT SCRES became a more popular topic because disturbances to this SC harmed other SCs, such as the defense SC. For instance, The U.S. ICT Supply Chain Risk Management Task Force of the Cybersecurity and Infrastructure Security Agency has completed a "Lessons Learned During the Covid-19 Pandemic Study" to strengthen ICT SCs. Common efforts are led by the U.S. Department of Commerce and Department of Homeland Security (2022). Those efforts stimulate ICT SCRES research. Guo et al. (2022) and Lei et al. (2023) pioneered studies on ICT SC under natural disasters and counterfeiting risks by developing simulations to identify optimal CM.

2.2 Simulation of Supply Chain Uncertainties and Resilience

As previously stated, SCRES improves business continuity, customer satisfaction, and national security for enterprises and consumers. Addressing SC uncertainties can improve performance and help businesses and economies thrive. This topic has a large corpus of literature from numerous fields. Part of it qualitatively explores disruptions and SCRES, while a larger part quantitatively models supply or demand interruptions and facility shutdowns to assess SCRES. Simulation has emerged as a valuable tool to address uncertainties in SCs, allowing for controlled experimentation and scenario analysis (Tordecilla et al. 2021). Simulation, for instance, allows us to determine the best SC demand forecasting strategy (Bradley et al. 2015), optimize inventory policies (Jalali and Nieuwenhuyse 2015; Maghoulan et al. 2022), determine the optimum transportation routes and schedules (De Sensi et al. 2008), overcome demand and lead time variability, and machine failures (Rahmani et al. 2022) and expose SCRES with counterfeits threat (Saleh et al. 2023).

Simulation and optimization are intensively used in studying SC disruptions and CMs. However, uncertainty in SC design remains a challenge. Uncertainty can be random, epistemic, or profound, each requiring different approaches. When data is sufficient to determine the parameter's probability distribution function, randomness occurs. Epistemic uncertainty describes a situation with input data typically provided as qualitative linguistic data from professionals. Furthermore, when there is a lack of knowledge about the relevant parameters, uncertainty is profound. Jabbarzadeh et al. (2016) estimate uncertain parameters' distribution lacking historical data. Gholami-Zanjani et al. (2021) assume known input parameter distributions to find the optimal solution. Bottani et al. (2019) use ant colony optimization with experimentally established parameters to find the optimal solution. Razavian et al. (2021) use possibilistic chance-constrained stochastic programming for expert elicitation. (Sazvar et al. 2021) develop reinforced merging of SCs using fuzzy optimization to address epistemic uncertainty. However, the interdependencies and performance metrics of disruptions are often overlooked in earlier studies.

2.3 Elicitation in Simulation

As shown in previous literature, empirical data is needed to calibrate, validate, generate input data, and more for simulation model creation and implementation. The hybrid simulation (HS) approach, merging Agent-Based Modelling (ABM) and Discrete Event Simulation (DES), captures the complexity of various systems (Mustafee et al. 2020). This approach allows for the integration of other methods to enhance the simulation study, driving innovation in modelling and simulation (M&S). Our method aligns with Mustafee's Type C or D HS, integrating simulation with empirical data. Using simulation along with empirical data improves accuracy and reliability, making them valuable for decision-making in diverse domains. However, data acquisition can be expensive, infeasible, and perhaps unavailable for new systems, which can impact model effectiveness and generalizability. Brailsford et al. (2019) extensively reviewed the growing interest of applications in hybrid models in operational research. Our study contributes to this literature by applying a hybrid approach to the less-explored ICT Supply Chains field with elicitation.

Elicitation is essential for simulation models with epistemic uncertainty and is used in many fields. In risk analysis, it extracts specialist opinions to define model parameters (Gregory et al. 2012). In the field of maintenance, simulation has been used to extract experts' knowledge (Edwards et al. 2004). Stakeholder preference elicitation is also used in disease transmission simulation to evaluate efforts across several scenarios (Petersohn et al. 2021; Talantsev et al. 2022). Elicitation has also been used in SC reliability (Klimov and Merkuryev 2008) logistics (Lyu et al. 2022). Existing literature demonstrates that many simulation studies have examined elicitation in model development, but it is rarely used in ICT SCRES simulations. Input parameter elicitation can be direct or indirect. Previous studies use direct methods like interviews, surveys, and workshops which are used more than indirect approaches like Bayesian inference or statistical methods by experts having difficulty expressing their expertise in responding to direct questions (Hudlicka 1996; Garthwaite et al. 2005). The most popular direct technique is the Delphi method which entails iteratively obtaining expert feedback to reach a consensus or expert judgment (Powell 2003).

2.4 Summary of the Literature and Paper's Contribution

A thorough review shows many simulation-based and non-simulation studies on SCRES. Mostly focusing on pharmaceutical and food SCs, they use ICT in their proposed CMs, oblivious to the need to fortify the ICT SCRES itself. SC key performance measures have also been ignored or poorly demonstrated in previous research. Further, while there is a large body of research on expert elicitation for determining simulation input parameters, its application to SCRES remains undeveloped. By addressing the theoretical gaps, we contribute to the summarized literature by: 1. Overcoming data privacy concerns and improving model adaptability using a novel mapping methodology that integrates data obtained from SMEs as input empirical distributions; 2. Capturing ICT SC complexity and uncertainty in a simulation model utilizing SME elicitation data; 3. Determining the most efficient CM based on SC performance metrics; and 4. Enabling the examination of various ICT SC disruptions by modifying the model's characteristics.

3 METHOD

3.1 Hybrid Simulation Approach

A single simulation technique can't fully capture the complexity of a SC system. By combining ABM, DES, and Elicitation, we leverage the strengths of each technique and mitigate their limitations. ABM models complex systems with multiple entities. It can explore heterogeneity and non-linear interactions within a system. However, ABM can be computationally intensive and may not efficiently handle the scheduling of events or the management of resources. DES is effective in modeling discrete state changes but may not fully capture the complex interactions of entities. Our hybrid approach uses ABM for complex interactions and DES for efficient event scheduling and resource management. Elicitation, while not a simulation technique, is used to gather expert knowledge and data. Such data can be gathered confidentially within a company, to improve simulations or, as here, generic elicitation can be used to illustrate the method. This hybrid M&S approach provides a more comprehensive and efficient system model.

