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Simulation-Optimization Framework for Designing Resilient Supply Chain Systems

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Abstract: ***This study proposes a simulation-optimization framework to support the design of resilient supply chain systems under prolonged disruption risks, such as those experienced during a pandemic. A discrete-event simulation model, integrated with the OptQuest optimization engine in Arena, is developed to evaluate and optimize key decisions in the supply chain, including inventory control and order allocation strategies. The model incorporates multi-sourcing and pre-positioning approaches to improve system robustness. Randomized disruption scenarios affecting suppliers and manufacturers are used to assess supply chain performance in terms of total cost and customer service level. The results provide actionable insights for systems engineers and decision-makers seeking to balance efficiency and resilience in complex supply chain networks under uncertainty.***

Keywords: Supply Chain Resilience, Discrete-Event Simulation, Inventory Policy, Order Allocation, Supply Disruption

1. Introduction

Outsourcing and lean practices have become common strategies in the global supply chain management, enabling companies to reduce costs, improve agility, and focus on core competencies [1, 2] . However, increasing complexity in supply chains also heightens vulnerability to disruptions such as natural disasters, regulatory changes, and pandemics [3]. The COVID-19 crisis exposed critical weaknesses, e,g., halting production due to raw material shortages and causing major supply-demand imbalances [4, 5].

These challenges have emphasized the need for resilient supply chains that can withstand and recover from disruptions. Simulation offers a valuable tool to model complex networks under such conditions, providing insights into system behavior, propagation effects, and the impact of various resilience strategies. Particularly, order allocation and inventory policies must adapt to minimize total expected costs while accounting for supply risks, capacity limits, and supplier reliability.

This study proposes a simulation-based framework for evaluating resilient order allocation and inventory strategies under disruption scenarios helping decision-makers maintain service levels, minimize costs, and improve recovery while supporting the shift toward sustainable and robust supply chains. Theoretically, it advances the literature by integrating dynamic simulation with supplier allocation and resilience measurements, bridging static optimization models and simulation studies to explain how adaptive strategies shape supply chain robustness under high-magnitude disruptions.

2. Literature Review

a) Resilient Supply Chain Network Design

The concept of supply chain (SC) resilience is defined as the ability of the system to anticipate, absorb, adapt to, and recover from disruptive events [6]. A resilient supply chain network design seeks to strategically balance operational capabilities with exposure to risks. While traditional views emphasized network strength, recent perspectives argue that resilience emerges from a deliberate trade-off between flexibility, redundancy, and vulnerability mitigation [7]. The framework proposed by Ivanov and Dolgui remains influential, identifying three core resilience capabilities: disruption readiness, responsiveness during crisis, and recovery to baseline or improved states [8].

Contemporary models increasingly integrate multi-objective optimization to simultaneously address sustainability and resilience goals. For example, Klibi et al. [6] proposed a multi-period mixed-integer linear programming (MILP) framework that incorporates environmental, social, and economic dimensions alongside operational risk. Their model enhances classical design by including scenario-based disruptions and region-specific vulnerabilities.

Although such quantitative models offer optimization insights, they often struggle to capture dynamic interactions such as disruption propagation, adaptive behavior, and network feedback loops. To address this, researchers have started integrating system dynamics and agent-based modeling with traditional MILP to better simulate the evolving behavior of SC networks under stress [9]. In parallel, supplier selection, which is an essential dimension of resilient SC design, has shifted toward hybrid decision-support frameworks. Afrasiabi et al. [10] introduced a fuzzy multi-criteria model that evaluates both sustainability and disruption-resilience factors.

More recently, AI-driven tools such as machine learning and metaheuristics have been explored to prioritize suppliers based on resilience metrics, such as responsiveness, adaptability, and network centrality [11].

b) Supplier Selection and Order Allocation under Uncertainty

Suppliers are pivotal in enhancing supply chain resilience, particularly in turbulent environments. Contemporary supplier selection strategies must account for a range of criteria, such as quality, responsiveness, risk mitigation capability, environmental sustainability, and cost efficiency [10, 11]. Recent studies emphasize that supplier resilience extends beyond static performance indicators, requiring adaptability, flexibility, and continuity planning mechanisms to mitigate the impact of disruptions.

