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A stochastic program to evaluate disruption mitigation investments in the supply chain

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Abstract

Supply chain risk management is becoming increasingly important due to a variety of natural and man-made uncertainties. We develop a methodology to evaluate the costs of disruptions and the value of supply chain network mitigation options based on a two-stage stochastic program. To solve the model, we rely on a solution scheme based on sample average approximation. We explicitly differentiate between disruption periods and business as usual periods to decrease the model size and computational requirements by approximately 85% and 95% respectively. Furthermore, the decrease in model complexity allows us to include the conditional value at risk in the objective function to incorporate the risk aversion of decisions makers. Based on a case study of a chemical supply chain, this study shows the trade-off between long-term expected costs minimization and short term risk minimization, where the latter leads to a more aggressive investment policy.

Keywords: stochastic programming, supply chain network design, supply chain risk management

1. Introduction

The Japanese earthquake and subsequent tsunami, hurricanes Katrina and Harvey, and the piracy attacks offshore Somalia are just some of the supply disruptions that have shown, in recent years, that the success of a company is highly dependent on the success of risk management in its supply chain (Baghalian et al., 2013). Sheffi and Rice (2005) show that incidents at a single plant of a key raw material supplier can already have disastrous effects on the continuity of supply. Despite this, evidence suggests that most companies continue to focus on planning to protect against recurrent low-impact risks while paying less attention to the high-impact, low-likelihood risks (Chopra

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and Sodhi, 2004). Hendricks and Singhal (2003) show that the stock market penalizes firms that experience supply chain glitches irrespective of which link in the supply chain is responsible for that glitch. Nonetheless, investing in long-term mitigation options addressing high-impact, low-likelihood risks is still perceived to be in conflict with the short-term focus on creating shareholder value. A major reason is stated by a manager in a study by Rice and Caniato (2003), ‘Nobody gets credit for solving problems that did not happen’.

In this study, we address this challenge by providing a methodology to evaluate the effect of supply disruptions and their associated potential mitigation options. We derive quantitative insights on the short- and long-term company performance based on a two-stage stochastic program. Our main methodological contribution is to exploit the distinction between business as usual (BAU) and disruption periods, which leads to a reduction in model size in the order of 95%. Further, we show counterintuitively that a higher short-term focus on minimizing the effect of low-likelihood, high-impact disruptions actually leads to a more aggressive investment policy in supply risk mitigation options compared to a long-term focus.

Ho et al. (2015) define supply chain risk as “the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational-, tactical-, or strategic-level failures or irregularities”. By focusing on disruptive supply risks, we build on the two major different types of categorizations of supply chain risks. The first categorization classifies supply chain risks according to what process or function of the supply chain is affected by the risk, e.g. supply, demand, procurement, or capacity risks (Chopra and Sodhi, 2004; Manuj and Mentzer, 2008; Tang and Musa, 2011). The second categorization divides risks between operational risk and disruption risk (or catastrophic risk) (Tang, 2006; Sodhi et al., 2012). Here, operational risk refers to the inherent BAU uncertainties in supply and demand. The effects of these disruptions are hedged by, for example, inventory and skilled supply chain planners. Disruption risk refers to major disruptions, either natural or man-caused, that have a low likelihood of occurrence, but a high impact transcending the safety measures that are in place to address uncertainty (Chopra and Sodhi, 2004). We argue that disruption risk can be split in two categories based on the duration of the impact; (1) risks that have a substantial, but temporary, impact, i.e. after a few days, weeks or months the affected supply chain returns to BAU, and (2) risks with severe impact that cause the supply chain to change for a significant amount of time, or maybe for good, thus redefining BAU. In both cases, mitigation options need to minimize the impact of disruptions; the associated investment decisions, however, will be different. In the first

case, given that the disruption lasts for a short period, attention can be focused on the speed of disruption mitigation compared to the daily cost of operating the mitigation option. In the latter case, however, returning to the BAU situation is not possible and more attention should be focused on reducing the operational costs of the mitigation option to sustainable long-term levels. In this paper, we focus on the first category; temporary, high impact risks.

Tang (2006) identifies supply chain network design (SCND) as one of the strategic approaches to mitigate supply chain risk. It involves strategic decisions on the number, location, and capacity of required production and distribution facilities of a company, or a set of collaborating companies, as well as the selection of suppliers, subcontractors, and Third-party logistics providers (3PLs) to serve demand in a timely and efficient manner (Klibi et al., 2010; Sadghiani et al., 2015). Simchi-Levi et al. (2004) argue that SCND is the primary and most important decision for decreasing the costs and increasing the profits of the whole supply chain. However, the structural decisions in SCND have to be made under uncertainty about the future realization of random variables and the associated tactical and operational decisions (Fleischmann and Koberstein, 2015; Farahani et al., 2014). Despite this stochastic nature, most models proposed in the literature are both static and deterministic. There is, however, no guarantee on the performance of the design obtained by deterministic models in future scenarios (Klibi et al., 2010; Sahling and Kayser, 2016).

Literature that integrates uncertainty in supply chain management and SCND is still scarce (Melo et al., 2009). However, two main directions of research appear to evolve to account for uncertainty in SCND (Fleischmann and Koberstein, 2015). The first one seeks to extend deterministic models in such a way that the solutions contain certain structures, e.g. based on graph theory, that improve their performance under uncertainty (e.g. Kauder and Meyr, 2009). The second research direction is based on the methodology of stochastic programming. A type of problem that is typically studied in SCND is the family of two-stage recourse problems that reflect the temporal hierarchy of decision making. In the first stage a decision is made on the structural strategic decisions of the supply chain network under uncertainty. Afterwards, there is a certain realization of the uncertain parameters (a scenario) and operational flow decisions are made to avoid the constraints of the problem becoming infeasible. Shapiro (2003) uses a Monte Carlo sampling technique to approximate the original recourse problem with infinite or an extremely large amount of possible scenarios by a linear problem, the so called Sample Average Approximation (SAA). This approach has been successfully applied to solve several SCND problems (e.g. Santoso et al., 2005; Schütz et al., 2009; Klibi and Martel, 2012; Hamta et al., 2015). Although stochastic models have shown

to outperform their deterministic counterparts in SCND, they tend to become intractable and this is worsened when adding second stage operational decisions (Klibi et al., 2010; Schütz et al., 2009).

In this study, we develop a methodology to evaluate the effect of high-impact, low-likelihood supply disruptions and potential mitigation options. Consequently, we do not take into account the BAU randomness, unless it directly relates or influences the frequency, duration, or impact of high-impact, low-likelihood disruptions. Contrary to most work that has been done in these fields, mainly focusing on operational demand uncertainty (see, e.g., Baghalian et al., 2013; Govindan et al., 2017) we focus explicitly on disruptive supply risks. Nonetheless, we include different categories of operational uncertainties such as demand and price uncertainties since they influence the effect of supply disruptions, e.g. disruptions have less impact if the demand is low compared to a period with high demand.

To motivate our study and to apply this model, we conduct a case study in cooperation with a global leading materials company focused on a European production site that is heavily integrated with an upstream cracker of a supplier. We show the impact of supply disruptions at this particular site and how the disruptions can be mitigated by investments in the supply chain infrastructure. Supply chain risk management is gaining increasing awareness in the European chemical industry. Chemical commodities are shipped in large quantities, and subject to strict safety restrictions, which makes storage and transportation a challenging effort. This causes high dependency of downstream companies on a limited fleet of aged crackers that are the first node in large integrated and divergent supply chains, resulting in significant impact of unplanned cracker outages. Preventive maintenance investments in commodity assets are not a priority of companies that own them, resulting in decreasing cracker reliability. Moreover, due to overcapacity, 11% of ethylene capacity has closed down since 2005—leading to a higher utilization of the remaining crackers, increasing the impact and likelihood of unplanned outages. Meanwhile, the pressure of shareholders on executives drives the dividing and restructuring of chemical companies into more focused entities. Traditionally integrated chemical supply chains have been split and, consequently, a cracker and its downstream nodes may no longer be owned by the same company. The high capital investment in the chemical industry makes the creation of new supply chains unattractive; companies need to evaluate potential investments in the current supply chain infrastructure to mitigate supply chain risks. The importance of a better understanding of supply chain risk mitigation is further underlined by the size of the global chemical industry, with annual global revenues exceeding \$5,000 billion (American Chemistry Council, n.d.). While being motivated and specifically applied in

the European chemical industry, it is worthwhile noting that the applicability of our methodology transcends the chemical industry to industries with similar supply chain characteristics, in particular, those industries that require high capital investments and consequently face inflexible supplier locations such as the steel and semi-conductor industries.

Our contribution to the literature is threefold. First, from a methodological perspective, we develop a modeling approach whereupon we exploit the distinction between BAU periods and disruption periods. Since disruption costs only occur during the periods that are affected by disruptions, it suffices to optimize the affected periods only to get an insight into the disruption costs and performance of suggested mitigation options. The benefit of this distinction is twofold. First, it addresses the computational challenge of solving stochastic SCND models in reducing model size by approximately 85% and hence increasing optimization speed by approximately 95%. This formulation allows to add more complexity to the model or to analyze a larger amount of potential scenarios. Furthermore, we are able to better capture the dynamic structure of disruptions since disruption information is only revealed to the model when the disruption hits. To put it differently, our model does not allow to prepare for an unexpected disruption by, for example, temporarily increasing inventory in advance of a disruption. Second, our methodology explicitly includes the conditional value at risk (CVaR) as a robustness measure in the objective function. Oliveira et al. (2013) argue to refrain from incorporating the CVaR due to its added complexity, but given the structure of our methodology the added complexity is manageable. Our methodology can be thus used to include CVaR in the risk analysis of a large number of supply chain applications. Finally, our results show that the impact of including the CVaR in the objective function increases with a decreasing time horizon under investigation or disruption frequency. From a managerial perspective, this finding has a number of consequences; on the one hand, it alerts decision makers on the importance of defining the time horizon in risk analyses; on the other hand, it allows for the screening of risk mitigation options that are robust to said effects.

