Multi-objective Route Planning for the Transportation of Dangerous Goods: Hong Kong as a Case Study

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ABSTRACT

of thesis entitled:

Multi-objective Route Planning for the Transportation of Dangerous Goods: Hong Kong as a Case Study

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The transportation of dangerous goods (DGs) can significantly affect human life and the environment if accidents occur during the transportation process. Such accidents can result in traffic disruption, fatalities, property and environmental damages. Therefore, safe DG transportation is of paramount importance, especially in high-density-living environments where population and socioeconomic activities are densely distributed over the transportation network.

Effective and rational routing of DGs is one of the powerful means to mitigate the DG transportation risk. DG transportation involves multiple stakeholders playing different roles and having different objectives that are generally conflicting. The solution of such problem is to search for one or a set of "compromise" solutions rendering the best possible trade-offs for conflict resolution among different objectives. Given the multi-objective nature of the DG routing problem, multi-objective optimization (MOP) becomes a sound framework for analysis and decision-making.

This research establishes a general framework for optimal route planning for DG transportation in a high-density-living environment. Within the framework, multi-criteria risk assessment and multi-objective route planning can be efficiently solved by novel compromise programming models and high performance algorithms. Non-linearity and non-convexity often exist in the optimal DG routing problem which cannot be solved appropriately by conventional models such as the weighed sum approach. This research has proposed three novel methods to facilitate the generation of a set of optimal solutions on the Pareto front representing various trade-offs

among the conflicting objectives. The proposed methodologies give full consideration to decision-makers' inclination and capability in determining the weights for different criteria. The compromise programming procedure allows decision-makers to exercise their preference structures in pursuing desired solutions rendering good compromises among different objectives. The adaptive weighting method approximates the Pareto front with a few suitable solutions to help decision-makers select the most satisfactory route without generating all of them. The genetic-algorithm-based approach uses a set of specifically designed genetic operators to efficiently capture a wide range of Pareto-optimal and near-optimal solutions, from which a decision-maker can choose the most preferred or best compromise one to implement. The diversity of methodologies provides decision-makers with more flexibility in choosing appropriate MOP methods to route DG shipments.

A real-life application in optimal route planning for the transportation of liquefied petroleum gas (LPG) in Hong Kong was performed to implement the proposed framework. A set of criteria fitting the context of Hong Kong were defined, and various optimal routing solutions with diverse compromise in different objectives were generated. The implementation of the proposed methodologies enables the avoidance of the pitfalls of preference-based techniques and the burden of generating a complete set of possible solutions, and provides decision-makers with an overview of the solution space and the possible trade-offs among the conflicting objectives. The application study demonstrated the effectiveness of the proposed methodologies. In light of the study results and limitations, some recommendations are provided for future research.

論文摘要

危險品在運輸過程中如果發生意外，將會給人們的生活及周圍環境造成嚴重影響。因此，危險品的安全運輸十分重要，特別是在人口和社會經濟活動高度密集的地區，這一重要性顯得尤為突出。

合理制訂危險品運輸路線是降低風險的有效手段之一。危險品運輸涉及到多個部門，危險品運輸的主管部門和運輸企業分別擁有不同的期望，一方追求最少的危害人數，而另一方則追求最低的運輸成本(如最短的運輸路線)。政府與企業的不同追求目標往往是相互衝突的，因此，危險品運輸線路的制訂並不是一個唯一方案，而是一組反映了各目標之間為緩解衝突而達成的不同妥協的折衷方案。多目標優化為危險品運輸線路的制訂提供了有效的分析與決策手段。

本文建立了一個針對高密度環境下的危險品路徑優化的基本理論框架。在這一框架內，多標準風險評估以及多目標路徑優化可通過新穎的妥協規劃模型及高性能的算法得以實現。危險品路徑選擇常涉及非線性和非凸性的問題，常規的優化模型，如加權疊加法，無法解決這些問題。對此，本文提出了三種優化方法可以有效地產生多個帕累托最優解，這些解能充分反映各目標之間為達到某種最優而形成的不同妥協。其中，妥協規劃方法可使決策者自行定義各目標的相對重要性，從而直接求出最符合一定偏好的理想解；自適應定權方法毋須用戶給定權重，它通過一種啟發式的搜索直接找出一組有效解，供決策者從中選出最滿意的路線；遺傳算法模擬自然進化過程，運用特別設計的遺傳算子搜索最優或近似最優解，為決策者提供多個備擇方案。三種方法分別考慮了決策者的不同需求和能力，為危險品運輸決策提供了便利。

以香港液化石油氣運輸路徑優化為研究案例，本文提出了一套針對高密度環境下的風險評估和路徑選擇標準，並應用上述三種優化方法分別對從青依油庫到各專用液化石油氣加氣站的運輸生成了多個不同的最優路徑方案。研究結果表明，本文提出的優化方法可行而且有效。根據研究中存在的不足，本文提出了將來可能的研究方向。

