A Scenario-Based Hazardous Material Network Design Problem with Emergency Response and Toll Policy

by

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Abstract

In the process of shipping hazmats on a road network from origins to destinations, two stakeholders are involved: The authorities who are concerned about the risk of incidents, and the carriers who are concerned about shipping costs. We propose a bilevel model in order to account for the conflicting interests of the two parties. The upper-level (authorities) use different policies: Proactive policies including road-closure, road-construction and toll policies, and Reactive policies including locating hazmat response teams. Furthermore, scenario-based uncertainty is considered to reflect the variations in demand and shipments. Due to the complexity of the bilevel model, we develop two methods to solve the problem. First, using dual variables and constraints, we reformulate our bilevel model into a single-level model. This method gives us exact optimal solutions. Second, a two-stage heuristic algorithm gives us solutions which are close to the optimal solutions. Then, based on a transportation network in China, experimental results and several sensitivity analyses are presented.

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Chapter 1

Introduction

Hazardous materials are defined by the Federal Motor Carrier Safety Administration (FMCSA) as “materials providing an unjustifiable threat to the public and the environment.” Explosives, gases, flammable liquids and solids, oxidizing substances, poisonous and infectious substances, radioactive materials, corrosive, and dangerous goods are the nine categories of hazmats. Several industries need these materials to be transported to them as a vital part of their productions. In addition, sometimes these materials are the unwanted industrial side-products that need to be carried to designated waste locations. Consequently, these hazmats are transported through a road network (highway), air, railway, and water. Undoubtedly, hazmat transportation is always associated with significant risks to the surrounding population and environment in case of an incident. Consequently, authorities often take reactive and proactive actions to reduce both the likelihood and impact of an incident.

One of the main mechanisms of reducing the likelihood of the incidents is to control hazmat traffic. In order to do that, authorities sometimes impose barriers against the carriers to prevent them from using certain roads, and sometimes offer them an incentive to encourage them to use certain roads. On the other hand, carriers whose objective is to minimize their shipping cost tend to use the fastest or cheapest routes towards their destinations. The aforementioned situation creates a conflict of interest between the two parties: the authorities and the carriers. A bilevel model can be used to depict this interaction, with the government at the upper-level and the carriers at the lower-level (Erkut et al., 2007).

Hazmat Transportation Network Design (HTND), which was first introduced by Kara and Verter (2004), is one of the major ways often implemented to control hazmat transportation risk and refers to constructing new network links, making current links available or restricting their use for the transportation of hazmat. Even though this method is considered a restrictive approach, it has been proved to be effective in significantly reducing the hazmat incident risks. In addition, toll policies, which encourage hazmat carriers to use less risky links by placing tolls on riskier links, can be adopted along with network design. Both these methods are considered proactive mechanisms as they tend to prevent hazmat incidents. Yet, there is always a chance of a hazmat incident despite all the mentioned safety measures. Therefore, reactive mechanisms are necessary in these types of situations. Locating hazmat response teams whose job is to control the spill of hazardous material is one of the reactive mechanisms. In our research, hazmat response teams (HRTs) can be positioned at a set of candidate locations to respond to potential hazmat incidents. Based on the links' distance from the HRTs, some of the links can be covered and the rest will remain uncovered.

Herein, we propose a bilevel model in which the upper-level (government authorities) minimizes the hazmat network risk by constructing new links, blocking and tolling the links, and locating HRTs. On the lower-level, carriers tend to minimize their transportation cost. Taking the above considerations into account, the upper-level objective function minimizes the mean system risk over different scenarios considering the emergency response coverage. In this paper, system risk refers to the total risk that the network is dealing with and is calculated and further explained in the next chapters. The lower level problem is a standard shortest path model which minimizes the mean transportation cost (including toll cost) over all scenarios. Moreover, by introducing an additional risk-relevant term based on the maximum risk of all shipments, a pessimistic solution is enforced for the lower level when multiple minimum-cost path alternatives exist.

Because of the bilevel structure of the model and its complexity, not only do we study an exact solution methodology, we also study a heuristic model. The time/accuracy trade-off between these two techniques is then demonstrated. Furthermore, a real transportation network in China is examined as a case study in order to better comprehend the applicability of the models. Later, we conduct a number of sensitivity analyses around several key parameters in order to assess how changing some important model parameters affects the optimal solution and computational time.

The thesis is structured as follows. Chapter 2 reviews the literature related to this research. In this chapter, we address related topics including risk assessment in hazmat transportation, hazmat transportation network design (HTND), toll policies in hazmat, hazmat emergency response management, and uncertainty issues in hazmat transportation. The mathematical formulations are then described in Chapter 3, which focuses on the bilevel structure of the problem to reflect the parties' conflicting interests. Chapter 4 covers the solution algorithms: a 2-stage heuristic approach and an exact method. At the end of this chapter, using several instance with various sizes, we test and compare the two models' performances. In Chapter 5, the proposed solutions are applied to the city of Nanchang's transportation system in China, demonstrating how the models behave in the setting of a real-world network and several sensitivity analyses are conducted. The research is concluded in Chapter 6, which summarises the key findings and suggests some potential directions for further study.

Chapter 2

Literature Review

As we have discussed in the first chapter, the authorities may apply various proactive and reactive policies to regulate hazmat transportation. With respect to these policies, this chapter conducts a comprehensive survey of several main research streams in hazmat transportation most relevant to this thesis, namely, risk assessment (Section 2.1), network design problems (Section 2.2), toll policies (Section 2.3), emergency response (Section 2.4), integrated regulation policy (Section 2.5), and uncertainty considerations (Section 2.6). The gaps in the literature are outlined accordingly along with a highlight of our contribution to the literature (Section 2.7).

2.1 Risk Assessment in Hazmat Transportation

In general, the risk associated with hazmat transportation can be evaluated either qualitatively or quantitatively. The qualitative approach mainly focuses on identifying the variables contributing to transportation accidents, but it sometimes fails to provide a specific degree of risk (Weng et al., 2021). On the other hand, the quantitative approach is advantageous as it can bridge a quantitative link between the influencing elements and the risk of a hazmat transportation incident (Erkut and Alp, 2007). Erkut et al. (2007) summarized different methods of quantifying hazmat risk. The main ones are discussed as follows, where the accident probability on arc (link, edge) (i, j) within the set of arcs $\mathcal{A}$ and its consequence are respectively represented by p_{ij} and c_{ij}.

Saccomanno and Chan (1985) investigated three distinct routing strategies for hazmat road transportation: minimum risk, minimum accident probability, and minimum truck operating costs. They incorporated the Incident Probability (IP) which is an approach to quantify risk based on the relative accident frequency that occurs on an arc. In this approach, the network total incident probability is calculated by summing all arc incident probabilities:

$$IP = \sum_{(i,j)\in\mathcal{A}} p_{ij}.$$

IP is most suitable for the networks having arcs with similar incident probabilities.

Batta and Chiu (1988) quantified the impact of an arc accident, summed all the the possible consequences and measured the overall risk. This approach, known as Population Exposure (PE), does not consider the probability of an incident, i.e., all the consequences, regardless of their probabilities, are given the same weighting:

$$PE = \sum_{(i,j)\in\mathcal{A}} c_{ij}.$$

To evaluate the consequence of an incident, ReVelle et al. (1991) considered a fixed neighborhood (λ-neighborhood) around the edges inside which the damages are taken into account, Patel and Horowitz (1994) modeled the impact area using the Gaussian plume model, and Erkut and Verter (1998) considered the impact area as a circle around the incident point with a radius varying depending on the type of hazmat that is being carried.

Batta and Chiu (1988) developed the idea by incorporating both the incident probability and consequence when quantifying the risk and combining the previous two approaches. This approach is known as the Traditional Risk (TR):

$$TR = \sum_{(i,j)\in\mathcal{A}} p_{ij} c_{ij}.$$

This approach implies that the occurrence of an incident on the previous arcs does not impact the probability of an incident on the next arcs, meaning the arcs are independent in terms of occurrence of an incident.

In contrast to a strict technical calculation like the above approaches, the public's perception of risk can also be involved in risk assessment (Abkowitz et al. (1992)). This approach is known as the Perceived Risk (PR):

$$PR = \sum_{(i,j)\in\mathcal{A}} p_{ij} (c_{ij})^k,$$

where $k > 0$ is the risk perception factor. While $k = 1$ indicates a risk-neutral position, a higher value of k means the population is risk averse.

Sivakumar et al. (1993) integrated the TR and IP approaches into a new risk model, called Conditional Risk (CR), which is able to account for multiple types of hazmat being transported simultaneously.

$$CR = \frac{\sum_{(i,j)\in\mathcal{A}} p_{ij} c_{ij}}{\sum_{(i,j)\in\mathcal{A}} p_{ij}}.$$

Erkut and Ingolfsson (2000) proposed three catastrophe avoidance models. First, Maximum Population Exposure (MPE) is a more conservative approach. This method attempts to control the worst-case risk situation and is appropriate when dealing with extremely dangerous hazmat with serious consequences:

$$MPE = \max(c_{ij}).$$

The second method is Mean Variance (MV) for limiting both the variance and traditional risk at the same time. As a result, the variance is kept within a certain range, and risk is distributed more uniformly across the network:

$$MV = \sum_{(i,j)\in\mathcal{A}} \left(p_{ij}c_{ij} + kp_{ij}(c_{ij})^2\right).$$

Expected Disutility (ED) is the third approach, where the number of people impacted by an incident is exponentially considered:

$$ED = \sum_{(i,j)\in\mathcal{A}} p_{ij}e^{(kc_{ij}-1)},$$

where $k > 0$, showing the degree of risk averse in both MV and ED.

While most studies have focused on the potential impact of hazmat incidents on the population, hazmat can also significantly harm the environment surrounding an incident. Zhao and Verter (2015) and Zhao and Ke (2017) focused on environmental risk measures by embedding the Gaussian plume model [1], respectively for used oil and explosive materials. In Zhao and Ke (2017) for example, the explosive risks of a node and an edge can be respectively computed as follows.

$$V^{node} = \frac{1}{2} \times \frac{4}{3}\pi(R^{node})^3,$$

[1] The Gaussian Plume Model which is one of the most common air pollution models describes the three-dimensional concentration field generated by a point source under stationary meteorological and emission conditions (Zhao and Verter, 2015).

$$V^{edge} = \frac{1}{2}\pi R^{edge} D^{edge},$$

where V^{node} and V^{edge} are respectively the impact volumes for the node and the edge, R^{node} and R^{edge} represent the corresponding impact radius, and D^{edge} gives the edge distance.

The term Value at Risk (VaR), originally a financial term, was explored by Kang et al. (2014a,b) in the field of hazmat transportation. This approach evaluates the maximum potential risk of an incident across a set of hazmat shipments, bounded by a confidence interval:

$$VaR^l_{\alpha k} = min\{\beta : Pr\{R^l_k > \beta\} \leq 1 - \alpha\}$$

In this equation, $\alpha \in (0, 1)$ is the confidence interval and β is the Value at Risk for shipment k on link l. Later on, a more sophisticated method, conditional value-at-risk (CVaR), was adapted by Toumazis et al. (2013) to derive flexible and risk averse routes for hazmat shipments.

Time-based risk assessment has been applied to toll and emergency related optimizations. Proposing a dual toll pricing approach that simultaneously controls both regular and hazmat vehicles, Wang et al. (2012) first evaluated the arc risk (AR) of (i, j) by multiplying the travel time ($t_{ij}(v_{ij})$, expressed in terms of the arc flow v_{ij}) and the potential risk of transporting hazmat on the arc (ρ_{ij}), i.e.,

$$AR = \sum_{(i,j)\in\mathcal{A}} t_{ij}(v_{ij})\rho_{ij}.$$

In the emergency literature, Zhao and Ke (2019) connected the efficiency of emergency response to the potential risk. Such a setting is consistent with a report by Portland Fire and Rescue (2008), which indicated that every one minute delay in the defibrillation process reduces the survival rate by 10%. To that end, a risk factor α is used to quantify the increase of risk due to the delay in emergency response. This method is also implemented in the present thesis. Details can be found in Chapter 3.

2.2 Hazmat Transportation Network Design (HTND)

The process of developing a suitable network for the transportation of hazardous materials is known as Hazmat Transportation Network Design (HTND). Such a network is typically built to meet specific risk factors to minimize the damage to the local environment (such as population). One primary approach that can be considered is to impose restrictions on certain segments of roads near highly-populated areas. The other option is to expand the network by adding new road connections.

The main characteristics of this problem are the presence of two independent parties (government authorities and carriers) with different goals and conflicting decisions. Furthermore, the interaction between such groups is crucial. When deciding how to structure the network, the regulator has a strong hand. Yet, it cannot randomly mandate which road segments carriers must use within the hazmat network. In contrast, it must consider that the carriers are freely allowed to choose whatever path resulting in the lowest cost to move from origin to destination using the routes available following the regulator's decision.

Bilevel models are suited to describe the transportation of hazmats over a network, indicating different goals of the parties involved, as used by Kara and Verter (2004) for the first time to tackle hazmat transportation problems. In our case, the upper-level (government authorities) has the power to reduce the impact of hazmat transportation on the population and the environment. Carriers, on the other hand, want to reduce their costs and ultimately evaluate the network's risk based on the routes they choose. The hazmat transportation network design problem has been represented by a number of models and solution methods over the years. Kara and Verter (2004) proposed a bilevel model in their paper. The upper-level (government authorities) creates a separate network for each hazmat category (based on risk) with no interaction between these categories. The government aims to design a network with minimum total risk, taking carrier route choices into account. The carriers within each category can pick any route they want within the available links. Kara and Verter (2004) used the Karush-Kuhn-Tucker (KKT) conditions to replace the lower-level model and reformulate their model as a linear mixed-integer problem, which they then solved.