The rest of this paper is organized as follows. In section 2 we develop the modeling approach. Next, in section 3, we introduce a two-stage stochastic program with recourse based on a discrete temporal framework to evaluate disruption costs and show how this model can be extended to evaluate risk mitigation options. To ensure tractability of the model, we introduce a solution scheme based on an approximated linear program for a finite set of scenarios in section 4. We apply the developed methodology in a case study in sections 5 and 6.

2. Modeling Approach

For modeling purposes, we distinguish between the supply chain structure, operational (BAU) uncertainty, disruption-related uncertainty, strategic decisions, and the associated disruption costs. The supply chain structure is defined by successive material links between upstream and downstream nodes. Operational uncertainty defines the stochastic nature of the BAU situation; e.g., uncertainty in demand and feedstock prices. Disruption-related uncertainty is defined by the set of random variables that define the start, severity, and duration of a disruption. Strategic decisions refer to risk mitigation options (investments) that are decided at time zero; i.e., prior to any knowledge of actual events. Such strategic decisions will constrain the possible operational decisions and the associated operational and emergency (i.e., disruption) production plans. The operational decisions include decisions on product flows, sourcing, and inventories. Strategic and operational decisions taken to mitigate disruptions result in disruption costs. In this section, we define our notation and parameters to model each of the above mentioned components, along with the conceptual notions of our modeling approach. Then, in section 3 we present the optimization models. We refer the reader to Appendix A for a complete summary of all the notation used in this paper.

2.1. Supply Chain Structure

Any generic supply chain can be described as a collection of supplier-customer pairs. In our model, a supply chain is comprised of a set of network components (or nodes), denoted by $\mathcal{L}$. These nodes are categorized (based on supplier-customer relationships) as upstream nodes, production-storage nodes, or downstream nodes. Upstream nodes supply feedstock to production-storage nodes, which produce and store material that is sold to downstream nodes. We denote the set of suppliers of feedstock (upstream nodes) as $\mathcal{L}^s$. We further differentiate production-storage nodes into separate components: a set of storage tanks, $\mathcal{L}^i$, a set of (un)loading stations, $\mathcal{L}^u$, a set of intermediate production plants, $\mathcal{L}^p$, and a set of final production plants, $\mathcal{L}^f$. Finally, we aggregate customers (downstream nodes) at the product level and denote these downstream nodes as the set $\mathcal{L}^d$. The structure of a generic supply chain network is thus completely determined by $\mathcal{L}^s, \mathcal{L}^i, \mathcal{L}^u, \mathcal{L}^p, \mathcal{L}^f, \mathcal{L}^d \subset \mathcal{L}$.

Each pair of linked nodes (i.e., each customer-supplier pair) has a number of defining characteristics, namely product flow conditions. For a given node i in a supply chain, we define a set of direct predecessor nodes upstream, $\mathcal{U}(i)$ and a set of direct successor nodes downstream, $\mathcal{D}(i)$.

The quantity of output from node i required by node $j \in \mathcal{D}(i)$ relative to the output of node j is described by a ‘recipe’ or unit ratio ρ_{ij} . Similarly, lead times are defined as the time elapsed between the shipment of a product by a given node and its reception by the linked node downstream; e.g., τ_{ij} is the lead time between node i and j . Furthermore, each node i is characterized by a maximum and minimum input capacity, output capacity, and inventory capacity for each period t (respectively α_{it}^{max} , α_{it}^{min} , β_{it}^{max} , β_{it}^{min} , γ_{it}^{max} and γ_{it}^{min}). The set of capacity, recipe, and lead time parameters that define the structural elements of the supply chain is denoted by $\mathcal{A}$. Figure 1 shows a graphical representation of $\mathcal{A}$ for a generic node i with two upstream nodes (g, h) and two downstream nodes (j, k).

Figure 1: Generic picture of node characteristics

2.2. Modeling Uncertainty

All future realizations of a given supply chain design depend on multiple random variables that fully define operational and disruption uncertainty. We call a given realization of all variables, a scenario $s \in S$. In particular, a scenario consists of the realization of the operational random variables (i.e., feedstock price, transportation cost, selling price, and demand) in addition to the realization of the disruption random variables (i.e., number of disruptions in a scenario, node pair affected by each disruption, start time of disruptions, duration of disruptions, and duration of additional recovery periods). At the modeling stage, we treat all these stochastic variables as generic time series. Then, in the scenario generation stage (Section 4.1) we discuss in detail how each time series is generated according to the particularities of the problem at hand.

2.2.1. Operational uncertainty

During BAU there are a number of stochastic operational variables. In particular, feedstock prices c_{its}^f , selling prices m_{its} , and demand D_{its} at node i in period t in scenario s , and transportation

costs c_{ijts}^t from node i to node j in period t in scenario s . Realizations of these variables define the performance of a firm in a given scenario; a set of decision rules is used to determine the operational decisions during BAU (see Section 4.1).

2.2.2. Disruption uncertainty

We define disruptions as an unfavorable change in the link between two nodes of a supply chain. A disruption can thus be a partial decrease in the supply of a node, an increase in the lead time of said supply, or a complete shutdown of a node for a given period of time. A given disruption is characterized by (1) the node(s) affected, (2) its start time, (3) its duration, (4) its severity, and (5) the duration of additional recovery. Note that (a) all the variables in $\mathcal{A}$ are susceptible to disruptions, and (b) a given scenario can have any number of disruptions.

Formally, given a discrete planning horizon T , we denote the total set of periods that the supply chain is affected by disruptions as the set $T^\epsilon \subset T$. The disruption state can further be divided into two sets of periods. The first set is the set of periods where the capacities and/or lead times of the nodes in the affected hazard zone are perturbed ($T_{\text{perturbed}}^\epsilon \subset T^\epsilon$). The second set is the set of recovery periods ($T_{\text{recovery}}^\epsilon \subset T^\epsilon$). In these periods, the disruption has ended but the supply chain is not yet back to BAU; extra product has to be sourced and produced to get inventories back to the base stock level and to let product flows return to those in BAU. Further, let t_{e-u} be the period $u \in \{1, \dots, U\}$ periods before the start of a disruption. We define $T_{-U} \subset T$ as the set of periods t that are $U \geq t \geq 1$ periods before the first period of one of the disruptions in a scenario.

Figure 2: Schematic overview of the periods before and during a disruption

Let E be the set of all disruptions in a given scenario; the sequence of events of a particular disruption $e \in E$ is as follows, and graphically presented in Figure 2. Let t_0 be the start of the planning horizon T , the system operates under the BAU regime until, at time t_e , a disruption starts. The disruption lasts for θ_e periods, after which it requires r periods to return to BAU conditions. Thus, at time $t_{e+\theta_e}$, the disruption ends but the supply chain is still operating in an emergency state. Finally, at time $t_{e+\theta_e+r}$ the disruption state ends, and the supply chain is again operating at BAU. Each disruption is also characterized by an impact parameter $0 < \phi_e \leq 1$ that indicates the

severity of the disruption; with $\phi_e = 1$ denoting the total severing of a supplier-customer link. In order to keep track of the beginning and end of perturbed states, we define two additional sets in line with the conventions introduced above. Set $T_{\text{begin}}^\epsilon$ encompasses period the first period t_e from every perturbed state in a scenario, and similarly set T_{end}^ϵ encompasses the last period $t_{e+\theta_e+r}$ from every perturbed state in a scenario¹.

To exclude operational risks from the scenario generation, we require disruptions to be of a minimum duration. Thus, we define the variable $\theta^{\min}$ and set $E = \{e | \theta_e \geq \theta^{\min}\}$, i.e. the supply chain is only considered to being disrupted state when affected by a disruption longer than $\theta^{\min}$. Note that the BAU periods only depend on the supply chain structure, strategic decisions, and operational uncertainty.

We denote the vector of the parameters that characterize operational and disruption parameters for a given scenario with $\omega_s = (E, c_s^f, c_s^t, m_s, D_s)$.

2.3. Operational and Strategic Decisions

We distinguish between two types of decisions that a decision maker can take to mitigate the effect of a disruption: operational decisions, and strategic decisions. Operational decisions take place immediately after a disruption starts. Said decisions have the aim to minimize the impact of the disruption by, for example, sourcing material from alternative suppliers. Strategic decisions are made before a disruption starts. These decisions are related to investments that change the SCND, making it more resilient to disruptions—for example, by adding nodes to the supply chain to enable dual-sourcing of critical materials.

The set of all operational decisions for a scenario s is represented by $\mathcal{X}_s$. These are decisions taken after the start of the disruption regarding product flows (product sourcing, production, and sales), inventory, and shutdown of plants. Operational decisions occur within the bounds of the current supply chain design $\mathcal{A}$.

Strategic decisions about potential risk mitigation options are made at design time, t_0 , without prior knowledge of forthcoming disruptions. This includes investments related to the supply chain structure, such as increasing capacities and reducing lead times (associated to existing supply chain structure $\mathcal{A}$), as well as potential new links between supply chain components to use during the

¹Note that in the case of overlapping disruptions, the sets T_{-U} , $T_{\text{begin}}^\epsilon$, T_{end}^ϵ , $T_{\text{perturbed}}^\epsilon$, and, $T_{\text{recovery}}^\epsilon$ do not track individual disruptions, but the perturbed state of the system, e.g., when two or more disruptions overlap $T_{\text{begin}}^\epsilon$ only contains the period t_e of the first of the overlapping disruptions.

planning horizon T (effectively changing the supply chain structure $\mathcal{A}$).

