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Zhen Zhou

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**DE**  
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Présentée par

**Zhen ZHOU**

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**Étude sur l'optimisation du transport de matières  
dangereuses par la réservation de voies**

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# **Study on Optimization of Hazardous Material Transportation via Lane Reservation**

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## Résumé

Le transport de matières dangereuses est connu pour son haut risque potentiel pour le réseau routier. Un accident peut avoir de graves conséquences pour la santé publique et l'environnement sur une longue période. L'optimisation du transport de matières dangereuses est une problématique importante. Cette thèse propose, pour la première fois dans la littérature, une stratégie de réservation de voies pour le transport de matières dangereuses. L'objectif est de proposer des itinéraires pour le transport de matières dangereuses qui minimisent à la fois le risque potentiel et l'impact négatif sur le trafic dans un réseau de transport dû à la réservation de voies.

Dans cette thèse, nous nous focalisons sur deux nouveaux problèmes : l'optimisation de transport de matières dangereuses grâce à la stratégie de réservation de voies dans un réseau de transport selon si le risque dépend de l'instant de passage (appelé LRPTDR) ou pas (appelé LRPTIR). Pour chaque problème étudié, nous proposons un nouveau modèle d'optimisation multi-critères. Pour le LRPTIR, nous développons d'abord une méthode combinant la méthode de  $\varepsilon$ -contrainte et la logique floue pour obtenir des solutions Pareto optimales and une solution préférée en fonction des critères du gestionnaire. Ensuite, une méthode qui combine le « cut-and-solve » and le « cutting plane » est proposée pour réduire le temps de calcul. Pour le LRPTDR, une méthode de « cut-and-solve » est appliquée, dans laquelle une nouvelle technique de « piecing cut » et une stratégie de relaxation partielle sont développées pour améliorer la performance. Les performances des algorithmes proposés sont évaluées à l'aide d'instances générées aléatoirement. Les résultats numériques montrent que les algorithmes proposés sont plus performants que le logiciel commercial CPLEX pour les problèmes étudiés.

**Mots clé:** Transport de matières dangereuses, Réservation de voies, Optimisation multi-critères, Optimisation combinatoire



## Abstract

Hazardous material transportation is well-known for its high potential risk. An accident may cause very serious economic damage and negative impacts on the public health and the environment over the long term. Optimization for hazardous material transportation is an important issue. For the first time in the literature, this thesis introduces the lane reservation strategy into the hazardous material transportation problem. The goal is to obtain a best compromise between the impact on normal traffic due to lane reservation and the transportation risk.

In this thesis, we focus on two novel problems: hazardous material transportation problem via lane reservation in networks with time-invariant and time-dependent risk, called LRPTIR and LRPTDR, respectively. For these problems, multi-objective integer programming and mixed integer programming models are formulated, respectively. For the LRPTIR, we first develop an  $\varepsilon$ -constraint and fuzzy-logic based method to obtain Pareto optimal solutions and a preferred solution. Then a cut-and-solve and cutting plane combined method is proposed to reduce the computation time. For the LRPTDR, an improved cut-and-solve based  $\varepsilon$ -constraint method is proposed, in which a new technique of generating piercing cuts is developed and a partial integral relaxation strategy is applied. The performance of the proposed algorithms is evaluated by randomly generated instances. Computational results demonstrate that for the considered problems, the cut-and-solve method outperforms software package CPLEX.

**Keywords:** Hazardous material transportation, Lane reservation, Multi-objective optimization, Combination optimization

# Contents

Chapter 1 Introduction .....	1
1.1 Background .....	1
1.2 Content .....	4
1.2.1 Contribution .....	4
1.2.2 Outline .....	5
Chapter 2 Literature review .....	7
2.1 Literature review on hazardous material transportation .....	7
2.1.1 Literature review on risk assessment .....	7
2.1.2 Literature review on routing problem for hazardous material transportation .....	9
2.1.3 Literature review on network design problem for hazardous material transportation .....	14
2.1.4 Literature review on other problems for hazardous material transportation .....	16
2.2 Literature review on lane reservation .....	18
2.2.1 Applications of lane reservation .....	19
2.2.2 Studies on lane reservation .....	23
2.3 Key technologies .....	26
2.3.1 Risk assessment .....	26
2.3.2 Multi-objective optimization problem .....	27
2.3.3 $\epsilon$ -Constraint method .....	28
2.3.4 Cut-and-solve method .....	30
2.3.5 Cutting plane method .....	34
2.4 Conclusion .....	38
Chapter 3 Model and Method for HMTLR with time-invariant risk .....	39
3.1 Introduction .....	39
3.2 Problem formulation .....	41
3.2.1 Problem description .....	41
3.2.2 Assumption, notation and formulation .....	42
3.3 Solution approach .....	44
3.3.1 $\epsilon$ -constraint method for the multi-objective problem .....	44
3.3.2 Selection of a preferred solution .....	48
3.4 Computational results .....	50
3.4.1 An instance based on a real network topology .....	51
3.4.2 Randomly generated test instances .....	52
3.5 Conclusions .....	58
Chapter 4 A new and exact method for transformed single objective problems of HMTLR with time-invariant risk .....	60
4.1 Introduction .....	60
4.2 Solution approach .....	61
4.2.1 Pre-processing .....	61
4.2.2 Definition of piercing cut, sparse problem and remaining problem .....	62

4.2.3 Cutting plane method to tighten remaining problem.....	64
4.2.4 Overall algorithm .....	66
4.3 Computational results .....	67
4.4 Conclusions.....	71
Chapter 5 Model and method for HMTLR with time-dependent risk.....	72
5.1 Introduction.....	72
5.2 Problem formulation .....	74
5.2.1 Problem description .....	74
5.2.2 Notation and formulation .....	74
5.3 Solution algorithm.....	77
5.3.1 Transformed single objective model .....	77
5.3.2 Cut-and-solve method .....	78
5.4 Computational results .....	82
5.5 Conclusions.....	87
Chapter 6 Conclusions and perspectives.....	88
Bibliography .....	91

# Notation

$G(V, A)$ : bidirected transportation network

$V$ : set of nodes  $i$

$A$ : set of directed arcs  $(i, j)$ ,  $i \neq j$ ,  $i, j \in V$

$O$ : set of origin nodes,  $\{o_1, o_2, \dots, o_{|W|}\} \in V$

$D$ : set of destination nodes,  $\{d_1, d_2, \dots, d_{|W|}\} \in V$

$W$ : set of hazardous materials shipments,  $\{1, 2, \dots, |W|\}$

$K$ : set of time periods,  $\{1, \dots, |K|\}$

$C_{ij}$ : impact on the normal traffic due to the lane reservation on arc  $(i, j)$

$T_{ij}$ : travel time on the reserved lane of arc  $(i, j)$

$\tau_{ij}$ : travel time on the general lane(s) of arc  $(i, j)$

$P_{ij}^w$ : accident probability of hazardous material  $w$  on a reserved lane of arc  $(i, j)$

$\pi_{ij}^w$ : accident probability of hazardous material  $w$  on the general lane(s) of arc  $(i,$

$j)$

$E_{ij}$ : population exposure along arc  $(i, j)$

$E_{ijk}$ : population exposure along arc  $(i, j)$  at time period  $k$

$M_{ij}$ : total number of lanes on arc  $(i, j)$

$S_w$ : deadline of accomplishing shipment  $w$

$Q_{ij}$ : threshold of the accident probability on arc  $(i, j)$

$T_{\text{int}}$ : safety time interval between any two shipments passing a same arc

$N$ : average degree of a graph



# List of Figures

Fig. 2.1 Examples of bus lane in a city .....	20
Fig. 2.2 Example of BRT lane in a city.....	20
Fig. 2.3 Example of HOV lane in a city.....	21
Fig. 2.4 Lane reservation for the Olympic Games in 2008 in Beijing .....	22
Fig. 2.5 General procedure of cut-and-solve method.....	31
Fig. 2.6 A cutting plane example.....	36
Fig. 3.1 Sketch of a road segment with reserved lanes .....	42
Fig. 3.2 Ideal and nadir points.....	47
Fig. 3.3 Procedure of the $\epsilon$ -constraint and fuzzy-logic based method .....	50
Fig. 3.4 Distribution of non-dominated points of the problem with a real network topology in Italy .....	52
Fig. 3.5 Computation times of sets 31-35 .....	55
Fig. 3.6 Computation times of sets 51-55 .....	57
Fig. 4.1 Procedure of the separation algorithm.....	66
Fig. 4.2 Procedure of the cut-and-solve and cutting plane combined method .....	67
Fig. 4.3 Comparison of T1 and T2.....	69
Fig. 5.1 Flow chart of the cut-and-solve method for the transformed single objective problem....	83
Fig. 5.2 Comparison of T1 and T2.....	86



# List of Tables

Table 2.1 Review on other problems for hazardous material transportation.....	17
Table 3.1 Computational results of Case 1 on the random generated instances with $N = 4$ .....	54
Table 3.2 Computational results of Case 1 on the random generated instances with different $N$ ...	56
Table 3.3 Computational results of Case 1 on the random generated instances with different $S$ ....	57
Table 3.4 Computational results of Case 1, 2 and 3 on the random generated instances .....	58
Table 4.1 Computational results on the random generated instances with $N = 4$ .....	68
Table 4.2 Computational results on the random generated instances with different $N$ .....	70
Table 5.1 Computational results with $N=3$ , $ W =5$ and $ K = 3$ .....	85
Table 5.2 Computational results with $N=3$ , $ W =10$ and $ K  = 3$ .....	86
Table 5.3 Computational results with $N=4$ , $ W =5$ and $ K =1-5$ .....	86





# CHAPTER 1 INTRODUCTION

This thesis investigates a hazardous material transportation problem via lane reservation (HMTLR). Its goal is to develop a new idea and methodology for reducing the risk during hazardous material transportation. This chapter first introduces the research background and then presents the outline and framework of the thesis.

## 1.1 Background

Hazardous materials are defined as the substances or materials that can potentially cause harm to people, property, and environment. With industrial development, the production of hazardous materials has been increasing year by year. Usually, most kinds of hazardous materials are not used directly in the place of production but disposed through long-distance transportation. This causes that a great amount of hazardous materials need to be shipped in the transportation network every day. According to related statistics, more than 95% of hazardous materials in China need to be transported among different cities. Annually, 200 million tons of hazardous materials are transported, of which 82% are transported through the road. For example, the annual transportation volume of liquid ammonia and liquid chlorine is 0.8 and 1.7 million tons, respectively. According to the Office of Hazardous Materials Safety of the U.S. Department of Transportation (US DOT), 800 000 hazardous material shipments were carried out daily in 1998 [1]. With a conservative estimation, production and shipment of hazardous materials tend to increase by 2% annually, and the total number of shipments every year in America has been over one million since 2005 [1]. Thus, large quantity and high frequency becomes a feature of hazardous material transportation.

Hazardous material transportation is well known for its high potential risk. *Transport Canada* reports that in 2002, over 99% of hazardous material shipments safely arrive at their destination in Canada [1]. Although rare, accidents do happen during their transportation. An accident can cause very serious economic damage and

might have a negative impact on public health and the environment over the long term. In particular, many transport routes pass through urban areas. In accordance with the US DOT statistics, there were 488 serious incidents (among a total of 15178 incidents) in 2003, resulting in 15 deaths, 17 major and 18 minor injuries, and total property damage of \$37.75 million [1]. In European countries, there are also many accidents involving hazardous material transportation on roads and railways. For example, the chemical accident in Seveso, Italy, in 1976 caused the contamination by 2, 3, 7, 8-tetrachlorodibenzo-p-dioxin (a kind of hazardous chemical substance) to a large population. Twenty years later, possible long-term effects, which were examined through mortality and cancer incidence studies, indicated that the consequences of hazardous material transportation accidents were not only enormous but also far-reaching [2]. Moreover, an accidental spill may also take place in environmentally sensitive areas, such as in or near the natural protection areas or World Heritages.

Nowadays, traffic safety has been one of the hot research issues in the field of intelligent transportation systems [3]-[5]. As for hazardous material transportation, many researchers have pointed out that the potential risks of transporting hazardous material may be as huge as those of fixed installations according to historical accidents [6], [7]. Thus, it is necessary to pay the same attention to the former to keep them under control and reduce them. It has been also pointed out in much relevant literature that the essential objective of hazardous material transportation is to minimize the transportation risk due to its nature. Therefore, how to reduce the hazardous material transportation risk becomes an important focus. Reducing transportation risks can be achieved by many different ways. Governments may enact some laws on hazardous material transportation and provide guidelines and specific requirements on it. For example, information with regard to hazardous material packaging, labeling and depositing, and specific training for carriers and regulations for vehicle maintenance are clearly specified by US DOT.

In transportation networks, risk varies with traffic flow and road structure etc. Hazardous material transportation via dedicated lines will make the overall traffic flow on these lanes more homogeneous and smooth, which may lead to a potential

decrease in the probability of accident [8]. It is also found in [9] that the likelihood of a traffic accident varies with road structure (e.g., the number of lanes and their use). The dedicated lane for special vehicles is called reserved lane in this thesis. Lane reservation strategy refers to reserving one or several lanes in road segments by specific traffic signs, such as marking or isolation facilities and so on, and allowing only special vehicles to use them (within a specified time), in order to provide the passage priority for them in public traffic. Lane reservation strategy is a flexible and economic option for special events or situation, such as sport games and emergencies. In fact, it has been successfully applied in real life. For example, reserved lanes were applied to the Asian Sport Games in 2010 in Guangzhou, China. In France, one of the lanes of A1 between Charles De Gaulle Airport and Saint Denis has been recently dedicated to taxis and buses only between 7:00 A.M.–10:00 A.M. Other applications, such as exclusive bus lanes and high-occupancy vehicle lanes have been applied in many cities around the world.

On a road segment, if one of its lanes is selected as a reserved lane, the other(s) are called the general lane(s) accordingly. Thus, the number of general-lanes will be decreased, which may make the general lanes more congested and worsen traffic situation on the network. The most direct impact of reserved lanes on public traffic is the increase in the travel time on the general lanes. Therefore, it is important to effectively select lanes to be reserved in the existing transportation network so as to minimize the total traffic impact on the network.

From the above analysis, the hazardous material transportation optimization problem via lane reservation can be considered as a multi-objective problem with at least two objectives: minimizing the total transportation risk and the total traffic impact. To the best of our knowledge, there are very few studies on the topic. The problem considered in this thesis is different from some classical hazardous material transportation problems, such as routing problem, combined facility location and routing problem, and network design problem. The hazardous material transportation optimization problem via lane reservation provides a new idea of reducing transportation risk. This thesis focuses on the application of lane reservation to

hazardous material transportation and developing new mathematical models and methods for it.

## 1.2 Content

This thesis mainly investigates hazardous material transportation via lane reservation in networks with time-invariant and time-dependent risk, respectively. Its aim is to choose lanes to be reserved in the existing transportation network and select the path for each shipment from the reserved lanes. Its objectives are to minimize the impact on normal traffic resulted from lane reservation and the transportation risk.

### 1.2.1 Contribution

The contributions of this thesis are presented as follows:

(1) A new hazardous material transportation problem via lane reservation in networks with time-invariant risk is investigated. A multi-objective integer programming model is formulated for the considered problem. To solve the model, an  $\varepsilon$ -constraint and fuzzy-logic based method is proposed to obtain Pareto optimal solutions and a preferred solution.

(2) A cut-and-solve and cutting plane combined method is developed to solve the transformed single objective problems, in which cut-and-solve method is applied to find an optimal solution and cutting plane method for finding valid inequalities is exploited to accelerate the convergence of cut-and-solve method. A property of the considered problem is developed to reduce the solution space.

(3) A new hazardous material transportation problem via lane reservation in networks with time-dependent risk is investigated. A multi-objective mixed integer programming model is developed. A property of this problem is also developed to reduce the solution space. An improved cut-and-solve based  $\varepsilon$ -constraint method is proposed for it, in which a new technique of generating piercing cuts based on the characteristics of the considered problem is developed and a partial integral relaxation strategy is applied.

## 1.2.2 Outline

This thesis is organized as follows:

Chapter 1 introduces the research background and the research significance. Then, the contribution and the outline of this thesis are presented.

In Chapter 2, a review on hazardous material transportation is first addressed. The related hazardous material transportation problems and their state of the arts, including risk assessment, routing problem and network design problem, are described in detail. Then, a review on lane reservation problem is also addressed. Some applications of lane reservation are introduced and their studies are reviewed. Finally, basic principles of key technologies, which will be applied to solving the proposed problems, are introduced.

Chapter 3 investigates a hazardous material transportation problem via lane reservation in networks with time-invariant risk. In this chapter, the background of the problem is first explained. Then, a multi-objective integer linear programming model is presented for the considered problem. An  $\varepsilon$ -constraint and fuzzy-logic based method is developed to obtain Pareto optimal solutions and a preferred solution. The  $\varepsilon$ -constraint method is applied to transform the multi-objective problem into the single objective ones. For the transformed single objective problems, optimization software package CPLEX is applied. Finally, computational results on an instance based on a real network topology and randomly generated instances are reported.

In Chapter 4, a cut-and-solve and cutting plane combined method is developed to solve the transformed single objective problems more efficiently. Cut-and-solve method is applied to find an optimal solution and cutting plane method is exploited to accelerating the process of cut-and-solve method. A property of the considered problem is also explored to reduce the solution space. Finally, the performance of the proposed method is evaluated by comparing the cut-and-solve method with CPLEX, and computational results on randomly generated instances are reported.

In Chapter 5, hazardous material transportation via lane reservation in networks with time-dependent risk is investigated. The background of the time-dependent

problem is given and then the problem is formulated as a multi-objective mixed integer programming one. Its property is also explored. Then an improved cut-and-solve based  $\varepsilon$ -constraint method is proposed. In the method, a new technique of generating piercing cuts based on the characteristics of the considered problem is developed and a partial integral relaxation strategy is applied. Finally, the performance of the proposed method is evaluated by comparing the cut-and-solve method with CPLEX, and computational results on randomly generated instances are reported.

Chapter 6 concludes the thesis, discusses its shortcoming, and indicates the direction of the future research.

# CHAPTER 2 LITERATURE REVIEW

This chapter provides literature reviews on hazardous material transportation and lane reservation. Firstly, several related hazardous material transportation problems and their formulation are presented. Their characteristics are analyzed to explain the differences between the considered HMTLR problem and them. Secondly, some applications of lane reservation and studies on it are reviewed. Its state-of-the-art indicates that hazardous material transportation via lane reservation is a promising application. This chapter also introduces the principles of some technologies in detail, which will be used for solution algorithms.

## 2.1 Literature review on hazardous material transportation

To summarize the studies on the hazardous material transportation problem, this subsection first classifies the problem. There are commonly three types of problems on hazardous material transportation [1]:

- (1) Risk assessment for hazardous material transportation;
- (2) Routing problem for hazardous material transportation;
- (3) Network design problem for hazardous material transportation.

These problems deal with hazardous material transportation from different perspectives. They are related to the HMTLR problem proposed in this thesis. This section provides a review on them.

### 2.1.1 Literature review on risk assessment

As we know, risk is the most important factor that distinguishes the hazardous material transportation problem from other transportation problems. For the hazardous material transportation problem, risk is a measure of the probability and severity of harm to an exposed receptor resulted from some potential undesired events involving a hazardous material [1][10]. The exposed receptor can be persons, environment, or properties in the neighborhood. The undesired event refers to the release of a



hazardous material due to an accident. Specifically speaking, the undesirable consequences of a release can be a health effect (death, injury, or long-term effects due to exposure), property loss, cleanup costs, product loss, an evacuation of nearby population, traffic interruption along the impacted route and an environmental effect (such as soil contamination or health impacts on flora and fauna) [1]. All the impacts should be converted to the same unit (for example dollars) to permit comparison and computation of the total impact cost [1].

Risk assessment can be qualitative and quantitative. In risk assessment, the identification of possible accident scenarios and the estimation of the undesirable consequences are required. When the reliable data to estimate the probability of an accident and its consequences are absent, the qualitative risk assessment is usually a helpful tool. The elements of quantitative risk assessment are probabilities and consequences. In order to obtain these data, the risk assessors ought to collect considerable historical information on accident frequencies and fairly accurate consequence models for hazardous material releases in case of accidents. Therefore, unlike in qualitative risk analysis, quantitative risk assessment can obtain a precise numerical result of risks. As the main purpose of this thesis is to develop mathematical models and their resolution approach, we focus on quantitative risk assessment in this thesis.

Next, the traditional method to assess risk in the literature will be introduced. In quantitative risk assessment, as stated previously, risk is defined as the product of the probability of a hazardous material accident and its consequences. Although there can be many kinds of consequences in a hazardous material accident, almost all studies in this area are only concerned with fatalities. They also assume that each individual within the danger zone should be impacted equally and nobody outside of this area can be affected. Therefore, the undesirable consequence is considered to be proportional to the size of the population in the neighborhood of the accident, where the size of the population exposure depends on the substance carried [11]. Population exposure refers to the number of population affected by a transportation accident. In a word, the traditional method to assess risk in the literature is to multiply the

probability of hazardous material accidents by population exposure. This method is used as a surrogate for risk measure, as expressed by

$$R = p * c$$

where  $p$  is the probability of a hazardous material accident, and  $c$  is the estimated population exposure.

Risk assessment intends to provide a risk analysis methodology for hazardous material transportation. It can be useful to practitioners in identifying effective ways to manage and reduce the risk during the transport of hazardous materials. Generally speaking, risk analysis for hazardous material transportation is not within the scope of Operations Research (OR), since most studies on risk assessment do not involve OR models and techniques but probability statistics, geometry and systematical analysis method such as logical diagram-based techniques. However, it can offer useful information on hazardous material transportation modeling and analysis for researchers in OR as well as other relevant fields.