Similarly, Erkut and Alp (2007) proposed a model in which each origin-destination shipment pair is assigned to a single feasible route. They considered the issue of establishing hazmat routes into and through a densely populated area. Initially, they focused on a connected network (a tree) in which they could accurately predict network flows. The tree design problem was formulated as an integer programming problem with the objective of minimizing total transport risk. They used commercial solvers to solve such moderate-size design problems. They then devised a simple construction heuristic to broaden the solution to the tree design problem by incorporating road segments. Such expansions provide carriers with routing options, which typically increase risks while decreasing costs.

Erkut and Gzara (2008) built on previous works by expanding the problem to the undirected case and analyzing it for the worst risk. They modeled the problem as a bilevel network flow formulation and compared it to three other decision scenarios to examine the bilevel design problem. They solved the problem through transformation to a single-level model using duality and a heuristic method. They discovered that heuristically designed networks reduce risk significantly more than single-level models when tested on random instances. The risk was very close to the least risk possible. However, this risk reduction came at a significant cost increase. They extended the bilevel model by including the cost in the first-level objective to account for the cost/risk trade-off. The biobjective-bilevel model enabled the generation of numerous good design solutions. This was the first bi-objective-bilevel model in the network design literature.

Bianco et al. (2009) proposed a linear bilevel model in which the regional government (upper-level) sought to minimize total risk, and the local government (lower-level) sought risk equity. By replacing the second level (follower) problem with its KKT conditions and linearizing the complementary conditions, they converted the bilevel model into a single-level mixed-integer linear program and then solved the MIP problem with a commercial optimization solver. They provided a heuristic algorithm for the bilevel model capable of always finding a stable solution because the bilevel model is difficult to solve optimally, and its optimal solution may not be stable. The heuristic approach they introduced is an iterative algorithm that constructs a feasible solution to the bilevel model and tests its stability at each iteration.

Later, Gzara (2013) proposed a bilevel multi-commodity network flow model and found a solution using an exact cutting plane approach. It involves identifying infeasible solutions to construct feasible ones for the bilevel problem, which are later added to the upper-level problem to solve the upper and lower-level iteratively. Taslimi et al. (2017) developed a bilevel model involving a regulatory authority as the leader and hazmat carriers as the followers. The regulatory authority decides where to locate the hazmat response teams and which additional links to include for hazmat travel. It aims to minimize the maximum transport risk incurred by a transportation zone, which is related to risk equity, while the hazmat carriers aim to minimize their travel cost. Taslimi et al. (2017) converted the non-linear bilevel model into a single-level mixed-integer linear program using optimality conditions for the purpose of solving medium size problems. They used a greedy heuristic model to solve large size problems.

Some practitioners and scholars find road-closure policy as an inflexible initiative that does not efficiently use the available resources. Toll setting policies can be considered a viable solution for such a problem. Ke et al. (2020) incorporated a dual-toll policy to mitigate the risk of hazmat transportation.

More recently, some scholars made effort in combining various other approaches with network design polices to regulate hazmat transportation. This group of literature is reviewed in Section 2.5.

2.3 Toll Policies for Hazmat

Closing specific road links leaves the carriers with few options and is criticized for being too rigid. In order to provide the carriers with more flexibility and leave fewer unused links, toll/subsidy policies have been proposed. Labbé et al. (1998) proposed a bilevel model to consider the concerns of the government and the carriers simultaneously. By imposing tolls on some links, the government aimed to maximize its profit while the carriers aimed to minimize their transportation cost. Extending the research by Labbé et al. (1998), Brotcorne et al. (2001) proposed their bilevel model on a multi-commodity transportation network. The problem that they were trying to solve was to determine the optimal tolls to be set on the links of the network. In a network with a single origin, Dial (1999) suggested a model for minimal revenue tolls. The model was then solved using a fast algorithm. Trying to solve both elastic demand traffic assignment and combined distribution assignment problems, Yildirim and Hearn (2005) considered the demand between an origin-destination pair as a function of the least total travel cost and proposed a toll pricing framework.

Eventually, with a bilevel model, Marcotte et al. (2009) proposed the first toll setting policy for hazmat. In order to minimize travel cost, hazmat carriers tend to use links passing through less populated areas when tolls are placed on the links in populated areas. Proposing a bilevel model, Bianco et al. (2016) aimed to reduce the risk imposed by the hazmat shipments by incorporating a toll setting policy. They used toll-related terms in the upper level objective function and the constraints to minimize the total network risk and the maximum link risk among the network links (i.e. ensuring risk equity) and the carriers aimed to minimize their shipping cost, including toll cost, in the lower level which was formulated as a Nash game. Referring to congestion pricing policies, in order to mitigate the hazmat incident risk, Zhang et al. (2019) incorporated link tolls as the decision variables and proposed a bilevel programming optimization model with a variation inequality. Then, they proposed a double-temperature simulated annealing algorithm inserted with a diagonalization algorithm to solved the model. Yang et al. (2021) proposed a model to optimize toll

and shipping network design policies aiming to minimize the carbon dioxide emissions of the system.
In our research, we incorporate toll policies in addition to other policies to encourage the hazmat carriers to use less risky links.

Recently, some scholars considered regular traffic in addition to hazmat shipments in toll policy domain which is known as dual toll policy. Proposing a single-level model, Wang et al. (2012) incorporated a dual toll policy in order to control both the regular and hazmat vehicles. In an attempt to have a more realistic perspective, Esfandeh et al. (2016) developed a bilevel dual toll model. In their model, while the upper level's aim is to mitigate the hazmat incident risk, the lower level finds the equilibrium route decision of the regular and hazmat vehicles. Then Ke et al. (2020) took a step further by equipping their bilevel dual toll model with more features such as risk equity and multiple carriers shipping different types of hazmat.

2.4 Hazmat Emergency Response Management

A hazmat Response Team's job is to control the spill of hazmats. Therefore, HRTs' timely response to hazmat incidents, which becomes possible if they are strategically placed, can significantly mitigate the imposed risk. That is why many researchers have proposed coverage models. Considering the maximum distance from facilities, Church and ReVelle (1974) proposed a maximal covering model which maximized the service coverage. ReVelle et al. (1976) formulated a set covering problem and emphasized the applicability of the maximal link coverage. Church and Meadows (1979) expanded the research to include placing facilities anywhere on the network as a maximal coverage location problem. Saccomanno and Allen (1987) specifically focused on hazmats and formulated a minimum set coverage problem meaning that a minimum response level is forced on all nodes in the network. The risk of hazmat spills to the local population and property determines the demand for response capability at these nodes. Incorporating multiple objectives in the model including minimizing the HRT response time, List (1993) considered maximum acceptable risk levels over the network. List and Turnquist (1998) considered shipment routing and the provision of emergency-response capabilities as their model's objectives and minimized the response time based on the traffic flow. Hamouda et al. (2004) proposed a risk-based decision-support model for locating HRTs on the nwtwork. While making sure that the response times to all the nodes are less than an acceptable limit, they aimed to reduce the overall network risk. In order to optimise the design of an emergency response network, Berman et al. (2007) provided a maximal arc-covering location model in which risk is measured in terms of population exposure on an edge and developed two formulations to solve the problem. Considering a maximum number of HRTs, the model optimizes their locations on the network attempting to maximize the link-coverage.

Jiahong and Bin (2010) proposed a more comprehensive model based on a maximal arc-covering, a multi-objective 0–1 integer linear programming model, for the location-allocation problem in emergency response network design. They also added time and cost to the objectives. Taslimi et al. (2017) investigated the network coverage of predefined zones that cover one or more links or nodes, as well as the surrounding area. They developed a risk function based on a certain distance from an edge where the severity of an accident has a positive linear relationship with response time. Zhao and Ke (2019) considered both the full and partial coverage in their model. They developed a bilevel optimization model to help the regulator locate facilities and determine their capacities. Later, using a two-stage robust optimization approach, Ke (2022) looked into how probable system disruptions might affect the effectiveness of an emergency logistics system for hazmats.

2.5 Integrated Network Regulations

Since Kara and Verter (2004) first used a bilevel model to describe the hazmat transportation problem, there have been many researchers trying to incorporate different policies such as blocking and constructing links, imposing tolls on links, locating hazmat response teams, etc., into their models to more efficiently address the problem. Xu et al. (2013) integrated the two policies of link-closure with response teams in their research. Masoud et al. (2015) considered two policies to mitigate the hazmat transportation risk. They proposed a two-stage simulation-based optimization approach incorporating two policies of road-closure and toll pricing. Taslimi et al. (2017) considered a bilevel hazmat transportation network design in which the upper-level and the lower level represent the regulatory authority and hazmat shipments, respectively. Considering the regulatory authority (upper level) attempts to minimize the maximum transport risk, Taslimi et al. (2017) incorporated two policies as the regulatory authority's control variables: locations of hazmat response teams and which additional links to include for hazmat travel. López-Ramos et al. (2019) proposed a mixed integer non-linear bilevel model. They considered toll policy as well as road construction policy to control both the regular and hazmat vehicles. In their model, the road network operator aims to maximize its profit, considering the toll income and road construction cost, and the vehicles aim to minimize their cost. Zahiri et al. (2020) propose a bi-objective mathematical model for hazmat transportation design in which both the proactive and reactive policies are considered. In their model, the locations of the HRTs to respond to the hazmat-related incidents (as the reactive policy) and the locations of the warehouses for storage (as the proactive policy) are decided simultaneously. Masoud et al. (2020) considered an integrated traffic control policy for hazmat transportation. Their model simultaneously blocks the roads in populated areas and also imposes a dual toll pricing policy in order to control both the regular and hazmat traffic.

To the best of our knowledge, most of the research in the past has been focused on one or two of the mentioned policies together. In our research, we incorporate different policies in order to better manage the hazmat-related risks. These policies include road closure, road construction, toll policy as well as locating hazmat response teams.

2.6 Uncertainty Issues in Hazmat Transportation

In the current literature, few studies focus on uncertainty in hazmat network design problems. Hall (1986) was one of the first researchers studying uncertainty in transportation. In a network with uncertain and time-dependent trip times, he presented the idea of determining the path with the least estimated travelling time between two nodes. Later, Saccomanno et al. (1993) reviewed the nature of some of the uncertainties concerning the estimation of risks for the hazmat transportation, and listed different sources of uncertainty in the hazmat risk analysis process. Later, focused on routing and scheduling of shipments of hazmats in networks with uncertain routing attributes, Chang et al. (2005) developed a model for finding nondominated paths for routing objectives. Bell (2007) studied uncertainty in link incident probabilities and studied mixed-routing strategies in hazmat transportation. Erkut et al. (2007) described two general methods to incorporate uncertainty in risk factors as mean-risk and stochastic dominance. Mudchanatongsuk et al. (2008) considered transportation cost and demand uncertainties in their study and presented a robust optimization-based formulation for the network design problem. Xin et al. (2013) developed a bilevel integer model to describe the hazardous materials transportation network design problem by using maximum regret criterion robust optimization methodology. They presented their model under edge risk uncertainty where an interval of possible risk values is associated with each link. Sun et al. (2016) investigated robust network design problems for hazardous materials transportation while accounting for risk uncertainty. In their research, risk uncertainty is considered in two ways: uncertainty on each link for each shipment, and uncertainty on each link across all shipments. Mohammadi et al. (2017) developed a mixed integer nonlinear programming model for designing a reliable hazardous material transportation network under uncertainties. A solution framework based on an integration of the well-known chance-constrained programming with a possibilistic programming approach was proposed to address the uncertainties in the model. Taslimi et al. (2017) addressed the uncertainties in the model parameters by examining possible boundaries and performing simulations to obtain a more robust solution. Considering unknown probabilities for hazmat incidents, Moghaddam and Kianfar (2021) address the issue of finding optimal links and routes to maintain a balance between safe and fast distribution of hazmats between origins and destinations through a transport network. A fuzzy-based bi-objective optimisation model was developed to solve the problem. In our research, through considering scenario-based uncertainty reflecting the variations in demand and shipments, we ensure the system robustness under different situations.

2.7 Literature Gap & Our Contribution

In the literature, especially over the past few years, there has been a variety of research aimed at addressing different aspects of hazmat transportation. In this thesis, we looked into several studies done in the past to investigate what has been done and what is missing. Considering the fact that there are many different factors impacting the hazmat network design problem, a comprehensive study is needed to include multiple factors in order to obtain a more realistic and practical solution. Aiming to minimize the risk imposed by hazmat transportation incidents, we integrate several policies in our model, something that has never been done before. Designing a network for hazmat transportation in which the incidents risk and carriers cost is minimized simultaneously, we take demand and shipment uncertainty into account to better mirror a real-world situation and have a robust system under different situations. Moreover, unlike studies done before in which only one or two control policies were practised by the government, we incorporate road-closure policy, road-instruction policy, toll policy as well as hazmat response policy. Table 2.1 provides a summary of the literature and our contribution in this thesis.