Our study employs a four-echelon structure modeling a U.S.-based laptop SC, comprising suppliers, manufacturing and distribution centers, and customers, with the same SC setup in Lei et al. (2023) to build the simulation model, analyze SC performance under counterfeit events and assess model resilience with CMs applied. Two CM scenarios, *FixedInspect* and *AdaptInspect*, are implemented at manufacturing centers. Table 1 summarizes all scenarios. The *FixedInspect* scenario uses continuous filtering and inspection of selected components, with approved parts proceeding to production and counterfeit ones discarded, while the *AdaptInspect* scenario employs a selective inspection mechanism that adjusts inspection stringency based on a triggering mechanism (Lei et al. 2023).

Table 1: Summary of simulation scenarios.

Model	**Description**
Baseline	Normal operation without disruptions
Threat only	Counterfeit motherboards from suppliers, random start
Threat + FixedInspect	Standard inspection with selection rate s and inspection accuracy a_1
Threat + AdaptInspect	Adaptive inspection and adaptive production schedule in manufacturing centers to compensate for the increased inspection time

3.2 Elicitation Method

This study adopts the elicitation methodology and data from Egan et al. (2022), combining elicitation probabilities as input with stochastic replications for more realistic SC performance compared to fixed input simulations. Elicitation techniques involve draw on subject matter experts (SMEs) with limited proficiency in mathematics or engineering, to refine scenarios and identify suitable CMs. Exercises and interviews from these SMEs prioritize the most effective CMs for mitigating the system risk. SMEs may have varying uncertainty levels regarding a CM's effectiveness. A general way of expressing risk R and effectiveness $\boldsymbol{E}$ is required for disruptions and CMs. Egan et al. (2022) defined unmitigated and reduced risk R_0 as:

$$R_0 = Consequences * Vulnerability * Threat;$$

$$Reduced\ Risk = (1 - \boldsymbol{E}) \times R_0.$$

Figure 2 explains obtaining elicitation data through interviews. In-depth interviews are conducted with SMEs from relevant sectors; they are asked to use a 5-point-dragable triangular distribution to define the range, median, and left/right tail fatness of the risk reduction *probability distribution* according to their domain knowledge. Egan et al. (2022) propose several aggregation approaches across different SMEs using weighting methods such as equal weights, confidence-weights, and width-based weights. After several Delphi method iterations (Powell 2003), the distribution is judged to converge. The averaged density function (for visualization) and median cumulative distribution function (CDF) are calculated, as well as the new mean and median for the aggregated distribution. Subsequently, this elicited distribution is employed to establish appropriate simulation parameter values. Effectiveness $\boldsymbol{E}$ is elicited for *specific CMs* as a response to *particular risk types*. For example, the aggregated CDF for applying database matching inspection reflects the effectiveness of applying a *standard database search for counterfeit events*.

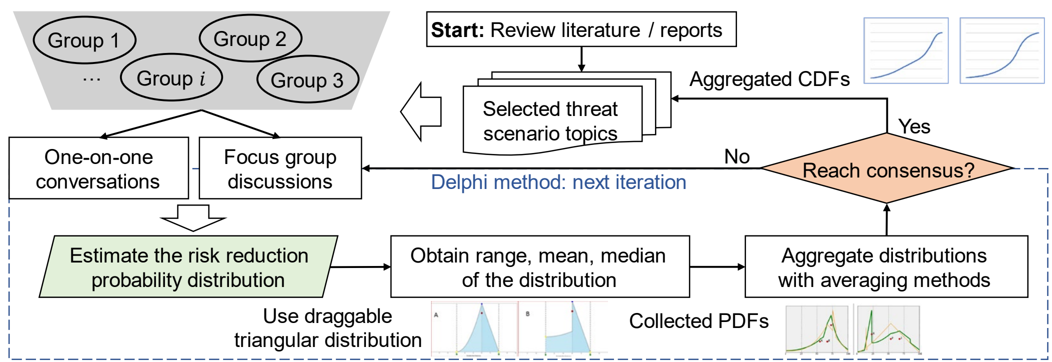

Figure 2: Flowchart of the elicitation process through expert interviews and aggregation.

The elicitation process yields a collection of CDFs for various CMs, from which we select two specific results as simulation inputs for *FixedInspect* and *AdaptInspect* scenarios. For the *FixedInspect* scenario, the elicitated countermeasure "Serialization of each item and match to database" is employed. This involves verifying the authenticity of individual components by cross-referencing their serial numbers with trusted databases. This approach fits well with the *FixedInspect* scenario, as it provides a continuous method of filtering incoming parts. In contrast, the *AdaptInspect* scenario utilizes the "careful examination of the product itself" countermeasure, indicating a more in-depth and responsive inspection process when counterfeit activity increases. After modeling CMs in the simulation, we gather statistical data to analyze SCRES improvement. To quantify this improvement in a counterfeit event with a specific CM l, the mitigated risk is denoted as R_l where $R_l \leq R_0$ and the performance effectiveness (PE) is calculated as:

$$PE_l = \frac{R_0 - R_l}{R_0} \times 100\%. \tag{1}$$

This equation captures the impact of each CM on the system's overall performance. In practice, a *Good Product Proportion* (GPP) metric is used to evaluate the CM efficacy across all scenarios. This metric assesses the cumulated proportion of good products at a given facility:

$$GPP^{(i)} = \frac{GPL}{TL}, \tag{2}$$

where i is the facility index, GPL is the number of authentic products received, and TL is the total number of products received. By comparing the GPP, we can determine the relative benefits of both CMs.