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ACRONYMS AND ABBREVIATIONS

AADT: Average Annual Daily Traffic
ADR: European Agreement Concerning the International Carriage of Dangerous Goods by Road
AHP: Analytic Hierarchy Process
CI: Consistency Index
CP: Compromise Programming
CR: Consistency Ratio
DG: Dangerous Good
DGO: Dangerous Goods Ordinance
DOT: Department of Transportation, United States
DP: Dynamic Programming
D-S theory: Dempster-Shafer theory of evidence
EA: Evolutionary Algorithm
EMSD: Electrical and Mechanical Services Department, Hong Kong SAR
ESRI: Environmental System Research Institute
FHWA: Federal Highway Administration, United States
FSD: Fire Services Department, Hong Kong SAR
GA: Genetic Algorithm
GIS: Geographic Information System
GP: Goal Programming
HAZMAT: Hazardous Material
LPHC: Low Probability High Consequence
LPG: Liquefied Petroleum Gas
MDR: Multiple Destination Routing
MOLP: Multi-objective Linear Programming
MOP: Multi-objective Optimization Problem
MOSP: Multi-objective Shortest Path Problem
NP-hard: Non-deterministic Polynomial-time hard
O-D pair: Origin-Destination pair
OHMS: The Office of Hazardous Materials Safety, United States
QRA: Quantitative Risk Assessment

RI:	Random Index
SP:	Shortest Path
SPEA:	Strength Pareto Evolutionary Algorithm
STEM:	Step Method
WS:	Weighted Sum

CHAPTER 1: INTRODUCTION

1.1 Background of the study

1.1.1 Dangerous goods transportation

Dangerous goods (DGs, also referred to as hazardous materials, HAZMATs) are substances, which by virtue of their chemical, physical or toxicological properties, could pose a catastrophic risk to health, safety, property and the environment if released or disposed improperly (Lepofsky *et al.* 1993). However, dependence on DGs is a fact of life in industrialized societies and there are thousands of different dangerous goods in use today (US DOT 2004). The United Nations sorts dangerous goods into nine classes according to their physical, chemical, and nuclear properties (UN 2001). In almost all instances, DGs originate at a location other than their destination. For example, oil is extracted from oil fields and shipped to a refinery (typically via a pipeline); oil products such as gasoline and liquefied petroleum gas are refined at the refinery and then shipped to storage tanks at different locations. Hence, transportation plays a significant role for DGs.

The Office of Hazardous Materials Safety (OHMS) of the US DOT estimated that there were 800,000 domestic shipments of HAZMATs, totaling approximately 9 million tons, in the USA each day in 1998 (US DOT 2000). Transport Canada estimated that nearly 30 million shipments of dangerous goods were moved by road, rail, water, and air in Canada every year (Transport Canada 2004). The Italian National Statistic Institute (ISTAT) reported that in year 2003, the total amount of goods transported by road in Italy was about 1.2 billion tons, among which 84.96 million tons (accounting for 6.8% of the total amount) were dangerous goods. In other European countries, such as Germany, France, and United Kingdom, the quantities of DG shipments were also over 80 million tons per year (Rindone and Iannò 2005). In China, according to incomplete figures, by the end of year 2008, the total amount of DGs transported by road has been over 400 million tons /year (Wang 2009).

The vast majority of shipments of DGs reach their destinations safely. Given the large number of DG shipments, however, there remains the potential for catastrophic incidents with multiple fatalities, injuries, large-scale evacuations, and severe environmental damage. DG accidents are perceived as low-probability-high-consequence (LPHC) events (Sherali *et al.* 1997). Most transportation accidents that impact a large number of people and result in significant economic loss involve a DG cargo. Therefore, safe DG transportation is of paramount importance, especially in a high-density-living environment where population and socioeconomic activities are densely distributed over the transportation network. DG transportation has become a strategic problem faced by various government departments, DG carriers, and the public in recent years (Erkut *et al.* 2007).

1.1.2 The risk of transporting dangerous goods

The transportation of dangerous goods is generally associated with significant levels of risk. In the context of DG transportation, risk refers to the likelihood of incurring the undesirable consequences of a possible accident (Alp 1995). For example, the release of petrochemical-type of DGs during the transportation process, i.e., the focus of this study, can lead to a variety of serious incidents such as a spill, fire or explosion in the case of flammable liquids or pressure-liquefied gasses. The undesirable consequences of these incidents include traffic disruption, fatalities, injuries, emergency evacuation, property damage, environmental damage, etc. Making decisions on the transportation of DG are difficult, not only because of the plausible catastrophic accidents, but also the intense public concern over this issue. It is thus important to carefully study such risks for strategic decision-making.

Quantitative risk assessment (QRA) methods are commonly used to assess the risk of DG transportation. The risk is generally defined as a function of DG release frequencies and the consequent damages resulting from such releases (Erkut and Verter 1998). The frequencies of DG releases depend on many factors such as the probability of a traffic accident, the conditional probability of release given the traffic accident, the probability of a certain release size taking place, and the volume of DG movements (Rhyne 1994). The consequences of a DG release are associated with the type of transported DG, the amount released, meteorological conditions, and potentially exposed population (List *et al.* 1991; Zhang *et al.* 2000). Accidents involving DG transportation near densely populated areas pose the largest risks due to the considerable number of potentially affected people. Also, areas prone to high frequencies of traffic accidents give rise to higher risk levels.