Table 2.1: A comparison with the existing literature

Literature	Road Closure	Road Construction	Toll Policy	HRT	Uncertainty
Xu et al. (2013)	$\surd$		$\surd$		$\surd$
Xin et al. (2015)	$\surd$				$\surd$
Taslimi et al. (2017)		$\surd$		$\surd$	$\surd$
López-Ramos et al. (2019)		$\surd$	$\surd$		
Masoud et al. (2020)	$\surd$		$\surd$		
Mohabbati-Kalejahi and Vinel (2021)	$\surd$				$\surd$
The present work	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$

Chapter 3

A bilevel Network Design Model for Hazardous Materials

3.1 Problem Statement

3.1.1 A bilevel structure

Figure 3.1 illustrates the interactions of the two decision makers in this work via a bilevel structure. As noted, we consider two decision makers, the authorities (e.g., government), who design the network along with the emergency location decisions, and the hazmat carriers, who ship hazmat freights in multiple types. At the upper level, the authorities make four decisions:

1. locating the hazmat emergency response teams at several pre-determined candidate locations,

2. choosing which link be closed for which type of hazmat,

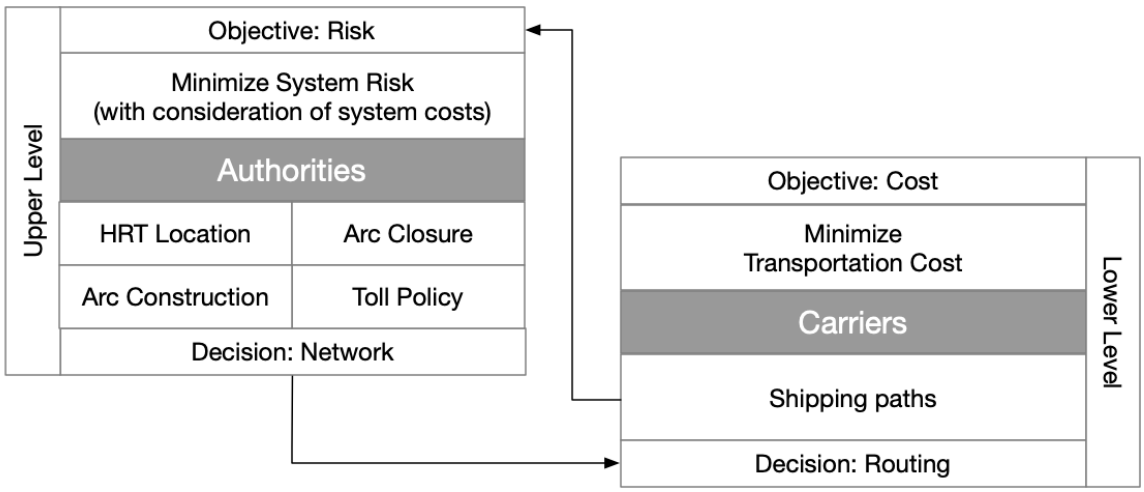

Figure 3.1: A bilevel structure

3. constructing necessary links, and

4. determining the hazmat-based toll for the links (different tolls for different hazmats).

In light of the network determined by the government, the hazmat carriers select paths with lowest transportation cost (including the toll expense) over several possible uncertainty scenarios.

3.1.2 Assumptions

Our model is based on the following assumptions:

1. The impact of ordinary vehicles is not considered.

2. Links (i,j) and (j,i) are assumed totally equal in terms of being available to hazmat shipments, toll price, and coverage, for example, if link (i,j) is blocked for hazmat shipments then link (j,i) is also blocked.

3. We do not consider limited capacities for HRTs, meaning that all the links in the zone of an HRT will be covered. So, all links are either fully covered or not covered.

4. We do not assume any shipment capacity limitations for the network, meaning the network is assumed to be uncapacitated.

5. It is assumed that each shipment carries a single type of hazmat. Without loss of generality, this assumption simplifies the model.

3.1.3 Arc sets

Corresponding to the decisions described in the previous subsection, the arc set $\mathcal{A}$ consists of four subsets:

$\mathcal{A}^t$ Set of arcs regulated by tolls,

$\mathcal{A}^b$ Set of arcs regulated by road closure,

$\mathcal{A}^n$ Set of unregulated arcs (i.e., arcs are exempt from any regulations), and

$\mathcal{A}^a$ Set of arc locations to be constructed.

Note that the first three sets are exclusive to each other, i.e., $\mathcal{A}^t \cap \mathcal{A}^b \cap \mathcal{A}^n = \emptyset$. For relationship, we have $\mathcal{A} = \mathcal{A}^t \cup \mathcal{A}^b \cup \mathcal{A}^n$. It is clear that the newly constructed arcs cannot be closed to hazmat, therefore, $\mathcal{A}^a \subset \mathcal{A} \setminus \mathcal{A}^b = \mathcal{A}^t \cup \mathcal{A}^n$.

3.1.4 Uncertain scenarios

We consider a set of demand uncertain scenarios, each with different shipment sets, i.e., for shipment $s \in S_h^u$ (S_h^u is the set of all shipments carrying hazmat h in scenario u), we have origin-destination pair $o^u(s), d^u(s) \in \mathcal{N}$ and demand D_s. $\mathcal{N}$ is the set of all the nodes in the network and D_s is the demand for shipment s.

3.2 A time-dependent risk assessment with arc coverage

For each arc (i, j), the unit risk can be evaluated by

$$R_{ijh} = POP_{ijh} DIS_{ij} RR_h IR_{ij},$$

where POP_{ijh} is the population exposure within a certain radius per unit distance on arc (i, j) for an incident caused by hazmat h, DIS_{ij} is the length of arc (i, j), RR_h is the release rate of hazmat h, and IR_{ij} is the incident rate on arc (i, j).

Moreover, the emergency response time can also influence the travel risk. Figure 3.2 illustrates the idea of arc coverage. We assume that the emergency response team m uses the shortest path to the midpoint of arc (i, j), which induces a response time of t_{ijm}. The shorter the response time, the lower the risk associated with the incident; and vice versa. Let $T_{\max}$ be the least desired response times and q_{ijm} a binary variable that indicates the link (i, j) is covered by the HRT m when it is 1. An arc is only considered to be covered when the least desired time can be met. Figure 3.2 shows $t_{i'j'm} < T_{\max} < t_{ijm}$, and hence arc (i', j') can be covered by team m, while arc

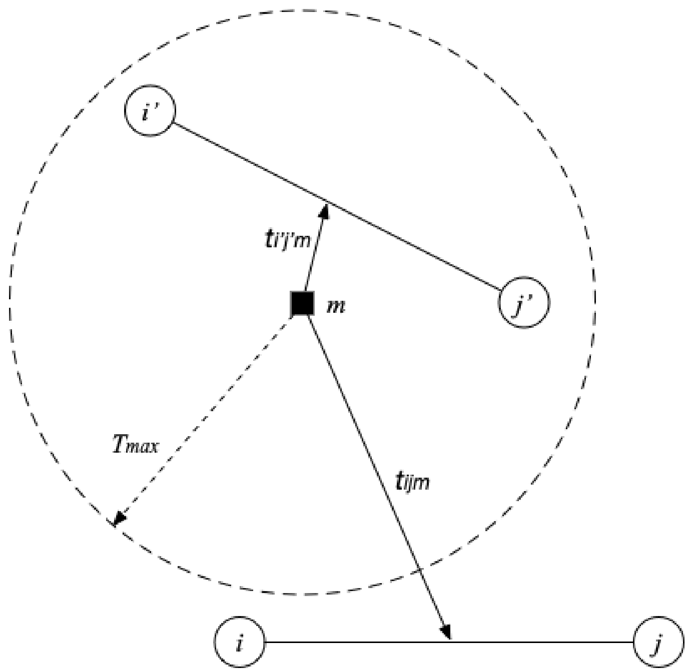

Figure 3.2: Arc coverage

(i, j) cannot. Note that this arc coverage method is different from what was proposed in Taslimi et al. (2017).

q_{ijm} 1, if arc $(i, j) \in \mathcal{A}$ is served by response team m; 0, otherwise.

Therefore, it is required that

$$t_{ijm} q_{ijm} \leq T_{\max}, \qquad \forall (i, j) \in \mathcal{A}, m \in \mathcal{M}, \tag{3.1}$$

which indicates that if arc (i, j) is served by location m (i.e., $q_{ijm} = 1$), then the response time has to be shorter than the maximum response time.

Moreover, at most one emergency team can be assigned to each arc, i.e.,

$$\sum_{m \in \mathcal{M}} q_{ijm} \leq 1, \qquad \forall (i, j) \in \mathcal{A}. \tag{3.2}$$

Taking the response time into account, the risk associated with shipping a unit of hazmat h on arc (i,j) given HRT m can be computed as

$$\sum_{h\in\mathcal{H}}\sum_{m\in\mathcal{M}} \alpha q_{ijm} R_{ijh},$$

where α is the confidence level for the arc coverage, i.e., a multiplier indicating the increase of risk due to delay in response. This is defined as a function in terms of the response time, specifically, the relation between the real response time and the desired one. A report by the Transportation Research Board (2011) suggested the following values for α:

$$\alpha_{ijm} = \begin{cases} 1, & t_{ijm} \leq 0.5T_{\max}; \\ 2.5, & 0.5T_{\max} < t_{ijm} \leq 0.75T_{\max}; \\ 4, & 0.75T_{\max} < t_{ijm} \leq T_{\max}; \\ 5, & t_{ijm} > T_{\max}. \end{cases} \tag{3.3}$$

Note that the above risk measure is computed given that arc (i,j) is covered by an HRT. It may also be possible that the arc cannot be covered by any HRT (i.e., $\sum_{m\in\mathcal{M}} q_{ijm} = 0$). In this case, the corresponding arc risk can be written as

$$\sum_{s\in\mathcal{S}_h} R_{ijh} D_s \alpha_{\max} x^u_{ijs}.$$

This uncovered arc risk needs to be included in the total system risk with function $\left(1 - \sum_{m\in\mathcal{M}} q_{ijm}\right)$.

3.3 Model Development

3.3.1 Notation

Sets:

$\mathcal{N}$ Node set, indexed by i and j.

$\mathcal{A}$ Arc set, indexed by (i, j). $\mathcal{A} = \mathcal{A}^t \cup \mathcal{A}^b \cup \mathcal{A}^n$, where $\mathcal{A}^t$, $\mathcal{A}^b$, and $\mathcal{A}^n$ are respectively the arc sets for setting tolls, road closure, and unregulated links.

$\mathcal{A}^a$ Set of candidate arc locations, $\mathcal{A}^a \subset \mathcal{A} \setminus \mathcal{A}^b = \mathcal{A}^t \cup \mathcal{A}^n$.

$\mathcal{H}$ Set of hazardous materials, indexed by h.

$\mathcal{M}$ Set of candidate locations for hazmat emergency response team, indexed by m.

$\mathcal{U}$ Set of uncertainty scenarios, indexed by u.

$\mathcal{S}_h^u$ Set of O-D pairs for hazmat shipments of hazmat type h in scenario u, indexed by s.

Parameters:

O_{ijh} Cost of open arc $(i, j) \in \mathcal{A} \in \mathcal{A}^b$ to hazmat h.

P_{ij} Cost of constructing a new arc $(i, j) \in \mathcal{A}^a$.

C_{ijh} Cost of shipping one unit of hazmat h on arc (i, j).

R_{ijh} Risk of shipping one unit of hazmat h on arc (i, j).

η_{ijhm} Risk of shipping one unit of hazmat h on arc (i, j) given HRT m.

α_{ijm} Confidence level for arc coverage in terms of t_{ijm}.

t_{ijm} Response time from team location m to arc (i, j).

ρ^u Probability of uncertainty scenario u.

D_s Number of required trucks for hazmat shipment s.

$T_{\max}$ Maximum (least desired) response time.

$Z_{\max}$ Maximum number of emergency teams need to be located.

$W_{\max}$	Maximum toll value.
$F_{\max}$	Maximum arc flow that requires coverage.
B	Budget for arc construction.
M	A large number.
ϵ, σ, ω	Small weights related to the tolls, constructed links, and blocked links, respectively, in the objective function.

Variables:

x_{ijs}^u	1, if arc $(i, j) \in \mathcal{A}$ is used for shipment s in scenario u; 0, otherwise.
y_{ijh}	1, if arc $(i, j) \in \mathcal{A}^b$ is available for shipments of hazmat h; 0, otherwise.
w_{ijh}	Toll charged to vehicles shipping hazmat h on arc $(i, j) \in \mathcal{A}^t$.
v_{ij}	1, if a new arc $(i, j) \in \mathcal{A}^a$ is constructed; 0, otherwise.
z_m	1, if a response team is positioned at location m; 0, otherwise.
q_{ijm}	1, if arc $(i, j) \in \mathcal{A}$ is served by response team m; 0, otherwise.

3.3.2 Mathematical model

Upper level:

$$\min \sum_{u \in \mathcal{U}} \rho^u \left(\sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}_h} \sum_{m \in \mathcal{M}} R_{ijh} D_s \alpha_{ijm} q_{ijm} x_{ijs}^u + \sum_{(i,j) \in \mathcal{A}} \left(1 - \sum_{m \in \mathcal{M}} q_{ijm} \right) \sum_{s \in \mathcal{S}_h} R_{ijh} D_s \alpha_{\max} x_{ijs}^u \right)$$
$$+ \omega \left(\sum_{(i,j) \in \mathcal{A}^b} \sum_{h \in \mathcal{H}} O_{ijh} y_{ijh} \right) + \sigma \left(\sum_{(i,j) \in \mathcal{A}^a} P_{ij} v_{ij} \right) + \epsilon \left(\sum_{(i,j) \in \mathcal{A}^t} \sum_{h \in \mathcal{H}} w_{ijh} \right) \tag{3.4}$$

s.t. Constraints (3.1)-(3.2), and

$$\sum_{m \in \mathcal{M}} z_m \leq Z_{\max}; \tag{3.5}$$

$$q_{ijm} \leq z_m, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}; \tag{3.6}$$

$$\sum_{s \in \mathcal{S}_h} x^u_{ijs} - F_{\max} \leq M \sum_{m \in \mathcal{M}} q_{ijm}, \qquad \forall (i,j) \in \mathcal{A}, u \in \mathcal{U}; \tag{3.7}$$

$$\sum_{(i,j) \in \mathcal{A}^a} P_{ij} v_{ij} \leq B; \tag{3.8}$$

$$w_{ijh} \leq W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, h \in \mathcal{H}; \tag{3.9}$$

$$y_{ijh}, z_m, q_{ijm}, v_{ij} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}; \tag{3.10}$$

$$w_{ijh} \geq 0 \qquad \forall (i,j) \in \mathcal{A}^t, h \in \mathcal{H}. \tag{3.11}$$

Objective (3.4) minimizes the mean system risk over different scenarios considering the emergency response coverage. The last three additional terms in the objective (3.4) have weights ω, σ and ϵ, respectively. The first and second additional terms transfer the opening and construction costs of arcs to hazmat risk, while the third term guarantees the obtained tolls are at the lowest level by integrating the total toll value and a very small weight ϵ. Constraint set (3.5) determines the number of located teams. Constraint set (3.6) ensures that only located teams can be allocated to arcs. Constraint set (3.7) indicates that an arc must be covered if the flow on this arc exceeds a specified threshold. Constraint set (3.8) describes the budget limit for constructing new links. Constraint set (3.9) poses the highest toll value. Constraint sets (3.10) and (3.11) clarify the domains of variables.

