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On product characteristics in multi-product two-echelon resilient network design

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Abstract
Ocean shipping is integral to today's global and interconnected supply chain networks. To supply products to the hinterland, inland waterway transport is vital due to its economic advantages wherever possible. However, major inland waterways are prone to recurring disruptions caused. These disruptions lead carriers to impose surcharges, which can severely affect firm performance. To mitigate these disruptions, different resilience strategies, which potentially influence each other, need to be evaluated for each product within the product portfolio. In this paper, we decide on the resilience strategies and transportation flows for a two-echelon inbound supply chain with multiple products that are needed to produce a single finished good under transportation cost and lead time uncertainty to minimize total expected costs. The problem is formulated as a two-stage stochastic mixed-integer linear program. To solve large instances, we propose model enhancements that strengthen the formulation and a heuristic approach to particularly solve large problem instances. We present a case study based on a chemical company at the border of the Rhine River. Considering disruptions, the cost-efficient mix of resilience strategies significantly depends on the specific product characteristics. Considering multiple products jointly reduces resilience costs by up to 79% compared with solving the problem separately for each product. Moreover, historical shifts in disruption probabilities and impacts over the past four decades require an adjustment of the resilience mix. Our findings demonstrate that multi-product considerations are essential for resilient supply chain network design and that resilience strategies must be tailored to product characteristics and evolving disruption risks.

Keywords Supply chain management · Logistics · Resilience · Stochastic programming

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1 Introduction

Supply Chain (SC) networks are exposed to disruptions that can seriously affect a firm's performance and result in stockouts, financial losses, higher costs, and the loss of market share. In today's increasingly global and interconnected SC networks, maritime shipments already deliver approximately 80% of the global trade volume, which is expected to increase even further (ITF 2020). To deliver these goods from global seaports to the mainlands, inland waterway transports play an essential role and will increase in importance due to their advantages in terms of energy consumption per km/ton transported compared to road and rail transport. Due to the increase in extreme weather events, particularly global inland waterway transport disruptions have gained growing attention as low- and high-water-level situations affect the shipment carrier's transport capacities and abilities on a recurring basis. As a result, carriers enforce contractual surcharges on top of their standard prices or even stop their service completely, which results in stockouts or cost increases for the overall SC network. These surcharges, however, are only determined by the actual water level on the day of shipment and therefore not known in advance. For example, in 2018, the Rhine River's low water levels forced a stop of all waterway transportation for 132 days, resulting in production stops due to material shortages for many companies (Ademmer et al. 2020). In 2022, the Mississippi River experienced a historic drought between September and December, with the lowest water levels observed in October. Despite a significant rise of transportation costs up to 400%, Steinbach and Zhuang (2023) estimated that the drought resulted in a 3.9% reduction in agricultural exports and an agricultural trade loss of 563.9mn USD. Recently, low water levels on the Panama Canal forced vessels to lighten their loads. As a result, Hapag Lloyd announced a 500 USD surcharge per TEU on all cargo between Asia and the US East Coast shipped through the canal. Due to climate change, many experts expect an increased frequency of these high and low water events on major waterways in the future (Koetse and Rietveld 2009).

To a certain extent, these negative consequences can be mitigated by building a resilient Supply Chain Network Design (SCND) combining different resilience strategies to reduce the adverse effects of a disruption. For a decision maker who manages the SC, this means ensuring that the corresponding actions are taken across the product portfolio. The efficiency of the resilience strategies, however, depends on the product's characteristics within the portfolio. For example, keeping extra inventory is cost-competitive for a low price product, while for a highly complex product, a competitive backup-supplier might not be available. Thus, the complexity and characteristics of a product portfolio play an essential role in the resilient SCND.

Regarding the general SCND problem, the influence of specific product characteristics on overall design and SC strategy has been identified early and refined over time (Fisher 1997). The complexity of managing a product portfolio within general SCND has also been addressed in decision models even though a large share of literature still assumes single-product settings (Govindan et al. 2017). While the general toolkit for achieving SC resilience is well understood in research and academia, there is a lack of quantitative work that addresses the impact on product characteristics of resilient SCND (Hosseini et al. 2019). To ensure that resilience strategies are applied in practice, however, the cost-effectiveness of the individual strategies needs to be assessed (Cohen and Kouvelis 2020). While existing resilient SCND models have discussed the cost-competitiveness for a single product or a SC in general, there is a lack of research that optimizes the mix of resilience strategies across many products with different characteristics (Ergun et al. 2023).

As a result, decision makers still lack a decision model that incorporates product characteristics into resilient SCND. They need to understand which product characteristics drive the cost-effectiveness of the different resilience strategies and how to assess these characteristics within their portfolio. To manage the resulting complexity, they require a segmentation of products into categories that behave similarly to their ideal set of resilience strategies.

Motivated by the recurring disruptions of major inland waterway transportation worldwide, we model the problem as two-echelon resilient SCND with multiple products. We study an inbound supply chain composed of multiple suppliers at regional and global levels that ship different raw materials (i.e., products) using different transportation modes to a production facility with centralized decision-making. Shipments from global suppliers are gathered at the first inventory echelon (i.e., a warehouse at the seaport). In contrast, regional suppliers directly ship to the second echelon at the production facility. The transportation mode (i.e., river) between the first and second echelon is prone to disruptions that are uncertain concerning their duration, impact, and occurrence along the planning horizon. These disruptions result in surcharges that increase the transportation costs between the first and second echelon. The value of the surcharge depends on the severity of the disruption on the actual day of shipment; thus is uncertain in advance. Depending on the specific product, global and regional suppliers might be available to deliver. In addition, products differ in their characteristics, such as the product value. Thus, a central decision maker decides on the mix of resilience strategies, such as near-shoring, investments in capacity increases, investments in backup suppliers, and additional inventory holding across the product portfolio. The overall objective is to minimize the total expected costs given the transportation cost and lead time uncertainty. Notably, we will address the trade-off of proactive investments in resilience strategies and potential surcharges or stockouts on the raw material level.

Our main contributions are as follows:

1. We introduce a two-stage stochastic program for the two-echelon resilient SCND with multiple products, transportation costs, and lead time uncertainty. The SCND problem considers multiple resilience strategies including near-shoring, inventory capacity increase, backup supplier investments, and additional inventory holding.
2. We propose problem-specific valid inequalities, lower-bound-lifting constraints, and a warm-start procedure to improve the solution time and quality of commercial solvers. To further find solutions for large multi-product settings, we introduce the rolling-product-integration heuristic (RPIH) to heuristically solve large problem instances efficiently.
3. We present a case study and discuss the influence of the product characteristics on the optimal mix of resilience strategies.

4. Via the case study, we derive managerial insights on the resilient SCND with multiple products and cost uncertainty. Particularly, we will discuss the effects of shifts in disruption probabilities through external effects, such as climate change.

This paper is structured as follows. Section 2 reviews the relevant literature while Sect. 3 describes the problem setting in detail. Then, Sect. 4 presents the mathematical model formulation. In addition, the RPIH is introduced. Section 5 presents the case result. Finally, Sect. 6 concludes by summarizing and detailing open research areas.

2 Literature review

Section 2.1 briefly reviews literature on the influence of product characteristics on general supply chain network design and strategy. Then, in Sect. 2.2 general strategies and levers are discussed to increase Supply Chain Resilience (SCR). Section 2.3 summarizes literature on multi-product SCND with a focus on increasing resilience as objective. Finally, Sect. 2.4 summarizes the research gaps.

2.1 The influence of product characteristics on SCND

Designing and managing supply chains effectively is a complex and challenging task. Within supply chain management, Fisher (1997) introduced the need to match product characteristics with the ideal supply chain design by distinguishing between functional and innovative products based on their demand characteristics. This original framework has been expanded by Lee (2002), who considered demand and supply uncertainty to distinguish between a need for efficient, responsive, risk-hedging, and agile supply chains based on product characteristics. Huang et al. (2002) differentiate between innovative, hybrid, and standard products and assess their fit to an agile, hybrid, or lean supply chain strategy and design. Based on the proposed frameworks, Wang et al. (2004) developed a decision-support model that decides on the multi-criteria optimal supplier selection for each product based on product characteristics. Kleindorfer and Saad (2005) developed a conceptual framework on managing disruption risks in supply chains. They highlight the need to fit the approach taken to the supply chain environment and product characteristics based on empirical results from the chemical industry. Qi et al. (2009) found empirical evidence in China that firms that adapt their supply chains' based on product characteristics outperform firm with a traditional strategy. In a similar effort, Eckstein et al. (2014) empirically investigated the effects of supply chain agility and adaptability on cost performance and identified a correlation with product complexity. Zimmermann et al. (2020) analyzed empirical data from 329 companies and identified that product characteristics are essential in adopting the right supply chain strategies. Wiedmer et al. (2021) analyzed the effect of the Tsunami in 2011 on the automotive sector's trade from Japan to the United States and found that alongside other characteristics product complexity influence a firm's ability to withstand and recover from disruptions. Cohen et al. (2022) conducted interviews with 16 supply chain executives to determine process, partnership, and product complexity as dominant drivers for the mix of resilience strategies in supply chain design.

