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Resilient transportation network design with disruption uncertainty and lead times

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ABSTRACT

Cost-efficient and reliable transports are needed to supply products competitively. Thus, particularly in increasingly complex and global supply chains, identifying the optimal transportation mode is a critical decision. Transportation modes, however, are prone to disruptions, such as hurricanes, low water levels, or port shutdowns, resulting in transportation stops and cost increases. To counteract these disruptions, different resilience strategies are studied to increase the capability of a network to withstand, adapt, and recover from disruptions. For a cost-optimal use, it is necessary to determine the optimal mix of strategic, tactical, and operational strategies.

We provide a decision-support model that decides on the optimal mix of resilience strategies, such as multi-sourcing, inventory, or operational re-routing, for a supply chain with transportation disruption uncertainty to minimize total expected costs. The problem is formulated as a two-stage stochastic mixed-integer linear program that explicitly considers lead times. To handle large instances, we propose a Benders decomposition approach enhanced through lower-bound lifting and valid inequalities, branch-and-benders-cut, and a warm-start heuristic. Computational experiments show that large instances can be solved to near-optimality, whereas a commercial solver does not find feasible solutions.

We present a case study for a company's inbound supply chain design with recurring transportation cost uncertainty. Considering disruption and lead time effects, a mix of resilience strategies from strategic to operational level leads to cost improvements of up to 50%. Furthermore, we show that the ability to predict disruptions can further reduce resilience-related costs by 10% if sufficient operational re-routing capacities are available.

1. Introduction

In October 2018, low water levels on the Rhine River, one of Europe's most important waterways, forced transportation for more than a month to a standstill. No barge, even if loaded only to a fraction of its original capacity, could travel without the risk of being grounded. As a result, missing raw materials forced several companies, including the chemical company BASF, to cut back production. This shortage and a rise in logistics costs led BASF to lower its yearly profit forecast. Experts estimate that the low water levels caused a 0.4% drop in GDP in Germany (Ademmer et al., 2020). More importantly, this was not the first time water levels limited the transportation capacities along the river. Unlike single-event disruptions, such as the Suez-Canal blockage, they occur regularly, even following seasonal patterns (Jonkeren et al., 2007). In 2015, 2017, and 2021, low water levels led to similar, yet not that extreme, reductions in shipping capacity and increases in transportation costs. Note that such recurring disruptive effects are not only seen in waterway transportation. The hurricane season in North America is another example of recurring yet impact-varying disruptions that regularly result in port shutdowns and damage to transportation infrastructure. While these disruptive events can be predicted somewhat, the exact timing and impact remain uncertain. This uncertainty challenges decision-makers to plan and prepare.

In parallel, margin pressure has pushed companies to design their supply chains increasingly complex, interdependent, and global. Thus, supply chains need reliable transportation to connect the various stages and ensure efficient operations. This need for reliability has motivated practitioners to rethink how to increase their supply chain resilience (SCR). One of the critical elements in improving SCR is the supply chain network design (SCND) (Tang, 2006). The SCND involves strategic decisions on the number, location, and capacity of own assets as well as the selection of suppliers to serve demand in a timely and efficient manner (Klibi et al., 2010). These strategic decisions are made under

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uncertainty about the future and require anticipating the consequences on the tactical and operational level (Farahani et al., 2014). Thus, SCND models need to account for the disruption uncertainty on the strategic level, while decisions made play a role in operational transport decisions once a disruption is known.

We study a SCND problem where a central decision-maker at the production facility sources from various suppliers and is in full responsibility of the inbound flows. Transportation modes are prone to uncertain disruptions concerning their duration, impact, and occurrence along the planning horizon. As a result of these disruptions, transportation carriers enforce surcharges on their regular transportation prices that increase the mode-specific transportation costs. In practice, these surcharges occur regularly due to, e.g., low water levels (St. Lawrence River Canada, Rhine River Germany, Panama Canal) accounting for lost shipment capacities within the general contractual obligations. Depending on the disruption impact, surcharges and thus cost increases range from modest surcharges to full transportation stops, i.e., infinitely high costs. In addition, we explicitly consider lead time differences between transportation alternatives. These lead time differences can occur from varying transportation modes or geographical distances between suppliers and the production facility. We aim to evaluate and compare the cost-effectiveness of strategic, tactical, and operational resilience measures.

The following contributions are made. First, we introduce a two-stage stochastic programming formulation to solve the multi-period SCND problem with recurring disruptions that are uncertain concerning their time of occurrence and impact on the mode-specific costs. Furthermore, we integrate strategic, tactical, and operational resilience strategies. Second, we are the first to explicitly consider individual lead times for all transportation modes in a resilient SCND problem to model the lead time-delayed disruption response through the network flow on operational level. Considering individual lead times allows us to quantify the trade-off in choosing a closer supplier at higher disruption-free costs (near-shoring) and their impact on the optimal resilience strategy mix. Third, we show the value of disruption prediction and assess the interdependence with daily operational re-routing capacities. Fourth, we methodologically propose an enhanced Benders decomposition (BD) algorithm with a non-standard split of decision variables to solve the resulting two-stage stochastic problem and compare its performance against a commercial solver and a standard BD implementation (L-shaped). Lastly, we present a case with time-dependent disruption probability shifts that follow seasonal patterns to study differences in the cost-optimal resilience mix to a numerical study with equal probabilities of disruption occurrence throughout the planning horizon.

This paper is structured as follows. Section 2 presents an overview of related literature. Section 3 details the research problem. Section 4 introduces the two-stage stochastic program. Next, we propose a solution procedure based on BD, including its enhancements in Section 5. Section 6 outlines numerical results, and a case study is discussed in Section 7. Finally, Section 8 concludes by summarizing findings and proposing future research areas.

2. Literature review

Section 2.1 discusses literature on general levers that aim at increasing the SCR. Then, in Section 2.2, work on resilient supply chain network design for the SCND problem under uncertainty is reviewed. Section 2.3 summarizes literature on resilient transportation systems while Section 2.4 reviews work on BD with a focus on two-stage stochastic programs. Finally, Section 2.5. summarizes research gaps.

2.1. Increasing supply chain resilience with consideration of lead times

Various authors defined SCR, including crucial design characteristics and capabilities in the past. We refer to Hosseini, Ivanov et al. (2019) for a detailed overview. Designing resilient supply chains involves uncertainty regarding both the impact and the occurrence of disruptions. 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). Various SCR drivers have been identified and discussed in analytical models, such as supplier segregation, multiple sourcing strategy, inventory positioning, multiple transportation channels, backup suppliers, re-routing, and product substitution (Hosseini, Ivanov 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 as immediate effects of disruptions and SCR strategies are common assumptions (Aldrighetti et al., 2023).

To date, the effects of lead time under uncertainty have mostly been discussed in related inventory control literature. de Treville et al. (2014) presented a case study with managers of three companies that underestimated the benefits of short lead times under uncertainty. Boute and Van Mieghem (2015) study single and dual inventory control policies and compare local and global sourcing alternatives based on the inclusion of capacity cost and flexibility in addition to sourcing costs and lead times. In further understanding the effects of fast but expensive suppliers, Sun and Van Mieghem (2019) determine a capped dual index policy for the dual replenishment decision. Gijsbrechts et al. (2022) extend this view by considering fast, thus local, supply that is less flexible and more expensive and identify that local suppliers need to improve their volume flexibility to compete with cheaper offshore supply. Boute et al. (2022) show that local SpeedFactories can be valuable even when purchasing costs from near-shored suppliers are higher than the offshore costs due to significant inventory savings. However, the attractiveness of the near-shoring option is strongly influenced by the demand uncertainty studied. While we assume known demands, we focus on the influence of lead time effects through near-shored suppliers given the influence of supply uncertainty that affect the transportation from global suppliers.

2.2. Supply chain network design under uncertainty

Quantitative decision models that decide on the cost-optimal mix of resilience strategies for the SCND under disruption risks have become increasingly relevant. We refer to Aldrighetti et al. (2021) and Snyder et al. (2016) for recent overviews. Overall, SCND problems under disruption uncertainty have developed from primary facility locations to more integrated decision problems. Qi et al. (2010) solved the facility location problem under disruption uncertainty and compared an integrated against a sequential supply chain design to achieve considerable cost benefits considering disruption uncertainty at the strategic design phase. In contrast, Mete and Zabinsky (2010) proposed a two-stage stochastic programming formulation to account for both the strategic and tactical design policies while considering operational re-routing decisions to solve the storage and distribution problem of medical supplies in disaster management. While they focus on the special case of earthquake disaster mitigation, we extend their work on an integration of strategic to operational resilience strategies for transportation uncertainty to wider disruption scenarios. Nooraie and Parast (2016) were the first to propose an end-to-end decision model for supply chain design from suppliers to customers under disruption uncertainty considering multiple time periods. Khalili et al. (2017) extended previous two-stage stochastic programming formulations by integrating production and distribution planning problems under disruption risk, considering both proactive and reactive resilience strategies. Similarly, Azad et al. (2016) used a network optimization model to study the cost-effectiveness of installing alternative links in railroad networks under random disruption scenarios. With an overall focus shift from outbound to inbound logistic network models, Namdar et al. (2018) analyzed the benefits of a multiple sourcing strategy under disruption risks of inbound suppliers. 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, Morshedlou 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 BD to solve the problem. We build on their contribution of explicitly considering partial disruption of facilities with uncertain recovery duration by considering disruptions that are uncertain concerning their timing, length, and impact with seasonal patterns across the planning horizon. Alikhani et al. (2023) used a multi-methodological approach to select the best resilience strategies for varying supply chain disruptions. Specifically, they quantified the synergistic effects of the best-fit of candidate strategies on different disruption characteristics, such as cyberattacks and natural disasters. Based on this idea, we study the general differences on cost-optimal resilience strategies between low-impact but high-probability against high-probability but low-impact disruption events. They considered facility fortification, direct shipping, inventory increase, facility dispersation, 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 and a case study focusing on the COVID-19 pandemic, they identified a good trade-off between resilience and investment costs with minimal investments 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. In a similar multi-period setting, we study the impacts of disruption probability shifts across the planning horizon on the optimal mix of resilience strategies. Besides, in comparison to assuming immediate impacts of particularly re-routing decisions, we explicitly consider lead times to account more realistically for the impacts of strategic decisions on the operational level, such as near-shoring.