Lower level:

$$\min \sum_{u \in \mathcal{U}} \rho^u \Bigg(\sum_{(i,j) \in \mathcal{A}} \sum_{h \in \mathcal{H}} \sum_{s \in \mathcal{S}_h} D_s C_{ijh} x^u_{ijs} + \sum_{(i,j) \in \mathcal{A}^t} \sum_{h \in \mathcal{H}} \sum_{s \in \mathcal{S}_h} D_s w_{ijh} x^u_{ijs} - \frac{1}{R_{\max}} \sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}_h} R_{ijh} D_s \alpha_{ijm} q_{ijm} x^u_{ijs} \Bigg), \tag{3.12}$$

s.t. (3.1)-(3.2), and

$$\sum_{(i,j)\in\mathcal{A}} x^u_{ijs} - \sum_{(j,i)\in\mathcal{A}} x^u_{jls} = \begin{cases} 1 & \text{if } i = o(s) \\ -1 & \text{if } i = d(s) \\ 0 & \text{otherwise} \end{cases}, \qquad \forall i \in \mathcal{N}, s \in \mathcal{S}_h, u \in \mathcal{U}; \quad (3.13)$$

$$x^u_{ijs} \le y_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U}; \quad (3.14)$$

$$x^u_{ijs} \le v_{ij}, \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U}; \quad (3.15)$$

$$x^u_{ijs} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_h, u \in \mathcal{U}. \quad (3.16)$$

The lower level problem is a standard shortest path model, which minimizes the mean transportation cost (including toll cost) over all scenarios in Objective (3.12). Note that, by introducing the additional risk-relevant term based on $R_{\max}$, the maximum risk of all shipments, a pessimistic solution is enforced for the lower level when multiple minimum-cost path alternatives exists. Hence, the leader's decisions about the network and tolls can prevent the worst situation (Amaldi et al., 2011). Constraint set (3.13) computes the flows of hazmat shipments. Constraint set (3.14) makes sure that the hazmat shipments can only be transported through those arcs allowing hazmats. Similarly, Constraint set (3.15) concerns the newly built arcs. An arc can only be taken when constructed. Constraint set (3.16) gives the variable domain.

Chapter 4

Solution Procedure

NP-hard problems, such as bilevel models, are computationally difficult to solve. In this chapter, two solving approaches are developed. First, we reformulate the bilevel model into a single-level linear problem. The second approach is in fact a heuristic algorithm that breaks the linearized problem into two parts.

4.1 Linearization

To linearize the product of two binary variables $q_{ijm}x^u_{ijs}$, we introduce a binary auxiliary variable γ^u_{ijms} with three additional constraints:

$$\gamma^u_{ijms} \leq q_{ijm}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.1}$$

$$\gamma^u_{ijms} \leq x^u_{ijs}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.2}$$

$$\gamma^u_{ijms} \geq q_{ijm} + x^u_{ijs} - 1, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U}. \tag{4.3}$$

Another nonlinear term is formed by the product of a binary variable and a continuous variable, i.e., $w_{ijh}x^u_{ijs}$. With a non-negative auxiliary variable δ^u_{ijs} and the following constraints, the term can be linearized.

$$\delta_{ijs}^u \leq W_{\max} x_{ijs}^u, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.4}$$

$$\delta_{ijs}^u \leq w_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.5}$$

$$\delta_{ijs}^u \geq w_{ijh} - (1 - x_{ijs}^u) W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.6}$$

4.2 Single-Level Reformulation (SLRF)

Taking the method designed by Amaldi et al. (2011), let π_{is}^u and π_{js}^u be the dual variables of Constraint (3.13). The lower model is substituted by Constraints (3.13)-(3.15), plus the following constraints:

$$\begin{aligned}\pi_{js}^u - \pi_{is}^u \leq \rho^u D_s C_{ijh} - \rho^u \frac{R_{ijh} D_s \alpha_{ijm}}{R_{\max}} \\ + M(1 - y_{ijh}), \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U};\end{aligned} \tag{4.7}$$

$$\begin{aligned}\pi_{js}^u - \pi_{is}^u \leq \rho^u D_s \left(C_{ijh} + w_{ijh}\right) - \rho^u \frac{R_{ijh} D_s \alpha_{ijm}}{R_{\max}} \\ + M(1 - v_{ij}), \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U};\end{aligned} \tag{4.8}$$

$$\pi_{js}^u - \pi_{is}^u \leq \rho^u D_s \left(C_{ijh} + w_{ijh}\right) - \rho^u \frac{R_{ijh} D_s \alpha_{ijm}}{R_{\max}} \qquad \forall (i,j) \in \mathcal{A}^t \setminus (\mathcal{A}^t \cap \mathcal{A}^a), s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.9}$$

$$\pi_{js}^u - \pi_{is}^u \leq \rho^u D_s C_{ijh} - \rho^u \frac{R_{ijh} D_s \alpha_{ijm}}{R_{\max}} \qquad \forall (i,j) \in \mathcal{A}^n \setminus (\mathcal{A}^n \cap \mathcal{A}^a), s \in \mathcal{S}_h, u \in \mathcal{U}; \tag{4.10}$$

$$\pi_{d^u(s)}^u - \pi_{o^u(s)}^u \geq \rho^u \sum_{(i,j) \in \mathcal{A}} \sum_{h \in \mathcal{H}} D_s C_{ijh} x_{ijs}^u$$

$$
\begin{aligned}
&+ \rho^u \sum_{(i,j)\in\mathcal{A}^t} \sum_{h\in\mathcal{H}} D_s \delta_{ijs}^u \\
&- \rho^u \sum_{(i,j)\in\mathcal{A}} \frac{R_{ijh} D_s \alpha_{ijm}}{R_{\max}} \gamma_{ijms}^u, \qquad \forall s \in \mathcal{S}_h, u \in \mathcal{U}.
\end{aligned} \tag{4.11}
$$

Constraint sets (4.7)-(4.10) are the classic dual constraints for a shortest path problem with consideration of network design. Particularly, constraints (4.7) are concerned with the arcs that can be closed and constraints (4.8) are concerned with the arcs that can be constructed. When the arc is opened (i.e., $y_{ijh} = 1$) or constructed (i.e., $v_{ij} = 1$), they coincide with the other two dual constraints, but are redundant otherwise. (4.9) and (4.10) address the tolled and unregulated arc (excluding newly constructed ones), respectively. Constraint set (4.11) ensures the dual objective is the same as the original problem.

Then, we can write the single-level reformulation as follows. Note that the objective function has been manipulated for a smoother expression.

$$
\begin{aligned}
\min \quad & \sum_{u\in\mathcal{U}} \rho^u \left(\sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}_h} R_{ijh} D_s \alpha_{\max} x_{ijs}^u - \sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}_h} \sum_{m\in\mathcal{M}} R_{ijh} D_s (\alpha_{\max} - \alpha_{ijm}) \gamma_{ijms}^u \right), \\
& + \omega \left(\sum_{(i,j)\in\mathcal{A}^b} \sum_{h\in\mathcal{H}} O_{ijh} y_{ijh} \right) + \sigma \left(\sum_{(i,j)\in\mathcal{A}^a} P_{ij} v_{ij} \right) + \epsilon \left(\sum_{(i,j)\in\mathcal{A}^t} \sum_{h\in\mathcal{H}} w_{ijh} \right)
\end{aligned}
$$

s.t.

$$
t_{ijm} q_{ijm} \le T_{\max}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M},
$$

$$
\sum_{m\in\mathcal{M}} q_{ijm} \le 1, \qquad \forall (i,j) \in \mathcal{A}.
$$

$$
\sum_{m\in\mathcal{M}} z_m \le Z_{\max},
$$

$$q_{ijm} \leq z_m, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M};$$

$$\sum_{s \in \mathcal{S}_h} x^u_{ijs} - F_{\max} \leq M \sum_{m \in \mathcal{M}} q_{ijm} \qquad \forall (i,j) \in \mathcal{A}, u \in \mathcal{U};$$

$$\sum_{(i,j) \in \mathcal{A}^a} P_{ij} v_{ij} \leq B;$$

$$w_{ijh} \leq W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, h \in \mathcal{H};$$

$$\sum_{(i,j) \in \mathcal{A}} x^u_{ijs} - \sum_{(j,i) \in \mathcal{A}} x^u_{jls} = \begin{cases} 1 & \text{if } i = o(s) \\ -1 & \text{if } i = d(s) \\ 0 & \text{otherwise} \end{cases}, \qquad \forall i \in \mathcal{N}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs} \leq y_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs} \leq v_{ij}, \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{js} - \pi^u_{is} \leq \rho^u D_s C_{ijh} - \rho^u \frac{R_{ijh} D_s \alpha_{ijm} q_{ijm}}{R_{\max}}$$
$$+ M(1 - y_{ijh}), \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{js} - \pi^u_{is} \leq \rho^u D_s \left(C_{ijh} + w_{ijh}\right) - \rho^u \frac{R_{ijh} D_s \alpha_{ijm} q_{ijm}}{R_{\max}}$$
$$+ M(1 - v_{ij}), \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{js} - \pi^u_{is} \leq \rho^u D_s \left(C_{ijh} + w_{ijh}\right) - \rho^u \frac{R_{ijh} D_s \alpha_{ijm} q_{ijm}}{R_{\max}} \qquad \forall (i,j) \in \mathcal{A}^t \setminus (\mathcal{A}^t \cap \mathcal{A}^a), s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{js} - \pi^u_{is} \leq \rho^u D_s C_{ijh} - \rho^u \frac{R_{ijh} D_s \alpha_{ijm} q_{ijm}}{R_{\max}} \qquad \forall (i,j) \in \mathcal{A}^n \setminus (\mathcal{A}^n \cap \mathcal{A}^a), s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{d^u(s)} - \pi^u_{o^u(s)} \geq \rho^u \sum_{(i,j) \in \mathcal{A}} \sum_{h \in \mathcal{H}} D_s C_{ijh} x^u_{ijs}$$
$$+ \rho^u \sum_{(i,j) \in \mathcal{A}^t} \sum_{h \in \mathcal{H}} D_s \delta^u_{ijs}$$
$$- \rho^u \sum_{(i,j) \in \mathcal{A}} \frac{R_{ijh} D_s \alpha_{ijm}}{R_{\max}} \gamma^u_{ijms}, \qquad \forall s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\gamma^u_{ijms} \leq q_{ijm}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\gamma^u_{ijms} \leq x^u_{ijs}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\gamma^u_{ijms} \geq q_{ijm} + x^u_{ijs} - 1, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\delta^u_{ijs} \leq W_{\max} x^u_{ijs}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\delta^u_{ijs} \leq w_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\delta^u_{ijs} \geq w_{ijh} - (1 - x^u_{ijs}) W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs}, y_{ijh}, z_m, q_{ijm}, v_{ij}, \gamma^u_{ijms} \in \{0,1\}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$w_{ijh}, \delta^u_{ijs} \geq 0, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{is}, \pi^u_{js} \quad \text{free} \qquad \forall i,j \in \mathcal{N}, s \in \mathcal{S}_h, u \in \mathcal{U}.$$

4.3 A Two-Stage Heuristic Algorithm (TSHA)

The above-presented single-level reformulation of the model can be solved to optimality. The computation process, however, may take a long time. This is due to the large number of variables representing the interaction of all the factors and the linearization processes making the problem complicated. To ensure the workability of our propose mathematical model, we then design a two-stage heuristic algorithm (TSHA), which can improve the computational time with minor compensation of overall risk.

Observing the original model presented in Chapter 3, the problem can be divided into two groups of decisions:

1. the proactive network design decisions including, choosing which links to block, which new links to add to the network, and determining the hazmat-based toll for the links; and

2. the reactive decisions associated with the location of HRTs.

So, instead of addressing the both groups of decisions simultaneously, we divide the problem into its two main stages that are solved sequentially.

Stage 1 An HTND problem with optimal solution $f^*(x^{u*}_{ijs}, y^*_{ijh}, w^*_{ijh}, v^*_{ij})$.

Stage 2 An HRT location problem with optimal solution: $s^*(z^*_m, q^*_{ijm})$ by taking $f^*(x^{u*}_{ijs}, y^*_{ijh}, w^*_{ijh}, v^*_{ij})$ as known parameters.

As shown, a network with all the details, blocked and added links, tolls and the shortest paths of the carriers, is designed in the first stage that becomes the network on which the HRTs can be properly placed.