The potential mitigation options, denoted by y , that a supply chain can adopt is a finite set represented by Y . The decision to implement mitigation option y is represented by q_y , with $q_y = 1$ if a mitigation option is implemented, $q_y = 0$ otherwise. Let $\mathbf{q}$ be a vector with a particular realization for each of these decisions, e.g., $\mathbf{q} = (0, 1, 0, 0)$ represents a potential set of 4 mitigation options, of which mitigation option 2 is implemented ($q_2 = 1$).

These strategic decisions regarding risk mitigation options Y constrain the set of feasible operational decisions over the planning horizon. Table 1 shows a summary of the potential strategic and operational decisions that can be taken to mitigate disruptions, and their associated costs.

Table 1: Operational and Strategic Decisions, and Associated Cost Components

<i>Operational decisions</i> ($\mathcal{X}_s$)	
x_{ijts}	product flow shipped from node i to node j in period t in scenario s , $i \in \mathcal{L}, j \in \mathcal{D}(i), t \in T, s \in S$
I_{its}	inventory at node i at the end of period t in scenario s , $i \in \mathcal{L}, t \in T, s \in S$
b_{its}	excess product to be disposed at node i in period t in scenario s , $i \in \mathcal{L}, t \in T, s \in S$
$h_{its}^{d,switch}$	1 if node i is either started up or shut down in period t in scenario s , 0 otherwise, $i \in \mathcal{L}, t \in T, s \in S$
$h_{its}^{d,shutdown}$	-1 if node i is shut down in period t in scenario s , 1 if it is started up, 0 otherwise $i \in \mathcal{L}, t \in T, s \in S$
h_{its}^d	1 if node i is down in period t in scenario s , 0 otherwise, $i \in \mathcal{L}, t \in T, s \in S$
h_{its}^b	1 if node i is standby in period t in scenario s , 0 otherwise, $i \in \mathcal{L}, t \in T, s \in S$
c_i^d	cost of shutting down or restarting node i due to cleaning and repairs.
c_i^b	cost of entering or leaving stand-by mode for node i .
<i>Strategic decisions</i> (Y)	
q_y	1 if mitigation option $y \in Y$ is implemented, 0 otherwise
c^y	investment cost to implement mitigation option y

2.4. Disruption Costs

Disruptions cause the supply chain to be unable to follow the operational production plan defined during the BAU state. In particular, during a disruption a firm can face additional costs due to: lost sales; changes in feedstock and/or transportation prices related to emergency sourcing; and/or costs associated with shutting down, cleaning, repairing, restarting, or putting an affected plant in standby.

Disruption costs can be expressed as a function of the deviation from the initial BAU production schedule during periods T^c . Therefore, it suffices to compare the operational decisions and product flows during a disruption to those as if the same periods were BAU. For notational convenience, we distinguish between the BAU capacities and operational decisions, and disruption capacities and

operational decisions by using the suffix ϵ to denote the variable or parameter during disruption. For example, γ_{its}^{max} represents the maximum inventory during the BAU state of node i in period t in scenario s whereas $\gamma_{its}^{max,\epsilon}$ represents the perturbed maximum inventory during disruption state of node i in period t in scenario s .

The total costs for a given supply chain in scenario s depend on the realization of ω_s , i.e., the realization of all the operational and disruption stochastic variables. Equation (1) states how the total costs depend on ω_s . The fixed costs do not change during a state change from BAU to disruption or vice versa, thus we only take into account variable costs: lost sales, resourcing costs, transportation costs and shutdown costs.

$$\begin{aligned}
C(\omega_s) = & \sum_{t \in T^\epsilon} \left(\sum_{i \in \mathcal{L}^d \cup \mathcal{L}^f} m_{its} \left(\sum_{j \in \mathcal{U}(i)} \rho_{ji} \right)^{-1} \sum_{j \in \mathcal{U}(i)} (x_{jits} - x_{jits}^\epsilon) + \sum_{i \in \mathcal{L}^s} c_{its}^f \sum_{j \in \mathcal{D}(i)} (x_{ijts}^\epsilon - x_{ijts}) \right. \\
& \left. + \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{D}(i)} c_{ijts}^t (x_{ijts}^\epsilon - x_{ijts}) + \sum_{i \in \mathcal{L}} (c_i^d h_{its}^{d,switch,\epsilon} + c_i^b h_{its}^{b,\epsilon}) \right) \quad (1)
\end{aligned}$$

The first term of Equation (1) represents the costs due to lost demand. During a disruption period t , the supply chain might not be able to sell the same quantity of product at selling price m_{its} at $i \in \mathcal{L}^d \cup \mathcal{L}^f$ compared to BAU. We account for the fact that the quantity of products that flows from the upstream nodes to the final production nodes is not equal to the quantity produced. The second term represents changes in production that lead to changes in the required quantity of supply and the price of the sourced feedstocks at node $i \in \mathcal{L}^s$ in period t . Third, a change in sourcing does not only change feedstock prices, but also the associated transportation costs c_{ijts}^t , as well as transportation costs for changed product flows further downstream in the supply chain. Lastly, if no input products are available at a company owned infrastructure component, the decision has to be taken to shutdown the process. There is a plant-dependent minimum time associated to shutdown to allow for the necessary cleaning and repairs. Moreover, we assume that the costs associated with shutting down a plant due to cleaning and repairs and subsequently restarting it (c_i^d) are paid both at shut down and at start up. For some production processes, it is possible to go into stand-by mode to avoid the high costs of a shutdown. In this mode, the production process is essentially circulating the last produced product at a cost of $c_i^b \leq c_i^d$ per day. Note that not every cost term needs to be positive. A disruption can lead to cost savings for one of the terms, e.g. less feedstock is acquired if there is a disruption at the production plant.

3. Optimization Model

SCND structural decisions impact results over a long period of time and risk-averse decision makers want to avoid structural decisions that lead to poor outcomes in some of the scenarios. Therefore, in addition to cost minimization, we include the conditional value at risk (CVaR) in the objective function. The value at risk (VaR) gives the maximum costs with a confidence level of ζ with $\zeta \in (0, 1)$ (Sahling and Kayser, 2016). The CVaR characterizes the mean value of the expected costs that are above the VaR. Therefore, the CVaR indicates the conditional mean value of the expected cost of the worst $(1 - \zeta)$ risk scenarios. A risk averse decision maker would choose a high value of ζ in order to minimize the worst expected costs. The objective function is the minimization of the weighted sum of the expected costs and the CVaR, based on the weighting factor $\eta \in (0, 1)$ that is chosen by the decision maker. To capture the variability of future scenarios, we model our supply chain as a two-stage stochastic program with recourse. In this section we present two optimization models. First, we introduce a base model that takes into account only the set of operational decisions $\mathcal{X}$ in Section 3.1. Then, we extend the base model to allow for strategic mitigation options to be made at design time (Section 3.3).

3.1. Base Model: Operational Decisions

This base model does not include the option to invest in strategic mitigation options. Therefore, the objective is operationalized by minimizing the expected costs over the set of potential future scenarios S , by making operational decisions $\mathcal{X}_s^\epsilon$ for every scenario $s \in S$. The contribution of each scenario depends on its probability of occurrence $\pi(s)$.

The resulting first-stage problem is:

$$\min \eta \sum_{s \in S} \pi(s) C(\omega_s) + (1 - \eta) CVaR \quad (2)$$

Subject to

$$VaR \geq 0 \quad (3)$$

With

$$CVaR = VaR + (1 - \zeta)^{-1} \sum_{s \in S} \pi(s) z_s \quad (4)$$

Where z_s is an auxiliary variable to determine the CVaR, and $C(\omega_s)$ is the solution of the second stage problem for scenario s :

$$\min C(\omega_s) \quad (5)$$

Subject to

$$C(\omega_s) - VaR \leq z_s \quad (6)$$

$$I_{i(t-1)s}^\epsilon + \sum_{h \in \mathcal{U}(i)} x_{hi(t-\tau_{hits}^\epsilon)s}^\epsilon = I_{its}^\epsilon + \sum_{h \in \mathcal{U}(i)} \rho_{hi} \sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon + b_{its} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (7)$$

$$x_{hi(t-\tau_{hits}^\epsilon)s}^\epsilon = \rho_{hi} \left(\sum_{g \in \mathcal{U}(i)} \rho_{gi} \right)^{-1} \sum_{g \in \mathcal{U}(i)} x_{gits}^\epsilon \quad i \in \mathcal{L}, h \in \mathcal{U}(i), t \in T^\epsilon \quad (8)$$

$$\sum_{h \in \mathcal{U}(i)} x_{hi(t-\tau_{hits}^\epsilon)s}^\epsilon \geq \sum_{h \in \mathcal{U}(i)} \rho_{hi} \cdot \alpha_{its}^{\epsilon, min} (1 - h_{its}^d - h_{its}^b) \quad i \in \mathcal{L}, t \in T^\epsilon \quad (9)$$

$$\sum_{h \in \mathcal{U}(i)} x_{hi(t-\tau_{hits}^\epsilon)s}^\epsilon \leq \sum_{h \in \mathcal{U}(i)} \rho_{hi} \cdot \alpha_{its}^{\epsilon, max} (1 - h_{its}^d - h_{its}^b) \quad i \in \mathcal{L}, t \in T^\epsilon \quad (10)$$

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon \geq \beta_{its}^{\epsilon, min} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (11)$$

