Optimizing facility locations and network design in hazardous material transportation

by

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Abstract

Optimizing the combined facility location and network design decisions in hazardous material (hazmat) transportation is a complicated problem. The problem involves two stakeholders, the government, whose objective is to minimize the total risk of population exposure to dangerous materials by closing certain roads and nodes, and the carrier, which aims to minimize the total transportation cost by choosing the shortest paths from hazmat generation nodes to processing facilities in addition to reducing hazmat processing and facility construction costs. The government's decisions regarding which roads to close and which nodes to ban impact the carrier's choice of paths and facility location respectively. Hence, the government must anticipate the carriers' reactions while making network (closure or banning) decisions. To address this problem, we propose a novel bi-level programming formulation that integrates both parties' objectives. A cutting plane algorithm is designed to address the bi-level structure for both stakeholders' decisions. Finally, a real-world case study of a transportation network is conducted to demonstrate the effectiveness of our proposed approach in reducing the total risk and cost and reveal insights that can be used to facilitate policy-making in terms of hazmat transportation and processing.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

Hazardous materials (hazmats) refer to any type of materials, from solids to gases and liquids that can harm people and the environment in any way (United Nations, 2009). These materials encompass a wide range of chemical, biological, radiological, and nuclear substances, each with the potential to cause harm if they are not properly handled or released into the environment or if humans are exposed to them. Hazardous materials are transported through different modes including air, water, road, rail, and pipeline. In this thesis, the focus is on road transportation as trucks are the most popular mode of hazmat transportation (Erkut et al., 2007).

The transportation and process of hazmat is a serious concern because accidents or mismanagement can lead to dire consequences, including toxic exposures, fires, explosions, and environmental contamination. Incidents can occur at any stage, including loading, unloading, shipping, and processing hazmat. The harm to people and the environment includes but is not limited to health impacts, environmental damage, and economic costs. As a result, governments around the world have developed regulations and strategies to manage and mitigate the risks associated with the transportation and management of hazardous materials. These efforts aim to prevent accidents and minimize the impact of any incidents.

To regulate the transportation of hazmat, governments employ various policies including banning certain roads for hazardous material carriers, applying tolls to links, and locating hazmat response teams (Ke et al., 2023). At the same time, hazmat carriers need to find the most cost-effective possible way for hazardous material transportation and processing. To do so, when choosing the route for hazmat transportation and the location for processing it, they usually choose the shortest path to the facilities to reduce the total cost. This shortest path is not always the safest route and therefore, is not aligned with the government's objective of reducing the risk of hazmat transportation. To deal with these conflicting goals of the involved decision-makers, one can utilize a bi-level model that depicts the objectives of the government and carrier respectively at the upper and lower level (Erkut et al., 2007). The government intends to minimize the risk of hazmat transportation but the carrier aims to minimize the cost associated with it. The government's policies impact the hazmat managers' decisions, and vice versa, which makes this a challenging and complex problem to solve (Liu and Kwon, 2020).

What mainly distinguishes our work from previous ones is considering hazmat facility location which is often overlooked in hazmat network design. Our thesis introduces a bi-level programming formulation that simultaneously addresses network design and facility location problems. We focus on developing an approach to modeling the relationship between the government and hazmat carriers, which takes into account the different objectives and constraints of each decision-maker. A key aspect of this approach is the incorporation of the government's node ban policy. That is, the government may restrict certain areas from being used for hazmat facilities due to their high risk. Integrating this concept into our model allows us to explore the interactions between government restrictions and hazmat carrier's facility and routing decisions.

More specifically, we construct a bi-level optimization model, where the upper level reflects the government's network decisions and the lower level represents the carrier's location-routing plan. To solve the proposed bi-level model, an exact cutting-plane algorithm tailored to our specific model that provides optimal solutions for both decision-makers is developed. We also conduct a detailed numerical analysis to validate our model, in order to prove its effectiveness in real-world scenarios. We also perform a robust analysis to assess the model's sensitivity to variations in key parameters, to ensure that the proposed solutions remain effective under different conditions. These contributions enhance our understanding of the closely linked relationship between regulatory policies and the design of hazmat transportation networks.

The rest of this thesis is structured as follows. Chapter 2 reviews the literature related to this research. In Chapter 3, the problem statement and mathematical formulation of the model are presented, while the solution procedure is given in Chapter 4. Moreover, the numerical tests of the model are outlined in Chapter 5. Finally, concluding remarks and future research directions are discussed in Chapter 6.

Chapter 2

Literature Review

In this chapter the literature is reviewed in three categories: Hazmat facility location problem (Section 2.1), hazmat network design problem (HNDP) (Section 2.2), and a combination of these two categories (Section 2.3). Then we describe the research gaps in Section 2.4 and state our contribution motivated by those.

2.1 Hazmat facility location problem

Scholars have considered various objectives in addressing hazmat facility locations. Goldman and Dearing (1975) are known to be the first researchers to address optimal locations for partially noxious facilities (Erkut and Neuman, 1989). Current and Ratick (1995) introduced a multi-objective model for combined hazmat location/routing decisions. Their facility location decisions were impacted by the population density around each location and the risk associated with facilities. Helander and Melachrinoudis (1997) focused on integrated location and routing models for minimizing the number of accidents during the transportation of hazmat. Besides considering two different routing policies, they proposed two types of location models: the reliable 1-median and a location framework for considering multiple routes. They also presented vertex optimality results for both problems.

Afterward, Cappanera et al. (2003) simultaneously addressed a facility location and routing problem of obnoxious materials and proposed a Lagrangean heuristic approach and a Branch and Bound algorithm to solve it. A multi-objective approach was presented by Zhang et al. (2005) for analyzing hazardous material location-routing decisions. Facility location decisions were made based on the costs associated with constructing a facility at a candidate location and risk equity. Carotenuto et al. (2007) explored the development of minimal risk paths for hazmat road transportation between specific origin-destination pairs in a regional area, focusing on selecting paths that not only minimize the overall risk of shipments but also distribute this risk equitably among the population. Xie et al. (2012) presented a multi-objective model, formulated as a mixed integer linear program that optimized transfer yard locations and hazmat transportation routes while considering risk and cost constraints. Jarboui et al. (2013) introduced several variable neighborhood search (VNS) heuristics to address the location routing problem involving multiple capacitated depots and one uncapacitated vehicle per depot, aiming to identify optimal depot locations and design cost-efficient vehicle routes. In a more recent work, Ardjmand et al. (2015), built a novel mathematical model for the location and routing in facilities that generate hazmat and disposal sites and used a genetic algorithm to solve it. Romero et al. (2016) utilized the Gini coefficient to evaluate equity in hazmat facility location and routing problem and presented a combination of Lagrangean relaxation with column generation to solve it.

Later, Hu et al. (2019) applied a multi-objective optimization method for the identification of the optimal routes in hazardous material logistics under the constraint of traffic restrictions on inter-city roads. They also assumed there are multiple paths between every possible origin-destination pair. To solve their model, a single genetic algorithm and an adaptive weight genetic algorithm were designed, whose chromosomes contained two types of genes, representing warehouses and transportation routes respectively. To tackle a hazmat location-routing problem with multiple origin-destination pairs and multiple products, Diego Beneventti et al. (2019) proposed a multi-objective programming model that considers maximizing the minimum weighted distance between hazardous facilities and the exposed vulnerable population, to minimize routing and location costs and the total hazard imposed on the non-vulnerable population. Tasouji Hassanpour et al. (2021)

used an augmented epsilon constraint method to address a hazmat location-routing problem with edge unavailability, time-dependent parameters, and delivery time window. The decision-making process focused on determining whether a warehouse should be opened on the available nodes.

Facility problems have also been broadly explored in the literature of hazardous waste management. Interested readers are referred to Delfani et al. (2021), Boonmee et al. (2023), and Zabihian-Bisheh et al. (2024) for detailed reviews.

2.2 Hazmat network design problem (HNDP)

Hazmat network design problem (HNDP) involves the strategic planning, optimization, and operational management of transportation networks to facilitate the safe and efficient transportation of hazardous materials. The ultimate objective of studies in HNDP is to design transportation networks that prioritize the safe and reliable delivery of hazardous materials while minimizing potential risks and environmental impacts, and ensuring the health and safety of communities along the transportation routes.

As a policy to regulate hazmat shipment, many papers investigated the impact of partial or full road closure. Kara and Verter (2004) were pioneers in examining the relationship between regulators and carriers and proposed a bi-level programming model for road network design. Erkut and Alp (2007) formulated a tree selection problem for a hazmat network design problem to identify hazmat routes in a major population center by closing roads with the highest risk. They offered alternative ways to the carriers by expanding the network. Erkut and Gzara (2008) presented a heuristic algorithm that was able to find low-risk networks in a short time for a network design problem in hazmat transportation. They formulated the problem as a bi-level network flow model and assessed it by comparing it to three other decision scenarios. Verter and Kara (2008) introduced a path-based formulation to address a network design problem in hazardous material transportation. They managed to develop various alternative solutions by changing the routing choices for each shipment and thus identify transport policies for hazardous materials that are mutually agreeable and balanced in terms of safety and cost-effectiveness. Bianco et al. (2009) assumed that regional and local government authorities have the responsibility to regulate hazmat transportation by imposing volume restrictions on network links. The regional authority seeks to minimize transport risks across the entire region, while local authorities focus on minimizing risks within their jurisdictions. This creates a challenge for the regional authority to ensure equity in risk distribution among different local jurisdictions. To overcome this challenge, the authors proposed a linear bi-level programming approach that considers both total risk minimization and risk equity in the design of the hazmat transportation network. Amaldi et al. (2011) considered a network design problem for hazmat transportation and they proved that a hazmat transport network design problem where the government bans some arcs is NP-hard even in its simplest form. Gzara (2013) studied a combinatorial bi-level formulation for hazmat network design and introduced an exact cutting plane algorithm to solve it, where minimum risk and minimum cost network flow problems were solved iteratively. To minimize the time that containers are at a terminal, Assadipour et al. (2014) proposed an analytical approach aiming at reducing the time for the unloading of inbound vessels and the loading of outbound vehicles in a hazmat intermodal network. Sun et al. (2016) delved into robust network design problems for hazmat transportation with risk uncertainty on each link for both each shipment and across all shipments. As a solution, they utilized an existing heuristic and a Lagrangian relaxation heuristic to address sub-problems within the framework. Taslimi et al. (2017) provided a bi-level network design problem for hazmat transportation in which the government was responsible for finding optimal locations for response teams and constructing extra links for hazmat transportation. For solving medium-size problems, they presented a single-level mixed integer linear model and a greedy heuristic algorithm for large-size problems. Esfandeh et al. (2018) modeled a hazmat network design problem with time-dependent road closure using an alternative-based model so that carriers' departure times and route choices were controlled. To solve their model, they provided heuristic algorithms based on column-generation and label-setting. Fontaine and Minner (2018) transformed a bi-level hazmat transport network design model into a mixed-integer linear program by applying the Karush–Kuhn–Tucker (KKT) optimality conditions. A multi-cut Benders decomposition and a partial decomposition technique were introduced to find an optimal solution.

As an alternative to road closure, scholars further proposed toll-setting approaches for regulating hazmat shipments. Using comparative analysis, Marcotte et al. (2009) indicated that setting tolls to regulate hazmat transportation can be more effective than road closure in hazmat network design. To control both regular and hazmat vehicles at the same time, Wang et al. (2012) introduced a dual toll pricing method to reduce the risk of transporting hazmat. Masoud et al. (2015) integrated hazmat network design with dual toll pricing to introduce an effective traffic control policy for hazmat. To mitigate the risk of hazmat transportation in a bi-level network design problem, Esfandeh et al. (2016) investigated the policy of toll setting and presented a two-stage solution with two different methodologies to solve each stage. Bianco et al. (2016) explored a toll-setting approach for managing hazardous material transportation, focusing on minimizing overall network risk while ensuring equitable risk distribution, and proposed mathematical programming with equilibrium constraints (MPEC). In their paper, Ke et al. (2020) proposed a dual-toll policy using a multi-degree fuzzy incident rate to manage hazardous material transportation risks in a road network by formulating a bi-level programming problem. They incorporated risk equity considerations and proposed a new risk measurement definition to reflect the uncertain nature of real transportation situations.

Some authors suggested a mixture of network design policies such as road construction, toll setting, and road closure for. López-Ramos et al. (2019) developed a mixed-integer non-linear bi-level problem for hazmat network design, in which the leader aims at maximizing its profit by considering toll income, road construction and closure costs, and hazmat risk exposure, while the followers minimize their travel costs including congestion and toll charges. A specialized local search was utilized to solve their model. Ke et al. (2023) constructed a scenario-based bi-level network design problem for hazmat and proposed some risk-mitigation mechanisms and considered factors like emergency response time, hazmat response team locations, toll schemes, road closures, and new road constructions, while also addressing demand uncertainties through a scenario-based approach. They managed to optimally solve the proposed model using a single-level reformulation and a three-stage heuristic method.

2.3 Combined hazmat facility location and Network design problem

Despite the close relationship between the facility and the transportation network, there are very few papers that consider facility location combined with network design for hazardous material transportation. Berglund and Kwon (2014) addressed a robust facility location problem in hazmat transportation in which the upper-level goal is to minimize the total cost construction cost and shipping risk while taking into account the routing decisions of hazmat carriers who aim to minimize their transportation cost. They assumed that the hazmat facility operators and hazmat carriers were two independent entities. The objective is to select optimal facility locations within a network to process hazmat generated at specific nodes. For smaller or medium-sized problems, they proposed an exact full enumeration method, while for larger problems, they investigated the use of a genetic algorithm.