Numerous models have been proposed to measure the risk of DG transportation over the years (Erkut *et al.* 2007). The common feature of all approaches is that a risk indicator is composed of the probabilities of occurrence of some undesirable events and their possible adverse consequences. Although there is a wealth of risk models, few of them are specifically designed for high-density living with respect to various risks. In most of these models, the undesirable consequences of an accident related to DG are mainly expressed in terms of potential injuries and fatalities (Erkut and Verter 1995; Verter and Kara 2001; Kara *et al.* 2003). These constitute the main part of impact costs and most decision-makers would prefer to minimize population exposure at the expense of financial profits (Kalelkar and Brooks 1978). In principle, the evaluation of DG transportation risk should consider not only the direct damages to individuals and vehicles travelling along the route where the incident occurs but also the indirect damages to population, properties, and environment near the incident location. However, most of the prevailing literature focuses only on the indirect damages; few of them take into account the direct damage simultaneously. Moreover, the capability of emergency response is rarely considered when assessing the risk of DG transportation. Clearly, prompt and efficient response is critical to the minimization of possible catastrophic consequences on human life and the environment in the event of a DG accident, especially in a high-density environment. In order to make an effective risk assessment for DG transportation in high-density living environments, it is necessary to take into account all of these factors and model the associated risks appropriately.

1.1.3 Route planning for dangerous goods transportation

The transportation of dangerous goods has a good safety record; however, accidents do take place, and the consequences can be significant due to the nature of the cargo. Reduction of the risk of DG transportation can be achieved in many different ways. Routing DG shipments reasonably and effectively is one of the powerful means to mitigate the DG transportation risk (Erkut *et al.* 2007).

DG transportation involves multiple stakeholders such as shippers, carriers, consignees, and governments; each playing a different role in safely moving DG from the origins to the destinations over a transportation network (Kara and Verter 2004). Moreover, different stakeholders usually have different priorities and perspectives on DG transportation (Erkut and Gzara 2008; Verter and Kara 2008). Thus, DG transportation is a typical multi-stakeholder and multi-objective problem which is generally complicated to solve. These objectives are usually competing or conflicting with each other so that a single "best" solution that can optimize every single objective is impossible. The solution of such problem is to search for one or a set of "compromise" solutions rendering the best possible trade-offs for conflict resolution among different objectives. Given the multi-objective nature of the DG routing problem, multi-objective optimization (MOP) thus becomes a sound framework for analysis and decision-making.

Despite the extensive research that has been done on route planning for DG transportation, only a few have addressed the multi-objective nature of the DG routing problem using an appropriate multi-objective optimization method. Vigorous multi-objective optimization methods are seldom employed to seek optimal routes for DG transportation based on the results of risk assessment. The weighted sum (WS) approach is most commonly used in DG route planning (Chin and Cheung 1989; ReVelle *et al.* 1991). Although it is the simplest and most straightforward multi-objective optimization technique, there are problems in using this method when objectives are nonlinear or the set of feasible solutions is not convex. Even for convex multi-objective problems, a uniform variation of the weights can hardly produce an even distribution of points in the efficient set (Das and Dennis 1997). To solve these problems, high performance MOP methods need to be developed to optimize the routes for DG transportation. It is instrumental to generate a set of efficient routes representing the inherent trade-offs among different objectives for decision-makers to choose the one that gives the best compromise among the conflicting objectives.

Compromise programming (CP) and genetic algorithms (GAs) provide promising solutions to such optimization problems. CP depends on a weighting mechanism to collapse multiple objectives into a single objective function and searches for the desired solution that is closest to the ideal solution in which each objective achieves its optimum value simultaneously (Zeleny 1982; Zhang 2003). As a highly efficient search strategy for global optimization, GAs demonstrate superior performance on solving multi-objective optimization problems that have a large and complex solution space. Moreover, being a population-based approach, a GA is able to find multiple feasible solutions in a single run (Goldberg 1989; Gen and Cheng 2000). Non-linearity and non-convexity often exist in multi-objective route optimization problem which cannot be appropriately solved by conventional models such as the weighed sum approach. CP and GAs, however, can handle these problems effectively.

The Dijkstra's algorithm (Dijkstra 1959) is most commonly used to search for the shortest path from the source node to one additional node within a network. DG route planning involves multiple objectives and thus multi-objective shortest paths should be derived. In this connection, the conventional Dijkstra's algorithm needs to be appropriately modified to effectively address the multiple components of link impedance, and to efficiently search for the optimal path.

1.1.4 Routing of dangerous goods in Hong Kong

Hong Kong is a large city with high population density and narrow streets. Due to the land constraints, vehicles carrying DGs inevitably have to pass through densely populated areas or their vicinities. Therefore safe DG transportation is of paramount importance. In an attempt to ensure public and environmental safety, the Government has issued rules and regulations for dangerous goods transportation. Each DG transport company is required to advise their drivers to follow major routes and to avoid heavy traffic and densely populated areas as much as possible. Currently, there are no designated routes for vehicles carrying DGs in Hong Kong. However, vehicles carrying dangerous goods such as explosives, flammable liquids, or pressure-liquefied gasses are forbidden to pass through any tunnels in Hong Kong. The existing regulations specify the forbidden spots or road sections rather than the approved routes. Given an origin and a destination, it is essential to find a number of possible routes from which the route(s) that gives a preferable compromise between cost and risk might be selected.