### 2.1.2 Literature review on routing problem for hazardous material transportation

Routing problems for hazardous material transportation have attracted the attention of many OR researchers since 1970s and there are fruitful results in this area. Hazardous material routing problem involves selecting a path for each shipment among its alternative paths between given origin-destination (OD) pairs so as to minimize total transportation risk. The problem can be distinguished into *local route planning* problem and *global route planning* problem. In local route planning problem, shipments can be considered independently from a carrier's perspective and a routing decision needs to be made for each shipment [1]. At the macro level, global route planning problem is a "many to many" routing problem with multiple origins and an even greater number of destinations [1] [12]; it is also a problem from different stakeholders' perspectives.

For each shipment, local route planning problem aims to find a single commodity and a single origin-destination route decision. Since these decisions are often made at

the micro level [1], some arcs in the transportation network are likely to be overused by hazardous material shipments. This could directly lead to an increase of accident probabilities on some road segments, and further cause the inequity in the spatial distribution of risk. Although transportation risk may be considered by most carriers in their routing decisions, the carriers still pay more attention to transportation cost. However, in global route planning problem, government has to make the global hazardous material route decision by taking into account all shipments. For this reason, this problem usually involves multicommodity and multiple origin-destination routing decisions. Besides the total transportation risk, government may consider the equity in the spatial distribution of risk.

In this subsection, route planning problem refers to the local one and it is reviewed. In next subsection, hazardous material network design problem, as a typical global route planning problem, will be reviewed.

#### 2.1.2.1 A basic routing problem for hazardous material transportation

The (local) routing problem is to select the route(s) between a given origin-destination pair for a given hazardous material, transport mode, and vehicle type. Iakovou investigated a classical routing problem for hazardous material transportation [13]. He considered a transportation network  $G = (V, A)$ , where  $V$  was the set of nodes and  $A$  was the set of arcs. An arc was characterized by its length, transport rate per ton mile, risk cost and capacity. To define the problem, the following notations are first defined.

$W \{1, 2, \dots, /W/\}$ : set of hazardous materials type

$O \{o_1, o_2, \dots, o_{/W/}\} \in V$ : set of origin nodes

$D \{d_1, d_2, \dots, d_{/W/}\} \in V$ : set of destination nodes

$X_{ij}^w$ : amount of commodity  $w$  which will be transported from node  $i$  to node  $j$

$c_{ij}^w$ : transportation cost for transporting one unit of volume of commodity  $w$  from node  $i$  to node  $j$

$R_{ij}^w$ : expected risk cost for transporting one unit of volume of commodity  $w$  from node  $i$  to node  $j$

$s_{jw}$  : amount of product  $w$  required at node  $j$

$U_{ij}$  : flow capacity for arc  $(i, j)$

Based on the above notations, the problem can be formulated as follows:

$$\min f_1 = \sum_{(i,j) \in A} \sum_{w \in W} c_{ij}^w X_{ij}^w \quad (2.1)$$

$$\min f_2 = \sum_{(i,j) \in A} \sum_{w \in W} R_{ij}^w X_{ij}^w \quad (2.2)$$

Subject to

$$\sum_{i:(i,j) \in A} X_{ij}^w - \sum_{l:(j,l) \in A} X_{jl}^w = \begin{cases} s_{jw}, & \text{if } j \in O, \forall w \in W \\ 0, & \text{if } j \in N \setminus O, D, \forall w \in W, \\ -s_{jw}, & \text{if } j \in D, \forall w \in W \end{cases} \quad (2.3)$$

$$\sum_{w \in W} X_{ij}^w \leq U_{ij}, \forall (i, j) \in A, \quad (2.4)$$

$$X_{ij}^w \geq 0, \forall (i, j) \in A, \forall w \in W. \quad (2.5)$$

Constraint (2.3) imposes the flow balance at nodes for each commodity, while Constraint (2.4) ensures that the total flow of commodities on arc  $(i, j)$  does not exceed the appropriate capacity.

The HMTLR problem addressed in this thesis is different from the routing problem for hazardous material transportation. Although both of them involve multiple origin-destination routing decisions and aim to find the set of Pareto optimal routes between given origin-destination pairs, the routing problem also involves multicommodity routing decisions while the considered problem in this thesis does not. The difference between the considered problem and other hazardous material transportations mainly comes from a novel way of reducing transportation risk, that is, via lane reservation.

#### 2.1.2.2 Classification of routing problems for hazardous material transportation

The models of the routing problem can be grouped according to their characteristics, for example, number of objectives and the nature of transportation networks. Thus, the existing route planning models are presented in various forms, including *single-objective* or *multi-objective* models, *time-invariant* or *time-dependent* models.

Hazardous material routing problem is usually considered to be multi-objective due to its nature of multiple stakeholders (e.g., Kalelkar and Brinks [14], Marianov and ReVelle [15], Huang *et al.* [16]). And a few studies focused on single objective problems such as Erkut and Verter [11]; Kara *et al.* [17]; Verter and Erkut [18]. A single objective routing problem with a given OD pair can be considered as the classical shortest path problem. A label-setting algorithm (e.g., Dijkstra's algorithm) can be applied to find an optimal route for this problem. Kara *et al.* [17] proposed a simple modification of Dijkstra's algorithm, called the *impedance-adjusting node labeling shortest path algorithm*, to find a route that minimizes the path incident probability. The modification relies on the adjustment of the link attribute (such as travel time, link volume, queue length, and so on [19]) that is used to update the node label and the scanning process. This modified algorithm has the same computational complexity as that of Dijkstra's. As for a multi-objective problem, there is often no solution that can simultaneously optimize all the conflicting objective functions. Instead, a set of Pareto optimal solutions can be found. A Pareto optimal solution is the one where an objective can be improved while without worsening at least one other objective. Multi-objective route planning is to find the set of Pareto optimal routes between given OD pairs, see for example [13][20].

In the literature, most hazardous material routing problems are time-invariant in risk, which fail to capture the dynamic nature of transportation risk at the tactical level. In fact, the traffic conditions and risk factors such as probabilities of hazardous material accidents and population exposure in transportation networks often vary with time. For example, for a truck carrying hazardous materials, risk on road segments is time-dependent on population density subject to time-of-day variation, peak and off-peak periods, various weather conditions and so on. The time-dependent risk is one of the important features of hazardous material transportation. Time-dependent hazardous material transportation problems can be distinguished into deterministic and stochastic settings.

In a deterministic time-dependent problem, all of the link attributes are assumed to be known and part or all of them vary over time. For example, Nozick *et al.* [21]

investigated a hazardous material routing and scheduling problem with deterministic time-dependent risk. But their approach could not guarantee to generate all Pareto optimal paths. Jia *et al.* [22] investigated a hazardous material transportation problem with deterministic time-dependent risk for minimizing the transportation risk. The model guaranteed the minimum distance between hazardous material shipments at any time. They transformed the problem into a set of time-dependent shortest path problems for each truck and proposed an iterative heuristic. In [23][24], given a departure time, a single least time path between an OD pair can be obtained by a specific search which mainly relies on comparing deterministic link attributes, such as label-setting and label-correcting algorithms.

In a stochastic time-dependent problem, part or all of the link attributes are known as random variables with distribution functions that vary over time. For example, the travel time and the transportation risk in [25]-[27] belongs to such a kind of link attribute. Erhan and Osman [25] proposed an integrated routing and scheduling problem for hazardous material transportation in a network with stochastic time-dependent accident probability, population exposure and travel time. The model aimed to minimize risk subject to a constraint on the total travel time of the shipment. Meng *et al.* [26] examined a similar problem with multiple objectives, which could be transformed into the time-dependent multi-objective shortest path problem subject to three kinds of time constraints. A dynamic programming method was developed by constructing a time-space network to solve this problem. Both the methods of two works [25] and [26] are pseudo-polynomial. Chang *et al.* [27] proposed an effective algorithm for finding a path in a stochastic time-dependent network that could address multiple optimization criteria. In their work, travel time, transportation risk and other link attributes along paths were random variables. However, the performance of the algorithm was sensitive to some parameters and the computational burden increases with the number of the dominated paths.

## 2.1.3 Literature review on network design problem for hazardous material transportation

### 2.1.3.1 A basic network design problem for hazardous material transportation

Network design problem for hazardous material transportation is a typical global route planning problem. Kara and Verter [28] first gave a definition of hazardous material transportation network design problem as follows: given an existing transportation network, the network design problem intends to select the road segments that should be open to hazardous material transportation so as to minimize total transportation risk. A classical hazardous material transportation network design problem was presented by Bianco *et al.* in [29]. Consider an undirected transportation network  $G' = (V, E)$ , where  $V$  is the set of nodes and  $E$  is the set of (undirected) links. Assume that each link  $\langle i, j \rangle \in E$  can be traversed in both directions; let  $A = \{(i, j), (j, i) : \langle i, j \rangle \in E\}$  be the set of (directed) arcs, where arc  $(i, j) \in A$  represents link  $\langle i, j \rangle$  when traversed from node  $i$  to node  $j$ . Let  $W$  denote a set of hazardous material shipments (in the remaining of this subsection also called hazardous material commodities). Each hazardous material commodity  $w$  corresponds to a source destination pair  $(o_w, d_w)$  and a amount of flow  $f_w$ . Let  $R_{ij}^w$ ,  $X_{ij}^w$ , and  $z_{ij}$  be the unitary risk of arc  $(i, j)$  related to commodity  $w$ , the amount of flow of commodity  $w$  on arc  $(i, j)$  and the capacity of arc  $(i, j)$ , respectively. The bi-level model is presented as follows:

$$(P1): \quad \lambda^* = \min_z \lambda \quad (2.6)$$

Subject to

$$\sum_{w \in W} (R_{ij}^w X_{ij}^{w'} + R_{ji}^w X_{ji}^{w'}) \leq \lambda, \forall \langle i, j \rangle \in E \quad (2.7)$$

$$z_{ij} \geq 0, \forall (i, j) \in A \quad (2.8)$$

where  $X' = \{X_{ij}^{w'}\}$  solves the low level problem

$$(P2): \quad R_{tot}^*(y) = \min_X \sum_{w \in W} \sum_{(i,j) \in E} R_{ij}^w X_{ij}^w \quad (2.9)$$

Subject to

$$\sum_{j:(i,j) \in E} X_{ij}^w - \sum_{j:(j,i) \in E} X_{ji}^w = \begin{cases} f^w, i = o_w, \forall w \in W \\ 0, \forall i \in N / \{o_w, d_w\}, \forall w \in W \\ -f^w, i = d_w, \forall w \in W \end{cases} \quad (2.10)$$

$$\sum_{w \in W} X_{ij}^w \leq z_{ij}, \forall (i, j) \in A \quad (2.11)$$

$$X_{ij}^w \geq 0, \forall (i, j) \in A, \forall w \in W \quad (2.12)$$

The high level formulation models the leader problem  $P1$ , where the government selects minimum risk routes as a subset of the transportation network. Expression  $\sum_{w \in W} (R_{ij}^w X_{ij}^w + R_{ji}^w X_{ji}^w)$  denotes the link total risk over link  $\langle i, j \rangle$ , thus  $\lambda$  is the maximum link total risk over each link  $\langle i, j \rangle$ . The leader problem  $P1$  assures an equitable distribution of the risk over the network. Constraint (2.7) states that the total risk over each link should not exceed  $\lambda$ , and constraint (2.8) is the non-negative restriction on  $z_{ij}$ .

The low level formulation models the follower problem  $P2$ , where the carriers select paths to minimize the transportation cost on the subnetwork. In  $P2$ , given the capacity vector  $z = \{z_{ij}\}$  imposed by the leader decision-maker (DM), the total risk over network  $G'$  is minimized. Constraint (2.10) is the flow balance equation. Constraint (2.11) ensures that the total flow on arc  $(i, j)$  cannot be greater than its capacity. Constraint (2.12) is the non-negative restriction on  $X_{ij}^w$ .

Both this classical problem and the considered problem in this thesis aim to select the road segments for hazardous material transportation so as to minimize the total transportation risk. Nevertheless, this does not mean that they are the same problem. In classical hazardous material transportation network design problem, vehicles carrying hazardous materials share all the lanes on the chosen road segments with other users in the transportation network implicitly. However, in the considered problem in this thesis, lane reservation strategy is introduced into hazardous material transportation problem.

### 2.1.3.2 Studies on network design problem for hazardous material transportation

Network design problem for hazardous material transportation has attained



relatively little attention in the literature compared to route planning problems. Therefore, there are only a few published works, see, for example, [28]-[33]. As mentioned above, Kara and Verter [28] first defined this problem and also presented a bi-level decision model for it. With some special transformations, the bi-level IP model is reformulated as a single level MIP model and solved by commercial optimization software package CPLEX. Erkut and Gzara [30] presented a bi-level bi-objective (cost and risk minimization) network design problem similar to that considered by Kara and Verter in [28]. They proposed a heuristic algorithm that exploited the network flow structure at both levels, instead of transforming the bi-level IP problem to a single level formulation. Erkut and Alp [31] addressed a hazardous material network design problem with the objective of minimizing risk. They considered it as a Steiner tree selection problem. With the topology of this tree, the bi-level problem was converted into a single level one by prohibiting the carriers to select route, but it also led to circuitous and high-cost routes. To avoid this drawback, they added edges to the Steiner tree. And they proposed a greedy heuristic, in which shortest paths were added to the tree so as to keep the risk increase to a minimum. These works have bi-level models in common. The difference among them is the approach that transforms the bi-level model into a single level one.

#### 2.1.4 Literature review on other problems for hazardous material transportation

In the literature, there are also other classical problems for hazardous material transportation, such as  $k$ -shortest path problem, network planning problem, vehicle routing and scheduling problem, and location and routing problem. A comprehensive literature survey on them is shown in Table 2.1.

Table 2.1 provides five important attributes of the problems considered in reference [33]-[47], including risk assessment, type of the considered problems, objectives of the considered problems, method of dealing with multiple objectives, and resolution method for the transformed single problem. We can observe from Table 2.1 that (1) the traditional risk measure is a common method of assessing the transportation risk in the literature such as [33]-[38] and in some works, population exposure is directly regarded as the surrogate of risk, see, for example, [42]-[46]; (2)

all of the problems are considered to be multi-objective and the common objectives include the transportation risk [33]-[47], the transportation cost [35]-[37],[40]-[41], [43]-[47] and the total travel time [33][34][38]; (3) the weighted sums method is extensively applied to transform the original multi-objective problem into a single objective one in the literature except [38]-[39]; (4) almost all of the problems are considered to be time-invariant and only reference [34] addressed a  $k$ -shortest path problem with time-dependent risk.

Table 2.1 Review on other problems for hazardous material transportation

Author(s)	Risk assessment	Problem	Objectives	Method of dealing with multiple objectives	Resolution method
Dadkar et. al [33]	traditional risk measure	$k$ -shortest path problem	minimizing travel time and risk	weighted sums method	mixed integer program
Androutsopoulos and Zografos [34]	traditional risk measure	$k$ -shortest path problem	minimizing time-dependent risk and travel time		Tabu search
Verma [35]	traditional risk measure with TRA dataset and GIS	network planning problem	minimizing risk and cost	weighted sums method	CPLEX Optimizer
Verma et. al [36]	traditional risk measure	intermodal planning problem	minimizing risk and cost	weighted sums method	an approach based on lead-time
Nema and Gupta [37]	traditional risk measure	planning and design problem	minimizing risk and cost	weighted sums method	
Pradhananga [38]	traditional risk measure		minimizing number of vehicles, travel time and risk	pareto-based evolutionary algorithm	ant colony algorithm
Ghatee <i>et al.</i> [39]	Risk is a given parameter.	fuzzy minimal cost flow problem	minimizing risk and fuzzy cost flow	pareto-based evolutionary algorithm	
Zografos and Androutsopoulos [40]	Risk is a given parameter.	vehicle routing and scheduling problem	minimizing risk and cost	weighted sums method	heuristic algorithm
List and Mirchandani[41]	traditional risk measure	location and routing problem	minimize risk, risk equity, and cost	weighted sums method	
Shobrys [42]	population exposure	location and routing problem	minimizing ton-miles and risk-tons	weighted sums method	$p$ -median problem
Alumur and Kara [43]	population exposure	location and routing problem	minimizing risk and cost	weighted sums method	mixed integer programming model
Revelle <i>et al.</i>	population	discrete location	minimizing cost and	weighted sums method	$p$ -median problem.

[44]	exposure	and routing problem	risk		
Giannikos [45]	population exposure	location and routing problem	minimizing four objectives*	weighted sums method	goal-programming technique
Current and Ratick [46]	population exposure	location and routing problem	minimizing five objectives**	weighted sums method	
Jacobs and Warmerdam [47]		location and routing problem	minimizing cost and risk	weighted sums method	

\* The five objectives are minimizing risk, cost, maximum individual risk and maximum disutility caused by the operation of treatment facilities

\*\*The five objectives are minimizing transportation risk, facility risk, maximum transportation exposure faced by any individual, maximum facility risk faced by any individual, and transportation, facility, and operating costs.

It can be concluded from this section that 1) the traditional risk measure is widely employed in hazardous material transportation problems because of its computational availability; 2) multi-objective hazardous material transportation problems are widely studied due to their nature; 3) weighted sums method is usually applied to deal with multiple objectives in hazardous material transportation problems because of its operational simplification, but studies on other methods such as  $\epsilon$ -constraint method and pareto-based evolutionary algorithms are still very few in the literature; 4) although there are many classical hazardous material transportation problems, the hazardous material transportation problem via lane reservation is still rare in the literature. This thesis will investigate hazardous material transportation problems via lane reservation in networks with time-invariant and time-dependent risk, respectively. Before proceeding, a comprehensive review on lane reservation is given in next section.

## 2.2 Literature review on lane reservation

With the development of society, urbanization accelerates quickly. Urban population and the number of vehicles are increasing year by year. Consequently, traffic congestion becomes a serious problem, which attracts more and more attentions of government and people. Traffic condition can be improved by means of economical and flexible traffic management strategies. For example, lanes on some

road segment can be reserved only for some special tasks. This is usually called *lane reservation strategy*. In other words, it refers to restricting one or several lanes in road segments and allowing only special vehicles to use them (within a specified time). In this section, some applications of lane reservation in real life, such as Bus lane and BRT, HOV, and lane for large special events, are first introduced. Then, studies on lane reservation are reviewed.

## 2.2.1 Applications of lane reservation

### 2.2.1.1 Bus lane and BRT

The first bus lane in the world appeared in Chicago, American, in 1940 [48][49]. Hamburg, Germany, built the first European public bus lanes in 1963 [50]. Afterwards, many European cities began to build bus lanes to relieve the increasingly serious congestion of urban traffic. In 1997, the first bus lane was put into operation on Chang'an Avenue in Beijing, which opens the door of bus lane strategy in China [51]. At present, the strategy of separating buses from other vehicles via bus lanes is prevalent in more and more countries. For example, bus lane strategy develops rapidly and is highly accepted by the public in Brazil, Thailand and Japan. In China, there are also many cities in which bus lane strategy is being implemented, such as Beijing, Kunming, Xi'an, Jinan, Guangzhou, Chengdu and so on.

The implementation of bus lanes has positive impact on the speed of buses with an increase from 10% to 30%, up to 20-35 km/h [52]. Choi and Choi [53] also pointed out that in South Korea, after the implementation of bus lanes, the travel time of buses was greatly reduced; as a result, about 12% of private car owners chose the public transit, and the rate of traffic accidents also decreased. However, the traditional bus lane strategy (usually referring to exclusive bus lane, XBL) may have negative impact on the general traffic. For example, in the peak hour, the general lanes will be more congested due to the exclusiveness of the bus lane. Thus, the vehicles on the general lanes would slow down. In order to weaken the negative impact due to bus lane strategy, a new innovative dynamic bus lane (DBL) operation system, in which bus lanes are opened only in some time periods, is introduced. Like XBL, DBL has the

positive impact on buses in terms of their travel time reduction and the negative impact on non-bus vehicles in terms of their travel time increase. However, it is shown that DBL performs better than XBL in improving bus operation and limiting the negative impact on non-bus vehicles in terms of traffic conflicts risk [54].

Bus Rapid Transit (BRT) system is a new and practicable passenger-transported traffic mode based on exclusive bus lanes. A BRT system generally includes specialized design, services and infrastructure [55]. One of its main features is that exclusive bus lanes in BRT system result in a faster travel and ensure that buses are not delayed by traffic congestion. Sometimes it is described as a "surface subway". BRT originated from Curitiba in Brazil 30 years ago. After employing BRT system in Curitiba, the bus travel rate of passengers is up to 75%, and the number of passengers in a day reaches up to 1.9 million. BRT system can apply to not only small cities with a population of hundreds of thousands but also super large cities [56]. Nowadays, BRT can be found in lots of cities all over the world. Fig. 2.1 and 2.2 show the bus lane and BRT lane in some cities, respectively [57].



a. Exclusive bus lane (XBL)



b. Dynamic bus lane (DBL)

Fig. 2.1 Examples of bus lane in a city

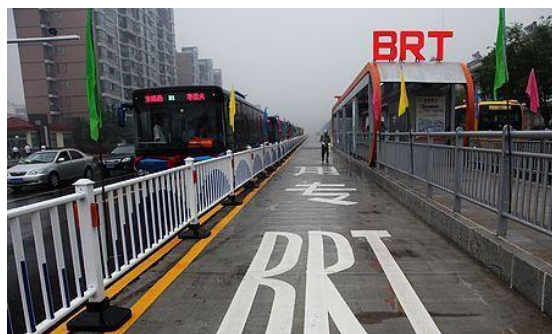


Fig. 2.2 Example of BRT lane in a city

### 2.2.1.2 High occupancy vehicle lane

High occupancy vehicle, HOV, is a vehicle with multiple occupants. An HOV lane is a lane reserved at peak hours for the exclusive use of vehicles with a driver and one or more passengers, including carpools, vanpools, and transit buses [58]. Sometimes vehicles on HOV lanes can be free for getting through toll bridges or roads. HOV lanes derived from North America in the late 1960s, and developed rapidly in the 1970s [59][60]. During this period, HOV lanes were prevalently installed in New York, Los Angeles, Seattle, San Francisco, Washington DC, and Honolulu. It was widely recognized in the mid of 1980s, and nowadays HOV lanes have been widely applying not only in more than 40 cities of North America, but also in many cities around the world, such as Canada, Australia, UK, Spain, the Netherlands, and Austria in Europe [61] [62]. Fig. 2.3 gives an example of HOV lane in a Canadian city [57].