2.3. Resilient transportation systems

Transportation systems are part of the critical infrastructure to provide essential commodities and services. Similar to supply chains, they have become more and more complex and interdependent, making them prone to disruptions and increasing the time to recover. As a result, research on resilient transportation systems is becoming increasingly popular (Mattsson & Jenelius, 2015).

Miller-Hooks et al. (2012) determined the optimal set of mitigation and recovery actions to achieve service constraints of a transportation system given a budget through a two-stage stochastic program for a rail-based container network. Omer et al. (2012) study the resilience of maritime transportation networks and the impacts of disruptions on port capacities by identifying three different resilience metrics. To increase the overall system understanding, Chen et al. (2017) study the port-hinterland container transportation network under disruption uncertainty. Motivated by the diverging operator interests, Chen et al. (2018) investigate the strategic resilience investments in a port-hinterland container transportation network. Due to its vulnerability and importance to the economy of China, Wang and Yuen (2022) conducted a simulation study on the Yangtze Estuary Deepwater Channel to develop a resilience assessment indicator tested for different accident scenarios. While the focus of port-hinterland networks has been on the effects of disruptions on port infrastructure and their capacity, we discuss a new case example in which disruptions affect the transportation links between the nodes, e.g., through water-level driven effects.

2.4. Benders decomposition for two-stage network design

As first proposed by Benders (1962), BD is a commonly used exact algorithm for problems with complicated and continuous variables in which, when fixing the complicated variables, an easier subproblem remains. Due to the popularity of two-stage stochastic programs in SCND under uncertainty (Govindan et al., 2017), we focus on the application and recent improvements of the BD algorithm in two-stage stochastic programs and recommend the detailed overview of Rahmaniani et al. (2017).

The L-shaped method, as introduced by Van Slyke and Wets (1969), is a BD algorithm applied to two-stage stochastic programs in which the problem is decomposed into a master problem (MP) that includes the first-stage decisions and a slave problem (SP) that contains the second-stage decision variables. In contrast, we compare the performance of this split against alternatives in which first-stage flow decisions are decomposed in the SP. Based on the idea of the L-shaped method, Birge and Louveaux (1988) introduced the multicut algorithm for two-stage stochastic programs in which a single cut is generated for each scenario from the subproblem. Still, a straightforward application of the BD algorithm might result in time-consuming iterations, poor feasibility, and zigzagging behavior. Thus, work has focused on exploring ways to improve the (problem-specific) performance of the BD algorithm. We classify these strategies that are relevant for this work into three different categories and discuss their benefits for the specific problem at hand.

The first category contains strategies that aim to improve and strengthen the cut-generation process itself. Particularly, we focus on improving the cut-generation process by adding problem-specific valid inequalities to complement or replace adding feasibility and optimality cuts. Cordeau et al. (2006) have shown that introducing problem-specific valid inequalities can significantly improve the algorithm's performance. While valid inequalities aim at strengthening the feasible solution space of the MP, Adulyasak et al. (2015) have shown that lower-bound lifting inequalities can significantly improve the performance of the BD algorithm for a two-stage production routing problem under demand uncertainty. Similarly, we derive lower-bound lifting inequalities for our problem setting. In addition, they included pareto-optimal cuts based on Papadakos (2008) and scenario group cuts in which, in contrast to Birge and Louveaux (1988), cuts are only generated for groups of scenarios.

The second category groups methods that are based on the idea of generating cuts without solving the master or subproblem to optimality each time. For example, Easwaran and Üster (2009) incorporated a tabu search in the BD algorithm to provide initial strong upper bounds and, thus, initial good Benders cuts for a capacitated closed-loop network design. Similarly, Pishvaee et al. (2014) used valid inequalities and a local branching strategy that does not solve the master problem to optimality at each iteration for a sustainable network design problem under uncertainty.

The third category includes strategies that adjust the decomposition strategy considering the separation of information and decisions into master and subproblem for two-stage problems itself. Crainic et al. (2021) introduced the idea of partial BD to include information from the SP into the MP and showed its benefits for a general class of two-stage stochastic multi-commodity network design problems. Recently, Rahmaniani et al. (2024) explored parallelization strategies in which multiple SPs are solved in parallel on different processors and implemented the algorithm in a branch-and-cut framework for a two-stage multi-commodity capacitated fixed-charge network design problem with stochastic demands.

2.5. Discussion of research opportunities

To date, there needs to be more research combining strategic, tactical, and operational resilience strategies to understand their interdependence and cost-competitiveness (Govindan et al., 2017). Only Mete and Zabinsky (2010) considered this combination for transportation uncertainty; however, for the specific case of immediate earthquake disaster mitigation. While multi-period models have been introduced, time-dependent changes of the disruption probabilities to adequately consider the dynamic nature of supply chain vulnerability still need to be addressed (Aldrighetti et al., 2021; Hosseini & Khaled, 2019). In addition, most models focus on low-probability/high-impact events that are impossible to predict. With few exceptions, such as the time-to-recover model (Simchi-Levi et al., 2015), common literature focuses on equal disruption probabilities and assumes immediate effects of disruptions and SCR strategies. However, this ignores both the effects of lead times on operational decisions and the potential benefits of short-term disruption prediction. As a result, research on disruption uncertainty remains on expert estimates or assumes known distributions that do not contribute towards an improved understanding of the proposed SCR strategies' cost-competitiveness (Aldrighetti et al., 2021).

3. Problem setting

Section 3.1 introduces the process and network structure of the SCND problem. We discuss the effect of disruptions on parameters in Section 3.2. Finally, the resilience strategies are introduced in Section 3.3.

3.1. Network and process description

We consider a SCND problem with a single product in a discrete-time horizon, where the transportation network consists of multiple suppliers *(as sources)*, multiple transportation modes *(as arcs)*, and a single production facility *(as sink)*. Each supplier can deliver in unlimited quantities and in each time period. To deliver, however, a supplier needs to be qualified in the initial stage of the decision problem. Such a qualification comes at an investment cost as it includes negotiations, development of contracts or receiving and testing of product samples. Different transportation modes are available for each supplier to deliver raw materials to the production facility. However, only a single transportation mode might be available depending on the supplier. These transportation modes differ in transportation lead times, costs, and disruption proneness. The production facility holds inventory to fulfill its production demands. At the beginning of each period, transport shipments arrive that were ordered lead time periods earlier. The inventory capacity is limited and storage results in inventory holding costs linear to the inventory quantity stored. Then, production demands are fulfilled. These demands at the sink are defined through a deterministic production schedule for each time period along the planning horizon. Such deterministic schedules, e.g., are common for capital-intensive process industries such as chemicals that often rely on a continuous production process (Silver et al., 1998). An unfulfilled production demand, thus if no inventory is available, forces a production stop that results in shortage costs. Inventory holding costs are charged to the inventory level at the end of the period and transportation costs to the period of ordering. The simplified structure is shown in Fig. 1.

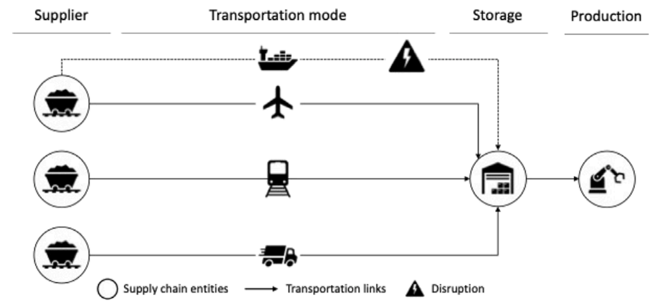

Fig. 1. Overview of SCND structure considered.

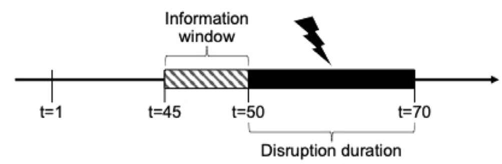

Fig. 2. Time window on information certainty of the transportation disruption impact.

3.2. Transportation disruptions

We define a transportation disruption as an unfortunate event causing a transportation cost increase to a single or multiple transportation modes along the planning horizon with varying duration and impact. Disruption events occur independently from each other. Merely the probability of occurrence and its impact depends on the transportation mode. These cost increases are a result of surcharges that transportation carriers enforce as reaction to disruptions to balance the lost capacities with the demands. Given these surcharge on top of the regular transportation costs, a transport is always available. Depending on the disruption impact and mode, these surcharges range from modest increases to full production stops, i.e., an unlimited increase in transportation costs. To account for full transportation stops, we bound the surcharges with the shortage costs. After the disruption event, its effects terminate immediately and transportation costs decrease to their disruption-free values.