3.3 Elicitation-Informed Input Probability Distribution Estimation

In the simulation, parameters are assigned initial values but can be replaced with distributions to accommodate varying scenarios. Due to uncertainties arising from diverse factors and external environments, scenario effectiveness may vary, presumably resembling the elicited distribution data from SMEs. To fit the estimate stochastic features, several representative key parameters in the model are selected as the *tunable* factors of the simulation and whose variation significantly changes the SC performance. Parameter variation experiments are then conducted for the CM scenarios using these key parameters. We impose the condition that the occurrence distribution of parameter pair combinations aligns with the elicitation distribution summarized from an SME, ensuring the distribution accurately reflects the approximate effectiveness of the corresponding CM in reducing the threat risk. A performance metric $0 \leq \Phi \leq 1$ that can be affected by these key parameters is selected to bridge the connection between the elicited risk reduction distribution and the simulation model. $\Phi = 1$ in the baseline scenario and under ideal conditions with fixed parameters. Of course, Φ will be significantly reduced in the *Threat-only* scenario when no CMs are applied. This unmitigated situation is our benchmark risk $R_0 = 1 - \Phi_0$. In CM scenarios, Φ_i can be obtained and $R_i = 1 - \Phi_i$ is compared with R_0 to determine how much of the risk is removed.

Given a specific scenario l, a set of key parameters $X_1, X_2, \dots, X_k$ are selected for a parameter variation experiment. With different parameter combinations, the simulation performance metric value forms an empirical distribution, associated with the key parameter sets and can be denoted as $\Phi = G(X_1, X_2, \dots, X_k)$. To ensure the credibility of the results, N_R replications are conducted for each combination with mean $\bar{\varphi}$ value calculated by averaging outcomes. The results form a grid of data points that captures the relationship between the key parameters and the performance metric Φ. In the meanwhile, given a CDF of the empirical elicitation distribution F^l for scenario l, the elicitation PE Φ_E^l can be represented as $\Phi_E^l = F^l(\cdot)$. For each parameter combination in $G(X_1, X_2, \dots, X_k)$, we find the corresponding probability value from $F^l(\cdot)$, forming a lookup table of the parameter's probability distribution. Each column of parameter values X_j is sorted in the table, and with dense observed probability distribution data points, we assume a monotonic probability value within each parameter range between adjacent data points. Linear interpolation is then applied when no exact match of values is found in the lookup table. Specifically, for a probability p_s sampled from the empirical probability distribution at the beginning of each simulation replication, and controlling a given key parameter X_j as the only changing parameter in the parameter combination, we look up all the possible nearest two data points pairs $(\boldsymbol{x}_{i-1}, \boldsymbol{x}_i)$, where $\boldsymbol{x}_{i-1} = \left(x_{i-1,j}, \boldsymbol{x}_{i-1,-j}\right), \boldsymbol{x}_i = (x_{i,j}, \boldsymbol{x}_{i,-j})$ in the grid values that the probability sits between, with other parameters the same as $\boldsymbol{x}_{i-1,-j} = \boldsymbol{x}_{i,-j}$. The interpolated value for parameter X_i and the corresponding parameter combination vector can be written as:

$$x_{i,j}^* = x_{i-1,j} + (x_{i,j} - x_{i-1,j}) \times \frac{p_s - G(\boldsymbol{x}_{i-1})}{G(\boldsymbol{x}_i) - G(\boldsymbol{x}_{i-1})};$$

$$\boldsymbol{x}_i^* = (x_{i,j}^*, \boldsymbol{x}_{i,-j}),$$

where $x_{i,j}$ denotes the j-th field value in the observation vector $\boldsymbol{x}_i$, and $\boldsymbol{x}_{i,-j}$ denotes the remaining of $\boldsymbol{x}_i$ excluding the j-th field. The set of possible $\boldsymbol{x}_i^*$ values form the collection S_j for parameter X_j. By iterating through the fields from X_1 to X_k and repeating the above operations, all the collections S_1 to S_k capture the possible parameter combinations. Next, equally randomly picking any possible value from these collections will yield the selection of parameter combinations in the simulation from the empirical distribution.

4 CASE STUDY

4.1 Simulation Implementation

We assessed our elicitation mapping methodology through a simulation-based case study of an ICT SC network in AnyLogic (Borshchev 2013). The hybrid model examines operations under normal and disruption conditions. Each facility agent type integrates several discrete event modules, and communication occurs between groups of the same type. Discrete event modules are embedded within each agent to facilitate normal operations, and each module features its own tasks. For example, a production module in the manufacturing center handles assembly tasks. Working together, these modules connect to a flow and define their facility functions. The model validation process includes verifying the logic flows, cross-checking the model's inventory daily changes with the built-in facilities of a well-established simulation software, and consulting with domain experts to validate the model's real-world applicability.

Following the design in Lei et al. (2023), in the *Baseline* scenario, all suppliers are trusted and approved, with no counterfeit threats assumed. The daily production of manufacturing centers meets customer orders, maintaining supply-demand equilibrium. Components are first sourced from S suppliers and delivered to M manufacturing centers for assembly. Assembled laptops are transported to D distribution centers and subsequently delivered to C customers. The objective of this SC is to ensure that customers receive authentic products within the estimated delivery time T. Further analyses are conducted to assess the performance of the SC under counterfeit events and model resilience when applying CMs. Figure 3 shows each agent's detailed system structure. Event blocks contain business logic that is periodically triggered, while queue blocks serve as buffers for agents waiting to be accepted by subsequent blocks.

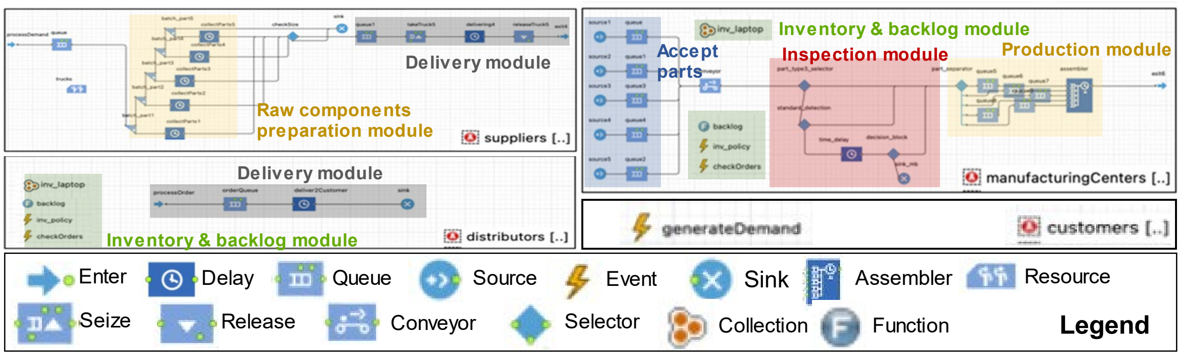

Figure 3: Supply chain network agent flowcharts.