Fig. 2.3 Example of HOV lane in a city

HOV lane is a large capacity vehicle lane, which helps to carry more passengers by fewer vehicles. Therefore, the installation of HOV lanes has been considered as an efficient traffic management measure of improving the efficiency of road use, easing traffic congestion, saving energy and reducing emission. It has been mainly applied on road segments where in the peak hours the congestion is very serious and saving travel time is particularly important. More information on HOV lanes can reference [63].

### 2.2.1.3 Lane for large special events

In modern society, many large special events such as Olympic Games and World Exposition are held frequently in many cities around the world. For example, in Shanghai, there were 30 international and 40 national sport events, 176 large expositions held in 2009 [64]. These events have a common feature that there are a lot of people entering the host city during the event period, which brings great pressure to its traffic in a short time. The organizers of the large special events have realized such a pressure and began to resort to some various measures. One of effective methods is to set up temporary reserved lanes on the existing road segments only for the participants of large special events.

In real life, lane reservation strategy has been successfully applied to some large events, for example, the Olympic Games in 2000 in Sydney [65], in 2004 in Athens [66], in Beijing and the Asia sports Games in Guangzhou, China [67]. Olympic lanes refer to the lanes reserved only for the vehicles among competition and training stadiums, Olympic family residence, Media Hotel, airport, Main Press Center, Broadcast and TV Center and other service facilities for the Olympic Games. Fig. 2.4.a shows Olympic lanes for the Olympic Games in 2008 in Beijing, and all the reserved road segments are remarked with red in the urban transportation network of Beijing, as illustrated in Fig. 2.4.b [68].



a. An Olympic lane for the Olympic Games



b. Reserved road segments in the city network

Fig. 2.4 Lane reservation for the Olympic Games in 2008 in Beijing

### 2.2.2 Studies on lane reservation

In the previous subsection, various applications of lane reservation in real life are introduced. As an interesting traffic management strategy, lane reservation has been extensively investigated in the literature. In this subsection, a review on lane reservation is given.

Study on the impact due to lane reservation is one of the interesting topics in intelligent transportation system. Li and Ju [69] presented a multimode dynamic traffic assignment (DTA) model for analyzing the impact of exclusive bus lanes. They found that the total bus queue length became zero after the installation of bus lanes and the average travel cost of bus travelers was significantly reduced compared with that of car travelers, which attracted more travelers to change their modes from private cars to buses. Chen *et al.* [70] presented a microscopic traffic simulation approach to analyze the impact of weaving sections on the capacity of general traffic caused by the installation of XBLs on an urban expressway. Three typical configurations of XBLs in Beijing were considered, including median bus lane with off-on-ramp, curbside bus lane with on-off-ramp, and curbside bus lane with off-on-ramp. It was found that the weaving section length and headway had different impacts on the capacity of general traffic in different configurations. Arasan and Vedagiri [71] developed a micro-simulation model to analyze the impact on heterogeneous traffic flow due to XBLs. The impact was measured by the reduction in speed of other vehicles on general lanes. With an XBL, the average speed of buses could be up to 65 km/h; at the capacitated level of traffic flow, the travel time for buses reduced around 70%; for other personal vehicles, the increase in travel time varied from 3% to 8%. Yang and Wang [54] employed micro-simulation approach to examine the impact on buses and non-bus vehicles due to XBL and DBL in terms of travel time and traffic conflicts. Simulation results showed that both XBL and DBL had positive impact on buses in terms of the decrease of their travel time and negative impact on non-bus vehicles in terms of the increase of their travel time. However, DBL performed better than XBL on achieving the improvement of bus operation and



limiting negative impact on other vehicles as traffic conflicts risk. Martin *et al.* [72] reported a two-year study evaluation on the impact of HOV lane on I-15 in Salt Lake City. It was reported that a HOV lane could carry the same number of people as a non-HOV lane with only 44% of vehicles during the P.M. peak period. The results also revealed that the average vehicle occupancy on HOV lane increased by 17% and HOV lane could save about 13% and 30% of travel time during the A.M. and P.M. peak period, respectively.

Another important topic is lane reservation network design problem. At the macro level, lane reservation network design problem is a global route planning problem from different stakeholders' perspectives. For example, in bus lane network design problem, the stakeholders include government transport agency, private car owners, and bus passengers. Therefore, lane reservation network design problem is usually considered as a bi-level problem. Chen *et al.* [73] developed a bi-level programming model for the layout of bus lanes. The upper level problem was to minimize the total travel time and the total bus lanes' length and the total transfer times; the lower level problem was formulated as a capacity-constrained traffic assignment model which described the passenger flow assignment on bus lanes. Mesbah *et al.* [74] investigated a network design problem to determine which lanes to be reserved as exclusive transit lanes on the existing network. The problem was formulated as a bi-level model. The upper level model was to minimize the impact due to XBLs from a manager' perspective, whereas the lower level model was formulated from a user' perspective and consisted of modal split model, traffic assignment model and transit assignment model. A decomposition method was adopted to solve the proposed model. Mesbah *et al.* [75] proposed a genetic algorithm approach for the above problem, which could be applied to large-size networks. Wu and Lam [76] addressed a bi-level model for the HOV lane design problem in a multi-modal transportation network. The upper level sought to minimize the total cost of the multi-modal transport system while in the lower level, a multi-modal stochastic traffic assignment model was formulated. The model was solved by two heuristic algorithms.

In recent years, there has been a new lane reservation problem in the literature. The essence of the lane reservation problem is to decide which lanes to be reserved in the existing transportation network so as to minimize the negative impact caused by lane reservation subject to a total travel time constraint. For this reason, this problem can be considered a global route planning problem from a manager's perspective, such as government transport agency. Wu *et al.* [67] first presented an integer programming model for lane reservation problem for the Asian Games in 2010 in Guangzhou, China. They proposed a heuristic to obtain near optimal solutions. Fang *et al.* [77] proposed a cut-and-solve algorithm for the lane reservation problem in automated truck freight transportation and proved that the problem was NP-hard. Then, their work was extended to a capacitated lane reservation problem [78]. Fang *et al.* [79] considered a lane reservation problem with time-dependent travel times. The problem was formulated as a mixed integer programming model and a cut-and-solve based algorithm was proposed for it. However, their work did not consider transportation risk.

From the analysis of the above related literature, the state of the arts on lane reservation problem can be concluded as follows. Firstly, researchers have paid close attention to studies on the impact due to lane reservation, including the performance of lane reservation, the effect on the travel behavior of people, and the travel time of special vehicles on reserved lanes and general vehicles on non-reserved lanes. The common approaches are based on empirical data and simulation experiments by some traffic simulators. These studies mainly provide sufficient supports for decision-makers when considering lane reservation as a traffic management strategy. Secondly, a few researchers have studied on lane reservation network design problem to some extent. The problems are usually formulated as multi-level and multi-criteria models from different perspectives of different stakeholders. These models are useful tools to analyze the requirements of different stakeholders in the different level. Thirdly, lane reservation strategy has been already applied to various applications such as HOV lane, bus lane and Olympic lane. However, few studies have focused on hazardous material transportation via lane reservation. To address this issue, this

thesis integrates hazardous material transportation with lane reservation strategy and proposes a multi-objective hazardous material transportation problem via lane reservation. Before proceeding, the principles of some key technologies that will be applied in this thesis are recalled.

## 2.3 Key technologies

### 2.3.1 Risk assessment

This subsection deals with how risk is incorporated into hazardous material transportation models, starting with the risk assessment on an arc and shifting it into the risk assessment along a path.

As pointed out in [11], researchers have not come to a consensus on how to model the risk associated with hazardous material transportation. Different measures can be used to estimate the transportation risk. Note that in quantitative risk assessment, it is common to define *risk* as the product of the probability of hazardous material accident and its consequence.

One of the simple methods to assess risk is to multiply the probability of hazardous material accidents by population exposure, assuming that the consequence is proportional to the size of the population in the neighborhood of the accident. Risk assessment is a quite important task, but it is out of the scope of this thesis. Therefore, in this thesis, this method is used as a surrogate for risk measure. The risk of transporting hazardous material  $w$  on arc  $(i, j)$  is defined as the following equation:

$$R_{ij} = p_{ij}c_{ij}$$

where  $p_{ij}$  is the probability of an incident on arc  $(i, j)$  and  $c_{ij}$  is the population exposure within the danger zone along arc  $(i, j)$ .

The risk of transporting hazardous material  $w$  along path  $P$  is defined as the following equation:

$$R_P = \sum_{(i,j) \in P} p_{ij}c_{ij}$$

How to deduce the transportation risk along a path from that on an arc can be found in [11].

As we know, it is difficult to estimate, a priori, the probability of an accident and its undesirable consequences. Therefore, like the most studies on hazardous material transportation in the literature, the probability of an accident and the consequences are considered as parameters when formulating the considered problems in this thesis.

### 2.3.2 Multi-objective optimization problem

Multi-objective optimization is a very important research topic both for scientists and engineers, not only because of the multi-objective nature of most real-world problems, but also because there are still many open questions in this area.

Without loss of generality, a multi-objective minimization problem can be formulated as follows:

$$\text{Minimize } f(x) = [f_1(x), f_2(x), \dots, f_m(x)]^T$$

Subject to

$$g_j(x) \leq 0, j=1, 2, \dots, J$$

$$h_l(x) = 0, l=1, 2, \dots, L$$

where  $m$ ,  $J$  and  $L$  are the number of objective functions, inequality constraints, and equality constraints, respectively, and  $x$  and  $f(x)$  is the decision variable vector and the objective vector, respectively.

A multi-objective optimization problem (MOP) requires the simultaneous satisfaction of a number of objectives. These objectives are usually different and conflicting, and often characterized by various measures of performance that may be (in)dependent and incommensurable [80]. The aim of a MOP is to determine, among the set of all feasible solutions, a particular one which provides the optimum values for all the objective functions. Thus, MOP can be reduced to finding an  $x$  such that  $f(x)$  is optimized. The difficulty encountered in solving MOPs is that this unique optimal solution seldom exists for practical problems. However, there commonly exists a set of good quality solutions. This set of solutions comprises all decision vectors that cannot be improved in one objective without causing any degradation in other objectives. Since the notion of an optimum solution of a MOP is different from that of a single objective optimization problem, the concept of *Pareto optimal* is introduced.

Let set  $\Omega = \{x | g_j(x) \leq 0, j=1,2,\dots,J \text{ and } h_l(x)=0, l=1,2,\dots,L\}$  be the *feasible solution space*.  $x^* \in \Omega$  is said to be a *weakly Pareto optimal* solution if and only if there is no  $x \in \Omega$  such that  $f_i(x) < f_i(x^*)$  for all  $i \in \{1,\dots,m\}$ .  $x^* \in \Omega$  is said to be a *strictly Pareto optimal* solution if and only if there is no  $x \in \Omega$  such that  $f_i(x) \leq f_i(x^*)$  for all  $i \in \{1,\dots,m\}$  and at least one strict inequality [81]. Set  $Z = \{f(x) | x \in \Omega\}$  is called the *feasible objective space*. The image of all the Pareto optimal solutions under objective functions is called *Pareto front*. The points on Pareto front are referred to as named *non-dominated points*.

### 2.3.3 $\epsilon$ -Constraint method

There have been many techniques proposed for solving multi-objective optimization problems over the last several years. The strategies of handling objectives for an MOP can be mainly divided into two general categories: scalarization method and Pareto-based evolutionary algorithm. Scalarization method often refers to transforming the multi-objective problem into the single objective problem by some scalarization techniques, such as weighted sum method, and  $\epsilon$ -constraint method. Pareto methods, which use the concept of Pareto dominance to evaluate the quality of a solution, are mainly combined with evolutionary algorithms, such as genetic algorithm.

The most popular scalarization method is the weighted sum method. The essence of this method is to add all the objective functions together using different weighting coefficients for each of them and transform the original MOP into a scalarized optimization problem. This technique is relatively easy to implement and can be used together with some heuristics or meta-heuristics. However, it still has several disadvantages. Firstly, it is a difficult task to determine appropriate weights according to the importance of the objectives. Secondly, this method can only find the solutions on the convex hull of the Pareto optimal set, but it does not work for the non-convex search spaces [82].

Pareto-based evolutionary algorithms use the concept of Pareto dominance to classify the individuals in the population and a mechanism to assign suitable fitness

values to promote the dispersion of the population. Since evolutionary algorithms use the concept of population, they may be able to obtain multiple Pareto optimal solutions simultaneously in a single run of algorithms. However, the performance of the Pareto-based evolutionary algorithms is highly dependent on an appropriate selection of initial population. In addition, it is difficult to evaluate the evolutionary algorithms.

To alleviate the difficulties faced by the weighted-sum method and Pareto-based evolutionary algorithms, the  $\varepsilon$ -constraint method is employed in this thesis. The  $\varepsilon$ -constraint method, also called the e-constraint or trade-off method, is introduced by Haimes *et al.* [83]. This method is aimed to minimize only one objective function  $n$  (commonly, it may be the most preferred or primary one) and bounding the others by some allowable values  $\varepsilon_i$ ,  $i \in \{1, \dots, m\} \setminus \{n\}$ . In this way, the multi-objective optimization problem can be transformed into a single objective one. Given a vector of  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_{j-1}, \varepsilon_{j+1}, \dots, \varepsilon_m)$ , one point on the Pareto front is produced. Accordingly, the entire Pareto front can be shaped by changing the vector of  $\varepsilon$ . To solve the single objective problem, appropriate  $\varepsilon_i$  needs be determined. A general mathematical guideline for selecting  $\varepsilon_i$  is provided as follows:

$$f_i(\bar{x}_i^*) \leq \varepsilon_i \leq f_i(\bar{x}_n^*), i \in \{1, \dots, m\} \setminus \{n\}$$

Note that for each objective function  $f_i$ , there is an optimal decision vector  $\bar{x}_i^*$  such that  $f_i(\bar{x}_i^*)$  is a minimum.

Miettinen in 1999 [84] proved the following theorems.

**Theorem 1.** If an objective  $n$  and a vector  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_{n-1}, \varepsilon_{n+1}, \dots, \varepsilon_m) \in R^{m-1}$  exist, such that  $x^*$  is an optimal solution to the following problem:

$$\text{Minimize } f_n(x)$$

Subject to

$$f_i(x) \leq \varepsilon_i, \quad \forall i \in \{1, \dots, m\} \setminus \{n\}$$

$$x \in \Omega,$$

then  $x^*$  is a weakly Pareto optimal solution.

**Theorem 2.**  $x^*$  is a strict Pareto optimal solution if and only if for each objective  $n$ ,  $n = 1, \dots, m$ , there exists a vector  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_{n-1}, \varepsilon_{n+1}, \dots, \varepsilon_m) \in R^{m-1}$  such that  $f(x^*)$  is the unique objective vector corresponding to the optimal solution to the problem above.

### 2.3.4 Cut-and-solve method

#### 2.3.4.1 Principle of cut-and-solve method

Cut-and-solve (CS) method was firstly proposed for combinatorial optimization problems by Climer and Zhang in 2006 and it was proved that CS method was very effective for Asymmetric Traveling Salesman Problem [85].

Traditionally, branch-and-bound method is a very general exact procedure for solving combinatorial optimization problems. Basically, branch-and-bound is a divide-and-conquer approach that tries to solve the original problem by splitting it into smaller problems. The splitting of problems can be represented by the branch-and-bound tree. If the entire tree is generated, every feasible solution can be represented by at least one leaf node. If feasible solutions are too many, the search tree will be too large to be completely explored. The efficiency of branch-and-bound heavily depends on its pruning rules, which means pruning some nodes while guaranteeing optimality. If the search tree is pruned to an enough small one, the problem can be easier to be solved to optimality. Branch-and-cut is an extension of branch-and-bound by increasing the probability of pruning. At some or all of the levels in the search tree, cutting planes are added to tighten the corresponding relaxed subproblems of the nodes, which can reduce its solution space.

Cut-and-solve method is different from traditional tree search methods such as branch-and-bound and branch-and-cut, since it has no branching steps. That is to say, it is a special branch-and-bound search strategy but can avoid making wrong choices in depth-first branch-and-bound. Cut-and-solve method owns two favorable properties. Firstly, there are no “wrong” subtrees in which the search may get lost because of the absence of branching. Furthermore, compared with branch-and-bound and branch-and-cut, its memory requirement is negligible. For these reasons, it has potential for problems that are difficult to solve using depth-first or best-first search

tree methods [85].

Given an integer programming problem (IP) with the minimization of an objective function, at each level of the CS search tree, there are only two nodes, corresponding to *Sparse Problem (SP)* and *Remaining Problem (RP)*, respectively. *SP*, whose solution space is relatively small, can be solved optimally within a reasonable time and its solution if it exists provides an upper bound of the IP, denoted as  $UB$ . And if it is “good” enough, then the best upper bound of the IP found so far, denoted as  $UB_{min}$  is updated. Meanwhile, a lower bound of the IP, denoted as  $LB$ , can be obtained by solving the linear relaxation of *RP*. Obviously, if this lower bound is greater than or equal to the best upper bound found so far, then the optimal value of *RP* is also greater than or equal to it. In this case, *RP* has no better feasible solutions than the solution corresponding to the best upper bound found. At this point, an optimal solution of the IP is found. Otherwise, the current *RP* is further decomposed into a new *SP* and a new *RP* by adding a branching constraint for the next iteration. The above procedure is repeated until a global optimum of the IP is found. The general procedure of cut-and-solve method is given in Fig 2.5.

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#### Cut-and-solve method

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1. define current problem as original problem. Solve the linear relaxation of current problem.
  2. generate a cut
  3. find an optimal solution in solution space removed by the cut and obtain the best upper bound,  $UB_{min}$
  4. update  $UB_{min}$  if necessary
  5. add the cut to remaining problem
  6. find a lower bound,  $LB$
  7. if  $(LB \geq UB_{min})$  return  $UB_{min}$   
otherwise, define the current problem as remaining problem and repeat from step 2
- 

Fig. 2.5 General procedure of cut-and-solve method

To well understand this method, the following points should be emphasized: 1)



Since  $SP$  is a subproblem of the original problem, its optimal value is an upper bound of the original problem. In the iteration, the best upper bound will be updated if it can be improved. 2) After solving  $SP$ , its corresponding solution space is removed away from the whole solution space. Hence, the size of the solution space of the current problem in the next iteration will be reduced. 3) It is relatively difficult to solve  $RP$  optimally because its solution space is larger. So only its linear relaxation problem is solved for the ease of resolution. Apparently, the optimal value of  $RP$  is greater than or equal to the lower bound obtained by its linear relaxation problem. 4) Since the solution space of the  $RP$  (that is, the current problem in the next iteration) is reduced iteratively, its linear relaxation problem may also be tighter with the iteration. If the constraints of this relaxed problem are tight enough, the lower bound is no less than the best upper bound. In this case, the termination criterion is satisfied and the iteration stops.

Climer and Zhang [85] explicitly gave two theorems to explain the optimality and termination criterion of the cut-and-solve method, as follows.

**Theorem 1** *When the cut-and-solve algorithm terminates, the current incumbent solution must be an optimal solution.*

**Theorem 2** *If the solution space for the original problem is finite, and both the algorithm for solving the relaxed remaining problem and the algorithm for selecting and solving the sparse problem are guaranteed to terminate, then the cut-and-solve algorithm is guaranteed to terminate.*

The proof of the two above theorems can be found in [85] and see it for more details.

#### 2.3.4.2 Definition of piercing cut, remaining problem and sparse problem

The key to the cut-and-solve method is how to cut the solution space of the current problem into  $RP$  and  $SP$ . Unlike the cutting planes in branch-and-cut search, the cuts used in cut-and-solve method intend to separate solutions from the original solution space, which leads to the generation of  $RP$  and  $SP$ . Climer and Zhang used the term *piercing cut* to refer to a cut that could remove at least one feasible solution

from the original (unrelaxed) problem solution space.

The piercing cuts play a very important role in the cut-and-solve method. Actually, the efficiency of this method heavily depends on selecting appropriate piercing cuts. For example, if the solution space of  $SP$ , partitioned by the piercing cut, is not small enough, it will be difficult to solve  $SP$  within a reasonable time; conversely, there may be no better feasible solutions in the solution space of  $SP$ , and thus the best upper bound found so far cannot also be improved rapidly in the iteration. Therefore, it is important to generate effective piercing cuts. Climer and Zhang also offered some desirable properties of piercing cuts, as follows [85]:

- 1) The piercing cut should remove the optimal solution of the relaxed  $RP$  in order to prevent this solution from being found in next iterations.
- 2) The subspace removed by the piercing cut from the solution space of the relaxed  $RP$  should be adequately small so that  $SP$  can be solved to optimality relatively easily.
- 3) The piercing cuts should attempt to capture an optimal solution of the original problem. The algorithm will not be terminated until an optimal solution of the original problem has been found in the sparse problem.
- 4) In order to guarantee termination, the subspace removed by each piercing cut should contain at least one feasible solution of the original problem.

Climer and Zhang defined a *variable set* that includes the decision variables whose *reduced cost* values are greater than a given value  $\alpha$ . Notice that each decision variable has a reduced cost value. The reduced cost value is defined as a lower bound on the increase of the LP solution cost if the value of the variable is increased by one unit, and can be obtained from the optimal solution of the linear relaxed  $RP$ . Then the piercing cut is defined as a constraint such that the sum of the decision variables in this special variable set is greater than or equal to one. The key of the problem becomes how to determine the variables in the certain set.