2.2 Strategies to increase resilience in SCND

SCR has been defined by various authors in the past, including crucial design characteristics and capabilities. We recommend the recent overviews by Hosseini et al. (2019) and Aldrighetti et al. (2021). Designing resilient supply chains involves understanding the nature of the disruption uncertainty at hand concerning probability and impact of its occurrence. Due to this uncertainty, supply chains require a detailed understanding of hidden interactions across different decision levels. In order to increase SCR, firms can adjust their network design as well as their tactical and operational decisions (Govindan et al. 2017). Different SCR strategies have been identified and discussed in analytic models, such as supplier segregation, multiple sourcing strategy, inventory positioning, multiple transportation channels, backup suppliers, re-routing, and product substitution (Hosseini et al. 2019). Even though most studies highlight the benefits of multiple sourcing and backup suppliers, the explicit role of lead time is still not well understood. Instead, lead time differences in multi-sourcing are neglected and immediate effects of disruptions and SCR strategies on sourcing decisions assumed (Aldrighetti et al. 2023).

One of the key implementation requirements for the adaptation of resilience strategies in practices is their cost-competitiveness. Thus, quantitative decision models that decide on the cost-optimal mix of resilience strategies for the SCND under disruption risks gained increasing relevance. Overall, SCND problems under disruption uncertainty developed from simple facility locations to complex integrated decision problems. Klibi and Martel (2013) proposed a new methodology to establish robust solutions to the SCND problem without the need to determine disruption probabilities. Snoeck et al. (2019) combined strategic mitigation with operational decisions by incorporating the inbound supply chain planning with production planning and setup for the chemical industry and proposing a solution scheme based on linear approximation. As an extension of previous supplier selection problems, Hosseini et al. (2019) incorporated decisions on additional manufacturing capacities and geographical separation of suppliers, considering regional disruption scenarios. Azad and Hassini (2019) developed an optimization model with partial failure of facilities and multi-mitigation strategies and proposed an enhanced Benders Decomposition (BD) to solve the problem. Rodríguez-Espíndola (2023) proposed a two-stage bi-objective stochastic model to propose an integrated approach for handling multiple simultaneous disasters. Studying recurring hurricane and tropical storm disruptions, they focused on the year 2013 where three simultaneous disasters caused economic and social implications simultaneously. Alikhani et al. (2023) used a multi-methodological approach to select the best resilience strategies for varying supply chain disruptions. They considered facility fortification, direct shipping, inventory increase, facility dispersion, multiple set covering, and cybersecurity in a single product flow and single time period environment. Aldrighetti et al. (2023) studied a resilient SCND in a multi-echelon, multi-period, and single-product setting with equal disruption probabilities for all locations. Through numerical experiments and a case study focusing on the COVID-19 pandemic, they identified a good trade-off between resilience and investment costs focusing on agile and reconfigurable supply chains. Particularly, backup suppliers outside the main supply chain footprint are most efficient for disruptions on the supply side, while re-routing of material flows was a key SCR strategy for disruptions at own facilities. However, they assumed all disruption and recovery events with immediate impacts, ignoring the potential impact of lead times. Specifically, the effect is ignored that with an increasing lead time of backup suppliers, the recovery times increase. Disruption effects might also not come into effect immediately as a disrupted supplier with long lead times might already have a number of deliveries shipped that are still being received even though the supplier is disrupted.

2.3 Decision models for resilient SCND with multiple products

Schmitt and Singh (2012) developed a simulation model to capture a multi-product, multi-echelon network to reduce supply chain risks. Based on their analysis, the whole system must be considered to find the optimal mix of resilience actions. Baghalian et al. (2013) considered demand and supply uncertainty in a multi-product supply chain to determine the ideal facility location in a robust supply chain network design. Particularly, they argue that the risk acceptance in the supply chain depends on the nature of the product. Sabouhi et al. (2018) considered partial and complete disruptions for the multi-product inbound SCND problem considering quantitative discount levels for the sourcing decision from multiple suppliers. In addition, they presented a pharmaceutical case highlighting the impact of holding cost on the optimal resilience mix. Bottani et al. (2019) developed a bi-objective mixed-integer programming formulation for the resilient SCND specific to the food supply chain. They identified the optimal resilience mix for each product based on the sourcing costs, lead time, capacity consumption, and supply disruption probability. Within their approach, they focused on the efficient redesign of a supply chain network when facing a disruption and proposed a metaheuristic based on an adapted ant colony optimization to solve the problem of redesigning when facing a disruption. Recently, Ghanei et al. (2023) studied an intertwined supply network under a fair collaboration with multiple products that incorporates different resilience strategies when facing transportation cost and facility capacity uncertainty. Using a Monte-Carlo simulation based on the sample average approximation scheme they estimated the expected value function to then solve the resulting network design problem by solving the deterministic optimization problem.

2.4 Summary of research opportunities

The effect of product characteristics on general supply chain design as well as their influence in building resilient supply chains has been extensively proven empirically. Still, there is a lack of decision models that deal with the real-life need for multi-product problems in resilient SCND (Govindan et al. 2017) to understand how product characteristics influence the cost-competitiveness of resilience strategies. Till date, many papers assume single product flows in resilient SCND to reduce model complexity. However, this neglects both the role of different product characteristics in the cost-optimal mix of resilience strategies as well as a potential interdependence between the products in SCND. Bridging the gap between the individual analysis of certain products as well as the influence of product characteristics on the optimal resilience strategy is seen as one of the key research gaps in SCR literature (Ergun et al. 2023).

3 Problem formulation

We introduce the resilient multi-echelon SCND problem with multiple products. Section 3.1 introduces the process and network structure while Sect. 3.2 outlines the relevant product characteristics within the product portfolio. We discuss the effect of uncertain transportation disruptions in Sect. 3.3. Finally, the different resilience strategies available to the decision maker are summarized in Sect. 3.4.

3.1 Network and process structure

We consider an SCND problem with multiple products needed to produce a single finished good in a discrete-time horizon where the transportation network consists of multiple suppliers (*as sources*), multiple transportation modes (*as arcs*), two-echelon inventory holding locations (*as nodes*), and a single production facility (*as sink*). Two different types of suppliers are relevant: Global suppliers, on the one hand, deliver to the inventory storage location at the first echelon, which is typically located close to a seaport. Here, all products are received, bundled, and then shipped to the second echelon through a distinct transportation mode, which is typically either inland shipping, rail or truck depending on the availability. Regional suppliers, on the other hand, deliver directly to the inventory storage location at the second echelon. Generally, each product is offered by both global and regional suppliers. Each supplier offers the product at a specific product price and transports the products through a specific transportation mode to the inventory storage of echelon 1 (global suppliers) or the inventory of echelon 2 (regional suppliers). Each of these transportation modes can differ in transportation costs and lead times. For the transport between the first and second echelon, all products share the same transportation mode, and thus time and costs. In addition, global suppliers offer an express delivery at higher transportation costs that are directly shipped to the second echelon. We focus on problem settings where the important transportation link between the first and second echelon of inventory holding is prone to disruptions (see Sect. 3.3). The overall network structure is visualized in Fig. 1.

At the beginning of each period, outstanding shipments at each of the inventory echelons that were ordered lead time periods in the past arrive. At the first echelon, shipments to the second echelon can be triggered from the resulting available inventory quantity. At the second echelon, the demand is fulfilled from the available inventory. The final inventory at the end of each period becomes the starting inventory for the next period at each echelon. In case available inventory of echelon 2 of any of the products is not sufficient to fulfill the finished good demands, shortages are consid-

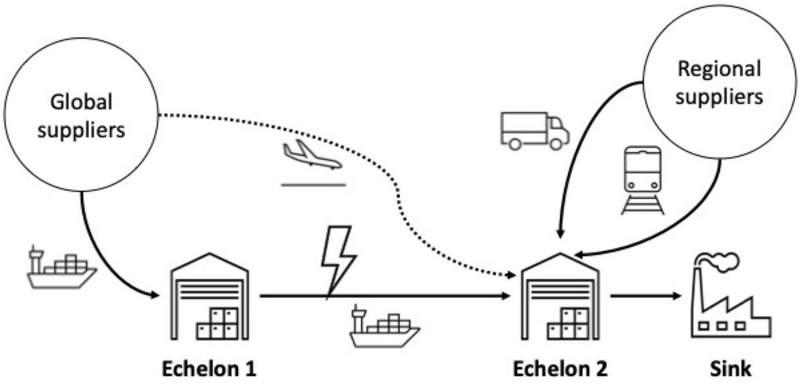

Fig. 1 Structure of the two-echelon resilient SCND problem with multiple products

ered as the production plan can not be executed as planned and production stops can be a result. As all products are needed to produce a finished good, the product with the highest shortage in each time period determines the overall shortage (i.e., lost production quantity and capacity) concerning the total costs. The overall effects are comparable to the lost sales assumption of an outbound supply chain.