Collaborative practices such as joint contingency planning and real-time information sharing have been found to significantly reduce ripple effects like the bullwhip effect and improve recovery speed [12]. Furthermore, dynamic capabilities such as the ability to switch to backup suppliers, implement flexible contracts, or reconfigure logistics networks are increasingly essential under evolving conditions [13].

In the context of order allocation under uncertainty, supplier reliability and capacity constraints must be balanced with cost objectives. Recent approaches integrate simulation and artificial intelligence to model the effects of supplier disruption and evaluate alternative allocation strategies under probabilistic scenarios [14]. However, despite growing interest in simulation-based planning, many frameworks still lack explicit modeling of disruption propagation and inter-supplier interdependence, which are key to accurate risk evaluation.

c) Simulation-Based Resilience Modeling

Simulation is a powerful approach for analyzing supply chain behavior under disruption and testing resilience strategies prior to real-world implementation. Unlike static optimization models, simulation captures dynamic interactions, cascading effects, and time-dependent recovery patterns. It allows decision-makers to explore "what-if" scenarios, measure cost and service trade-offs, and evaluate both the short- and long-term impacts of disruption response strategies. While MILP models like those proposed by [15] provide optimal static solutions, simulation excels at capturing system evolution, non-linearity, and behavioral dynamics, making it indispensable for resilience testing in volatile environments.
Recent work by Moosavi and Hosseini [16] demonstrates the utility of discrete-event simulation (DES) in evaluating recovery strategies in a three-echelon SC affected by pandemic-related disruptions. Their model incorporated gradual disruption onset and evaluated backup inventory and supplier activation strategies, focusing on financial and fulfillment metrics. However, their study did not consider adaptive order allocation, a key factor in maintaining performance during crises.

Building on these foundational efforts, recent research has expanded simulation applications to model ripple effects, propagation patterns, and inter-supplier dependencies. For instance, Zhang et al. [14] integrated agent-based modeling with optimization techniques to simulate multi-supplier networks and test decentralized decision-making under uncertainty. Similarly, Wang et al. [10] introduced a hybrid simulation-optimization framework to explore the interplay of logistics delays, order allocation, and supplier switching in resilient network design.

Simulation also plays a key role in epidemic-aware SC modeling. Ivanov [17] laid groundwork for epidemic disruption forecasting, and more recent studies have emphasized data-driven, AI-supported models for predicting SC stress points and autonomously adjusting recovery strategies[18]. Such developments enhance decision support by incorporating real-time feedback loops and learning mechanisms—something traditional mathematical programming lacks.

3. Methodology

1) Simulation framework

This study evaluates the impact of resilience strategies on a supply chain under pandemic-related disruptions using the framework in Figure 1. A DES model is developed in the ARENA software with aims to support redesign decisions by analyzing system performance through financial metrics, i.e., revenue, profit, cost, and demand fulfillment. Random disruptions are introduced to simulate pandemic effects, allowing for assessment of system behavior under uncertainty and testing of alternative order allocation strategies.

The supply chain model consists of three main components: suppliers, a manufacturer, and customers. Customers arrive periodically with randomly assigned demand while suppliers receive fixed orders from the manufacturer and can accept additional quantities if capacity allows. Optimization is supported via the OptQuest module within ARENA. The objective is to minimize the total expected cost while ensuring service continuity. Simulation results will inform the most effective resilience strategy under disruption scenarios.

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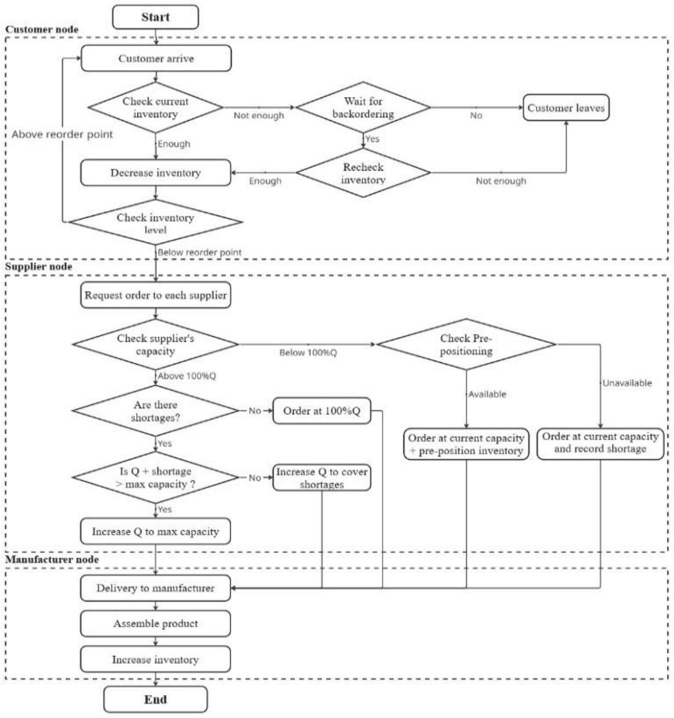