Let  $U_r$  ( $r \geq 1$ ) denote such a set composed of some decision variables in  $r$ -th iteration. As decision variables are all binary ones, the sum of the values of the variables in  $U_r$  must be either equal to zero, or greater than or equal to one. With the piercing cut at  $r$ -th iteration, denoted by  $PC_r$ ,  $RP_r$  is generated by adding the

constraint such that the sum of the values of the variables in  $U_r$  is greater than or equal to one to the current problem  $CP_r$ ;  $SP_r$  is generated by adding the constraint such that the sum of the values of the variables in  $U_r$  is equal to zero to  $CP_r$ . Note that the cut-and-solve method will not terminate until an optimal solution of  $SP_r$  is found and the solution is proved to be the optimal solution of the original problem. Then the variables whose values are non-zero in this optimal solution cannot be in  $U_r$  because all variables in  $U_r$  are set to zero in  $SP_r$ .

As stated above, Climer and Zhang introduced a concept of *reduced cost* as a tool to select variables for  $U_r$ . An optimal solution of the linear relaxation of  $RP_r$  can provide the *reduced cost* value of each variable, which is defined as a lower bound on the increase of the objective value if the value of this variable is increased by one unit. For example, given a variable  $x$ , suppose that its reduced cost is ten and its value is zero in the optimal solution of an LP problem. If the value of  $x$  is increased by one unit, in other words,  $x$  has the value of one, then the objective value will be increased by at least ten. Moreover, the values of decision variables with large reduced cost have a small chance of being non-zero in the optimal solution of the original IP problem. Therefore,  $U_r$  can be defined as a set of the decision variables whose reduced costs are greater than a positive given parameter  $h_r$ . In this thesis, the value for  $h_r$  is chosen according to the following way: if the expected number of elements in  $U_r$  is  $n$ , the  $n$ -th largest reduced cost of these decision variables in  $U_r$  is set as the value of  $h_r$ .

### 2.3.5 Cutting plane method

As we know, integer programming (IP) problem is a kind of optimization problem which is usually NP-hard and difficult to be solved. There have been many solution approaches for solving it, such as enumeration method, branch-and-bound. Bounding is commonly considered to be crucial for solving IP problems by these methods. In recent years, valid inequalities have received increasing attention as a bounding technique. One purpose of this thesis is to propose a cutting plane method as a way of finding valid inequalities to obtain a tighter lower bound for linear programming (LP) problems so that the convergence of the cut-and-solve method can

accelerate.

The fundamental principle of the cutting plane method can be briefly described as follows. Initially, there is such an integer linear program (IP) with the non-negativity constraints. IP and its corresponding LP relaxation can be formulated as  $\min\{c\chi : \chi \in S_{IP}\}$  and  $\min\{c\chi : \chi \in S_{LP}\}$  respectively, where  $S_{IP} = S_{LP} \cap Z^n$  and  $S_{LP} = \{\chi \in R^n : A\chi \leq b\}$ . To explain the cutting plane method, consider an integer programming problem as follows:

$$\begin{aligned} & \text{Minimize} && -2x_1 - 3x_2 \\ & \text{Subject to} && \\ & && x_1 + 3x_2 \leq 7, \\ & && x_1 - x_2 \leq 3, \\ & && x_1, x_2 \in N. \end{aligned}$$

This problem is illustrated in Fig. 2.6. The feasible integer points of the problem are indicated by black solid dots. The LP relaxation of the IP problem is obtained by relaxing the integrality restrictions and its feasible solution space is represented by the polygon contained in the solid lines. The boundary of the *convex hull* of these feasible integer points, denoted by  $\text{conv}(S_{IP})$ , is indicated by dashed lines. Obviously, it represents the smallest convex set that can contain the solution space of IP,  $S_{IP}$ . If the optimal solution of LP,  $\chi_{LP}^*$ , is integral, it will be an extreme point of  $S_{IP}$ ; that is to say, it is on the  $\text{conv}(S_{IP})$ . If not, it is absolutely outside of  $\text{conv}(S_{IP})$ . There may exist a linear inequality that can separate  $\chi_{LP}^*$  from  $\text{conv}(S_{IP})$ . The linear inequality is satisfied by all the feasible integer solutions of IP and violated by  $\chi_{LP}^*$ . Such linear inequality is called a *cutting plane* for  $S_{IP}$ . The inequality is added to LP as an additional linear constraint, and a new LP is generated. Thus, the non-integer solution  $\chi_{LP}^*$  is no longer feasible for the new LP. This process continues until an integral optimal solution of the new LP is found. It is also an optimal solution of the original IP.

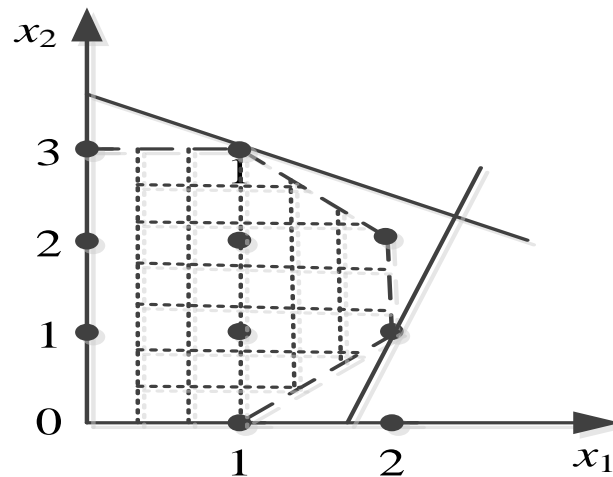


Fig. 2.6 A cutting plane example

The general procedure of a cutting plane method is illustrated as follows:

Step 1. Solve the LP relaxation of an IP problem.

Step 2. If the solution to the LP relaxation is also feasible for the IP problem, the optimal solution of IP problem is obtained and the algorithm terminates. Otherwise, go to Step 3.

Step 3. Find one or more cutting planes that separate the optimal solution of the LP relaxation from the convex hull of feasible integer points, and add these constraints to the LP relaxation.

Step 4. Return to Step 1.

In a word, at each iteration, the current LP problem is first solved, and valid inequalities that are violated by the optimal solution of LP problem are found. Then these inequalities are added to the LP problem until the optimal solution of the IP problem is found.

From the above analysis, we know that a cutting plane is a linear constraint which can reduce the solution space without loss of optimal feasible points and cutting plane method combined with other techniques can be used to obtain bounds for the global optimum. Then, the key to the cutting plane method is to find inequalities violated by the current LP relaxation, that is, the generation of valid cutting planes.

The generation of cutting planes is also called *separation algorithm*, which is the main feature of various cutting plane methods. Specifically speaking, the separation

algorithm is to find inequalities violated by a given fractional solution  $\Delta^*$ , but valid by a given set of linear inequality constraints of the original problem, or verify that any such inequalities do not exist. The separation algorithm is presented as follows.

As we know, a knapsack constraint can be usually written as follows:

$$\sum_{i \in \Pi} \omega_i \delta_i \leq b \quad (2.13)$$

where  $\Pi$  is a set of items,  $\omega_i$  is the weight of item  $i$ ,  $b$  is the capacity of the knapsack. Binary variable  $\Delta = \{\delta_1, \delta_2, \dots, \delta_{|\Pi|}\} \in \{0,1\}^{|\Pi|}$  indicates that whether item  $i$  is selected in the knapsack (i.e.,  $\delta_i = 1$ ) or not (i.e.,  $\delta_i = 0$ ). Its knapsack polytope is the convex hull of feasible solutions in the following formula:

$$H_t = \text{conv}\{\Delta \in \{0,1\}^{|\Pi|} \mid \sum_{i \in \Pi} \omega_i \delta_i \leq b\}. \quad (2.14)$$

Set  $C \subseteq \Pi$  is called a *cover* for (2.13) if  $\sum_{i \in C} \omega_i > b$ . For any cover  $C$ , the *cover inequality* (CI) for (2.14) is defined in the following form:

$$\sum_{i \in C} \delta_i \leq |C| - 1. \quad (2.15)$$

Constraint (2.15) is valid by all points in  $H_t$ . A CI is called *valid* if it is satisfied by the all points in  $H_t$  and violated by the given fractional solution,  $\Delta^*$ .

It was pointed out in [86] that valid CIs could be obtained by solving a 0-1 knapsack problem,  $P_{KP}$ , as follows:

$$\theta = \min \sum_{i \in \Pi} (1 - \delta_i^*) v_i \quad (2.16)$$

Subject to

$$\sum_{i \in \Pi} \omega_i v_i > b, \quad (2.17)$$

$$v_i \in \{0, 1\} \forall i \in \Pi \quad (2.18)$$

The above problem can be solved by the dynamic program proposed by Kaporis and Letchford [87].

Define cover  $C = \{i \in \Pi \mid v_i^* = 1\}$ , where  $v^*$  is the optimal solution of problem  $P_{KP}$ . Thus, we have

$$\theta = \sum_{i \in \Pi} (1 - \delta_i^*) v_i^* = \sum_{i \in C} (1 - \delta_i^*) v_i^* + \sum_{i \in \Pi \setminus C} (1 - \delta_i^*) v_i^*.$$

According to the definition of  $C$ , if  $i \in C$ ,  $v_i^* = 1$ ; otherwise  $v_i^* = 0$ . Then the following formula holds:

$$\theta = \sum_{i \in C} (1 - \delta_i^*) v_i^* = |C| - \sum_{i \in C} \delta_i^*.$$

If  $\theta < 1$ , that is,  $|C| - \sum_{i \in C} \delta_i^* < 1$ , we have

$$\sum_{i \in C} \delta_i^* > |C| - 1.$$

The above process proves that the CI defined by (2.15) is violated by fractional solution  $\Delta^*$  and it is a valid CI. Therefore, in order to find CIs for (2.13), problem  $P_{KP}$  needs be solved. If its optimal value is greater than one, then the CI defined by (2.15) is a valid CI.

## 2.4 Conclusion

In this chapter, hazardous material transportation problems were divided into three categories. For each related problem, its description, notation and formulation are introduced, its characteristics were analyzed to explain the differences between it and the considered problem in this thesis and its literature review was conducted. Then, lane reservation strategy was introduced as a traffic management measure and several applications of this strategy in real life were described in detail. Additionally, the state of the arts on the impact of lane reservation and the lane reservation network design problem was reviewed. Thus, this thesis was motivated to apply lane reservation strategy to hazardous material transportation for the sake of reducing the transportation risk. Finally, some optimization methods and techniques for solving multi-objective and single objective problems were introduced, which would be used for the considered problems in this thesis.

# CHAPTER 3 MODEL AND METHOD FOR HMTLR WITH TIME-INVARIANT RISK

## 3.1 Introduction

As stated in Chapter 1, in industrial production, a huge quantity of hazardous substances are shipped everyday through the transportation networks. Although almost hazardous material shipments can safely arrive to their destination [1], hazardous material accidents can happen en-route and result in undesirable consequences. Under this background, hazardous material transportation problems have been widely studied in the literature.

It has been pointed out in much relevant literature that the essential objective of hazardous material transportation problems is to minimize the transportation risk due to its nature. As we know, the selection of routes in a network for hazardous material transportation can affect its risk factors, such as the probability of hazardous material accidents and the risk exposure to the surrounding population and environment. Therefore, appropriate routing decisions are very important for hazardous material transportation management. In the last couple of decades, various applications of Operations Research models to hazardous material transportation have focused on risk reduction and fruitful achievements in this area have been published, please see [1] for details. As reviewed in Chapter 2, the hazardous material transportation problem can be divided into the time-invariant problem and the time-dependent problem according to the feature of the transportation network. Like most hazardous material transportation problems studied in the literature, we first investigate in this chapter a time-invariant HMTLR problem, in which the transportation risk is considered constant throughout the day.

As reviewed in Chapter 2, the problems closely related to HMTLR include the routing problem, the network design problem and the location and routing problem



for hazardous material transportation. The routing problem for hazardous material transportation involves multiple stakeholders, such as carriers and governments, which have their own different role in safely shipping hazardous materials from origins to destinations. In addition, each stakeholder may have different priority. For example, the transportation department authorized by government is commonly responsible for designating allowable routes with less risk as soon as possible in view of public safety and healthy, while carrier companies usually try to choose a route that can minimize transportation costs and travel times. Therefore, this problem can be considered a typical multi-objective problem with multiple stakeholders. Other hot research topics in this area, such as the network design problem and the location and routing problem for hazardous material transportation, also indicates the nature of multiple criteria of hazardous material transportation problem.

It can be observed from section 2.2 that in all the models presented in the literature, hazardous material shipments share the chosen road segments with other transportation tasks. In this chapter, an alternative transportation way involving a lane reservation strategy is presented. The essence of a lane reservation strategy is to reserve lanes on some road segments (in some time intervals) in the transportation network and to only allow special transportation tasks to pass through them. Transporting hazardous materials on reserved lanes can reduce the risk. However, the lane reservation strategy may worsen the traffic situation. Therefore, when planning the reserved lanes for hazardous material transportation, a government agency has to consider minimizing the negative impact caused by the lane reservation strategy. As stated in Chapter 2, it has been successfully applied in bus traffic, and sportive games. It is worthwhile to point out that there have been a few mathematical models to optimally determine which road segments to be reserved [67] [77]-[79]. However, their work did not consider transportation risk factor explicitly. This chapter addresses a *multi-objective* HMTLR problem with *time-invariant* risk.

In this chapter, the HMTLR problem with time-invariant risk is formulated as a multi-objective model. Then, an  $\epsilon$ -constraint method is adopted to solve the multi-objective model and a fuzzy-logic-based approach is applied to choose a

preferred solution. An instance based on real network topologies and randomly generated instances are tested to evaluate the proposed method. Finally, the conclusions and some potential directions for future research are discussed.

## 3.2 Problem formulation

### 3.2.1 Problem description

Let  $G = (V, A)$  be a bidirected hazardous material transportation network, which is composed of a number of nodes.  $V$  is the set of nodes.  $A$  is the set of the arcs that connect the nodes. Arc  $(i, j)$  denotes a road segment from node  $i$  to node  $j$ .  $|W|$  kinds of hazardous materials must be carried from origins  $O \in V$  to their corresponding destinations  $D \in V$ .

The problem considered in this chapter is to choose lanes to be reserved in the transport network and select the path of each shipment from the reserved lanes to guarantee that each shipment must be finished within its deadline, and the risk caused by all the shipments that pass the same road segment cannot exceed its threshold of the accident probability. In the considered network, if one of the lanes on a road is selected as a reserved lane, the other(s) are called the general lane(s), as shown in Fig.3.1. Hazardous material transportation through the reserved lanes can reduce the probability of accidents. Nevertheless, lane reservation will certainly impact the normal traffic because only special shipment can pass them. The goal of the problem is to seek a best tradeoff for minimizing the total impact on the normal traffic and the total transportation risk, which provides useful decision supports for decision-makers. Risk is the primary ingredient that distinguishes hazardous material transportation problems from others. Before proposing a formulation, some notions of risk assessment is recalled.

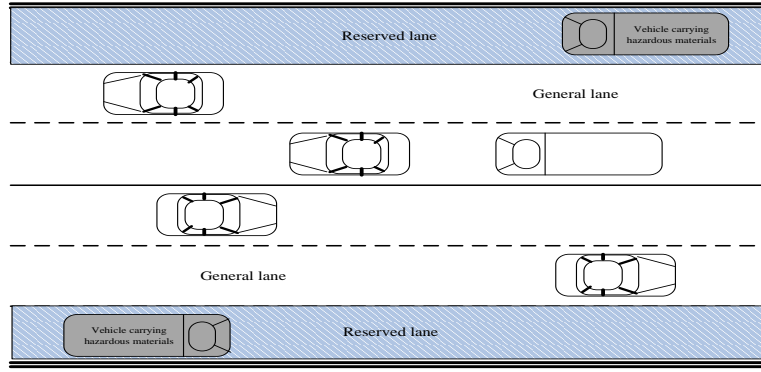


Fig. 3.1 Sketch of a road segment with reserved lanes

### 3.2.2 Assumption, notation and formulation

Before proposing the multi-objective model, some assumptions and notations are presented here.

**Assumptions:**

1. Both the probability of a hazardous material accident happening on an arc and the population exposure along a road segment are constant, and time-invariant.
2. Potential accidents involving hazardous materials independently happen.
3. There are at least two lanes on a road such that one lane is allowed to be reserved; otherwise, the impact on the normal traffic will be too heavy.
4. Hazardous material shipments pass only through reserved lanes. That is, it is required to reserve a lane on an arc if there is at least one type of hazardous shipment passing through this arc.

**Notations:**

$W \{1, 2, \dots, /W/\}$ : set of hazardous materials type

$T_{ij}$ : travel time on the reserved lane of arc  $(i, j)$

$\tau_{ij}$ : travel time on the general lane(s) of arc  $(i, j)$ . Note that  $\tau_{ij} > T_{ij}$

$C_{ij}$ : impact on the normal traffic due to the lane reservation on arc  $(i, j)$

$M_{ij}$ : total number of lanes on arc  $(i, j)$

$S_w$ : deadline of accomplishing shipment  $w$

$Q_{ij}$ : threshold of the accident probability on arc  $(i, j)$

$P_{ij}^w$ : accident probability of hazardous material  $w$  on a reserved lane of arc  $(i, j)$

$\pi_{ij}^w$ : accident probability of hazardous material  $w$  on the general lane(s) of arc  $(i,$

$j)$ . Note that  $\pi_{ij}^w > P_{ij}^w$

$E_{ij}$ : population exposure along arc  $(i, j)$

**Decision variables:**

$$x_{ij}^w = \begin{cases} 1 & \text{if there is a reserved lane on arc } (i, j) \in A \text{ and the shipment } w \text{ passes the arc} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if there is a reserved lane on arc } (i, j) \in A \\ 0 & \text{otherwise} \end{cases}$$

**Formulation:**

The hazardous material transportation problem with lane reservation can be formulated as the following two-objective integer linear programming model.

Problem P:

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (3.1)$$

$$\text{Minimize } f_2 = \sum_W \sum_{(i,j) \in A} E_{ij} P_{ij}^w x_{ij}^w \quad (3.2)$$

Subject to

$$\sum_{j:(o_w, j) \in A} x_{o_w j}^w = 1, \quad \forall w \in W, o_w \in O, \quad (3.3)$$

$$\sum_{i:(i, d_w) \in A} x_{i d_w}^w = 1, \quad \forall w \in W, d_w \in D, \quad (3.4)$$

$$\sum_{j:(i, j) \in A} x_{ij}^w = \sum_{j:(i, j) \in A} x_{ji}^w, \quad \forall w \in W, \forall i \neq o_w, d_w, \quad (3.5)$$

$$x_{ij}^w \leq y_{ij}, \quad \forall (i, j) \in A, \forall w \in W \quad (3.6)$$

$$\sum_{(i,j) \in A} T_{ij} x_{ij}^w \leq S_w, \quad \forall w \in W \quad (3.7)$$

$$\sum_{w \in W} P_{ij}^w x_{ij}^w \leq Q_{ij}, \quad \forall (i, j) \in A \quad (3.8)$$

$$x_{ij}^w \in \{0, 1\}, \quad \forall (i, j) \in A \quad (3.9)$$

$$y_{ij} \in \{0, 1\}, \quad \forall (i, j) \in A \quad (3.10)$$

Objective (3.1) is to minimize the total impact of all reserved lanes on the normal traffic, where  $C_{ij}$  is defined by  $\frac{\tau_{ij}}{M_{ij} - 1}$  according to [67]. The impact can be

considered as the increase in travel time on the general lane(s) caused by the lane

reservation strategy, which is proportional to the travel time on the general lane(s) of arc  $(i, j)$  and inversely proportional to the total number of lanes on arc  $(i, j)$ . According to [70], an actual statistical result showed that the travel time of the general lanes increased about 53% after one of three lanes was reserved in A1 highway in Paris. This figure is very close to the theoretical test result (50%) obtained by the computational experiment done in [77] using the above formula. If the lane is not reserved, then  $C_{ij} = 0$ . Objective (3.2) is to minimize the total transportation risk. Constraints (3.3) and (3.4) respectively mean only one path for each shipment  $w$  starting from its origin  $o_w$  and arriving to its destination  $d_w$ . Constraint (3.5) ensures the flow conservation. Constraint (3.6) expresses that there is a shipment  $w$  on arc  $(i, j)$  if and only if a lane is reserved on it. Constraint (3.7) guarantees that the total travel time of shipment  $w$  cannot exceed its deadline  $S_w$ . Constraint (3.8) requires that the risk caused by all the shipments that pass arc  $(i, j)$  cannot exceed its risk threshold for the sake of equity in the spatial distribution of risk. Constraints (3.9) and (3.10) specify that 0-1 restrictions on the variables.

### 3.3 Solution approach

In this section, an  $\varepsilon$ -constraint method is adopted to solve the proposed problem. After that, a fuzzy-logic-based approach is applied to obtain a preferred solution.

#### 3.3.1 $\varepsilon$ -constraint method for the multi-objective problem

There are several common techniques to solve a multi-objective problem, such as the weighted sum method, the  $\varepsilon$ -constraint method, the goal attainment approach and metaheuristics [81]. The advantages of the  $\varepsilon$ -constraint method have been presented in Section 2.3.2. With the  $\varepsilon$ -constraint method, the multi-objective IP model in this chapter can be transformed into a series of single objective IP models, which can be solved with a commercial MIP solver, such as CPLEX.

The model proposed in Section 3.2.3 has two competing objective functions subject to a set of constraints. The first one  $f_1$  is the impact on the normal traffic due to lane reservation while the second one  $f_2$  is the total transportation risk on those

reserved lanes. Only when the lane is reserved for hazardous material transportation, the shipment can pass the road segment. Therefore, the first objective function is considered as the main objective function. Then, the multi-objective model is transformed into a single one, in which only  $f_1$  is minimized while  $f_2$  is added as a new constraint to the feasible solution space.

The  $\varepsilon$ -constraint method for the proposed problem is described as follows:

1) Problem P in Section 3.2.3 is transformed into problem  $P_0(\varepsilon)$  according to basic principles of the  $\varepsilon$ -constraint method. Problem  $P_0(\varepsilon)$  can be represented as follows.

