Information sharing for cost-effective risk mitigation in supply chains: A methodological framework

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Abstract

Process systems and their supply chains are becoming increasingly susceptible to a plethora of exogenous factors that can induce disruptions. Information from supply chain stakeholders regarding an impending disruption can help decision-makers plan operation schedules to minimize their impact and improve supply chain resilience. Multiscale modeling and optimization frameworks often assume perfect information. Nevertheless, this assumption fails to capture the value of information sharing about potential upcoming disruptions from supply chain stakeholders who often have precious and timely advanced knowledge. Notably, there can be a lag in information flows sharing which can impede the ability of decision-makers to plan for and then respond to an impending change of state. Lack of timely and effective information sharing among stakeholders erodes supply chain resilience. To this end, we present a first effort mathematical programming-based methodological framework to quantify the impact of information sharing for supply risk mitigation. In the multiperiod modeling framework, the information set is made available to the decision-makers at different time periods in the planning horizon. The nominal scenario, wherein information is made available at the start of the temporal horizon is compared to scenarios wherein the information is made available at later stages. In doing so, the economic benefit of sharing information is quantified, and managerial insights are obtained.

**Keywords**: information flow, supply chain optimization, multiscale modeling, supply chain risk mitigation, resilience

* 1. Introduction

Supply chains play a crucial role in facilitating the production and distribution of essential (and often critical for national security) commodities and products, ranging from energy carriers and specialty chemicals to consumer goods. Chemical and energy supply chains comprise interconnected chemical process plants that encompass various unit operations, while also establishing multi-echelon connections with key stakeholders such as suppliers, distributors, third party logistics operators (3PLs), industrial customers, and consumers alike. However, geographically dispersed chains are increasingly exposed to exogenous factors which renders them vulnerable to disruptions occurring across multiple operational scales, resulting in significant human and economic consequences (El-Halwagi et al., 2020) and reduced supply chain resilience (Iakovou and White, 2020). Incidents such as the Bhopal gas leak (1984), the Deepwater Horizon oil spill (2010), and the Beirut explosion (2020), have underscored the inherent risks posed by operational discord. Additionally, global “black swan” disruptions, including the COVID-19 pandemic, natural disasters, wars, tariff wars, and labour shortages continue to have a profound impact on business continuity, leading to significant financial losses, disruptions in production, and escalated costs of critical consumer goods. New modelling approaches are needed to design cost-competitively resilient supply chains and assess the relevant trade-offs (“optionalities”) between cost efficiency and resilience (Gopal et al., 2023).

Multiscale modeling and optimization can be applied to plan and manage end-to-end supply chains with awareness to phenomena occurring at disparate spatiotemporal scales. Decisions taken at different temporal levels can be categorized into strategic (long-term), tactical (mid-term), and operational (short-term) (Shapiro, 1999). Often, supply chain stakeholders (such as an upstream supplier at a faraway location) have intimate knowledge and local insights about upcoming regionalized disruptions, such as labor strikes, resource shortages, social upheaval, and manufacturing capacity reductions. While the flow of resources and information have been modeled under an integrated purview (Perez et al., 2023), the role of efficient and timely information sharing during pre, and post stages of disruptions is not well studied. To this end, we present a first effort methodology to gauge the impact of information sharing for upcoming disruption scenarios. Operational and scheduling decisions for a fixed network-design are analyzed under varying levels of access to information. The multiperiod problem is formulated as a linear program (LP) and different scenarios are compared where in the decision-maker has: 1) early and perfect information regarding upcoming disruptions; 2) delayed access to information at various temporal levels; 3) no insight until the disruption occurs. The primary goals of the framework are to: 1) quantitatively assign an economic value to information sharing; and 2) determine the optimal time epoch of sharing information. The system is modeled in the *energiapy* python package (Kakodkar and Pistikopoulos, 2023).

* 1. Methodology

The developed framework utilizes a rolling-horizon multiperiod methodology to model the sharing of information and the corresponding adjustments for supply chain recovery. At the beginning of each period, the decision-maker has perfect information on disruptions and operational parameters (for that individual period) and has an anticipated dataset for the following periods which may be updated through information sharing. To model the temporal flow of information, the information set is updated at discrete time epochs of the temporal horizon. For example, in the perfect information (nominal) scenario, the decision-maker has access to the entire information set about the upcoming disruption at the start of the planning period itself. In scenarios with time lag, the decision-maker gains access to updated information from other supply chain stakeholders only in later time periods. In terms of mathematical modeling, this corresponds to solving distinct problems for varying partitions of the temporal horizon: few with the expected information set (P1) and others with the updated information set (P2). Notably, the end state of the problem with expected information (P1) is used to initialize the latter (P2) to maintain continuity. For instance, in a scenario where the supply chain tiers obtain revised information at time period *K+1* concerning a deviation occurring at time period *D* from the anticipated dataset, the state variables (at time period *K+1*) from problem (P1) can be employed to initialize problem (P2) with the updated information set (Figure 1). Subsequently, problem (P2) is solved for time periods *K+1* to *N* with the updated information set. Furthermore, it is assumed that once the disruption occurs, the information is immediately made available across the supply chain stakeholders.