Limited time prior to a disruption, its duration and impact on the transportation costs becomes known to the central decision-maker. We define this time as the *information window*. This information window is determined through the ability of a decision-maker to predict a disruption prior to its occurrence. On a longer horizon, however, the occurrence and impact of a disruption remain uncertain. For example, this applies to hurricanes where the route and intensity of the storm is known days before a landfall or strikes that are announced in advance. Fig. 2 visualizes an example of a single disruption during the planning horizon. In the example, the transportation disruption lasts from $t = 50$ to $t = 70$. With $t^{info} = 5$, the disruption becomes known in $t = 45$ regarding its duration (20 days) and impact. Concerning the model formulation in Section 4, this translates to $T_s = \{45; 70\}$. In practice, the possibility of predicting disruptions strongly depends on the specific situation. We highlight the relevance of the information window as part of our case study in Section 7.2.

3.3. Resilience strategies

A central decision-maker at the production facility sources from various suppliers and is in full responsibility of the inbound flows. The goal is to minimize the expected costs through an optimal mix of SCR strategies. Thus, we minimize the trade-off between the costs of paying a cost premium for strategic and tactical resilience capacities when no disruption occurs and the uncertain cost increase from a disruption given the potential limited re-routing abilities on the operational level. We consider the following strategic, tactical, and operational SCR strategies in a two-stage stochastic decision problem.

***Multi-sourcing** (strategic, first-stage).* Qualification of multiple suppliers. This includes both multi-sourcing, i.e., purchasing from two or more suppliers in parallel, and the investment in a backup supplier.

***Near-shoring** (strategic, first-stage).* Qualification of a supplier that offers a transportation mode with a shorter lead-time (Chang & Lin, 2019) or less prone to disruptions at a cost-premium.

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

Inventory *(tactical, first-stage)*. Decision to increase inventory through tactical transportation plan.

Re-routing *(operational, second-stage)*. Decision to re-route quantities from the tactical transportation plan due to a disruption. Besides the differences in mode-specific transportation costs, re-routing comes at a cancellation cost for the originally planned transportation quantities on the tactical level.

In contrast, the decision-maker can decide for risk-taking and against any SCR strategy but execute the same transportation plan across all scenarios.

4. Model formulation

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

4.1. Sets

A set of suppliers $\mathcal{I}$ delivers a product using a set of transport modes $\mathcal{M}$ to the production facility over a time horizon $\mathcal{T}$. To account for the stochastic nature of the decision problem, we introduce a set of disruption scenarios $\mathcal{S}$ and model the decision problem as two-stage stochastic program. For each disruption scenario, we introduce $\mathcal{T}_s \subset \mathcal{T}$ as disruptive time periods including a potential information window (see Section 3.3) where operational re-routing is allowed.

4.2. Parameters

Scenarios occur with probability π_s, with $0 \le \pi_s \le 1$ and $\sum_{s\in\mathcal{S}} \pi_s = 1$. Each scenario s represents a specific disruption situation as they can occur along the planning horizon. Thus, the transportation costs c^M_{mts} reflect the scenario-specific (s) transportation costs for each time period (t) as an outcome of the transportation mode-specific (m) base costs and disruption-driven cost increases.

Per time period and product units stored, inventory holding costs c^H occur. Each unfulfilled unit of demand d_t results in shortage costs c^N. The total sum of all demands across the planning horizon is d^A. The operational re-routing of transportation quantities requires cancellation costs c^P_i specific to supplier i. To qualify a supplier i, qualification costs f^I_i are needed that depend on the specific supplier. The initial inventory capacity to store inventory on hand is Y. Through an investment decision this capacity can be increased by multiples of Y^+ at costs f^Y per multiple. In the starting period, an initial inventory of j_0 is available. Transportation lead times l_m are considered that depend on the transportation time via mode m.

4.3. Decision variables

The model decides between different SCR strategies (see Section 3.3) to minimize the total expected costs in a two-stage stochastic program. Thus, the interlink between the strategic and tactical decisions (first-stage) and the operational decisions (second-stage) are considered.

The first-stage decisions determine the network structure. The binary decision z_i determines if supplier i is qualified (= 1) or not (= 0). The initial inventory capacity can be extended through an integer investment decision w in multiples of additional inventory capacity. Lastly, a tactical transportation plan x_{imt} determines transportation quantities across scenarios. On the second-stage, this transportation plan can be adapted whenever disruptions occur in scenario s. This operational re-routing consists of additional shipments $\hat{x}_{imts}$ or quantity reductions $\check{x}_{imts}$ from the original plan.

Additional decision variables are needed to formulate the SCND problem. Variables x_{imts} reflect the final transportation quantities from supplier i via transport mode m in scenario s based on the tactical plan x_{imt} (first-stage) and the operational re-routing decisions (second-stage) ($\check{x}_{imts}$, $\hat{x}_{imts}$). In addition, we introduce the on-hand inventory y_{ts} in period t and scenario s. Instead of negative inventories, shortages p_{ts} occur.

4.4. Model formulation

4.4.1. Objective function

$$\text{minimize} \quad \overbrace{f^Y \cdot w + \sum_{i\in\mathcal{I}} f^I_i \cdot z_i}^{\text{first-stage}} + \sum_{s\in\mathcal{S}} \pi_s \cdot \underbrace{\left(\sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}} c^M_{mts} \cdot x_{imts} + \sum_{t\in\mathcal{T}} c^H \cdot y_{ts} + \sum_{t\in\mathcal{T}} c^N \cdot p_{ts} + \sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}_s} c^P_i \cdot \check{x}_{imts} \right)}_{\text{second-stage}} \tag{1}$$

The objective function (1) minimizes the total expected costs across scenarios by considering first-stage and second-stage decisions. Investment costs, on the first-stage, occur depending on the decision to invest in multiples (w) of inventory capacity (Y^+) and supplier qualification (z_i). On the second-stage, we consider transportation costs based on the quantities shipped (x_{imts}), inventory holding costs driven by inventory on hand (y_{ts}), shortage costs (p_{ts}), and cancellation costs for transportation plan changes ($\check{x}_{imts}$). Note that disruptions affect the transportation mode-specific costs (c^M_{mts}) in scenario s.

4.4.2. Constraints

$$\sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}} x_{imt} = d^A \tag{2}$$

Across the planning horizon, quantities that equal the total demand (d^A) must be assigned to the tactical transportation plan on the first-stage decision, ensured by constraints (2).

$$\sum_{m\in\mathcal{M}} x_{imts} \le d^A \cdot z_i \qquad \forall i \in \mathcal{I}, t \in \mathcal{T}, s \in \mathcal{S} \tag{3}$$

$$y_{ts} \le Y + Y^+ \cdot w \qquad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{4}$$

A supplier can only deliver once qualified (z_i), ensured by constraints (3). Constraints (4) limit the inventory on hand to the respective capacity, which is the sum of the initial available capacity Y and the integer multiples w of additional inventory capacity Y^+ invested for.

$$y_{ts} = y_{(t-1)s} + p_{ts} - d_t + \sum_{i\in\mathcal{I},m\in\mathcal{M}} x_{im(t-l_m)s} \qquad \forall t \in \mathcal{T} \setminus \{1\} | t > l_m, s \in \mathcal{S} \tag{5}$$

$$y_{1s} = j_0 - d_1 \qquad \forall s \in \mathcal{S} \tag{6}$$

Constraints (5) describe the inventory balance between two consecutive periods t and $t-1$. The inventory on hand for each period t consists of the sum of the final inventory of the previous period $t-1$, incoming units ($x_{im(t-l_m)s}$) ordered lead time (l_m) periods earlier and demands (d_t). The starting inventory for the initial period t is defined in constraints (6). If the demands d_t exceed the available inventory, shortages (p_{ts}) occur, leading to lost sales,which are penalized in the objective function (1).

$$x_{imts} = x_{imt} + \hat{x}_{imts} - \check{x}_{imts} \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}, t \in \mathcal{T}_s, s \in \mathcal{S} \tag{7}$$

$$x_{imts} = x_{imt} \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T} \setminus \{\mathcal{T}_s\}, s \in \mathcal{S} \tag{8}$$

$$\check{x}_{imts} \le x_{imt} \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T}_s, s \in \mathcal{S} \tag{9}$$

$$\sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}_s} \hat{x}_{imts} - \check{x}_{imts} = 0 \qquad \forall s \in \mathcal{S} \tag{10}$$

Constraints (7) ensure that actual transported quantities for each scenario s equal the tactical transport plan (x_{imt}) while taking operational re-routing options during a disruption ($t \in \mathcal{T}_s$) into account. This approach is motivated by Lanza et al. (2021), who propose a similar decomposition strategy of tactical and operational decisions for scheduled service networks. The re-routing consists of transport cancellations ($\check{x}_{imts}$) from the tactical plan and short-term orders from alternative suppliers or transportation modes ($\hat{x}_{imts}$). Without disruptions and outside of the information window, the actual transportation quantities x_{imts} equal the tactical transportation plan x_{imt} as defined in constraints (8). Constraints (9) limit the cancellation quantity to the quantities of the tactical transport plan from supplier i via transport mode m and in time period t. On the operational level, constraints (10) ensure that operational cancellations and additional order quantities are balanced.

$$w \in \mathbb{Z} \tag{11}$$

$$z_i \in \{0,1\} \qquad \forall i \in \mathcal{I} \tag{12}$$

$$y_{ts}, p_{ts} \geq 0 \qquad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{13}$$

$$x_{imts}, x_{imt} \geq 0 \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T}, s \in \mathcal{S} \tag{14}$$

$$\hat{x}_{imts}, \check{x}_{imts} \geq 0 \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T}_s, s \in \mathcal{S} \tag{15}$$

The non-negativity and variable definition constraints are summarized in (11)–(15).