The supplier view in Figure 3 demonstrates the internal system structure of this agent type. The time blocks represent unit packaging time for every line; with each responsible for packaging a specific type of part. An intermediate Part agent type stores essential information for each raw material unit as it moves along the flow. After all requested parts are packed, a Truck agent type is occupied from the vehicle resource pool, and the agent starts the transportation to the Manufacturing center agent. In the manufacturing center agent, five raw materials fill the input side, lining up on the conveyor module. A selection block, controlled by the *selection rate* parameter, separates motherboards from other parts, sending a proportion of motherboards to the inspection module. The distribution center agent models transportation between any manufacturing center and distribution center as 5 hours and distribution center to customers as a 3-day delay. A backlog policy module manages incoming demand orders in a FIFO queue when inventory is insufficient. Manufacturing center M_i has scheduled daily production of $Q_{i,t}$ on day t.

The *Threat* scenario introduces suppliers providing counterfeit parts, with Commercial Off-The-Shelf (COTS) suppliers having a higher probability of introducing counterfeit components. Counterfeit motherboards are mixed with authentic one entering manufacturing centers. In FixedInspect, each center samples incoming motherboards at a selection rate s, and inspection modules have an accuracy a_1 in determining part authenticity. *AdaptInspect* adjusts inspection stringency based on counterfeit activities (Guo et al. 2022), triggering tighter inspection with a higher selection rate, higher inspection accuracy, and longer unit inspection time, as shown in Algorithm 1. This tight inspection module deactivates when counterfeit activities normalize. To compensate for the time lost to inspection, manufacturing centers will accelerate production and adjust the daily production schedule during the threat period. A stopping mechanism also notifies suppliers to cease sending counterfeit components, further mitigating the risk. Key parameters identified for the *FixedInspect* scenario are the inspection accuracy a_1 and selection rate s. Key parameters identified for *AdaptInspect* are the tight inspection accuracy, a_2, and the selection rate for parts from trusted suppliers, s_T. Since COTS suppliers may be less trustworthy than trusted suppliers, the selection rate for parts from COTS suppliers, s_C, is set to 0.1 higher than s_T. For the parameter variation experiment, the range a_1 is selected with dynamic changing of step size, and for selection rate the fixed step size of 0.1 is used for ranging from 0.1 to 1.0. The step size for a_2 is set much smaller to capture the gradual performance change. Then, the heatmap is formed by the experiment. For each cell, N_R replications are run with the same input parameters and take the average to visualize the effectiveness of different countermeasure strategies. Table 2 showcases parameter values applied to the simulation. For comparison purposes, simulation experiments using fixed input distribution parameters are conducted, with $s = 0.2, a_1 = 0.9, a_2 = 0.95,\ s_T = 0.4, s_C = 0.6$ applied consistently across all replications.

Algorithm 1. Inspection process for incoming parts.

BEGIN
FOR each incoming batch of parts **DO**
Determine supplier source (trusted or COTS)
IF trigger indicating an increase in counterfeit activities is not detected **THEN**
Perform standard inspection by selecting a predefined percentage of incoming parts
IF inspected parts pass **THEN**
Send parts to the production module
ELSE
Discard parts
END IF
ELSE
Perform tight inspection based on the supplier source: increase the selection rate on parts for inspection for both sources
IF inspected parts pass **THEN**
Send parts to the production module
ELSE
Discard parts
END IF
END IF
END FOR

Table 2: Parameter descriptions and values in the case study.

Parameter	**Description**	**Value**
S	Number of suppliers	3
M	Number of manufacturing centers	2
D	Number of distribution centers	2
C	Number of customers	100
T_{sim}	Total simulation period	1 year
T	Days allowed for delivery	3 days
N_R	Number of replications in simulation	5
a_1	Inspection accuracy for *FixedInspect*	[0.1, 0.4, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95, 1.0]
s	Selection rate for *FixedInspect*	[0.1, 1.0] step size 0.1
a_2	Inspection accuracy for *AdaptInspect*	[0.0, 0.8] step size 0.1, [0.8, 1.0] step size 0.02
$Q_{i,t}$	Scheduled daily production at manufacturing center M_i on day t	150
s_T	Selection rate for parts from trusted suppliers in *AdaptInspect*	[0.1, 1.0] step size 0.1
s_C	Selection rate for parts from COTS suppliers in *AdaptInspect*	$s_T + 0.1$

4.2 Results of Empirical Distribution Mapping

In simulation experiments, the average *PE* for each parameter combination is calculated from the *GPP* metric, resulting in a *PE* heatmap for *FixedInspect*, as shown in Figure 4(a). The axes show the value combinations, with lighter colors indicating higher *PE* values. The cell values and effectiveness points are mapped onto the elicitation CDF plot in Figure 4(b). For example, a cell value of 0.8029 can represent an 80.29% probability that $a_1 \leq 95\%$ and $s \leq 90\%$. For a probability value 0.85, which is absent from the table, several possible data cells are identified for interpolation related to the parameter "selection rate": $(a_1 = 1.0, 0.8 \leq s \leq 0.9), (a_1 = 0.95, 0.9 \leq s \leq 1.0), (a_1 = 0.9, 0.9 \leq s \leq 1.0)$; while interpolating the parameter "inspection accuracy", there are also a few options: $(s = 1.0, 0.85 \leq a_1 \leq 0.9), (s = 0.9, 0.95 \leq a_1 \leq 1.0)$. A pair of combinations is selected from these options and interpolation is conducted. If $(a_1 = 1.0, 0.8 \leq s \leq 0.9)$ is chosen, the interpolation calculates as $s = 0.8 + 0.1 \times (0.85 - 0.8)/(0.9 - 0.8) = 0.85$. Similarly, heatmaps are generated for *AdaptInspect*, shown in Figure 5(a) and (b).

