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Self-Organised Criticality-Based Adaptive Approach to Mitigating Dynamic Disruptions in Global Supply Chains

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Abstract

This research develops a theoretical framework to demonstrate how a self-organized global supply network can transition from a critical to a sub-critical state using a diversification-based risk mitigation strategy. In self-organized critical systems, the critical state represents a fragile equilibrium where small disruptions can escalate into disproportionately large avalanches due to interconnected dependencies and heightened sensitivity. In contrast, a sub-critical state signifies a more stable regime where disruptions are effectively contained, and large-scale failures are curtailed. Transitioning to this state reduces the system's inherent fragility while preserving its operational dynamics. We integrated two foundational concepts from Complexity Science: the Bak-Sneppen model and the Barabási-Albert model and perform Discrete Event Simulation and Agent-Based Modelling to simulate diversification strategy that increases the number of alternate suppliers and limits production capacity to the most vulnerable nodes for events with major disruptions. The strategy is applied continuously and adaptively to address the network's natural tendency to evolve back into a critical state. The results demonstrate that this approach effectively transitions the network to a sub-critical state, reducing the Vulnerability Index of critical nodes and curtailing the scale of dynamic disruptions. The findings underscore the efficacy of SOC-Based approach in stabilizing the network and mitigating dynamic failures.

Keywords
SOC-Based, Dynamic Disruptions, Sub-Critical State, Global Supply Chain, Diversification Strategy.

1. Introduction
The complexity and interconnectedness of global supply chain have heightened their susceptibility to dynamic disruptions, particularly in systems that have evolved into a state of Self-Organized Criticality (SOC). In such systems, small disruptions occur frequently, while large, systemic failures are rare but probable. This unique behaviour stems from the interdependencies and feedback mechanisms intrinsic to such networks.

Traditional supply chain models, which focus on localized and linear risks, fail to account for these emergent, network-wide dynamics. Consequently, supply chain managers are often ill-equipped to address both the minor and catastrophic effects of disruptions. Historical events such as the 2011 Tōhoku earthquake and the 2020 COVID-19 pandemic have exposed the limitations of conventional approaches to mitigating dynamic disruptions (Carvalho et al., 2012). These crises revealed critical vulnerabilities, particularly in supply chains overly dependent on single-source suppliers or centralized production hubs. The dynamic nature of these disruptions often amplifies their impact, further underscoring the need for more robust frameworks.

Current supply chain risk management strategies lack an integrated Complexity Science perspective, which is vital for understanding the emergent behaviours of SOC-driven networks. While traditional frameworks emphasize robustness through redundancy and localized assessments, they often neglect the interconnected and adaptive nature of modern supply chains. The absence of models that can capture power-law dynamics leaves critical vulnerabilities unaddressed, perpetuating risks of both frequent minor disturbances and occasional large-scale failures.

1.1 Objectives

The primary objective of this paper is to demonstrate how adaptive strategies can effectively curtail large disruptions by transitioning the network from a critical to a sub-critical state for a SOC-based GSN, with a specific focus to reduce the Vulnerability Index of critical nodes and curtail the scale of dynamic disruptions. These disruptions are characterized by a power-law distribution, where both small and large disruptions are inevitable.

The remainder of the paper is organized as follows. Section 2 provides an in-depth literature review. Section 3 outlines the methodology and simulation framework employed in the study. Section 4 presents the simulation results and their analysis. Section 5 provides a discussion on the insights of transitioning SOC-based network from critical to sub-critical state and we conclude in Section 6.

2. Literature Review

2.1 Dynamic Disruptions in SOC-Based Systems

In the context of SOC systems, dynamic disruptions refer to disturbances that exhibit scale-invariance and unpredictability, making them a defining feature of these networks. Dynamic disruptions encompass both minor, localized events and widespread systemic failures that propagate through interdependent networks. SOC dynamics have been observed across various domains, including ecosystems, financial markets, and global supply chain, where dynamic effects can amplify both the frequency and impact of these disruptions.

In global supply chain, SOC behaviour manifests through interdependencies and feedback mechanisms that make networks highly sensitive to perturbations. Small disruptions, such as delays in transportation or minor supply shortages, are common and often resolved locally. However, large disruptions, such as those caused by natural disasters or global pandemics, have far-reaching impacts, exposing the fragility of interconnected networks.