A bi-level optimization problem was considered by Liu and Kwon (2020), wherein both facility locations and network design in hazardous materials transportation were simultaneously optimized. The authors accounted for uncertainty in hazmat exposure and hazmat transport demand by adopting a robust optimization approach with multiplicative uncertain parameters and polyhedral uncertainty sets. The resulting problem entailed a min-max problem in the upper level with the objective of minimizing facility construction cost and worst-case risk and a shortest-path problem in the lower level to minimize total shipment cost.

To simultaneously optimize facility locations and network design in hazmat transportation, Yue et al. (2022) studied a Stackelberg game and lane reservation approach as a bi-level optimization problem. The government's objective at the upper level is to reduce the cost of establishing facilities, traffic impact cost, and hazardous material exposure risk. This is achieved by implementing a reserved lane network and mandating carriers to transport goods within this network. In the lower level, the follower aims to minimize shipping expenses by choosing a route that meets the time limit. The authors used a genetic algorithm to solve the model.

2.4 Literature gaps and our contribution

Scholars have dedicated considerable effort to addressing hazmat-related facility and network design issues from diverse perspectives, as evident in the literature reviews above. However, this area still presents significant research opportunities, with noticeable gaps that require thorough attention.

Firstly, considering the fact that very few studies have considered facility location combined with network design for hazardous material transportation, there is a clear need for further research in this domain. Our contribution lies in offering a comprehensive framework for a combined bi-level network design and facility location for hazmat transportation that accounts for the conflicting objectives of the government and the hazmat carrier. This approach not only fills the gap in existing literature but also provides a practical solution for industry stakeholders.

Secondly, through our extensive review of existing literature, we have found no prior studies that have examined the concept of node bans, either in the hazmat domain or in any other field. Implementing regulations that prohibit construction in nodes with high population density can significantly reduce the risk of population exposure to hazardous materials. In this thesis, we introduce this concept to control the risk associated with facility location. Additionally, we consider road segment closure for hazmat transportation, which serves the same purpose as facility location closure and reduces the risk of population exposure to hazmat along the roads. Moreover, while previous studies that considered combined facility location and network design problems (Berglund and Kwon (2014); Liu and Kwon (2020); Yue et al. (2022)) have assigned the responsibility of hazmat facility location to the government, our thesis presents a more realistic scenario where the carrier makes these decisions, guided by the government's node policy. This approach provides a closer representation of actual industry practices, where the government designates several potential locations and the carrier decides on the exact sites for the facilities.

Moreover, acknowledging the fact that heuristic and meta-heuristic algorithms only provide near-optimal solutions at best, more research is needed with exact methodologies that provide more realistic and accurate solutions. In this thesis, we propose a cutting-plane algorithm to solve our problem that can be used to inform policy decisions and improve the transportation and processing of hazardous materials. This methodological contribution aims to enhance the precision and applicability of solutions in the hazmat transportation sector.

In addition to addressing the aforementioned gaps, our research includes thorough numerical analyses, specifically focusing on the sensitivity and robustness of our combined facility location and network design model. Through detailed breakdowns of risk and cost, we demonstrate the model's efficacy in managing hazmat transportation and facility location under various scenarios, including changes in facility capacity, incident rates, shipping costs, and the number of trucks. Our analyses revealed important insights into the impacts of network connectivity, the number of nodes and arcs, and shipment quantities on overall risk and computational performance, and highlighted the importance of these factors in optimizing hazmat transportation networks. These findings show the model's practical applicability and robustness in real-world settings, which provides valuable guidance for policymakers.

Chapter 3

Model Development

3.1 Problem statement

In this thesis, we examine a problem that involves simultaneous considerations of network design and hazmat facility location. Two parties are engaged: the authority (i.e., the government) that design the network and the hazmat carrier that transports different types of hazardous materials and makes facility location decisions. The upper-level authority aims to minimize hazmat exposure risk, while the carrier seek to minimize transportation costs, facility construction costs, and hazmat processing costs. The government must make decisions regarding road closures and node bans, while the carrier selects the transportation routes and make facility location decisions. We assume that the points of origin for hazardous materials are known, but processing facility locations are not. If multiple facilities are available within the network, the carrier chooses the closest one. The authority should take into account facility location decision and route choice of the carrier (assuming that they choose the shortest path) while making decisions regarding road and node closure and the carrier's route decisions depend on the choices made by the authority, who considers road and node bans when designing the hazmat network. The bi-level structure of the problem is illustrated in Figure 3.1.

We consider the following assumptions for our problem.

1. It is assumed that the network is indirect, which means shipments can go either

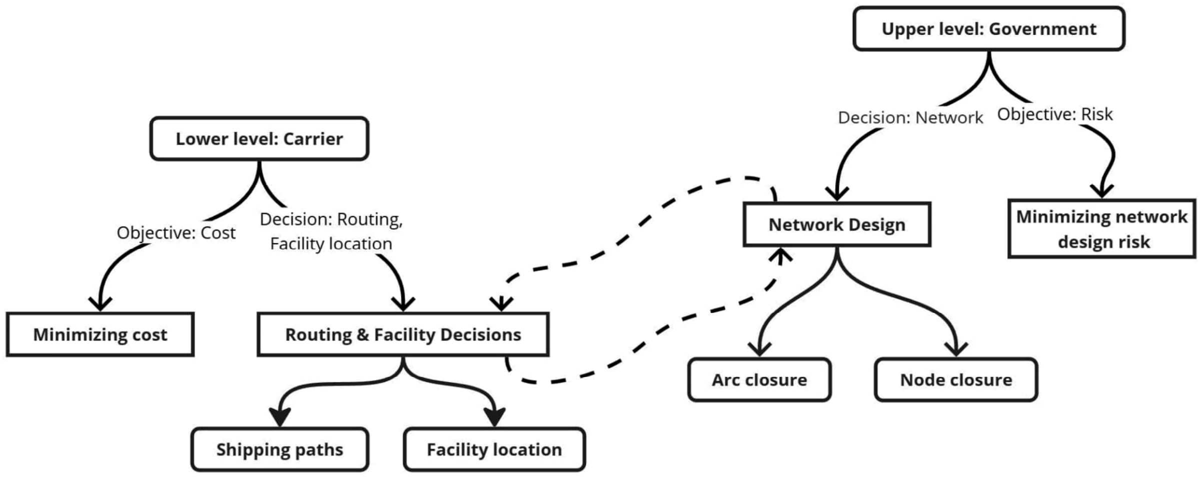

Figure 3.1: Bi-level structure.

way on a link.

2. The same policy is applied to both directions on one link. For instance, if link (i, j) is closed for one type of hazmat shipment, then link (j, i) is also restricted to that hazmat.

3. Our model operates under the assumption that only one type of hazmat can be processed in any processing facility.

4. All hazmat generation nodes are known but their destination nodes, hazmat processing facilities, are to be determined.

3.2 Mathematical model

We consider a graph $(\mathcal{N}, \mathcal{A})$ in which $\mathcal{N}$ is the set of nodes and $\mathcal{A}$ is the set of arcs. We assume that hazmat generation nodes are known while processing facilities are not. The carrier wants to determine the optimal number and locations for processing facilities. We also consider that these facilities may be sources of hazmat. At the upper level, authority aims to minimize hazmat exposure risk. At the lower level, carrier's objective is to minimize transportation costs, facility construction costs, and hazmat processing costs. We calculate the unit risk for each arc (i, j) as stated in Ke et al. (2023):

$$SR_{ijs} = POP_{ijs}\ DIS_{ij}\ RR_h\ IR_{ij},$$

where POP_{ijs} indicates the population exposure within a specific radius per unit distance on arc (i, j) for an incident caused by shipment s, DIS_{ij} is the length of arc (i, j), RR_h is the release rate of hazmat h, and IR_{ij} stands for the incident rate on arc (i, j). We evaluate the unit risk for each node i in the same way:

$$FR_{ih} = POP_{ih}\ RR_h\ IR_i,$$

where POP_{ih} is the population exposure within a specific radius per unit distance on node i for hazmat h and RR_h is the release rate of hazmat h and IR_i stands for the incident rate on node i.

We formulate the bi-level optimization problem for the combined location-network design using the notation presented in Table 3.1.

3.2.1 Upper level

$$\min_{y,z} \quad \sum_{(i,j)\in\mathcal{A}} \sum_{h\in\mathcal{H}} \sum_{(o,h)\in\mathcal{S}} SR_{ijh}\ N_{oh}\ x_{ijoh} + \sum_{i\in\mathcal{M}} \sum_{h\in\mathcal{H}} FR_{ih}\ q_{ih} \tag{3.1}$$

s.t.

$$\sum_{h\in\mathcal{H}} FR_{ih}\ q_{ih} \leq RiskCap_i\ w_i \qquad \forall i \in \mathcal{M} \tag{3.2}$$

$$z_i \in \{0,1\} \qquad \forall i \in \mathcal{M} \tag{3.3}$$

$$y_{ijh} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, \forall h \in \mathcal{H} \tag{3.4}$$

In the upper level objective function (3.1), the first part represents risk of shipping hazmat on arc (i, j) and the second component shows risk of processing hazmat at node i. Constraint (3.2) ensures that the total amount of risk at node i does not exceed the

Table 3.1: Mathematical notation

Sets	
$\mathcal{N}$	Set of nodes, indexed by i and j.
$\mathcal{A}$	Set of arcs, indexed by (i,j).
$\mathcal{H}$	Set of hazardous materials, indexed by h.
$\mathcal{S}$	Set of hazmat shipments of hazmat type h and origin o indexed by (o,h).
$\mathcal{M}$	Set of potential facility locations for the government.
$\mathcal{O}(o,h)$	Origin node (Generation node) for shipment with origin o and hazmat type h, $(o,h) \in \mathcal{S}$, $\mathcal{O}(o,h) \cap \mathcal{M} = \emptyset$.
Parameters	
N_{oh}	The number of trucks required for shipment with origin o and hazmat type $h \in \mathcal{H}$.
SC_{ijh}	Cost of shipping one unit of hazmat $h \in \mathcal{H}$ on arc $(i,j) \in \mathcal{A}$.
SR_{ijh}	Risk of shipping one unit of hazmat $h \in \mathcal{H}$ on arc $(i,j) \in \mathcal{A}$.
FC_i	Cost of facility construction at node $i \in \mathcal{M}$.
PC_{ih}	Cost per unit for processing hazmat $h \in \mathcal{H}$ at node $i \in \mathcal{M}$.
FR_{ih}	Risk per unit of hazmat $h \in \mathcal{H}$ processed at node $i \in \mathcal{M}$.
Cap_i	Capacity of facility at node $i \in \mathcal{M}$ for processing hazmat. (How much hazmat it can process).
$RiskCap_i$	Maximum allowable risk at facility i.
Upper-Level Variables	
y_{ijh}	1, if arc $(i,j) \in \mathcal{A}$ is available for shipments of hazmat $h \in \mathcal{H}$; 0, otherwise.
z_i	1, if the carrier is allowed to build a facility at node $i \in \mathcal{M}$; 0, otherwise.
Lower-Level Variables	
x_{ijoh}	1, if arc $(i,j) \in \mathcal{A}$ is chosen for shipment with origin o and hazmat type h, $(o,h) \in \mathcal{S}$; 0, otherwise.
w_i	1, if a facility is built at node $i \in \mathcal{M}$; 0, otherwise.
q_{ih}	The total amount of hazmat $h \in \mathcal{H}$ processed at node $i \in \mathcal{M}$.

maximum allowable risk capacity at facility i. Constraints (3.3) and (3.4) clarify the domains of decision variables.

3.2.2 Lower level

$$\min_{x,w,q} \quad \sum_{(i,j)\in\mathcal{A}} \sum_{h\in\mathcal{H}} \sum_{(o,h)\in\mathcal{S}} SC_{ijh}\ N_{oh}\ x_{ijoh} + \sum_{i\in\mathcal{M}} FC_i\ w_i + \sum_{i\in\mathcal{M}} \sum_{h\in\mathcal{H}} PC_{ih}\ q_{ih} \tag{3.5}$$

s.t.

$$\sum_{(i,j)\in\mathcal{A}} x_{ijoh} - \sum_{(j,i)\in\mathcal{A}} x_{jioh} \begin{cases} = 1 & \text{if } i \in \mathcal{O}(o,h) \\ \geq -w_i & \text{if } i \in \mathcal{M} \\ = 0 & \text{Otherwise} \end{cases} \qquad \forall i \in \mathcal{N}, \forall (o,h) \in \mathcal{S} \tag{3.6}$$

$$x_{ijoh} \leq y_{ijh} \qquad \forall (i,j) \in \mathcal{A}, \forall h \in \mathcal{H} \tag{3.7}$$

$$w_i \leq z_i \qquad \forall i \in \mathcal{M} \tag{3.8}$$

$$\sum_{h\in\mathcal{H}} q_{ih} \leq Cap_i \; w_i \qquad \forall i \in \mathcal{M} \tag{3.9}$$

$$q_{ih} = \sum_{(o,h)\in S} N_{oh} \; (\sum_{(j,i)\in\mathcal{A}} x_{jioh} - \sum_{(i,j)\in\mathcal{A}} x_{ijoh}) \qquad \forall i \in \mathcal{M}, \forall h \in \mathcal{H} \tag{3.10}$$

$$x_{ijoh} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, \forall (o,h) \in \mathcal{S} \tag{3.11}$$

$$w_i \in \{0,1\} \qquad \forall i \in \mathcal{M} \tag{3.12}$$

$$q_{ih} \geq 0 \qquad \forall i \in \mathcal{M}, \forall h \in \mathcal{H} \tag{3.13}$$

The objective function of the lower level (3.5) minimizes the carrier's transportation cost, the construction cost of facilities, and the processing cost of hazmat. Constraint (3.6) ensures that origin nodes have a net outflow of 1. If node i is chosen as a facility ($w_i = 1$), it can have a net outflow of -1 if it is selected as a destination, or 0 otherwise. If node i is not selected as a facility ($w_i = 0$), it is considered an intermediate node with zero net outflow. All other intermediate nodes must also have a zero balance. Constraint (3.7) indicates that the hazmat shipments can only be transported through available arcs and constraint (3.8) makes sure that the processing facilities can only be used if it is not banned. Constraint (3.9) guarantees that the total amount of all types of hazmat processed at each facility does not exceed the facility's capacity. Moreover, it indicates that hazmat can only be processed at a facility that has been built. Constraint (3.10) states that the total amount of hazmat processed at facility i is equal to the sum of all hazmat shipped to that facility. Constraints (3.11), (3.12), and (3.13) clarify the domains of variables.