1.2 Objectives of the study

This study aims to contribute to the literature of dangerous goods transportation by constructing a general framework applicable to multi-objective route planning for the conveyance of DGs in high-density living environment. Within the framework, multi-criteria risk assessment and multi-objective route planning can be efficiently solved by novel compromise programming models and high performance algorithms. The study focuses on the development of vigorous multi-objective optimization methods to search for optimal routes for DG transportation based on the multi-criteria risk assessment. As a basis, a set of criteria fitting the context of high-density living will be identified and a risk model with respect to various risks will be designed to assess the risk associated with DG transportation. A real-life application in optimal route planning for the transportation of liquefied petroleum gas (LPG) in Hong Kong will be carried out to implement the framework and to evaluate the proposed methodologies. The objectives of this study are:

1. To construct a general multi-objective optimization framework for DG route planning for high-density living.
2. To identify a set of criteria fitting the context of high-density living environment for risk estimation.
3. To develop appropriate methods of risk assessment for the transportation of petrochemical-type of DGs suitable for high-density living.
4. To develop novel methods for the routing analysis of DG transportation under conflicting objectives.
5. To devise high performance algorithms for the implementation of the corresponding multi-objective optimization methods for the routing of DG transportation.

6. To make a real-life application in optimal route planning for the transportation of liquefied petroleum gas (LPG) in Hong Kong, a high-density city, to implement the framework and to evaluate and improve the proposed methodologies.

1.3 Significance of the study

The transportation of dangerous goods can significantly affect human life and the environment if accidents occur during the transportation process. Therefore, safe DG transportation is of paramount importance, especially in high-density-living environments. Risk assessment and route planning play a crucial role in the prevention or minimization of possible catastrophic consequences on human life and the environment. However, effort has seldom been made to analyze such problems in the literature. Hence there is an urgent need to carry out risk assessment and optimal route planning for DG transportation in a high-density environment. This study aims to establish a general framework for optimal DG routing in such an environment, within which non-convexity and non-linearity can be handled, risk assessment applicable to high-density living can be made, and the best compromise solution can be obtained along the Pareto front stipulating various trade-offs among the conflicting objectives. The results obtained from this research will benefit the research and applications in the field of DG transportation.

DG transportation remains a great public concern due to its potentially catastrophic consequence. It is thus important to carefully assess the associated risks for strategic decision-making. In this study, risk is measured by means of accident probability, different exposure risks, and emergency response capabilities. A model with emphasis on high-density living is developed to evaluate the risk of transporting DG in the road network. On the basis of risk assessment, route planning can then be conducted using MOP methods with efficient solution algorithms.

DG transportation is a multi-objective problem with multiple stakeholders playing different roles and having different objectives. Although there is a wealth of literature on the DG transportation problem, most of it focuses on risk assessment by various risk models. Lesser effort has been made on route planning for DG transportation under conflicting objectives, particularly in high-density environment. This study proposes novel multi-objective optimization methods for DG routing analysis. High performance algorithms guarantee speedy convergence via efficient searches. The methodologies developed in this study gives full consideration to decision-makers' inclination and capability in determining the weights for different routing criteria. The diversity in methodologies provides decision-makers more flexibility in choosing applicable MOP methods for effective DG route planning.

Different types of DGs possess different characteristics whose risk assessments and routings call for a wide spectrum of technical knowledge and practical considerations. This study concentrates mainly on the transportation of petrochemical-type of DG. The framework can, however, be extended to solve more complicated problems involving the transportation of a large variety of DGs in a high-density environment. The study will advance the research and applications of optimal route planning for DG transportation for high-density living.

1.4 Organization of the thesis

This thesis consists of six chapters. Following this introductory chapter, Chapter 2 introduces the definition and classification of dangerous goods, as well as the concept of risk in the transportation of DGs. Current practices of DG transportation in Hong Kong are reviewed. The methodologies commonly used in the risk assessment for DG transportation are examined. The multi-objective optimization techniques and their applications to the vehicle routing problem, in particular, multi-objective route planning for DG transportation are discussed in detail.

Chapter 3 and Chapter 4 focus on the methodological framework, where three distinct multi-objective optimization methodologies proposed in the study are presented. Chapter 3 concentrates on the deterministic multi-objective path optimization methods. It begins with an introduction of the multi-objective shortest path problem that underlies the optimal route planning for DG transportation. It then introduces the concept of Pareto optimality, an important notion in the multi-objective problems. Subsequently, the simplest and most straightforward multi-objective optimization method, weighted sum of objective functions, is discussed. Following that is a detailed description of compromising programming (CP), a mathematical programming technique for finding a compromise solution amongst a set of conflicting objectives. Specifically, the utility functions commonly employed in CP are introduced. The construction of criteria weights is then described. In particular, the analytical hierarchy process (AHP) is specified and the procedure of multi-objective DG route planning based on compromise programming is detailed accordingly. In addition to the CP approach, an adaptive weighting method for multi-objective route planning is proposed to avoid the pitfalls of preference-based techniques. The framework of this approach to explore the Pareto front is presented, followed by the procedure of approximating such a front. The implementation issues are also specified.