5. Benders decomposition

In our two-stage stochastic program for the SCND problem, the first-stage decisions consist of a set of binary and integer investment decisions and a continuous variable x_{imt}. By fixing all first-stage decisions, a network flow problem results as subproblem, which can be decomposed by scenario and is easy to solve. However, our numerical tests showed that this significantly increases the complexity of the MP, and keeping x_{imt} (as first-stage decision) in the SP, with the drawback of not decomposing the SP by scenario, outperforms the L-shaped method. We show the performance of both formulations in Section 6. Algorithm 1 outlines the proposed BD algorithm with x_{imt} in the SP. After initialization and warm start, the MP (see Section 5.2) is solved to obtain the supplier qualification decision ($\bar{z}_i$), the investment decision in inventory multiples ($\bar{w}$), as well as the master objective, which equals the current lower bound (LB). Using the fixed decision outputs of the MP ($\bar{z}_i$, $\bar{w}$), the dual slave problem (DSP) (see Section 5.1) is solved, and we check whether the current upper bound (UB) is better than the known UB. Using the dual variables, an optimality cut is added to the MP in each iteration l of the cutting plane procedure as the dual is always feasible (see Section 5.1). This procedure repeats until the tolerance TOL is met. Particularly due to the many time periods and thus decision variables, the BD algorithm as outlined in Algorithm 1 does, even for small instances, not converge in an acceptable time limit. Thus, we solve the two-stage stochastic SCND problem by deriving enhancements from ideas previously investigated in literature. These are lower-bound lifting and valid inequalities (Section 5.3.1), branch-and-benders-cut (Section 5.3.2), and warm-start (Section 5.3.3).

5.1. Slave problem

Upon fixing the first-stage decisions to $\bar{w}$ and $\bar{z}_i$, we obtain a continuous linear program that is much easier to solve but not separable by scenario s due to x_{imt}. Due to the presence of decision variables p_{ts}, the SP is always feasible since negative inventory levels can be avoided if at least one supplier is qualified (see Section 5.3.1). The total expected costs $v(\bar{w}, \bar{z}_i)$ of the second-stage can be calculated as weighted sum across all scenarios s with their probability of occurrence π_s. In addition, since all cost parameters in (16) are finite and subject to constraints (5)–(6), any feasible solution of the SP must be bounded. As a result, the dual of the SP is feasible and bounded as well. Thus, we solve the following SP:

Algorithm 1 Benders decomposition algorithm.

Initialize $l \leftarrow 1$, TOL, $UB \leftarrow +\infty$, $LB \leftarrow -\infty$
Conduct warm start to obtain starting solution
Solve master problem to obtain $\bar{w}^l$ and $\bar{z}_i^l$
$LB \leftarrow$ Master objective
while $UB - LB \geq TOL$ **do**
  Solve dual slave problem with $\bar{w}^l$ and $\bar{z}_i^l$
  $UB \leftarrow$min[UB, (Master objective) + (Dual slave objective)]
  Add a new optimality cut to master problem
  $l \leftarrow l + 1$
  Solve master problem to obtain $\bar{w}^l$ and $\bar{z}_i^l$
  $LB \leftarrow$ Master objective
end while

$$v(\bar{w}, \bar{z}_i) := min \sum_{s\in\mathcal{S}} \pi_s \cdot \Big(\sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}} c^M_{mts} \cdot x_{imts} + \sum_{t\in\mathcal{T}} c^H \cdot y_{ts} + \sum_{t\in\mathcal{T}} c^N \cdot p_{ts} + \sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}_s} c^P_i \cdot \check{x}_{imts} \Big) \tag{16}$$

subject to:

$$\sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T}} x_{imt} = d^A \tag{17}$$

$$x_{imts} \leq d^A \cdot \bar{z}_i \qquad \forall i \in I, m \in M, t \in T, s \in \mathcal{S} \tag{18}$$

$$y_{ts} \leq Y + Y^+ \cdot \bar{w} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{19}$$

(5)–(10), (13)–(15).

To derive the Benders cuts, we define the DSP. In the DSP, the variable α is the dual variable of constraint (17), which ensures that the tactical transportation plan matches the total demand. The variables β_{imts} are the dual variables of the transportation limitation to suppliers qualified (18), γ_{ts} are the duals of the inventory capacity constraint (19), δ_{ts} are the dual variables of the inventory balance constraints (5) and (6), ε_{imts} are the dual variables of re-routing constraints (7)–(8), and ζ_{imts} are the dual variables of constraints (9) limiting cancellations, and θ_s the dual variables of the operational re-routing balance constraints (10). The DSP can be stated as follows:

$$v(\bar{w}, \bar{z}_i) = max \quad d^A \cdot \alpha + \sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T},s\in\mathcal{S}} \bar{z}_i \cdot d^A \cdot \beta_{imts} + \sum_{t\in\mathcal{T},s\in\mathcal{S}} (Y + Y^+ \cdot \bar{w}) \cdot \gamma_{ts} + \sum_{s\in\mathcal{S}} (j_0 - d_1) \cdot \delta_{1s} + \sum_{s\in\mathcal{S}} \sum_{t=2}^{\mathcal{T}} d_t \cdot \delta_{ts} \tag{20}$$

subject to:

$$\beta_{imts} + \delta_{(t+L_m)s} + \varepsilon_{imts} \leq \pi_s \cdot c^M_{mts} \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T} \setminus \{1\}, s \in \mathcal{S} \tag{21}$$

$$\beta_{imts} - \delta_{ts} + \varepsilon_{imts} \leq \pi_s \cdot c^M_{mts} \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t = 1, s \in \mathcal{S} \tag{22}$$

$$\gamma_{ts} + \delta_{(t+1)s} \leq \pi_s \cdot c^H \qquad \forall t \in \mathcal{T} \setminus \{n\}, s \in \mathcal{S} \tag{23}$$

$$\gamma_{ts} + \delta_{ts} \leq \pi_s \cdot c^H \qquad \forall t = 1, s \in \mathcal{S} \tag{24}$$

$$\delta_{ts} \leq \pi_s \cdot c^N \qquad \forall t \in \mathcal{T} \setminus \{1\}, s \in \mathcal{S} \tag{25}$$

$$\varepsilon_{imts} + \zeta_{imts} - \theta_s \leq \pi_s \cdot c_i^P \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T}_s, s \in \mathcal{S} \tag{26}$$

$$\alpha \leq 0, \beta_{imts} \leq 0, \delta_s \leq 0, \zeta_{imts} \leq 0, \gamma_{ts}, \varepsilon_{imts}, \theta_s \in \mathbb{R}, \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T}, s \in \mathcal{S} \tag{27}$$

5.2. Master problem

The MP is a relaxation of the two-stage stochastic problem defined in Section 4 that only considers the binary and integer first-stage decisions w and z_i. At each iteration l of the BD algorithm, an optimality cut (29) needs to be added to the MP from the DSP($\bar{w}$, $\bar{z}_i$). We formulate the master problem as follows:

$$min \qquad f \cdot w + \sum_{i\in\mathcal{I}} f_i \cdot z_i + \psi \tag{28}$$

subject to:

$$d^A \cdot \bar{\alpha}^l + \sum_{i\in\mathcal{I},m\in\mathcal{M},t\in\mathcal{T},s\in\mathcal{S}} d^A \cdot \bar{\beta}^l_{imts} \cdot z_i + \sum_{t\in\mathcal{T},s\in\mathcal{S}} (Y + Y^+ \cdot w) \cdot \bar{\gamma}^l_{ts} + \sum_{s\in\mathcal{S}} (j_0 - d_1) \cdot \bar{\delta}^l_{1s} + \sum_{s\in\mathcal{S}} \sum_{t=2}^{T} d_t \cdot \bar{\delta}^l_{ts} \leq \psi \qquad \forall l = 1, 2, 3, \dots \tag{29}$$

$$w \in \mathbb{Z}, \psi \geq 0, z_i \in \{0, 1\} \qquad \forall i \in \mathcal{I} \tag{30}$$