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon \leq \beta_{its}^{\epsilon, max} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (12)$$

$$I_{its}^\epsilon \geq \gamma_{its}^{\epsilon, min} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (13)$$

$$I_{its}^\epsilon \leq \gamma_{its}^{\epsilon, max} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (14)$$

$$I_{its}^\epsilon + \sum_{\{j|j \in \mathcal{L}^u \cap \mathcal{U}(i)\}} x_{jits}^\epsilon \geq S_i \quad i \in \mathcal{L}^i, t \in T_{end}^\epsilon \quad (15)$$

$$x_{ijts}^\epsilon \geq x_{ijts} \quad i \in \mathcal{L}^s, j \in \mathcal{D}(i), t \in T_{recovery}^\epsilon \quad (16)$$

$$h_{i(t-1)s}^{d,\epsilon} - h_{its}^{d,\epsilon} \leq h_{its}^{d,switch,\epsilon} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (17)$$

$$h_{its}^{d,\epsilon} - h_{i(t-1)s}^{d,\epsilon} \leq h_{its}^{d,switch,\epsilon} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (18)$$

$$h_{i(t-1)s}^{d,\epsilon} - h_{its}^{d,\epsilon} = h_{its}^{d,shutdown,\epsilon} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (19)$$

$$M h_{its}^{d,shutdown,\epsilon} + 1 \geq \sum_t^{t+\kappa_i} (1 - h_{its}^{d,\epsilon}) \quad i \in \mathcal{L}, t \in T^\epsilon \quad (20)$$

$$h_{its}^{d,\epsilon} + h_{its}^{b,\epsilon} \leq 1 \quad i \in \mathcal{L}, t \in T^\epsilon \quad (21)$$

$$\mathcal{X}_{its} = \mathcal{X}_{its}^\epsilon \quad t \in T_{-\max(\tau_{ijt^*s})}, j \in \mathcal{D}(i), \quad i \in \mathcal{L}, t^* \in T_{begin}^\epsilon \quad (22)$$

$$h_{its}^{b,\epsilon}, h_{its}^{d,\epsilon}, h_{its}^{d,switch,\epsilon} \in \{0, 1\} \quad i \in \mathcal{L}, t \in T^\epsilon \quad (23)$$

$$x_{ijts}^\epsilon, I_{its}^\epsilon, b_{its}, z_s \geq 0 \quad i, j \in \mathcal{L}, t \in T^\epsilon \quad (24)$$

The linear formulation of the CVaR in constraint (6) and equation (4) is based on Krokmal et al. (2001). Constraints (7) ensure conservation of flow. At each node, the quantity received plus starting inventory should be equal to the quantity shipped or disposed plus ending inventory. Constraints (8) ensure the unique ratio of products of the different upstream nodes. Constraints (9) and (10) limit the inflow of products to its capacity during a disruption, or to 0 when the node is in shutdown or standby. Constraints (11) to (13) limit the outflow and inventory of the nodes. Constraints (15) force the inventory plus what is in process at the related unloading facility to be equal or larger than the basestock at the end of the recovery period. Constraints (16) force the external sourcing decisions to be similar to those of BAU, for supply that is ordered during periods t for which $t \in T$ but $t \notin T^e$. Constraints (17) and (18) keep track of each shutdown cycle (including shutdown and start up) to compute shutdown costs. The Big M method is used in constraints (19) and (20) to force the shutdown to last the minimal length κ_i specified for a shutdown at node i (i.e., once started, a shutdown cannot be immediately reversed). Constraints (21) ensure that a node cannot be in standby and in shutdown at the same time. Constraints (22) ensure the transition of BAU to the disruption stage, i.e. decisions in the periods before the disruption actually occurs should be equal to BAU decisions and cannot be anticipatory of the upcoming disruption.

3.2. Risk Mitigation Model: Strategic Decisions

The base model introduced in the previous section serves as a basis to determine costs of supply disruptions. By introducing the first-stage strategic investment decisions we build on this model to evaluate the risks of supply chain mitigation options. In this section, we adapt the first stage of the optimization model to facilitate strategic decisions, introduce five types of risk mitigation options, and show how they can be implemented in the model.

By including mitigation options in the model, we need to explicitly account for investment costs in the objective function. Furthermore, mitigation options can potentially change the supply chain structure $\mathcal{A}$; thus, the costs for a scenario also depend on $\mathbf{q}$. The objective function of the risk mitigation optimization model is formally:

$$\min_{\eta} \eta \sum_{s \in S} \pi(s) C(\omega_s, \mathbf{q}) + (1 - \eta) CVaR + \sum_{y \in Y} c^y q_y \quad (25)$$

Subject to

$$VaR \geq 0 \tag{26}$$

$$q_y \geq 0 \qquad y \in Y \tag{27}$$

where c^y is the cost of implementing risk mitigation option y . The dependence of the scenario on y also changes the objective of the second stage problem

$$\min C(\omega_s, \mathbf{q}) \tag{28}$$

In the remainder of these section, we will introduce how to implement different mitigation options into the model by adapting constraints in second stage problem.

3.3. Risk Mitigation Options

Several risk mitigation options influence the starting situation of a disruption. However, we do not want to compute BAU for every combination of risk mitigation options since computational time increases exponentially with the number of risk mitigation options. Nonetheless, mitigation options, by definition, do not alter the operational performance of the system during BAU. Therefore, we implement the mitigation options by explicitly including them only during the disruption periods, and then calculate their impact on the BAU cost².

3.3.1. Increase Output or Input Capacity.

A common risk mitigation option is to invest in increasing the maximum in- or output capacity of a supply chain node, e.g. extra production capacity or increased contract quantities with suppliers. Alternatively, one could also investigate the option to decrease the minimum in- or output capacity, which causes a plant to run on reduced rates instead of going into an expensive shutdown. Such mitigation options can be modeled without changing BAU, and it can be done by changing the right hand side (with α and β) of constraints (9) to (12). As an example, let us increase the output capacity of node i by changing equation (12). We define q_β as the decision to invest in an output capacity increase of β^y . Note that we have to include the risk mitigation capacity vector β^y in the

²For example, if the mitigation option consists of a higher inventory level, we initialize the disruption with the new inventory level in place, and approximate the additional cost of having held the extra inventory over the entire BAU period.

disruption generation procedure to determine $\beta^{\epsilon,y}$, since the extra capacity can also be disrupted. The new constraint is as follows

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^{\epsilon} \leq \beta_{its}^{\epsilon,max} + q_{\beta} \beta_{its}^{\epsilon,y}, \quad t \in T^{\epsilon} \quad (29)$$

A similar modification applies to (11). The adaptation of constraints (9) and (10) is more convoluted. As an example, we adapt equation (10). We define q_{α} as the decision to invest in an input capacity increase of α^y . The new set of constraints is as follows

$$\sum_{h \in \mathcal{U}(i)} x_{hi(t-\tau_{hits}^{\epsilon})s}^{\epsilon} \leq \sum_{h \in \mathcal{U}(i)} \rho_{hi} \cdot (\alpha_{its}^{\epsilon,max} (1 - h_{its}^d - h_{its}^b) + v_{its} \alpha_{its}^{\epsilon,y}) \quad t \in T^{\epsilon} \quad (30)$$

$$q_{\alpha} - h_{its}^d - h_{its}^b \leq v_{its} \quad t \in T^{\epsilon} \quad (31)$$

$$1 - h_{its}^d - h_{its}^b \geq v_{its} \quad t \in T^{\epsilon} \quad (32)$$

$$q_{\alpha} \geq v_{its} \quad t \in T^{\epsilon} \quad (33)$$

$$v_{its} \in \{0, 1\} \quad t \in T^{\epsilon} \quad (34)$$

Where v_{its} indicates that the extra capacity mitigation option is implemented and node i is not in shutdown or standby in period t . If the node would be in shutdown, the extra capacity cannot be used. Constraints (31) to (34) ensure the correct behavior of v_{its} .

3.3.2. Increase Inventory Capacity.

In the case of a disruption, production is only decreased (and consequently loss sales incurred) if the available inventory is depleted. The first part of including the mitigation option to increase inventory capacity in the model is similar to that of increased (or decreased) input and output capacity. Let q_{γ} be the decision to invest in an increase of inventory capacity at node i and γ^y be the extra inventory capacity to evaluate. The effect of adding inventory on model (2) is a change in constraints (14) that reflects the new maximum inventory capacity to

$$I_{its}^{\epsilon} \leq \gamma_{its}^{\epsilon,max} + q_{\gamma} \gamma_{its}^{\epsilon,y}, \quad t \in T^{\epsilon} \quad (35)$$

However, if the basestock level S_i at node i depends on γ_i (e.g. by the percentage s_i), the effect of adding extra storage capacity would be underestimated with only changing constraints (14). The

actual inventory and S_i will change in BAU, and this effect has to be accounted for by changing the starting inventory, i.e. I_{its} for $t \in T_{-1}$, and by changing S_i . For simplicity, to keep the model non-quadratic, it is assumed that the extra inventory required by the increase of S_i is stored in node i at $t \in T_{-1}$ for each disruption e in scenario s . To account for these changes, we adapt the part of (22) that deals with inventory in the periods T_{-1} to (36) and we need to alter constraints (15) to constraint (37).

$$I_{its}^\epsilon = I_{its} + q_\gamma s_i \gamma_{its}^y, \quad t \in T_{-1} \quad (36)$$

$$I_{its}^\epsilon + \sum_{\{j|j \in \mathcal{L}^u \cap \mathcal{U}(i)\}} x_{jits}^\epsilon \geq S_i + q_\gamma s_i \gamma_{its}^y, \quad t \in T_{\text{end}}^\epsilon \quad (37)$$

3.3.3. Increase Basestock Level.

Investing in a higher basestock level makes a supply chain better prepared for disruptions, but increases the holding costs and decreases the amount of free capital. An increase in basestock level can be operationalized in two ways. First, if the basestock level is defined by a percentage of the inventory capacity, the percentage can be increased. Otherwise, the basestock level can be increased by a fixed quantity. In the first case, let q_{s_i} be the decision to increase the basestock percentage at node i to $s_{i,y}$. Since the basestock level influences the inventory at a start of a disruption we adapt the part of (22) that deals with inventory in the periods T_{-1} to (38). Second, to ensure that the inventory position at returns back to BAU again after a disruption, we change (15) to (39).

$$I_{its}^\epsilon = (1 - q_{s_i}) I_{its} + q_{s_i} s_{i,y} \gamma_{its}^{max}, \quad t \in T_{-1} \quad (38)$$

$$I_{its}^\epsilon + \sum_{\{j|j \in \mathcal{L}^u \cap \mathcal{U}(i)\}} x_{jits}^\epsilon \geq (1 - q_{s_i}) s_i \gamma_{its}^{max,\epsilon} + q_{s_i} s_{i,y} \gamma_{its}^{max,\epsilon}, \quad t \in T_{\text{end}}^\epsilon \quad (39)$$

To implement a fixed increase of the basestock level, we define $S_{i,y}$ as the new basestock level. We can replace $s_{i,y} \gamma_{its}^{max,\epsilon}$ by $S_{i,y}$ and $s_i \gamma_{its}^{max,\epsilon}$ by S_i in Equations (38) and (39).