One notable example of a major disruption is the 2020 COVID-19 pandemic, which triggered unprecedented global lockdowns and severely disrupted the flow of information and materials across the world. The impact of the pandemic impact cascaded across the global supply chain, causing widespread factory shutdowns, severe logistics bottlenecks, and unprecedented demand fluctuations. This led to significant economic losses, estimated in trillions of dollars, and exposed critical vulnerabilities in supply chain resilience and risk management strategies (Ivanov & Dolgui, 2020).

Fat-tail risks in SOC systems are challenging to manage due to their scale-invariance and unpredictability. Unlike Gaussian distributions, where extreme events are unlikely, power-law distributions ensure that large disruptions remain a persistent threat. For example, in 2011, the Thailand floods severely disrupted global supply chain, particularly in the automotive and electronics sectors. The floods submerged numerous factories, leading to a global shortage of hard drives and critical automotive components. This cascading disruption increased production costs and delayed shipments worldwide, revealing the vulnerabilities of highly centralized supply chain networks (Haraguchi & Lall, 2015). Such events highlight the critical importance of strategies that not only address frequent, minor disruptions but also mitigate the profound impacts of rare, large-scale events.

The focus of this study is on curtailing large disruptions within SOC-based systems. Our conjecture posits that while small disruptions are an inherent feature of SOC systems and are often manageable at local levels, addressing large disruptions requires systemic interventions to curtail cascading failures and mitigate widespread impacts. For example, the 2003 North American blackout highlighted the cascading failures within critical infrastructure networks. Triggered by a single transmission line fault, the blackout spread across eight U.S. states and parts of Canada, disrupting power for over 50 million people and causing significant economic losses (Amin, 2005). This event underscored the interconnected vulnerabilities in SOC-driven systems, emphasizing the need for robust strategies to prevent large-scale cascading disruptions.

2.2 Supply Chain Vulnerabilities

Supply chain vulnerabilities refer to the susceptibility of a supply chain to disruptions due to internal weaknesses or external threats. These vulnerabilities can arise from various factors, including the complexity of the network, interdependencies among nodes, reliance on single-source suppliers, and the geographical concentration of critical components. In the context of global supply chain, vulnerabilities are amplified by the interconnectedness of suppliers, manufacturers, and distribution networks, where a disruption in one node can cascade across the entire system (Ivanov & Dolgui, 2020).

A common approach to quantifying vulnerabilities in supply chains is the use of a Vulnerability Index (VI), which evaluates the relative risk of a node within the network. The VI is calculated using centrality measures derived from network theory, such as degree centrality, betweenness centrality, and eigenvector centrality (Kim et al., 2015). These metrics provide insights into the importance of a node in terms of connectivity, influence, and potential to disrupt the network. For instance, a node with high betweenness centrality plays a critical role in the flow of goods or information and is more likely to cause significant disruptions if it fails.

The VI is often normalized to ensure comparability across nodes, with values typically ranging from 0 to 1. Nodes with a normalized VI above a threshold of 0.7 are considered highly vulnerable and require targeted risk mitigation (RM) strategies (Scheibe & Blackhurst, 2018). This threshold is particularly useful for prioritizing interventions, as it identifies the most critical nodes that could cause cascading failures. Studies have demonstrated that by focusing on these high-VI nodes, supply chain managers can significantly reduce the overall risk of disruptions (Borgatti & Li, 2009).

In global supply chain, the application of VI has been instrumental in identifying systemic risks and implementing mitigation strategies. For example, Carvalho et al. (2012) used centrality-based measures to analyse the vulnerabilities in automotive supply chains, highlighting the critical role of tier-1 suppliers in maintaining network stability. Similarly, Kim et al. (2015) explored the use of eigenvector centrality to identify nodes with high influence over the network, providing a basis for targeted interventions to enhance resilience.

The normalization of VI and the threshold setting are critical components in this analysis. This threshold is not arbitrary but is derived from empirical studies that analyse the tipping points of cascading failures in networks. Nodes above this threshold are more likely to act as critical hubs or chokepoints, necessitating continuous monitoring and adaptive RM. This aligns with the findings of Borgatti & Li (2009), who emphasized the importance of dynamic monitoring and intervention to maintain a sub-critical state in SOC-based supply chain.