Chapter 4

Solution Procedure

Bi-level models, such as the one we have developed, are proven to be inherently NP-hard, making them computationally challenging to solve. This complexity arises from the hierarchical structure of the problem, where decisions at the upper-level influence and are influenced by decisions at the lower level. Due to this complexity, many researchers tackle bi-level problems using heuristic and meta-heuristic algorithms, such as the Genetic Algorithm and Tabu Search. These methods, while useful, typically yield near-optimal solutions rather than guaranteeing exact optimality.

This thesis introduces an innovative approach by developing a cutting-plane algorithm specifically designed for our integrated facility location and network design model for hazardous materials (hazmat). Inspired by the methodology presented by Gzara (2013) and Liu and Kwon (2020), our algorithm iteratively refines the feasible region of the optimization problem by incorporating additional linear constraints, called cuts. This powerful exact solution method aims to improve the accuracy and effectiveness of the optimization process, delivering precise solutions that are essential for the meticulous management of hazmat transportation and facility location planning.

4.1 A cutting-plane algorithm

The cutting-plane algorithm addresses the intricacies of bi-level optimization by decomposing the problem into two interrelated components: the master problem (upper level) and the sub-problem (lower level). The algorithm iteratively solves these problems, generating and incorporating cuts until convergence is achieved. we first need to transfer the location and network design problem (LNDP) to a pure network design problem (PNDP), following the method introduced by Melkote and Daskin (2001) and add a dummy node 0, which is connected to all candidate facility locations through dummy links with zero cost and zero risk as illustrated in 4.2 (Liu and Kwon, 2020).

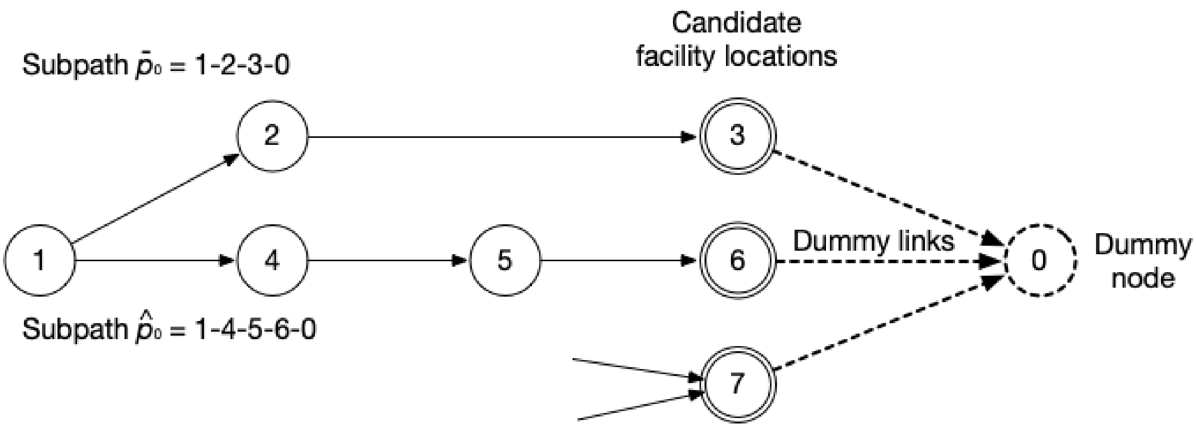

Figure 4.1: Convert from LNDP to PNDP (adapted from Liu and Kwon (2020))

The following flowchart (Figure 4.2) and sections detail the cutting-plane algorithm's steps and its application to our bi-level model.

4.1.1 Algorithm overview

Initialization Start with an initial feasible solution for the master problem, solving it to obtain the decision variables $(\overline{x}, \overline{y}, \overline{z}, \overline{w}, \overline{q})$ and the risk associated with them.

Sub-Problem Solution Use the values of $\overline{y}$ and $\overline{z}$ from the master problem to solve the sub-problem, yielding the solution set $(\widehat{x}, \widehat{w}, \widehat{q})$ and obtain the risk for the sub-problem.

Optimality Check Compare the risks of master problem and sub-problem. If the sub-problem risk value is equal to or smaller than the master problem risk value, the optimal solution is found, and the algorithm stops.

Cut Generation If the risks differ, generate new cuts based on the sub-problem's dual variables and add them to the master problem.

Iteration Resolve the master problem with the added cuts and repeat the process until convergence.

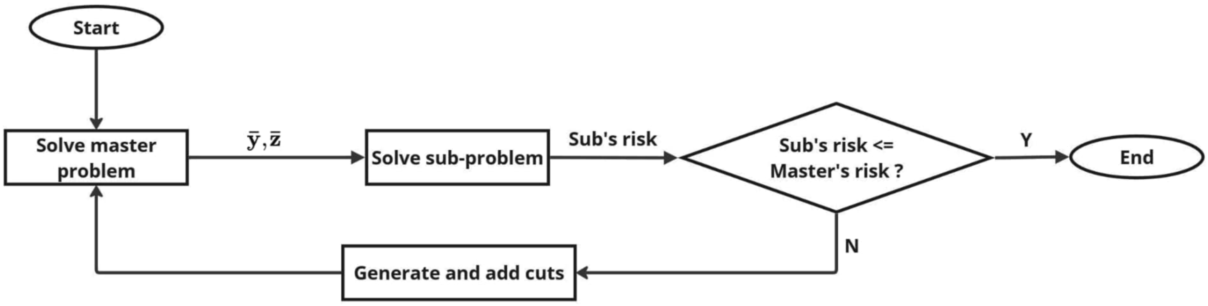

Figure 4.2: Flowchart for the cutting-plane algorithm

4.1.2 Master problem formulation

The master problem focuses on minimizing the total risk associated with hazmat transportation and facility operations. It is formulated as follows.

$$\min_{x,y,z,w,q} \quad \sum_{(i,j)\in\mathcal{A}} \sum_{h\in\mathcal{H}} \sum_{(o,h)\in\mathcal{S}} SR_{ijh}\ N_{oh}\ x_{ijoh} + \sum_{i\in\mathcal{M}} \sum_{h\in\mathcal{H}} FR_{ih}\ q_{ih} \tag{4.1}$$

s.t.

$$\sum_{h\in\mathcal{H}} FR_{ih}\ q_{ih} \leq RiskCap_i\ w_i \qquad \forall i \in \mathcal{M} \tag{4.2}$$

$$\sum_{(i,j)\in\mathcal{A}} x_{ijoh} - \sum_{(j,i)\in\mathcal{A}} x_{jioh} \begin{cases} = 1 & \text{if } i \in \mathcal{O}(o,h) \\ \geq -w_i & \text{if } i \in \mathcal{M} \\ = 0 & \text{Otherwise} \end{cases} \qquad \forall i \in \mathcal{N}, \forall (o,h) \in \mathcal{S} \tag{4.3}$$

$$x_{ijoh} \leq y_{ijh} \qquad \forall (i,j) \in \mathcal{A}, \forall h \in \mathcal{H} \tag{4.4}$$

$$w_i \leq z_i \qquad \forall i \in \mathcal{M} \tag{4.5}$$

$$\sum_{h \in H} q_{ih} \leq Cap_i \ w_i \qquad \forall i \in \mathcal{M} \tag{4.6}$$

$$q_{ih} = \sum_{(o,h) \in S} N_{oh} \ (\sum_{(j,i) \in \mathcal{A}} x_{jioh} - \sum_{(i,j) \in \mathcal{A}} x_{ijoh}) \qquad \forall i \in \mathcal{M}, \forall h \in \mathcal{H} \tag{4.7}$$

$$x_{ijoh} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, \forall (o,h) \in \mathcal{S} \tag{4.8}$$

$$y_{ijh} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, \forall h \in \mathcal{H} \tag{4.9}$$

$$z_i \in \{0,1\}, w_i \in \{0,1\} \qquad \forall i \in \mathcal{M} \tag{4.10}$$

$$q_{ih} \geq 0 \qquad \forall i \in \mathcal{M}, \forall h \in \mathcal{H} \tag{4.11}$$

4.1.3 Sub-problem formulation

After solving the master problem and gaining the solution set $(\overline{x}, \overline{y}, \overline{z}, \overline{w}, \overline{q})$, we move forward to solve the sub-problem which focuses on minimizing the total cost for the hazmat carrier, given the fixed decisions from the master problem.

$$\min_{x,w,q} \quad \sum_{(i,j) \in \mathcal{A}} \sum_{h \in \mathcal{H}} \sum_{(o,h) \in \mathcal{S}} SC_{ijh} \ N_{oh} \ x_{ijoh} + \sum_{i \in \mathcal{M}} FC_i \ w_i + \sum_{i \in \mathcal{M}} \sum_{h \in \mathcal{H}} PC_{ih} \ q_{ih} \tag{4.12}$$

s.t.

$$\sum_{(i,j) \in \mathcal{A}} x_{ijoh} - \sum_{(j,i) \in \mathcal{A}} x_{jioh} \begin{cases} = 1 & \text{if } i \in \mathcal{O}(o,h) \\ \geq -w_i & \text{if } i \in \mathcal{M} \\ = 0 & \text{otherwise} \end{cases} \qquad \forall i \in \mathcal{N}, \forall (o,h) \in \mathcal{S} \tag{4.13}$$

$$x_{ijoh} \leq \overline{y}_{ijh} \qquad \forall (i,j) \in \mathcal{A}, \forall h \in \mathcal{H} \tag{4.14}$$

$$w_i \leq \overline{z}_i \qquad \forall i \in \mathcal{M} \tag{4.15}$$

$$\sum_{h \in H} q_{ih} \leq Cap_i \ w_i \qquad \forall i \in \mathcal{M} \tag{4.16}$$

$$q_{ih} = \sum_{(o,h) \in S} N_{oh} \ (\sum_{(j,i) \in \mathcal{A}} x_{jioh} - \sum_{(i,j) \in \mathcal{A}} x_{ijoh}) \qquad \forall i \in \mathcal{M}, \forall h \in \mathcal{H} \tag{4.17}$$

$$x_{ijoh} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, \forall (o,h) \in \mathcal{S} \tag{4.18}$$

$$w_i \in \{0,1\} \qquad \forall i \in \mathcal{M} \tag{4.19}$$

$$q_{ih} \geq 0 \qquad \forall i \in \mathcal{M}, \forall h \in \mathcal{H} \tag{4.20}$$

4.1.4 Cut generation

Solving the sub-problem yields the solution set $(\widehat{x}, \widehat{w}, \widehat{q})$. If the sub-problem risk value is equal to or smaller than the master problem risk value, we have reached the optimal solution and the algorithm stops; otherwise, cuts are generated and added to the master problem. For each shipment $(o, h) \in \mathcal{S}$ and each node $k \in \mathcal{M}$, the cut is:

$$\sum_{(i,j)\in\widehat{p}} (1 - y_{ijh}) + \sum_{k\in\mathcal{M}} \widehat{\delta}_k (1 - z_k) \geq 1 - |\overline{p}| + \sum_{(i,j)\in\overline{p}} x_{ijoh}, \tag{4.21}$$

where

$$\widehat{\delta}_k = \begin{cases} 1, & \text{if } \widehat{p} \text{ includes node } k; \\ 0, & \text{otherwise.} \end{cases} \tag{4.22}$$

4.2 Computational performances

In this section, we conduct a series of numerical experiments to evaluate the computational performance of our proposed cutting-plane algorithm. The experiments are conducted on a computer with a 64-bit Windows 11 system, featuring a Ryzen 5 processor and 8 GB of RAM. We implement the cutting-plane algorithm and the associated model using Python 3.11.4 and solve the optimization problems using Gurobi Optimizer 10.0.2.

We randomly generate problem instances based on the sets $\mathcal{N}$, $\mathcal{A}$, $\mathcal{M}$, and $\mathcal{S}$, corresponding to the number of nodes, arcs, potential facility locations, and shipments (total shipments across all hazmat types), respectively. Specifically, we use five groups of instance sets with node counts of 20, 50, 100, 150, and 200. Each group includes variations in network parameters. Across all instances, three types of hazardous materials are considered. The arc cost and risk values are randomly selected from the ranges [10, 100] and [1000, 100000], respectively. Table 4.1 summarizes the computational results, presenting the average values over the five instances in each set. All tests are subjected to a maximum runtime of 7200 seconds (2 hours).

