Simulation Framework to Quantify Supply Chain Resilience

Bhavya Gupta
Department of Industrial Engineering and Operations Research (IEOR), IIT Bombay
Powai, Mumbai, Maharashtra, India, 400076
bhavyagupta292@iitb.ac.in

Jayendran Venkateswaran
IEOR, IIT Bombay
jayendran@iitb.ac.in

Keywords: Supply chain resilience, quantify resilience, resilience strategy, backup supplier, disruptions, system dynamics

Funding Source: Prime Minister Research Fellowship (PMRF), Government of India

Introduction: A supply chain is highly complex and prone to disruptions. There has been a recent focus on supply chain resilience due to various social/ technical/ political situations worldwide that have significantly disrupted supply chain operations. Supply Chain Resilience is defined as the ability of the system to maintain operational functionality during disruptions and recover quickly (Zhao et al., 2011; Behzadi et al., 2020). This highlights the importance of accurately measuring resilience to identify gaps and assess the effectiveness of the strategies implemented. Supply chain disruption refers to an unanticipated event that interrupts the normal flow of goods and services within a supply chain, affecting production, sales, or distribution (Blackhurst et al., 2011). This research focuses on how disruptions affect supply chain operations and how to strengthen supply chain performance amid disruptions. This study developed a comprehensive framework based on a system dynamics approach to quantitatively assess supply chain resilience, demonstrating how resilience-enhancing strategies are incorporated into the model. Prior research suggests that the quantification of resilience is often approached through case studies. This study highlights two critical points in the supply chain by focusing on supply and dispatch disruptions that, if disrupted, can severely affect overall operational efficiency and customer satisfaction. Furthermore, scenarios are simulated to analyze the impact of the timing of the implementation of the resilience strategy after the onset of a disruption, including the effects of delayed implementation or postponement of arranging backups.

Methodology: A system dynamics model, represented as a stock and flow diagram, is developed to simulate a supply chain at the aggregate level. Figure 1 depicts a two-echelon supply chain consisting of a manufacturer and a retailer is considered where backup strategies are employed during production and dispatch disruption. The model considers the unmet demand as lost sales. Customer demand and lead time are constant at 10 units/week and 2 weeks, respectively. Demand is forecasted and used as information delay in decision support for quantity in transit and inventory to maintain desired levels. The fixed delay is incorporated into the delivery rate. α and β are adjustment rates for quantity-in-transit and inventory, respectively. Vensim, as a toolbox, is used to model and perform simulation. The time step of 0.25 seconds is considered.

Resilience Metrics: They are based on cost, quantity, and time, including indicators such as lead time ratio, recovery time, fill rate, and lost contribution. Lost Contribution (LC) metric is uniquely defined Equation 1. Lead Time Ratio (LTR) (Equation 2) has been used in previous studies, including Carvalho et al., 2012 and Sazvar et al., 2021. Recovery Time (T_r), though different from the one used in this paper, has been employed by Mirzaaliyan et al., 2024, and Silva et al., 2023. The recovery time metric (Equation 3) is formulated as a combination of the lead time ratio and the control engineering concept of settling time. The Fill Rate (FR) (Equation 4) has been utilized in studies such as Suryawanshi and Dutta, 2022, and Camur et al., 2023. t_0 and t_1 represent the start and end time of a disruption. t_r denotes time when LTR returns to its baseline value of 1, considering a tolerance of ±2% error, after the disruption has ceased

$$LC_r = \sum_{i=t_0}^{i=t_r} Lost\ sales_i * unit\ margin_i,\ \ LC_1 = \sum_{i=t_0}^{i=t_1} Lost\ sales_i * unit\ margin_i \tag{1}$$

$$LTR_r = \frac{1}{t_r - t_0} \sum_{i=t_0}^{i=t_r} \frac{Perceived\, LT_i}{Lead\, Time\, (LT)},\ \ LTR_1 = \frac{1}{t_1 - t_0} \sum_{i=t_0}^{i=t_1} \frac{Perceived\, LT_i}{Lead\, Time\, (LT)} \tag{2}$$