2.3 Current Risk Mitigation Strategies in Managing Disruptions in SOC-Based Systems

One of the most widely adopted strategies for managing disruptions in SOC-based systems is redundancy. This involves adding extra capacity, such as maintaining backup suppliers, alternate transportation routes, or reserve inventories, to absorb the impact of disruptions. Studies have shown that redundancy can mitigate the propagation of disruptions by providing alternative pathways and resources (Ivanov et al., 2014). For instance, building dual sourcing strategies has proven effective in reducing reliance on single suppliers, particularly for critical components. However, redundancy often comes at a high cost, as maintaining excess capacity can strain financial resources and operational efficiency (Chopra & Sodhi, 2004).

Decentralizing production hubs is another strategy frequently employed to manage fat-tail risks in SOC-driven networks. By dispersing production facilities across multiple regions, firms can reduce their exposure to localized disruptions such as natural disasters or geopolitical conflicts. Scheibe & Blackhurst (2018) highlighted the effectiveness of this approach in mitigating cascading failures by limiting the interdependence between critical nodes. However, decentralization can introduce coordination challenges, as managing dispersed operations requires robust communication and logistics systems.

Supplier diversification is a key strategy aimed at reducing over-reliance on high-risk nodes within the supply chain. Diversification enhances network resilience by ensuring that disruptions at a single node do not cascade across the system. Haraguchi & Lall (2015) emphasized the importance of supplier diversification in mitigating the impact of large-scale disruptions such as the 2011 Thailand floods. While effective, diversification can dilute economies of scale and increase complexity in supplier relationships.

Advanced modelling techniques, including stochastic optimization and simulation-based approaches, have been employed to optimize network configurations and improve resilience. These models integrate centrality measures, such as betweenness and eigenvector centrality, to identify critical nodes and allocate resources effectively (Kim et al., 2015). While these models provide valuable insights, they often rely on extensive data collection and computational resources, making them less accessible to smaller firms with limited capabilities.

Despite the advancements in RM strategies, several gaps remain in managing SOC-driven disruptions. Traditional approaches often focus on robustness rather than adaptability, overlooking the dynamic nature of SOC systems. For example, redundancy and decentralization are static measures that may not respond effectively to evolving network conditions. Furthermore, many strategies fail to account for the power-law distribution of disruptions inherent in SOC systems. Additionally, current strategies often lack integration with real-time data analytics and predictive modelling. The absence of adaptive frameworks limits the ability of supply chain managers to anticipate and respond to emerging disruptions dynamically.

3. Methodology

This study is based on the conjecture that for a network that has evolved into SOC, represented by the power law distribution of disruptions, it is possible to transition from a critical to a sub-critical state. This transition is achieved through a diversification strategy involving increasing the number of alternate suppliers and limiting the production capacity of critical nodes.

To analyse the evolution and propagation of disruptions within a multi-echelon GSN comprising tiered suppliers, manufacturers, distributors, retailers, and consumers, we develop a hybrid simulation framework grounded in Complexity Science. The model integrates Discrete Event Simulation and Agent-Based Modelling, orchestrated by the Bak-Sneppen (Bak & Sneppen, 1993) and Barabási models (Barabasi, 2002), using profit as a proxy for fitness for the evolution of nodes within the supply chain network. This dual-framework approach captures both the cyclical and adaptive processes of disruption dynamics within the network. Each simulation cycle begins with the identification of agents with the lowest profitability (P_{min}), representing stress points within the network. Agents with P_{min} and their connections are removed and replaced with new agents linked through randomized connections, simulating the introduction of new entities. The network is then restructured using preferential attachment principles to maintain connectivity, followed by a recalculation of agent profitability to identify new P_{min}. This cyclical process continues until predefined thresholds are met or the simulation transitions to a new event. We define Size of Disruption as the number of nodes removed from the network in each event due to their low performance (P_{min}).

The simulation mechanism is configurable, allowing for the execution of a required number of events, providing a comprehensive understanding of both small and major disruptions. By employing this hybrid simulation framework, we effectively model the dynamic failures inherent in SOC-driven supply chains and collect critical data on disruption size and frequency.

The framework proposed in this study involves an eight-step process designed to validate our conjecture that it is possible to shift an SOC-based network from a critical to a sub-critical state.

Step 1: Simulation of the GSN

The first step involves running a simulation over 30,000 events to observe the network's behaviour and evolution. The large number of events allows long-term interactions, ensuring the network evolves into a state of SOC, as described in the foundational work on self-organized criticality by (Pruessner, 2012). The objective is to determine when the network transitions into a state of SOC, characterized by a power-law distribution of disruptions. During the simulation, the network's dynamic disruptions are analysed, identifying both small-scale and major disruptions.