5.3. Algorithmic enhancements

5.3.1. Lower-bound lifting and valid inequalities

In BD, specifically in this problem setting, the optimality gap, which is the delta between upper and lower bound divided by the upper bound, may be large in initial iterations due to the poor quality of the LB. To address this issue, Adulyasak et al. (2015) proposed using initial cuts, called lower-bound lifting inequalities, for a production routing problem. Following this idea, we derive problem-specific lower-bound-lifting cuts for the MP by focusing on the flow costs, i.e., transportation and inventory costs. These constraints are added to the MP formulation of Section 5.2. We observe that, depending on the suppliers qualified in the master problem, the total flow costs cannot be lower than the transportation costs in the disruption-free state $\hat{c}^M_{im}$ of the most cost-efficient transportation mode from a supplier qualified. We define the additional auxiliary decision variable $\tilde{x}_{im} \geq 0$ to define the lower-bound lifting inequalities:

$$\sum_{i\in\mathcal{I}} z_i \geq 1 \tag{31}$$

$$\sum_{i\in\mathcal{I},m\in\mathcal{M}} \tilde{x}_{im} = d^A \tag{32}$$

$$\tilde{x}_{im} \leq d^A \cdot z_i \qquad \forall i \in \mathcal{I}, m \in \mathcal{M} \tag{33}$$

$$\sum_{i\in\mathcal{I},m\in\mathcal{M}} \hat{c}^M_{im} \cdot \tilde{x}_{im} + c^H \cdot \tilde{J}_0 \ \leq \psi \tag{34}$$

$$\tilde{x}_{im} \geq 0 \qquad \forall i \in \mathcal{I}, m \in \mathcal{M} \tag{35}$$

Constraint (31) ensures that at least one supplier is qualified. Constraint (32) ensures that the total demand is transported via one of the available transportation modes from qualified suppliers ($z_i = 1$) as defined in constraints (33). Based on this, constraint (34) provides a lower bound for the transportation costs, which account for the largest part of the total flow cost, and the initial inventory holding cost based on the pre-defined average starting inventory $\tilde{J}_0$ until its full consumption without any transports. Through these inequalities, we ensure a higher LB in the initial iterations and a faster convergence as suppliers with transportation modes that would already be higher in terms of disruption-free transportation costs are neglected.

5.3.2. Branch-and-benders-cut

Instead of solving the updated MP at each iteration, we solve the Benders reformulation in a BC framework, often referred to as branch-and-benders-cut. To avoid a large number of optimal cuts added within a single tree, these cuts are added to the master problem only when an incumbent solution is found. This technique has yielded promising results in recent research (e.g., Codato & Fischetti, 2006; Crainic et al., 2021).

5.3.3. Warm start

We obtain a starting solution by solving the deterministic, disruption-free transportation problem and obtaining its objective value Z^{Det}. To further strengthen the model formulation, we add the deterministic solution as a lower bound for the master problem for the initial iterations.

$$Z^{Det} \leq \psi \tag{36}$$

6. Numerical study

We performed numerical tests on eight problem instances of different sizes. Section 6.1 outlines the numerical setup. We evaluate the effectiveness of our proposed BD solution method in Section 6.2. Numerical results and sensitivities are shown in Section 6.3.

6.1. Numerical setup

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. All computational results are reported in seconds. We generate eight different problem sets as summarized in Table 1. Each problem set is generated in six problem sizes with the number of suppliers $|I|$ ranging from 2 to 32, suppliers $|M|$ ranging from 2 to 64, 100 scenarios $|S|$, and a planning horizon of 365 days. While the number of scenarios significantly drives computational complexity in two-stage network design (Alikhani et al., 2023), we obtain first-stage decisions with only minor differences in inventory capacity investments with 100 scenarios. Of the 24 problem set-size combinations that were solved to optimality for all test instances, only 10 show a difference between the maximum and minimum inventory capacity investment observed while the overall mean of this delta is 0.61, thus less than a single incremental integer investment capacity. Especially for commodities, even for single product cases, many suppliers are available to source products from various distribution facilities worldwide. Demands are constant and deterministic. We distinguish between problem sets with ($P1-P4$) and without ($P5-P8$) a backup transportation mode per supplier. For the main transportation mode, we assume a linear dependence between disruption free costs $\hat{c}^M_{im}$ and lead time l_m as shown in Eq. (37):

$$\hat{c}^M_{im} = -l_m \cdot a + b \tag{37}$$

Specifically, we distinguish a low ($a = 0.0025, b = 0.215$) and a high ($a = 0.005, b = 0.30$) delta on mode costs. All problem instances have the same disruption-free costs for the supplier with the longest lead time, and, thus, are comparable. For this supplier with the longest lead time, transportation costs in the disruption-free state account for 13% of the product value in comparison to 20% of inventory holding costs, which represents a typical ratio in the process industry. Thus, the difference is in the higher disruption-free costs of suppliers with a shorter lead time (high Δ on mode costs). Transportation lead times range from 3 to 34 time periods (days). Each additional supplier is considered to have a lower lead time on the main transportation mode but higher transportation costs. For all backup transportation modes m, the transportation costs are set to $\hat{c}^M_{im} = 0.3$ with a lead time of $l_m = 14$.

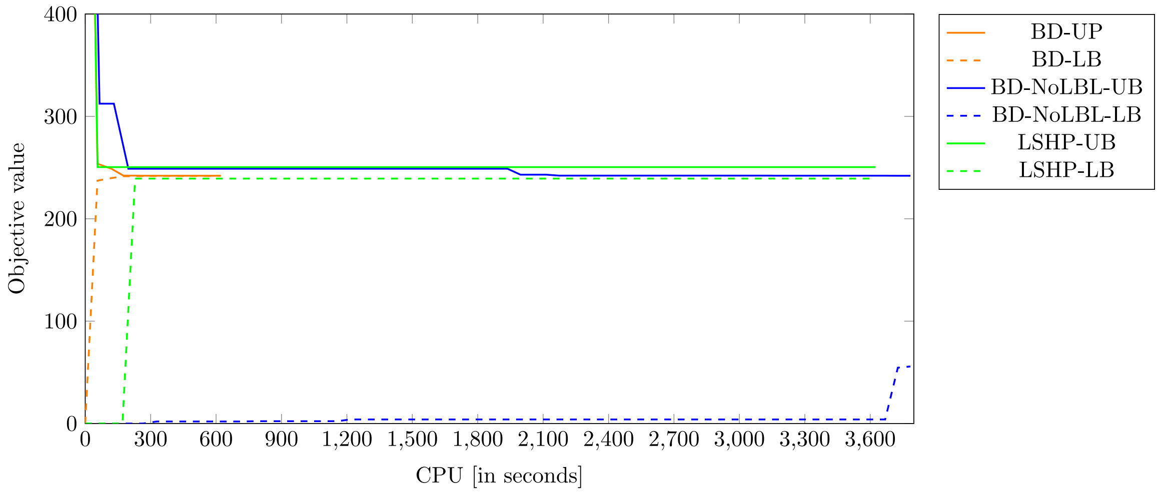

Fig. 3. Convergence behavior of upper and lower bound.

Table 1
Overview of problem sets.

Problem instance	Modes per supplier	Δ Mode costs	Disruptions	
			Probability	Impact
P1	1	Low	Low	High
P2	1	High	Low	High
P3	1	Low	High	Low
P4	1	High	High	Low
P5	2	Low	Low	High
P6	2	High	Low	High
P7	2	Low	High	Low
P8	2	High	High	Low

Disruption events within and across scenarios occur independently of each other. Scenarios occur with equal probability. In each scenario, each transport mode can either face no disruption, a single or two disruptions. We differentiate low-probability but high-impact and a high-probability but low-impact disruption situation. All disruption probabilities and impacts are motivated by the case example of recurring disruptions at the Rhine River. We consider a low-probability situation of 16% probability of a single and 4% of two disruptions during the planning horizon. In this situation, disruption impacts range from a 200% transportation cost increase to a full transportation stop, modeled through a Big-M increase of transportation cost. This represents a situation in which severe disruptions occur every five years with severe impacts. In the case of a high-probability but low-impact, a single disruption occurs with a probability of 75% and two disruptions with a probability of 20%. Their impacts range from a 40%–80% cost increase, representing a nearly annual recurring disruption that affects the cost-competitiveness of suppliers but not the general ability to deliver goods. Each disruption occurs randomly during the planning horizon with a uniformly distributed disruption length between 20 and 40 days. To account for the disruption uncertainty, we generate three instances for each problem set in each problem size, thus solving 144 instances in total.

6.2. Algorithm performance

We benchmark our BD against the branch-and-bound algorithm of Gurobi (GB) and the classical L-shaped implementation (LSHP) with all first-stage decisions in the MP, enhanced with partial BD (Crainic et al., 2021; Rahmaniani et al., 2017) and lower-bound-lifting constraints. The algorithms are terminated after 3600 s if no optimal solution is found prior. Table 2 summarizes the average results by problem size and across problem sets with a backup transportation mode ($P5$–$P8$). For each problem size, the number of instances solved to optimality is reported. In addition, we report whether or not a feasible solution was found. While GB can prove optimal solutions faster for small problem sizes, the BD algorithm starts to outperform GB, starting with a problem size of 8 suppliers and 16 transportation modes. Particularly for large instances, where GB cannot find feasible solutions within the time limit, the BD can still identify solutions with low average optimality gaps of 1.27%. Additionally, three instances can still be solved to optimality. Further, the enhanced LSHP leads to sub-optimal results. When keeping x_{imt} in the MP, a facility location problem structure with flows remains. This is known to converge slowly. While the SP is solved faster, an enormous number of cuts are needed to prove optimality, which we can avoid through the alternative split of decision variables in our BD.