Chapter 4 introduces a heuristic method – the genetic algorithm, for the problem of optimal route planning. As a powerful and broadly applicable stochastic search and optimization technique, GAs and their characteristics are briefly introduced at the beginning. The major components and basic structure of normal GAs are examined, and the typical parameters in a genetic algorithm are discussed. This is followed by a detailed introduction of the proposed GA-based heuristic approach to multi-objective route planning for DG transportation. The genetic representation scheme of candidate solutions, the initialization of population, and the fitness evaluation are elaborated. The genetic operators used in the proposed GA are also detailed and the implementation issues are specified.

Chapter 5 focuses on the case study of routing road tankers conveying liquefied petroleum gas (LPG) in the road network of Hong Kong. The set of criteria fitting the context of high-density living, and Hong Kong in particular, is identified, and the model for evaluating the risks associated with the transportation of LPG is detailed. This is followed by an elaboration on the implementation of three proposed multi-objective optimization methodologies in optimal route planning for transporting LPG in Hong Kong. The composition of risks in each solution is examined and the actual trade-offs involved are interpreted. Particular issues with reference to the implementation of each method are specified. Chapter 5 concludes with a discussion of the execution efficiency and application condition of each method.

Chapter 6 concludes the thesis by summarizing the major research contributions. In light of the study results and limitations, recommendations are provided for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter reviews the academic body of literature in areas relevant to dangerous goods transportation, risk assessment, and multi-objective optimization techniques. The definition and classification of dangerous goods are introduced, the feature of dangerous goods transportation is described, and current practices of DG transportation in Hong Kong are reviewed. The methodologies commonly used in the risk assessment for DG transportation are examined. The multi-objective optimization techniques and their applications to the vehicle routing problem, in particular, multi-objective route planning for DG transportation are discussed in detail.

2.1 Definition and classification of dangerous goods

2.1.1 Definition

The European Agreement Concerning the International Carriage of Dangerous Goods by Road (ADR) proposes the definition of dangerous goods as follows (ADR 2009):

> "Dangerous goods mean those substances and articles the carriage by road of which is prohibited by ADR, or authorized only under the conditions prescribed therein."

According to ADR, dangerous reaction means:

(a) Combustion or evolution of considerable heat;

(b) Evolution of flammable, asphyxiant, oxidizing or toxic gases;

(c) The formation of corrosive substances;

(d) The formation of unstable substances; or

(e) Dangerous rise in pressure (for tanks only).

The US Department of Transportation (US DOT 2004) defines hazardous materials or dangerous goods as any substances or materials that may pose an unreasonable risk to health, safety or property. These materials can cause harm to people, the environment, and property if release or dispose improperly due to their physical, chemical, and biological properties.

2.1.2 Classification

The UN Recommendations on the Transport of Dangerous Goods sorts dangerous goods into 9 classes according to their physical, chemical, and nuclear properties, in order to regulate the transportation, packaging, and labeling of dangerous goods with respect to their hazards (UN 2001). Some of these classes are subdivided into divisions. Class or division is a number assigned to the article or substance according to the criteria of one or more of the nine UN hazard classes. Substances (including mixtures and solutions) and articles subject to the Regulations are assigned to one of the nine classes according to the hazard or the most predominant of the hazards they present.

These classes and divisions include (UN 2001):

Class 1: Explosives

- Division 1.1: Substances and articles that have a mass explosion hazard
- Division 1.2: Substances and articles that have a projection hazard but not a mass explosion hazard
- Division 1.3: Substances and articles that have a fire hazard and either a minor blast hazard or a minor projection hazard or both, but not a mass explosion hazard
- Division 1.4: Substances and articles that present no significant hazard
- Division 1.5: Very insensitive substances which have a mass explosion hazard
- Division 1.6: Extremely insensitive articles which do not have a mass explosion hazard

Class 2: Gases

- Division 2.1: Flammable gases
- Division 2.2: Non-flammable, non-toxic gases
- Division 2.3: Toxic gases

Class 3: Flammable liquids

Class 4: Flammable solids; substances liable to spontaneous combustion; substances which, in contact with water, emit flammable gases

Division 4.1: Flammable solids, self-reactive substances and solid desensitized explosives

Division 4.2: Substances liable to spontaneous combustion

Division 4.3: Substances that in contact with water emit flammable gases

Class 5: Oxidizing substances and organic peroxides

Division 5.1: Oxidizing substances

Division 5.2: Organic peroxides

Class 6: Toxic and infectious substances

Division 6.1: Toxic substances

Division 6.2: Infectious substances

Class 7: Radioactive material

Class 8: Corrosive substances

Class 9: Miscellaneous dangerous substances and articles

2.2 The risk of transporting dangerous goods

2.2.1 Dangerous goods transportation – an industry at risk

In almost all instances, dangerous goods originate at a location other than their destination. For example, oil is extracted from oil fields and shipped to a refinery (typically via a pipeline); oil products such as gasoline and liquefied petroleum gas are refined at the refinery and then shipped to storage tanks at different locations. Hence, transportation plays a significant role for DGs. The transportation of DGs poses special risks to the neighboring population, environment, and property due to the nature of the cargo. Therefore, DG transportation requires specific safety measures with respect to packaging of the material, design and operation of vehicles, training of crew, handling methods, and emergency response procedures.