Step 2: Identification of Major Disruptions

Major disruptions are defined as those exceeding a threshold. For our simulation experiment, we have set the threshold to be 10,000 disruptions but this setting can be set based on historical Black Swan events and based on empirical evidence. This threshold, while adjustable, serves as a benchmark to differentiate significant disruptions from routine disturbances. The identification of major disruptions enables a focused analysis of the network's critical states.

Step 3: Capture of Network Configurations

For each identified major disruption, the full network configuration is captured from upstream to downstream tiers. This includes recording the state of nodes, their connectivity, and the overall structure of the network at the time of the disruption. These configurations provide the basis for subsequent analysis.

Step 4: Analysis of Network Connectivity and Normalized VI Calculation

The network's connectivity is scrutinized, and the Normalized VI is calculated for each node. The VI is derived using centrality metrics such as degree centrality, betweenness centrality, and eigenvector centrality. These metrics provide a quantitative measure of each node's importance and susceptibility to disruptions. Normalization ensures comparability across nodes, with values ranging from 0 to 1.

Step 5: Ranking and Connectivity Analysis of Critical Nodes

Nodes are ranked based on their Normalized VI values for each major disruption. Nodes with normalised VI values >0.7 are identified as critical nodes, and their upstream and downstream connectivity is analysed (Scheibe & Blackhurst, 2018). This analysis provides insights into the dependencies and potential cascading effects associated with these nodes.

Step 6: Prescribing RM

For all critical nodes identified in each major event, a diversification RM strategy is prescribed. This strategy involves increasing the number of alternate suppliers and limiting the production capacity of these nodes to reduce their overall vulnerability and the likelihood of major failures.

Step 7: Rerunning the Simulation

The simulation is rerun over 30,000 events, incorporating the prescribed diversification strategy for the critical nodes for all major events. This process ensures the strategy is prescribed in a continuous and adaptive manner to ensure the network remains in sub-critical state for major events. This step evaluates the impact of the intervention on the network's behaviour and resilience.

Step 8: Analysis of Results

The final step involves analysing the outcomes of the rerun simulation before and after risk RM is prescribed. The size and frequency of disruptions over the 30,000 events are compared to the original simulation to determine the effectiveness of the diversification strategy. Additionally, the changes in the Normalized VI values of critical nodes are evaluated to assess the reduction in network vulnerability

The simulation experiments are conducted on a multi-echelon GSN with network size of 1,600 nodes consisting of multiple Tiered Suppliers, Manufacturers, Distributors, Retailers and end Customers.

4. Results and Analysis

4.1 GSN evolving into SOC

Figure 1 depicts the PDF of disruptions for network size 1,600 nodes plotted on a log-log scale. The x-axis represents the Size of Disruptions on a logarithmic scale, and the y-axis represents the Probability Density Function (the probability that a disruption of a certain size will occur), also on a logarithmic scale. From the simulation experiments, it is observed that for each network size, the data points fall on a straight line exhibiting a power law distribution with a power law exponent of approximately 1.70.

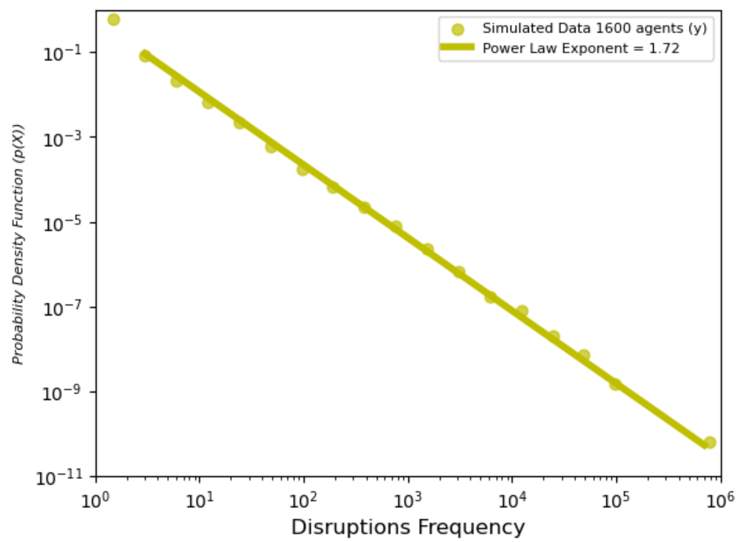

Figure 1. PDF versus Size of Disruptions for network size with 1600 nodes

Figure 2 demonstrates the network evolving into a state of SOC. At the critical point, where *Pmi*n stabilizes, the system reaches a state of SOC. It is in this state that the network exhibits scale-invariant behaviour, meaning that both small and large disruptions follow the same statistical rules, similar to how fitness evolves toward a critical threshold in the Bak-Sneppen model.