Problem  $P_0(\varepsilon)$ :

$$\text{Minimize } \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (3.1)$$

Subject to

$$\sum_W \sum_{(i,j) \in A} E_{ij} P_{ij}^w x_{ij}^w \leq \varepsilon, \quad (3.11)$$

and constraints (3.3)-(3.10).

where  $\varepsilon$  is an upper limit of the value of  $f_2$ .

**Complexity analysis:** If the shipments all start from the same origin and the deadline of each shipment, the risk threshold of each arc and the upper limit of the second objective function are all large enough, then the single objective IP problem  $P_0(\varepsilon)$  can be reduced to a Steiner tree problem [88]. As a Steiner tree problem is NP-hard [89], the single objective IP problem is also NP-hard. At present, the commercial IP solver like CPLEX can be strong enough to solve medium-size IP problems. Hence, CPLEX is applied to solve the single objective IP problems,  $P_0(\varepsilon)$ , in this chapter.

2) In order to solve problem  $P_0(\varepsilon)$ , it is necessary to determine  $\varepsilon$  that is limited by the range of objective function  $f_2$ . To obtain the appropriate range of  $f_2$ , the multi-objective problem P is decomposed into two single problems  $P_1$  and  $P_2$  with objective functions  $f_1$  and  $f_2$  respectively.

*A. Lower limit of each objective*

The optimum values  $f_1^l$  and  $f_2^l$  of objective function  $f_1$  and  $f_2$  can be obtained

by solving the following problems P<sub>1</sub> and P<sub>2</sub>, respectively.

Problem P<sub>1</sub>:

$$\text{Minimize } \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (3.1)$$

Subject to

constraints (3.3)-(3.10).

Note that an optimal vector  $(y_{ij}^{*1}, x_{ij}^{w*1})$  can be found by solving P<sub>1</sub>.

Obviously,  $f_1^I = f_1(y_{ij}^{*1})$ .

Problem P<sub>2</sub>:

$$\text{Minimize } \sum_W \sum_{(i,j) \in A} E_{ij} P_{ij}^w x_{ij}^w \quad (3.2)$$

Subject to

constraints (3.3)-(3.10).

Note that an optimal vector  $(y_{ij}^{*2}, x_{ij}^{w*2})$  can be found by solving P<sub>2</sub>. Similarly,

$f_2^I = f_2(x_{ij}^{w*2})$ .

Let vertical and horizontal axes represent the values of  $f_1$  and  $f_2$  respectively, as shown in Fig.3.2. The objective vector,  $(f_2^I, f_1^I)$ , minimizing each of the objective functions corresponds to a point in the objective space, called the *ideal point*. If the ideal objective vector were feasible, the optimal solution of the multi-objective model is found. Generally, this is impossible because some conflicts among objectives exist. Nevertheless, it can be considered as a reference point. The ideal point indicates the lower limit of each objective.

#### B. Upper limit of each objective

The *nadir objective vector* represents the upper limit of each objective in the entire Pareto set, but not in the entire objective space. We calculate the upper limit of each objective according to the following process. Firstly, let  $f_2$  and  $f_1$  equal  $f_2^I$  and  $f_1^I$  obtained by solving P<sub>2</sub> and P<sub>1</sub>, respectively. They can be considered as new constraints (3.12) and (3.13) respectively. Then new constraint (3.12) (resp. (3.13)) and constraints (3.3)-(3.10) with objective function  $f_1$  (resp.  $f_2$ ) compose problem P<sub>3</sub>

(resp. P<sub>4</sub>).

Problem P<sub>3</sub>:

$$\text{Minimize } \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (3.1)$$

Subject to

$$\sum_W \sum_{(i,j) \in A} E_{ij} P_{ij}^w x_{ij}^w = f_2^I \quad (3.12)$$

constraints (3.3)-(3.10).

Problem P<sub>4</sub>:

$$\text{Minimize } \sum_W \sum_{(i,j) \in A} E_{ij} P_{ij}^w x_{ij}^w \quad (3.2)$$

Subject to

$$\sum_{(i,j) \in A} C_{ij} y_{ij} = f_1^I \quad (3.13)$$

constraints (3.3)-(3.10).

Optimal values of problems P<sub>3</sub> and P<sub>4</sub> are noted as  $f_1^N$  and  $f_2^N$  respectively. Obviously,

$f_1^I < f_1^N$  and  $f_2^I < f_2^N$ .  $(f_2^N, f_1^N)$  is defined as the *nadir point*, as shown in Fig.3.2.

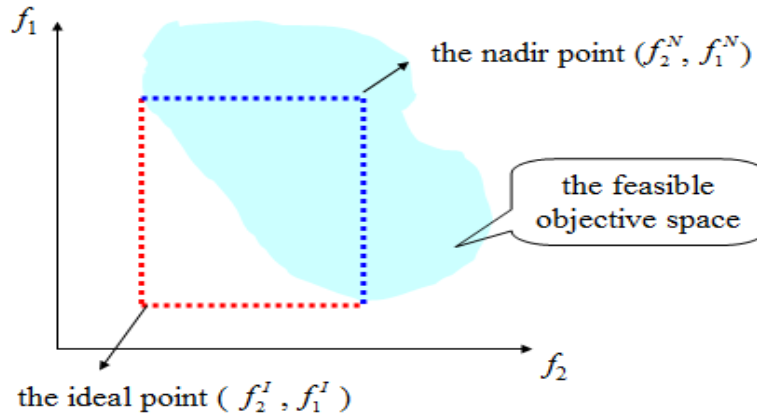


Fig. 3.2 Ideal and nadir points

3) In order to calculate the values of  $\varepsilon$ , the range of the objective function  $f_2$ ,  $range_2$ , needs to be determined. For values of  $f_2$  bounded by  $[f_2^I, f_2^N]$ ,  $range_2$  can be defined as

$$range_2 = f_2^N - f_2^I \quad (3.14)$$



where  $f_2^I$  and  $f_2^N$  are obtained by solving problems  $P_2$  and  $P_4$ .

Then  $range_2$  is divided into  $S$  equal intervals by  $S + 1$  points, namely *equidistant grid points*.  $\varepsilon$  in constraint (11) is set by these grid points as the following formula

$$\varepsilon^s = f_2^N - \frac{range_2}{S} * s, s = 0, 1, \dots, S \quad (3.15)$$

4) Repeat to solve problem  $P_0(\varepsilon)$  with different values of  $\varepsilon$ , and finally obtain  $S+1$  Pareto optimal solutions.

### 3.3.2 Selection of a preferred solution

After  $S + 1$  solutions are obtained, a DM may wish to select a preferred one from them and also wants to know its degree of optimality. In the literature, there are several approaches related to the selection of preferred solutions, such as the k-mean clustering procedure, the weighted-sum approach and the fuzzy-logic-based approach. Cluster analysis can classify data into groups in which individuals are similar to each other [90]. As one of the most common clustering techniques, the *k-mean clustering procedure* [91] is used when any preference of the objectives is absent. This method chooses a set of solutions rather than a single solution and moreover, it is usually used together with evolution algorithms such as genetic algorithms. The DM can choose a preferred solution by the *weighted-sum approach* when a preferred weight vector is provided. However, the method only gives the absolute weighted-sum of objective values of a solution, but fails to indicate the degree of optimality of a solution. The *fuzzy-logic-based approach* [92] cannot only provide a most preferred solution but also indicate its degree of optimality. Therefore, in this chapter, *fuzzy-logic-based approach* is applied to assist a DM in choosing a preferred solution.

In the  $m$ -objective optimization problem with  $S+1$  Pareto optimal solution, the *membership function*  $\delta_i(f_i^s)$  indicates the degree of optimality for the  $i$ -th objective function in the  $s$ -th solution [92]. It is defined as follows.

In the case of objective functions being minimized,

$$\delta_i(f_i^s) = \begin{cases} 1 & f_i^s \leq f_i^l \\ \frac{f_i^N - f_i^s}{f_i^N - f_i^l} & f_i^l < f_i^s < f_i^N, 1 \leq i \leq m, 1 \leq s \leq S+1 \\ 0 & f_i^s \geq f_i^N \end{cases} \quad (3.16)$$

where  $f_i^l$  and  $f_i^N$  denote the lower and upper limits of objective function  $f_i$  of P respectively, and  $f_i^s$  represents the value of the  $i$ -th objective function in the  $s$ -th Pareto optimal solution, such that  $f_i^s \in [f_i^l, f_i^N]$ .

For each solution  $s$ , the membership degree  $\delta^s$  is calculated based on its individual membership functions as follows [92].

$$\delta^s = \frac{\sum_{i=1}^m \delta_i(f_i^s)}{\sum_{s=1}^{S+1} \sum_{i=1}^m \delta_i(f_i^s)} \quad (3.17)$$

The solution with the maximum value of  $\delta^s$  is selected as the most preferred solution. If a DM can offer a preferred weight vector for impact on normal traffic and transportation security, another way of calculating  $\delta^s$  is provided by adding weight factors, i.e.,

$$\delta^s = \frac{\sum_{i=1}^m \omega_i \delta_i(f_i^s)}{\sum_{i=1}^m \omega_i} \quad (3.18)$$

where  $\omega_i$  is the weight of the  $i$ -th objective function and it can be any positive real number. The weight factor  $\omega_i$  can be selected by a DM according to his/her specific preference of the application. In this chapter, the latter formula is employed.

Generally, the algorithm to obtain a single preferred solution for the proposed multi-objective problem is described in the following figure.

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**Algorithm**

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**I. Apply the  $\varepsilon$ -constraint method to obtain Pareto optimal solutions**

1. Transform the multi-objective model P into a single objective model  $P_0(\varepsilon)$
2. Solve problems  $P_1 - P_4$  to obtain ideal and nadir points
3. Determine the range of objective function  $f_2$  by (3.14)
4. Set S and determinate values of  $\varepsilon$  by (3.15)
5. Solve problem  $P_0(\varepsilon)$  and obtain Pareto optimal solutions

**II. Apply the fuzzy-logic-based approach to choose a preferred solution**

6. Calculate the membership function  $\delta_i(f_i^s)$  by (3.16)
  7. Calculate the membership degree  $\delta^s$  by (3.18)
  8. Select a preferred solution
- 

Fig. 3.3 Procedure of the  $\varepsilon$ -constraint and fuzzy-logic based method

### 3.4 Computational results

In this section, the performance of the proposed algorithm is evaluated by an instance using a real network topology and 85 sets of randomly generated instances. Each set includes five randomly generated instances and each item in the computational result tables is the average value of the five instances. The algorithm was implemented in C, with which CPLEX (Version 12.5) was combined to solve the transformed single objective IP problems, i.e., Problems  $P_0(\varepsilon)$ - $P_4$ . CPLEX was run in default settings. All the computational experiments were done on a HP PC with a Pentium IV Processor 3.1 GHZ and 4.00GB RAM in the window 7 environment.

In this thesis, the *average degree* of graph  $G$  is defined as  $N = |A|/|V|$  [93] [94], where  $|V|$  and  $|A|$  is the number of nodes and arcs, respectively. The average degree of graph  $G$  is defined as its number of arcs per node, which implies the density of the graph. Parameter  $S$  is set to 20. That means 21 Pareto optimal solutions can be obtained for an instance. Total computation time represents the total running time for obtaining  $S + 1$  solutions and choosing a preferred solution.

To check whether it is beneficial to reserve lanes for hazardous material

transportation, the total transportation risk and average transportation duration of shipments using reserved lanes will be compared with those on a no reserved-lane network. To achieve this purpose, it is also necessary to solve a new shipment problem with minimum-risk objective on a no reserved-lane network. That means finding a minimum-risk path for each shipment when no lanes are reserved. The no lane-reservation problem is modeled with decision variable  $x_{ij}^w$  which is redefined as  $x_{ij}^w=1$  if and only if shipment  $w$  passes arc  $(i, j)$ , and constraints (3.2)-(3.5), (3.7)-(3.9) in which  $P_{ij}^w$  and  $T_{ij}$  are replaced by  $\pi_{ij}^w$  and  $\tau_{ij}$  respectively. However, since both the accident probability and the travel time would be higher compared to those of the lane-reservation case, it is possible that no feasible solutions exist for this new problem due to the deadline constraint (3.7) and risk threshold constraint (3.8). Hence, in this no lane-reservation problem, these two constraints are relaxed to guarantee that feasible solutions can be obtained.

Let  $Risk_r$  and  $Duration_r$  represent the total transportation risk and average transportation duration of shipments for problem P, respectively. Let  $Risk_{nr}$  be the total transportation risk for the relaxed problem without using reserved lanes and  $Duration_{nr}$  be its corresponding average transportation duration of shipments. To check whether it is beneficial to reserve lanes for hazardous material transportation, the ratios  $Risk_r/Risk_{nr}$  and  $Duration_r/Duration_{nr}$  should be calculated. They indicate how the transportation risk and duration change before and after reserving lanes for hazardous material vehicles. On the other hand, it can also examine how much the travel time on the general lane(s) increases due to the lane reservation strategy. Let  $GR$  be the growth rate of travel time, which is defined as the total increase in travel time divided by the total travel time on the general lane(s) before implementation of

the lane reservation strategy. That is, 
$$GR = \frac{\sum_W \sum_{(i,j) \in A} C_{ij} x_{ij}^w}{\sum_W \sum_{(i,j) \in A} \tau_{ij} x_{ij}^w} .$$

### 3.4.1 An instance based on a real network topology

Firstly, an instance based on a real network topology from the city of Ravenna,

Italy [31] was tested. In [31], the instance of Ravenna has 105 nodes, 134 arcs. A transportation network with the same number of nodes and arcs as those of the network of Ravenna was produced based on Waxman's network topology generator [95]. 12 shipments in the form of origin-destination pairs were set. The data of the parameters including  $\tau_{ij}$ ,  $T_{ij}$ ,  $\pi_{ij}^w$ ,  $p_{ij}^w$  and  $S_w$  were generated based on the Euclidean distance between nodes. Let  $U(a, b)$  be a uniform distribution between parameters  $a$  and  $b$ , with  $a < b$ . The value of  $T_{ij}$  was generated as  $T_{ij} = \tau_{ij} * U(0.5, 0.8)$

and  $Q_{ij}$  was generated as  $Q_{ij} = \sum_{w=1}^W p_{ij}^w * U(0.4, 0.6)$ . The proposed algorithm finds the

Pareto solutions in 53.305s. The transportation risk and the transportation duration can be reduced by 73.8% and 12.5% after reserving lanes for hazardous material vehicles, respectively. The travel time on the general lane(s) due to the lane reservation strategy increases 11.9%. For the instance, 21 grid points are produced and 15 different objective vectors are obtained. The distribution of the non-dominated points on the trade-off curve is shown in Fig. 3.4, where vertical ordinate and horizontal abscissa represent the value of the first and second objective functions, respectively. It is observed that the points are diverse and well distributed over the Pareto front. DMs can choose one of them as a preferred one for the problem according to the proposed fuzzy-logic-based approach.

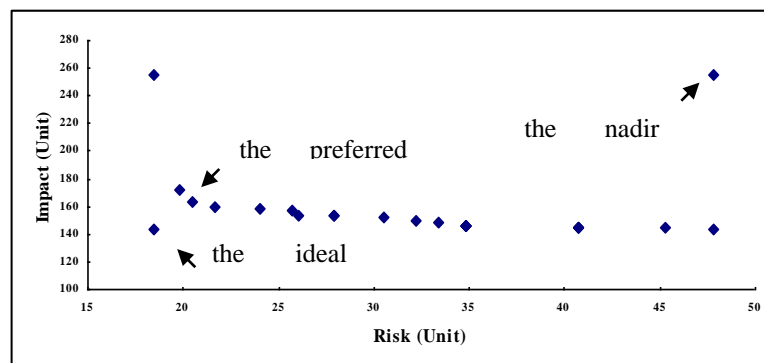


Fig. 3.4 Distribution of non-dominated points of the problem with a real network topology in Italy

### 3.4.2 Randomly generated test instances

Test instances were generated in the following way. The transportation network  $G$

$(V, A)$  was generated based on the random network topology generator introduced by Waxman [95]. The nodes were randomly and uniformly generated in the plane  $[0, 100] \times [0, 100]$  and the arcs were generated by the probability function that depended on the distances between the nodes. The probability function between two nodes  $i, j$  was defined as  $p_{(i,j)} = \beta \exp \frac{-d(i,j)}{\alpha L}$ , where  $d(i, j)$  and  $L$  were the Euclidean distance and the maximum distance between nodes  $i$  and  $j$ , respectively, and  $0 < \alpha, \beta \leq 1$ . The OD pairs were randomly generated from the set of nodes.

Let  $\tau_{ij} = d(i, j)$  and  $T_{ij} = \tau_{ij} * U(0.5, 0.8)$ . The deadline  $S_w$  was set to be  $dis(o_w, d_w) * U(1, \sqrt{2})$  [77], where  $dis(o_w, d_w)$  was the shortest travel time from  $o_w$  to  $d_w$  in a reserved path. Similarly, let  $\pi_{ij}^w = d(i, j) * U(8, 20)$ , considering the effects of the number of lanes, truck configuration, population density, and road condition on the accident probability given by [96].  $P_{ij}^w = \pi_{ij}^w * U(0.2, 0.3)$ , whose unit was  $10^{-7}$ . Note that  $Q_{ij} = \sum_{w=1}^W p_{ij}^w * U(0.4, 0.6)$ .  $E_{ij}$  was generated by  $U(10, 80)$ , whose unit was  $10^4$ .

Lastly,  $M_{ij}$  was generated by  $U(2, 5)$  [96].

For simplicity, in Case 1, the weights for the two objective functions are set to be equal, i.e.,  $\omega_1 = \omega_2 = 0.5$ . Table 3.1 summarizes the computational result of Case 1 on the random generated instances with  $N = 4$ . It is observed in Table 3.1 that the total computation time (in CPU seconds) moderately increases with the number of nodes and shipments but not for the membership degree of the preferred solution. Given the number of shipments, the more the number of nodes is, the more computation time is needed. For example, the computation times of sets 31-35 dramatically increase with  $|V|$  from 70 to 110, as shown in Fig. 3.5. Likewise, given the number of nodes, the more the number of shipments, the more time is needed. For example, the computation time for sets 16-19 is more than that for sets 12-15, respectively. One of the largest instances that can be solved by CPLEX within 3 h of CPU time limit has 110 nodes, 440 arcs, and 30 shipments, while the membership degree of the preferred solution for each set almost settles down between 0.8 and 0.9. From Table 3.1, the

values of  $Risk_r/Risk_{nr}$  and  $Duration_r/Duration_{nr}$  range from 0.247 to 0.283 and from 0.590 to 1.335, respectively, while GR ranges from 0.121 to 0.137. In other words, the transportation risk can be reduced from 71.7% up to 75.1% after reserving lanes, and the average transportation duration of shipments after reserving lanes is less than or almost equal to that before reserving lanes. On the other hand, the travel time on the general lane(s) caused by the lane reservation strategy increases by no more than 34%. This indicates that lane reservation can offer great benefits to hazardous material transportation at a reasonable cost.

Table 3.1 Computational results of Case 1 on the random generated instances with  $N = 4$

set	$/V/$	$/W/$	Membership degree of the preferred solution	Total computation time (CPU s)	$Risk_r / Risk_{nr}$	$Duration_r / Duration_{nr}$	GR
1	30	10	0.822	14.527	0.253	0.841	0.134
2	40	10	0.818	20.463	0.263	0.886	0.127
3	50	10	0.782	22.761	0.247	0.685	0.134
4	60	10	0.854	29.688	0.252	0.709	0.134
5	70	10	0.835	47.155	0.270	0.800	0.126
6	40	15	0.875	31.430	0.248	0.923	0.132
7	50	15	0.860	58.578	0.280	1.017	0.136
8	60	15	0.859	104.721	0.271	0.971	0.128
9	70	15	0.886	142.079	0.258	1.040	0.129
10	80	15	0.868	159.863	0.263	0.900	0.127
11	50	20	0.848	93.207	0.267	0.882	0.134
12	60	20	0.872	158.480	0.258	1.000	0.130
13	70	20	0.870	212.329	0.259	0.987	0.137
14	80	20	0.863	317.590	0.261	0.956	0.133
15	90	20	0.867	750.118	0.250	1.119	0.126
16	100	20	0.867	785.301	0.275	1.124	0.124
17	110	20	0.875	587.669	0.261	1.006	0.127
18	120	20	0.825	3464.027	0.259	0.976	0.127
19	130	20	0.854	3188.770	0.254	1.055	0.123
20	140	20	0.869	9263.910	0.265	1.067	0.129
21	150	20	0.870	14159.337	0.251	0.964	0.120
22	160	20	0.860	10303.592	0.260	0.951	0.124
23	170	20	0.856	23491.573	0.265	1.054	0.119

24	180	20	0.878	38234.871	0.251	1.088	0.136
25	190	20	0.861	21964.948	0.259	1.062	0.121
26	60	25	0.862	285.351	0.269	1.057	0.136
27	70	25	0.893	714.119	0.280	1.065	0.133
28	80	25	0.847	748.568	0.274	1.054	0.130
29	90	25	0.883	1498.118	0.250	1.119	0.126
30	100	25	0.868	4518.394	0.283	1.155	0.126
31	70	30	0.871	1033.827	0.270	1.050	0.135
32	80	30	0.889	1556.263	0.262	1.104	0.131
33	90	30	0.881	3214.654	0.260	1.198	0.130
34	100	30	0.894	10639.205	0.270	1.335	0.127
35	110	30	0.885	30164.856	0.270	1.174	0.121

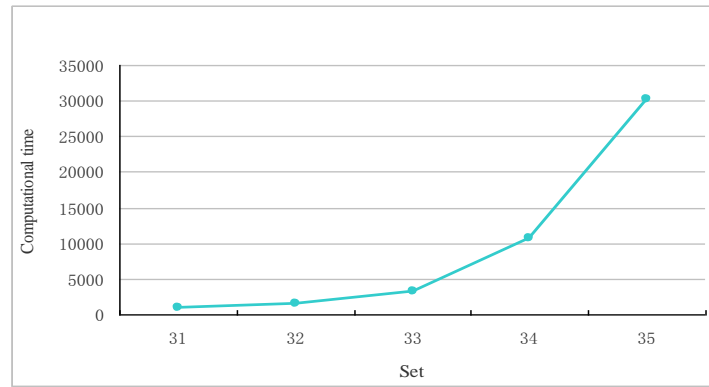


Fig. 3.5 Computation times of sets 31-35

Table 3.2 shows that, given the number of nodes and shipments, the total computation time increases with the graph degree. For example, the computation times of sets 51-55 increase with  $N$  from 5 to 9, as shown in Fig. 3.6. It is worth pointing out that the larger the size of the instances is, the sharper the increase is. For example, the computation time for set 40 with  $|V| = 50$ ,  $|W| = 5$ , and  $N = 9$  is 1.683 times more than that of set 36 with  $|V| = 50$ ,  $|W| = 5$ , and  $N = 5$ , whereas the computation time for set 60 with  $|V| = 90$ ,  $|W| = 25$ , and  $N = 9$  is 17.759 times more than that of set 56 with  $|V| = 90$ ,  $|W| = 25$ , and  $N = 5$ .