3.2 Product characteristics

We are interested in the influence of product characteristics on the cost-competitiveness of resilience strategies (see Sect. 3.4). Particularly, we stylize characteristics of products that influence the costs of holding them as inventory, the difficulty of qualifying a supplier to be able to deliver the product, capacity consumptions for inventory storage, and the transportation costs. Thus, we distinguish products based on the following characteristics:

- *Product value*. The product value is a direct driver of inventory holding cost as this is assumed to correlate. Therefore, we distinguish between low- and high-priced products in terms of their holding costs per unit.
- *Volumetric weight*. The combination of weight and volume is an important driver for air freight cost. As we assume express operational reorders via air freight, the higher the volumetric weight, the higher the express reorder costs.
- *Space requirement*. When multiple products are stored in a single warehouse, there are significant differences in the space requirements and thus in the capacity consumption of the respective warehouse. Thus, we differ in the capacity consumption of inventory storage capacity per unit stored.
- *Product complexity*. The qualification efforts for suppliers correlate to the overall product complexity. The more complex a product, the higher the efforts in testing and maintaining the specifics. A commodity on the other hand can be obtained at lower qualification costs as specifications are rather standard and qualification requires mainly administrative efforts.
- *Availability of suppliers for near-shoring*. Some products are generally available

to be sourced either regionally or globally while others might only be available globally. This includes, for example, raw materials that might not be available in the specific region such as rare-earth needs as highlighted in the "Critical Raw Materials Act" of the European Union (Cohen et al. 2022; Hool et al. 2023).

Table 1 summarizes these product characteristics. To be able to understand the implications of these characteristics on network design decisions under cost and lead time uncertainty, we define 16 archetypical products relevant to resilient transportation network design. We define extreme values for each of the product characteristics so that each archetypical a unique combination of product characteristic values. Regarding the availability of suppliers for near-shoring, we consider case situations with and without regional supplier availability. In addition, the cost ratio between the transportation costs, the total sourcing costs, and the shortage costs play a significant role in the cost-competitiveness of resilience strategies. While for products and industries with a low share of transportation costs, disruptions that result in pure transportation cost increases might not play a relevant role, the same disruptions might be of major importance for the overall cost-competitiveness in other industries as surcharges account for a much higher share on overall costs.

Using the Rhine River as an example, we outline the typical variety of product characteristics but also the subsets of products where decision-makers are relying on waterway transport. Thus, we highlight the differences in planning challenges for decision makers within and across industries, such as chemicals, commodities (including agricultural products), and automotive.

To illustrate the stylized products outlined in Table 1, we indicate some real-world examples as follows. Companies within the chemical industry source and produce a wide variety of products and, as an industry, are often dependent on waterway transport. Within the chemical industry, some major product groups include com-

Table 1 Overview of product portfolio characteristics

Product	Product value	Volumetric weight	Space requirement	Complexity
P1	Low	Low	Low	No
P2	High	Low	Low	No
P3	Low	High	Low	No
P4	High	High	Low	No
P5	Low	Low	High	No
P6	High	Low	High	No
P7	Low	High	High	No
P8	High	High	High	No
P9	Low	Low	Low	Yes
P10	High	Low	Low	Yes
P11	Low	High	Low	Yes
P12	High	High	Low	Yes
P13	Low	Low	High	Yes
P14	High	Low	High	Yes
P15	Low	High	High	Yes
P16	High	High	High	Yes

modity chemicals, specialty chemicals, and petrochemicals. Commodity chemicals are typically produced continuously and traded on a large scale in global markets with no differentiation between different suppliers and sourcing options (e.g., $\mathcal{P}1$). Similarly, petrochemicals are also produced on a large scale. However, they differ in a way that during petrochemical production, a number of related products often need to be produced, which can differ greatly in value and storage requirements (e.g., $\mathcal{P}5$). Specialty chemicals, on the other hand, are products made in discrete batch processes, often following specific and unique customer requirements of high value (e.g., $\mathcal{P}10$). Since a typical chemical production site produces a variety of commodity, petrochemical, and specialty chemical products (not exhaustive), decision makers need to balance various different products that could be affected through identical transportation disruptions (e.g., $\mathcal{P}1, \mathcal{P}5, \mathcal{P}10$).

In addition, a large share of the transport volumes is driven by agricultural products and commodities, such as coal, oil, and steel. In contrast to the chemical products involved, many of these commodity products cannot be switched to other modes due to the pure quantities involved that cannot be covered in the short or mid-term elsewhere (e.g., $\mathcal{P}7$). Thus, despite cost implications, the primary threat for decision makers is the non-availability of alternative transportation modes in the short term, requiring potentially different resilience strategies. Generally, however, these products are widely available and can be sourced from many different modes if the respective capacities are ensured.

Lastly, to significantly reduce environmental emissions, the automotive industry has increasingly relied on waterway transport for the transport of its finished vehicles (e.g., $\mathcal{P}16$). While road and rail transport has generally been used within the industry, where available, waterway transport offers significant environmental benefits that are becoming increasingly important to decision-makers due to regulatory changes and challenges.

Overall, various products are affected by the water-level driven disruptions that result in surcharges or transportation stops. Depending on the specifics of the products to be transported, however, differences in alternative transportation modes, environmental effects, and cost implications need to be considered differently and balanced against the overall objectives and focus of a decision maker.

3.3 Disruption uncertainty

We define a transportation disruption as an unfortunate event causing a capacity reduction to the critical transportation mode between the first and second echelon of inventory holding. In practice, this is related to a main transportation channel that a vast majority of transport relies on, such as main canals or rivers for inland shipping or railroad infrastructure that connects major seaports with the hinterland. To account for the lost transport capacities, transportation carriers enforce contractually defined surcharges on top of their regular transportation costs based on the actual conditions (e.g., water levels) of the actual day of shipment. These surcharges further balance the transportation demand with the reduced supply based on short-term alternatives. Depending on the disruption impact and mode, the cost effects range from modest increases to full transportation stops, i.e., an unlimited increase in transportation costs. In addition, disruptions can increase the lead time as alternative routes of the affected modes might need to be taken into account.

The resulting uncertainty affects the decision-maker's shipment decisions differently. All direct shipments from the suppliers (tactical level) to either the first or the second echelon must be made under complete uncertainty, i.e., not knowing when, how long, and with which impact a disruption occurs. However, shipments between the two echelons and the express delivery from global suppliers can be made with a significantly lower lead time and thus, with full knowledge of the disruption occurrence.

3.4 Resilience strategies

A central decision-maker at the production facility sources from various suppliers and is in full responsibility of the inbound logistic flows for all products within the portfolio. The goal is to minimize the expected costs by determining the optimal mix of resilience strategies on the product level. We consider the following strategic, tactical, and operational resilience strategies in a two-stage stochastic decision problem.

Multi-sourcing (strategic, first-stage). Qualification of multiple suppliers including multi-sourcing, i.e., purchasing from two or more suppliers in parallel, and the investment in a back-up supplier that is only used in case a disruption occurs at the transportation modes of the primary supplier.

Near-shoring (strategic, first-stage). Qualification of a regional supplier that directly transports to the second echelon of inventory holding and thus avoids the transportation uncertainty between the echelons but comes at a cost-premium.

Inventory capacity adjustment (strategic, first-stage). Investment decision in additional inventory capacity for the first and second echelon inventory storage that increases the flexibility of decisions on the tactical and operational level.

Inventory increase (tactical, first-stage). Decision to increase inventory on the tactical level at the first or second echelon of inventory holding.

Express re-orders (operational, second-stage). Decision for express delivery from a qualified supplier at a higher short-term price from a global supplier.

4 Model development

Sets, decision variables and parameters are introduced in Sections 4.1, 4.2 and 4.3 before we introduce the two-stage stochastic programming formulation in Sect. 4.4.

4.1 Sets

Multiple products $\mathcal{P}$ need to be supplied to a production facility over a discrete time horizon $\mathcal{T}$. Products are transported from multiple suppliers *I*. Based on the geographical distance between the suppliers and the production facility, we distinguish between global suppliers $\mathcal{I}^G$ and regional suppliers $\mathcal{I}^R$. The two supplier types deliver to different echelons $\mathcal{N}$ of the supply chain. Regional suppliers directly deliver to the production facility $n = 2$ while global supplier transports are first stored in an external inventory stage at level $n = 1$. In addition, $\mathcal{I}_p$ describes the subset of all suppliers $\mathcal{I}$ that are able to supply product p. These can include both global and regional suppliers.

4.2 Parameters

Scenarios occur with probability π_s, where $0 \leq \pi_s \leq 1$ and $\sum_{s \in S} \pi_s = 1$ with $\mathcal{S}$ describing the full scenario set during the planning horizon. Scenarios affect the transportation costs (c^T_{pts}) between the first and second echelon inventory locations. Based on a base cost of transportation, scenarios reflect the disruption-driven increase of the transportation mode used between the two echelons.