Although accidents involving DGs are infrequent, this number is likely to be proportional to the number of shipments. The statistics for Hong Kong are not available, but the US Department of Transportation (DOT) maintains a comprehensive database of historical records that provides good insight into the practices associated with DG transportation. The Office of Hazardous Materials Safety (OHMS) of the US DOT estimated that there were 800,000 domestic shipments of HAZMATs, totaling approximately 9 million tons, in the USA each day in 1998 (US DOT 2000). Approximately 94% of total daily HAZMAT shipments were shipped by trucks (Table 2.1). In Europe and China, the quantities of DG shipments transported by road are also tremendous. Therefore, ensuring efficient and safe routing of vehicles carrying DGs is of utmost importance for public safety.

Table 2.1 Average daily hazmat shipments in the United States

Shipment mode	Number of shipments	% of total shipments
Truck	768,907	93.98%
Air	43,750	5.35%
Rail	4,315	0.53%
Pipeline	873	0.11%
Water	335	0.04%
Daily total	818,180	100%

Source: US DOT (2000)

The risk of DG transportation differs from the risk of fixed facilities for HAZMAT storage in that the exposure of population and the environment along the routes to the DG shipments is dynamic rather than fixed. Certain DGs are transported on the road network in quantities that would exceed the threshold for safety if stored in a fixed facility. On the other hand, recent analyses and historical events have shown that risks arising from DG transportation are almost of the same magnitude as those resulting from fixed facilities (Fabiano *et al.* 2002). A survey of the literature from 1926 to 1997 reveals that among 3,222 accidents related to the handling, transportation, processing, storage of chemicals involving different types of DGs, 54% were related to fixed facilities, 41% were transportation accidents and 5% miscellaneous accidents (Khan and Abbasi 1999). Gorys (1987) found, from the 1983 Commercial Vehicle Survey, that approximately one third of all DGs release in Ontario results from transportation related incidents. Given that transportation activities take place beyond the control of fixed facilities, there is a justifiable concern that dangerous goods should be transported in the safest manner possible.

The major concern in the process of DG transportation is the likelihood of incurring an undesirable event, as might occur could lead to a release or explosion. Such an event can cause severe damage to society and can involve multiple fatalities, serious injuries, large-scale evacuations, and can require significant clean-up effort. For instance, at 2:45 p.m. January 13, 2004, a fuel tanker traveling south on Maryland's I-895 (the Harbor Tunnel Thruway) veered off the overpass and landed on the northbound lanes of I-95 just south of Baltimore. The explosion involved 8,000 gallons of gasoline. The crash led to I-95 shutdown in both directions for more than nine hours and took four lives (Buck *et al.* 2004).

Greenberg (2001) estimated the economic impact of hazardous material accidents in the United States by averaging the accidents records over the period of 1995-1997. Table 2.2 contrasts the average costs (per event) of HAZMAT and non-HAZMAT motor carrier accidents and incidents for one year. Although the cost of an average HAZMAT incident is not significantly higher than that of a non-HAZMAT incident, the cost of a HAZMAT incident resulting in fire or explosion is significantly higher. DG transportation accidents are perceived as low-probability-high-consequence (LPHC) events. The LPHC feature of DG transportation accidents tends to mislead public perceptions of the actual danger of transporting DGs, and it poses a challenge to the scientific community on quantitative risk assessment for DG transportation.

Table 2.2 Comparative costs of HAZMAT and non-HAZMAT motor carrier accidents/incidents

Type of accident/incident events	Average cost (in US$)
non-HAZMAT events	340,000
all HAZMAT events	414,000
HAZMAT events with spill/release	536,000
HAZMAT events with fire	1,200,000
HAZMAT events with explosion	2,100,000

Source: Greenberg (2001)

DG transportation involves multiple stakeholders such as shippers, carriers, consignees, and governments; each playing a different role in safely moving DG from the origins to the destinations over a transportation network (Kara and Verter 2004). Moreover, different stakeholders usually have different priorities and perspectives on DG transportation (Erkut and Gzara 2008). Given the low accident probabilities, shippers, carriers, and receivers of DG are primarily interested in maintaining the throughput of DGs in terms of timely shipment and minimum cost. Although safety is a reasonable objective, throughput remains their dominant concern. As a result, government agencies are responsible to administrate regulations over the safety of DG transportation with thorough consideration on the economic cost and public risk, and striking a balance between economy and safety (Verter and Kara 2008).

2.2.2 Current practices in Hong Kong

The transportation of DGs can significantly affect human life and the environment if accidents occur during the transportation process. Hong Kong is a large city with high population density and narrow streets. Due to the land constraints, vehicles carrying DGs inevitably have to pass through densely populated areas or their vicinities. Therefore safe DG transport is of paramount importance.

In Hong Kong, the Dangerous Goods Ordinance (DGO), Cap. 295, Laws of Hong Kong provides for the control on land and at sea of about 400 types of dangerous goods under ten broad categories in accordance with their inherent characteristics, i.e. explosive, flammable, corrosive, toxic, etc. According to the Schedule of Dangerous Goods (Application and Exemption) Regulation, dangerous goods are classified into the following categories (FSD 2004):

Category 1: Explosives and Blasting Agents. (The Authority is the Commissioner of Mines.)

Category 2: Compressed Gases.
Class 1 - Permanent Gases
Class 2 - Liquefied Gases

Class 3 - Dissolved Gases

Category 3: Corrosive Substances.