Table 4.1: Numerical tests results

#	$\mathcal{N}$	$\mathcal{A}$	$\mathcal{M}$	$\mathcal{S}$	CPU time (s)	**Total risk**	Tran. risk	Facility risk	**Total cost**	Trans. cost	Facility cost	Proc. cost
1	20	80	5	10	2.39	1,181,018	470,023	710,995	8,606	594	6,812	1,200
2	20	80	10	10	4.56	1,453,901	394,308	1,059,593	12,830	578	11,052	1,200
3	20	160	5	10	10.11	905,528	194,533	710,995	8,664	652	6,812	1,200
4	20	160	10	10	19.88	1,016,271	230,532	785,739	14,530	329	13,001	1,200
5	20	160	10	30	32.51	3,726,650	1,134,871	2,591,779	18,204	1,603	13,001	3,600
6	50	160	10	30	45.82	5,269,421	1,600,667	3,668,754	30,179	2,525	24,054	3,600
7	50	160	20	30	72.29	4,944,177	1,392,726	3,551,451	35,244	2,111	29,533	3,600
8	50	240	10	30	98.76	3,136,563	1,198,120	1,938,443	23,859	2,395	17,864	3,600
9	50	240	20	30	96.81	2,808,683	665,057	2,143,626	28,517	1,567	23,350	3,600
10	50	240	20	60	112.56	8,998,771	2,595,841	6,402,930	34,412	3,862	23,350	7,200
11	100	240	20	60	117.75	12,541,474	4,794,284	7,747,190	42,108	6,028	28,880	7,200
12	100	240	40	60	115.08	12,139,293	6,211,597	5,927,696	41,879	4,184	30,495	7,200
13	100	400	20	60	146.95	10,840,745	6,225,034	4,615,711	46,299	7,574	31,525	7,200
14	100	400	40	60	187.70	11,309,300	6,463,985	4,845,315	47,974	7,960	32,814	7,200
15	100	400	40	100	246.83	23,186,843	11,765,738	11,421,105	58,972	14,158	32,814	12,000
16	150	400	40	100	382.02	23,344,725	14,007,029	9,337,696	60,518	18,356	30,162	12,000
17	150	400	60	100	574.26	24,142,716	12,006,249	12,136,467	61,379	18,658	30,641	12,080
18	150	600	40	100	963.09	17,727,587	9,766,108	7,961,479	57,939	15,595	30,214	12,130
19	150	600	60	100	1267.26	17,489,070	9,300,051	8,189,019	57,460	13,972	31,488	12,000
20	150	600	60	120	1371.62	27,624,030	10,124,671	17,499,359	63,601	17,713	31,488	14,400
21	200	600	60	120	1820.31	35,659,389	23,596,171	12,063,218	69,273	21,643	33,180	14,450
22	200	1500	60	120	6368.57	20,224,062	11,494,003	8,730,059	70,405	21,945	34,060	14,400

By analyzing Table 4.1, it becomes evident how the size of the network influences the optimal solution and computational performance. Notably, we observe that as the network complexity grows, indicated by an increase in nodes, arcs, or shipments, the CPU time also escalates accordingly. This correlation highlights the scalability challenges faced when dealing with larger-scale networks, as they demand more computational resources and time for optimization processes. (Figure 4.3).

By analyzing Table 4.1, it is evident that network size has an impact on the CPU time. First, we observe that as the number of nodes increases, the CPU time rises accordingly. For example, comparing cases 15 and 16, where the number of nodes increases from 100 to 150, the CPU time rises from 246.83 to 382.02 seconds. Next, it is evident that increasing the number of arcs in the network while keeping the number of nodes, facilities, and shipments constant also results in higher CPU times. For example, in cases 1 and 3, where the number of nodes is fixed at 20 but the number of arcs increases from 80 to 160, the CPU time rises from 2.39 to 10.11 seconds. This suggests that denser networks demand more computation. Additionally, the number of shipments has a direct impact on CPU time. In cases 4 and 5, where the number of shipments increases while keeping other factors constant, CPU time rises from 19.88 to 32.51 seconds. This demonstrates that handling more shipments requires greater computational effort, as expected, yet the algorithm manages these increases efficiently.

Overall, while larger networks and higher numbers of shipments and links increase the CPU time, most instances are solved in relatively short times. Figure 4.3 illustrates that for the majority of problem sets, the CPU time remains below 1000 seconds, underscoring the efficiency of the cutting-plane algorithm. Only in cases with significantly large networks, such as cases 21 and 22, we see notable increases in computation time, which reflects the heightened complexity of larger networks.

The impact of network size on cost and risk values is also clear. As the number of nodes increases, both the total risk and total cost rise accordingly. For instance, in cases 10 and 11, where the number of nodes increases from 50 to 100, total risk rises from 8,998,771 to 12,541,474, while total cost increases from 34,412 to 42,108.

Conversely, an interesting trend emerges when examining the impact of increasing the number of arcs while keeping the number of nodes constant. For instance, comparing cases 6 and 8, where the number of arcs increases from 160 to 240, we observe a reduction in total risk from 5,269,421 to 3,136,563, and a reduction in total cost from 30,179 to 23,859, despite maintaining the same number of nodes, facilities, and shipments. Similarly, in cases 16 and 18, where the number of links rises from 400 to 600 while nodes, facilities, and

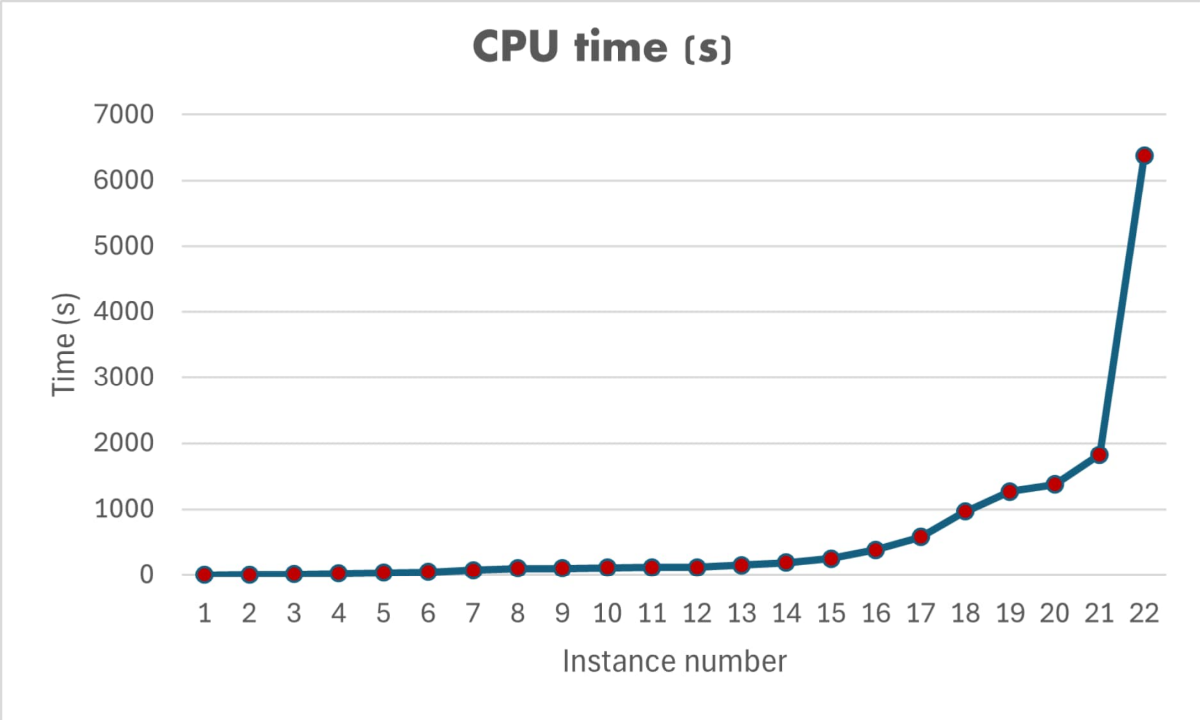

Figure 4.3: CPU time

shipments remain constant, the total risk and cost decrease from 23,344,725 to 17,727,587 and from 60,518 to 57,939 respectively. This pattern exists across all other comparable pairs. This phenomenon suggests that increasing the connectivity within the network, represented by a higher number of arcs, can lead to a more efficient and optimized risk and distribution, resulting in reduced overall risk exposure and incurred costs. This finding underscores the importance of network design and connectivity considerations in hazmat transportation optimization, highlighting the potential benefits of enhancing network links to achieve improved risk and cost management outcomes.

For the impact of the number of shipments on the model's objectives, when the number of shipments increases while all other factors are fixed, it is intuitive to see that the risk and cost increase drastically. For example, comparing cases 4 and 5 indicates that the total risk increases from 1,016,271 to 3,726,650, and the total cost increases from 14,530 to 18,204.

In summary, while larger networks increase both the CPU time and risk/cost values, the cutting-plane algorithm demonstrates strong efficiency for all network sizes. Most instances are solved within a short time frame, making the algorithm suitable for practical applications where quick decisions are needed.

Chapter 5

Numerical Case Study

In this chapter, we present a detailed numerical case study to demonstrate the effectiveness and efficiency of the combined facility location and network design model. This case study is crucial in validating the proposed model and solution methodology under realistic conditions.

5.1 Network data

The transportation network for the city of Nanchang in China is illustrated in Figure 5.1. The network contains 32 nodes (circles), 102 links (straight lines), representing the possible transportation routes, 8 candidate facility locations (gray circles) that may be chosen for facility construction, and 24 hazmat generation nodes (white circles). The nodes and arcs are characterized by attributes such as population density, distance, and risk factors associated with hazmat transportation.

5.1.1 Risk

The risk associated with each transportation link and facility location is a critical component of the model. The data on population density utilized in this study is derived from the 2020 China Population Census conducted by the National Bureau of Statistics of China. This study examines three types of hazardous materials (hazmats), each associated with distinct exposure radii, 0.5 kilometers, 0.8 kilometers, and 1.6 kilometers,

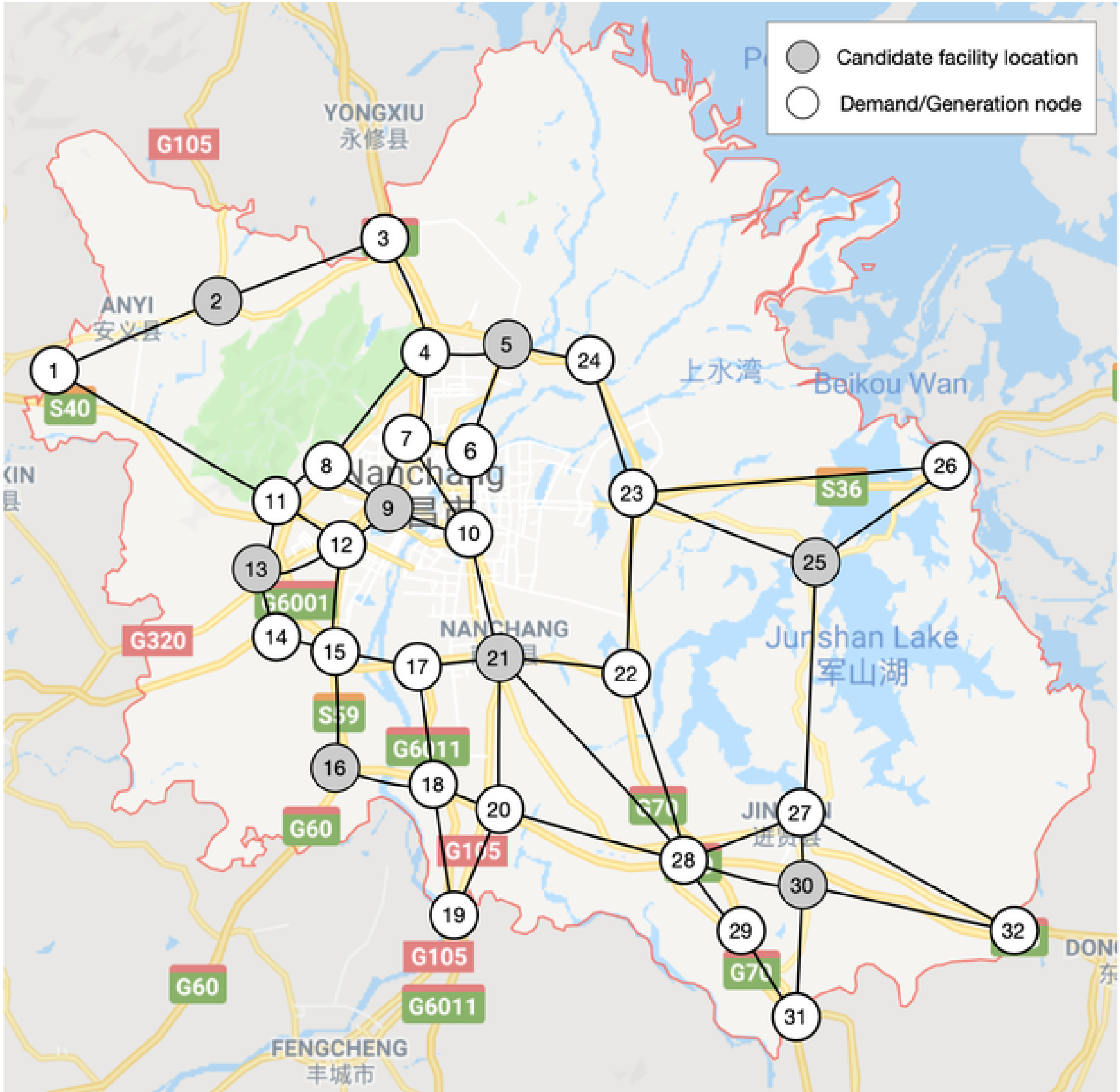

Figure 5.1: Nanchang network

respectively.