(a) Inspection Accuracy a_1

Select Rate s	0.10	0.40	0.70	0.75	0.80	0.85	0.90	0.95	1.00
0.0	0.035	2.972	2.972	0.117	11.193	-8.187	2.972	0.117	2.972
0.1	-4.981	1.214	5.763	7.233	7.503	8.428	8.642	10.391	10.779
0.2	-14.551	-1.568	9.184	11.135	12.244	13.606	15.336	17.169	18.808
0.3	-24.991	-4.555	13.636	15.767	19.128	21.319	23.288	25.926	29.282
0.4	-36.372	-5.897	18.026	21.720	24.794	28.410	31.185	34.941	38.128
0.5	-49.261	-7.074	23.887	28.754	32.775	36.995	40.513	45.006	48.460
0.6	-66.478	-8.862	30.354	35.727	41.043	45.562	50.671	54.362	58.924
0.7	-87.450	-10.408	37.378	42.018	49.005	54.552	59.723	64.529	68.734
0.8	-114.749	-10.571	43.491	51.123	57.730	63.907	69.466	73.880	79.275
0.9	-153.013	-14.369	51.482	59.097	65.886	73.217	78.864	84.128	89.880
1.0	-209.730	-16.887	59.152	68.182	75.619	82.363	88.660	94.656	100.000

(b) Inspection Accuracy a_1

Select Rate s	0.10	0.40	0.70	0.75	0.80	0.85	0.90	0.95	1.00
0.0	0.000	0.003	0.003	0.002	0.014	0.000	0.003	0.000	0.003
0.1	0.000	0.002	0.008	0.008	0.008	0.009	0.011	0.001	0.016
0.2	0.000	0.000	0.012	0.014	0.016	0.020	0.022	0.027	0.033
0.3	0.000	0.000	0.022	0.025	0.033	0.039	0.046	0.058	0.076
0.4	0.000	0.000	0.030	0.043	0.054	0.066	0.080	0.102	0.120
0.5	0.000	0.000	0.046	0.071	0.091	0.114	0.133	0.169	0.202
0.6	0.000	0.000	0.085	0.108	0.140	0.177	0.220	0.249	0.301
0.7	0.000	0.000	0.120	0.147	0.211	0.202	0.259	0.367	0.419
0.8	0.000	0.000	0.169	0.220	0.291	0.355	0.419	0.510	0.693
0.9	0.000	0.000	0.220	0.301	0.379	0.488	0.654	0.803	0.913
1.0	0.000	0.000	0.311	0.405	0.559	0.751	0.913	0.987	1.000

Figure 4: (a) *PE* heatmap for *FixedInspect*. (b) Probability heatmap for *FixedInspect*.

(a) Inspection Accuracy a_2

Select Rate s_T	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.82	0.84	0.86	0.88	0.90	0.92	0.94	0.96	0.98	1.00
0.0	-4.278	-1.048	0.990	1.617	3.672	3.622	4.711	6.035	21.978	18.473	45.598	49.133	68.775	84.496	84.598	84.233	77.645	71.355	96.050
0.1	-11.639	-8.294	-5.591	-2.050	1.437	3.594	6.245	9.602	11.771	36.147	13.561	50.076	89.540	89.317	90.771	91.347	89.413	87.109	81.646
0.2	-23.847	-17.599	-12.332	-7.588	-1.664	4.101	8.370	13.252	18.074	18.478	19.814	33.196	57.264	92.976	92.536	92.813	92.548	92.115	96.852
0.3	-34.381	-25.789	-18.385	-10.059	-2.118	5.275	11.820	19.063	24.157	25.775	38.552	52.493	79.909	92.195	94.028	93.657	94.150	93.347	85.553
0.4	-45.410	-33.021	-20.708	-10.734	-0.550	8.592	18.281	25.024	32.679	46.026	35.445	36.446	49.110	94.601	95.239	95.147	95.673	95.560	97.296
0.5	-57.545	-42.226	-26.612	-11.573	1.279	11.977	23.662	32.646	41.382	43.439	44.704	46.542	70.517	91.421	95.888	96.371	95.493	95.557	97.520
0.6	-72.192	-49.243	-29.105	-13.039	1.380	16.039	28.645	39.586	50.645	51.973	54.618	63.412	76.765	96.271	95.770	96.348	96.451	96.448	97.546
0.7	-91.573	-61.109	-36.397	-13.836	4.171	20.025	34.304	47.687	57.983	60.415	69.695	70.758	80.987	96.921	97.137	97.563	97.069	96.876	93.653
0.8	-113.734	-74.603	-44.259	-17.274	6.356	23.840	40.786	55.043	66.827	69.031	71.178	73.337	90.409	97.647	97.548	97.439	97.618	97.645	95.996
0.9	-141.956	-91.527	-50.963	-18.280	8.669	28.162	46.888	62.754	75.828	78.188	83.483	83.966	93.653	97.767	97.883	97.860	98.038	97.947	98.166
1.0	-149.940	-100.556	-55.484	-20.267	5.864	28.947	47.699	63.421	77.792	79.851	85.268	89.845	94.388	96.813	97.924	97.924	97.982	97.902	97.792