4.3.1 First-stage problem - HTND

Removing the HRT-related features, including the parameter based on the response time to assess risk, the total risk is measured merely according to R_{ijh}. Our mathematical model then can be simplified as follows.

$$\min \quad \sum_{u\in\mathcal{U}} \rho^u \left(\sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}_h} R_{ijh} D_s x^u_{ijs} \right) + \omega \left(\sum_{(i,j)\in\mathcal{A}^b} \sum_{h\in\mathcal{H}} O_{ijh} y_{ijh} \right) + \sigma \left(\sum_{(i,j)\in\mathcal{A}^a} P_{ij} v_{ij} \right) + \epsilon \left(\sum_{(i,j)\in\mathcal{A}^t} \sum_{h\in\mathcal{H}} w_{ijh} \right)$$

s.t.

$$\sum_{(i,j)\in\mathcal{A}^a} P_{ij} v_{ij} \leq B;$$

$$w_{ijh} \leq W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, h \in \mathcal{H};$$

$$x^u_{ijs}, y_{ijh}, v_{ij}, \in \{0,1\}, \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$w_{ijh} \geq 0, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h;$$

$$\begin{aligned} x \in \arg\min \sum_{u\in\mathcal{U}} \rho^u \Bigg(& \sum_{(i,j)\in\mathcal{A}} \sum_{h\in\mathcal{H}} \sum_{s\in\mathcal{S}_h} D_s C_{ijh} x^u_{ijs} \\ & + \sum_{(i,j)\in\mathcal{A}^t} \sum_{h\in\mathcal{H}} \sum_{s\in\mathcal{S}_h} D_s w_{ijh} x^u_{ijs} \\ & - \frac{1}{R_{\max}} \sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}_h} R_{ijh} D_s x^u_{ijs} \Bigg), \end{aligned}$$

s.t.

$$\sum_{(i,j)\in\mathcal{A}} x^u_{ijs} - \sum_{(j,i)\in\mathcal{A}} x^u_{jls} = \begin{cases} 1 & \text{if } i = o(s) \\ -1 & \text{if } i = d(s) \\ 0 & \text{otherwise} \end{cases}, \qquad \forall i \in \mathcal{N}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs} \leq y_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs} \leq v_{ij}, \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs}, y_{ijh}, v_{ij}, \in \{0,1\}, \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$w_{ijh} \geq 0, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h;$$

By applying the dual theory with dual variables π^u_{is} and π^u_{js}, we can next reformulate the above model to a single level format.

$$\begin{aligned} \min \quad & \sum_{u\in\mathcal{U}} \rho^u \left(\sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}_h} R_{ijh} D_s x^u_{ijs} \right) + \omega \left(\sum_{(i,j)\in\mathcal{A}^b} \sum_{h\in\mathcal{H}} O_{ijh} y_{ijh} \right) + \sigma \left(\sum_{(i,j)\in\mathcal{A}^a} P_{ij} v_{ij} \right) \\ & + \epsilon \left(\sum_{(i,j)\in\mathcal{A}^t} \sum_{h\in\mathcal{H}} w_{ijh} \right) \end{aligned}$$

s.t.

$$\sum_{(i,j)\in\mathcal{A}^a} P_{ij} v_{ij} \leq B;$$

$$w_{ijh} \leq W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, h \in \mathcal{H};$$

$$\sum_{(i,j)\in\mathcal{A}} x^u_{ijs} - \sum_{(j,i)\in\mathcal{A}} x^u_{jls} = \begin{cases} 1 & \text{if } i = o(s) \\ -1 & \text{if } i = d(s) \\ 0 & \text{otherwise} \end{cases}, \qquad \forall i \in \mathcal{N}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs} \leq y_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x^u_{ijs} \leq v_{ij}, \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\begin{aligned} \pi^u_{js} - \pi^u_{is} \leq{} & \rho^u D_s C_{ijh} - \rho^u \frac{R_{ijh} D_s}{R_{\max}} \\ & + M(1 - y_{ijh}), \qquad \forall (i,j) \in \mathcal{A}^b, s \in \mathcal{S}_h, u \in \mathcal{U}; \end{aligned}$$

$$\begin{aligned} \pi^u_{js} - \pi^u_{is} \leq{} & \rho^u D_s \left(C_{ijh} + w_{ijh}\right) - \rho^u \frac{R_{ijh} D_s}{R_{\max}} \\ & + M(1 - v_{ij}), \qquad \forall (i,j) \in \mathcal{A}^a, s \in \mathcal{S}_h, u \in \mathcal{U}; \end{aligned}$$

$$\pi^u_{js} - \pi^u_{is} \leq \rho^u D_s \left(C_{ijh} + w_{ijh}\right) - \rho^u \frac{R_{ijh} D_s}{R_{\max}} \qquad \forall (i,j) \in \mathcal{A}^t \setminus (\mathcal{A}^t \cap \mathcal{A}^a), s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi^u_{js} - \pi^u_{is} \leq \rho^u D_s C_{ijh} - \rho^u \frac{R_{ijh} D_s}{R_{\max}} \qquad \forall (i,j) \in \mathcal{A}^n \setminus (\mathcal{A}^n \cap \mathcal{A}^a), s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\begin{aligned} \pi^u_{d^u(s)} - \pi^u_{o^u(s)} \geq{} & \rho^u \sum_{(i,j)\in\mathcal{A}} \sum_{h\in\mathcal{H}} D_s C_{ijh} x^u_{ijs} \\ & + \rho^u \sum_{(i,j)\in\mathcal{A}^t} \sum_{h\in\mathcal{H}} D_s \delta^u_{ijs} \\ & - \rho^u \sum_{(i,j)\in\mathcal{A}} \frac{R_{ijh} D_s}{R_{\max}} x^u_{ijs}, \qquad \forall s \in \mathcal{S}_h, u \in \mathcal{U}; \end{aligned}$$

$$\delta^u_{ijs} \leq W_{\max} x^u_{ijs}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\delta^u_{ijs} \leq w_{ijh}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\delta_{ijs}^u \geq w_{ijh} - (1 - x_{ijs}^u) W_{\max}, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$x_{ijs}^u, y_{ijh}, v_{ij}, \in \{0,1\}, \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$w_{ijh}, \delta_{ijs}^u \geq 0, \qquad \forall (i,j) \in \mathcal{A}^t, s \in \mathcal{S}_h, u \in \mathcal{U};$$

$$\pi_{is}^u, \pi_{js}^u \quad \text{free} \qquad \forall i,j \in \mathcal{N}, s \in \mathcal{S}_h, u \in \mathcal{U}.$$

4.3.2 Second-stage problem - HRT location

The second problem uses the network designed in the previous stage and assigns HRTs' coverage to the various available road links by determining the number of HRTs needed and locating them. The second stage problem is computationally fast to solve because the optimal carrier routes have already been determined by the previous step, and the variables x_{ijs}^{u*}, y_{ijh}^*, w_{ijh}^*, and v_{ij}^* in this stage have become constants.

The usual constraints for the arc coverage problem apply, resulting in the following formulation.

$$\min \quad \sum_{u \in \mathcal{U}} \rho^u \left(\sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}_h} \sum_{m \in \mathcal{M}} R_{ijh} D_s (\alpha_{\mathrm{ijm}} - \alpha_{max}) x_{ijs}^{u*} q_{ijm} \right)$$

s.t.

$$t_{ijm} q_{ijm} \leq T_{\max}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M},$$

$$\sum_{m \in \mathcal{M}} q_{ijm} \leq 1, \qquad \forall (i,j) \in \mathcal{A}.$$

$$\sum_{m \in \mathcal{M}} z_m \leq Z_{\max},$$

$$q_{ijm} \leq z_m, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M};$$

$$\sum_{s \in \mathcal{S}_h} x_{ijs}^{u*} - F_{\max} \leq M \sum_{m \in \mathcal{M}} q_{ijm} \qquad \forall (i,j) \in \mathcal{A}, u \in \mathcal{U};$$

$$z_m, q_{ijm} \in \{0,1\}, \qquad \forall (i,j) \in \mathcal{A}, m \in \mathcal{M}.$$

4.4 Computational Performances

Herein, a series of numerical tests over random problem instances are conducted to compare the computational performances of the two proposed solution methods. The underlying models and algorithms are coded in Python 3.9 and solved by Gurobi Optimizer 9.1.1. All experiments are run on a 5-core processor (Intel-Corei5 processor) and 8 GB of RAM.

We randomly generate problem instances based on $|\mathcal{N}|$, $|\mathcal{A}|$, and $|\mathcal{S}|$, respectively the number of nodes, arcs, and shipments (total shipments over all hazmats and scenarios). The number of HRTs, $|\mathcal{M}|$, is set as 20% of the number of nodes, and $Z_{\max} = |\mathcal{M}|/2$. In more detail, four groups of instance sets based on the number of nodes are employed: small, medium, large, and extra large. Within each group, there are four variations over other two network indicators. In all instances, we consider two types of hazmats and two scenarios. For various arc categorizes and policies, we take a fixed proportion setting of 30%, 30%, 30%, 10% respectively for $\mathcal{A}^b$, $\mathcal{A}^t$, $\mathcal{A}^n$, and $\mathcal{A}^a$. The arc cost and risk are randomly drawn from ranges $[100, 500]$ and $[100, 10000]$, respectively. Other parameters are carefully set to ensure the feasibility of all instances. Taking these configurations, 5 instances for each set are derived, given a total of 80 instances. Table 4.1 lists the computational results, which are the

Table 4.1: Performance comparison

#	Instance set			CPU Time (s)			Gap (%)			Optimal risk		
	$\lvert\mathcal{N}\rvert$	$\lvert\mathcal{A}\rvert$	$\lvert\mathcal{S}\rvert$	SLRF	TSHA	Δ%	SLRF	TSHA	Δ%	SLRF	TSHA	Δ%
I-01	10	30	20	0.34	0.25	-26.2	0	0	0	1954	1973	1.0
I-02		80	20	2.56	1.10	-57.1	0	0	0	1258	1365	8.6
I-03			40	10.77	4.08	-62.2	0	0	0	2413	2577	6.8
I-04	30	80	40	15.83	2.74	-82.7	0	0	0	5744	6258	8.9
I-05		180	40	1864.98	109.69	-94.1	0	0	0	2792	3632	30.1
I-06			60	4850.52	993.94	-79.5	0	0	0	4218	5099	20.9
I-07	60	180	60	4966.22	219.84	-95.6	0	0	0	7136	8586	20.3
I-08		240	60	7200	2458.62	-65.9	0.02711	0.00335	-87.6	4907	6471	31.9
I-09			80	-	5069.34	-	-	0.009646	-	-	8822	-
I-10	100	400	60	-	2986.23	-	-	0.003325	-	-	4910	-
I-11	200	800	60	-	4329.53	-	-	0.005347	-	-	3535	-
I-12	300	1200	50	-	3341.41	-	-	0	-	-	2671	-
I-13	500	2000	40	-	2467.11	-	-	0	-	-	1985	-

average values over the 5 instances. A time limit of 7200 seconds (2 hours) is applied to all tests.

By analyzing Table 4.1, we can observe the impact of the size of the network on the optimal solution. Comparing the cases I-01 and I-02, we observe that with the increase in the number of links from 30 to 80, while the number of nodes and shipments are unchanged, the optimal risk is reduced and the CPU time is slightly increased in both models. The same result is observed by comparing the pair cases of (I-04, I-05) and (I-07, I-08), yet the optimal risk decline and CPU time increase in significant in both cases. The first insight is when there are more links available in a

Table 4.2: Impact of $|\mathcal{M}|$ on SLRF (I-07)

$\lvert\mathcal{M}\rvert$	CPU TIme (s)	Gap (%)	Optimal risk
12	4966.217	0	7136.17
18	6813.89	0	5090.89
24	7200	0.0179	4077.09
50	-	-	-

network, the models have more options in terms of providing the carriers with paths to reduce the shipment risk, however, the CPU time increases because the models need more time to optimize a larger network. The second insight is that in network with more nodes, the change in the number of links has a bigger impact on optimal risk and CPU time in both models.

Comparing the pair cases (I-02, I-03), (I-05,I-06) and (I-08,I-09) indicates the impact of the number of shipments on the performance of the two models. Keeping the number of nodes and links unchanged, the increase in the number of shipments significantly increases the optimal risk and CPU time in both models. This impact is obviously larger than that of the number of links. Higher number of hazmat shipments in a network means higher incident risk and also a higher number of carriers to manage in the network, consequently, both the optimal risk and CPU time increases as the number of shipments rises in both models.

Comparing pair cases of (I-03,I-04) and (I-06,I-07) indicates the impact of the number of nodes on the performance of the two models. The results show that in both models, the increase in the number of nodes has a positive relationship with the optimal risk. The higher ratio of the links number to the nodes number means higher network connectivity which leads to lower optimal risk because the models can perform better in a more connected network. In addition, the results show that the increase in the number of nodes has an negative relationship with the CPU time in the TSHA models. This relationship is insignificant for the SLRF model.

Comparing the performance of the two models, we can see that in all cases, the TSHA model resulted in a larger optimal risk, however, it performed faster. In case I-01, the TSHA model improved the CPU time by 26.2% with 1% increase in optimal risk. As we move to the larger cases in Table 4.1, the difference becomes more tangible. For example, in case I-07, the computational time decreases by 95.6% while the optimal risk increases by only 20.3%. So, for larger cases, using the SLRF model could be considered impractical as it takes too long. In fact, for the cases larger than I-07, the SLRF model was not able to end with a 0% gap under our time limit of 7200 seconds yet, the TSHA model was able to solve problems in a reasonable amount of time.

Table 4.2 demonstrates the impact of maximum number of HRTs on the SLRF model performance. To clarify, $|M| = 12$ means there are 12 candidate locations in the network and the model can choose up to 6 of them to be active and used to cover the links in case of an incident. As this number goes up, the model has more HRT candidates to use to alleviate the risk, consequently, the optimal risk decreases as shown in the table. However, the computational time increases.

Chapter 5

Numerical Case Study

This chapter presents a detailed numerical case study to demonstrate the effectiveness and efficiency of our proposed network design model with emergency response and toll policy.