5.1.1.1 Arc risk

To determine the exposure area, we consider the length of each transportation link in conjunction with these specified radii. The risk associated with each link is subsequently calculated by considering the population density of the surrounding area, the length of the link, and the respective exposure radii of each hazmat. We have 102 arcs and for each one of them, we have three distinct risks, each related to one hazmat type. For incident rate data, we reference a comprehensive 20-year survey conducted from 1997 to

2016, as documented in the Large Truck and Bus Crash Facts report by Federal Motor Carrier Safety Administration (FMCSA) (2018). This extensive dataset provides incident rates for various links, offering a robust basis for understanding and mitigating the risks associated with the transportation of hazardous materials.

5.1.1.2 Node risk

Similar to the arc risk, the risks at facility locations are estimated by evaluating the population density in conjunction with the exposure radii for the three types of hazmats. As mentioned before, we have 32 nodes, but only 8 are candidate facility locations. The other 24 nodes are hazmat generation nodes. For each of these 8 nodes, there are three specific risk values, each for one hazmat type. The maximum allowable risk at each facility, with consideration of safety and regulatory guidelines, is set at 8×10^6 units, ensuring that the facilities operate within safe limits while processing hazardous materials. The impact of variations in this parameter is examined in Section 5.3.

5.1.2 Cost

For network cost, we have three different types of costs: transportation cost, fixed cost of facility construction, and hazmat processing cost. We strive to ensure that all relevant factors influencing costs are accounted for, providing a detailed and accurate estimation of expenses related to hazmat transportation, facility operation, and processing hazmat.

5.1.2.1 Transportation cost

The calculation of transportation costs is based on travel time combined with the cost per unit of time. Travel time for each arc is determined by dividing the distance between successive nodes by the speed limit applicable to that segment. Assuming an annual travel distance of 10,000 kilometers, the costs per unit of time for the three types of hazmats are estimated to be 100 RMB, 150 RMB, and 200 RMB, respectively. These estimates account for factors such as fuel consumption (including gas mileage and fuel prices), insurance premiums, and maintenance expenses. Variations in cost arise from differences in mileage and additional charges associated with commercial vehicles used for transporting different types of hazmats.

5.1.2.2 Facility and processing costs

In our case study, we have 8 candidate facilities. The fixed cost of facility construction is calculated by taking into account the local population density and the facility's capacity. This cost is then distributed over a period, assuming 300 operational days per year for five years to get the final daily values for fixed costs. Moreover, each facility has a capacity for processing hazmat and the cost of processing hazmat is different for each hazmat type.

5.1.3 Shipments and demand

In our analysis of shipments, we account for various shipments associated with each type of hazardous material. Specifically, we have 24 generation nodes in the network with 19 distinct shipments for hazmat type 1, 16 for hazmat type 2, and 7 for hazmat type 3. Each shipment is characterized by its origin node, the quantity of demand, and the specific type of hazmat it is transporting. The demand for these shipments varies, with the number of shipments (demand) ranging between 0 and 10 units for each hazmat type.

5.2 Basic performance

In this section, we provide the results of the cutting-plain algorithm considering the information mentioned above and analyze the performance of this method on our case study network. Table 5.1 lists the risk and cost breakdowns for our case study.

Any link not blocked by the model needs to be prepared for hazmat transportation and imposes a cost on the network. There are 47 links that are to be blocked and cannot be used by the carrier. Shipping of hazmat type 1 is banned on 14 links, type 2 on 14 links, and type 3 on 19 links. There are also four blocked nodes, nodes 5, 16, 21, and 30. This means the carrier cannot use these two nodes to construct facilities. The final location decisions for the carrier are nodes 2 and 25.

Table 5.1: Risk and cost breakdowns

Total risk	**16,009,952**
Transportation risk	9,015,073
Facility risk	6,994,879
Total cost	**32,523**
Transportation cost	9,202
Facility cost	13,001
Processing cost	10,320
Number of banned roads	47
Number of banned nodes	4
Banned nodes	5, 16, 21, 30
Constructed nodes	2, 25

5.3 Sensitivity analysis on $RiskCap$

This section performs the sensitivity analysis on the maximum allowable risk at facilities ($RiskCap$) and examines scenarios where $RiskCap$ at facilities varies. Table 5.2 summarizes the results for different values of $RiskCap$.

The results show that as $RiskCap$ increases, the total risk across the network decreases. When $RiskCap$ is low, the model has limited flexibility, and therefore, shipments are forced to be distributed across more facilities, which leads to higher transportation risks. As $RiskCap$ increases, there is more flexibility in routing shipments to fewer facilities, which results in a more optimal risk distribution.

Moreover, with the increase in $RiskCap$, the total cost increases. This is mainly because with higher $RiskCap$, facilities can handle more risk, so the model transports more shipments to fewer facilities. This routing focuses on reducing risk, even if it means choosing longer or less direct paths to avoid higher-risk areas. With more shipments concentrated on specific routes and facilities, the increased demand can increase transportation costs, leading to higher overall costs. This analysis shows the trade-off between total risk and total cost.

Table 5.2: Sensitivity analysis on *RiskCap*

RiskCap	8×10^6	9×10^6	12×10^6	15×10^6	18×10^6
Total risk	16,009,952	15,563,767	15,450,305	15,248,992	15,099,470
Transportation risk	9,015,073	8,710,153	8,567,542	8,283,262	8,479,048
Facility risk	6,994,879	6,853,614	6,882,763	6,965,730	6,620,422
Total cost	32,523	32,881	33,244	33,490	33,341
Transportation cost	9,202	9,560	9,923	10,169	10,020
Facility cost	13,001	13,001	13,001	13,001	13,001
Processing cost	10,320	10,320	10,320	10,320	10,320
Number of banned roads	47	47	49	42	47
Number of banned nodes	4	4	4	4	4
Banned nodes	5,16,21,30	5,9,21,30	5,13,21,30	5,9,16,30	5,13,21,30
Constructed nodes	2,25	2,25	2,25	2,25	2,25

As *RiskCap* increases, some nodes become more important to the network's operation. For example, node 16 is not constructed at lower *RiskCap* levels but is constructed when *RiskCap* reaches 15×10^6, indicating that with higher flexibility, this node becomes a more attractive facility location. Similarly, different nodes are banned at varying *RiskCap* levels because of shifts in the optimal routing and facility selection. These changes are due to the trade-off between transportation and facility risks.

This analysis also highlights the trade-off between total risk and risk equity. Higher *RiskCap* can concentrate risk in fewer facilities, potentially increasing their vulnerability. Therefore, selecting the appropriate *RiskCap* requires balancing the goals of minimizing total risk and ensuring equitable risk distribution across the network.

5.4 Impacts of different policies on model outcomes

In this subsection, we examine the influence of imposing different policies on the outcomes of the proposed model. In more detail, the following policies are evaluated:

- the two-ban policy (the government posing both node ban and road closure mechanisms),

- the road closure only policy (focusing only on closing certain links to hazmat shipments),
- the node ban only policy (pre-selected location policy, i.e., restricting facility construction to pre-determined nodes, without any additional link closures), and
- no risk mitigation policy (no restriction is applied to roads and facility construction).

Each of these policies affects both transportation and facility risks, as well as the associated costs. Table 5.3 summarizes the results of applying these policies to the model.

Table 5.3: A comparison of different policies

Ban policies	**Two-ban**	**Road-closure**	**Node-ban**	**No-ban**
Total risk	**16,009,952**	**28,082,281**	**18,844,923**	**32,255,654**
Transportation risk	9,015,073	6,681,678	11,879,193	6,860,228
Facility risk	6,994,879	21,400,603	6,965,730	25,395,426
Total cost	**32,523**	**30,222**	**30,674**	**29,148**
Transportation cost	9,202	4,320	7,353	3,239
Facility cost	13,001	15,582	13,001	15,589
Processing cost	10,320	10,320	10,320	10,320
Number of banned roads	47	56	0	0
Number of banned nodes	4	0	4	0
Banned nodes	5,16,21,30	0	9,13,21,30	0
Constructed nodes	2,25	9,16,30	2,25	9,13,16

For the two-bans policy, both road closure ($x_{ijoh} \leq y_{ijh}$) and node ban ($w_i \leq z_i$) constraints are active. This policy imposes both road closures and facility restrictions, resulting in the lowest total risk (16,009,952). However, the total cost under this policy is the highest (32,523). This increase in cost can be attributed to the limited flexibility in transportation routes and facility locations, which forces the carrier to choose paths and facility locations with higher costs.

The only road-closure policy can be obtained by setting $w_i = 1$, which means all locations are available for facility construction, which results in a higher total risk (28,082,281) compared to the two-bans policy, but it offers a reduction in total cost (30,222) which suggests that this policy allows for greater flexibility in facility locations, leading to cost savings. The facility risk under this policy (21,400,603) is notably higher than in the two-bans scenario, which indicates that allowing more freedom in facility placement can lead to increased risk exposure.

Under the only node-ban policy, the carrier has the freedom to choose any road they want, and hence we set $x_{ijoh} = 1$. It can be seen that, without posing link restriction, the total risk (18,844,923) is higher compared to the two-ban policy, particularly the transportation risk (11,879,193). However, it results in a lower total cost (30,674). This is because the policy offers the carrier great flexibility in transportation route selection, which helps minimize transportation costs (7,353); but this flexibility leads to higher transportation risk. The limited choice in facility locations under this policy forces the model to route hazmat shipments through cheaper yet riskier paths, which explains the high transportation risk.

Setting both w_i and x_{ijoh} to one generates the no-ban policy, which allows the greatest flexibility in both transportation routes and facility locations. Removing all the government's enforcement results in the highest total risk (32,255,654) and the lowest total cost (29,148) among all the policies. The rationale here is that, under the no-ban scenario, the carrier can select the most cost-efficient routes and facility locations without any restrictions. While this flexibility results in lower costs, it also increases exposure to risks. Since there are no restrictions on the use of roads and nodes, the carrier can pick the ones with the lowest costs. The higher facility risk indicates that facilities are built in locations where public safety is more vulnerable. This policy's outcomes suggest that 1) the government's policies can effectively achieve the purpose of risk mitigation, and

2) in scenarios where cost minimization is prioritized without consideration of risk, the potential consequences to the population can be severe.

5.5 Robust solution development

In this section, we apply a robust experiment similar to that proposed by Taslimi et al. (2017) to seek a robust policy over different scenarios. This approach ensures that the chosen policies remain effective across different scenarios, each characterized by varying levels of demand, fuel costs, and exposure risks. The following steps are applied.

Step 1: Policy generation We first introduce 27 scenarios by varying the values of three key parameters: Shipping Cost (SC), Demand (N), and Shipping Risk (SR), each at three levels: Low (L), Medium (M), and High (H). For each scenario, we evaluate the model's outcomes, including total risk, transportation risk, facility risk, total cost, and other relevant metrics. The results are summarized in Table 5.7. By running the 27 scenarios we find the corresponding system settings/policies (Table 5.8).

Step 2: Policy test The obtained policies are applied to all 27 scenarios for resulting costs and risks (Tables 5.9 and 5.10). We then compare the solutions across all scenarios and policies to identify the most robust solution. A robust solution is defined as one that maintains an acceptable performance across scenarios. We evaluate the variability in outcomes and select the solution that shows minimal variability and consistently performs well.

The details of each step are discussed next.