Figure 1: Conceptual model

2) *Inventory Policy*

A continuous review (s, S) inventory policy is applied at the manufacturer node to ensure high service levels. Here, *S* is the fixed order-up-to level, and *s* is the reorder point. Orders are placed when inventory reaches *s*, but to avoid overlapping replenishment, particularly under multi-sourcing, new orders are only triggered if at least 70% of previously placed orders have been received. This constraint helps manage lead-time variability among suppliers.

a) *Resilience Strategies*

Two resilience strategies are implemented independently and in combination: (1) *Multi-sourcing* - Engaging multiple suppliers to reduce dependence on any single source, thereby lowering the risk of supply failure; (2) *Pre-positioned Inventory* - Storing additional raw materials at the supplier's location to be used during emergencies. Though it adds moderate holding costs, it provides a buffer during disruptions.

b) *Disruption Events*

Disruptions are modeled as high-impact, long-duration events that occur randomly at the supplier node. These events reduce supplier capacity, increase transportation lead times, order processing times, and transportation cost. The simulation does not model recovery and each disruption is assumed to last up to 360 days, occurring once during the planning horizon. In each simulation run, one to two suppliers may be disrupted.

3) *Notations and Input Data*

Let $i \in I$ where $I=\{1,2,3\}$ denote the set of suppliers. Table 1 lists all notations used in the simulation model. The input data is arbitrarily generated based on the model published by Moosavi and Hosseini [19] (Table 2-4).

The total cost (TC) of the manufacturer throughout the entire period and the customer service level (CSL) are calculated by Equation 1, 2.

$$Total\ cost = \sum_i^I (FO_c + FT_c + (VO_c + VT_c) * Q_i) * N_i + inv * H_c * 360\ (days) + \sum_i^I (PI_i * PIC_i) * 360\ (days) \quad (1)$$

$$CSL = \frac{(Satisfied + Backorder)}{(Satisfied + Backorder + Lost\ sale)} \quad (2)$$

Table 1: List of notations used in the simulation model

Deterministic Parameters		Stochastic Parameters	
FO_i	Fix ordering cost	C_i	Capacity
FT_i	Fix transportation cost	inv	Inventory
VO_i	Variable ordering cost	OP_i	Order processing time
VT_i	Variable transportation cost	L_i	Leadtime
PIC_i	Pre-position cost	D	Demand
Hc	Holding cost	Q_i	Order quantity
invi	On-hand inventory	N_i	Number of orders
invm	Maximum inventory		
OHt	Order handling time	Decision variables	
At	Assembling time	ROP	Reorder point
De	Delivery time	PI_i	Pre-position inventory

Table 2: Supplier data

	Undisrupted			Disrupted		
	Supplier 1	Supplier 2	Supplier 3	Supplier 1	Supplier 2	Supplier 3
C_i (100%)	1.2	1.2	1.2	UNIF (0, 0.7)	UNIF (0, 0.7)	UNIF (0, 0.7)
OP_i (mins)	NORM (20, 2)	NORM (30, 2)	NORM (30, 2)	NORM (40, 2)	NORM (40, 2)	NORM (40, 2)
L_i (days)	TRIA (2.4, 2.6, 2.8)	TRIA (2.1, 2.3, 2.5)	TRIA (2.6, 2.8, 3.0)	TRIA (2.6, 4.4, 5.2)	TRIA (2.3, 3.8, 4.6)	TRIA (2.8, 4.9, 5.7)
FO_i ($)	128	110	103	128	110	103
VO_i ($)	21	22	21	21	22	22
FT_i ($)	1135	1024	985	1250	1260	1323
VT_i ($)	0.06	0.07	0.05	0.06	0.08	0.08
PIC_i ($)	0.2	0.2	0.2	0.2	0.2	0.2