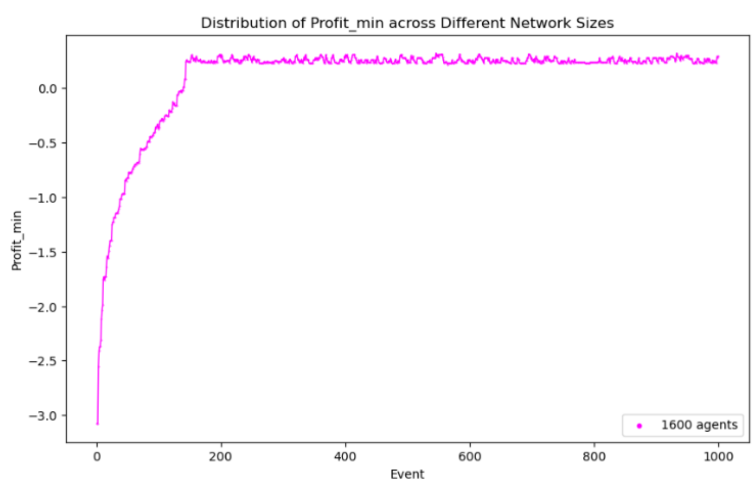

Figure 2. Profile of P_{min} for network size with 1600 nodes

Figure 3 depicts the size of disruptions over 30,000 events which shows the occurrence of small and major disruptions.

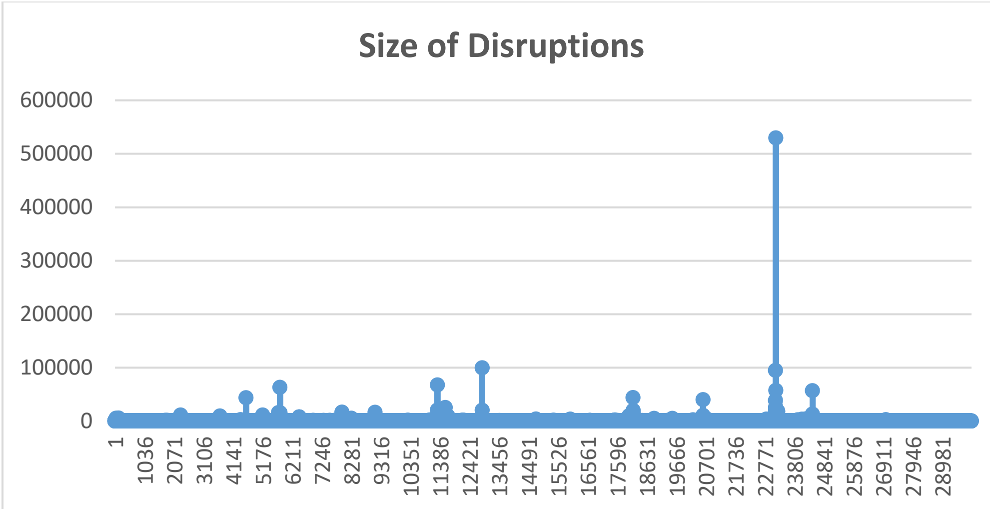

Figure 3. Dynamic disruptions for network size with 1600 nodes

From the dynamic disruptions, major events exceeding 10,000 units are identified.

4.2 Observation on Power Law Distribution with Diversification Strategy

The application of the RM strategy significantly alters the power-law distribution, as observed in Figure 4. The "fall-out" in the tail of the distribution indicates a notable reduction in the frequency and magnitude of large disruptions. The power-law exponent increases slightly from 1.67 to 1.72, reflecting a shift in network dynamics from a critical to a sub-critical state. This shift results in smaller and more frequent disruptions, effectively reducing the risk of rare but catastrophic events. By increasing the number of alternate suppliers and limiting the production capacity of critical nodes, the diversification strategy caps the size of disruptions originating from these nodes. This containment mechanism ensures that disruptions, even when initiated, do not escalate to affect the entire network. The "fall-out" in the power-law distribution visually represents this containment, as the system no longer supports the possible major disruptions as before.