5.1 Network Data

Figure 5.1 depicts the transportation network for the city of Nanchang. The network contains 32 nodes (white circles), 102 existing links (straight lines), and 12 candidate links (dashed lines) that may be constructed. Ten candidate locations (black squares) can be chosen to position HRTs. In this case study, we assume that only those links within the shaded area (i.e., city center) can be closed, while other links (both existing and future links) may be regulated by toll policy.

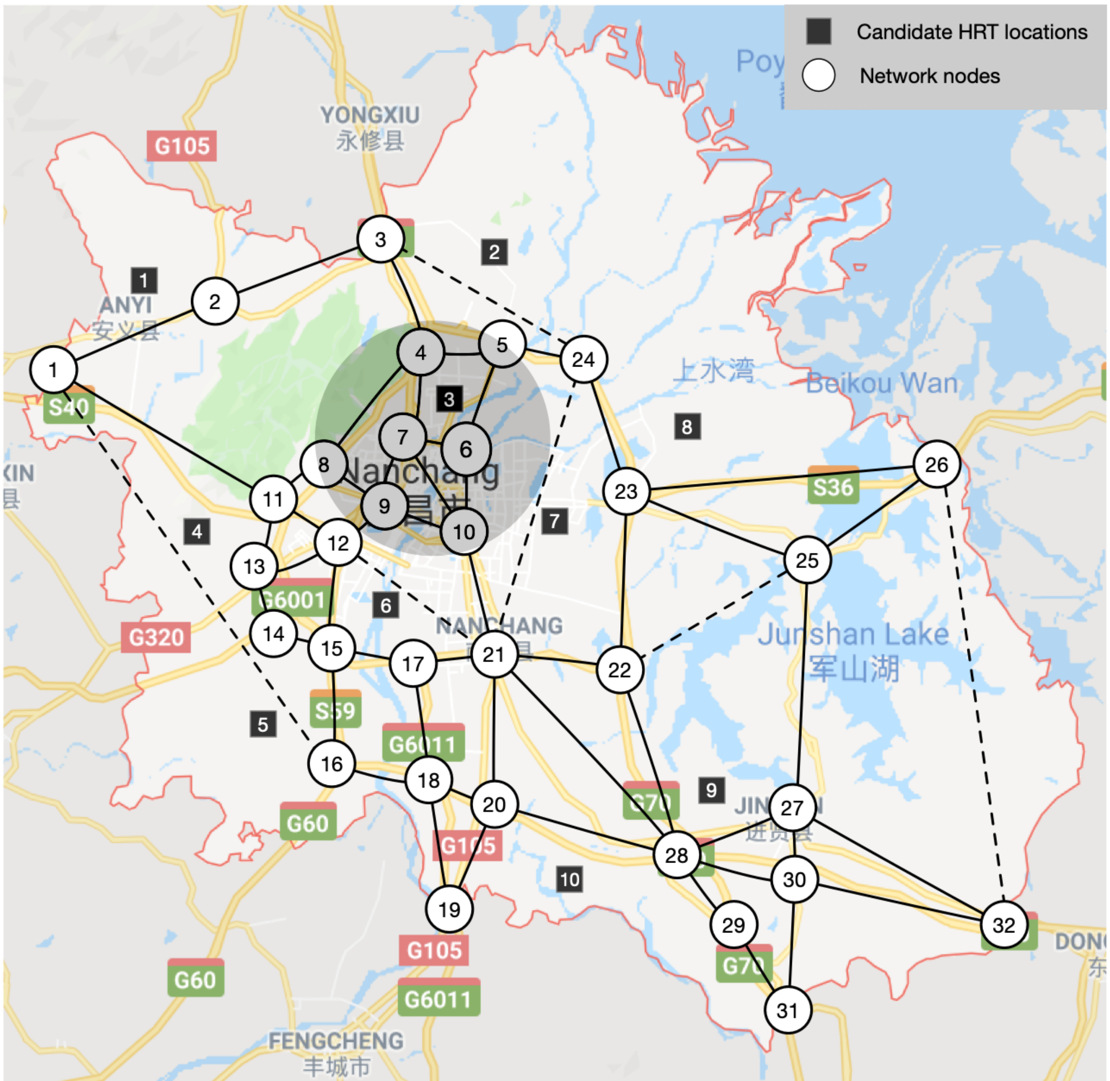

Figure 5.1: Nanchang Network

5.1.1 Risk

The population density information is adopted from the 2020 China Population Census by the National Bureau of Statistics of China. We herein consider three types of hazmats. The exposure radii for the three hazmats are respectively defined as 0.5km, 0.8km, and 1.6km. The exposure area is calculated in terms of the length of the link together with these radii. The corresponding release rates are 0.091, 0.072 and 0.187 (random numbers). For the incident rate, the 20-year survey data from 1997 to 2016 in the Large Truck and Bus Crash Facts 2016 (Federal Motor Carrier Safety Administration, 2018) is taken as the reference, and the incident rates for links are randomly generated between the smallest and largest numbers.

5.1.2 Cost

The transportation cost is computed with travel time and cost per unit time. In more detail, the travel time for each arc is computed by dividing the distance between the pairs of consecutive nodes by the corresponding speed limit. Assuming an annual mileage of 10,000 km, the costs per unit time for the three types of hazmats can be estimated respectively as 100 RMB, 150 RMB, and 200 RMB considering fuel (gas mileage and fuel price), insurance, and maintenance expenses. Note that the differences in costs are caused by various mileage and other charges of commercial vehicles used for different hazmat shipments.

The maximum toll value is set to 200 RMB, which is estimated on the basis of the 2018 Chinese National Highway Toll Standards. The road construction cost is estimated as 3 million RMB for every kilometer according to the Ministry of Transport of the People's Republic of China (2018). A 200-million RMB construction budget is applied to the base case.

5.1.3 Shipments and Demand

As mentioned in previous sections, we consider a set of demand uncertain scenarios, each with different shipment sets. So, each shipment belongs to a scenario and has a specific demand. Scenarios 1, 2, and 3 contain 10, 30, and 60 different shipments respectively, each with a randomly generated demand. Each shipment is defined by its corresponding origin, destination, scenario, and the hazmat it is carrying, i.e., D_s is the demand for shipment $s \in S_h^u$, which carries hazmat $h \in H$ between O-D pair $o^u(s), d^u(s) \in \mathcal{N}$.

5.1.4 Others

Table 5.1 summarizes the parameter values used in our case study (the Nanchang network); a sensitivity analysis around some of these parameters is explored later in this chapter.

In addition, Table 5.2 lists the 10 shipments in scenario 1 (out of 100 shipments in all scenarios).

5.2 Basic Performance

In this section, we provide the results of the single-level reformulation method considering the information mentioned above and analyze the performance of this method

Table 5.1: Summary of the Parameters

Parameter	Value
Number of hazmat types ($\|H\|$)	3
Hazmat demand for each shipment (D_s)	U([1,10])
Number of uncertainty scenarios ($\|U\|$)	3
Maximum (least desired) response time (T_{max})	10 Minutes
Maximum number of emergency teams (Z_{max})	5
Maximum arc flow that requires coverage (F_{max})	7
ω, ϵ, σ	0.1, 0.01, 0.001
Probability of uncertainty scenario u (ρ^1, ρ^2, ρ^3)	0.2, 0.3, 0.5

on Nanchang network. Given the size of the network, the case model is solved by the SLRF method.

Table 5.3 summarizes the objective results for each scenario. Table 5.3 shows an upward trend in system risk and transportation cost from scenario 1 to scenario 3 which is mainly because of the different number of shipments in different scenarios (there are 10, 30 and 60 shipments in scenario 1, 2 and 3 respectively). So, more hazmat shipments in a network is equivalent to more system risk and transportation cost. By looking at the covered links in Table 5.4, we can see that in a network with 5 activated HRTs and 106 links, 22 percent of the network is covered by at least one hazmat response team, in all scenarios.

Table 5.4 summarizes the results in more detail. The numbers in this table are not separated by scenarios as they are not dependent on different scenarios. Road

Table 5.2: Shipments in scenario 1

	Origin-Destination $(d^1(s), d^1(s))$	hazmat type (h)	Demand (D_s)
1	(2,29)	2	2
2	(4,20)	1	8
3	(7,22)	3	7
4	(8,19)	1	8
5	(6,32)	1	1
6	(10,26)	2	7
7	(31,12)	1	8
8	(27,3)	1	1
9	(16,23)	2	10
10	(25,9)	3	8

Table 5.3: Basic performance

	Scenario 1	Scenario 2	Scenario 3
System risk	3052	6118	14934
Transportation cost (Including tolls)	2803 RMB	6006 RMB	13903 RMB

operation cost is related to opening and preparing the existing links for hazmat carriers. Any link that is not blocked by the model needs to be prepared for hazmat transportation and will impose a cost on the network. The only links that are allowed to be blocked are the 22 links in the city centre (shaded area in Figure 5.1). Our model has restricted 18 of these links and covered the remaining 4 links. Moreover,

Table 5.4: Basic performance (details)

Road operation cost	1470 RMB
Road construction cost (million RMB)	1.26
Average toll price on links (Hazmat 1)	2 RMB
Average toll price on links (Hazmat 2)	14 RMB
Average toll price on links (Hazmat 3)	19 RMB
Restricted road links (Hazmat 1)	10
Restricted road links (Hazmat 2)	8
Restricted road links (Hazmat 3)	18
Tolled road links (Hazmat 1)	16
Tolled road links (Hazmat 2)	20
Tolled road links (Hazmat 3)	10
Constructed road links	4
Covered road links	24

our model has constructed 4 new links (out of 12 candidate links) to reduce the hazmat risk which has imposed 1.26 million RMB on our network. In addition, 34 links are tolled by the model in total. The links used to carry different hazmats are tolled based on the hazmat risk. Hazmat 3 is our most risky hazmat in this case study. Accordingly, the average toll price imposed on the links used by hazmat 3 carriers is higher.

Next, we analyze a shipment example to see how this randomly selected carrier has performed while carrying hazmat 1 from node 6 to node 32. Tables 5.5 indicates

Table 5.5: Shipment(Origin,Destination,Hazmat):(6,32,1) in the SLRF algorithm scenario 1

arc(i,j)	Coverage	Toll
(6,7)	covered	not tolled
(7,9)	not covered	not tolled
(9,12)	covered	not tolled
(12,21)	covered	not tolled
(21,20)	not covered	not tolled
(20,28)	covered	not tolled
(28,30)	not covered	not tolled
(30,32)	not covered	not tolled

every link this particular carrier has used on its path. In this example, the carrier used 8 links to carry the hazmat from node 6 to node 32 and has not paid any toll and 4 out of 8 links selected by the carrier are covered.

5.3 Effectiveness of risk mitigation mechanisms

In this section, we investigate the effectiveness of proactive v.s. reactive risk-mitigation mechanisms. For this purpose, we define three additional model settings on top of the integrated model for comparison. The four models are explained next.

Integrated model (IM): This is the base model solved in section 5.1 in which all policies are incorporated.

Proactive tools only (PT): All policies are used except the hazmat response policy which is our reactive policy.

Reactive tool only (RT) : Hazmat response policy is the only policy used.

No regulation (NR): There are no policies incorporated.

Table 5.6: A comparison of risk mitigation mechanisms

	IM	PT	RT	NR
System risk	9808	13957	24987	31160
Transportation cost	9314 RMB	9225 RMB	7474 RMB	7474 RMB
Road operation cost	1470 RMB	1470 RMB	1530 RMB	1530 RMB
Road construction cost (Million RMB)	1.26	1.26	0	0
Toll cost	507 RMB	459 RMB	0	0
Restricted road links	18	18	0	0
Constructed road links	4	4	0	0
Tolled road links	34	34	0	0
Covered road links	24	0	22	0

Table 5.6, which is based on the maximum flow of 10, lists the results of the four models defined above, and Figures 5.2 and 5.3 depict these results. In this table, the system risk, and the transportation cost which includes the toll, are equal to averages over the three scenarios. It can be observed in Table 5.6 that in no regulation policy (NR) we have the highest system risk. The risk goes high as there is no risk mitigation policy and the transportation cost is lower than that of IM and PT as the carriers

can freely select the most economically efficient links. Also, the road operation cost is highest compared to other models because all links are available and needed to be prepared for hazmat transportation.

By adding the proactive tools (road construction, road restriction and tolls) to the NR model we have the PT model. In this case, the total risk significantly decreased, yet the transportation cost increased because the carriers are directed through less risky links which are not necessarily the most economically efficient links. The table also shows that adding the reactive policy to the NR model, which gives us the RT model, has reduced the system risk. However, the reactive policy did not have any impact on transportation cost. Moreover, the road construction cost in IM and PT models are equal because there are the same number of links constructed in both models. Finally, considering the toll policy, the total toll cost the IM model imposed on the carriers is higher than PT which might lead into inaccurate conclusions.

When analyzing the results in more detail, the IM model has imposed lower toll values than PT model as the values of toll mean and median are less in IM model than PT model (IM's toll mean and median are 9 RMB and 5 RMB and PT's toll mean and median are 11 RMB and 8 RMB). In addition, the number of tolled links in IM is higher than that of PT model. So, the IM model has imposed lower toll values on more links which led to higher total toll cost in Table 5.6.

So far, we can see that even though both sets of our risk mitigation policies were successful in mitigating the system risk, the proactive policies were more effective. However, using both sets of policies simultaneously will result in the least system risk. Comparing the IM and PT policies, we can see that both models performed very similarly in terms of the number of restricted, constructed and tolled links, yet the IM led into less system risk because it benefits from hazmat response teams as the reactive policy. In addition, in terms of coverage metrics, the IM and RT models acted almost similarly as they both covered almost 20 percent of all the links. So, when implementing these policies, the authorities should make the best decision regarding the trade-off between the system risk and the transportation cost imposed on the carriers.