5.5.1 Step 1: Policy generation

5.5.1.1 Shipping cost estimation

Fuel price directly affects the shipping cost. Hence we use the data published on fuel costs in China over the past five years as a basis for analysis (petrol prices, 2024). With

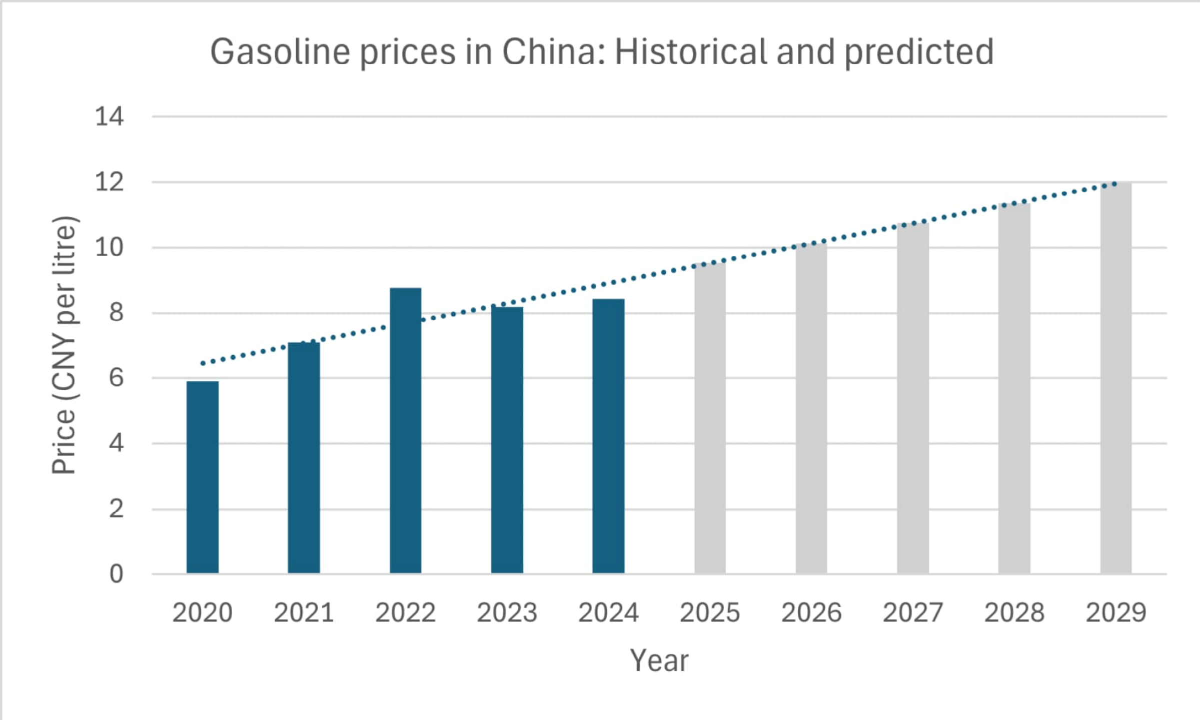

Figure 5.2: Gasoline prices in China: historical and predicted

the historical data, a linear regression model is applied to predict future fuel prices for the next five years as illustrated in Figure 5.2.

Given the regression results, we classify the past fuel price as “Low” (L), the current fuel price as “Medium” (M), and the predicted future price as “High” (H). These classifications are made by taking the average values for the fuel costs within each period. Specifically, the Low fuel cost (5.91 CNY per litre) represents the average fuel price observed in the earlier part of the five-year historical data. The Medium fuel cost (8.43 CNY per litre) corresponds to the most recent observed price at the time of analysis. The High fuel cost (11.97 CNY per litre) is obtained from the projected fuel prices over the next five years, based on the regression trend line. The predicted price of 11.97 CNY per litre is the value forecasted for the year of 2029, as shown in the graph. Table 5.4 shows the aforementioned data. these values are used to assess the impact of fuel price variations on shipping costs under different scenarios.

Table 5.4: Variation in SC

	L	M	H
Fuel Cost (CNY per litre)	5.91	8.43	11.97

5.5.1.2 Demand estimation

As for the demand, which is assessed as the number of trucks (N), we vary the hazmat generation rate among low (L), medium (M), and high (H) to observe its influence on the model outcomes. The generation rate refers to the quantity of hazardous material generated at each location per unit time. This generation rate directly affects the number of trucks required for transportation. The higher the generation rate, the more trucks are needed to transport the hazmat materials to the required locations.

In our model, we consider three scenarios with different hazmat generation rates:

1. Low generation rate (L): hazmat type 1 = [0-4], hazmat type 2 = [0-2], and hazmat type 3 = [0-0.5]. This scenario represents areas where hazmat generation is minimal and thus, fewer number of trucks are needed for transportation.

2. Medium generation rate (M): hazmat type 1 = [0-5], hazmat type 2 = [0-3], and hazmat type 3 = [0-1]. In this scenario, hazmat generation is moderate and requires more number of trucks compared to the low-generation scenario.

3. High generation rate (H): hazmat type 1 = [0-7], hazmat type 2 = [0-5], and hazmat type 3 = [0-2]. This scenario shows regions with high hazmat generation, which necessitates the highest number of trucks due to the large volume of hazmat produced.

Table 5.5 summarizes the variations in hazmat generation rates across different scenarios:

5.5.1.3 Shipping risk estimation

For shipping risk (SR), we vary the incident rate, which is derived from a 20-year survey data from 1997 to 2016 in the "Large Truck and Bus Crash Facts 2016" report (Federal

Table 5.5: Variation in N

Generation rate	**L**	**M**	**H**
Hazmat type 1	[0-4]	[0-5]	[0-7]
Hazmat type 2	[0-2]	[0-3]	[0-5]
Hazmat type 3	[0-0.5]	[0-1]	[0-2]

Motor Carrier Safety Administration (FMCSA), 2018). The estimated low, medium, and high incident rates are respectively estimated at 0.96×10^{-6}, 1.74×10^{-6}, and 2.34×10^{-6}.

In our model, we consider the impact of varying these incident rates on different links in the transportation network. Specifically, we assign incident rates to the links in the following manner.

Medium Incident Rate (M) We assume that all links are initially associated with the medium incident rate. This serves as the baseline scenario where the average rate of incidents is applied across the entire network.

Low and High Incident Rates (L and H) To investigate the impact of varying incident rates, we randomly assign 20 percent of the links to have the low incident rate (0.96×10^{-6}) and 20 percent of the links to have the high incident rate (2.34×10^{-6}). The remaining links retain the medium incident rate of 1.74×10^{-6}.

Specifically, Table 5.6 summarizes the variation in incident rates. By varying the incident rates in this manner, we can observe the effect of different risk levels on the overall transportation risk and cost. The random selection of links for the low and high rates ensures that the variation is spread throughout the network, allowing us to assess the sensitivity of the model's outcome to changes in incident rates.

Table 5.6: Variation in SR

	L	**M**	**H**
Incident rate	80% medium 20% low	100% medium	80% medium 20% high

5.5.1.4 Policy generation

Integrating the above three parameters each with three value cases, 27 scenarios can be derived. At this stage, we solve these 27 scenarios to identify the changes in the model outcomes. Table 5.7 records the resulting upper- and lower-level objective values, and Table 5.8 summarizes the corresponding policies.

As illustrated in Table 5.7, increasing shipping costs, driven by higher fuel prices, intuitively result in a corresponding increase in transportation costs. However, this does not affect the total risk or other types of costs, such as facility and processing costs. For example, comparing scenarios 1, 10, and 19, in which only SC has changed from low (L) to medium (M) to high (H), the total risk remains constant at 22,811,066, while the total cost increases from 43,622 to 44,818 and then to 46,398. This indicates that higher shipping costs directly raise transportation expenses but do not influence the overall risk levels or other cost components.

An increase in demand (N) results in higher total risks due to the increased probability of accidents on the road. This also leads to higher transportation costs. For example, comparing scenarios 1, 4, and 7, when the number of trucks increases from L to M and then to H, the total risk increases from 22,811,066 to 29,701,358 and then further escalates to 46,321,677. The total cost also increases from 43,622 to 50,949 to 57,973. This trend shows that the number of trucks significantly impacts both risk and transportation costs, with higher numbers of trucks leading to greater risks and costs.

Higher shipping risks, reflected by increased incident rates, elevate transportation risk but do not affect facility risk or any cost types (transportation, facility, and processing). For instance, comparing scenarios 1, 2, and 3 in which only SR increases, we observe an increase from 22,811,066 to 26,371,394 and then to 27,695,859 in the total risk.

When considering the combined effects of SC, N, and SR, it is evident that changes in SC primarily affect transportation costs, N influences both risk and transportation costs, and IR predominantly impacts total risk. For example, in scenarios with high values for all three parameters (such as Scenario 27 with $SC = H$, $N = H$, and $SR = H$), the total risk and costs are at their highest with total risk at 51,725,026, and total cost at 59,720.

Table 5.7: Model outcomes of the 27 scenarios

#	*SC*	*N*	*SR*	Risks			Costs			
				Total	Trans.	Facility	Total	Trans.	Facility	Proc.
1	L	L	L	22,811,066	14,794,077	8,016,989	43,622	4,479	28,583	10,560
2	L	L	M	26,371,394	18,352,071	8,019,323	43,643	4,500	28,583	10,560
3	L	L	H	27,695,859	19,676,536	8,019,323	43,643	4,500	28,583	10,560
4	L	M	L	29,701,358	16,500,413	13,200,945	50,949	6,286	28,583	16,080
5	L	M	M	35,050,760	21,750,582	13,300,178	50,800	6,137	28,583	16,080
6	L	M	H	36,589,553	23,289,375	13,300,178	50,800	6,137	28,583	16,080
7	L	H	L	46,321,677	25,031,621	21,290,056	57,973	10,430	28,583	18,960
8	L	H	M	48,994,514	25,452,845	23,541,669	54,980	8,520	27,360	19,100
9	L	H	H	51,725,026	28,007,316	23,717,710	54,769	8,309	27,360	19,100
10	M	L	L	22,811,066	14,794,077	8,016,989	44,818	5,675	28,583	10,560
11	M	L	M	26,371,394	18,352,071	8,019,323	44,836	5,693	28,583	10,560
12	M	L	H	27,695,859	19,676,536	8,019,323	44,836	5,693	28,583	10,560
13	M	M	L	29,701,358	16,500,413	13,200,945	52,647	7,984	28,583	16,080
14	M	M	M	35,050,760	21,750,582	13,300,178	52,452	7,789	28,583	16,080
15	M	M	H	36,589,553	23,289,375	13,300,178	52,452	7,789	28,583	16,080
16	M	H	L	46,321,677	25,031,621	21,290,056	60,575	13,032	28,583	18,960
17	M	H	M	48,994,514	25,452,845	23,541,669	57,038	10,316	27,360	19,100
18	M	H	H	51,725,026	28,007,316	23,717,710	56,776	10,316	27,360	19,100
19	H	L	L	22,811,066	14,794,077	8,016,989	46,398	7,255	28,583	10,560
20	H	L	M	26,371,394	18,352,071	8,019,323	46,410	7,267	28,583	10,560
21	H	L	H	27,695,859	19,676,536	8,019,323	46,410	7,267	28,583	10,560
22	H	M	L	29,701,358	16,500,413	13,200,945	54,876	10,243	28,583	16,080
23	H	M	M	35,050,760	21,750,582	13,300,178	54,861	10,228	28,583	16,080
24	H	M	H	36,589,553	23,289,375	13,300,178	54,861	10,228	28,583	16,080
25	H	H	L	46,321,677	25,031,621	21,290,056	59,773	13,132	27,360	19,100
26	H	H	M	48,994,514	25,452,845	23,541,669	59,773	13,132	27,360	19,100
27	H	H	H	51,725,026	28,007,316	23,717,710	59,720	13,260	27,360	19,100

By carefully reviewing Table 5.7 and Table 5.8, we realize that some policies yield identical model outcomes, meaning they can be combined into one policy. Policies 4, 13, and 22 have the same impact on the model, and as a result, we only keep one of them.

Table 5.8: Resulting policy details

#	SC	N	SR	# of banned links	# of banned nodes	Banned nodes	Constructed nodes	Total hazmat processed
1	L	L	L	69	3	5,13,21	2,9,16,25,30	88
2	L	L	M	67	3	5,13,21	2,9,16,25,30	88
3	L	L	H	72	3	5,13,21	2,9,16,25,30	88
4	L	M	L	60	1	21	2,9,16,25,30	134
5	L	M	M	59	1	21	2,9,16,25,30	134
6	L	M	H	34	1	21	2,9,16,25,30	134
7	L	H	L	43	2	13,21	2,9,16,25,30	158
8	L	H	M	38	2	13,21	2,9,16,25,30	158
9	L	H	H	46	2	13,30	2,9,16,21,25	158
10	M	L	L	71	3	5,13,21	2,9,16,25,30	88
11	M	L	M	75	3	5,13,21	2,9,16,25,30	88
12	M	L	H	67	3	5,13,21	2,9,16,25,30	88
13	M	M	L	60	1	21	2,9,16,25,30	134
14	M	M	M	59	1	21	2,9,16,25,30	134
15	M	M	H	34	1	21	2,9,16,25,30	134
16	M	H	L	43	2	13,21	2,9,16,25,30	158
17	M	H	M	35	2	13,30	2,9,16,21,25	158
18	M	H	H	46	2	13,30	2,9,16,21,25	158
19	H	L	L	70	3	5,13,21	2,9,16,25,30	88
20	H	L	M	71	3	5,13,21	2,9,16,25,30	88
21	H	L	H	62	3	5,13,21	2,9,16,25,30	88
22	H	M	L	60	1	21	2,9,16,25,30	134
23	H	M	M	59	1	21	2,9,16,25,30	134
24	H	M	H	34	1	21	2,9,16,25,30	134
25	H	H	L	43	2	13,30	2,9,16,21,25	158
26	H	H	M	37	2	13,30	2,9,16,21,25	158
27	H	H	H	50	2	13,30	2,9,16,21,25	158

Policies 5, 14, and 23, policies 6, 15, and 24, policies 7 and 16, and policies 9 and 18, are also identical and each pair can be combined into one policy. Some other policies, such as policies 8 and 17, are also very similar but not the same. We continue our analysis using the 19 distinct policies.

The reason for these similarities can be attributed to the limited impact of some parameters, particularly the shipping cost, on the overall model outcomes. While we vary three parameters, the sensitivity analysis reveals that changes in SC often do not significantly affect the outcomes of the model. More specifically, in policies where SC

fluctuates between Low, Medium, and High levels, but N and SR remain constant, the variation in the total risk, facility risk, and transportation risk remains negligible. This suggests that the model is more sensitive to variations in N and SR, while SC tends to have a less pronounced influence on the risk outcomes.