Each product is supplied based on a tactical plan from each supplier at the costs c^T_{ip} which include transportation costs and the product price. Per time period and product units stored, inventory holding costs c^H_{np} occur that differ between the products and between the echelon of inventory holding. The product with the highest unfulfilled unit of demand d_{pt} in each time period determines the shortage costs c^P. The total sum of all demands across the planning horizon is $\hat{d}_p$ for each product p. On the operational level, the short-term express delivery from suppliers to the second echelon comes at a cost of c^E_{ip}. Depending on the disruption scenario s, the transportation costs between the two inventory echelons in time period t are described by x^T_{pts}. To qualify a supplier to deliver product p, qualification costs f^I_p are needed that depend on the product complexity. For example, while a commodity product can be sourced with minimal qualification steps to be fulfilled, a more specialized and complex product requires more detailed product quality testing and specification sharing. The initial inventory capacity to store inventory on hand is Y^0_n. Through an investment decision this capacity can be increased by multiples of Y^+_n at costs f^Y_n per multiple. In the starting period, an initial inventory of j^0_{np} is available. Transportation lead times l_{its} are considered that depend on the administrative and transportation time from supplier i and might be affected by disruptions in scenario s during time period t. For global suppliers, the lead time for express reorders is $\hat{l}_i$. For the transport between the first and second inventory echelon, a lead time of l_0 is considered. Each product has specific inventory capacity requirements a_p that consume the inventory storage capacity.

All parameters are summarized in Table 2.

4.3 Decision variables

The model decides between different resilience strategies, as introduced in Section 3.4, to minimize the total expected costs across all products and inventory storage echelons in a two-stage stochastic program.

The first-stage decisions determine the network structure and capacities for product flows between the suppliers and the echelons of inventory holding. The binary decision z_{ip} determines if supplier i is qualified ($= 1$) or not ($= 0$) to deliver product p. The starting inventory storage capacity Y^0_n can be increased at each echelon n

Table 2 Overview of parameters

Parameter	Description
π_s	Probability of occurrence scenario s
c^T_{ip}	Transportation costs for product p from supplier i on tactical level (first-stage)
c^H_{np}	Inventory holding costs at echelon n for each unit of product p
d_{pt}	demand units of period p in time period t
c^T_{pts}	Transportation costs between inventory echelons depending on scenario s in time period t
c^P	Shortage costs
$\hat{d}_p$	Total demand for each product p across planning horizon $\mathcal{T}$
c^E_{ip}	Transportation costs for product p from supplier i on operational level (second-stage)
f^I_p	Supplier qualification costs for product p
Y^0_n	Initial inventory capacity echelon n
Y^+_n	Inventory capacity increase units echelon n
f^Y_n	Inventory increase investment costs echelon n
j^0_{np}	Starting inventory product p at echelon n
l_{its}	Transportation lead time from supplier i in time period t and scenario s
$\hat{l}_i$	Transportation lead time express re-orders operational level (second-stage)
l_0	Transportation lead time between echelon $n = 1$ and $n = 2$
a_p	Inventory capacity consumption of product p

through integer investments w_n in additional inventory capacity. For each supplier i and each product p, transportation quantities x_{ipt} are defined at the first-stage for each time period t. These represent the tactical flows from global and regional supplier to the respective inventory echelon n. On the second-stage, the operational routing $\bar{x}_{pts}$ between the first and second echelon of inventory holding takes place. Here, the decision maker already knows the disruption in scenario s and can decide on the routing based on the available tactical shipments and respective inventory holding capacities. In addition, it is possible to decide for operational express re-orders $\hat{x}_{ipts}$ from global suppliers shipped through an alternative transportation mode at shorter lead times.

Additional decision variables are needed to formulate the problem. The on-hand inventory at the beginning of each time period t in each scenario s for each product p and in each echelon of inventory holding n is defined by y_{npts}. In case product demand d_{pt} exceeds the available on-hand inventory, shortages v_{pts} occur. For each time period, the overall cost-relevant shortages are determined by the highest shortages v_{ts} that occur across all products.

4.4 Model formulation

$$\begin{aligned} min \quad & \sum_{n\in\mathcal{N}} f_n^Y \cdot w_n + \sum_{i\in\mathcal{I}_p, p\in\mathcal{P}} f_{ip}^I \cdot z_{ip} + \sum_{i\in\mathcal{I}_p, p\in\mathcal{P}, t\in\mathcal{T}} c_{ip}^T \cdot x_{ipt} \\ & + \sum_{s\in\mathcal{S}} \pi_s \cdot \Bigg(\sum_{p\in\mathcal{P}, t\in\mathcal{T}} c_{pts}^T \cdot \bar{x}_{pts} + \sum_{i\in\mathcal{I}_p^G, p\in\mathcal{P}, t\in\mathcal{T}} c_{ip}^E \cdot \hat{x}_{ipts} \\ & + \sum_{n\in\mathcal{N}, p\in\mathcal{P}, t\in\mathcal{T}} c_{np}^H \cdot y_{npts} + \sum_{t\in\mathcal{T}} c^P \cdot v_{ts} \Bigg) \end{aligned} \tag{1}$$

subject to:

$$\sum_{t\in\mathcal{T}} x_{ipt} \le z_{ip} \cdot \hat{d}_p \qquad \forall i \in \mathcal{I}_p, p \in \mathcal{P} \tag{2}$$

$$\sum_{t\in\mathcal{T}} \hat{x}_{ipts} \le z_{ip} \cdot \hat{d}_p \qquad \forall i \in \mathcal{I}_p^G, p \in \mathcal{P}, s \in \mathcal{S} \tag{3}$$

$$\sum_{p\in\mathcal{P}} a_p \cdot y_{npts} \le Y_n^0 + w_n \cdot Y_n^+ \qquad \forall n \in \mathcal{N}, t \in \mathcal{T}, s \in \mathcal{S} \tag{4}$$

$$y_{1pts} = y_{1p(t-1)s} - \bar{x}_{pts} + \sum_{i\in\mathcal{I}_p^G} x_{ip(t-l_{its})} \qquad \forall p \in \mathcal{P}, t \in \mathcal{T} \setminus \{1\} | t > l_i, s \in \mathcal{S} \tag{5}$$

$$\begin{aligned} y_{2pts} = y_{2p(t-1)s} + v_{pts} - d_{pt} + \bar{x}_{p(t-l_0)s} + \sum_{i\in\mathcal{I}_p^R} x_{ip(t-l_{its})} + \sum_{i\in\mathcal{I}_p^G} \hat{x}_{ip(t-\hat{l}_i)s} \\ \forall p \in \mathcal{P}, t \in \mathcal{T} \setminus \{1\} | t > l_i, s \in \mathcal{S} \end{aligned} \tag{6}$$

$$y_{np1s} = j_{np}^0 \qquad \forall n \in \mathcal{N}, p \in \mathcal{P}, s \in \mathcal{S} \tag{7}$$

$$v_{ts} \ge v_{pts} \qquad \forall p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S} \tag{8}$$

$$z_{ip} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, p \in \mathcal{P} \tag{9}$$

$$w_n \in \mathbb{Z} \qquad \forall n \in \mathcal{N} \tag{10}$$

$$x_{ipt}, \bar{x}_{pts}, \hat{x}_{ipts}, y_{npts}, v_{pts} \ge 0 \qquad \forall n \in \mathcal{N}, i \in \mathcal{I}, p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S} \tag{11}$$

The objective function (1) minimizes the total expected costs through first-stage and second-stage decisions across all scenarios. First-stage decisions drive the overall investment costs that occur independent of the respective scenario. They include: Investment decision in additional inventory capacity (w_n) at the two echelons of inventory holding at investment costs of f_n^Y, the decision to qualify a supplier (z_{ip}) to deliver product p at costs f_{ip}^I, and the shipment costs (c_{ip}^T) for the tactical transportation volumes (x_{ipt}) from the qualified suppliers to the inventory storage locations. On the second-stage, the costs per scenario s are determined by the shipments $\bar{x}_{pts}$ from the first to the second echelon, the emergency transports $\hat{x}_{ipts}$ from global suppliers, the inventory holding costs driven by the inventory levels at both echelons (y_{npts}), and the shortage costs in each time period driven by the product with the highest individual shortages v_{ts}.

Constraints (2) and (3) ensure that products are only supplied from qualified suppliers. The inventory storage at each echelon n can not exceed the inventory capacity as ensured in constraints (4). Constraints (5) and (6) ensure the inventory balance at each of the echelons while the starting inventory is defined in constraints (7). Constraints (8) determine the highest shortage across all products as for an inbound SCND problem the highest shortage across all products determines the amount of finished good shortage through production. The remaining constraints (9)-(11) declare the decision variables.