$$T_r = t_r - t_1, \tag{3}$$

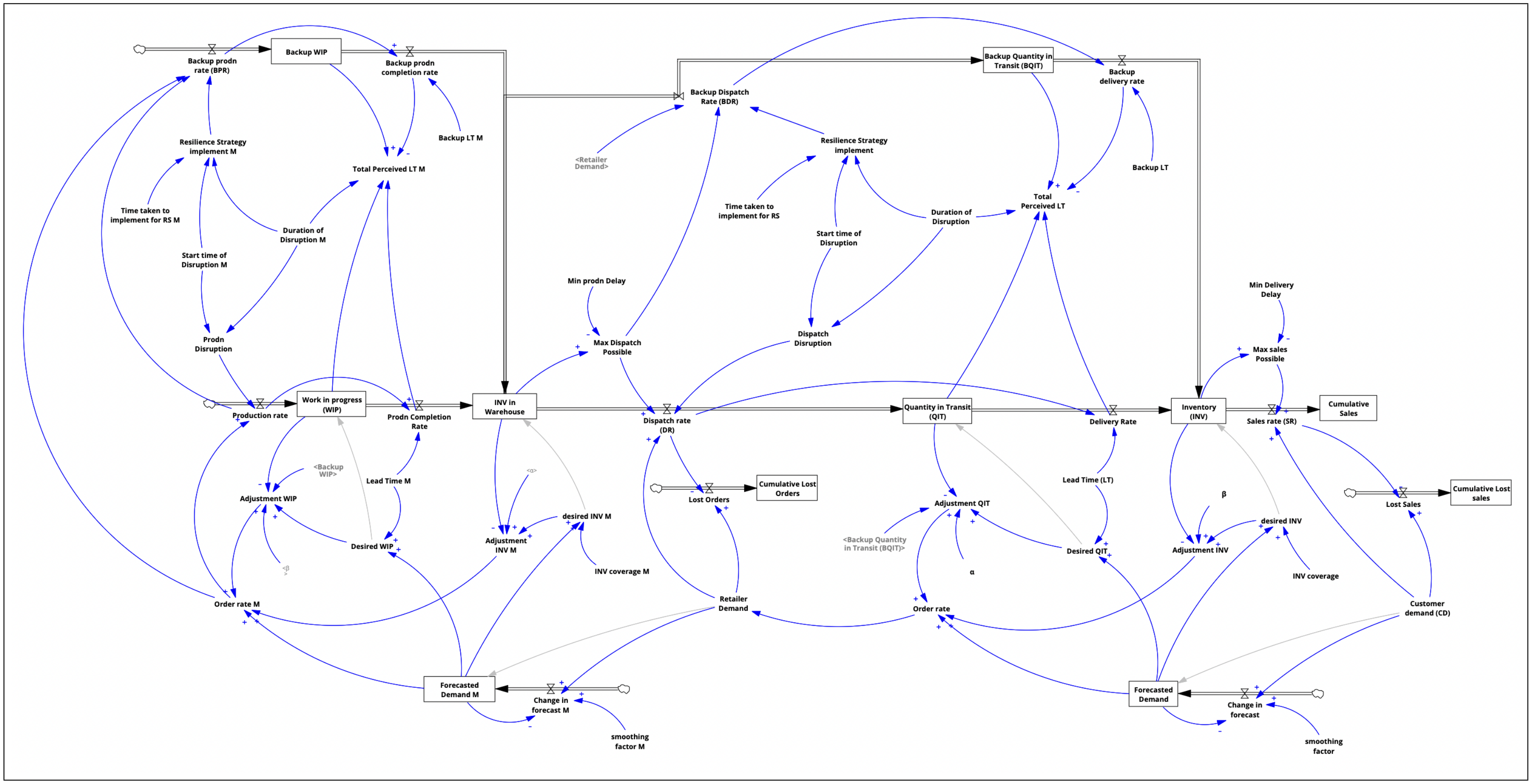

Figure 1: Backup Supplier and logistics strategy incorporated during Production and Dispatch Disruption (Two-echelon)

$$FR_r = \frac{1}{t_r - t_0} \sum_{i=t_0}^{i=t_r} \frac{Sales\,rate_i}{Customer\;Demand_i}, \quad FR_1 = \frac{1}{t_1 - t_0} \sum_{i=t_0}^{i=t_1} \frac{Sales\,rate_i}{Customer\;Demand_i} \tag{4}$$

Disruptions Incorporated and Resilience Strategies: Production and dispatch disruption is modeled along with the resilience strategies. The backup strategy has been previously employed to enhance resilience and mitigate the impact of disruptions in studies such as Sawik, 2022, Behzadi et al., 2020, and Mirzaaliyan et al., 2024. The strategies are implemented immediately upon disruption or with a delay of 4 weeks. The duration of disruption considered is 20 and 30 weeks.

Production Disruption occurs when the availability of raw materials, parts, or components is affected which leads to production delays or halts. Additionally, production can be disrupted due to machine breakdowns, labor shortages, scheduled or unscheduled maintenance, fire or complete factory shutdowns. This scenario is modeled by setting the production rate to zero, representing a complete halt in production for a certain duration. Backup Supplier is employed during a production disruption to fulfill retailer demand with a backup lead time of 6 weeks.