Figure 1. Modeling methodology for information flow

The system is represented using the resource task network (RTN) methodology and modeled as a multiperiod LP. Notably, to incorporate both partial and complete failures normalized capacity factors are introduced to processes and transports to capture the effects of supply chain disruptions (Eqns. 1 & 2). Notations and descriptions for parameters and variables reported in the rest of the manuscript are shown in Table 1.

Table 1. Notations and Descriptions for parameters and variables

|  |  |
| --- | --- |
| **Notation** | **Description** |
|  | Set of resources that can be transported |
|  | Production level of p |
|  | Capacity factor for the production levels of process p |
|  | Installed production capacity for process p |
|  | Amount exported between sources and sinks for an individual resource |
|  | Capacity factor for export between locations |
|  | Installed export capacity of a transport mode |
|  | Operating costs for the network |
|  | Penalty incurred due to unmet demand for the network |
|  | Inventory storage costs for the network |

|  |  |
| --- | --- |
|  | (1) |
|  | (2) |

The objective function is the minimization of total cost over the finite planning horizon. This includes the operating costs (for processing, maintaining inventory, and transport), and penalties incurred due to unmet demand. Since, this is a distribution planning problem and no value is being added to the commodity within the network, procuring and selling prices are assumed to be fixed. The cost objective is thus given by Eq 3:

|  |  |
| --- | --- |
|  | (3) |

* 1. Motivating Example

Figure 2 depicts the distribution planning problem (DPP) adapted with modifications that is based on an indicative tactical problem proposed and studied by Ivanov et al. (2014). A non-perishable commodity is available at two network locations, 1 and 6. The commodity has a nominal daily demand of 100 kgs at location 5. Storage facilities are available in all locations throughout the network. The analysis is conducted for 12 months of a calendar year as the planning horizon. Each month is further divided into 30 scheduling days. Furthermore, we assume a given supply chain network structure, i.e., encompassing fixed processing facilities and capacities, distribution centers, inventory buffer capacities, and transport arc facilities. In addition, the information set can be updated only at the beginning of each month.

|  |  |
| --- | --- |
|   | A graph with red and blue lines  Description automatically generated |
| Figure 2. Case Study - Distribution Network | Figure 3. Case Study - Expected vs Actual resource availability |

Information Sharing Scenarios

The processing facility at location 6 is going to experience a catastrophic failure at the beginning of month 7. To compare the cost of information sharing, the overall cost is obtained for three scenarios:

1. Scenario 1 - Information is shared at the beginning of month 1;
2. Scenario 2 - Information is shared at the beginning of month 6; and
3. Scenario 3 - Information is shared at the beginning of month 7 when the disruption occurs.

To assess the resilience of the supply chain network, we are using the overall demand fill rate as a key performance indicator:

* 1. Results and Discussions

Initially, the DPP is solved with the expected information set (problem P1) to obtain the system state variables (inventory levels) values at the beginning of months 6, and 7. The initial inventory values for all locations were zero. This follows from the fact the under the assumption of no disruption, the system is fully capable of meeting the daily demand without storing the commodity. Using these values, instances of problem (P2) are initialized for their respective scenarios 2, and 3. The results obtained from the four scenarios are reported below:

Table 2. Cost performances for different scenarios

|  |  |  |
| --- | --- | --- |
| **Scenario** | **Total Cost ($USD)** | **Fill Rate (%)** |
| Scenario 1 | 657,231.25 | 88 |
| Scenario 2 | 657,231.25 | 88 |
| Scenario 3 | 662,274.0 | 87.5 |

Results show that Scenario 3 incurs the highest cost, as the information set is updated concurrently with the disruption event, hindering supply chain risk mitigation and response. Furthermore, Scenario 3, has a lower demand fulfilment (fill) rate indicating lower supply chain resilience due to lack of timely information. Higher costs for Scenario 3 are due to the incurred penalty resulting from unsatisfied demand. However, Scenarios 1 and 2 exhibit equitable cost performance and demand fill rates. The observed behaviour suggests a temporal threshold (at month 6) after which when information is shared, the overall cost increases. It can also be seen from the inventory build-up results that the network does not start building up inventories until after month 6 (Figure 4). This observation suggests that sharing information earlier than that, does not result in a competitive advantage. This managerial insight could provide valuable guidance for decision-makers to determine a deadline for information sharing to avoid incurring additional penalties.

|  |
| --- |
|  |
| Figure 4. Inventory levels at network locations during Scenario 1 |

* 1. Conclusions and Future Directions

In this work, we have presented a first effort towards a methodological framework to model the value of information sharing about upcoming disruptions in the supply chains. The approach involves partitioning the problem into two parts: before (P1) and after the information is received (P2). After receiving the latest information regarding an upcoming disturbance, the optimization problem (P2) is constructed by utilizing the system state variables (such as inventory, product flows, etc.) from the initial formulation (P1) for initialization. The results show that early sharing information not only has economic benefits, but also enables higher supply chain performance. Moreover, the system can accommodate some lag in information transfer without incurring a high penalty. Thus, the framework allows for the quantitative assessment of not only the cost of information sharing but also provides an ideal time of sharing critical information. In the near future, we intend to expand the presented work by including the early sharing of probability-based disruption scenarios in the analysis through stochastic modeling.

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