To understand the behaviors of the different BD algorithms and their improvements, Fig. 3 visualizes the convergence curves for our proposed BD algorithm, our proposed algorithm without problem-specific valid inequalities and lower-bound-lifting constraints (BD-NoLBL), and the LSHP when solving $P5$ with an instance size of 8 suppliers and 16 transportation modes. Starting with the classical LSHP, one can see that because of the lower-bound-lifting constraints, the lower bound approaches the optimal solution relatively fast after 300 s of computation time. In addition, a strong incumbent solution is found even slightly faster than for our BD algorithm. However, no further improved incumbent solution is found, resulting in a remaining gap after the algorithm is terminated after one hour. Next, we analyze the behavior of our proposed BD without the problem-specific valid inequalities and lower-bound-lifting constraint. It takes the longest for this algorithm to find a strong first incumbent solution (after 2100 s). This incumbent solution is even better than the LSHP incumbent solution after 3600 s. However, without the lower-bound-lifting-constraints, we still see no significant improvement of the lower bound after one hour of computation time, and thus a remaining large optimality gap. After continuing the algorithm, finally, a slight improvement of the lower bound can be observed. Our BD, in comparison, finds the strongest incumbent solution with a very low gap to optimality because of the lower-bound-lifting constraints. After 600 s, optimality of the incumbent solution is proven and the algorithm terminates.

These analyses have demonstrated the added value of both the problem-specific lower-bound-lifting constraints and the choice of the tactical transportation decision variable x_{imt} in the subproblem as non-standard split of decision variables in two-stage stochastic programs.

Table 2
Comparison of proposed BD algorithm against Gurobi and LSHP.

$\|I\|$	$\|M\|$	Average optimality gap			Average CPU			Feasibility			Optimality		
		BD	LSHP	GB	BD	LSHP	GB	BD	LSHP	GB	BD	LSHP	GB
2	4	0.00%	0.81%	0.00%	306	3600	221	12/12	12/12	12/12	12/12	0/12	12/12
4	8	0.00%	1.62%	0.00%	1053	3600	1000	12/12	12/12	12/12	12/12	0/12	12/12
8	16	0.04%	2.97%	0.71%	2031	3600	2356	12/12	12/12	12/12	9/12	0/12	8/12
16	32	0.25%	2.63%	2.44%	3257	3600	3600	12/12	12/12	5/12	3/12	0/12	0/12
32	64	1.27%	3.49%	–	3412	3600	–	12/12	12/12	0/12	3/12	0/12	0/12

Table 3
Average optimal strategic resilience decisions across problem instances.

Problem	Single-supplier case			Multi-supplier case		
	ResC	$\|z\|$	$\|w\|$	$ResC$	$\|z\|$	$\|w\|$
Without backup transportation mode	13.13	1.00	4.42	3.87	2.00	0.31
With backup transportation mode	8.98	1.00	5.08	3.80	2.00	0.44

Table 4
Average optimal strategic resilience decisions and costs for different probability characteristics.

	Single-supplier case			Multi-supplier case		
	ResC	$\|z\|$	$\|w\|$	ResC	$\|z\|$	$\|w\|$
Low-probability/high-impact	9.80	1.00	6.58	2.62	2.00	0.08
High-probability/low-impact	12.31	1.00	2.92	5.01	2.00	0.69

6.3. Sensitivity analysis

We discuss the benefits of considering multiple SCR strategies in a joint decision framework. Specifically, we study the impact of backup transportation modes (Section 6.3.1), the influence of disruption characteristics (Section 6.3.2), and the benefits of near-shoring (Section 6.3.3) on optimal decisions and costs by analyzing the differences between the problem sets P1–P8. We split the total objective value in a theoretical minimum cost ($MinC$) obtained by excluding disruptions from each instance and define the resilience cost ($ResC$) as the delta between the total expected costs and $MinC$. In addition, we discuss the impact of lead time aspects for a single supplier with different backup transportation mode cost settings in Section 6.3.4. Finally, Section 6.3.5 summarizes the insights from the sensitivity analysis.

6.3.1. Value of a backup transportation mode

Depending on the specific problem set, there might only be a single transportation mode that is available to ship products from the supplier to the production location. Thus, we are interested in understanding the impact of the availability of a backup transportation mode per supplier (P5–P8) against sets without this availability (P1–P4). Table 3 summarizes the average results. The availability of a backup transportation mode has significant effects in the single-supplier case, decreasing $ResC$ by 32% on average. Compared to sets with multiple suppliers, the improvement reduces to 2%. Interestingly, the availability of a backup transportation mode increases the tendency for inventory investments w, as additional capacities might be required to grasp the savings from operational re-routing fully. Overall, we see a significant drop in the cost-competitiveness of inventory investments once multiple suppliers are available.

6.3.2. Influence of disruption characteristics

Research in SCR literature has focused mostly on low-probability high-impact events. Table 4 presents the average results for the single and multi-supplier case when faced with different disruption characteristics. Interestingly, we see a shift in the importance of inventory investments. For low-probability but high-impact disruptions, significant investments of 6.58 additional inventory capacity units for the single-supplier case are needed, while they are reduced to nearly no investments when multiple suppliers are available. For high-probability disruptions, investments remain at least of some significance. While the resilience costs $ResC$ are not directly comparable between the two disruption probability characteristics, we see that the costs of the low-probability but high-impact disruptions can be more efficiently reduced through using multiple suppliers.

6.3.3. Cost-competitiveness of near-shoring

Lastly, we study the effects of near-shoring, thus sourcing from closer suppliers at higher transportation prices. We solve problem sets P5–P8 with 16 suppliers and set lead times from 4 to 34 days without changing the disruption-free transportation costs $\hat{c}^M_{im}$. Thus, transportation costs of the fastest supplier are 30% higher than the slowest for the low delta on mode cost sets (60% for Δ Mode: High). By only allowing suppliers with high lead times, we obtain the optimal costs and decisions without near-shoring. Table 5 summarizes the results by the delta on mode costs and the disruption characteristics. For our high delta on mode costs, near-shoring is not a cost-competitive strategy as no closer supplier is considered in any of the instances. This changes for the low delta scenario. While near-shoring can reduce the $ResC$ slightly for the low-probability and high-impact disruption situation (2.63%), these costs can be reduced by 23.93% for a high disruption probability.

6.3.4. Influence of time for the backup transportation mode

We discuss the impact of lead time aspects for the backup transportation mode on the optimal total resilience costs. So far, we have assumed a backup transportation mode with a fixed lead time of 14 days and a 130% cost increase compared to the lowest-cost sourcing option in the disruption-free state. While we have analyzed the impact of multiple suppliers with shorter lead-times at higher costs, we want to understand the interdependence between the backup transportation mode costs and lead times in a single supplier setting. Fig. 4 summarizes the results for three different costs of the backup transportation mode $\hat{c}^M_{im}$, a lead time from 4 to 34 days, and a main transportation mode with a lead time of 14 days that is prone to disruptions with costs of 0.13 in the disruption-free state.

Three main insights are drawn. First, as past orders triggered lead time periods prior to a disruption cannot be canceled, there is limited value in lead times of a backup transportation modes that are shorter than the incumbent main transportation mode lead time. In contrast, we even observe negligible resilience cost increases due to inventory effects in operational re-routing. However, secondly, if backup transportation mode lead times increase above 14 days, the overall resilience costs increase dramatically by up to 186% in the case of $\hat{c}^M_{im} = 0.15$. Lastly, this potential increase strongly depends on the cost delta between the main transportation mode and the backup transportation mode. While this 186% increases reduces to 19% for $\hat{c}^M_{im} = 0.3$, even these high backup transportation mode costs still can lower the resilience costs.

6.3.5. General insights on cost-competitiveness of resilience strategies

We summarize the findings of the numerical study based on the test instances P1–P8, which cover a variety of potential situations decision-makers will face in practice.

Table 5
The effect of near-shoring on average resilience costs with different disruption characteristics.

	Low-probability/high-impact						High-probability/low-impact					
	Δ Mode costs: Low			Δ Mode costs: High			Δ Mode costs: Low			Δ Mode costs: High		
	ResC	$\lvert z\rvert$	$\lvert w\rvert$	ResC	$\lvert z\rvert$	$\lvert w\rvert$	ResC	$\lvert z\rvert$	$\lvert w\rvert$	ResC	$\lvert z\rvert$	$\lvert w\rvert$
No near-shoring	2.63	2.00	0.00	2.72	2.00	0.00	4.85	2.00	0.67	5.09	1.67	2.67
W. near-shoring	2.56	2.00	0.00	2.72	2.00	0.00	3.91	2.00	0.33	5.09	1.67	2.67

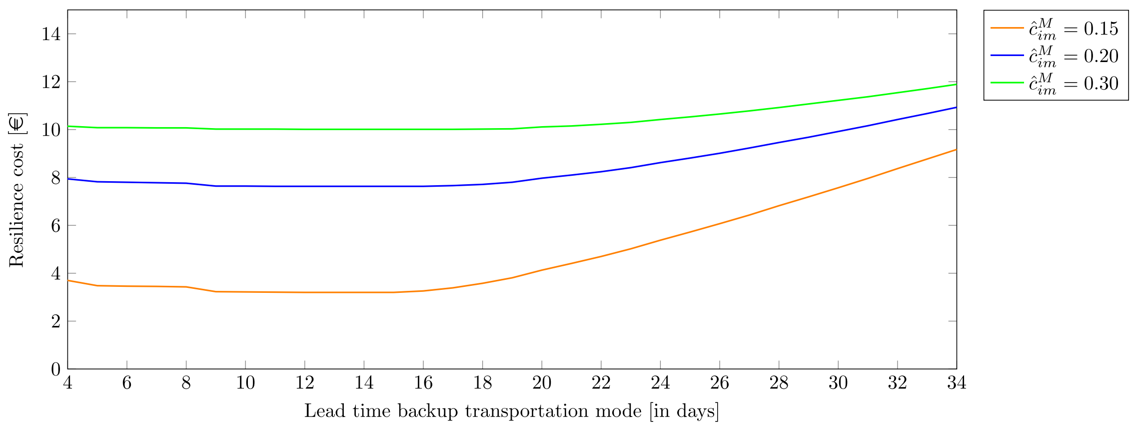

Fig. 4. Relationship between backup transportation mode costs and lead time.