4.5 Model enhancements

Particularly with a larger number of products, the model becomes increasingly difficult to solve for commercial solvers. To improve the convergence behavior and provide strong initial solutions, lower-bound-lifting and valid inequalities (Sect. 4.5.1) and a warm start solution (Sect. 4.5.2) are added to improve the standard model formulation.

4.5.1 Lower-bound lifting and valid inequalities

Following the idea of lower-bound-lifting inequalities as introduced by Adulyasak et al. (2015), we derive problem-specific lower-bound-lifting inequalities by adding the following constraints.

$$\sum_{i \in \mathcal{I}} z_{ip} \geq 1 \qquad \forall p \in \mathcal{P} \tag{12}$$

$$q_p \geq \hat{d}_p - \sum_{i \in \mathcal{I}, t \in \mathcal{T}} x_{ipt} - \sum_{n \in \mathcal{N}} j_{pn}^0 \qquad \forall p \in \mathcal{P} \tag{13}$$

$$q^{max} \geq q_p \qquad \forall p \in \mathcal{P} \tag{14}$$

$$\begin{aligned} &\sum_{p \in \mathcal{P}, t \in \mathcal{T}} c_{pts}^T \cdot \bar{x}_{pts} + \sum_{i \in \mathcal{I}_p^G, p \in \mathcal{P}, t \in \mathcal{T}} c_{ip}^E \cdot \hat{x}_{ipts} + \sum_{n \in \mathcal{N}, p \in \mathcal{P}, t \in \mathcal{T}} c_{np}^H \cdot y_{npts} + \sum_{t \in \mathcal{T}} c^P \cdot v_{ts} \\ &\geq \sum_{i \in I_p^G, p \in P, t \in T} c_{pt_{min}}^T \cdot x_{ip(t+l_i)} + \min(c_{ip}^E \cdot P, c^P) \cdot q^{max} \qquad \forall s \in \mathcal{S} \end{aligned} \tag{15}$$

Constraints (12) ensure that at least one supplier is qualified for each product. Constraints (13) set lower bound on the total shortage quantity as defined by the difference between the total demand, tactical shipments, and the starting inventories. Constraints (14) define the relevant shortage quantity overall through the highest shortage across all products $\mathcal{P}$. Lastly, constraints (15) define the lower bound on all scenario-dependent costs in the objective function (1) as the sum of the shipment costs between the echelons determined by the shipments from global suppliers $i \in \mathcal{I}^G$ assuming they can be executed disruption-free ($c^T_{pt_{min}}$), and the shortage costs as determined through the minimum between the express delivery costs c^E_{ip} multiplied with the number of products that need to be sourced P and the shortage costs c^P.

4.5.2 Warm start

We obtain a starting solution by using the expected cost scenario and solving the deterministic version of the multi-product problem. We then obtain the solution for each product $p \in \mathcal{P}$ and insert this solution into the mixed-integer linear programming formulation.

4.6 A rolling-product-integration heuristic

We propose our RPIH based on the idea of rolling horizon algorithms that are established heuristics in production planning problems (Ovacikt and Uzsoy 1994). Instead of updating solutions through a time horizon, the idea is to update solutions based on the iterative integration of additional products in the multi-product problem setting. The approach of solving the multi-product problem through the RPIH can be described as follows.

Given is a multi-product problem with a set of products $\mathcal{P}$. At the beginning, a single product p_1 is elected randomly from the set of products $\mathcal{P}$ and the single-product problem is solved to optimality. All tactical flow decisions x_{i1t} are stored. Next, a second product p_2 is chosen randomly. Then, the dual-product setting is formulated while the initial stored tactical flow decisions are added as constraints and fix the tactical flow decision for product p_1 in the dual problem setting. After that, the dual-problem is solved to optimality and the tactical flow decisions x_{i2t} are stored. All non-product specific first-stage decisions (w_n, z_{ipt}) as well as the operational routing decisions ($\bar{x}_{pts}$, $\hat{x}_{ipts}$) are taken independently of the previous step results. These process steps are repeated and a new product p added at each step randomly until the last product of the multi-product problem is added. Thus, the overall complexity is significantly reduced while integrative effects are taken into account for the product added at each of the iteration steps.

5 Numerical results

We test our approach using a case study motivated by a real-life example with real disruption data. Sect. 5.1 introduces the case in detail and describes the numerical setup. We compare the algorithmic performance of the standard and enhanced model formulation in Sect. 5.2. Section 5.3 presents the numerical results. Finally, in Sect. 5.4, managerial insights are drawn. The algorithm is implemented in Python 3.8 using Gurobi 10.0.3. A desktop PC with an AMD Ryzen 9 5950X 16-Core processor with 3.4 GHz and 128 GB of RAM is used for model execution.

5.1 Case introduction

Our case study is based on a real-life example from a chemical company with a production facility on the border of the Rhine River, Germany. For the case company, a large share ($\geq 40\%$) of all products required for the production of a typical finished good are sourced from global suppliers and shipped through the Rhine River. Each of these products can be sourced regionally as well at a cost-premium. Within our analysis, we focus on one exemplary finished good in a continuous production with different products needed that form the bill of materials (see Sect. 3.2). Any product missing leads to shortage costs as this forces production to a standstill. In the chemical industry, material shortage costs typically exceed the sum of finished good lost margins and customer penalty costs as complex production systems need to be shut down and re-started. After a restart, it can take hours to days to produce again a quality of the finished good sufficient for customer requirements.

For each product, one global and one regional supplier is available. Inventory holding costs c_p^H are 20% of the product value which is three times higher in the case of a high-value product. Thus, annual inventory holding costs are as well three times higher. Inventory holding costs consist of the warehouse costs itself (space, rent, electricity), the possibility of destroyed and damaged inventory, theft, obsolete and outdated inventory, and handling costs. Given a low volumetric weight, the express shipment is four times more costly than the steady state transportation from the global supplier. For high volumetric weights, air freight costs rise even more significantly to a multiple of 12 times compared to the disruption-free costs of regular global transport. Generally, we assume that all products can be shipped through air freight. In practice, however, some products are prohibited such as lithium batteries that can not be transferred through air, posing significant challenges to the respective supply chains. Compared to a low space requirement, products with a high space requirement require three times more inventory space units. Lastly, a complex product has three times higher supplier qualification costs as more samples are needed and suppliers need to conduct specific investments on their own.

Without disruptions, most global sourced products are transported cost-optimal through ocean freight to one of the major European ports combined with the hinterland transport through inland shipping via the Rhine River. At all major ports worldwide, inventory storage areas can be rented to hold inventory prior to the hinterland transport (first echelon of inventory holding). The inland shipping mode, however, is prone to recurring disruptions due to water level changes that lead to surcharges depending on daily water levels as part of long-term contractual agreements between the transportation carriers and the case company. Due to the high volumes typically transported through inland shipping, there is no alternative transportation mode available in the short-term to ship from the port to the inventory holding at the production facility (second echelon). Instead, products can be sourced from regional suppliers through alternative transportation modes on the tactical level or through short-term express deliveries from global suppliers at significantly higher costs. Without disruptions, the transportation costs and product price difference are 50% higher than the global sourcing whereas the express deliveries are 400% higher. Lead times differ as well with shipments between the two echelons as the fastest with three days, regional sourcing and express delivery arrive after seven days, and the transport to the first inventory echelon with 14 days of lead time from global suppliers.

Concerning the disruption uncertainty that affects the inland shipping transportation between the first and second echelon of inventory holding, Fig. 2 visualizes the water level fluctuations on the river Rhine from 2015–2022. As can be seen, transportation stops due to low water levels occurred in 2015, 2017, 2018, 2020, and 2022, while high tides caused transportation stops in 2018 and 2021. In addition, occurrences where low water levels force vessels to carry reduced capacities and thus result in surcharges occur regularly. In addition, Fig. 2 shows seasonal patterns as well. For example, high tides happen exclusively in winter while low water levels are typically seen in late summer or autumn.