Table 3.2 Computational results of Case 1 on the random generated instances with different  $N$

set	$ V $	$ W $	$N$	Membership degree of the preferred solution	Total computation time (CPU s)	Risk <sub>r</sub> / Risk <sub>nr</sub>	Duration <sub>r</sub> / Duration <sub>nr</sub>	GR
36	50	5	5	0.855	13.069	0.266	0.711	0.126
37			6	0.768	15.253	0.267	0.618	0.131
38			7	0.774	16.561	0.257	0.659	0.126
39			8	0.742	18.600	0.286	0.642	0.128
40			9	0.765	21.995	0.282	0.643	0.121
41	60	10	5	0.836	47.444	0.266	0.719	0.127
42			6	0.817	51.377	0.259	0.714	0.120
43			7	0.816	55.393	0.273	0.662	0.117
44			8	0.808	71.565	0.254	0.660	0.126
45			9	0.860	146.428	0.257	0.821	0.119
46	70	15	5	0.852	114.028	0.255	0.962	0.120
47			6	0.846	200.269	0.258	0.943	0.120
48			7	0.843	310.696	0.265	0.867	0.122
49			8	0.870	350.886	0.274	0.895	0.120
50			9	0.858	418.692	0.269	0.943	0.118
51	80	20	5	0.870	360.217	0.259	1.005	0.127
52			6	0.862	646.714	0.254	1.340	0.120
53			7	0.850	1137.061	0.260	0.965	0.122
54			8	0.838	1487.926	0.300	0.953	0.120
55			9	0.865	2853.311	0.327	1.332	0.117
56	90	25	5	0.886	2835.420	0.281	1.217	0.123
57			6	0.868	12828.213	0.290	1.203	0.127
58			7	0.864	8310.987	0.270	1.173	0.149
59			8	0.872	9033.214	0.290	1.095	0.111
60			9	0.863	50355.016	0.318	1.064	0.118

Table 3.3 shows how the membership degree of the preferred solution and the average membership degree of solutions change with the number of grid points given the number of nodes, number of shipments, and graph degree. The average membership degree is defined as the total membership degree of all solutions divided by the number of solutions. It can be observed from Table 3.3 that the membership degree of the preferred solution does not necessarily increase with the number of grid points. However, the average membership degree of solutions increases with it.

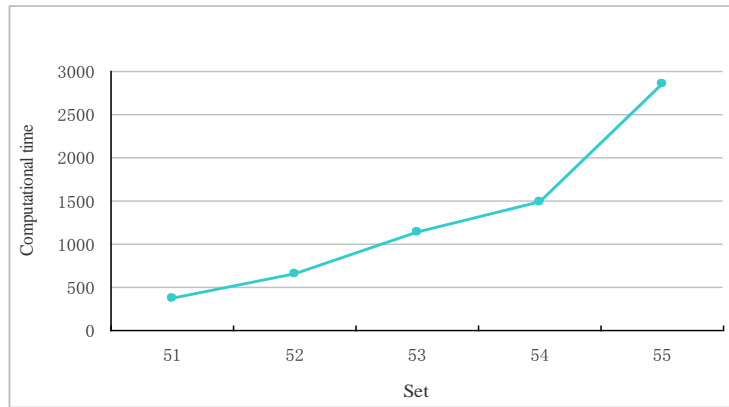


Fig. 3.6 Computation times of sets 51-55

Table 3.3 Computational results of Case 1 on the random generated instances with different  $S$

set	$ V $	$ W $	$N$	$S$	Membership degree of the preferred solution	Average membership degree for a solution
61	50	8	7	10	0.813	0.682
62				15	0.813	0.691
63				20	0.824	0.701
64				25	0.815	0.695
65				30	0.814	0.697
66	75	12	6	10	0.863	0.744
67				15	0.861	0.746
68				20	0.869	0.751
69				25	0.868	0.754
70				30	0.868	0.754
71	100	16	5	10	0.857	0.705
72				15	0.855	0.716
73				20	0.859	0.719
74				25	0.858	0.723
75				30	0.860	0.724
76	125	20	4	10	0.863	0.722
77				15	0.864	0.727
78				20	0.866	0.733
79				25	0.866	0.734
80				30	0.866	0.734

Now, it is the turn to analyze how the membership degree of the preferred solution and the average membership degree of solutions change with the weight

vector given the number of nodes, number of shipments, and graph degree. Note that, in Case 1, the weights for the two objective functions are set to be equal, i.e.,  $\omega_1 = \omega_2 = 0.5$ . Let us consider other two cases, called Cases 2 and 3, in which the weight factor for the main objective function is larger than the other one. In Case 2, set  $\omega_1 = 0.7$  and  $\omega_2 = 0.3$ ; in Case 3, set  $\omega_1 = 0.9$  and  $\omega_2 = 0.1$ . In Table 3.4, both the membership degree of the preferred solution and the average membership degree of solutions for Case 2 (respectively, Case 3) are higher than those for Case 1 (respectively, Case 2). As we know, the membership degree indicates how ideal the solution is. It is clear that the performance of the preferred solution is degraded when the weight of the main objective function is reduced.

Table 3.4 Computational results of Case 1, 2 and 3 on the random generated instances

set	$ V $	$ W $	$N$	Case	Membership degree of the preferred solution	Average membership degree for a solution
81	40	5	9	1	0.842	0.713
				2	0.842	0.773
				3	0.913	0.833
82	50	10	8	1	0.856	0.762
				2	0.864	0.806
				3	0.943	0.906
83	60	15	7	1	0.864	0.722
				2	0.878	0.803
				3	0.928	0.875
84	70	20	6	1	0.883	0.736
				2	0.885	0.815
				3	0.943	0.906
85	80	25	5	1	0.873	0.732
				2	0.886	0.812
				3	0.936	0.885

### 3.5 Conclusions

In this chapter, a new hazardous material transportation problem with a lane reservation strategy was presented. The proposed multi-objective model intended to

minimize two competing objective functions: the impact on the normal traffic and the transportation risk. Then, an efficient algorithm based on the  $\varepsilon$ -constraint method was developed to solve the multi-objective model and a fuzzy-logic-based approach was proposed to help DMs derive a best compromise solution. The results of computational experiments showed that the  $\varepsilon$ -constraint method could solve the multi-objective optimization problem within a reasonable time and find efficient Pareto optimal solutions. The computational results also showed that the lane reservation strategy could greatly reduce the transportation risk at a reasonable cost of its traffic impact on the normal traffic.

# CHAPTER 4 A NEW AND EXACT METHOD FOR TRANSFORMED SINGLE OBJECTIVE PROBLEMS OF HMTLR WITH TIME-INVARIANT RISK

## 4.1 Introduction

In Chapter 3, we investigated a problem which intended to choose lanes to be reserved in the transportation network and select the path of each shipment from the reserved lanes. Its objectives were to minimize the total impact due to lane reservation and minimize the total transportation risk. We developed a multi-objective integer programming model for HMTLR with time-invariant risk and proposed an  $\varepsilon$ -constraint method for it. With the  $\varepsilon$ -constraint method, the proposed problem was transformed into a series of single objective IP problems. In this method, the transformed single objective problems were solved by a commercial optimization software package CPLEX, which was easy to be carried out. It is well known that the performance of the  $\varepsilon$ -constraint method depends on the solution time of the transformed single objective problems. However, although CPLEX is able to optimally solve the transformed single objective problem, the time consumption of CPLEX is a big burden for large size instances, as indicated in Chapter 3. So it is necessary to resort to other efficient algorithms for these single objective problems based on their characteristics, with which it may be possible to solve larger-size problems within a shorter time.

As described in Chapter 2, the cut-and-solve method has two favorable properties. Firstly, unlike the traditional tree searches, the cut-and-solve search have no branching but a search path. That means that there are no “wrong” subtrees in which the search may get lost. In addition, the cut-and-solve search consumes very little memory space so that its memory requirement can be neglected. Due to these

properties of the cut-and-solve method, it has a high potential for problems that are difficult to solve using depth-first or best-first search tree methods [85]. In this chapter, to reduce the computation time of the transformed single objective problems, we propose a new cut-and-solve and cutting plane combined method for them.

## 4.2 Solution approach

In this section, the cut-and-solve and cutting plane combined method is introduced to solve the transformed single objective problems. In this method, based on the property of the problem, a pre-processing is presented to reduce the search space of solutions. After that, the remaining problems and sparse problems related to the transformed single objective problems are presented. To obtain better lower bounds, a cutting plane method is embedded in the cut-and-solve method to tighten the remaining problems.

### 4.2.1 Pre-processing

Before using the cut-and-solve method, properties of the model proposed in Chapter 3 are analyzed so as to reduce the search space. If the values of some variables can be determined in advance, the search space can be reduced, which may help to reduce the solution time.

In transformed single objective model  $P_0(\varepsilon)$ , for  $\forall j \in N$ , let  $p(o_w, j)$  and  $p(j, d_w)$  denote the shortest travel durations from  $o_w$  to  $j$  and from  $j$  to  $d_w$  in an exclusively reserved path, respectively, where  $o_w$  and  $d_w$  are the original node and destination node of shipment  $w$ , respectively.  $p(o_w, j)$  and  $p(j, d_w)$  can be obtained using Floyd's shortest path algorithm. Define set  $A_w$  as follows:

$$\text{For } \forall w \in W, A_w = \{j \mid p(o_w, j) + p(j, d_w) > S_w, \forall j \in N\}.$$

Apparently, if shipment  $w$  passes through the nodes in  $A_w$ , the travel time deadline constraint (3.7) will be violated. So in any feasible solution, shipment  $w$  would not pass through any node in  $A_w$ . Thus, we have:

$$\sum_{i:(i,j) \in A} x_{ij}^w + \sum_{i:(j,i) \in A} x_{ji}^w = 0, \forall w \in W, \forall j \in A_w \quad (4.1)$$

With the pre-processing, the solution space of the original problem is reduced

without losing the optimality of the original problem, because the values of some decision variables are fixed to zero and no feasible solution of  $P_0(\varepsilon)$  is excluded. After the pre-processing, a new tightened model  $P'(\varepsilon)$  is obtained by adding constraint (4.1) to  $P_0(\varepsilon)$ . In the next subsection, a cut-and-solve and cutting plane combined method for  $P'(\varepsilon)$  will be presented.

#### 4.2.2 Definition of piercing cut, sparse problem and remaining problem

The principle of the cut-and-solve method has been described in Chapter 2. In the cut-and-solve method, piercing cut ( $PC_r$ ), sparse problem ( $SP_r$ ) and remaining problem ( $RP_r$ ) play a very important role. To apply the cut-and-solve method, we need to define them.

For  $P_0(\varepsilon)$ , we use the technique of generating piercing cuts introduced by Climer and Zhang [85]. They defined a *variable set* including the decision variables whose *reduced cost* values are greater than a given value *alpha*. Then the piercing cut is defined as a constraint such that the sum of the decision variables in this special variable set is greater than or equal to one. The key to generating piercing cuts becomes how to determine the variable set.

Let  $U_r$  ( $r \geq 1$ ) denote such a set. The  $U_r$  should be also defined according to some properties of the problem. As our problem is different from the asymmetric traveling salesman problem studied in [85], it is necessary to analyze its properties to obtain an appropriate  $U_r$ . Note that our problem has two kinds of decision variables in two different levels: the lane reservation variable  $y_{ij}$  in the strategic level and the shipment path variable  $x_{ij}^w$  in tactical level. The former variable  $y_{ij}$  is considered to be more important than  $x_{ij}^w$  for the following reason. The path of each shipment is composed of all reserved lanes, which means that only the reserved lane can be selected for the shipment path. For example, given an arc  $(i, j)$ , if  $y_{ij} = 0$ , then  $x_{ij}^w = 0$  for all shipments. Because arc  $(i, j)$  is not reserved, any shipment cannot pass through it. As implied in constraint (3.6), the reservation of one lane or not may result in different shipment paths. Therefore,  $y_{ij}$  is considered as the more relevant variable to  $U_r$ , rather

than  $x_{ij}^w$ .

Let  $Y(y_{ij})$  denote the reduced cost value of  $y_{ij}$  in the optimal solution of the linear relaxation problem of  $CP_r$ . Then  $U_r$  ( $r \geq 1$ ) is defined as follows:

$$U_r = \{ y_{ij} / Y(y_{ij}) > h_r, \forall (i, j) \in A \} \quad (4.2)$$

where  $h_r$  is a given positive number.

Once  $U_r$  is determined,  $PC_r$  ( $r \geq 1$ ) is defined as the following formula:

$PC_r$ :

$$\sum_{y_{ij} \notin U_r} y_{ij} \geq 1, \forall (i, j) \in A \quad (4.3)$$

Using  $PC_r$ , the solution space of  $CP_r$  is separated into two subspaces, and  $SP_r$  and  $RP_r$  can be obtained by adding new constraints to  $CP_r$ .

$SP_r$  and  $RP_r$  are defined as follows:

$SP_r$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (3.1)$$

Subject to

Constraints (3.3)-(3.11), (4.1)

$$\text{and } \sum_{y_{ij} \notin U_r} y_{ij} \geq 1, \forall (i, j) \in A, \quad (4.4)$$

$$\sum_{y_{ij} \in U_r} y_{ij} = 0. \quad (4.5)$$

$RP_r$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (3.1)$$

Subject to

Constraints (3.3)-(3.11), (4.1), (4.4),

$$\text{and } \sum_{y_{ij} \in U_r} y_{ij} \geq 1. \quad (4.6)$$

It is worth pointing out that when  $r = 1$ , the original problem  $P'$  is considered as  $CP_1$ . For this reason, constraint (4.4) should be removed for  $RP_1$  and  $SP_1$ .



### 4.2.3 Cutting plane method to tighten remaining problem

As described in Chapter 2, in the cutting plane method, cutting planes are iteratively generated and their corresponding constraints are added successively to the current relaxed problem until its fractional solution becomes an integer one. Valid inequalities for a problem, separated by the cutting plane method, can reduce the solution space. A tight lower bound of the remaining problem for HMTLR can be obtained by the cutting plane method. In the cut-and-solve method, when the lower bound obtained by the remaining problem is greater than or equal to the current best upper bound, an optimal solution of the original problem is found and the CS method stops. If a tighter lower bound is obtained, fewer iterations should be required. On the other hand, a tight lower bound can also provide some useful information for the generation of the piercing cut. In a word, the cutting plane method may contribute to faster convergence of the cut-and-solve method.

The separation algorithm for the proposed problem is presented as follows.

As stated in Chapter 2, a knapsack constraint can be written in the following form:

$$\sum_{i \in \Pi} \omega_i \delta_i \leq b \quad (2.13)$$

where  $\Pi$ ,  $\omega_i$ , and  $b$  are a set of items, the weight of item  $i$ , and the capacity of the knapsack, respectively.  $\delta_i$  is a binary variable, and if  $\delta_i = 1$ , item  $i$  is selected in the knapsack; otherwise, it is not.

Set  $C \subset \Pi$  is called a *cover* for (2.13) if  $\sum_{i \in C} \omega_i > b$ . Then, the *cover inequality* (CI) for (2.13) is defined as follows:

$$\sum_{i \in C} \delta_i \leq |C| - 1. \quad (2.15)$$

A CI is called *valid* if it is satisfied by the feasible solution and violated by a given fractional solution of the original problem.

Let  $T_{ij}$ ,  $S_w$ ,  $x_{ij}^w$  correspond to  $\omega_i$ ,  $b$  and  $\delta_i$  in the knapsack problem, respectively. Then, travel time deadline constraint (3.7)  $\sum_{(i,j) \in A} T_{ij} x_{ij}^w \leq S_w, \forall w \in W$  can

be considered as a standard knapsack constraint form. Therefore, the CI for (3.7) has the following form:

$$\sum_{(i,j) \in A_x} T_{ij} x_{ij}^w \leq |A_x| - 1, \forall w \in W$$

where  $A_x$  is a subset of  $A$ .

Similarly, the CI for risk threshold constraint (3.8) has the following form:

$$\sum_{w \in W_x} P_{ij}^w x_{ij}^w \leq |W_x| - 1, \forall (i, j) \in A$$

where  $W_x$  is a subset of  $W$ .

Valid CIs for constraints (3.7) and (3.8) could be obtained by solving a 0-1 knapsack problems,  $P_{kp1}$  and  $P_{kp2}$ , respectively, as follows:

Problem  $P_{kp1}$ :

$$\theta_1 = \min \sum_{w \in W} (1 - x_{ij}^{w*}) v_w \quad (4.10)$$

Subject to

$$\sum_{w \in W} T_{ij} v_w > S, \quad (4.11)$$

$$v_w \in \{0, 1\}, w \in W \quad (4.12)$$

Problem  $P_{kp2}$ :

$$\theta_2 = \min \sum_{(i,j) \in A} (1 - x_{ij}^{w*}) u_{ij} \quad (4.13)$$

Subject to

$$\sum_{(i,j) \in A} P_{ij}^w u_{ij} > Q_{ij}, \quad (4.14)$$

$$u_{ij} \in \{0, 1\}, j \in A \quad (4.15)$$

The above problems can be solved by the dynamic program proposed by Kaparis and Letchford [87]. The separation algorithm for finding valid CIs for constraint (3.7) is presented in the following figure, and that for constraint (3.8) is omitted here.

---

### Separation algorithm

---

Given a fraction solution  $x^*$ , for  $h = 1, \dots, /W/$  and  $n = 0, \dots, S_w$ , define:

$$f(h, n) := \min \left\{ \sum_{w=1}^h (1 - x_{ij}^{w*}) v_w \mid \sum_{w=1}^h T_{ij} v_w = n, v_w \in \{0, 1\}, w = 1, \dots, h \right\}$$

$$g(h) := \min \left\{ \sum_{w=1}^h (1 - x_{ij}^{w*}) v_w \mid \sum_{w=1}^h T_{ij} v_w \geq S_w + 1, v_w \in \{0, 1\}, w = 1, \dots, h \right\}$$

1. Set  $f(h, n) := \infty$  for  $h = 1, \dots, /W/$  and  $n = 0, \dots, S_w$ . Set  $f(0, 0) := 0$ .
  2. Set  $g(h) := \infty$  for  $h = 1, \dots, /W/$ .
  3. **for**  $h = 1$  to  $/W/$  **do**
  4.     **for**  $n = 0$  to  $S_w$  **do**
  5.         **if**  $f(h - 1, n) < f(h, n)$  **then**
  6.             Set  $f(h, n) := f(h - 1, n)$
  7.         **end if**
  8.     **end for**
  9.     **for**  $n = 0$  to  $S_w - T_{ij}$  **do**
  10.         **if**  $f(h - 1, n) + (1 - x_{ij}^{h*}) < f(h, n + T_{ij})$  **then**
  11.             Set  $f(h, n + T_{ij}) := f(h - 1, n) + (1 - x_{ij}^{h*})$
  12.         **end if**
  13.     **end for**
  14.     **for**  $n = S_w - T_{ij} + 1$  to  $S_w$  **do**
  15.         **if**  $f(h - 1, n) + (1 - x_{ij}^{h*}) < g(h)$  **then**
  16.             Set  $g(h) := f(h - 1, n) + (1 - x_{ij}^{h*})$
  17.         **end if**
  18.     **end for**
  19.     **if**  $g(h) < 1$  **then**
  20.         Output the violated cover inequality.
  21.     **end if**
  22. **end for**
- 

Fig. 4.1 Procedure of the separation algorithm

#### 4.2.4 Overall algorithm

The procedure of the proposed algorithm combined the cut-and-solve method

with the cutting plane method is given in the Fig. 4.2.

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### **Cut-and-solve and cutting plane combined method**

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1. Set  $r := 0$  and best upper bound  $UB_{min} := +\infty$ .
  2. Obtain a new model  $P'$  after the pre-processing for original model  $P$ , and then set current problem  $CP_1 := P'$ .
  3. Solve the linear relaxation problem of  $CP_1$  and obtain a lower bound  $LB_0$  and its corresponding solution. If the solution is integral, an optimal solution of the original problem is found and the algorithm terminates.
  4. Find possible CIs by the separation algorithm. If there exist any CIs, add them to  $CP_1$  and go to step 3.
  5. **while** ( $LB_r \leq UB_{min}$ ) **do**
  6. Set  $r := r + 1$ .
  7. Define piercing cut  $PC_r$  by (4.4) and obtain  $SP_r$  and  $RP_r$ .
  8. Solve  $SP_r$  optimally and obtain its optimal value  $UB_r$  if it exists. Set  $UB_{min} := UB_r$  if  $UB_r < UB_{min}$ .
  9. Solve the linear relaxed  $RP_r$  and obtain a lower bound  $LB_r$  and its solution. If the solution is integral, set  $UB_{min} := LB_r$  if  $LB_r < UB_{min}$ , and go to step 13.
  10. Find possible CIs by the separation algorithm described in Fig. 4.1. If there exist any CIs, add them to  $RP_r$  and go to step 9; otherwise set  $CP_{r+1} := RP_r$ .
  12. **end while**
  13. Return  $UB_{min}$  and its corresponding solution as the optimal value and the optimal solution of the original problem, respectively.
- 

Fig. 4.2 Procedure of the cut-and-solve and cutting plane combined method

## **4.3 Computational results**

In this section, the performance of the proposed method is evaluated. In order to compare the computation time of the cut-and-solve method with that of CPLEX, the same randomly generated test instances in Chapter 3 were used. The proposed method was coded in C. The computational experiments were also carried out on an HP PC with a 3.10-GHz Intel Core processor and 4-GB RAM under Windows 7 environment.