3.3.4. Decrease Supplier Lead Time.

Decreasing the lead time from supply nodes increases the resilience of a supply chain in its speed to react upon disruptions. However, changing lead time is impossible to do by altering characteristics of a node without making model (2) non-linear. Therefore, we introduce an equivalent node k which is a copy of node $i \in \mathcal{L}^s$, except that the lead time of node k is different.

Let q_k be the decision to shorten the lead time, then constraints (11) and (12) have to be replaced by constraints (40) to (43).

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon \geq (1 - q_k) \beta_{its}^{\epsilon, min}, \quad t \in T^\epsilon \quad (40)$$

$$\sum_{j \in \mathcal{D}(k)} x_{kjts}^\epsilon \geq q_k \beta_{kts}^{\epsilon, min}, \quad t \in T^\epsilon \quad (41)$$

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon \leq (1 - q_k) \beta_{its}^{\epsilon, max}, \quad t \in T^\epsilon \quad (42)$$

$$\sum_{j \in \mathcal{D}(k)} x_{kjts}^\epsilon \leq q_k \beta_{kts}^{\epsilon, max}, \quad t \in T^\epsilon \quad (43)$$

Furthermore, since supply is ordered in BAU based on the old lead time, there is still supply coming in that should have been arrived already with the new lead time. This leads to ‘free supply’, no placed orders in the first few periods of T^ϵ and an overestimation of the positive effect on costs of this mitigation option. To avoid this phantom supply coming in, we adapt the part of constraints (22) that deals with incoming supply to constraint (44).

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon \leq (1 - q_k) \sum_{j \in \mathcal{D}(i)} x_{ijts}, \quad t \in T_{-(\tau_{ijts} - \tau_{kjts})} \quad (44)$$

Lastly, we have to adapt constraints (16) in a similar way. To return back to BAU, we can delay forced minimum ordering by the differences between the new and the old lead time.

3.3.5. Shorten Disruption Duration.

For some disruptions it is possible to shorten the duration of disruptions by making upfront investments. One way to implement this, is to generate two sets of perturbed capacity vectors for the nodes for which the duration of a disruption can be decreased. As example, we take the maximum output, $\beta^{\epsilon, max}$ and the alternative $\beta^{\epsilon, max, y}$. The maximum output capacity value is set for each time period in the optimization model. Therefore, we account for the shortened impact of the disruption by reducing the number of periods from the start of the disruption that has a reduced output capacity. Let q_d be the decision to invest in a mitigation option to shorten the effect of a disruption on capacity at node i . Constraints (12) should be adapted to the following form

$$\sum_{j \in \mathcal{D}(i)} x_{ijts}^\epsilon \leq (1 - q_d) \beta_{its}^{\epsilon, max} + q_d \beta_{its}^{\epsilon, max, y}, \quad t \in T^\epsilon \quad (45)$$

We can adapt inventory and input capacity vectors in a similar way. Note that, in line with increasing input or output capacity as presented in Section 3.3.1, indicator variables might be required to avoid non-linearity.

4. Solution Scheme

In most practical cases, the number of possible scenarios is infinite. This leads to an intractable optimization model. In this section, we propose a four-stage solution scheme based on a linear approximation of the model. First, we generate samples of scenarios using a Monte Carlo method. Second, we apply a scenario selection procedure to create a more representative sample of scenarios by dividing the sample of scenarios into ‘high-cost’ and ‘acceptable-cost’ scenarios. Third, we solve a set of large MIPs for these samples, similar to how it is done when solving stochastic programs with the SAA (Kleywegt et al., 2001). Fourth, we evaluate the resulting limited set of proposed designs by solving the model with fixed risk mitigation options. Since this eliminates the first stage decisions, this reduces to solving a large set of independent deterministic problems, thus a larger sample can be used to achieve better cost estimates.

4.1. Scenario Generation

Independent of the state of the supply chain, the environment is characterized by operational uncertainty. During BAU, neither suppliers nor company owned assets are disrupted. We assume that supply is always enough to satisfy demand and that demand is high enough to justify production above minimum capacities. The first step of the scenario generation procedure is to generate values for the operational stochastic variables: demand D_{its} , selling price m_{its} , feedstock price, c_{its}^f , and transportation costs, c_{ijts}^t .

The second step of the procedure determines BAU values for the operational decision variables based on decision rules (all other operational variables are determined using balance equations). The purpose of determining BAU operational decisions is twofold. First, it ‘sets the stage’ for when a disruption occurs. Based on sourcing and production decisions during BAU, inventories fluctuate and the quantity sourced at different nodes may vary. Both influence the effect a disruption has on

the supply chain. Second, after a disruption, product flows and inventories need to return to their BAU quantities. The reason to rely on heuristics over optimization to determine BAU decisions is twofold. First, robust and simple decision rules offer a good representation of how decisions are made by supply chain planners; optimization requires resources that are not always available, e.g. the required training of supply chain planners (Zoryk-Schalla et al., 2004). Second, decision rules are more efficient than optimization from a computational perspective.

The third step of the scenario generation procedure is to generate the disruption stochastic variables and associated perturbed capacity and lead time vectors. To identify risks, we rely on a structured approach based on a combination of a supply chain flow diagram (Adhitya et al., 2009) and an overview of potential risk factors (Rao and Goldsby, 2009). Second, based on Klibi and Martel (2012), we partition the supply chain in hazard zones $z \in Z$, delineating sets of nodes with similar exposure characteristics. For each zone, the set of potential risks can be aggregated into multihazards to capture similar known and unknown risky events in a single probability distribution. Based on historical data, expert opinion and literature, we generate associated inter arrival time, duration, and impact distributions ($F_z^\Lambda(\cdot)$, $F_z^\Theta(\cdot)$ and $F_z^\Phi(\cdot)$) (e.g Banks, 2005; Snyder et al., 2016; Klibi and Martel, 2012). These distributions serve as input to generate the set of disruptions E .

4.2. Scenario Selection

To make the optimization model tractable, we approximate by solving the model M times with N scenarios. Based on the scenario generation procedure, we generate M independent samples of $N^\# > N$ scenarios using Monte Carlo methods, where $N^\#$ is a number big enough so that sampling can take place without the need for reuse of scenarios. Our scenario partitioning approach differs from prior literature (e.g., Klibi and Martel, 2012) in that we use cost information to define the partitions. This is because, due to the use of the CVaR, we are especially interested in the high disruption cost scenarios. In particular, we approximate the cost of each individual scenario under the risk mitigation model (Section 3.3) by computing its base cost (using the model presented in Section 3.1). Intuitively, scenarios that are inexpensive in the base model will also be inexpensive in the full model (note that the reverse is not necessarily true). This renders the scenarios for individual decisions to be independent and allows us to quantify the inherent cost of a scenario (i.e., the cost of reacting to a disruption using only operational tools) without having to solve the full stochastic problem. Using this information, we are able to derive a representative set of high cost scenarios without being forced to increase the sample size N . We partition the set of generated

scenarios $N^\#$ into a set of high cost scenarios $S^H = \{s | C(s) > (2 \cdot \zeta\%)VaR\}$ with associated high risk probability π^H and conditional scenario probabilities $\pi(s|H), s \in S^H$, and a set acceptable cost scenarios $S^A = \{s | C(s) < (2 \cdot \zeta\%)VaR\}$ with associated normal risk probability π^A and conditional scenario probabilities $\pi(s|A), s \in S^A$ (Klibi and Martel, 2012). The objective function (25) thus changes to:

$$\min \eta \sum_{i \in A, H} \pi^i \sum_{s \in S} \pi(s|i) C(\omega_s, \mathbf{y}) + (1 - \eta) CVaR + \sum_{y \in Y} c^y q_y \quad (46)$$

Note that we adjust probabilities by multiplying conditional probabilities by the probability of being in a set. This formulation ensures that, although we relatively have more scenarios from S^H than from S^A , their effect is not overrepresented in the objective function.

For each of the M samples that are used to generate designs, we select $N/2$ scenarios from S^A and $N/2$ scenarios from set S^H . Consequently, not all $N^\#$ scenarios are used.

4.3. Design Generation

Based on our limited set of scenarios the optimization model becomes tractable. Solving the problem for M samples of N scenarios leads to one or more (maximum M) different proposed combination of optimal investment decisions $\mathbf{q}^{m,*}$. Increasing sample size N leads to a convergence in proposed combinations that result from this step since it better approximates the real case where $N = \infty$. However, previous work shows that even with relatively small sample sizes N , e.g. N between 20 and 40, the set of different investment decisions for model solution m ($\mathbf{q}^{m,*}$) is small (e.g Santos et al., 2005; Schütz et al., 2009; Klibi and Martel, 2012; Hamta et al., 2015).

4.4. Design Evaluation

The result of the design generation phase is a set of maximum M candidate designs. For each of these designs, we can solve N^* independent deterministic problems for independent scenarios. N^* can be chosen a lot bigger than N , e.g. $N^* = 1000$, therefore, the objective value associated to decisions $\mathbf{q}^{m,*}$ can be determined with greater accuracy. Finally, the $\mathbf{q}^*$ can be chosen as the candidate solution ($\mathbf{q}^{m,*}$) that provides the biggest decrease in disruption costs. Note that the final solution is not necessarily optimal for the individual scenarios, but it minimizes the objective based on expected costs and CVaR (Birge and Louveaux, 1997).