Category 4: Poisonous Substances.

Class 1 - Substances giving off poisonous gas or vapour

Class 2 - Certain other poisonous substances

Category 5: Substances giving off inflammable vapours.

Class 1 - flash point below 23°C

Class 2 - flash point of or exceeding 23°C but not exceeding 66°C

Class 3 - flash point of or exceeding 66°C (applicable to diesel oils, furnace oils and other fuel oils only)

Division 1 - immiscible with water (applicable to Class 1 & 2 only)

Division 2 - miscible with water (applicable to Class 1 & 2 only)

Category 6: Substances which become dangerous by interaction with water

Category 7: Strong supporters of combustion

Category 8: Readily combustible substances

Category 9: Substances liable to spontaneous combustion

Category 9A: Combustible goods exempted from Sections 6 to 11 of the Ordinance.

Category 10: Other dangerous substances.

In Hong Kong, the DG transportation on land is controlled by relevant authorities. The conveyance of Cat.1, 2 and 5 DGs on road by vehicles is subject to licensing control. Pursuant to the Section 6 of the Ordinance, no person shall convey any Cat. 2 or 5 DGs using any vehicle, provided that a license is granted by the Director of the Fire Services Department (FSD). Cat.1 DG (Explosives) is under the control of the Mines Division of the Civil Engineering and Development Department. It can only be manufactured, transported, or stored as required by the Commissioners of Mines.

Control and licensing aspects of Liquefied Petroleum Gas (LPG) in Cat. 2 are under the jurisdiction of Electrical and Mechanical Services Department (EMSD). The radioactive materials and chemical waste are governed by the Department of Health and the Environmental Protection Department, respectively.

To ensure public and environmental safety, the Government has issued rules and regulations for DG transportation, involving packaging of the material, design and operation of vehicles, training of crew, handling methods, etc. The vehicles used for the conveyance of DGs must comply with the safety standards as required by the Director of Fire Services. The containers and tankers for bulk chemical transportation must be designed, manufactured and tested in accordance to the internationally acceptable standards. A third party inspection body must certify that they have met the stipulated standards before use on Hong Kong roads. While in service, all containers, tankers and vehicles must be properly labeled and carry appropriate hazard warning panels. The carriers are required to put up an adequate emergency response plan describing specific actions that will be taken by the driver or the company's emergency response team in the event of a DG release. All drivers must undergo specific training course and examination, and observe the safety instructions and emergency procedures as stipulated in the document provided by the consignors. DG vehicles must be equipped with adequate stock of emergency equipment, such as chemical fire extinguisher, neutralising agent, adsorbents, oversized drums, protective gears, etc. In case of an incident, the carriers are required to take immediate action and notify the corresponding authorities.

In addition to the these rules and regulations, each DG transport company is also required to advise their drivers to follow major routes and to avoid heavy traffic and densely populated areas as much as possible. DG transportation can only take place between 9:00 am and 5:00 pm from Monday to Saturday, excluding Sundays and public holidays. This is to ensure that there is ample daylight when responding to any incident and that emergency response teams will be readily available. Currently, there are no designated routes for vehicles carrying DGs in Hong Kong. However, under the Road Tunnels (Government) Regulations, vehicles carrying Cat.1, 2 and 5 dangerous goods are forbidden to pass through any tunnels in Hong Kong. Tung Chung Road and South Lantau Road are closed roads. Any vehicle that has to access to these two roads are required to apply for special permits and have to observe special conditions attached to the access permits. In terms of the terrain conditions, roads of steep gradients must be avoided unless in absolutely necessary circumstances.

2.2.3 Quantitative risk assessment

Risk is the primary ingredient that separates DG transportation problems from other transportation problems. The transportation of DGs is generally associated with significant levels of risk. In the context of DG transportation, risk refers to the likelihood of incurring the undesirable consequences of a possible accident (Alp 1995). For example, the release of petrochemical-type of DGs during the transportation process can lead to a variety of serious incidents such as a spill, fire or explosion in the case of flammable liquids or pressure-liquefied gasses. The undesirable consequences of these incidents can be a health effect (death, injury, or long-term effects due to exposure), property loss, an environmental effect (such as soil contamination or health impacts on flora and fauna), an evacuation of nearby population in anticipation of imminent danger, or stoppage of traffic along the impacted route.

Quantitative Risk Assessment (QRA) methods are commonly used to assess the risk of DG transportation. In general, a QRA involves hazard identification, frequency estimation, consequence analysis, and risk calculation. Ang and Briscoe (1989) suggested the following three-stage framework for risk analysis in transportation:

1) Determining the probability of an undesirable event (e.g. an accident involving the release of a dangerous good);
2) Determining the level of potential population and property exposure, given the nature of the event;
3) Estimating the magnitude of consequences (e.g. fatalities, injuries and property damage) given the level of exposure.

Each stage of the process produces one or more probability distributions; two of them (2 and 3) produce conditional distributions, for which statistical records are seldom available. In practice, the above process is seldom carried all the way through

(List *et al.* 1991). Most researchers simplify the analysis by only using the product of the probability of a release accident and the extreme consequence of the accident to estimate the risk, i.e., Risk = Probability × Consequences. The extreme consequence is often represented by the potentially impacted population.