Table 4.1 summarizes the computational results on the randomly generated instances with  $N=4$ . Columns T1 and T2 represent the average computation time (in CPU seconds) of five instances for each set by CPLEX and the cut-and-solve method, respectively. Firstly, it is worth pointing out that the total computation times of the cut-and-solve method moderately increase with the number of nodes and shipments. Given the number of shipments, the more the number of nodes, the more computation time is required. For example, the computation times for sets 11-15 increase with the number of nodes. Given the number of nodes, the more the number of shipments, the more time is required. For example, the computation time for sets 16-19 is more than that for sets 12-15, respectively.

Secondly, it can be also observed from Table 4.1 that the proposed method is more efficient than CPLEX for large size instances. For example, for most instances in Table 4.1, i.e., sets 4-35, the computation time required by the cut-and-solve method is less than that by CPLEX. Fig. 4.3 gives the trends of two curves of T1 and T2 for instances with  $|W|=20$ . As illustrated in the figure, the trend of T2 curve is almost identical to T1 curve, but T1 increases with the number of nodes more sharply than T2. For example, for set 11 with  $|V| = 50$ , the ratio T1/T2 is only 1.060 times, while for set 24 with  $|V| = 170$ , T1 is 5.904 times as much as T2.

Table 4.1 Computational results on the random generated instances with  $N = 4$

set	$ V $	$ W $	T1	T2	T1/T2
1	30	10	14.527	17.979	0.808
2	40	10	20.463	21.899	0.934
3	50	10	22.761	25.327	0.899
4	60	10	29.688	27.457	1.081
5	70	10	47.155	38.446	1.227
6	40	15	31.430	23.946	1.313
7	50	15	58.578	49.445	1.185
8	60	15	104.721	89.514	1.170
9	70	15	142.079	110.060	1.291
10	80	15	159.863	119.234	1.341
11	50	20	93.207	87.957	1.060
12	60	20	158.480	120.276	1.318

13	70	20	212.329	177.132	1.199
14	80	20	317.590	253.652	1.252
15	90	20	750.118	463.054	1.620
16	100	20	785.301	671.657	1.169
17	110	20	1587.669	950.602	1.670
18	120	20	3464.027	1820.074	1.903
19	130	20	3188.770	2142.012	1.489
20	140	20	9263.910	4172.901	2.220
21	150	20	14159.337	7448.342	1.901
22	160	20	10303.592	4641.092	2.220
23	170	20	23491.573	4747.636	4.948
24	180	20	38234.871	6475.983	5.904
25	190	20	21964.948	6900.594	3.183
26	60	25	285.351	189.817	1.503
27	70	25	714.119	597.049	1.196
28	80	25	748.568	579.046	1.293
29	90	25	1498.118	964.507	1.553
30	100	25	4518.394	2478.616	1.823
31	70	30	1033.827	786.720	1.314
32	80	30	1556.263	1082.922	1.437
33	90	30	3214.654	1946.094	1.652
34	100	30	10639.205	7689.428	1.384
35	110	30	30164.856	13391.541	2.252

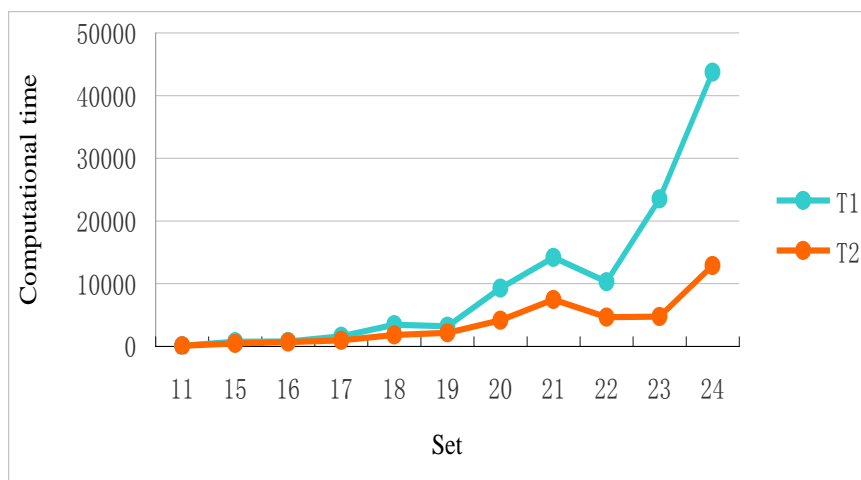


Fig. 4.3 Comparison of T1 and T2

Table 4.2 gives the total computation times of the proposed method with different  $N$ . It can be seen from this table that given the number of nodes and shipments, the

total computation time increases with the graph degree. For example, the computation time for set 45 is 2.269 times more than that for set 41. It is worth pointing out that the larger the size of the instances is, the rapider the increase is. For example, the computation time for set 40 with  $N = 9$  is 1.301 times more than that of set 36 with  $N = 5$ , while the computation time for set 60 with  $N = 9$  is 17.299 times as much as that of set 55 with  $N = 5$ .

Table 4.2 Computational results on the random generated instances with different  $N$

set	$ V $	$ W $	$N$	T1	T2	T1/T2
36	50	5	5	13.069	16.627	0.786
37			6	15.253	18.471	0.826
38			7	16.561	20.048	0.826
39			8	18.600	20.655	0.901
40			9	21.995	21.624	1.017
41	60	10	5	47.444	43.728	1.085
42			6	51.377	48.834	1.052
43			7	55.393	48.141	1.151
44			8	71.565	58.642	1.220
45			9	146.428	99.238	1.476
46	70	15	5	114.028	103.394	1.103
47			6	200.269	101.326	1.976
48			7	310.696	174.949	1.776
49			8	350.886	222.472	1.576
50			9	418.692	250.411	1.672
51	80	20	5	360.217	346.435	1.040
52			6	646.714	403.757	1.602
53			7	1137.061	709.389	1.603
54			8	1487.926	1177.199	1.264
55			9	2853.311	1550.122	1.841
56	90	25	5	2835.420	1327.554	2.149
57			6	12828.213	7742.349	1.657
58			7	8310.987	6472.951	1.245
59			8	9033.214	4795.675	1.884
60			9	50355.016	22965.672	2.193

## **4.4 Conclusions**

In this chapter, the transformed single objective model proposed in Chapter 3 was solved by a cut-and-solve and cutting plane combined method. A specific property of the considered problem was explored to reduce the solution space of the original problem. Moreover, a cutting plane method was developed to tighten remaining problem, which could help to accelerate the process of cut-and-solve method. Computational results showed that for the transformed single objective problems, the proposed method outperformed the software package CPLEX.



# CHAPTER 5 MODEL AND METHOD FOR HMTLR WITH TIME-DEPENDENT RISK

## 5.1 Introduction

As mentioned in the previous chapters, hazardous material transportation has become an increasingly important problem worldwide and has attracted many researchers' attentions in the related field. Like almost all of the hazardous material transportation problems, Chapters 3 and 4 have investigated the HMTLR problem with time-invariant risk. That is to say, the risk of a road segment in a transportation network is assumed to be constant, which fails to capture the dynamic nature of the real-life traffic environment. In real life, for example, risk on road segments may be time-dependent on population density subject to time-of-day variation, peak and off-peak periods, various weather conditions and so on. The time-dependent risk is one of the important features of hazardous material transportation. The time-dependent transportation problem is to decide the path for each shipment and its starting time of each arc on the path so as to minimize the transportation risk.

Note that time-dependent hazardous material transportation problems can be distinguished into deterministic and stochastic settings. The dynamic characteristic of transportation networks is usually expressed by one or more link attributes for a road segment. For a deterministic time-dependent transportation problem, part or all of the link attributes are assumed to be variant but all of the link attributes are known. For a stochastic time-dependent transportation problem, the link attributes are considered as random variables with time-dependent distribution functions. For time-dependent hazardous material transportation, the main link attributes usually include travel time and transportation risk.

Time-dependent hazardous material transportation problems have not been widely studied and only a few related publications can be found in the literature, such as Nozick *et al.* [21], Jia *et al.* [22], Erhan and Osman [25], Meng *et al.* [26], Chang

*et al.* [27]. These works has been reviewed in Chapter 2. In this chapter, we propose a new problem: HMTLR with time-dependent risk, in which the transportation risk is considered to be deterministic and time-dependent. The considered problem will aim to reserve lanes both on some road segments and in some specific time periods in a transportation network. To the best of our knowledge, this is the first work for hazardous material transportation via lane reservation with time-dependent risk.

As we know, the factors of the transportation risk generally include the hazardous material accident probability and the population exposure to the accidents. The accident probability estimation is influenced by the nature of roads, characteristics of the trucks, transportation environment and driver conditions [96], etc. Estimating the accident probability is a complicate and difficult work. For simplification, the probability of an accident is regarded to be time-invariant in this chapter. Population exposure is determined by population density and area. In real life, the population density along a road segment strongly depends on time and space. The population density in hospitals, schools, factories and so on in day time is greater than that in night, and the opposite happens in residential areas. In this work, the accident probability on reserved lanes is assumed to be known and the population exposure along road segments is assumed to be time-dependent. Therefore, the transportation risk varies with time and space. This work was motivated by the dynamic characteristic of risk and it is a natural extension of our previous work in Chapter 3.

In this chapter, the HMTLR problem with time-dependent risk is formulated as a new multi-objective model. The objectives are to minimize the total impact on the normal traffic and the total transportation risk. Then, some properties of the model are explored to reduce the search space of solutions and a cut-and-solve based  $\epsilon$ -constraint method is developed. Finally, randomly generated instances are tested to evaluate the proposed method.

## 5.2 Problem formulation

### 5.2.1 Problem description

The network considered in this chapter is identical to that in Chapters 3 and 4. Compared with Chapter 3, the additional assumptions in this chapter include: 1) any two hazardous material shipments on the same road segment must maintain a minimum time interval, called *safety time interval*. 2) travel time on a reserved lane is time-invariant throughout the day; nevertheless, the risk on a road segment is time-dependent because the population exposure varies with time in nature. The population exposure on each arc  $(i, j)$  at *time period*  $[I_k, I_{k+1})$ , denoted as  $E_{ijk}$ , depends on the departure time from node  $i$ . Without loss of generality, set  $I_1 = 0$  as the beginning time of the first period. Usually, there are only several time periods in a day [97]. So travel time  $T_{ij}$  on the reserved lane is less than the length of a time period, i.e.  $T_{ij} < I_{k+1} - I_k$ . The problem is to choose lanes to be reserved, select the path for each hazardous material shipment, and decide the travel time period for each shipment on each arc in its path. The objective of this problem is to seek a best trade-off for minimizing the total traffic impact on the normal traffic and the total transportation risk.

### 5.2.2 Notation and formulation

In addition to those defined in Chapter 3, the following notations are introduced to model the considered problem.

**Additional sets and parameters:**

$K \{1, \dots, /K/\}$ : set of time periods

$T_{\text{int}}$ : safety time interval between any two shipments passing a same arc

$E_{ijk}$ : population exposure along arc  $(i, j)$  at time period  $k$

**Decision variables:**

$t_i^w$  is the arriving or leaving time of shipment  $w$  at node  $i$ .

$$\chi_{ijk}^w = \begin{cases} 1 & \text{if shipment } w \text{ passes the reserved lane on arc } (i, j) \\ & \text{when time } t_i^w \text{ occurs at time period } k \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if there is a reserved lane on arc } (i, j) \\ 0 & \text{otherwise} \end{cases}$$

$$\beta_{ik}^w = \begin{cases} 1 & \text{if time } t_i^w \text{ occurs at time period } k \\ 0 & \text{otherwise} \end{cases}$$

$$z_{iww'} = \begin{cases} 1 & \text{if } t_i^w < t_i^{w'}, w \neq w' \\ 0 & \text{otherwise} \end{cases}$$

### Formulation:

The mathematical model for the HMTLR problem in networks with time-dependent risk is presented by constraints (5.3)-(5.17).

Problem  $P^l$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (5.1)$$

$$\text{Minimize } f_2 = \sum_{w \in W} \sum_{(i,j) \in A} \sum_{k \in K} P_{ij}^w E_{ijk} x_{ijk}^w \quad (5.2)$$

Subject to

$$\sum_{j:(o_w, j) \in A} \sum_{k=1}^K x_{o_w j k}^w = 1, \quad \forall w \in W, \quad (5.3)$$

$$\sum_{i:(i, d_w) \in A} \sum_{k=1}^K x_{i d_w k}^w = 1, \quad \forall w \in W, \quad (5.4)$$

$$\sum_{j:(i, j) \in A} \sum_{k=1}^K x_{ijk}^w = \sum_{j:(j, i) \in A} \sum_{k=1}^K x_{jik}^w, \quad \forall w \in W, \forall i \in V \setminus \{o_w, d_w\}, \quad (5.5)$$

$$\sum_{k=1}^K x_{ijk}^w \leq y_{ij}, \quad \forall (i, j) \in A, \forall w \in W, \quad (5.6)$$

$$t_j^w - t_i^w \leq T_{ij} + M(1 - \sum_{k=1}^K x_{ijk}^w), \quad \forall (i, j) \in A, \forall w \in W, \forall i \neq d_w, \forall j \neq o_w, \quad (5.7)$$

$$t_j^w - t_i^w \geq T_{ij} + M(\sum_{k=1}^K x_{ijk}^w - 1), \quad \forall (i, j) \in A, \forall w \in W, \forall i \neq d_w, \forall j \neq o_w, \quad (5.8)$$

$$\sum_{k=1}^K \beta_{ik}^w = 1, \forall w \in W, \forall i \neq d_w, \quad (5.9)$$

$$\sum_{k=1}^K \beta_{ik}^w I_k \leq t_i^w < \sum_{k=1}^K \beta_{ik}^w I_{k+1}, \forall w \in W, \forall i \neq d_w, \quad (5.10)$$

$$t_i^{w'} - t_i^w \geq T_{\text{int}} \left( \sum_{k=1}^K x_{ijk}^w + \sum_{k=1}^K x_{ijk}^{w'} - 1 \right) - M(1 - z_{iww'}), \quad (5.11)$$

$$\forall (i, j) \in A, \forall i \neq o_w, o_{w'}, d_w, d_{w'}, \forall w, w' \in W, w \neq w'$$

$$t_i^w - t_i^{w'} \geq T_{\text{int}} \left( \sum_{k=1}^K x_{ijk}^w + \sum_{k=1}^K x_{ijk}^{w'} - 1 \right) - Mz_{iww'}, \quad (5.12)$$

$$\forall (i, j) \in A, \forall i \neq o_w, o_{w'}, d_w, d_{w'}, \forall w, w' \in W, w \neq w',$$

$$t_i^w \geq 0, \forall i \in N, \forall w \in W, \quad (5.13)$$

$$y_{ij} \in \{0, 1\}, \forall (i, j) \in A, \quad (5.14)$$

$$x_{ijk}^w \in \{0, 1\}, \forall (i, j) \in A, \forall w \in W, \forall k \in K, \quad (5.15)$$

$$z_{iww'} \in \{0, 1\}, \forall i \in N, \forall w, w' \in W, w \neq w', \quad (5.16)$$

$$\beta_{ik}^w \in \{0, 1\}, \forall i \in N, \forall w \in W, \forall k \in K. \quad (5.17)$$

where  $M$  is a very large positive number.

Objective (5.1) is to minimize the total impact on the normal traffic. Objective (5.2) is to minimize the total transportation risk. Constraint (5.3) (resp. (5.4)) means that for shipment  $w$ , there is one and only one path departing from the source node  $o_w$  (resp. arriving at the destination node  $d_w$ ) during one and only one time period. Constraint (5.5) ensures the flow conservation constraint for node  $i$  in  $V \setminus \{o_w, d_w\}$  on space and time. It represents that if shipment  $w$  arrives at a node  $i$  ( $i \neq o_w, d_w$ ) via a reserved lane during time period  $k$ , it must also depart from  $i$  via a reserved lane during time period  $k$ , or it does not visit  $i$ . Constraint (5.6) guarantees that no shipment would pass through arc  $(i, j)$  during any time period if no lane on the arc has been reserved. Constraints (5.7) and (5.8) mean that if shipment  $w$  passes through the reserved lane on arc  $(i, j)$ , then its travel time is  $T_{ij}$ . Constraint (5.9) means that there is exactly one time period  $k$  for  $t_i^w$  on any node  $i$ . In a feasible solution, shipment  $w$

passes through arc  $(i, j)$  if and only if two conditions are satisfied:  $t_i^w > 0$  and

$\sum_{k=1}^K \chi_{ijk}^w = 1$ . Constraints (5.9) and (5.10) imply that arrive time  $t_i^w$  should be located

within one and only one time period and on exactly one arc. Constraints (5.11) and (5.12) guarantee that if two or more shipments pass the same reserved lane, then the safety time interval between any two shipments must be satisfied. Constraints (5.13)-(5.17) specify the restriction on the decision variables.

### 5.3 Solution algorithm

In this section, an improved cut-and-solve based  $\varepsilon$ -constraint method is developed for solving the multi-objective model. The principle of  $\varepsilon$ -constraint method has been presented in Chapter 3. In this chapter, we present only the transformed single objective problem and an improved cut-and-solve method, in which a new technique of generating piercing cuts according to the characteristic of the considered problem is developed.

#### 5.3.1 Transformed single objective model

Similarly, objective function  $f_1$  is chosen as the main objective function. With the  $\varepsilon$ -constraint method presented in Chapter 3, the multi-objective model  $P^t$  can be transformed into a single objective model  $P_0^t(\varepsilon_2)$ , which is presented as follows:

Problem  $P_0^t(\varepsilon_2)$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (5.1)$$

Subject to

Constraints (5.3) - (5.17)

$$\sum_{w \in W} \sum_{(i,j) \in A} \sum_{k \in K} P_{ij}^w E_{ijk} \chi_{ijk}^w \leq \varepsilon_2, \quad (5.18)$$

**Complexity analysis:** Problem  $P_0^t(\varepsilon_2)$  is NP-hard.

**Proof:** If only one time period is considered and its length is large enough, the proposed time-dependent problem will be reduced to a time-invariant one. Moreover,

if the shipments all start from the same origin and the safety time interval,  $T_{int}$ , is small enough and the upper limit of the second objective function is large enough, then the single objective problem  $P'_0$  can be reduced to a Steiner tree problem [88], which is a famous NP-hard problem. Therefore, the single objective MIP problem is also NP-hard.

For solving problem  $P'_0(\varepsilon_2)$ , it is necessary to determine the range of  $\varepsilon_2$ . Once the range of  $\varepsilon_2$  is determined, then a series of  $\varepsilon_2$  can be fixed. Please see Chapter 3 for how to determine the range of  $\varepsilon_2$ .

### 5.3.2 Cut-and-solve method

In this section, an improved cut-and-solve method is proposed to solve problem  $P'_0(\varepsilon_2)$ . The improved CS method has two characteristics compared with that presented in Chapter 4. The first one is a partial integral relaxation strategy, which is applied to get a “good” LBs. The second one is a new technique of generating piercing cut, which is proposed to accelerate the CS method.

#### 5.3.2.1 Pre-processing

Before using the cut-and-solve method, properties of the model are analyzed in order to reduce the search space. If the values of some variables can be fixed in advance, the search space may be reduced so as to speed up the CS process.

As defined in Section 5.2,  $\beta_{ik}^w=1$  means that the arriving time of shipment  $w$  at node  $i$  occurs at time period  $k$  and otherwise  $\beta_{ik}^w=0$ . The following property holds.

**Property 1.** If  $\chi_{ijk}^w=1$ , then  $\beta_{jk}^w + \beta_{j(k+1)}^w = 1$ ,  $\forall (i, j) \in A, i \neq d_w, k \in K, w \in W$ .

*Proof.* Note that if  $\chi_{ijk}^w=1$ , then  $\beta_{ik}^w=1$ . It implies that  $t_i^w \in [I_k, I_{k+1})$ . That is,  $I_k \leq t_i^w < I_{k+1}$ . For arc  $(i, j)$ , it can be deduced that  $I_k + T_{ij} \leq t_j^w = t_i^w + T_{ij} < I_{k+1} + T_{ij}$ . Note that  $T_{ij} < I_{k+1} - I_k$ . Thus  $I_k \leq I_k + T_{ij} \leq t_j^w < I_{k+1} + T_{ij} \leq I_{k+2}$  holds, which implies two cases. In one case,  $I_k \leq I_k + T_{ij} \leq t_j^w < I_{k+1}$ , and in the other case,

$I_{k+1} \leq t_j^w < I_{k+1} + T_{ij} \leq I_{k+2}$ . This is to say, either  $t_j^w \in [I_k, I_{k+1})$  or  $t_j^w \in [I_{k+1}, I_{k+2})$ . It follows that  $\beta_{jk}^w + \beta_{j(k+1)}^w = 1$ .

From Property 1, constraint (5.19) will be added to problem  $P'_0(\varepsilon_2)$  to obtain problem  $P'_1$ .