Transportation surcharges for low and high water levels are significant, as highlighted in Table 3. Overall, the contractual surcharges range from a 78% to a 261%

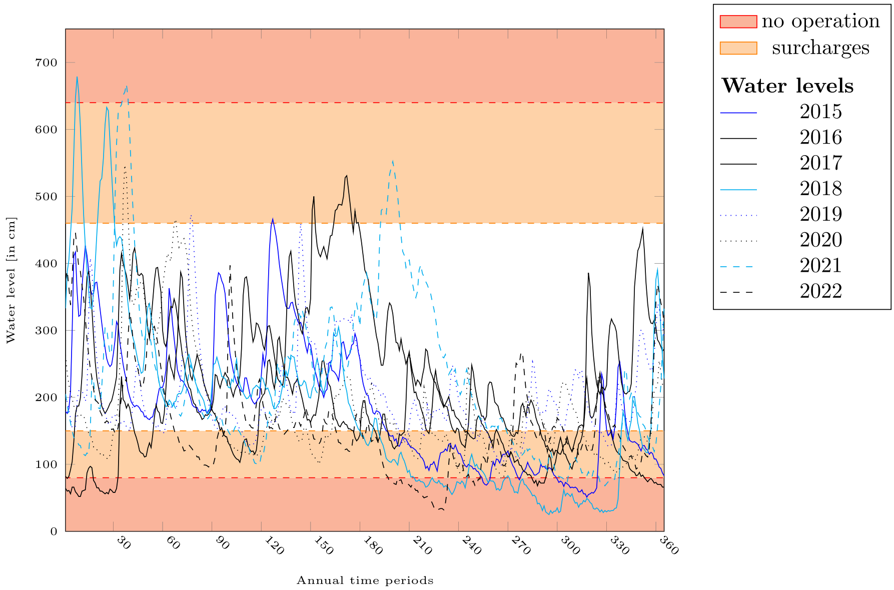

Fig. 2 Historical water levels at shipment critical point for river Rhine as main transportation mode ($m = 1$)

Table 3 Transportation costs per container transported depending on water level

Water level [cm]	< 80	< 90	< 100	< 110	< 130	< 150	< 460	< 640	>= 640
Costs [EUR]	–	415	340	295	250	205	115	205	–

cost increase compared to water levels between 150 and 460 cm, while on water levels less than 80 cm and higher than 640 cm, no transportation is possible. The orange line in Fig. 2 highlights water level thresholds for cost increases and the red line indicates transportation stops. We consider the last 42 years of water level history as scenarios that cover the uncertainty space with an equal possibility of occurrence of $\pi_s = \frac{1}{42}$. In the case example, lead time uncertainty can be neglected as through the contractually defined surcharges, transportation carriers can typically maintain pre-defined lead times as the overall transportation demand reduces. While lead time uncertainty is therefore not of relevance for the case company, we are further interested in extending the problem setting to account for lead time uncertainty that will be discussed in Sects. 5.2 and 5.3.6.

5.2 Algorithm performance

We benchmark our enhanced model formulation as well as our RPIH against the standard model formulation, solving all algorithms with the commercial solver Gurobi using a branch-and-bound algorithm, and the solutions obtained solving the single-product problems independently. In addition to the case specifics, we further assume lead time uncertainty on the tactical flows x_{ipt} during a disruption and increase the number of scenarios $\mathcal{S}$ to 100 to account for both lead time and transportation cost uncertainty. The planning horizon $\mathcal{T}$ consists of one year, thus 365 time periods. The algorithms are terminated after four hours (14,400 s) or after ensuring an optimality gap of at least 2%. We increase the number of products from 1 to 6. To ensure comparability of all algorithms, we ensure that the same (random) products are considered for the different problem sizes. Figure 4 summarizes the results. The enhanced model formulation outperforms the standard formulation for all problem sizes considered. Compared to the standard implementation in Gurobi that is not able to indicate lower bounds for three products within the four hours of computation time, up to four products in the multi-product problem setting can be solved to optimality within the time limits. Starting with five products, however, also the enhanced model formulation is challenged with the problem complexity. Compared to the RPIH and solving the single-product problem, the enhanced model formulation improves the overall objective significantly while still solved to optimality. Starting with three products, the RPIH as heuristic is terminated faster than the enhanced model formulation converges while terminating at solutions slightly worse than the enhanced model formulation. Overall, the RPIH outperforms the single-product optimal solutions, highlighting the need for a multi-product integration.

Table 4 Computational complexity with increasing number of products

	Objective				Gap				Runtime			
$\|\mathcal{P}\|$	GB	GB_LBL	RPIH	Indiv	GB	GB_LBL	RPIH	Indiv	GB	GB_LBL	RPIH	Indiv
1	169.4	168.9	169.4	169.4	2%	2%	2%	2%	1562	777	1210	1150
2	340.9	339.4	341.2	342.8	2%	2%	–	–	14400	1945	2702	2115
3	782.9	507.1	509.1	512.8	inf	2%	–	–	14400	6380	5942	4400
4	1041.1	677.7	680.7	686.7	inf	2%	–	–	14400	10720	8601	5336
5	1295.7	1701.2	860.5	864.5	inf	99%	–	–	14400	14400	14424	6373
6	1555.7	1879.9	1039.9	1046.5	inf	99%	–	–	14400	14400	19011	7690

5.3 Sensitivity analysis

5.3.1 Product characteristic influence for the single-product problem

We solve the single-product resilient SCND problem for each product independently to compare and evaluate the influences of the different product characteristics in the single product setting. Table 5 summarizes the results for products $\mathcal{P}1$-$\mathcal{P}16$ and the average $\overline{\mathcal{P}}$.

Overall, we see that the optimal resilience mix differs significantly across the products including the optimal mix of global and regional transportation on the tactical level. Whereas for all low-complexity products (i.e., low supplier qualification costs) a multi-sourcing strategy is cost-optimal, specific products with a high complexity are supplied through single sourcing ($|z| = 1$) in the cost-optimal way. This, however, comes at significant investments in additional inventory capacity for $\mathcal{P}9$ and $\mathcal{P}11$. Thus, for highly complex products with low value and space requirements, carrying additional inventory outperforms a multi-sourcing strategy. Specifically the inventory capacity investments vary across the products. Still, we see that capacities are increased equally across both echelons of inventory holding instead of purely on a single echelon. This allows that not only sufficient inventory can be buffered at the first echelon of inventory holding but then as well shipped in large batches once a disruption-free time period occurs. Lastly, the model split between global, regional, and express transports varies significantly from pure global transport (e.g., $\mathcal{P}9$) to products with at least an equal split across regional and global suppliers (e.g., $\mathcal{P}6$). The key drivers are high inventory holding costs and a high consumption in inventory capacity for these products. Interestingly, this effect is independent from the product complexity ($\mathcal{P}6, \mathcal{P}8$).

As highlighted, a geographical diversification of its supplier base might be challenging or simply not possible for highly complex products or those that require specific raw materials (Cohen et al. 2022). Especially within the European Union certain products can be unavailable and need to be sourced globally due to a lack of key raw materials (Hool et al. 2023). Thus, we compare the previous optimal resilience mix with the mix when only considering global suppliers. The results can be found in Table 6.

The following insights can be drawn. First, a missing opportunity to source regionally can influence the total expected costs. The second column (Δ costs) quantifies the cost increase on product level up to 37%. However, depending on the product characteristics only considering a single, global supplier strategy leads to no or very significant cost increases. Generally, cost increases are higher for products that are more costly in terms of inventory holding due to their product value or higher inventory storage capacity consumption and specifically for products with a high volumetric weight where express orders are higher in comparison. Second, we observe a significant rise in express shipments through alternative transportation modes from global suppliers. Thus, the non-availability of alternative short-term mitigation measures forces an increase in costly air shipments while it is not cost-efficient to fully capture the disruption uncertainty through inventory alone. Lastly, we see a significant increase in inventory capacity investments on strategic level as well as an

Table 5 Single product optimal resilience mix

	Costs	CPU	$\|z\|$	Capacity investments		Average inventory		Share transport volumes		
				Echelon 1	Echelon 2	Echelon 1	Echelon 2	Global (%)	Regional (%)	Express (%)
$\mathcal{P}1$	187.46	69	2	3	3	8.27	21.43	78	21	1
$\mathcal{P}2$	193.85	105	2	1	1	5.22	3.77	63	35	1
$\mathcal{P}3$	188.99	65	2	3	3	9.30	21.36	78	21	1
$\mathcal{P}4$	195.17	89	2	1	1	5.50	4.23	63	37	0
$\mathcal{P}5$	198.04	171	2	2	2	2.71	5.99	53	46	1
$\mathcal{P}6$	199.68	198	2	0	0	1.29	0.62	45	54	1
$\mathcal{P}7$	198.68	134	2	1	1	2.60	4.81	50	50	0
$\mathcal{P}8$	200.28	137	2	0	0	1.35	0.92	44	56	0
$\mathcal{P}9$	204.84	70	1	9	9	15.15	46.33	96	0	4
$\mathcal{P}10$	211.85	135	2	1	1	5.22	3.77	63	35	1
$\mathcal{P}11$	206.98	68	1	9	10	16.86	56.73	99	0	1
$\mathcal{P}12$	213.17	98	2	1	1	5.50	4.23	63	37	0
$\mathcal{P}13$	216.04	195	2	2	2	2.71	5.99	53	46	1
$\mathcal{P}14$	217.68	190	2	0	0	1.29	0.62	45	54	1
$\mathcal{P}15$	216.68	142	2	1	1	2.60	4.81	50	50	0
$\mathcal{P}16$	218.28	149	2	0	0	1.35	0.92	44	56	0
$\overline{\mathcal{P}}$	204.23	126	1.9	2.13	2.19	5.43	11.66	62	37	1

Table 6 Single product optimal resilience mix without regional supplier availability