5. Case Study

In the remainder of this paper, we apply the proposed methodology to a case study at a leading global materials company, which we denote as ChemComp. The supply chain is concentrated around one site and is schematically depicted in Figure 3, showing the nodes and interrelationships. ChemComp owns 6 production plants, producing different types of P1, P2 and P3 (P3a, P3b, P3c, P3d and P3e) based on three major feedstocks F1, F2 and F3. The output of the P1 plant is used as feedstock for the other production plants. The major supplier of feedstock of this integrated site is the cracker of a firm we denote CrackComp.

Figure 3: Schematic depiction of the ChemComp supply chain

P1 and F3 are stored in tanks that have a maximum inventory capacity, but also a minimum inventory capacity to ensure safe operation of the tanks, pumps and pipelines. We also add two dummy nodes with zero inventory to channel the flow of the different F1 and F2 supply nodes to the P1 plant. Furthermore, there are two individual unloading nodes for P1 and F3.

The CrackComp cracker is currently the only supplier of F1 and the major supplier of F2. For both products, minimum and maximum contractual quantities are determined and extra F1 can be purchased from CrackComp, generally at the same price as the contractual price. For F2, there is a minor contract with another partner and further required F2 could potentially be purchased on the spot market. For F3, ChemComp has the first right on F3 from CrackComp at site S1 and from a second major supplier external to the site, F3Comp. About a third of the supply is acquired via contracts with other suppliers and on the spot market. P1 is acquired on the spot market only if it is not produced at site S1.

P1 produced at S1 is sold to a P1 customer on site S1 via contracts. Produced P1 that remains

after the demand of the other production plants and the P1 customer is sold externally.

5.1. Supply Risks

Table 2: Identified risk categories threatening the site S1 supply chain

Nr. (z)	Risk	Location	Affected nodes	Inter arrival time (Distribution, parameters)	Duration (Distribution, parameters)	Impact (Distribution, parameters)
1	ChemComp cracker outage	S1a (Crack- Comp)	F1 CrackComp Contract F1 CrackComp Spot F2 CrackComp Contract F3 CrackComp Contract	Exponential $\lambda = \frac{1}{143}$	Bi-Modal Log Normal $\mu_1 = 1.22, \sigma_1 = 0.06$ $\mu_2 = 2.75, \sigma_2 = 0.13$ $W_1 = 0.86$ (Weight μ_1, σ_1)	Fixed 1
2	F3 outage	S1a (Crack- Comp)	F3 CrackComp Contract	Exponential $\lambda = \frac{1}{335}$	Bi-Modal Log Normal $\mu_1 = 0.62, \sigma_1 = 0.63$ $\mu_2 = 2.8, \sigma_2 = 0.5$ $W_1 = 0.67$	Fixed 1
3	P1 plant outage	S1a (Chem- Comp)	P1	Exponential $\lambda = \frac{1}{287}$	Bi-Modal Log Normal $\mu_1 = 0.86, \sigma_1 = 0.59$ $\mu_2 = 2.35, \sigma_2 = 0.05$ $W_1 = 0.71$	Fixed 1
4	Distillation tower outage	S1b	P3a P3b P3d P3e	Exponential $\lambda = \frac{1}{670}$	Fixed 7 days	Fixed 1
5	Site external disruption	Supplier, rail	F2 External P1 External F3 F3Comp Contract F3 Other	Exponential $\lambda = \frac{1}{41}$	Exponential $\lambda = \frac{1}{2.56}$	Fixed 0.5
6	Unloading P1 outage	S1b	Unloading P1	Exponential $\lambda = \frac{1}{40}$	Exponential $\lambda = \frac{1}{1.3}$	Fixed 1
7	Unloading F3 outage	S1b	Unloading F3	Exponential $\lambda = \frac{1}{40}$	Exponential $\lambda = \frac{1}{1.3}$	Fixed 1

Time is measured in days

We present the relevant identified risks in Table 2. Risks 1, 2 and 3 are related to capital intensive production assets. Based on a probability distribution fit for data available for outages in the period 2011-2015, the distribution appears to be a mixture distribution. This is confirmed by the experience that most of the disruptions can be solved quickly, or temporarily solved without a

big influence on production. However, some accidents or disruptions have a different nature, they are harder to repair and their duration is significantly longer. To address this nature, we describe these outages by a mixture distribution that combines two log normal distributions, with a high probability peak for low duration risks and a more flattened distribution for the longer duration risks, comparable to a similar phenomenon studied in electromigration failure research in reliability theory (Fischer et al., 2000). The distillation tower under effect for risk 4 has a back-up option taking over after 7 days, therefore outages never last longer than 7 days.

The remaining three identified risks individually have a negligible effect, but they significantly inflate the disruption costs when they occur simultaneously with one of the four risks introduced above. Therefore, we define risks 1, 2, 3, and 4 as primary risks, and risks 5, 6, and 7 as secondary risks. The latter include risks related to incoming external supply due to transportation or unloading issues. We only include secondary risks in the analysis if they coincide with one of the primary risks. Furthermore, most of the secondary risks can be anticipated better (e.g. an announced strike or expected snowstorm) than the unplanned asset outages. This is accounted for by the fact that the information about these risks, is available when a primary risk occurs.

In the analysis, we categorize disruptions shorter than three days as operational uncertainty, since the inventory capacity of the different kind of feedstock cover about three days of full-capacity production. We exclude these disruptions in our analysis. We evaluate the effect of the mitigation options presented in Table 3 on the remaining supply disruptions.

5.2. Scenario Generation

We executed the following process to generate BAU uncertainty. Based on historic data and supply chain expert opinion we assume transportation costs to be constant. Furthermore, given the nature of the non-volatile production capacities of chemical plants, we assume supply availability is constant in BAU and only variable during disruption periods.

Prices of sold products depend for a major part on monthly contracts that depend on the feedstock price. This means that margins and the cost of disruptions depends on the volatility of feedstock prices relative to the contract price. Therefore, in modeling feedstock prices we do not focus on the absolute values, but on the volatility and price differences between the different kind of feedstocks. We use a Geometric Brownian Motion (Geman, 2007; Li and Kouvelis, 1999) to model the oil derivative prices as a random walk in combination with an adapted jump-diffusion model (Krichene, 2006) to capture sensitivity of prices to supply-demand shocks. Selling prices

Table 3: Identified risk mitigation options to address supply risks at site S1

Nr. (<i>n</i>)	Mitigation option	Quantity	Minimum value (\$ million / 5 year)
1	Extra storage P1 S1b	+2,000,000 kg	5
2	Increase basestock P1	90% (of max inv)	2.5
3	Extra storage F3 S1b	+2,000,000 kg	12
4	Extra unloading P1 S1b	+350,000 kg	2.5
5	Extra unloading F3 S1b	+350,000 kg	2.5
6	P1 independent of cracker	after 2 days	23
7	Shorten distillation tower backup	2 days	1
8	Reduce lead time P1 External	2 days	2.5
9	Reduce lead time F3 F3Comp	2 days	2.5
10	No minimum contract quantity F1	0	7
11	No minimum contract quantity F2	0	7

are based on the sum of feedstock prices and a margin, mostly fixed in contractual agreements. For the final production nodes, we assume production schedule is a proxy for demand since the plants run at full capacity. To determine demand we partition the production schedule of the past two years in weeks, excluding the weeks with lower production due to supply disruptions, and categorize them in representative sets representing seasonality and longer planned cleaning periods. To generate demand for a scenario, we use a bootstrapping methodology to build up a representative production schedule for the time horizon under study. Lastly, we assume that there is always external P1 demand. However, the decision how much P1 to produce to sell to other ChemComp plants or at the market depends on the margin of P1 over its feedstock. If this margin exceeds a certain threshold, the P1 plant will run at full capacity and if it is lower, the plant will run at minimum capacity. The external P1 demand is assumed to be the remainder between the full capacity and the site S1 demand of P1.

To determine the BAU operational decisions we define six decision rules. The first four rules are profit-related and the last two rules are capacity-related. First, sell as much as possible if margins are positive, second, source at the cheapest possible option, third, internal demand has priority over external demand, and fourth, do not shutdown plants or put them in standby. Since demand always exceeds supply and margins are positive, rules one to four are aimed at achieving maximum profit. The fifth rule is to respect minimum and maximum capacities, and lastly, the sum of the

physical inventory at each node $i \in \mathcal{L}^i$ and products in transit at unloading nodes $j \in \mathcal{U}(i)$ is larger than or equal to the adjusted basestock-level S_i . Rule five forces the decisions to be within the structural boundaries of the supply chain. Rule six accounts for the fact that in the chemical industry companies work with target inventories, that take into account the trade-off between the costs of capital captured in inventories and the preparedness for risks. Note that S_i is an input parameter in this case and can either be determined as an absolute quantity, or it can be based on a certain basestock percentage (s_i) of the maximum inventory capacity (γ_i^{max}). The BAU decision rules will translate the demand into a production schedule for the final production nodes and a ‘demand delivery schedule’ for the demand nodes. In a commodity market, generally there are no back-orders, thus the inability to meet this schedule results in lost sales. The result of this step, are values for each BAU decision variable in $\mathcal{X}$. Furthermore, decisions propagate from the most downstream demand and final production nodes to sourcing decisions at suppliers. Subsequently, according to the process described in section 4.1 and quantified risk categories presented in Table 3 we generate disruptions.