Dispatch Disruption arises when the supplier has produced the quantity, but delivery is obstructed due to external disruptions along the route and supplier is unable to dispatch the goods to retailer. Dispatch disruptions can occur due to transport network failures, labor strike, regulatory and customs-related delays. This is captured in the model by setting the dispatch rate to zero for a certain duration, as the supplier is unable to dispatch the goods to the retailer. Backup Logistics is employed during a dispatch disruption when the manufacturer is unable to deliver produced goods to the retailer. A backup lead time of 4, 6, and 8 weeks is considered.

Results: During the disruptions, all metrics indicate worst performance of supply chain. The implication is that it takes longer for system to recover even after disruption ends. Recovery time is consistent regardless of the duration of the disruption. With an increase in the duration of disruption, other metrics become worse. An increase in backup lead time further weakens the resilience of the system, making timely implementation crucial. Another interesting finding is that resilience is better when the implementation of the backup strategy is delayed by 4 weeks with a lead time of 4 weeks than when the strategy is implemented immediately with a lead time of 8 weeks. the results highlight the importance of upstream preparedness as the manufacturer take considerably longer to recover from disruptions. Interestingly, while the application of backup logistics during a dispatch disruption worsens the retailer's recovery time (almost doubled), other resilience metrics significantly improve, indicating an overall enhancement in supply chain resilience. These improvements come with a trade-off between time-based and quantity-based metrics. It highlighted the importance of focusing on all metrics before arriving at a conclusion on the resilience of the supply chain.

Conclusions and Future Research: This study develoeped general framework to quantify resilience of two-echelon supply chains amid disruptions. The disruptions represented worst-case scenarios and were modeled using a system dynamics approach, simulating supply and transportation halts for a specified duration. The backup strategies were also illustrated.

Future research can expand on this work by considering multi-product and multi-echelon supply chains, allowing for a more realistic representation of complex real-world operations. Additionally, investigating multiple simultaneous disruptions and modeling other types of disruptions could provide deeper insights into supply chain vulnerabilities. Further improvements can be made by incorporating alternative resilience strategies, such as multiple supplier, inventory management, repurpose, backup capacity, and material substitution. Supply chains must strike a balance between cost efficiency and resilience, as an excessive focus on cost minimization can leave them ill-prepared for unexpected shocks. Further work could be to fully understand what it means for a supply chain to be resilient. Additionally, the costs of implementing resilience strategies could be explicitly considered.

References

Behzadi, G., O'Sullivan, M. J., & Olsen, T. L. (2020). On metrics for supply chain resilience. *European Journal of Operational Research*, *287*, 145–158. https://doi.org/10.1016/j.ejor.2020.04.040

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. *Journal of Business Logistics*, *32*, 374–391. https://doi.org/10.1111/j.0000-0000.2011.01032.x

Camur, M. C., Thanos, A. E., Yund, W., Tseng, C.-Y., White, C. C., & Iakovou, E. (2023). An integrated system dynamics and discrete event supply chain simulation framework for supply chain resilience with non-stationary pandemic demand. *2023 Winter Simulation Conference (WSC)*, 1617–1628. https://doi.org/10.1109/wsc60868.2023.10407779

Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., & Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering*, *62*, 329–341. https://doi.org/10.1016/j.cie.2011.10.003

Mirzaaliyan, M., Hajian Heidary, M., & Amiri, M. (2024). Evaluating the supply chain resilience strategies using discrete event simulation and hybrid multi-criteria decision-making (case study: Natural stone industry). *Journal of Simulation*, 1–17. https://doi.org/10.1080/17477778.2024.2342927

Sawik, T. (2022). Stochastic optimization of supply chain resilience under ripple effect: A covid-19 pandemic related study. *Omega*, *109*, 102596. https://doi.org/10.1016/j.omega.2022.102596

Sazvar, Z., Tafakkori, K., Oladzad, N., & Nayeri, S. (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*, 107406. https://doi.org/10.1016/j.cie.2021.107406

Silva, A. C., Marques, C. M., & de Sousa, J. P. (2023). A simulation approach for the design of more sustainable and resilient supply chains in the pharmaceutical industry. *Sustainability*, *15*, 7254. https://doi.org/10.3390/su15097254

Suryawanshi, P., & Dutta, P. (2022). Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions. *Transportation Research Part E: Logistics and Transportation Review*, *157*, 102553. https://doi.org/10.1016/j.tre.2021.102553

Zhao, K., Kumar, A., Harrison, T. P., & Yen, J. (2011). Analyzing the resilience of complex supply network topologies against random and targeted disruptions. *IEEE Systems Journal*, *5*, 28–39. https://doi.org/10.1109/jsyst.2010.2100192