5.5.2 Step 2: Policy test

In this step, we apply the 19 distinct policies obtained in the first step to all 27 scenarios to evaluate the robustness of the proposed policies. The results of risks and costs associated with each policy and scenario are illustrated in Figures 5.3 and 5.4, providing a comprehensive view of how each policy performs across different scenarios. The detailed data are presented in Table 5.9 for risks and Table 5.10 for costs.

The above tables and figures show that Policy 19 consistently yields the lowest cost and moderate to low risk across most scenarios, indicating it as the strongest candidate for robust performance. It maintains a balance between managing risk and controlling costs. This makes Policy 19 the strongest overall candidate. However, it is important to note that not all policies are feasible for all scenarios. The N/As in Tables 5.10 and 5.9 indicate infeasibility. This condition arises because some policies, optimized for specific scenarios, do not work under different values of shipping cost (SC), demand (N), or shipping risk (SR) and they especially seem to be more sensitive to higher demand values. For example, a policy that works well with low demand might exceed facility capacities in high-demand scenarios. Similarly, a policy suited to low-risk conditions may violate risk limits when risk is higher. Despite this, it is still possible to compare policies' outcomes. Policies like Policy 19, which has fewer infeasibilities, provide valuable insights into a policy's overall robustness.

The results further reveal that five policies — Policies 6, 9, 13, 17, and 18 - are feasible across all scenarios. These policies have moderate risk and cost levels, and their performances across all scenarios are shown in Figures 5.5 and 5.6 for the corresponding risks and costs across all scenarios. The feasibility of these policies across all scenarios suggests that they maintain a high level of flexibility, which makes them viable options

Table 5.9: Risk values across 27 scenarios for each policy

Risk	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 17	Scenario 18	Scenario 19	Scenario 20	Scenario 21	Scenario 22	Scenario 23	Scenario 24	Scenario 25	Scenario 26	Scenario 27
Policy 1	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A
Policy 2	52,457,285	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,457,285	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,457,285	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A
Policy 3	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A
Policy 4	51,720,674	62,467,976	65,800,952	62,702,184	78,792,195	83,421,534	N/A	N/A	N/A	51,720,674	62,467,976	65,800,952	62,702,184	78,792,195	83,421,534	N/A	N/A	N/A	51,720,674	62,467,976	65,800,952	62,702,184	78,792,195	83,421,534	N/A	N/A	N/A
Policy 5	51,616,165	62,223,193	65,543,209	62,602,187	78,551,924	83,168,303	N/A	N/A	N/A	51,616,165	62,223,193	65,543,209	62,602,187	78,551,924	83,168,303	N/A	N/A	N/A	51,616,165	62,223,193	65,543,209	62,602,187	78,551,924	83,168,303	N/A	N/A	N/A
Policy 6	49,884,135	60,491,163	63,811,179	62,602,187	78,551,924	83,168,303	101,540,687	112,110,590	117,130,320	49,884,135	60,491,163	63,811,179	62,602,187	78,551,924	83,168,303	96,806,748	112,110,590	117,443,984	49,884,135	60,491,163	63,811,179	62,602,187	78,551,924	83,168,303	96,806,748	112,110,590	117,443,994
Policy 7	N/A	N/A	N/A	N/A	N/A	N/A	93,001,502	102,351,720	108,160,155	N/A	N/A	N/A	N/A	N/A	N/A	87,800,300	102,351,720	109,703,287	N/A	N/A	N/A	N/A	N/A	N/A	87,800,300	102,351,720	109,720,287
Policy 8	N/A	N/A	N/A	N/A	N/A	N/A	91,193,139	98,681,649	104,973,714	N/A	N/A	N/A	N/A	N/A	N/A	85,691,298	98,681,649	104,523,351	N/A	N/A	N/A	N/A	N/A	N/A	85,691,298	98,681,649	104,833,351
Policy 9	48,440,236	59,083,711	62,202,466	73,681,857	85,457,229	95,591,391	90,992,203	98,334,325	104,579,833	48,440,236	59,083,711	62,202,466	73,681,857	85,457,229	95,591,391	85,502,008	98,334,325	104,520,391	48,440,236	59,083,711	62,202,466	73,681,857	85,457,229	95,591,391	85,502,008	98,334,325	104,520,391
Policy 10	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A
Policy 11	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A
Policy 12	52,456,154	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,456,154	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,456,154	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A
Policy 13	49,162,973	60,028,460	63,191,906	74,947,664	86,941,961	96,913,406	91,193,139	98,681,649	104,973,714	49,162,973	60,028,460	63,191,906	74,947,664	86,941,961	96,913,406	91,193,139	98,681,649	104,833,351	49,162,973	60,028,460	63,191,906	74,947,664	86,941,961	96,913,406	85,691,298	98,681,649	104,833,351
Policy 14	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A	52,399,220	63,100,376	67,069,682	N/A	N/A	N/A	N/A	N/A	N/A
Policy 15	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,486,757	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A
Policy 16	52,457,285	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,457,285	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A	52,457,285	63,075,536	67,048,931	N/A	N/A	N/A	N/A	N/A	N/A
Policy 17	50,201,668	60,890,743	64,022,458	68,966,528	85,705,697	90,248,786	92,795,544	101,631,807	107,766,009	50,201,668	60,890,743	64,022,458	68,966,528	85,705,697	90,248,786	92,795,544	101,631,807	107,829,805	50,201,668	60,890,743	64,022,458	68,966,528	85,708,697	90,248,786	84,184,792	101,631,807	107,892,805
Policy 18	53,184,598	61,756,201	63,959,966	73,789,710	85,757,316	95,925,075	91,193,139	98,681,649	104,973,714	53,184,598	61,756,201	63,959,966	73,789,710	85,757,316	95,925,075	91,193,139	98,681,649	104,744,896	53,184,598	61,756,201	63,959,966	73,789,710	85,757,316	95,925,075	85,691,298	98,681,649	104,744,986
Policy 19	48,693,508	59,354,971	62,473,726	73,968,010	85,832,908	95,967,070	N/A	N/A	N/A	48,693,508	59,354,971	62,473,726	73,968,010	85,832,908	95,967,070	N/A	N/A	N/A	48,693,508	59,354,971	62,473,726	73,968,010	85,832,908	95,967,070	N/A	N/A	104,755,336

Table 5.10: Cost values across 27 scenarios for each policy

Cost	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 17	Scenario 18	Scenario 19	Scenario 20	Scenario 21	Scenario 22	Scenario 23	Scenario 24	Scenario 25	Scenario 26	Scenario 27
Policy 1	43,584	43,584	43,584	N/A	N/A	N/A	N/A	N/A	N/A	44,776	44,776	44,776	N/A	N/A	N/A	N/A	N/A	N/A	46,348	46,348	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Policy 2	43,615	43,615	43,615	N/A	N/A	N/A	N/A	N/A	N/A	44,800	44,800	44,800	N/A	N/A	N/A	N/A	N/A	N/A	46,364	46,364	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Policy 3	43,643	43,643	43,643	N/A	N/A	N/A	N/A	N/A	N/A	44,836	44,836	44,836	N/A	N/A	N/A	N/A	N/A	N/A	46,410	46,410	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Policy 4	42,437	42,437	42,437	50,827	50,827	50,827	N/A	N/A	N/A	43,318	43,318	43,318	52,277	52,277	N/A	N/A	N/A	N/A	44,486	44,486	54,187	54,187	54,187	N/A	N/A	N/A	N/A
Policy 5	42,127	42,127	42,127	50,800	50,800	50,800	N/A	N/A	N/A	42,994	42,994	42,994	52,320	52,320	N/A	N/A	N/A	N/A	44,163	44,163	54,246	54,246	54,246	N/A	N/A	N/A	N/A
Policy 6	43,047	43,047	43,047	50,800	50,800	50,800	57,310	57,310	57,310	44,109	44,109	44,109	52,452	52,452	52,452	59,613	59,613	59,613	45,506	45,506	45,506	54,621	54,621	54,621	61,847	62,632	59,912
Policy 7	N/A	N/A	N/A	57,973	57,973	57,973	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	60,575	60,575	60,575	N/A	N/A	N/A	N/A	N/A	N/A	63,089	64,037	67,850
Policy 8	N/A	N/A	N/A	N/A	N/A	N/A	54,980	54,980	54,980	N/A	N/A	N/A	N/A	N/A	N/A	57,038	57,038	57,038	N/A	N/A	N/A	N/A	N/A	N/A	58,926	59,773	59,613
Policy 9	41,431	41,431	41,431	48,790	48,790	48,790	54,769	54,769	54,769	42,373	42,373	42,373	50,258	50,258	50,258	56,776	56,776	56,776	43,628	43,628	43,628	52,213	52,213	52,213	58,642	59,445	59,501
Policy 10	43,542	43,542	43,542	N/A	N/A	N/A	N/A	N/A	N/A	44,714	44,714	44,714	N/A	N/A	N/A	N/A	N/A	N/A	46,270	46,270	46,270	N/A	N/A	N/A	N/A	N/A	N/A
Policy 11	43,643	43,643	43,643	N/A	N/A	N/A	N/A	N/A	N/A	44,836	44,836	44,836	N/A	N/A	N/A	N/A	N/A	N/A	46,410	46,410	46,410	N/A	N/A	N/A	N/A	N/A	N/A
Policy 12	38,982	38,982	38,982	N/A	N/A	N/A	N/A	N/A	N/A	40,262	40,262	40,262	N/A	N/A	N/A	N/A	N/A	N/A	41,956	41,956	41,956	N/A	N/A	N/A	N/A	N/A	N/A
Policy 13	37,041	37,041	37,041	49,079	49,079	49,079	54,980	54,980	54,980	38,109	38,109	38,109	50,626	50,626	50,626	57,038	57,038	57,038	39,554	39,554	39,554	52,680	52,680	52,680	58,926	59,773	59,613
Policy 14	43,622	43,622	43,622	N/A	N/A	N/A	N/A	N/A	N/A	44,818	44,818	44,818	N/A	N/A	N/A	N/A	N/A	N/A	46,398	46,398	46,398	N/A	N/A	N/A	N/A	N/A	N/A
Policy 15	43,605	43,605	43,605	N/A	N/A	N/A	N/A	N/A	N/A	44,794	44,794	44,794	N/A	N/A	N/A	N/A	N/A	N/A	46,360	46,360	46,360	N/A	N/A	N/A	N/A	N/A	N/A
Policy 16	43,615	43,615	43,615	N/A	N/A	N/A	N/A	N/A	N/A	44,800	44,800	44,800	N/A	N/A	N/A	N/A	N/A	N/A	46,364	46,364	46,364	N/A	N/A	N/A	N/A	N/A	N/A
Policy 17	41,601	41,601	41,601	49,812	49,812	49,812	55,422	55,422	55,422	42,596	42,596	42,596	51,748	51,748	51,748	57,690	57,690	57,690	43,931	43,931	43,931	54,300	54,300	54,300	59,400	60,694	60,638
Policy 18	37,026	37,026	37,026	48,981	48,981	48,981	54,980	54,980	54,980	38,126	38,126	38,126	50,496	50,496	50,496	57,038	57,038	57,038	39,590	39,590	39,590	52,508	52,508	52,508	58,926	59,773	59,592
Policy 19	33,246	33,246	33,246	45,241	45,241	45,241	N/A	N/A	N/A	34,609	34,609	34,609	47,140	47,140	47,140	N/A	N/A	N/A	36,422	36,422	36,422	49,649	49,649	49,649	N/A	N/A	59,720