The impact of the RM strategy is further validated by the comparison of disruption sizes before and after its implementation, as depicted in Figure 5. Event 23,149 serves as a striking example of this effectiveness. Before applying the RM strategy, this event resulted in the largest disruption, with a staggering size of 529,331 units. This underscores the severe vulnerability of the network in its critical state, where disruptions originating from critical nodes cascade through interconnected dependencies, resulting in catastrophic failures. Post-mitigation, the size of the same event dropped dramatically to just 2 units. This remarkable reduction highlights the effectiveness of the RM strategy in transitioning the network from a critical to a sub-critical state, curtailing extreme disruptions. Although smaller disruptions persist in the post-mitigation data, their manageable scale reinforces the network's resilience, reflecting a more stable and adaptive supply chain configuration.

The effectiveness of the diversification RM strategy is also evident in the changes in the Normalized VI of critical nodes, as shown in Figure 6. Before mitigation, several nodes had VI values exceeding the critical threshold of 0.7, indicating their central role in the network's vulnerabilities. Post-mitigation analysis reveals a substantial reduction in VI values, with all critical nodes dropping below the threshold of 0.7. This redistribution of risk across the network reduces the likelihood of major disruptions and stabilizes the system.

Event 23,149 provides a clear validation of the RM strategy's impact. Initially, this event's extraordinary disruption size underscored the network's susceptibility to cascading failures. After implementing the diversification strategy, the size of this disruption was curtailed to a negligible level. More so, this observation is consistent across the simulation, with major disruptions significantly reduced after mitigation. The simultaneous reduction in disruption sizes and VI values demonstrates the strategy's capacity to stabilize the network, mitigate vulnerabilities, and ensure a more resilient supply chain configuration.