Problem  $P'_1$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (5.1)$$

Subject to

Constraints (5.3) - (5.18),

$$\beta_{ik}^w + \beta_{(i+k)}^w \geq \chi_{ij}^w, \forall (i,j) \in A, \forall k \in K, \forall w \in W \quad (5.19)$$

### 5.3.2.2 Definition of piercing cut, remaining problem and sparse problem

The principle of the cut-and-solve method has been described in Chapter 2. An important factor which influences the efficiency of the cut-and-solve method is that tight *LBs* should be generated at each iteration. For an integer programming model, *LB* is usually obtained by solving a linear relaxation problem of *RP*. Our preliminary simulation experiments showed that the linear relaxation of *RP* commonly provided very “bad” *LBs*. To obtain an improved *LB*, the partial integral relaxation strategy is applied to *RP*, in which only  $\chi_{ijk}^w$  and  $\beta_{ik}^w$  are relaxed as continuous variables while the integrality of  $y_{ij}$  and  $z_{iww}$  is maintained. The partial integral relaxation strategy is based on the following observations:

1) The variables related to the paths of shipments are  $\chi_{ijk}^w$  and  $y_{ij}$ . Note that  $\chi_{ijk}^w = 1$  means that shipment  $w$  passes through the reserved lane on arc  $(i, j)$  during time period  $k$  and otherwise,  $\chi_{ijk}^w = 0$ . If  $\chi_{ijk}^w$  are not relaxed, the results of our preliminary simulation experiment show that most of them take the values of zero, which means that very few reserved lanes are passed by the shipments at any time period. The *LB<sub>r</sub>* obtained in this case is usually very “bad”. Therefore,  $\chi_{ijk}^w$  should be



relaxed to obtain more subpaths. Similar observation can be also found for  $\beta_{ik}^w$ .

2) Another important decision variable  $y_{ij}$  means whether there is a reserved lane on arc  $(i, j)$ . Constraint (5.6) implies that only when the lane is reserved for hazardous material transportation, the shipment can pass the road segment; and reserving one lane or not may result in completely different paths of shipments. Our preliminary simulation experiments show if  $y_{ij}$  are relaxed as the same as  $\chi_{ijk}^w$ , a considerable number of  $y_{ij}$  take the values greater than zero. It means that there may exist a reserved lane on the corresponding arc. However, the experiments also show if  $y_{ij}$  are not relaxed, a better  $LB_r$  can be obtained. Therefore,  $y_{ij}$  are considered as integer variables in this chapter. Similar observation can be also found for  $z_{iww'}$ .

Another key issue for the cut-and-solve method is to find an appropriate piercing cut that separates the current remaining problem into a new sparse problem and a new remaining problem. If the solution space of  $SP$  is too small, the optimal solution is not “good” enough to update the upper bound; if the solution space of  $SP$  is too large, it will take too much time to obtain an optimal solution. Climer and Zhang introduced a general procedure for generating piercing cuts based on reduced cost from an optimal solution of linear relaxed problem [85]. In their work,  $PC_r$  was defined as a set including the decision variables with large reduced cost. But the general procedure is not appropriate to MIP because it has been shown by our preliminary experimental results that the lower bound of the proposed problem obtained by the linearly relaxed  $RP$  is not good enough and the reduced costs of decision variables are often missing. Reference [79] proposed a new piercing cut technique for MIP using the number of

“critical links”. Since the value of  $\sum_{k=1}^K \chi_{ijk}^w$  may be fractional in an optimal solution of the relaxed  $RP$ ,  $(\bar{t}_i^w, \bar{\chi}_{ijk}^w, \bar{y}_{ij}, \bar{z}_{iww'})$ , there may be multiple paths for some shipments.

The link with the greatest value of  $\sum_{k=1}^K \chi_{ijk}^w$  is called “critical link”. For more details of the piercing cut based on “critical link”, please see [79]. The considered problem in

this chapter is different from that in [79]. The piercing cut in [79] cannot be used directly for our problem. A new piercing cut based on “critical link” is proposed as follows.

Let  $L_r$  represent the set of shipments which have multiple paths in the fractional solution and  $i_v$  represent the first node where multi-path appears for shipment  $v$ . Define  $a_r$  as the set of the most potential arcs for all shipments in  $L_r$ , which implies that the arcs in  $a_r$  are very likely to be selected in the final optimal solution of  $P_1$ . That is,

$$a_r = \{(i^*, j^*) \mid (i^*, j^*) = \arg \max_{(i, j) \in A} \sum_{k=1}^K \chi_{i, j, k}^v, v \in L_r\}, \quad (5.20)$$

where  $(i_v, j_v)$  refers to the arc with the largest value among all the arcs outgoing from node  $i_v$ .

The piercing cut is a combination of some decision variables in a certain set, called  $U_r$ . In this chapter,  $U_r$  refers to the set of these decision variables  $\chi_{i_v, j_v, k}^v$ , where  $v$  is a shipment which has multiple paths in the fractional solution and  $(i_v, j_v)$  is the most potential arcs for shipment  $v$ . Set  $U_r$  is defined as follows:

$$U_r = \{\chi_{i_v, j_v, k}^v \mid (i_v, j_v) \in a_r\}, \quad (5.21)$$

The piercing cut ( $PC_r$ ) is defined as follows:

$$\sum_{k=1}^K \sum_{\chi_{i_v, j_v, k}^v \in U_r} \chi_{i_v, j_v, k}^v \leq h_r - 1, \quad (5.22)$$

where  $h_r$  is a given integer in  $[1, |L_r|]$ .

Accordingly, the additional constraint associated with  $SP_r$  can be written as follows:

$$\sum_{k=1}^K \sum_{\chi_{i_v, j_v, k}^v \in U_r} \chi_{i_v, j_v, k}^v \geq h_r. \quad (5.23)$$

As mentioned above,  $RP_r$  and  $SP_r$  are generated by adding constraints (5.22) and (5.23) to  $CP_r$ , respectively. That is,

$RP_r$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (5.1)$$

Subject to

Constraints (5.3)-(5.19), (5.22)

$$\text{and } \sum_{k=1}^K \sum_{\chi_{i,j,k}^v \in U_l} \chi_{i,j,k}^v \leq h_l - 1, l = 1, \dots, r-1. \quad (5.24)$$

$SP_r$ :

$$\text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij} \quad (5.1)$$

Subject to

Constraints (5.3)-(5.19), (5.23) and (5.24).

It is worth pointing out that when  $r = 1$ , the original problem  $P_1^t$  is considered as  $CP_1$ . Hence, constraint (5.24) should be removed for  $RP_1$  and  $SP_1$ .

The process of the improved cut-and-solve method is illustrated in Fig. 5.1.

## 5.4 Computational results

To evaluate the efficiency of the proposed method, 155 instances (31 sets  $\times$  5 instances) were randomly generated. The proposed algorithm was coded in C. The computational experiments were carried out on an HP PC with a 3.10-GHz Intel Core processor and 4-GB RAM under Windows 7 environment. The CPLEX MIP solver (version 12.5) under default settings was used to solve problem  $P_1^t$ . It was run until problem  $P_1^t$  was solved to optimality.

The transportation network  $G(V, A)$  in this work was generated according to the random network topology generator proposed by Waxman [95]. The origin-destination pairs were randomly selected from the set of nodes. Parameter  $K$  was set from 1 to 5 because in real life the number of time periods was not very large [97]. Let  $\pi_{ij}^w$  be the accident probability of hazardous material  $w$  on the general lane(s) of arc  $(i, j)$ . Note that  $\pi_{ij}^w > P_{ij}^w$ . Our preliminary experimental results showed

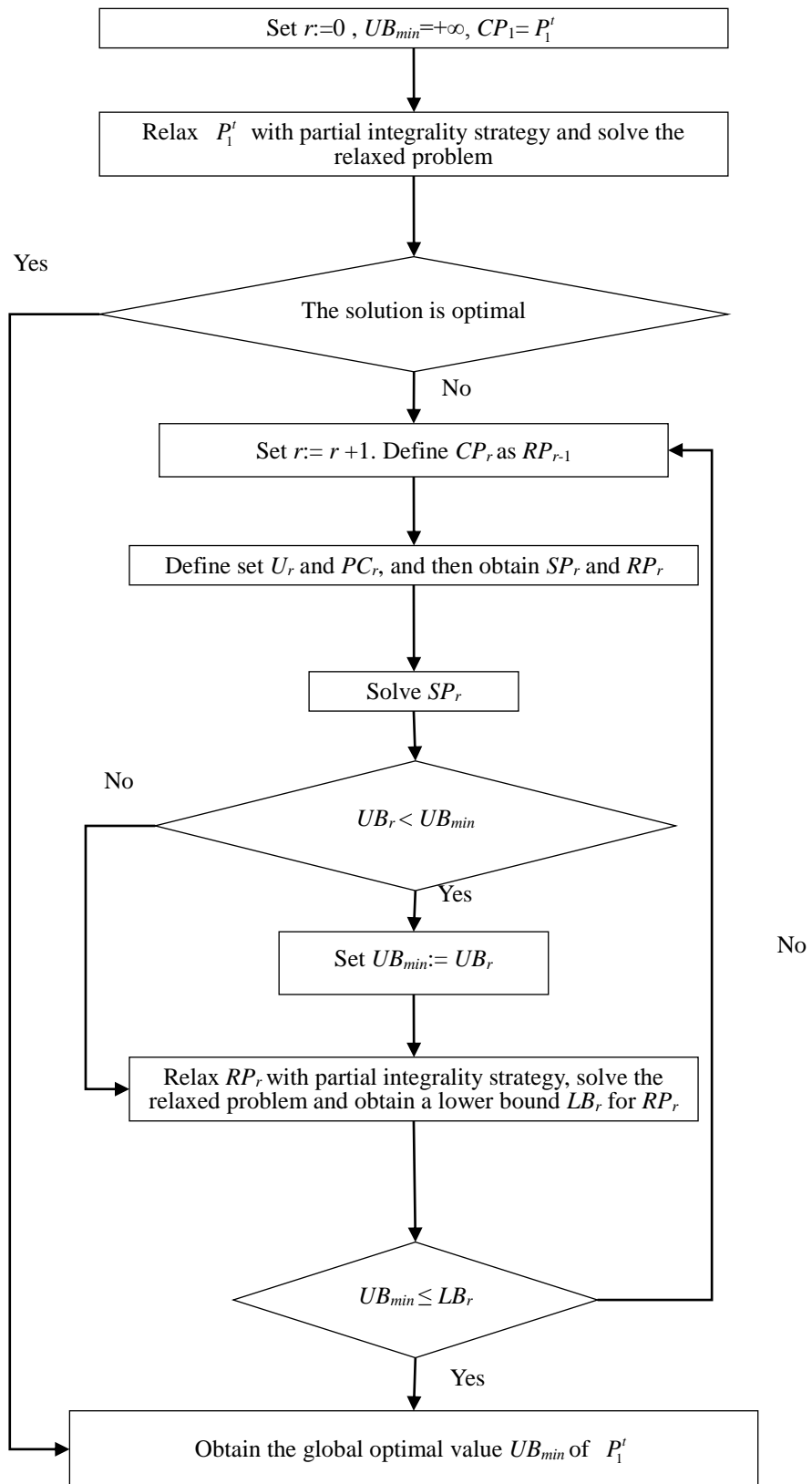


Fig. 5.1 Flow chart of the cut-and-solve method for the transformed single objective problem

that the values of the input parameters  $\pi_{ij}^w$ ,  $P_{ij}^w$ ,  $T_{ij}$ ,  $\tau_{ij}$ ,  $E_{ijk}$ ,  $T_{\text{int}}$ , and  $M_{ij}$ , had little effect on the performance of the proposed algorithm for a considerable number of instances and they were generated according to the following ways. The data of parameters were set in the similar way in Chapter 3:  $\tau_{ij} = d(i, j)$  and  $T_{ij} = \tau_{ij} * U(0.6, 0.9)$ , where U was a uniform distribution;  $\pi_{ij}^w = d(i, j) * U(8, 20)$ ;  $P_{ij}^w = \pi_{ij}^w * U(0.6, 0.9)$ , whose unit was  $10^{-7}$ ;  $E_{ijk}$  was generated by  $U(10, 80)$ , whose unit was  $10^4$ ;  $T_{\text{int}} = 10$ ;  $M_{ij}$  was generated by  $U(2, 5)$ . The number of iterations of  $\varepsilon$ -constraint method,  $S$ , was set to 20.

Table 5.1 summarizes the computational results on the randomly generated instances with  $N = 3$ ,  $|W| = 5$  and  $|K| = 3$ . The total computation time for an instance represents its total running time for obtaining 21 solutions in the  $\varepsilon$ -constraint method. Columns T1 and T2 represent the average computation time (in CPU seconds) of five instances for each set in which problem  $P_1$  is solved by the optimization software package CPLEX and the CS based method, respectively. It can be observed from Table 5.1 that the proposed CS based method is more efficient than CPLEX and both the total computation times moderately increase with the number of nodes. It is worth pointing out that the trends of two curves of T1 and T2 are almost the same. But T2 increases with the number of nodes more slightly than T1 in Fig. 5.2. For example, for set 1 with  $|V| = 20$ , T1 is only 1.261 times as much as T2, whereas for set 9 with  $|V| = 100$ , the ratio T1/T2 is 2.223 times.

Table 5.2 summarizes the computational results on the randomly generated instances with  $N = 3$ ,  $|W| = 10$  and  $|K| = 3$ . It can be observed from Table 5.2 that the computation times of CPLEX and the proposed method drastically increase with the number of nodes, but the latter increases more slightly than the former. Take sets 10 and 11 for example, given the number of shipments and time periods, the computation times T1, T2 for set 11 are 6.636 and 4.440 times as much as those for set 10, respectively. From Tables 5.1 and 5.2, it can be also found that the CS based method is more efficient for the sets with  $|W| = 10$  than for the sets with  $|W| = 5$ . For example, given the number of nodes and time periods, T1/T2 for set 3 is only 1.476, while it

increases to 3.573 for set 12.

When the number of nodes increases to 60 in Table 5.2, CPLEX cannot find 21 optimal solutions of  $P'_0(\varepsilon_2)$  within 36000s, but the proposed method can do it well for sets with up to 80 nodes. Set a threshold of the computation time for each problem  $P'_0(\varepsilon_2)$  to 36000s/21. When the threshold is reached and a problem is not solved to optimality, CPLEX is terminated. For sets 14-16, although CPLEX fails to find all optimal solutions, it can provide lower bounds and upper bounds of  $P'_0(\varepsilon_2)$  (s) which were not solved to optimality when CPLEX is terminated. The gap between the lower and upper bound is denoted as (upper bound – lower bound)/upper bound and it implies the extent of optimality. GAP in Table 5.2 denotes the average gap for problems  $P'_0(\varepsilon_2)$  (s) that were not solved to optimality. The average gap of sets 14-16 are 5.309%, 3.217% and 3.949%. The gaps are relatively small, which means that the obtained solutions might be relatively close to optimality for sets 14-16. The gap of set 14 is bigger than those of sets 15-16, which is because of one of the instances with complex structure. In Table 5.2, given that  $|W|=10$ , the computation time for set 16 is nearly up to 36000s so that this set can be considered as one of the largest-scale problems which can be solved in reasonable time.

Table 5.1 Computational results with  $N=3$ ,  $|W|=5$  and  $|K|=3$

set	$ V $	T1	T2	T1 / T2
1	20	42.492	33.689	1.261
2	30	159.133	101.038	1.575
3	40	229.150	155.282	1.476
4	50	328.191	174.990	1.875
5	60	319.409	200.318	1.593
6	70	865.940	252.524	3.429
7	80	1375.141	465.900	2.956
8	90	2089.713	830.784	2.515
9	100	2353.960	1058.735	2.223

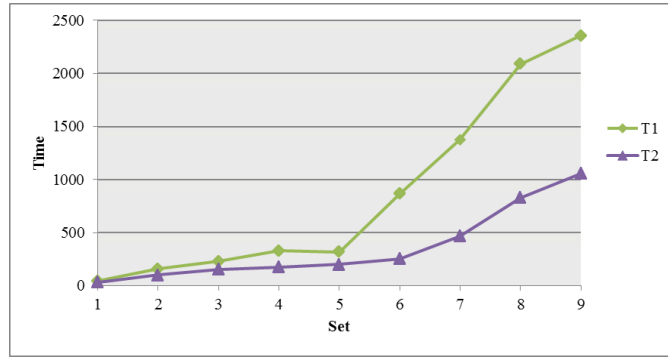


Fig.5.2 Comparison of T1 and T2

Table 5.2 Computational results with  $N=3$ ,  $|W|=10$  and  $|K|=3$

set	$ V $	T1	T2	T1 / T2	GAP
10	20	529.566	385.258	1.375	0
11	30	3514.437	1710.633	2.055	0
12	40	11489.591	3215.313	3.573	0
13	50	28094.791	6698.321	4.194	0
14	60	>36000.000	5703.657	—	5.309%
15	70	>36000.000	7568.321	—	3.217%
16	80	>36000.000	35434.740	—	3.949%

Table 5.3 shows the total computation times of the proposed method with  $N=4$ ,  $|W|=5$  and different  $|K|$ . It can be seen from Table 5.3 that for a given number of  $V$ , the computation time increases quickly with the value of  $K$ . For example, the computation times for 100 nodes with  $|K|=3$  (set 30) and  $|K|=5$  (set 31) are 11.329 and 24.237 times more than that with  $|K|=1$  (set 29), respectively. As shown in Table 5.1 and Table 5.3, the computation time also increases with the average degree of network. When  $|K|=3$ , given the number of nodes and shipments, the computation time with  $N=4$  is more than that with  $N=3$ . For example, the computation time for set 24 is 2.645 times as much as that for set 5.

Table 5.3 Computational results with  $N=4$ ,  $|W|=5$  and  $|K|=1-5$

set	$ V $	$ K $	T1	T2	T1/T2
17	20	1	26.923	23.804	1.131
18		3	63.177	41.690	1.515

19		5	160.727	141.198	1.138
20		1	45.259	31.647	1.430
21	40	3	202.990	165.206	1.229
22		5	311.470	251.380	1.239
23		1	53.883	37.412	1.440
24	60	3	625.306	529.896	1.180
25		5	1289.057	1141.264	1.129
26		1	83.724	51.417	1.628
27	80	3	2920.514	831.624	3.512
28		5	4002.699	1575.911	2.540
29		1	149.272	101.348	1.473
30	100	3	3885.786	1148.121	3.384
31		5	9610.322	2456.343	3.912

## 5.5 Conclusions

This chapter investigated the HMTLR problem with time-dependent risk, in which the transportation risk varied with time throughout the day. A new multi-objective mixed integer programming model was first presented for this problem. A pre-processing property of the considered problem was explored to reduce the solution space. Then an improved cut-and-solve method was developed for the transformed single objective problems, in which partial integral relaxation strategy and new piercing cut generation technique were proposed. Computational results showed that the proposed method outperformed the software package CPLEX.



# CHAPTER 6 CONCLUSIONS AND PERSPECTIVES

This thesis investigated hazardous material transportation problems via lane reservation in networks with time-invariant and time-dependent risk for designing time-and-safety guaranteed routes for each hazardous material shipment by optimally selecting lanes to be reserved from the existing transportation network. The objectives are to minimize the total traffic impact due to lane reservation and the total transportation risk.

Firstly, a hazardous material transportation problem with lane reservation strategy in networks with time-invariant risk was investigated. A multi-objective integer linear programming model for the proposed problem was formulated. The  $\varepsilon$ -constraint method was used to transform the multi-objective problem into the single objective ones. The complexity of these single objective problems was proved to be NP-hard and optimization software package CPLEX was applied to obtain Pareto optimal solutions. A fuzzy-logic-based approach was also exploited to help DMs select a preferred solution from Pareto optimal solutions. Computational results on an instance based on a real network topology and randomly generated instances showed that the  $\varepsilon$ -constraint method could efficiently solve the considered multi-objective optimization problem within a reasonable time and find efficient Pareto optimal solutions. Computational results also demonstrated that the lane reservation strategy could greatly reduce the transportation risk.

Secondly, a new resolution method, called a cut-and-solve and cutting plane combined method, was developed to solve the transformed single objective problem in Chapter 3. A pre-processing property was also explored to reduce the solution space. Cutting plane method for finding valid inequalities was developed to accelerate the convergence of cut-and-solve method. Computational results on randomly generated instances demonstrated that the proposed algorithm was more efficient since it took about an average of 66.45% computation time of CPLEX for different

sized problems.

Finally, hazardous material transportation via lane reservation in networks with time-dependent risk was investigated, in which population exposure along road segments was assumed to be time-dependent. A multi-objective mixed integer linear programming model was formulated. A pre-processing property was also explored to reduce the solution space. Then an improved cut-and-solve based  $\varepsilon$ -constraint method was proposed. The improved cut-and-solve method, different from that in Chapter 4, adopted a new technique of generating piercing cuts and a partial integral relaxation strategy was proposed for this method. Computational results showed that the proposed algorithm could find Pareto optimal solutions faster than CPLEX for the transformed single objective problems. It could be seen that the proposed algorithm took about an average of 43.23% computation time of CPLEX for problems with different sizes.

Future works may be conducted from several aspects:

(1) Firstly, the transportation risk and the negative impact due to lane reservation are assumed as known parameters in this thesis. Note that risk is defined as the product of the accident probability and population exposure. Assessing the probability of each hazardous material release may need many historical data and some techniques such as using logical diagram-based approach; determining population exposure depends on not only the nature of hazardous materials but also the geometrical shapes of the impact area. Additionally, the negative impact on normal traffic is a complicated issue related to traffic flow, the size and type of vehicles in the transportation networks, etc. Generally speaking, when performing the assessment of transportation risk and impact, some hypotheses are usually introduced. If such hypotheses are removed, finding resolution methods becomes more challenging.

(2) Another future work may be to expand the mathematical model. For example, hazardous material vehicles are allowed to stop during their trip so as to avoid peak risk periods on some road segments.

(3) The  $\varepsilon$ -constraint method used in this thesis can only obtain the weak Pareto optimal solutions. Thus, one of the future research directions is to improve

$\varepsilon$ -constraint method so as to seek for all the strict Pareto optimal solutions.

(4) Although the cut-and-solve based  $\varepsilon$ -constraint method is able to optimally solve the considered problems within a reasonable time, there is still a heavy computational burden on large size problems. Studying properties of the model may help to reduce the search space. Exploiting efficient piercing cuts is another way to improve the efficiency of the cut-and-solve method. Additionally, it is necessary to develop efficient heuristic algorithms based on the characteristics of the considered problems.

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