- Especially in sourcing situations where only a single supplier is available (e.g., highly specialized products to be sourced), there is a high need to understand the possibilities of backup transportation modes in case the main transportation mode is disrupted. Even if these backup transportation modes require significant cost increases (e.g., more than 100%), they can still be valuable as long as they represent an improvement compared to the maximum disruption surcharges. The same accounts for sourcing situations in which multiple suppliers are generally available but sourcing is limited to a specific region in which multiple suppliers share the same transportation mode (e.g., ports, sea routes, inland waterways, etc.).
- Disruption probabilities and impacts have a direct effect on the cost-competitiveness of resilience strategies. Interestingly, there is an inter-dependence between the various measures and the characteristics of low-probability/high-impact and high-probability/low-impact disruption scenarios. While in cases where only one supplier is available, optimal inventory investments in the cost-optimal state are higher, this characteristic changes in the multi-supplier case.
- Near-shoring can be an efficient resilience strategy for disruptions that occur often enough and in situations where the lead times of the main transportation mode prone to disruptions can be significantly reduced. While in the low-probability but high-impact disruption scenario both high and low Δ mode costs are significantly lower for the fastest supplier (60% and 120%), the resilience costs can only be reduced on a modest level. At the same time, significant savings can be achieved through near-shoring for the high-probability/low-impact case.

7. Case study

A case study, motivated by a real-life example, assesses the cost-competitiveness of resilience strategies based on actual disruption data. Section 7.1 introduces the case in detail, while Section 7.2 presents numerical results. Finally, managerial insights are drawn in Section 7.3.

7.1. Case introduction

This case is based on a real-life example from a chemical company located on the border of the Rhine River, Germany. Typical for the region, more than 40% of the inbound supply is transported through inland shipping via the Rhine River and transportation accounts for up to 10% of sourcing costs. Within our analysis, we focus on one exemplary product whose transport costs account for 10% of the sourcing costs, normalized at a value of 1. Inventory holding consist of capital, handling, storage, and depreciation costs. We assume annual inventory holding costs of 20% of the product value ($c^H = 0.2$). 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 sufficient for customer requirements. Thus, we assume shortage costs that equal product value ($c^N = 1$).

Without disruptions, sourcing from Asia via ocean transport followed by inland shipping is the most cost-efficient transportation mode ($m = 1$). This mode has the longest lead time of $l_1 = 21$ and, without disruptions, the lowest transportation costs of $\hat{c}^M_{11} = 0.1$ per unit transported. However, this mode 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. We focus on three transportation alternatives to highlight the influences of lead time and cost differences. All are assumed to be free of disruptions. The product can be air shipped ($m = 2$), however at very high transportation costs $\hat{c}^M_{22} = 0.5$ but in short lead time ($l_2 = 7$) by the main supplier ($i = 1$). Two additional near-shore suppliers ($i = 2; i = 3$) are available to deliver the products. From the closest supplier, products can be transported via truck ($m = 3$) in very short lead time ($l_3 = 3$) at a modest price increase $\hat{c}^M_{23} = 0.14$. Even at lower costs $\hat{c}^M_{34} = 0.12$, but with higher lead times ($l_4 = 14$), rail shipments ($m = 4$) from eastern Europe are possible.

Concerning the disruption uncertainty of the cheapest transportation mode, Fig. 5 shows the water level fluctuations on the river Rhine

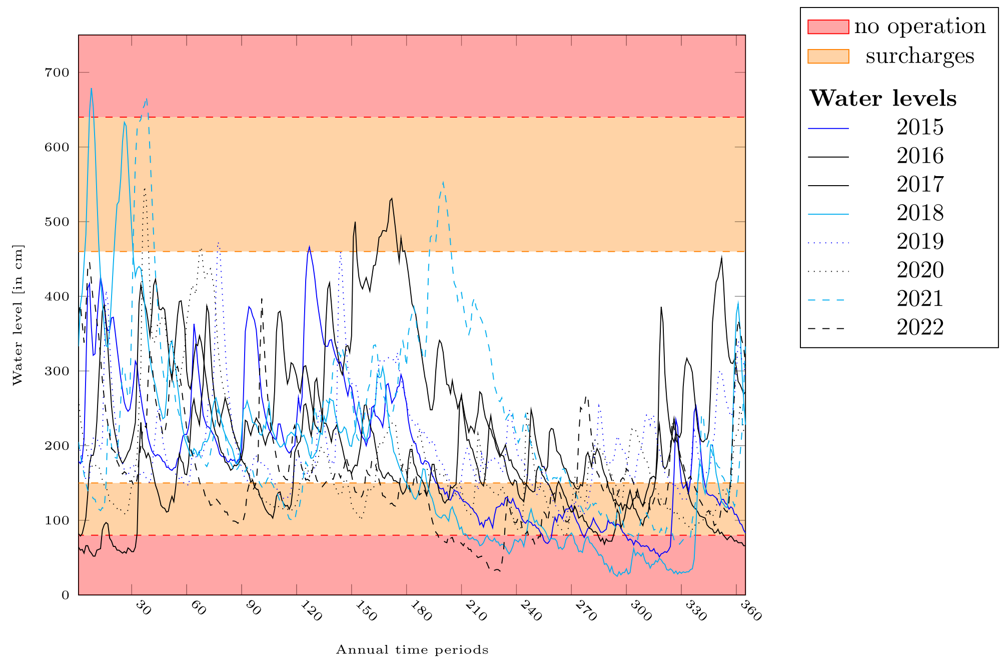

Fig. 5. Historical water levels at shipment critical point for river Rhine as main transportation mode ($m = 1$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
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	–

for the last eight years. 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. 5 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 6. Overall, the contractual surcharges range from a 78% to a 261% 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. 5 highlights water level thresholds for cost increases and the red line indicates transportation stops. To ensure that we cover the uncertainty of the problem entirely, we construct additional scenarios beyond the eight years of history and surcharges available (Contargo, 2023) by combining all quarters of each year randomly. As a result, we obtain 92 additional scenarios where each scenario occurs with a possibility of $\pi_s = \frac{1}{100}$.

7.2. Numerical results

7.2.1. Cost-optimal decision with uncertainty

Fig. 6 summarizes the cost-effectiveness from risk-taking to the full integrated decision model. Each delta (light blue bars) describes the cost-impact for the decision maker to consider the resilience strategies mentioned starting from the risk-taking strategy. The tactical bar describes the total expected costs when only allowing second-stage decisions. As a result, the following conclusions can be drawn. First, decision-makers need to invest in resilience as risk-taking results in the highest total expected costs of 386 (123% cost increase compared to the disruption-free costs). Second, there is a clear need for a joint consideration of resilience strategies. For example, allowing operational re-routing as well as a tactical inventory decision without any strategic measures improves the expected costs by 30% while the incorporation of all resilience strategies improves the total expected costs by 50%. In addition, the interdependence of the resilience strategies is highlighted as the incorporation of multi-sourcing increases the optimal inventory investment by 33% additional capacity. Lastly, still, the total expected costs across the eight years are 10% higher than the disruption-free ideal state. This shows that all strategies can only limit the disruption-driven cost increase. However, significant cost savings can be achieved compared to risk-taking.

Besides the optimal resilience strategies chosen, we are further interested in the potential effects of seasonality. Fig. 7 shows the average inventory across all scenarios and for the planning horizon of one year. As can be seen, the average inventory level varies throughout. Peak inventories can be seen in January ($t = 0$–10), May ($t = 120$–130, and August ($t = 230$–240) while no inventory is held in parts of April ($t = 90$–120) and July ($t = 180$–200). These peaks follow seasonal water level fluctuations. Time periods with no disruptions are either used to avoid inventory carrying, as in April, or increase inventory to peaks just prior times of increased disruption uncertainty, as in August for September. Thus, the tactical inventory decision is clearly influenced by seasonal characteristics. As a result, this emphasizes the need to evaluate potential disruption probability shifts during the planning horizon.