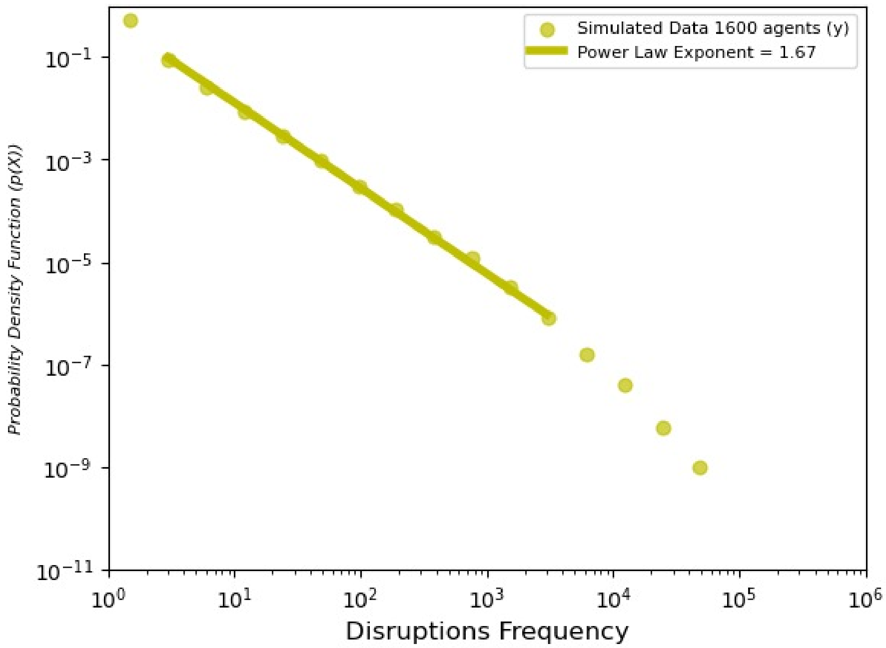

Figure 4. "Fall-out" in power law with RM

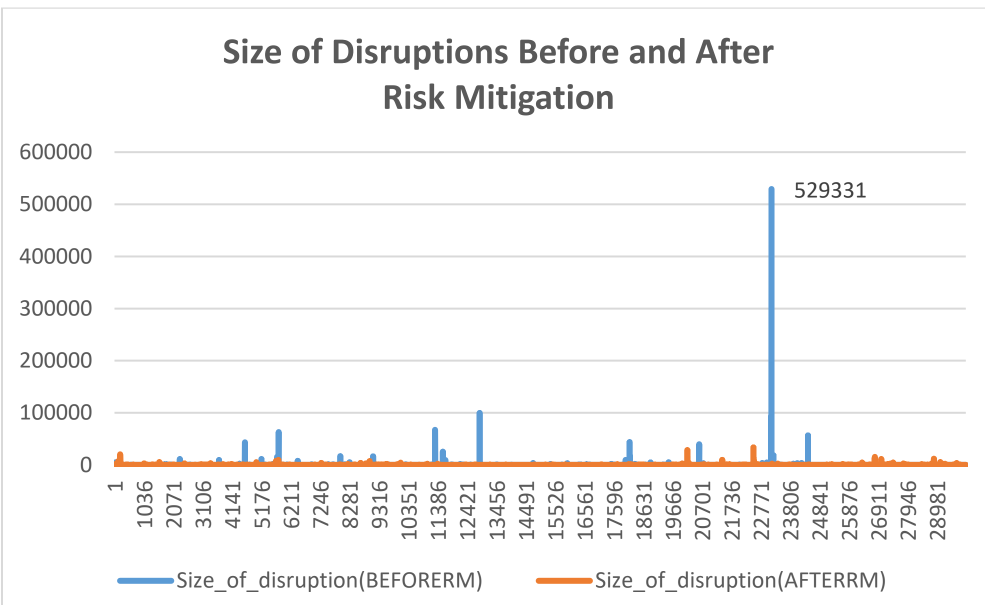

Figure 5. Comparison of Dynamic disruptions Before and After RM

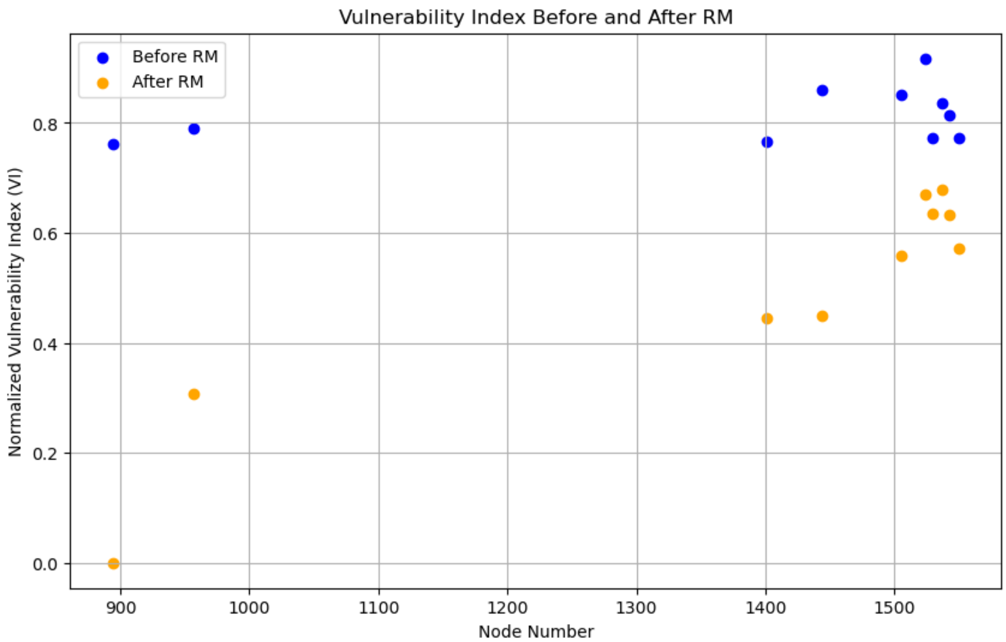

Figure 6. Reduction in VI for Critical Nodes in Event 23,149

5. Discussion

The results of this study provide compelling evidence for the effectiveness of the proposed framework in transitioning a GSN from a critical to a sub-critical state. This transition is substantiated by the observed curtailment of Size of Disruption and a significant reduction in the VI of critical nodes. The ability to achieve this shift highlights the practical implications of the framework for managing dynamic disruptions for a SOC-based network.