(b) Inspection Accuracy a_2

Select Rate s_T	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.82	0.84	0.86	0.88	0.90	0.92	0.94	0.96	0.98	1.00
0.0	0.000	0.000	0.000	0.001	0.001	0.002	0.002	0.003	0.002	0.009	0.140	0.242	0.618	0.966	0.967	0.966	0.869	0.696	0.997
0.1	0.000	0.000	0.000	0.000	0.001	0.002	0.003	0.004	0.006	0.009	0.006	0.242	0.983	0.983	0.986	0.988	0.984	0.977	0.955
0.2	0.000	0.000	0.000	0.000	0.000	0.002	0.004	0.006	0.009	0.009	0.010	0.032	0.387	0.992	0.990	0.992	0.990	0.990	0.997
0.3	0.000	0.000	0.000	0.000	0.000	0.002	0.006	0.010	0.014	0.017	0.055	0.301	0.926	0.990	0.994	0.993	0.994	0.992	0.973
0.4	0.000	0.000	0.000	0.000	0.000	0.040	0.009	0.016	0.032	0.157	0.039	0.044	0.242	0.995	0.995	0.995	0.996	0.996	0.998
0.5	0.000	0.000	0.000	0.000	0.000	0.006	0.014	0.032	0.080	0.104	0.137	0.157	0.672	0.988	0.996	0.997	0.996	0.996	0.998
0.6	0.000	0.000	0.000	0.000	0.000	0.008	0.022	0.065	0.286	0.309	0.353	0.513	0.859	0.997	0.995	0.997	0.997	0.997	0.998
0.7	0.000	0.000	0.000	0.000	0.002	0.010	0.035	0.226	0.404	0.443	0.662	0.682	0.947	0.998	0.998	0.998	0.998	0.997	0.994
0.8	0.000	0.000	0.000	0.000	0.003	0.014	0.080	0.353	0.587	0.443	0.696	0.758	0.985	0.998	0.998	0.998	0.998	0.998	0.997
0.9	0.000	0.000	0.000	0.000	0.004	0.014	0.181	0.493	0.841	0.894	0.962	0.966	0.993	0.998	0.998	0.998	0.999	0.998	0.999
1.0	0.000	0.000	0.000	0.000	0.003	0.022	0.226	0.513	0.894	0.936	0.970	0.985	0.995	0.998	0.998	0.999	0.999	0.998	0.999

Figure 5: (a) *PE* heatmap for *AdaptInspect*. (b) Probability heatmap for *AdaptInspect*.

4.3 Comparison of CM Scenarios

All scenarios are simulated 30 replications with fixed and elicitation-informed input parameters, to account for the inherent variability and uncertainty in the system. Results on *PE* and *GPP* are calculated using (1) and (2). The *Threat* scenario determines the unmitigated risk R_0 for both DCs ($R_0^1 = 0.049, R_0^2 = 0.050$) with *GPP* values 0.951 for DC_1 and 0.950 for DC_2. Meanwhile, the corresponding *PE* values are calculated for both scenarios. Table 3 shows the average results for DC_1 and DC_2 from 30 replications. For example, in the experiments with elicitation-informed input, the mitigated risk for DC_1 after applying *FixedInspect* drops to 1 – 0.961 = 0.039. Therefore, *PE* = (0.049 – 0.039)/0.049 × 100% = 20.408%.

In experiments with the fixed input, *FixedInspect* applied SC has *GPP* for both DCs increased slightly compared to the *Threat* scenario. *AdaptInspect* significantly improved *PE* compared to *FixedInspect*. However, the fixed input model may not fully capture SC complexities and uncertainties, especially with advanced CMs. In elicitation-informed simulation, *AdaptInspect* also outperformed *FixedInspect*. The highest performance is achieved in the *AdaptInspect* scenario, with *PE* improving correspondingly.

Table 3: Comparison of *GPP* and *PE* between fixed input and elicitation-informed input experiments.

Countermeasure \ Experiment	Fixed Input Simulation				Elicitation-Informed Simulation			
	DC1		DC2		DC1		DC2	
	GPP	PE (%)	GPP	PE (%)	GPP	PE (%)	GPP	PE (%)
Threat + *FixedInspect*	0.957	12.551	0.956	11.290	0.961	20.408	0.960	20.000
Threat + *AdaptInspect*	0.985	68.826	0.985	69.758	0.989	77.551	0.989	78.000

4.4 Discussion

The heatmaps reveal trends and outliers in the data. For instance, higher inspection accuracy and selection rate generally improve performance, but optimal performance requires both parameters to be high. Some outliers indicate negative improvement when $a_1 = 85\%$ and $a_2 = 0\%$. This occurs because the selection rate is 0 as the inspection module is ineffective. These negative cells in the effectiveness heatmap are set to 0 probability and corresponding parameter combinations are dropped. It has been found that both CMs improve risk reduction. However, *FixedInspect* is found to be less effective. For instance, the *GPP of*, DC_1 in *FixedInspect* was 0.957 [0.943, 0.971] (*PE* = 12.551%), while in *AdaptInspect*, it rose to 0.985 [0.977, 0.993] (*PE* = 68.826%). Similar trends were observed for DC_2. In the elicitation-informed simulation, GPP reached 0.961[0.952, 0.969] and 0.960 [0.951, 0.969] for DC_1 and DC_2 respectively under *FixedInspect*, and 0.989 [0.983, 0.995] for both under *AdaptInspect*. PE also improved, reaching 77.551% for DC_1 and 78.000% for DC_2 in the *AdaptInspect* scenario. This is not surprising as *FixedInspect* cannot adapt to variations, as its inspection accuracy is not as effective as those in *AdaptInspect*. Moreover, the use of elicitation-informed input consistently outperforms the fixed input approach by leveraging domain experts' knowledge, which allows for a more accurate and detailed representation of real-world conditions.

Consequently, the resulting CM scenarios are more closely aligned with the complexities and uncertainties present in actual crisis situations. Using elicitation-informed input offers a significant advantage over fixed-parameter data as it enables the development of more adaptive and resilient CM strategies. This is because the elicitation-informed input data can be continuously updated and refined based on expert feedback, resulting in a more dynamic and realistic simulation environment. However, we acknowledge the potential limitations. One limitation is the presence of expert bias, which may impact the accuracy and reliability of the elicitation process. Experts may overestimate or underestimate certain parameters based on their personal experiences or beliefs. They may also be influenced by cognitive biases. To mitigate this impact, we employed the use of multiple expert groups to cross-validate.