	Costs	Δ costs (%)	$\|z\|$	Capacity investments		Average inventory		Share transport volumes		
				Echelon 1	Echelon 2	Echelon 1	Echelon 2	Global (%)	Regional (%)	Express (%)
$\mathcal{P}1$	195.84	4	1	9	9	15.15	46.33	96	0	4
$\mathcal{P}2$	209.92	8	1	9	5	9.38	11.70	83	0	17
$\mathcal{P}3$	197.98	5	1	9	10	16.86	56.73	99	0	1
$\mathcal{P}4$	219.87	13	1	13	8	14.07	28.69	98	0	2
$\mathcal{P}5$	228.33	15	1	15	10	10.97	23.12	73	0	27
$\mathcal{P}6$	236.09	18	1	13	8	6.66	6.80	67	0	33
$\mathcal{P}7$	246.54	24	1	20	30	21.23	79.26	98	0	2
$\mathcal{P}8$	274.92	37	1	26	31	14.66	32.26	96	0	4
$\mathcal{P}9$	204.84	0	1	9	9	15.15	46.33	96	0	4
$\mathcal{P}10$	218.92	3	1	9	5	9.38	11.70	83	0	17
$\mathcal{P}11$	206.98	0	1	9	10	16.86	56.73	99	0	1
$\mathcal{P}12$	228.87	7	1	13	8	14.07	28.69	98	0	2
$\mathcal{P}13$	237.33	10	1	15	10	10.97	23.12	73	0	27
$\mathcal{P}14$	245.09	13	1	13	8	6.66	6.80	67	0	33
$\mathcal{P}15$	255.54	18	1	20	30	21.23	79.26	98	0	2
$\mathcal{P}16$	283.92	30	1	26	31	14.66	32.26	96	0	4
$\overline{\mathcal{P}}$	230.69	13	1	14.25	13.88	13.62	35.61	89	0	11

increase in average inventory average. However, whereas inventory capacity investments increase by a factor of seven on average, average inventory increases only by a factor of three, which indicates a shift in the optimal policies of inventory holding instead of a sole linear increase in average inventory.

5.3.2 Benefit of multi-product integration

We now compare the optimal solution on single-product level against the integrated multi-product problem. We focus our analysis on incorporating incrementally products from $\mathcal{P}1 - \mathcal{P}8$ that are required for the production of a single finished good and showing the improvements in resilience costs compared against the optimal solutions of the single-product separated problems. While we accept an optimality gap of 1% as termination criteria for the integrated model, we force true optimality for the separated problems. The results are summarized Table 7.

We define the resilience costs as delta between the theoretical minimum costs that occur without disruptions and the total expected costs with disruption uncertainty. Overall, for eight products, the resilience costs decrease by 4.2% in the integrated model compared to the sum of all single-product expected resilience costs. The most important driver for this change are constraints (8), which sets the shortage costs in each time period to the highest shortage across all products. As a result, in single-product models, the shortage costs might be overestimated and result to inefficient resilience strategies as in cases where multiple products (raw materials) are affected, the shortage costs might be lower than over-investments in resilience strategies. While no major differences in inventory investments are observed, we see significant differences in the share of transport volumes from global suppliers compared to regional ones as in the integrated models these are significantly higher. In addition, the resilience cost improvements increase with the number of products considered in the integrated model. Overall, the single-product resilient SCND models might overestimate the resilience costs needed as effects between products are not included. However, the integrated model comes at a significant increase in computational complexity (see Sect. 5.2). Thus, it might be worthwhile to evaluate the case-specific interdependence between the products in order to evaluate whether a single-product model might be justified or an integrated model is needed.

Table 7 Comparison of integrated and single-product results for the resilient SCND

Products	Model	Total costs	Resilience costs	Δ Costs (%)	Global (%)	Capacity investments	
						Echelon 1	Echelon 2
2	Integrated	380.41	83.20	1.08	74.38	5	4
	Separated	381.31	84.10		27.93	4	4
4	Integrated	762.42	168.01	1.82	70.90	8	7
	Separated	765.47	171.06		28.48	8	8
6	Integrated	1152.51	260.89	4.10	65.99	9	8
	Separated	1163.19	271.58		35.77	10	10
8	Integrated	1547.10	358.28	4.20	62.55	10	10
	Separated	1562.16	373.33		40.03	11	11

5.3.3 Shortage costs driving the need for integration

As highlighted in Sect. 5.3.2, the need for an integration evaluation of multi-product settings can depend on the specific application context and mainly depends on the existence of constraints (8). To understand the relevance of the shortage costs on the need for multi-product integration, we conduct a sensitivity analysis on the case-specific shortage costs to understand further implications for the need for multi-product integration. Thus, we reduce the ratio of shortage costs against the disruption-free transportation costs from 25 to 10. The results are outlined in Table 8.

With decreasing shortage costs (*cSh*), the resilience cost improvements start to increase with only four products considered. In comparison, for eight products the disruption-free transportation costs for all products are 0.64 per unit. Thus, $cSh = 0.8$ represents only a minor increase of 25%, resulting in significantly less required capacity investments and resilience costs. Given the disruption-driven cost surcharges as outlined in Sect. 5.1, the importance solving the integrated multi-product problem increases with the number of products and a decrease in shortage costs considered.

5.3.4 Resilience shifts in multi-product sourcing

In Table 8, we have analyzed the benefits and reductions in resilience costs for solving the integrated model with multiple products assuming a single combination of product characteristics. We have shown that solving the integrated model with two products (i.e., $p_1 = \mathcal{P}1, p_2 = \mathcal{P}2$) leads to improvements in resilience costs of 1.08% in comparison to the single-product optimal solutions. As highlighted in Sect. 5.3.1, the resilience mix for the single product cases depends on the specific product characteristics. After discussing the general improvement potential of considering the joint integrated problem in Sects. 5.3.2 and 5.3.3, we now analyze the behavior of the optimal solutions for different product portfolio combinations in the multi-product setting. Table 9 compares the resilience costs for the integrated two-product problem with different product combinations.

Major differences in the resilience cost deltas can be observed based on the product characteristics. Interestingly, in the two product-problem, solving the integrated problem increases in benefits once the product characteristics vary significantly among the two products. For example, solving the integrated problem where $p_1 = \mathcal{P}1$ and $p_2 = \mathcal{P}1$ are both of the same product archetype leads to no improvements in resilience costs. Overall, the highest observed benefits for solving the integrated problem with equal product types is 3.80% whereas for very different product archetypes considered the lowest improvement observed is 5.80%. Overall, the average improvement increases from 1.36% for equal product archetypes to 7.87% for highly different product archetypes considered in the two-problem case. Thus, the

Table 8 Resilience cost improvements based on number of products and shortage costs

cSh	$\lvert\mathcal{P}\rvert$			
	2 (%)	4 (%)	6 (%)	8 (%)
2	1.08	1.82	4.10	4.20
1.2	1.08	1.82	4.20	12.72
0.8	1.08	2.46	6.63	78.82

Table 9 Influence of product mix on multi-product necessity

	Single-product			Integrated multi-product		
	Capacity investments		Costs	Capacity investments		Resilience costs
	p_1 p_2 Echelon 1	Echelon 2	Total	Echelon 1	Echelon 2	Δ Single (%)
Equal characteristics	$\mathcal{P}1\mathcal{P}1$ 6	6	374.91	6	6	0.00
	$\mathcal{P}2\mathcal{P}2$ 2	2	387.71	3	1	0.09
	$\mathcal{P}3\mathcal{P}3$ 6	6	377.98	6	6	3.80
	$\mathcal{P}4\mathcal{P}4$ 2	2	390.35	3	1	2.92
	$\mathcal{P}5\mathcal{P}5$ 4	4	396.08	4	4	0.00
Different characteristics	$\mathcal{P}1\mathcal{P}11$ 2	13	394.43	9	8	7.44
	$\mathcal{P}2\mathcal{P}9$ 10	11	400.83	9	9	5.80
	$\mathcal{P}3\mathcal{P}11$ 2	13	395.97	9	8	8.87
	$\mathcal{P}4\mathcal{P}9$ 10	10	400.01	9	9	7.00
	$\mathcal{P}5\mathcal{P}11$ 2	13	395.97	11	8	10.27

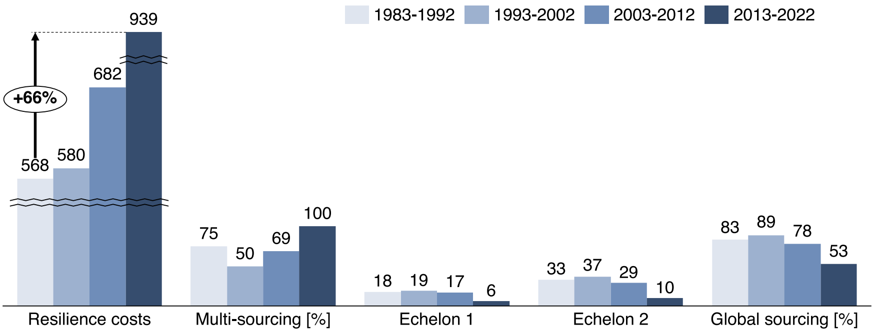

Fig. 3 The effects of changes in historical disruption probability and impacts

more differences in the product portfolio to be sourced, the higher the benefits of solving the integrated problem. In general, the improvements not only depend on the number of products and shortage costs (see Sect. 5.3.3) but as well on the specific mix of product archetypes considered.