The framework's foundation lies in the recognition that SOC systems are inherently prone to both frequent small disruptions and rare but catastrophic events due to the power-law distribution of disruptions. By applying a diversification RM strategy, increasing the number of alternate suppliers and capping production capacities of high-VI nodes, the framework effectively redistributes network dependencies and mitigates the propagation of cascading failures. The simulation results, particularly for Event 23149, demonstrate the framework's success in reducing the size of the largest disruptions from 529,331 units to just 2 units. This dramatic reduction in disruption magnitude underscores the efficacy of targeted interventions in stabilizing SOC-driven networks. Equally significant is the observed reduction in the VI of critical nodes following the application of the diversification RM strategy. Before mitigation, several nodes exhibited VI values exceeding the critical threshold of 0.7, indicating their high susceptibility to disruptions and their central role in cascading failures. Post-mitigation data reveals a marked decrease in these values, with many nodes falling below the critical threshold. This reduction not only validates the effectiveness of the diversification RM strategy but also underscores the framework's ability to enhance network resilience by addressing the most vulnerable components of the supply chain.

For supply chain managers, the implications of these findings are profound. First, the ability to curtail major disruptions provides a pathway to mitigate fat-tail risks, which have historically led to significant economic losses and operational challenges. By transitioning the network to a sub-critical state, managers can reduce the likelihood of catastrophic failures while maintaining the system's inherent dynamism. This balance is critical in today's global supply chain, where efficiency and resilience must coexist.

Second, the framework offers a data-driven approach to identifying and addressing vulnerabilities. The use of normalized VI as a metric provides managers with a quantitative tool to prioritize RM efforts. Nodes with high VI values can be systematically targeted for interventions, ensuring that resources are allocated effectively to maximize network stability. This strategic focus is particularly valuable in resource-constrained environments, where blanket RM measures may be impractical.

Third, the continuous and adaptive nature of the framework aligns with the dynamic characteristics of SOC systems. Supply chain networks naturally evolve, and their state of criticality can re-emerge over time. The framework's iterative process, analysing network configurations, prescribing interventions, and reassessing outcomes ensures that RM strategies remain relevant and effective. This adaptability is crucial for long-term resilience, allowing managers to respond proactively to emerging risks.

6. Conclusion

In conclusion, the proposed framework demonstrates a robust and practical approach to managing disruptions in SOC-driven supply chains. By shifting the network from a critical to a sub-critical state, it addresses both the frequency & magnitude of disruptions and the VI of critical nodes, providing actionable insights for supply chain managers. The results not only advance the theoretical understanding of SOC systems but also offer a scalable solution for mitigating risks in complex, interconnected networks. This dual contribution highlights the framework's potential to transform risk management practices in GSN.

This study bridges the gap between theoretical insights and practical applications, offering supply chain managers actionable tools for enhancing resilience. Future research could build upon this foundation by providing full visibility of network connectivity, with the goal of enhancing inter-collaboration between business enterprises, further improving resilience and efficiency. Additionally, integrating real-time data analytics and machine learning techniques could enable predictive risk management, allowing for dynamic adjustments to evolving network conditions. Exploring sector-specific applications, such as in healthcare, technology, or automotive supply chains, could validate its effectiveness further. Finally, incorporating sustainability metrics into the framework could address the growing need for environmentally conscious supply chain practices, ensuring relevance in addressing both operational and societal challenges.

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Biographies

Mohamed Faisal Bin Mohamed Salleh is a dedicated PhD candidate in the Department of Industrial Systems Engineering and Management at the National University of Singapore (NUS). With a career that spans over two decades, he brings a wealth of experience and a deep commitment to advancing knowledge in industrial systems and supply chain resilience. He holds a Bachelor of Engineering degree from NUS, awarded in 1994, and a Master of Science from NUS, completed in 2014, where he developed a strong foundation in engineering principles and complex systems analysis.
His current research focuses on the application of Complexity Science to the study of supply chain disruptions, aiming to develop robust frameworks for managing and mitigating the impact of rare but high-impact events within global supply networkss. His work seeks to provide novel insights into the dynamics of supply chain resilience, particularly under the lens of fat-tail risks and Black Swan events. His interdisciplinary approach combines rigorous academic research with practical applications, reflecting his goal to bridge the gap between theoretical advancements and real-world solutions in supply chain management.

Professor Eng Seng CHIA is currently an associate professor with the Industrial Systems Engineering and Management Department of the National University of Singapore. He holds PhD, MSc and Beng degrees in Electrical Engineering, an MBA and a BSc in Psychology.
His research focuses on large scale systems engineering, urban issues such as sustainable development, enterprise architecture, and risk management, with an emphasis on applying systems thinking to multifaceted, real-world issues. Professor Chia published in wide variety of journals and conferences due to the systems and interdisciplinary nature of his research.