5 CONCLUSION

The study develops an elicitation-informed simulation model to enhance decision-making. An elicitation mapping methodology is proposed to fit elicitation data to corresponding CMs, demonstrating their effectiveness in risk reduction. By integrating expert knowledge, this approach enhances the model's reliability and representation of real-world strategies. Moreover, the model's adaptability allows for different inputs at various strategy levels, making it useful in dynamic and rapidly changing environments.

Although not discussed in detail, the work developed in this study helps reduce data privacy concerns, as it relies on the aggregation of SMEs' opinions instead of those of a single expert, and the interviews are conducted anonymously. This aspect is particularly relevant to industries where data privacy is a critical concern. To address the limitations mentioned in the Discussion Section, future research could explore the use of multiple experts, diverse backgrounds, and more rigorous methods for assessing and mitigating biases. Another area for future study is the refinement of the elicitation mapping process. The current study uses a linear interpolation method for empirical data, but other techniques could enhance the interpolation. In this study, we assessed the influence of inspection delays and countermeasures on supply chain resilience, without considering the potential impact of boosting production rates. This unexplored countermeasure warrants further investigation in future research.

ACKNOWLEDGMENTS

This material is based upon work supported by the U.S. Department of Homeland Security under Grant Award Number 17STQAC00001-05-00. **Disclaimer:** The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Department of Homeland Security.

REFERENCES

Borshchev, A. 2013. *The Big Book of Simulation Modeling: Multimethod Modeling with Anylogic 6*. Oakbrook Terrace, Illinois, United States:AnyLogic North America.

Bottani, E., T. Murino, M. Schiavo, and R. Akkerman. 2019. "Resilient Food Supply Chain Design: Modelling Framework and Metaheuristic Solution Approach". *Computers & Industrial Engineering* 135:177-198.

Bradley, R. L., J. J. Bergman, J. S. Noble, and R. G. Mcgarvey. 2015. "Evaluating a Bayesian Approach to Demand Forecasting with Simulation". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, V. W. K. Chan, I.-C. Moon, T. M. K. Roeder, C. Macal and M. D. Rossetti, 1868-1879. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Brailsford, S. C., T. Eldabi, M. Kunc, N. Mustafee, and A. F. Osorio. 2019. "Hybrid Simulation Modelling in Operational Research: A State-of-the-Art Review". *European Journal of Operational Research* 278(3):721-737.

Chen, H. Y., A. Das, and D. Ivanov. 2019. "Building Resilience and Managing Post-Disruption Supply Chain Recovery: Lessons from the Information and Communication Technology Industry". *International Journal of Information Management* 49:330-342.

De Sensi, G., F. Longo, and G. Mirabelli. 2008. "Inventory Policies Analysis under Demand Patterns and Lead Times Constraints in a Real Supply Chain". *International Journal of Production Research* 46(24):6997-7016.

Edwards, J. S., T. Alifantis, R. D. Hurrion, J. Ladbrook, S. Robinson, and A. Waller. 2004. "Using a Simulation Model for Knowledge Elicitation and Knowledge Management". *Simulation Modelling Practice and Theory* 12(7):527-540.

Egan, N., V. Menkov, and P. Kantor. 2022. "Eliciting Uncertain Resilience Information for Risk Mitigation". In *Proceedings of the 55th Hawaii International Conference on System Sciences*, edited by T. X. Bui, 2421-2430. Hawaii: University of Hawaii at Manoa.

Garthwaite, P. H., J. B. Kadane, and A. O'hagan. 2005. "Statistical Methods for Eliciting Probability Distributions". *Journal of the American Statistical Association* 100(470):680-701.

Gholami-Zanjani, S. M., M. S. Jabalameli, and M. S. Pishvaee. 2021. "A Resilient-Green Model for Multi-Echelon Meat Supply Chain Planning". *Computers & Industrial Engineering* 152:107018.

Gregory, R., L. Failing, M. Harstone, G. Long, T. Mcdaniels, and D. Ohlson. 2012. *Structured Decision Making: A Practical Guide to Environmental Management Choices*. Chichester, West Sussex:John Wiley & Sons.

Guo, W. G., P. Kantor, E. Elsayed, E. Rosenberg, R. Lei, S. Patel, B. Ruskey, and F. Roberts. 2022. "Supply Chain Threats and Countermeasures: From Elicitation through Optimization". In *Proceedings of the 55th Hawaii International Conference on System Sciences*, edited by T. X. Bui. Hawaii: University of Hawaii at Manoa.

Hudlicka, E. 1996. "Requirements Elicitation with Indirect Knowledge Elicitation Techniques: Comparison of Three Methods". In *Proceedings of the Second International Conference on Requirements Engineering*, edited by C. Shekaran and J. Siddiqi, 4-11. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers Computer Society.

Jabbarzadeh, A., B. Fahimnia, J.-B. Sheu, and H. S. Moghadam. 2016. "Designing a Supply Chain Resilient to Major Disruptions and Supply/Demand Interruptions". *Transportation Research Part B: Methodological* 94:121-149.

Jalali, H., and I. V. Nieuwenhuyse. 2015. "Simulation Optimization in Inventory Replenishment: A classification". *IIE Transactions* 47(11):1217-1235.

Klimov, R., and Y. Merkuryev. 2008. "Simulation Model for Supply Chain Reliability Evaluation". *Technological and Economic Development of Economy* 14(3):300-311.

Lei, R., S. Saleh, W. G. Guo, E. Elsayed, and F. Roberts. 2023. "Simulation Modeling of the Counterfeit Threat and Countermeasures in Ict Manufacturing Supply Chains". In *Proceedings of the 51st SME North American Manufacturing Research Conference*, June 12th-16th, New Jersey.

Lyu, Z., D. Pons, Y. Zhang, and Z. Ji. 2022. "Minimum Viable Model (MVM) Methodology for Integration of Agile Methods into Operational Simulation of Logistics". *Logistics* 6(2):37.