5.3.5 Historical trends in disruption probability and impact shifts

So far, we have assumed all available 42 years of water levels to account for 42 scenarios that represented the uncertainty space of future disruption probability and impact. However, through global warming, droughts and high-water level events might have increased in likelihood (Middelkoop et al. 2001). To understand potential historical shifts, we split the available historical data along the timeline in four decades, assuming that each decade represents the full uncertainty space. Figure 3 visualizes the results for the resilience costs, the share of multi-sourcing, the corresponding investments in additional inventory capacity at both echelons, and the share sourced from the global supplier. We obtain all results solving the integrated model for products $\mathcal{P}1 - \mathcal{P}16$.

Overall, the results differ significantly across the different decades. In recent decades, an increase in water-level driven disruption impacts and probability are observed leading to an increase in resilience costs. As shown, the optimal resilience costs for the years 2013–2022 are 66% higher than the resilience costs between 1983 and 1992. In addition, across all products a multi-sourcing strategy is cost-optimal for the most recent time periods while only for 50% of the products multi-sourcing was cost-efficient from 1993–2002. In comparison, average inventory investments across the first and second echelon of inventory holding are rather stable. For a decision maker, these results highlight one of the distinct challenges in increasing SCR when trends in historical data can be observed. Thus, to increase SCR in the future, assessments of the future probability and impact developments are needed. For inland waterway transport, our results indicate an increased competitiveness of resilience strategies in the future.

5.3.6 The effect of lead time uncertainty on single-product decisions

While lead time uncertainty can be neglected in case-specific analyses, we are interested in examining its impact in the general problem setting. To this end, we allow lead times to be uncertain during disruption events. A recent example is the Red Sea crisis, where rerouting via the Cape of Good Hope not only increased transportation costs but also extended transportation lead times (ITF 2024). To understand the behavior of the first-stage decisions and the additional cost implications of lead time uncertainty, we generate additional scenarios and assume random lead time increases during the time of disruption.

Four different products are considered. For these products, the lead time uncertainty is incrementally increased from a uniform distribution between [0;7] and [28;35] time periods affecting the first-stage flow decisions. The resulting optimal decisions and their resilience costs including the delta to the lowest lead time uncertainty situation of [0;7] are visualized in Table 10. The following observations are made. First, an increase in lead time uncertainty generally increases the resilience costs significantly up to 14%. While the specific increases vary from product to product, strategic investment decisions are not influenced by the lead time uncertainty. For all products, two suppliers are qualified and one additional capacity unit for echelon 1 (E1) and echelon 2 (E2) is chosen. Thus, the increase or existence of lead time uncertainty has no influence on the strategic investment decisions. In contrast, the tactical flow and inventory decisions are adjusted. In general, we see an increase in average inventory, particularly for E2. In addition, we see a general increase in the average express orders that are needed, suggesting a higher likelihood of shortages under greater uncertainty. However, no clear trend emerges in the share of global versus regional flows, which appears to depend more on product characteristics than on lead time uncertainty. Overall, for the single-product problem, lead time uncertainty has a clear influence on the resilience and thus total costs expected but only seems to have minor effects on the strategic and tactical decisions taken.

Table 10 Influence of lead time uncertainty on single product setting

	Disruption	Resilience Costs		Strategic investments			Flows			Avg. Inventory	
p	LT range	Total	Delta (%)	$\mid \mathcal{I} \mid$	E1	E2	Global	Regional	Express	E1	E2
$\mathcal{P}1$	[0;7]	22.55		2	1	1	1073	697	1	7.54	3.98
$\mathcal{P}1$	[7;14]	23.27	3	2	1	1	1091	681	1	9.20	5.14
$\mathcal{P}1$	[14;21]	23.82	6	2	1	1	1068	704	1	8.74	6.07
$\mathcal{P}1$	[21;28]	24.32	8	2	1	1	1086	689	3	6.85	8.55
$\mathcal{P}1$	[28;35]	25.26	12	2	1	1	1088	692	2	7.47	8.77
$\mathcal{P}2$	[0;7]	26.10		2	1	1	990	786	2	2.33	3.07
$\mathcal{P}2$	[7;14]	26.79	3	2	1	1	973	802	2	2.80	3.72
$\mathcal{P}2$	[14;21]	27.48	5	2	1	1	984	795	1	3.96	2.51
$\mathcal{P}2$	[21;28]	28.53	9	2	1	1	1005	779	2	3.50	4.97
$\mathcal{P}2$	[28;35]	29.56	13	2	1	1	936	844	4	4.82	3.05
$\mathcal{P}3$	[0;7]	22.80		2	1	1	1032	739	0	8.65	3.45
$\mathcal{P}3$	[7;14]	23.44	3	2	1	1	1035	736	0	6.55	7.98
$\mathcal{P}3$	[14;21]	23.98	5	2	1	1	1023	747	1	6.41	7.48
$\mathcal{P}3$	[21;28]	24.57	8	2	1	1	1035	743	0	10.38	5.81
$\mathcal{P}3$	[28;35]	25.84	13	2	1	1	1056	724	2	9.46	6.97
$\mathcal{P}4$	[0;7]	26.46		2	1	1	932	844	0	2.08	3.22
$\mathcal{P}4$	[7;14]	28.12	6	2	1	1	950	825	1	3.01	4.81
$\mathcal{P}4$	[14;21]	28.29	7	2	1	1	943	832	1	5.23	2.68
$\mathcal{P}4$	[21;28]	28.16	6	2	1	1	961	823	0	2.34	5.46
$\mathcal{P}4$	[28;35]	30.22	14	2	1	1	920	869	1	5.28	2.99

5.4 Managerial insights

To summarize, the following managerial insights are drawn:

- Product characteristics play an important role in the optimal set of resilience strategies. Thus, practitioners need to understand their existing product portfolio as basis for a selection. For highly specific products, even if available, multi-sourcing might not be cost-competitive but rather investments in additional inventory capacity while for other product characteristics holding inventory is not cost-competitive.
- In order to protect against inbound product shortages, obtaining a multi-product view is beneficial and leads to a change in the optimal resilience mix. The need increases with the number of products, a decrease in shortage costs, and high differences in product archetypes within the product mix to be sourced. For homogeneous product portfolios or in specific industries with comparably high shortage costs, a single-product view might not lead to substantially different results and be sufficient.
- In case disruptions lead to lead time and cost uncertainty, the relevant resilience costs increases while changes to the optimal decisions remain on tactical flow level. The effects on strategic decisions, particularly to the impact of product characteristics, remains negligible.
- Our results support that the proclaimed climate change-driven trend in an increase

in higher winter-discharge and lower summer-discharge for the Rhine River does not only result in higher resilience costs but as well a shift in strategic resilience strategies. For example, it would have been cost-optimal to multi-source all products independent of their characteristics for the last 10 years while 30 years ago only very specific products would have been multi-sourced. This highlights the need for practitioners to not only think about historical disruption occurrence but as well on drivers that might influence their future occurrence when designing resilient SCND today.

6 Conclusion and outlook

We have addressed disruption uncertainty in the multi-product two-echelon transportation problem within a two-stage decision process. Through a case study from the chemical industry, we have shown how various product characteristics affect the cost-optimal mix of resilience strategies on strategic and tactical level. Considering multiple products in network design can influence both the total expected cost and the cost-optimal mix of resilience strategies. Particularly, considering multiple products with high differences in product characteristics increases the observed benefits of multi-product resilient network design compared to single-product solutions. Despite lead time uncertainty in combination with transportation cost uncertainty increasing the overall expected total costs, the effects on strategic and tactical resilience decisions remain negligible. In addition, we have shown that likely through climate change, more resilience investments are needed in the future to protect networks that rely on inland waterway transportation.

Although we have highlighted the benefits of our model, our study is not without limitations. While we have shown that the solution time of a commercial solver can be significantly reduced through enhancements to the model formulation and that heuristic approaches can yield promising results to particularly large problem instances, multi-product resilient network design problems remain computationally challenging to solve. Thus, alternative exact solution procedures and heuristic should be further elaborated. We studied a supply chain with a single demand destination. While we considered multiple products that are needed for the production of a single finished good, there might be further interrelationships between the different finished goods that might be relevant. Besides, transshipment between a larger number of inventory storage areas could be evaluated as an alternative strategy as well. Thus, the proposed model can set the stage for future multi-product models that more accurately reflect the practical, relevant settings in resilient SCND to increase the adaptability in practice.

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