Table 3: Manufacturer and customer data

Manufacturer	
OHt (mins)	TRIA (15, 30, 60)
At (mins)	NORM (3, 0.3)
De (days)	TRIA (0.5, 1.0, 1.5)
invi	700
invm	700
Hc ($)	0.5
Customers	
Demand	POIS (40)
Backorder probability	50%
Arrival time (days)	CONST (1)

Table 4: Disruption probability of the supply chain and suppliers

Supply chain	Disruption probability
1 disrupted supplier	100%
2 disrupted suppliers	50%
3 disrupted suppliers	0%
Creation time	UNIF (0, 360)
Suppliers	Disruption probability
Supplier 1	30%
Supplier 2	40%
Supplier 3	30%

4. Results and Discussion

1) *Model validity*

To validate the model logic, the system was tested under two baseline scenarios: undisrupted and disrupted, both without the implementation of resilience strategies. The initial setup included a reorder point of 400, with all demand allocated to Supplier 3. The simulation ran for 360 days with 30 replications to ensure statistical consistency.

In the undisrupted scenario, the model achieved a 100% service level, demonstrating effective inventory replenishment under stable conditions. In contrast, the disrupted scenario resulted in a reduced service level of 82.05%, consistent with expectations under supply constraints. The total cost in the undisrupted case was $419,543.34, higher than the disrupted case at $349,865.70, due to lower order quantities resulting from supplier capacity limitations, which averaged 70% during the disruption period.

Disruptions occurred randomly around day 150, approximately halfway through the simulation horizon, with timing and capacity losses distributed across suppliers. Furthermore, the results indicate that an 18% reduction in supplier capacity led to a comparable 18% decline in service level, confirming a strong and expected relationship between supply availability and customer satisfaction.

These outcomes demonstrate that the model responds logically to disruption scenarios and behaves in accordance with theoretical expectations, thereby supporting its validity for subsequent resilience strategy analysis.

2) *Simulation optimization*

The OptQuest module in Arena was employed to identify optimal solutions under both the undisrupted and disrupted conditions. In the disrupted case, two resilience strategies—multi-sourcing and pre-positioned inventory—were tested and compared. The optimization aimed to identify the best combination of reorder point, supplier order allocation, and pre-position inventory level that minimizes the total cost while maintaining the level of customer service higher than 95%. The number of replications in OptQuest is set at 10 replications.

Under disruption conditions, the optimal strategy identified by OptQuest highlights a synergistic approach to supply chain resilience. Specifically, the manufacturer should allocate 50% of the order quantity to Supplier 1 and 50% to Supplier 2, while reinforcing Supplier 1 with 30 units of pre-positioned inventory. This dual strategy results in the lowest expected cost while preserving a service level exceeding 95%.

Table 5: Comparison between undisrupted and disrupted scenario

	Undisrupted	Disrupted
Average inventory level	375.02	265.82
Satisfied customer	361	291.63
Backorder customer	0	4.4
Unsatisfied customer	0	64.73
Supplier 3 cost per order	7449	6938.16
`Number of orders	47.26	43.53
Capacity of supplier 1	120%	64.25%
Capacity of supplier 2	120%	76.07%
Capacity of supplier 3	120%	78.55%
Average time of occurrence	0	146.92
Service level	100%	82.05%
Total cost	$ 419,543.34	$ 349,865.70

Table 6: Simulation optimization results in different scenarios

	Undisrupted	Disrupted – multi-sourcing	Disrupted – pre-positioned inventory	Disrupted – multi-sourcing and pre-positioned inventory
Total expected cost	$ 405,233.0	$ 420,181.679	$ 398,571.865	$ 414,169.01
CSL	100%	97.15%	94.12%	97.15%
ROP	350	200	300	200
Supplier 1	_	0.5	1	0.5
Supplier 2	_	0.5	_	0.5
Supplier 3	1	_	_	_
PI1	_	_	50	30
PI2	_	_	_	_
PI3	_	_	_	_

These findings align with the literature advocating for flexibility-enhancing practices. For instance, Carvalho et al. [20] showed that offering alternative transport modes to suppliers improved performance under disruption—functionally equivalent to multi-sourcing in promoting adaptive capacity. Similarly, Moosavi and Hosseini [16] found that excessive inventory can serve as a buffer, but is often outperformed financially by strategic backup sourcing. However, unlike previous studies that explored these resilience levers independently, the present analysis highlights the benefits of a combined strategy, offering a more robust response to supply-side uncertainties.