Maghoulan, S., H. M. Ondemir, and M. Dehghanimohammadabadi. 2022. "Covid-19 Supply Chain Planning: A Simulation-Optimization Approach". In *Proceedings of the 2022 Winter Simulation Conference*, edited by B. Feng, P. Y. Yijie, G. Pedrielli, S. Eunhye, S. Shashaani and C. Gunes Corlu, 533-544. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Mensah, P., and Y. Merkuryev. 2013. "The Role of ICT in the Supply Chain Resilience". In *International Conference on Applied Information and Communication Technologies*, edited by M. Szala. Jelgava, Latvia: Faculty of Information Technologies, Latvia University of Agriculture.

Mensah, P., and Y. Merkuryev. 2014. "Developing a Resilient Supply Chain". *Procedia - Social and Behavioral Sciences* 110(24):309-319.

Mensah, P., Y. Merkuryev, and S. Manak. 2015. "Developing a Resilient Supply Chain Strategy by Exploiting ICT". *Procedia Computer Science* 77:65-71.

Mustafee, N., A. Harper, and B. S. Onggo. 2020. "Hybrid Modelling and Simulation (M&S): Driving Innovation in the Theory and Practice of M&S". In *Proceedings of the 2020 Winter Simulation Conference*, edited by K.-H. G. Bae, S. Lazarova-Molnar, Z. Zheng, B. Feng and S. Kim, 3140-3151. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Petersohn, S., S. E. Grimm, B. L. T. Ramaekers, A. J. Ten Cate-Hoek, and M. A. Joore. 2021. "Exploring the Feasibility of Comprehensive Uncertainty Assessment in Health Economic Modeling: A Case Study". *Value in Health* 24(7):983-994.

Ponomarov, S. Y., and M. C. Holcomb. 2009. "Understanding the Concept of Supply Chain Resilience". *The International Journal of Logistics Management* 20(1):124-143.

Powell, C. 2003. "The Delphi Technique: Myths and Realities". *Journal of advanced nursing* 41(4):376-382.

Rahman, T., S. K. Paul, N. Shukla, R. Agarwal, and F. Taghikhah. 2022. "Supply Chain Resilience Initiatives and Strategies: A Systematic Review". *Computers & Industrial Engineering* 170(4):108317.

Rahmani, M., A. Romsdal, F. Sgarbossa, J. O. Strandhagen, and M. Holm. 2022. "Towards Smart Production Planning and Control; a Conceptual Framework Linking Planning Environment Characteristics with the Need for Smart Production Planning and Control". *Annual Reviews in Control* 53(2):370-381.

Razavian, E., A. Alem Tabriz, M. Zandieh, and M. R. Hamidizadeh. 2021. "An Integrated Material-Financial Risk-Averse Resilient Supply Chain Model with a Real-World Application". *Computers & Industrial Engineering* 161:107629.

Saleh, S., R. Lei, W. Guo, and E. A. Elsayed. 2023. "A Survey on Counterfeits in the Information and Communications Technology (ICT) Supply Chain". In *Proceedings of Seventh International Congress on Information and Communication Technology*, edited by X.-S. Yang, S. Sherratt, N. Dey and A. Joshi, 849-870. Singapore: Springer Nature Singapore.

Sazvar, Z., K. Tafakkori, N. Oladzad, and S. Nayeri. 2021. "A Capacity Planning Approach for Sustainable-Resilient Supply Chain Network Design under Uncertainty: A Case Study of Vaccine Supply Chain". *Computers & Industrial Engineering* 159(1):107406.

The US Departments of Commerce and Homeland Security. 2022. "Assessment of the Critical Supply Chains Supporting the U.S. Information and Communications Technology Industry".

Talantsev, A., T. Fasth, C. Wenner, E. Wolff, and A. Larsson. 2022. "Evaluation of Pharmaceutical Intervention Strategies against Pandemics in Sweden: A Scenario-Driven Multiple Criteria Decision Analysis Study". *Journal of Multi-Criteria Decision Analysis* 29(1-2):49-66.

Tordecilla, R. D., A. A. Juan, J. R. Montoya-Torres, C. L. Quintero-Araujo, and J. Panadero. 2021. "Simulation-Optimization Methods for Designing and Assessing Resilient Supply Chain Networks under Uncertainty Scenarios: A Review". *Simulation Modelling Practice and Theory* 106:102166.

AUTHOR BIOGRAPHIES

RONG LEI is a PhD student in Industrial and Systems Engineering at Rutgers University, focusing on supply chain simulation, data analytics in manufacturing, and federated learning. He utilizes simulation to enhance supply chain performance analytics, and drive innovation in applications of machine learning in manufacturing. His email address is rl839@scarletmail.rutgers.edu.

SAMAR SALEH is a PhD student in Industrial and Systems Engineering at Rutgers University. Her industrial background focused on enhancing productivity and profitability via data analysis and process design. She is keenly interested in the use of operations research to optimize supply chain processes. Her email address is shs164@scarletmail.rutgers.edu.

WEIHONG (GRACE) GUO is an associate professor in Industrial and Systems Engineering at Rutgers University. Her research focuses on data-driven methods for process monitoring, anomaly detection, and predictive quality. Her email address is wg152@soe.rutgers.edu, and her website is https://ise.rutgers.edu/weihong-guo.

ELSAYED A. ELSAYED is a Distinguished Professor in the Department of Industrial and Systems Engineering at Rutgers University. His research focuses on quality, reliability engineering, and production planning and control. Elsayed has authored numerous books and publications, and served in editorial roles for several journals. His email address is elsayed@soe.rutgers.edu.

FRED S. ROBERTS is a Distinguished Professor in the Department of Mathematics at Rutgers University and Director of the CCICADA Center, a DHS university center of excellence. His research interests span mathematical models. He has authored or edited 30 books, published over 210 papers, and received multiple awards. His email address is froberts@dimacs.rutgers.edu.

PAUL KANTOR is a Distinguished Research Professor at Rutgers University, focusing on information systems for storage and retrieval. He has worked on diverse projects ranging from brain image indexing to nuclear sensor management. Kantor is affiliated with RUTCOR, DIMACS, CCICADA, and the Department of Computer Science. His email address is paulbkantor@gmail.com.