6. Results

6.1. Computational Performance

The calculations were carried out on a Intel Core i7 CPU @ 3.10 GHz running a 64-bit operating system with 16.0 GB of installed RAM. The model is implemented in Python 2.7 and uses Gurobi Optimizer 6.50 for the optimization. Table 4 provides an overview of running times for 24 problem instances. For each of the problem instances we include the risks and mitigation options identified in section 5. We include three different time horizons under investigation, a quarter of a year, one year and 5 years, to reflect different decision horizons. Furthermore, we solve the model for different numbers of scenarios: 1, 10, 20 and 40. Lastly, we compare the computation times of our model, exploiting the differentiation between BAU and disruption periods by only explicitly modeling the periods where the supply chain is affected by disruptions, and a similar model where we do not exploit this difference, i.e. where every period in the time horizon is explicitly modeled. Note that this full optimization is conducted only in this section to show the computational differences; in the remainder of the paper all operations BAU decisions are made by the application of business rules.

The results show that the supply chain of ChemComp faces disruptions in approximately 9% of the total number of periods. This leads to a model size reduction of approximately 85% compared

Table 4: Computational results of runtime experiments with $\eta = 0.5$, $\zeta = 0.1$ and $M = 20$. Number of periods in optimization model, runtime, variables and constraints are averages.

T	S	Number of periods in optimization model	Runtime (s)	Variables	Constraints
Exploit differentiation BAU and disruption periods					
0.25	1	6.0	0.05	6,597	3,536
	10	10.1	1.5	98,548	54,130
	20	9.3	2.9	188,380	102,856
	40	9.7	8.7	378,973	207,693
1	1	27	0.1	28,749	15,550
	10	33.1	6.4	344,668	187,843
	20	34.5	17.1	696,628	381,675
	40	33.7	48.4	1,373,931	751,918
5	1	133	0.6	142,137	76,924
	10	148.1	50.3	1,541,735	839,260
	20	145.4	145.8	3,056,690	1,661,039
	40	147.0	775.5	6,185,048	3,361,592
Model every period explicitly					
0.25	1	91	0.2	42,081	26,936
	10	91	13.0	420,815	269,380
	20	91	50.7	841,615	538,760
	40	91	355.9	1,683,215	1,077,520
1	1	365	0.8	153,873	101,464
	10	365	357.3	1,538,735	1,014,660
	20	365	1,288.4	3,077,455	2,029,320
	40	365	2,695.5	6,154,895	4,058,640
5	1	1825	6.5	749,553	498,584
	10	1825		*	
	20	1825		*	
	40	1825		*	

* solutions could not be obtained with the allotted amount of memory

to modeling every period explicitly in terms of number of variables and constraints. The reason why the model size reduction achieved by only modeling the disruption periods does not scale proportionally with the number of disruption periods is that for each disruption not only the disruption periods are optimized, but also the recovery period to return to BAU. The decrease in model size leads to significantly bigger reductions in computation time, varying from 94 to 99% for the different problem instances. The reduction in computation time is driven by two factors. First, by the reduction in model size. Second, if the model sizes are comparable, instances where T is split up in smaller disruption periods achieve significantly shorter computation times than instances where the whole horizon is considered. This is likely caused by the fact that each disruption and

the associated set of periods is optimized independently in the second stage and is only linked by the first stage decision variables. If the whole horizon is optimized, all decisions in a scenario in the second stage depend on each other, creating a harder optimization problem.

In addition to the 24 problem instances discussed in Table 4, Table 5 compares computation time for models including and excluding CVaR for 3 problem instances. Including CVaR leads to an average increase in computation time of 14% without significantly influencing the model size. The added computation time can be accounted to including the CVaR constraints.

Table 5: Computational results of excluding CVaR from the objective function

T	S	Including CVaR				Excluding CVaR			
		Disruption periods	Runtime (s)	Variables	Constraints	Disruption periods	Runtime (s)	Variables	Constraints
0.25	20	9.4	3.2	191,051	104,558	9.4	2.2	191,030	104,537
1	20	32.7	14.2	670,372	366,971	32.7	11.0	670,351	366,950
5	20	150.6	112.9	3,123,879	1,705,334	150.6	101.4	3,132,858	1,705,313

Next to computational duration challenges, large dynamic two-stage stochastic optimization models face memory issues from a computational perspective. Under the set-up used in this study to solve the model, if the whole horizon is considered not enough memory is available to solve the problem instances for $T = 5$ and the number of scenarios is 10, 20 or 40. The memory pressure reduction associated to the achieved model size reduction points to another benefit of the model presented in this paper.

6.2. Solution Properties

The expected supply disruption costs for ChemComp negatively impact the annual reported earnings by 4.4%, or \$20.2 million. However, only judging the costs of disruptions based on the expected value is not doing justice to the nature of disruptions. There are scenarios with limited disruptions, where earnings do not suffer as much as an average scenario, and there are considerably worse scenarios. In Table 6 we present the expected costs and 10%-CVaR for three different time horizons, reflecting the long-term, balanced and short-term focus of a company, and two different disruption frequencies, the original frequency and a scenario where disruptions are four times less likely to happen. The results are based on 2000 independent scenarios per problem instance. The expected costs scale linearly with the time horizon under consideration and the disruption frequency. However, the relative value of the CVaR increases with a decrease in horizon or disruption frequency. The reason for this is that, both in the case of increasing the horizon and increasing the frequency,

a larger sample of independent disruptions is considered in one scenario. This leads to a higher probability of having low disruptive periods and high-disruptive periods in one scenario. Therefore, the extremes tend to be flattened out to the mean.

Table 6: Disruption costs without mitigation options

T	Disruption Frequency	Expected Costs (million \$)	CVaR (million \$)	CVaR/Expected Costs	Average Disruption Days
0.25	Original	4.5	18.0	4.0	6.0
	25%	1.2	9.6	8.1	1.5
1	Original	20.2	45.9	2.3	26.8
	25%	5.2	20.1	3.9	7.1
5	Original	100.0	156.0	1.6	132.6
	25%	24.8	54.6	2.2	34.4

To evaluate mitigation options, we assume that mitigation options are linearly paid off over 5 years. Table 7 shows the number of generated designs, the optimal design and the optimal mitigation options suggested by the model for the 6 different problem instances without taking CVaR into account in the objective function. We optimize the model with 20 scenarios for 20 runs. The number of suggested designs converges with an increasing T or an increasing frequency, caused by the higher number of independent disruptions taken into account. Furthermore, as we would expect, the optimal suggested combination of mitigation options is independent from T but changes with frequency, i.e. less frequent disruptions do not justify the investment in MO-10.

Table 7: Suggested mitigation options and associated disruptions costs without including CVaR

T	Disruption Frequency	Number of generated designs	Optimal Design	Expected Costs (million \$)	CVaR (million \$)
0.25	Original	6	MO-5, MO-7, MO-10, MO-11	2.2	7.9
	25%	5	MO-5, MO-7, MO-11	0.6	4.6
1	Original	5	MO-5, MO-7, MO-10, MO-11	9.6	20.7
	25%	2	MO-5, MO-7, MO-11	2.8	9.6
5	Original	1	MO-5, MO-7, MO-10, MO-11	47.7	71.4
	25%	1	MO-5, MO-7, MO-11	13.4	27.4

Table 8 shows that the effect of including the CVaR in the objective function with a weight of 50% depends on T and the disruption frequency. For $T = 5$ with the original disruption frequency, there is no effect on the suggested designs. As expected, the effect is biggest for scenarios with the highest value for the ratio CVaR/Expected Cost. For both $T = 0.25$ and the ‘ $T = 1$ - original’

instances, the optimal design changes into a more conservative design, i.e. higher investments in mitigation options, while for ‘ $T = 1 - 25\%$ ’ and ‘ $T = 5 - 25\%$ ’ the original design remains optimal, but alternative suggested designs in the design generation step are more conservative. These results indicate an important trade-off between the short- and long-term optimal results. Dependent on the type of company and the value of non-variable and forecastable reported earnings per quarter, different design decisions will be made.

Table 8: Suggested mitigation options and associated disruption costs while including CVaR in the objective function

T	Disruption Frequency	Number of generated designs		Optimal Design	Expected Costs (million \$)	CVaR (million \$)
		$S = 20$	$S = 40$			
0.25	Original	6	4	MO-3*, MO-5, MO-7, MO-10, MO-11	2.0	7.3
	25%	5	2	MO-5, MO-7, MO-10*, MO-11	0.6	4.1
1	Original	5	3	MO-3*, MO-5, MO-7, MO-10, MO-11	9.0	19.2
	25%	2	2	MO-5, MO-7, MO-11	2.8	9.6
5	Original	1	1	MO-5, MO-7, MO-10, MO-11	47.7	71.4
	25%	1	1	MO-5, MO-7, MO-11	13.4	27.4

*mitigation option not suggested when CVaR is not included in the objective function

For every instance, increasing the number of scenarios per run in the design generation step (from $S = 20$ to $S = 40$) leads to a decrease in or even number of suggested designs because the increased sample sizes provide a better representation of the total population of future scenarios. This effect is strongest for the $T = 0.25$ instances, since they contain the least number of independent disruptions in the total optimization model. This result shows that for longer time horizons with higher disruption frequencies, less scenarios per run are required to arrive at only the optimal design in the design generation step. However, there is a trade-off between the time horizon, the number of disruptions and the computational time. For ChemComp, the optimal combination of mitigation options for the long-term horizon of 5 years is to invest in MO-5, MO-7, MO-10 and MO-11. This will lead to an expected annual reduction in disruption costs and CVaR of \$10.5 million and \$16.9 million respectively, with an average annual estimated investment of \$3.5 million. To arrive at the optimal design for a mid-term or short-term horizon, the increased importance of the CVaR leads to an additional annual investment in MO-3 of \$2.4 million to further reduce the expected annual disruption costs and CVaR by \$0.7 and \$9.8 million respectively. It is immediately clear that an investment in MO-3 does lead to a net decrease in expected reported earnings since the savings do not outweigh the expected costs. However, the investment is justified by decreasing the CVaR, thus reducing the impact of the highly disrupted scenarios.