This suggests that resilience does not necessarily require overinvestment in any single strategy, but can instead be optimized through a balanced portfolio of mitigation actions, tailored to specific network structures and risk profiles.

3) Sensitivity analysis

Sensitivity analysis was conducted to assess the model's responsiveness to internal (inventory policy) and external (demand fluctuation) factors under disruption conditions. Resilience strategies, including multi-sourcing and pre-positioning, were implemented to evaluate their moderating effects.

As shown in Table 7, varying the order quantity revealed that increasing order size generally led to lower total costs and improved service levels. A 14.29% increase in order quantity (from 500 to 600) resulted in a 0.02% reduction in total cost and a 1.84% decline in service level. This outcome is attributed to a reduction in the total number of orders placed annually, which helped mitigate the effects of disruptions. The trend suggests that larger, less frequent orders can enhance system stability during disruption events.

In contrast, changes in overall demand had a more substantial impact (Table 8). Although demand followed a Poisson distribution and remained structurally consistent before and after disruption, a 12.5% increase in average demand (from 40 to 45) led to a 7.46% rise in total cost and a 4.09% decrease in service level. These findings highlight the critical role of demand forecasting and capacity planning in maintaining supply chain resilience under uncertainty.

Table 7: Sensitivity analysis of order quantity

invm	Q	s1	s2	s3	PI1	PI2	PI3	inv	Total cost	CSL
450	250	0.5	0.5	0	30	0	0	154.564	$ 431,875.11	87.54%
500	300	0.5	0.5	0	30	0	0	180.766	$ 432,430.99	93.20%
600	400	0.5	0.5	0	30	0	0	204.276	$ 424,705.60	94.75%
700	500	0.5	0.5	0	30	0	0	230.621	$ 414,169.01	97.15%
800	600	0.5	0.5	0	30	0	0	251.773	$ 414,106.17	95.36%
850	650	0.5	0.5	0	30	0	0	272.166	$ 407,019.09	95.36%
900	700	0.5	0.5	0	30	0	0	290.543	$ 417,561.38	97.15%

Table 8: Sensitivity analysis of demand

ROP	D	s1	s2	s3	PI1	PI2	PI3	inv	Total cost	CSL
200	30	0.5	0.5	0	30	0	0	259.059	$ 338,051.49	99.16%
200	40	0.5	0.5	0	30	0	0	230.621	$ 414,169.01	97.15%
200	45	0.5	0.5	0	30	0	0	209.963	$ 445,060.22	93.18%
200	50	0.5	0.5	0	30	0	0	195.288	$ 476,497.03	88.20%
200	55	0.5	0.5	0	30	0	0	200.188	$ 512,218.40	86.83%

5. Conclusion

This study developed a simulation model that effectively captures the dynamics of supply chain disruptions, especially the impact of supplier constraints on manufacturer performance. It highlights how supplier's capacity during events like COVID-19 can significantly affect inventory levels and service quality. The ripple effects of disruption were evident, with customer satisfaction declining in proportion to inventory shortages.

The research extends existing literature by demonstrating the effectiveness of combining multi-sourcing with pre-positioned inventory. This integrated strategy enhances both resilience and cost efficiency under disruption. Diversifying order allocations across multiple suppliers reduces vulnerability, while strategically placed pre-positioned inventory supports continuity during critical periods. The optimized model maintained a service level above 95%, and the procurement cost difference between disrupted and undisrupted scenarios remained minimal—around 2%—underscoring the system's robustness. Finally, the findings offer practical guidance for supply chain managers to strategically adjust—such as modifying service level targets or selectively investing in inventory buffers—can help tailor resilience efforts to organizational priorities and cost constraints.

Future work could expand this model to more complex, multi-product supply chains with diverse suppliers and interdependent components, incorporating additional performance factors (e.g., delivery cost, resource utilization) and examining multi-node disruptions for a more comprehensive view of system vulnerabilities and resilience-building opportunities.

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