Table 5.7 summarizes the results of the 4 settings for a shipment carrying hazmat 2 in scenario 1 from origin node 10 to destination node 26. In this table, have used superscripts and subscripts to convey more information. A link superscripted with c and a indicates a covered and constructed link, respectively, and a link subscripted with the letter t indicates a tolled link. Figures 5.4, 5.5, 5.6, and 5.7 depict the path of this specific carrier in each model. As shown in Table 5.7 and Figure 5.4, in NR model, the carrier has chosen the shortest path possible, with the lowest cost and highest risk, compared to other settings. In the no regulation policy, there are no restricting policies and the carrier is able to choose the most economically efficient path to the destination. Considering the setting RT in Table 5.7 and Figure 5.5, the carrier has selected the same links as setting NR with the same cost, yet, the risk in this setting is lower because one of the links is covered by an HRT. Considering model PT in Table 5.7 and Figure 5.4, we can see a lower risk with longer path to the destination which is equivalent to higher carrier cost. In this setting, two of the links selected by the carrier are constructed but only one is tolled by the model. So, using this model, the upper-level was able to significantly reduce the network risk and the carrier was able to avoid the tolled links to decrease its cost. Using both reactive and proactive policies in the IM model, as shown in Table 5.7 and Figure 5.7, results in the lowest risk among all settings. Moreover, the carrier cost is even less than that of setting PT. This model was able to reduce the risk by constructing new links, two of which are used by the carrier in this setting. In setting IM, the carrier has to select either the less risky links or the riskier links that are covered or tolled. For instance, in the IM setting, to reach node 21, the carrier diverted its path and did not use the link 10-21 because it is a non-covered, non-blocked, risky link (risk=869) which is also tolled (T = 25 RMB).

Table 5.7: Shipment example

Sequence of links	IM	PT	RT	NR
Link 1	$(10,9)^c$	(10,7)	(10,21)	(10,21)
Link 2	$(9,12)^c$	(7,9)	(21,22)	(21,22)
Link 3	${}^a(12,21)$	(9,12)	$(22,23)^c$	(22,23)
Link 4	(21,22)	${}^a(12,21)$	(23,26)	(23,26)
Link 5	${}^a(22,25)$	$(21,22)_t$	-	-
Link 6	(25,26)	${}^a(22,25)$	-	-
Link 7	-	(25,26)	-	-
Carrier cost	580 RMB	590 RMB	382 RMB	382 RMB
Path risk	494	694	1091	1103

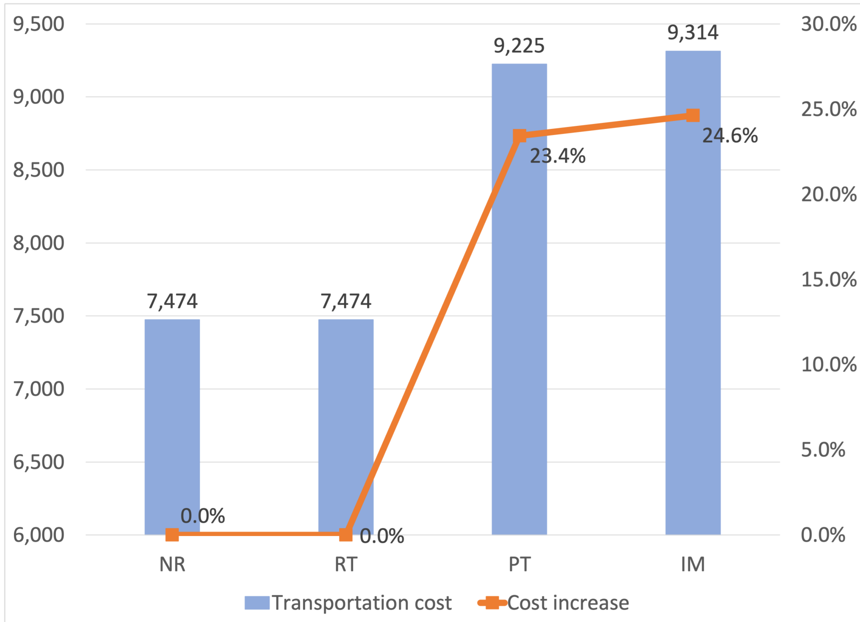

Figure 5.2: Policies' impact on cost

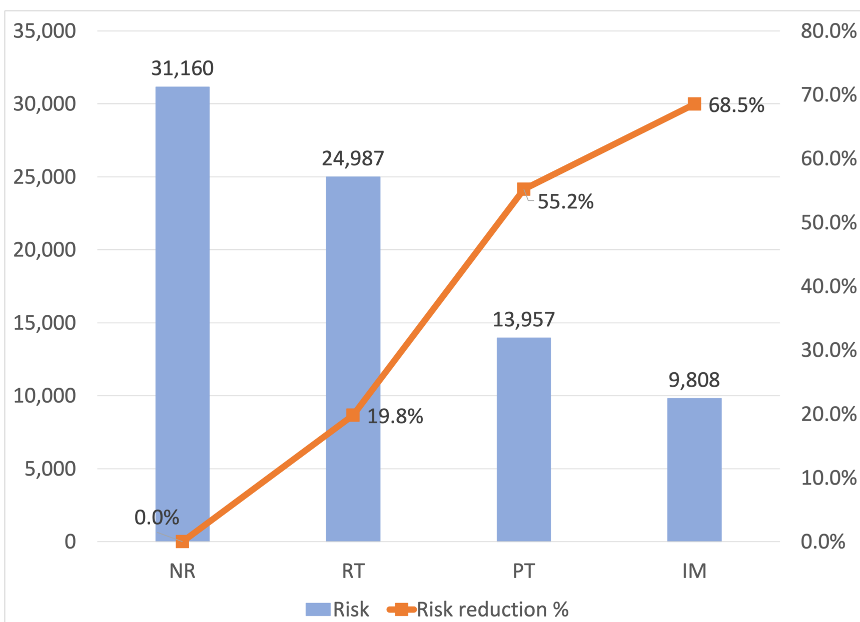

Figure 5.3: Policies' impact on risk

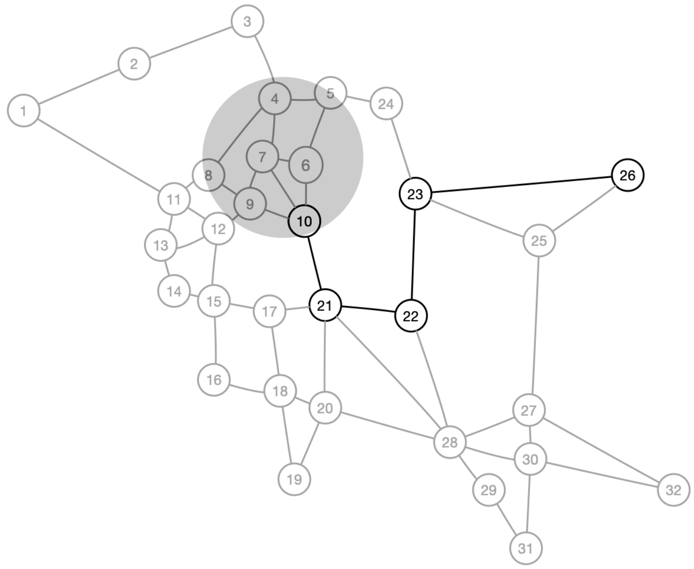

Figure 5.4: Selected links, NR model

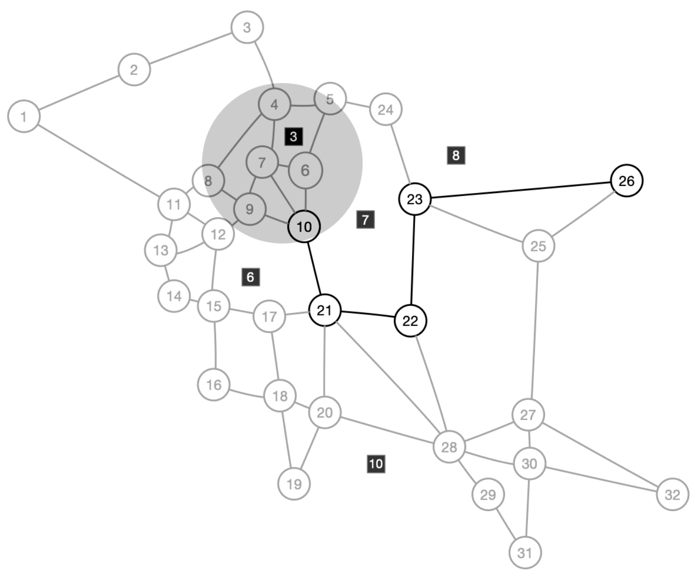

Figure 5.5: Selected links, RT model

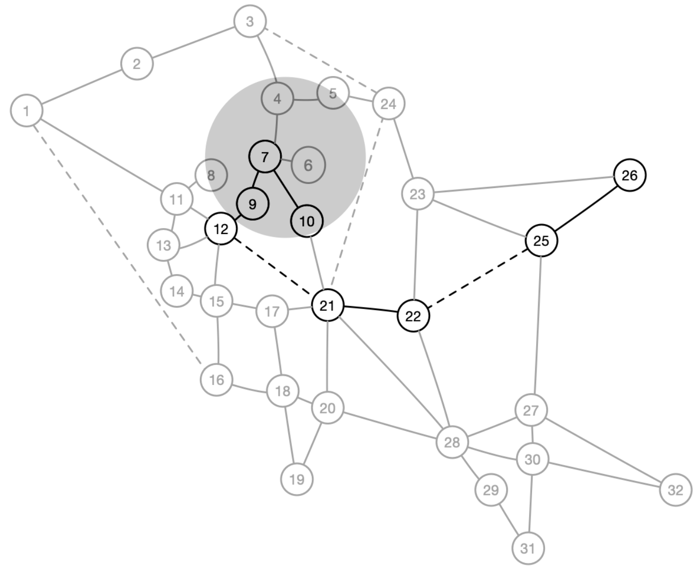

Figure 5.6: Selected links, PT model

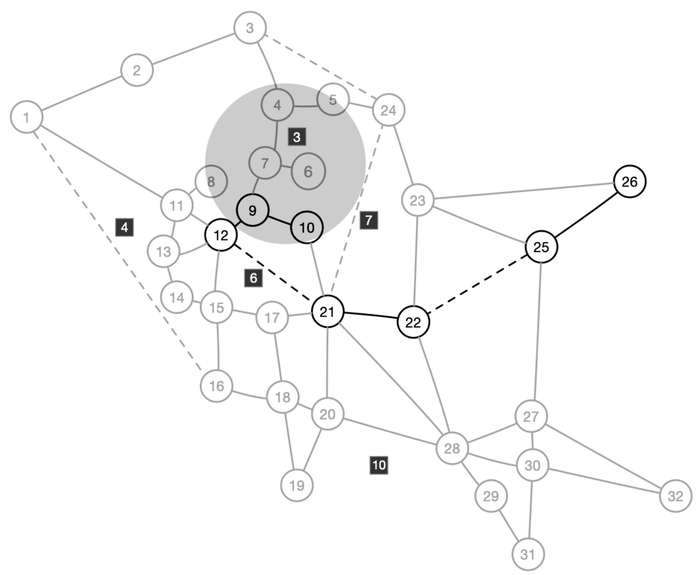

Figure 5.7: Selected links, IM model

5.4 Sensitivity Analyses

In this section, we perform a series of sensitivity analyses around several key parameters of our algorithm in order to examine how changing those parameters impact the optimal solution. Uncertainty probabilities, maximum number of HRTs, desirable response times, budget, and maximum link flow are the parameters around which the sensitivity analyses is conducted in the following subsections.

5.4.1 Uncertainty probabilities

As mentioned in previous sections, we consider a set of demand uncertain scenarios, each with different shipment sets. Each shipment belongs to a scenario and has a specific demand. Scenarios 1, 2, and 3 contain 10, 30, and 60 different shipments respectively. In addition, each scenario happens with a different probability. In Table 5.8, we change the probabilities to observe how they impact the optimal solution.

First, we consider the probability of scenario 3 with 60 shipments to be 0 and the two other scenarios to be 0.5 and then slowly increase the probability of scenario 3 up to 1, while decreasing the probabilities of scenarios 1 and 2 to 0. As shown in the table, with increasing the probability of scenario 3 from 0 to 1, the optimal risk increases from 4567 to 14946 which is equal to a 212% increase in optimal risk. So, we can see as the scenario 3 becomes more probable, both the risk of the network and the cost of the carriers significantly increase.

Then, we tried the same process with scenario 2 which contains 30 shipments. Referring to the same table (Table 5.8), as the probability of scenario 2 increases from 0 to 1, the optimal risk decreases from 9002 to 6094 which is equal to a 32%

Table 5.8: Uncertainty probabilities

Uncertainty probabilities (ρ^1, ρ^2, ρ^3)	System risk	Transportation cost (RMB)	CPU time (s)
(0.5,0.5,0)	4567	4351	14.68
(0.45,0.45,0.1)	6507	7231	50.69
(0.3,0.3,0.4)	8725	8388	73.49
(0.15,0.15,0.7)	11228	11023	102.11
(0,0,1)	14946	13869	37.59
(0.5,0,0.5)	9002	8468	79.03
(0.45,0.1,0.45)	8436	8012	70.91
(0.3,0.4,0.3)	7847	7514	43.56
(0.15,0.7,0.15)	7012	6852	68.08
(0,1,0)	6094	5909	35.06
(0,0.5,0.5)	10519	1087	152.78
(0.1,0.45,0.45)	9778	9302	46.26
(0.4,0.3,0.3)	7506	6953	52.75
(0.7,0.15,0.15)	5013	4989	51.2
(1,0,0)	3041	2966	8.43

decrease in optimal risk. What has happened here is, as the probability of scenario 2 increases from 0 to 1, the probability of scenarios 1 and 3 increases from 0.5 to 0. Considering the fact that scenario 3 has more number of shipments than the other two scenarios, the decrease in its probability has overshadowed the impact of the decrease in the probability of scenario 2. Then, we implement the same process for the first scenario. As we increase the probability of scenario 1 from 0 to 1 and decrease the probabilities of scenarios 2 and 3 from 0.5 to 0, the optimal risk of the network decreases from 10519 to 3041 which is equal to a 68% decrease in the risk.