7. Conclusion

In this paper, we have presented a methodology to evaluate the costs of disruptions and the value of mitigation investments in the chemical supply chain. To capture the temporal hierarchy between the strategic design decisions and the operational decisions we modeled the chemical supply chain as a two-stage stochastic program with recourse based on a discrete temporal framework that makes a decision about all mitigation options integrally. Furthermore, we integrate a new formulation to model the minimum shutdown length in a set of balance equations into the model. To make the problem tractable, we solve a discrete approximation of the model as part of a solution scheme that relies on the SAA. Furthermore, we exploit the nature of the origin of disruption costs by dividing the time horizon under investigation in BAU periods and disruption periods by only explicitly evaluating the periods that a supply chain is under the effect of a disruption. This allows us to capture the true dynamic nature of disruptions and reduces computational time by approximately 95%. Although we focused on supply risks in the chemical industry in this study, the model structure allows it to be extended to account for different types of risks, e.g. demand risks and for other commodity industries with similar market structures, e.g. the food industry.

We extended the model by introducing the CVaR in the objective function to account for the uncertain nature of supply chain disruptions and the potential costs of highly disrupted scenarios. Our results show that the impact of including the CVaR in the objective function increases with a decreasing time horizon under investigation or disruption frequency. This insight indicates a trade-off between long-term expected costs minimization and short term risk minimization, where the latter leads to a more aggressive investment policy. Thus, for decision-makers, this implies that the time horizon of the analysis should be treated as an implicit decision variable, and thus given careful consideration. Moreover, the modeling approach presented in this paper allows us to distinguish which risk mitigation options are robust to changes in time horizon.

Although the nature of the model does not allow the supply chain to predict the arrival of a disruption, all information about the disruption is known at the start of it. It would be worthwhile to explore methodologies to better reflect the uncertainty faced during a disruption period into the options evaluation model. Furthermore, modeling the effect that customers might permanently switch to another supplier would improve the insight in the effect of disruptions for companies.

For industry practitioners, our model helps to create insight in the highly uncertain costs of supply disruptions. Furthermore, it assesses the potential value of a set of interdependent mitigation options, e.g. the effect of implementing one option on the impact of a second option. Our model

supports the identification of vulnerabilities in the supply chain and, by including the CVaR into the objective function, we allow decision makers to reflect their risk aversion in the optimal solution of risk mitigation options. This implies that better trade-offs can be made between the expected value of the long-term reported earnings and the associated volatility and forecastability. The results of this analysis should be used as input to support decision making, rather than the definitive answer to a question. Within companies, different stakeholders have different interests if it comes to short term value or long term security. The interpretation of the results of these analysis depends on the balance between these interests.

8. References

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Appendix A. Notation

Table A.9: Abbreviations

3PLs	Third-party logistics providers
BAU	Business As Usual
CVaR	Conditional Value At Risk
SAA	Sample Average Approximation
SCND	Supply Chain Network Design
VaR	Value At Risk

Table A.10: Indices used to further specify earlier defined notation

i, j, h, g, k	Node
t, t^*	Time period
s	Scenario
e	Disruption
ϵ	Indicator for parameter or variable during disruption

Table A.11: Sets defined in Section 2

$\mathcal{A}$	Set of capacity, recipe and lead time parameters that define the structural elements of the supply chain
$\mathcal{D}(i)$	Set of nodes directly downstream of node i
E	Set of disruptions
$\mathcal{L}$	Set of supply chain nodes
$\mathcal{L}^d$	Set of demand nodes
$\mathcal{L}^f$	Set of final production nodes
$\mathcal{L}^i$	Set of inventory nodes
$\mathcal{L}^p$	Set of intermediate production nodes
$\mathcal{L}^s$	Set of supplier nodes
$\mathcal{L}^u$	Set of (un)loading nodes
T	Set of time periods
T_{-U}	Set of periods t that are $U \geq t > 0$ periods before the first period of one of the disruptions in a scenario
T^ϵ	Set of periods that the supply chain is affected by a disruption, i.e. duration of disruption and recovery
$T_{\text{begin}}^\epsilon$	Set of periods that captures the first period of every disruption period
T_{end}^ϵ	Set of periods that captures the last period of every disruption period
$T_{\text{perturbed}}^\epsilon$	Set of periods where the capacities and/or lead times of the nodes in the affected hazard zone are perturbed
$T_{\text{recovery}}^\epsilon$	Set of periods after the disruption ended to get back to BAU
S	Set of scenarios
$\mathcal{U}(i)$	Set of nodes directly upstream of node i
Y	Set of potential mitigation options, i.e. the strategic decision variables
$\mathcal{X}$	Set of all operational decision variables
Z	Set of hazard zones

Table A.12: Decision variables defined in Section 2

b_{its}	Excess product to be disposed at node i in period t in scenario s
I_{its}	Inventory at node i at the end of period t in scenario s
h_{its}^b	1 if node i is standby in period t in scenario s , 0 otherwise
h_{its}^d	1 if node i is down in period t in scenario s , 0 otherwise
$h_{its}^{d,shutdown}$	-1 if node i is shut down in period t in scenario s , 1 otherwise
$h_{its}^{d,switch}$	1 if node i is either shut down or started up in period t in scenario s , 0 otherwise
q_y	1 if Mitigation option y is implemented, 0 otherwise
$\mathbf{q}$	Vector that captures decisions for all mitigation options
x_{ijts}	Product flow shipped from node i to node j in period t in Scenario s , $j \in \mathcal{D}(i)$

Table A.13: Parameters defined in Section 2

α_{its}^{max}	Maximum input capacity of node i in period t in scenario s
α_{its}^{min}	Minimum input capacity of node i in period t in scenario s
β_{its}^{max}	Maximum output capacity of node i in period t in scenario s
β_{its}^{min}	Minimum output capacity of node i in period t in scenario s
γ_{its}^{max}	Maximum inventory capacity of node i in period t in scenario s
γ_{its}^{min}	Minimum inventory capacity of node i in period t in scenario s
θ_e	Duration of disruption e
θ^{min}	Threshold duration for disruptions to be included in $\mathcal{E}$
κ_i	Minimum shutdown time of node i
ρ_{ji}	Unit ratio of required product from node j by node i relative to the output in node i , $j \in \mathcal{U}(i)$
τ_{ijts}	Lead time of shipping from node i to node j in period t in scenario s , $j \in \mathcal{D}(i)$
ω_s	Vector with realization of uncertain parameters for scenario s
ϕ_e	Impact of disruption e , i.e. level of capacity perturbation
c_i^b	Standby costs for node i (per period)
c_i^d	Shutdown and start-up costs for node i (per event)
c_{its}^f	Feedstock price at node i in period t in scenario s , $i \in \mathcal{L}^s$
c_{ijts}^t	Cost of shipping from node i to node j in period t in scenario s , $j \in \mathcal{D}(i)$
c^y	Cost of mitigation option y
D_{its}	Demand at node i in period t in scenario s , $i \in \mathcal{L}^d \cap \mathcal{L}^f$
m_{its}	Selling price at node i in period t in scenario s , $i \in \mathcal{L}^d \cap \mathcal{L}^f$
r	Duration of recovery period after disruption, i.e time required to get back to BAU
S_i	Basestock level at node i
s_i	Basestock level percentage of maximum inventory at node i ($S_i = s_i \gamma_i^{max}$)
t_0	Design time
t_e	Start of disruption e
t_{e-u}	The period $u \in \{0, \dots, U\}$ periods before the start of a disruption e

Table A.14: Parameters and decision variables defined in Section 3

$\alpha_{its}^{\epsilon,y}$	Additional input capacity of node i in period t in scenario s that is operational during a disruption associated to the mitigation option of increasing input capacity
$\beta_{its}^{\epsilon,y}$	Additional output capacity of node i in period t in scenario s that is operational during a disruption associated to the mitigation option of increasing output capacity
$\gamma_{its}^{\epsilon,y}$	Additional inventory capacity of node i in period t in scenario s that is operational during a disruption associated to the mitigation option of increasing inventory capacity
ζ	Indicator of percentage of scenarios to include in computing the CVaR
η	Factor to determine weight of expected costs and CVaR in objective function
$\pi(s)$	Probability of scenario s
v_{its}	Indicator variable that indicates that the extra capacity mitigation option is implemented and node i is not in shutdown or standby in period t in scenario s
$CVaR$	Variable indicating the Conditional Value At Risk
$s_{i,y}$	Basestock level percentage at node i associated to the mitigation option of increasing the basestock level
q_α	Strategic decision variable associated with input capacity increase
q_β	Strategic decision variable associated with output capacity increase
q_γ	Strategic decision variable associated with inventory capacity increase
q_d	Strategic decision variable associated with shortening the effect of a disruption
q_k	Strategic decision variable associated with shortening the lead time
q_{s_i}	Strategic decision variable associated with increasing the basestock percentage
VaR	Variable indicating the Value At Risk
z_s	Auxiliary variable to determine CVaR

Table A.15: Parameters and sets defined in Section 4

π^A	Probability of normal risk scenarios
π^H	Probability of high risk scenarios
$F_z^\Lambda(\cdot)$	Cumulative distribution function of inter arrival of disruptions in hazard zone z
$F_z^\Theta(\cdot)$	Cumulative distribution function of duration of disruptions in hazard zone z
$F_z^\Phi(\cdot)$	Cumulative distribution function of impact of disruptions in hazard zone z , $z \in Z$
M	Number of times the model is solved with an independent set of N scenarios
N	Number of scenarios used to solve the deterministic equivalent of the stochastic program
$N^\#$	Number of scenarios generated from which scenarios that are used to solve the model are sampled
N^*	Number of scenarios used to evaluate candidate designs
S^A	Set of acceptable cost scenarios
S^H	Set of high cost scenarios
$\mathbf{q}^{m,*}$	Vector that captures optimal investment decisions for model solution m