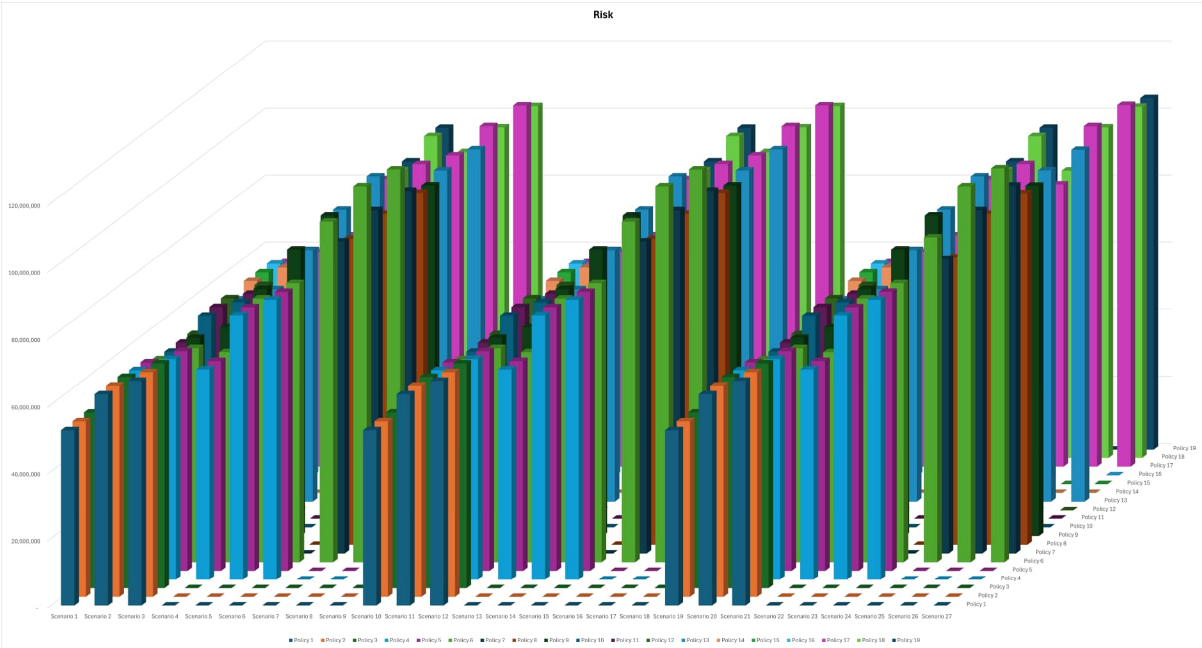

Figure 5.3: Risk figure for all policies

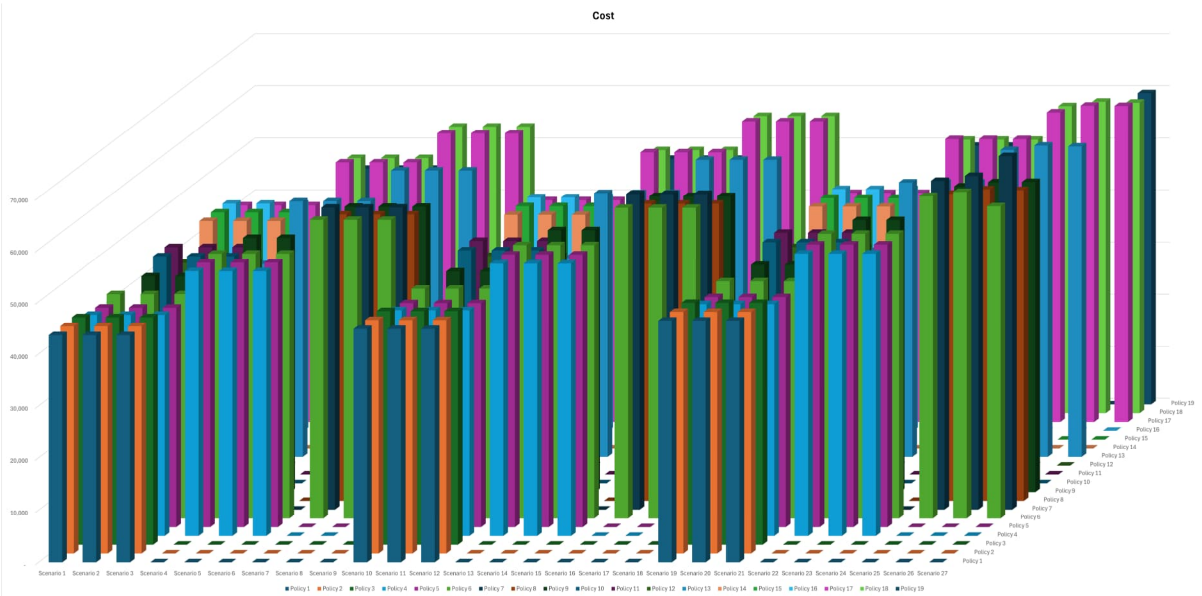

Figure 5.4: Cost figure for all policies

in terms of robustness.

In proposing the most robust policy among the five feasible ones, policy 9 stands out among others. Policy 9 has a better balance in terms of risk distribution and it leads to moderate to low costs. Additionally, this policy handle variations in risk without a significant increase in cost. This makes it a reasonable choice for decision-makers seeking a policy that remains flexible and performs well under a wide range of conditions. Policies 13 and 18 show the lowest costs across most scenarios, among the 5 policies, making them

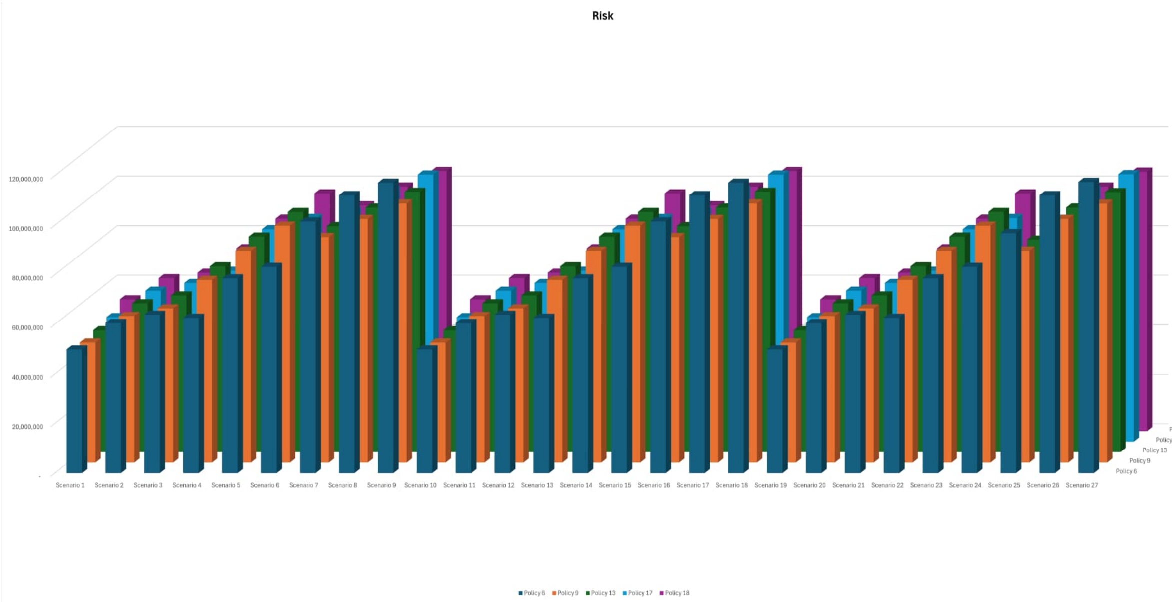

Figure 5.5: Risk figure for feasible policies

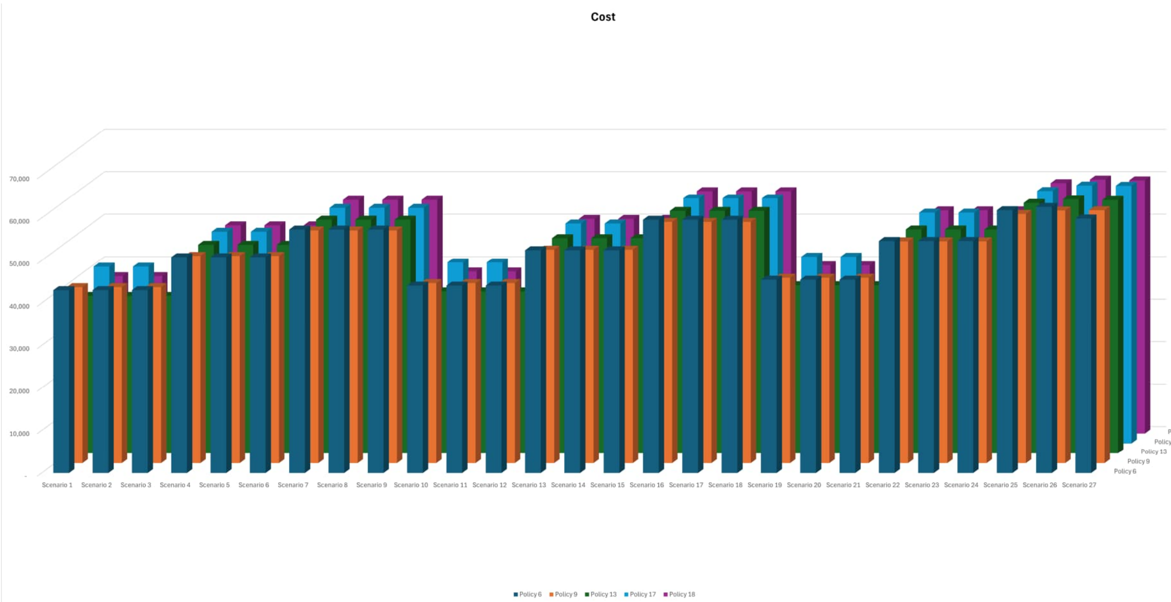

Figure 5.6: Cost figure for feasible policies

the optimal choices in situations where minimizing cost is the primary concern.

Chapter 6

Conclusions and Future Directions

This thesis addresses the pivotal issue of optimizing combined facility location and network design for hazardous materials (hazmat) transportation. The transportation of hazmat poses serious risks to public safety and the environment due to the possibility of accidents, leaks, and other hazardous incidents. Managing these risks while maintaining cost efficiency in transportation and facility operations is a complicated problem that involves two stakeholders, the government and the hazmat carrier.

To tackle this problem, we develop a bi-level programming model that takes into account the conflicting objectives of the government and the hazmat carrier. At the upper level, the government aims to minimize the total risk of population exposure by strategically closing certain roads and nodes. This risk management approach considers the potential consequences of hazmat incidents in densely populated areas and important infrastructures. On the other hand, at the lower level, the hazmat carrier seeks to minimize the total transportation cost, which includes the costs of choosing the shortest paths from hazmat generation nodes to processing facilities, as well as the costs associated with hazmat processing and facility construction.

The novelty of this research is in its integration of both facility location and network design within a single bi-level optimization framework. This combined approach has been largely overlooked in previous studies, which typically address either facility location or network design independently. Our model also provides the government's decisions towards arc closures and introduces the concept of node ban, which has never been addressed in the literature before. This dual consideration of nodes and arcs management in governmental decisions provides a more realistic and comprehensive solution to the hazmat transportation problem, marking a significant contribution to the literature.

To solve the bi-level model, we employ an exact cutting-plane algorithm. This algorithm iteratively solves the master problem (upper level) and the sub-problem (lower level), generating and adding cuts to the master problem until convergence is achieved. The cutting-plane method ensures that the optimal solution is reached by continuously refining the feasible region based on the interaction between the two levels of decision-making.

The numerical case study presented in this thesis demonstrates the effectiveness of the proposed model and solution methodology. By applying the model to a real transportation network, the city of Nanchang in China, we show how the integrated approach can significantly reduce both the risk and cost associated with hazmat transportation. The computational results highlight the scalability of the model, proving its applicability to networks of varying sizes and complexities.

In summary, this thesis makes a significant contribution to the field of hazmat transportation by providing a robust framework for optimizing combined facility location and network design. The proposed bi-level model and cutting-plane algorithm offer a practical tool for policymakers and industry practitioners to enhance the safety and efficiency of hazmat transportation networks.

6.1 Theoretical implications

The insights gained from this research have important theoretical contributions to the field of hazmat transportation:

1. The integrated model highlights the significance of strategic facility location and network design in minimizing population exposure to hazmat risks. This emphasizes the importance of considering both facility location and network design in risk

management models, which can provide a more comprehensive approach to hazard exposure mitigation.

2. The bi-level framework offers a structured theoretical approach for implementing policies such as road closures and node bans. This framework provides a new way to understand how regulatory decisions can influence carriers' routing and facility location choices, aligning operational strategies with public safety objectives.

3. The model's ability to handle different network sizes and complexities illustrates its versatility. This indicates that the provided optimization framework can be scaled and adapted to various contexts, which makes it applicable to both small and large-scale networks.

4. The use of real data in the case study highlights the importance of data-driven decision-making. This enhances the literature by demonstrating how accurate and up-to-date data can be leveraged to optimize hazmat transportation networks, which ensures both safety and cost efficiency.

6.2 Managerial insights

The insights that follow are the important implications for managers and policymakers involved in hazmat transportation:

1. The dominance of transportation risk in the total risk profile suggests that policymakers should focus on optimizing transportation routes and improving safety measures along these routes. Investments in infrastructure that enhance transportation safety can significantly mitigate the overall risk.

2. Policies aimed at increasing the capacity of hazmat processing facilities can lead to lower overall risks and costs, as larger facilities can handle more materials efficiently, eliminating extensive transportation and associated negative impacts. However, the risk at each facility should also be properly controlled by applying a reasonable risk threshold.

3. To deal with the high processing costs, managers ought to focus on the development of more efficient processing technologies that can lead to significant cost savings without boosting risks.

4. Fuel cost variations highlight the necessity of policies that promote fuel-efficient transportation methods or alternative energy sources to reduce transportation costs.

6.3 Future plans

Building on the findings of this thesis, several avenues for future research and development are proposed:

1. While our current model integrates node and arc decisions by the government, future work could consider integrating multiple policies such as tolls, road constructions, emergency response team allocation, and other regulatory measures. This would provide a more holistic policy framework for optimizing hazmat transportation networks.

2. Our current model uses deterministic parameters. Incorporating uncertainty in parameters such as demand, incident rates, and costs into the model would enhance its robustness. Developing robust optimization techniques to handle these uncertainties is a promising area for future research, which ensures that solutions remain effective under varying conditions.

3. The current model primarily considers road transportation. Expanding the model to include multiple transportation modes (e.g., rail, sea, and air) would provide a more comprehensive approach to hazmat transportation. Multi-modal optimization reflects the complexity of real-world logistics and can lead to more efficient and safer transportation solutions.

4. This thesis focuses on minimizing risk and cost without explicitly considering environmental impacts. Future studies could integrate environmental impact assessments into the model to evaluate the ecological footprint of hazmat transportation.

This would provide a more comprehensive approach to risk management, considering both human and environmental health.

5. The current model is designed for offline optimization. Developing real-time applications and decision support systems based on the proposed model could facilitate real-time decision-making for managers and policymakers. Real-time optimization tools would enhance the responsiveness and adaptability of hazmat transportation networks, which leads to improved safety and efficiency.

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