In addition, when the probability of scenario 3 is 1, the network has the highest optimal risk which is 14946 while this number is 6094 and 3041 for scenario 2 and 1, respectively. Consequently, we conclude that scenario 3 has the largest impact and scenario 1 has the smallest impact on the risk of the network, which means that the number of shipments in a scenario plays the main role in determining the impact of a scenario on the optimal risk.

5.4.2 Maximum number of HRTs

In this section, we analyze the impact of the maximum number of HRTs on the optimal solution of our algorithm. In our case study network, there are 10 candidate locations from which the algorithm is allowed to select the HRT locations. Table 5.9 lists the results of our analysis. Having a higher maximum number of HRTs means the model is allowed to assign more response teams in case of hazmat incidents. As this number goes up, we expect to see a downward trend in optimal risk.

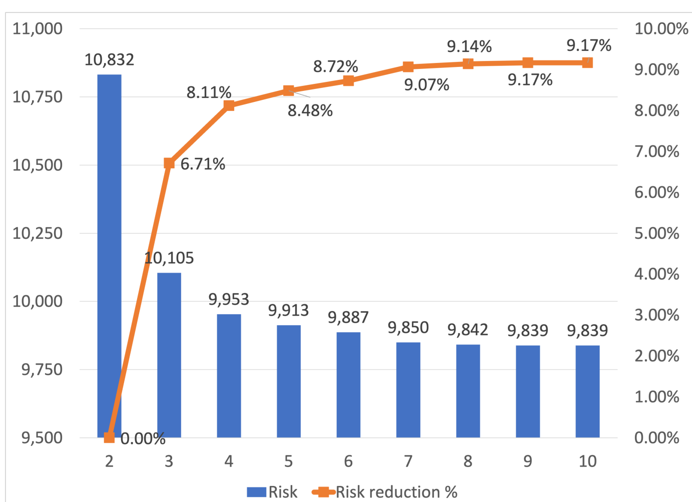

Figure 5.8: Maximum number of HRTs

Table 5.9: Maximum number of HRTs

Maximum number of HRT	System risk	Transportation cost (RMB)	CPU time(s)
2	10832	9197	89
3	10105	9189	69
4	9953	9385	110
5	9913	9314	110
6	9887	9350	91
7	9850	9386	80
8	9842	9452	80
9	9839	9289	60
10	9839	9289	109

5.4.3 Desirable response times

As defined before, response time is the time an HRT needs to respond to a hazmat incident. Maximum response time is the least desired response time which means a link is only considered to be covered when the least desired time can be met. Higher maximum response time means more links can be covered by an HRT because the HRT is capable of covering farther links. In this section, we analyze the impact of maximum response time on optimal risk. As shown in Table 5.10, as we increase the maximum response time of the HRTs, the optimal risk decreases.

Table 5.10: Maximum response time

Maximum response time	System risk	Transportation cost (RMB)	CPU time (s)
5	12086	9286	180
10	9913	9314	110
15	8787	9332	480
20	7101	9132	1120
25	6003	9087	1560

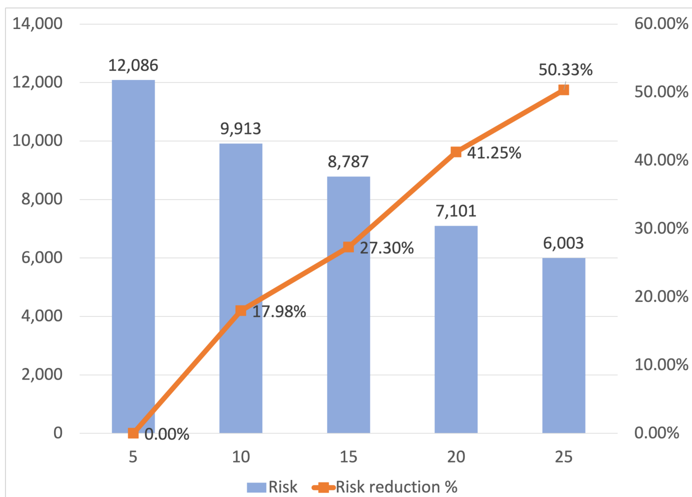

Figure 5.9: Maximum response times

5.4.4 Budget

Next, we change the budget for arc construction, whose results are summarized in Table 5.11. We begin our analysis with no budget, which means no new link will be added to the network. As shown in the table, as the construction budget increases, the optimal risk decreases because the algorithm is able to add links to the network to facilitate carriers' movements through less risky links if needed. Yet, the aforementioned improvement in optimal risk is not ever-going, and stops from a certain point where the algorithm has enough budget to add all the candidate links to their networks and any extra budget would not make any difference.

Table 5.11: Budget (Million RMB)

Budget	System risk	Transportation cost (RMB)	CPU time(s)
0	12543	10345	85
2	9913	9314	110
4	8878	9625	50
6	8808	9236	84
8	8808	9354	89

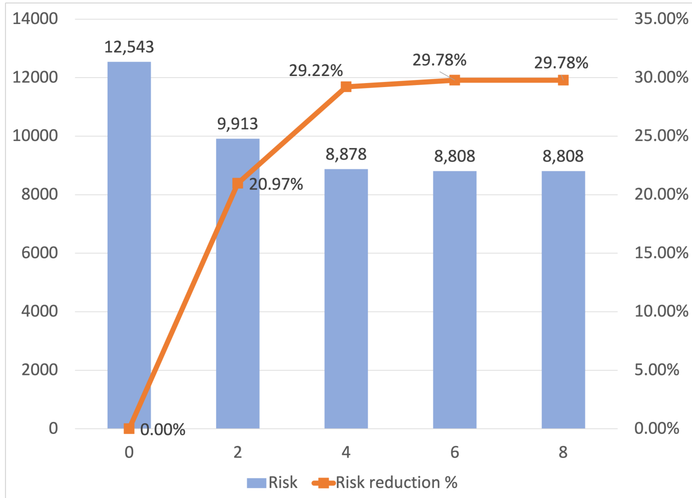

Figure 5.10: Budget

5.4.5 Maximum flow

Constraint (3.7) in our upper-level model confirms the emergency coverage of an arc with a flow above a specified value F_{max}. Table 5.12 compares the system risks for cases with respectively 5, 7, 10, and 12 as the values of F_{max}. The trend of risk shows a similar pattern as previous analyses, where the risk drops first and then becomes stable when the maximum flow is beyond 10. To explain this negative effect, we look into the original purpose of introducing this parameter, which is to prevent the overuse of less-risky links. Such overuse may cause public concern, especially the population living around those links. For this reason, this constraint can be considered as an assurance of the spatial distribution of risk (i.e., risk equity) in the transportation network. On the other hand, sending shipments through less-risky links can certainly mitigate the overall risk. Therefore, Table 5.12 can be seen as an indication of the trade-off between the system risk and risk equity. It is also worth mentioning that decreasing the maximum flow by half (from 10 to 5) distinctly secures the risk equity, with only inconsiderable rise in the total system risk (roughly 1.6%).

Table 5.12: Risk, Cost, and Time vs Flow

Flow	System risk	Transportation cost (RMB)	CPU time(s)
5	9974	9399	90
7	9913	9314	110
10	9812	9313	128
12	9812	9280	130

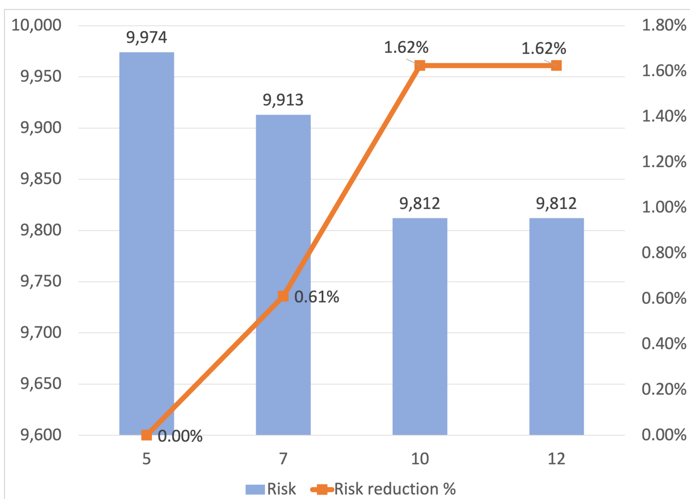

Figure 5.11: Impact of maximum flow on Risk

Chapter 6

Summary and Conclusions

This thesis studies a scenario-based hazardous material network design problem with emergency response and toll policy. In our bilevel model, the upper level represents the network design decision of the authority that is using a number of tools as incentives to encourage hazmat shipments to use certain links and discourage or in some cases, totally prevent them from using riskier links as well as locating response teams in different places in case of any incidents. The aforementioned tools are divided into two categories: Proactive mechanisms and Reactive mechanisms.

Proactive mechanisms are used to lower the chance of a hazmat incident include designing network structure (blocking some of the links and constructing new links) and imposing toll policy. Reactive mechanisms, on the other hand, are used for the aftermath and in our case consist of locating response teams in different locations to cover certain links. The lower-level reflects the hazmat carriers' routing decisions to minimize the transportation costs. Considering all that, we developed a bilevel optimization model that jointly determines road closures, constructions, tolls, and

HRT locations, such that the system risk associated with hazmat transportation, as well as carriers' cost, is minimized.

In order to solve the problem, we incorporated two algorithms. First, using dual variables and constraints, we reformulated our bilevel model into a single-level model and then solved it. This method gives us exact optimal solutions. Second, we incorporated a two stage heuristic algorithm that gives us near-optimal solutions. In our several analyses, we showed that the heuristic algorithm (the TSHA algorithm) is capable of solving the problem in a significantly shorter amount of time compared to the single-level reformulation (the SLRF algorithm). That is why we recommend using the TSHA algorithm for larger networks as it provides a solution very close to the optimal solution in significantly shorter time.

We also concluded that the number of links and shipments have a negative relationship with computational time in both algorithms and more specifically, the number of hazmat shipments has the bigger impact than the number of links. We observed that more number of links causes higher connectivity which leads to smaller optimal risk. However, higher number of shipments causes larger optimal risk. Moreover, the results show that more HRTs available helps both the algorithms to reduce the risk. In our case study, we considered a set of demand uncertain scenarios, each with different shipment sets and probabilities of occurrence. Each shipment belongs to a scenario and has a specific demand. We showed that both the reactive and proactive policies can effectively reduce the system risk when used individually and can reduce the system risk even more significantly when used simultaneously. Yet, the proactive policies proved to be more effective than the reactive policy when used separately. Our sensitivity analysis on the scenarios showed that the scenario with the most number of shipments has the largest impact on the optimal results. We showed that HRT's desirable response time, which indicates how far can an HRT cover the links, and the construction budget, has a negative relationship with the optimal risk. Finally, through comparing the four risk mitigating policies we incorporated in our study, we showed that placing HRTs in a hazmat network is our best initiative for authorities to reduce hazmat risk. On the other hand, we also showed that the three proactive policies can be used as tools by the authorities to prevent the hazmat carriers from using risky links.

6.1 Managerial Insights

- The proposed risk-mitigation mechanisms, namely network design, toll policy, and emergency response, can effectively reduce the system risk associated with hazmat transportation. The simultaneous incorporation of the aforementioned mechanisms, provides the authorities with an efficient control over the hazmat traffic. Toll policy works as the incentive for carriers to try to minimize their cost while using the safe links. On the other hand, optimal locating of hazmat response teams makes it possible for authorities to act efficiently in case of any hazmat incidents.

- After comparing the four policies of road closure, road construction, road tolling and hazmat response teams, we found the proactive policies to be a more effective way of risk control. On the other hand, the reactive policy of locating response teams imposes less transportation cost on the carriers while mitigating the system risk. So, we suggest that the authorities should select either or both of the policies considering such a trade-off between the cost and risk.

- We recommend that the authorities make sure that the networks hazmat shipments are using are connected enough. Sufficient connectivity happens when there are enough links in a network so that the authorities have more links to guide the hazmat shipments through and hazmat shipments have enough routing options to optimize their costs.

- It is necessary to implement various mechanisms based on the specific properties of the corresponding regions. For example, the city center area should be managed more rigidly (arc-blocking), while the rural areas can be controlled rather more flexibly (toll). These flexible initiatives are possible when there are different mechanisms incorporated in a model.

- The scenario-based uncertainty consideration can practically reflect the variations in both the shipping volume and type, and at the same time, ensure the system robustness under different situations.

6.2 Future Plans

This research can be further explored in many directions in the future:

- Both the single-level and the heuristic algorithms can be modified to include external traffic. Ordinary traffic affects many factors such as hazmat traffic flow, HRTs' response time and incident risks.

- In our thesis, we accounted for demand uncertainty in order to better accommodate for real-world circumstances. In future research, we suggest the incorporation of more uncertain factors such as response time.

- We assumed that each link can be covered only by one HRT. Considering some incidents might need more than one hazmat response team due to the intensity of an incident, it is more realistic to allow the model to assign more than one team to cover links.

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