7.2.2. Benefit of information window increase through disruption prediction

As defined in Section 3.2, the information window describes the time a disruption is known to the decision-maker in its length and impact prior to the actual occurrence. To this end, all results are obtained taking no information window into account, i.e., assuming a disruption is not known in advance. However, significant efforts have been made to forecast disruptions, such as the water levels on the river Rhine in Germany (e.g., Bazartseren et al., 2003; Toonen, 2015). Thus,

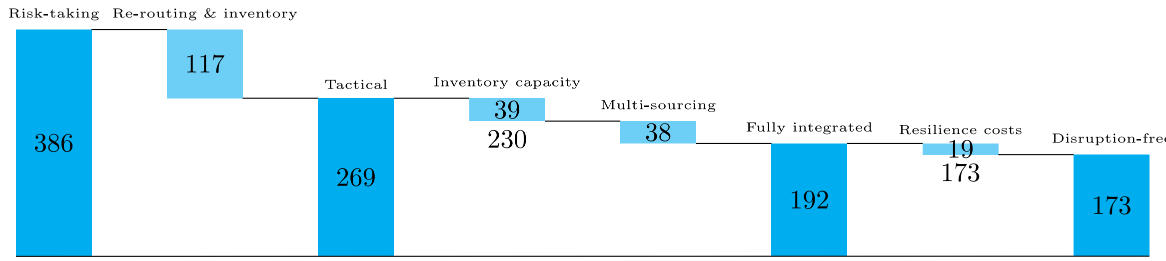

Fig. 6. Impact of resilience strategies on total expected cost. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

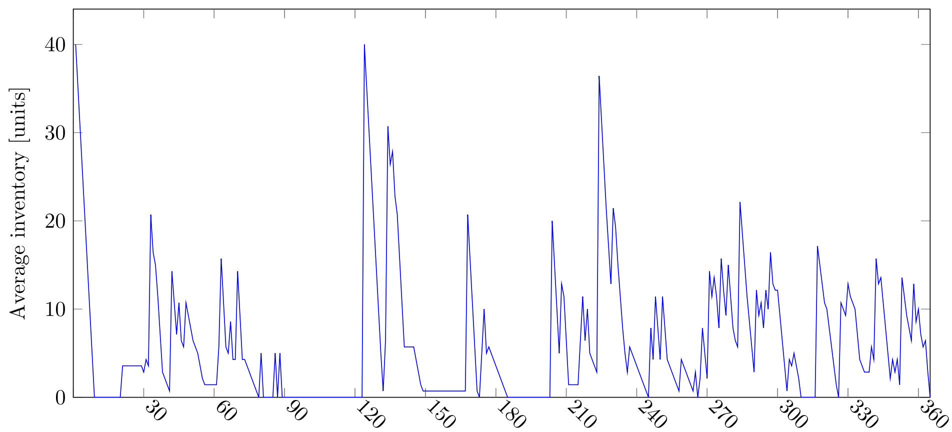

Fig. 7. Optimal average inventory for all scenarios across the planning horizon.

we want to understand the impact of the ability to predict disruptions while varying the lead times of the alternative transportation modes.

We increase the information window from 0 to 21 days, representing a maximum ability to predict disruptions of three weeks. Further, we analyze three different situations for the backup transportation modes. First option I with very short lead times ($l_3 = 1, l_4 = 7$), second option II with modest lead times ($l_3 = 7, l_4 = 14$), and third option III with long lead times ($l_3 = 14, l_4 = 21$). In practice, this represents three situations with varying geographical distances and available transportation modes of the backup suppliers. Fig. 8 highlights the results and their effects on the total resilience costs in %. The highest costs are observed for the last option with a time window of 0 days (set to 100% resilience costs). In comparison, without the ability to predict the disruption, shorter lead times already lower the resilience costs by more than 17%. In addition, knowing disruptions up to three weeks in advance can reduce resilience costs by up to 10%. Thus, the combination of shorter lead times and the ability to predict disruptions can reduce resilience costs by 27%. Generally, the resilience costs decrease with the information window, while the degree of reduction depends on the specific lead times. Overall, backup transportation modes' lead time significantly impacts the resilience costs. Thus, considering a backup transport alternative with shorter lead times but higher transportation costs could be more cost-competitive.

7.2.3. Limited operational re-routing capacities

So far, we have assumed unlimited operational re-routing capacities. However, alternative suppliers or transportation modes might only offer limited capacities on the operational level depending on the disruption characteristics or the product to be sourced. Thus, we conduct a sensitivity analysis by limiting the second-stage additional order quantities $\hat{x}_{imts}$ to a maximum of daily demand R_{im} by adding constraints (38) to the model formulation. We increase R_{im} from 0% to 180% in steps of 20%. In addition, we vary the information window from 0 to 3 days.

$$\hat{x}_{imts} \leq R_{im} \qquad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{T}_s, s \in \mathcal{S} \tag{38}$$

Table 7 summarizes the results. All information windows result in the identical total expected costs for a re-routing capacity of 0%. Using this as a baseline, we show the resilience cost improvements in %. The highest reductions can already be achieved if only a share of the daily demand can be operationally re-routed from alternative suppliers or through alternative transportation modes. In the case example, a re-routing capacity of 40% of the daily demand volume already achieves more than half of the full potential with unlimited re-routing. This effect can be explained through additional inventory requirements to benefit from unlimited re-routing capacities fully. Whereas no inventory investment w is required for the low capacities, starting from 80%, the benefits of re-routing require an inventory investment of $w = 1$, and in case of unlimited re-routing capacities, an investment of $w = 2$. The effects on the information window become increasingly relevant the higher the overall operational re-routing capacity. Whereas an information window of 1 day has only a minor cost effect for capacities $\leq$ 60%, the resilience costs are reduced by more than 10% for the unlimited capacities case (see Section 7.2.2).

7.3. Managerial insights

To summarize, the following insights are drawn:

- For high-probability but low-impact disruption situations, near-shoring can significantly reduce resilience costs even when transportation costs are 30% higher in the disruption-free state.
- Disruption probability characteristics influence the cost-competitiveness of inventory as SCR strategy. For equal probabilities, as in our numerical study, inventory investments are mainly competitive when backup transportation modes or alternative suppliers are unavailable. In the case, however, the

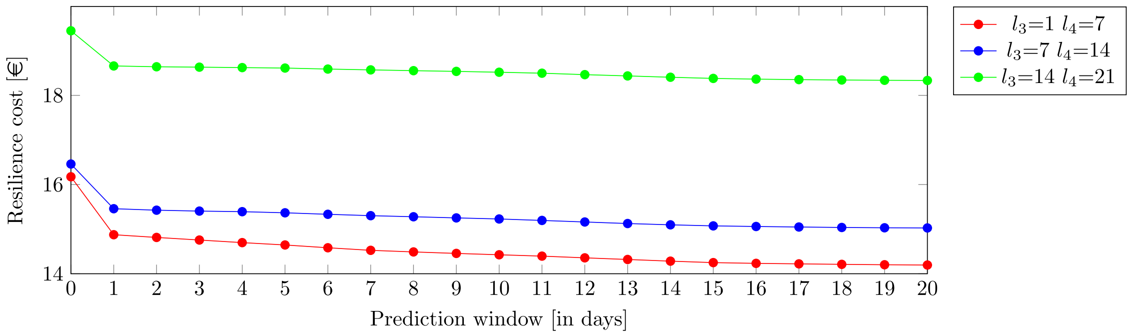

Fig. 8. Effect of disruption prediction on various lead-times of backup transportation modes.

Table 7
Potential of re-routing capacities on resilience cost reduction based on scenario without re-routing.

Information window [days]	Maximum capacities for daily operational re-routing [% of daily demand]										
	0	20	40	60	80	100	120	140	160	180	∞
0	–	9%	13%	16%	18%	20%	20%	20%	20%	20%	21%
1	–	9%	14%	17%	20%	21%	22%	22%	22%	23%	24%
2	–	10%	15%	18%	21%	22%	23%	23%	23%	24%	24%
3	–	10%	15%	19%	21%	23%	23%	24%	24%	24%	25%

seasonal disruption characteristics result in time-dependent inventory build-ups along the planning horizon. Inventory build-ups can be efficient in time periods with low disruption probability prior to time periods with an increased disruption probability. In comparison, equal disruption probabilities would demand high inventory levels throughout the planning horizon, which lowers the cost-competitiveness of inventory as SCR strategy.

- The possibility to predict disruptions in the short-term, i.e., days in advance, can significantly lower resilience costs. Most notably, the biggest reductions can already be achieved if a disruption is known a day earlier, as operational re-routing can be triggered. To benefit from this potential, sufficient operational re-routing capacities must be available. Similar to the prediction ability, the largest share of improvement potential is already achieved if at least 60% of the daily demand can be re-routed on the operational level. In addition, investing a premium in near-shore backup suppliers, i.e., at higher transportation rates but lower lead times, can be cost-competitive, particularly with the ability to predict disruptions.

8. Conclusion and outlook

We have addressed disruption uncertainty in the integrated transportation problem from the strategic to operational level within a two-stage decision process. To solve large problem instances efficiently, we have proposed a BD algorithm enhanced through valid and lower-bound-lifting inequalities, branch-and-benders-cut, and a warm-start heuristic. The computational results show that the BD algorithm finds strong solutions for large problem instances, or even optimal ones, where commercial solvers do not find feasible solutions. Through numerical studies and a case from the chemical industry, we have shown that disruption probability characteristics influence the choice of optimal resilience strategies on strategic and tactical levels as well as costs. Near-shoring, even at higher disruption-free costs, can help to significantly lower costs when disruptions occur regularly. If sufficient daily operational re-routing capacities are available, predicting disruptions at least a day in advance can significantly lower resilience costs.

Although we have highlighted the benefits of our models and solution approach, our study is not without limitations. We studied a single-product SCND problem with a single echelon and demand destination. Thus, the proposed model can set the stage for future models that consider lead times for transporting multiple products with multiple inventory storage points under disruption uncertainty to understand the effects of various product characteristics on the optimal SCR strategy mix. Further, it would be interesting to analyze the impact of resilience strategy mixes for other industries with different cost structures. Another interesting research direction would be incorporating data-driven techniques to more adequately account for the stochastic nature of the problem at hand.

CRediT authorship contribution statement

Daniel Müllerklein: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pirmin Fontaine:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

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