The probability estimates are usually based on accident rates with respect to DG trucks, and the frequency of release sizes given the type of accident. When historical data are unavailable or incomplete, techniques such as fault tree analysis or event tree analysis (Alp 1995) are sometimes used by researchers to derive relevant parameters (Abkowitz *et al.* 1984; Harwood *et al.* 1993; Nicolet-Monnier and Gheorghe 1996). Occasionally, general truck accident rates are simply used to serve as a substitute of such probability. In practice, accident probability of DG transportation is associated with road design characteristics, traffic condition, and random influences of weather condition. Saccomanno and Chan (1985) demonstrated that changes in probability due to the variation in environmental conditions could result in no route being absolutely safe under any circumstances.

For transportation QRA, the common practice is to estimate, a priori, the impact area of a potential accident along each link and to use the number of people living within this area as the consequence measure. The shape and size of an impact area depends not only on the substance being transported but also on other factors such as topography, weather, and wind speed and direction. Different geometric shapes have been used to model the impact area, e.g., a band of fixed width around each route segment (Batta and Chiu 1988; ReVelle *et al.* 1991); a circle with a substance-dependent radius centered at the incident location (Erkut and Verter 1998; Kara *et al.* 2003); and rectangle around the route segment (ALK Associates 1994). The radius of the circle approximation or the bandwidth of the rectangle approximation and the fixed-bandwidth approximation is substance-dependent. But the radius or the bandwidth is assumed to be constant for a given shipment, which means that the approximation does not consider the distance effect on the level of impact. In an airborne dangerous good (e.g., chlorine, propane, and ammonia) accident, however, the concentration of the airborne contaminant varies with distance from the source of accident. It will be lower as the gas disperses with distance and wind. In this case, researchers resort to the Gaussian plume model (Patel and Horowitz 1994;

Chakraborty and Armstrong 1995; Zhang *et al.* 2000) to approximate the impact area with an ellipse shape. The central assumption in all aforementioned models is that each individual within the danger zone will be impacted equally and no one outside of this area will be impacted.

Unlike fixed DG facilities in which DG types, sources, and accident location conditions are all known, risk assessment for DG transportation is carried out on a road network and has the property of uncertainty with reference to the expected location and condition of the accident site. A common approach to transportation risk analysis is to divide a DG route into segments (links) where a parameter can be assumed homogeneous. The total risk along the DG route is then estimated as the sum of the risks of all its constituent segments.

Although numerous models have been proposed to measure the risk of DG transportation along a route (Table 2.3), few of them are specifically designed for high-density living with respect to various risks. In most models, the undesirable consequences of an accident related to DG are mainly expressed in terms of potential injuries and fatalities. In practice, the evaluation of the risk of DG transportation should consider not only the direct damage to individuals and vehicles travelling along the route where the incident occurs, but also the indirect damage to population, properties and environment near the incident location. While most of the prevailing literature focuses on the indirect damage, few of them take into account the direct damage simultaneously. Moreover, the capability of the emergency response has rarely been considered when assessing the risk of DG transportation. Apparently, prompt and efficient response is critical to the minimization of possible catastrophic consequences on human life and the environment in the event of a DG accident, especially in a high-density environment. In order to make a comprehensive risk assessment for DG transportation in high-density living environments, it is imperative to take into account all of these factors and model the associated risks properly.

Table 2.3 Summary of the risk models suggested in the literature for DG transportation risk (adapted from Erkut et al. 2007)

Approach	Model	Sample References
Traditional risk	$\sum_{i=1}^{n(r)} p_i C_i$	Alp 1995 Jin and Batta 1997 US DOT 1994
Expected damage	$\sum_{i=1}^{n(r)} p_i \prod_{j=1}^{i-1} (1-p_j) C_i$	Erkut and Verter 1998
Population exposure	$\sum_{i=1}^{n(r)} C_i$	Batta and Chiu 1988 ReVelle *et al.* 1991
Incident probability	$\sum_{i=1}^{n(r)} p_i$	Saccomanno and Chan 1985 Abkowitz *et al.* 1992 Jin and Batta 1997
Incident probability	$-\sum_{i=1}^{n(r)} \ln(1-p_i)$	Helander and Melachrinoudis 1997
Perceived risk	$\sum_{i=1}^{n(r)} p_i C_i^{\alpha},\ \alpha > 0$	Abkowitz *et al.* 1992
Mean-variance	$\sum_{i=1}^{n(r)} p_i \left(C_i + kC_i^2\right),\ k > 0$	Erkut and Ingolfsson 2000
Expected disutility	$\sum_{i=1}^{n(r)} p_i \left(\exp(kC_i) - 1\right),\ k > 0$	Erkut and Ingolfsson 2000
Maximum population exposure	$\max_{1 \le i \le n(r)} (C_i)$	Erkut and Ingolfsson 2000
Conditional risk	$\sum_{i=1}^{n(r)} p_i C_i \Big/ \sum_{i=1}^{n(r)} p_i$	Sivakumar *et al.* 1995 Jin and Batta 1997 Sherali *et al.* 1997
Demand satisfaction	$\sum_{i=1}^{n(r)} p_i \prod_{j=1}^{i-1} (1-p_j) C_i \Big/ \prod_{i=1}^{n(r)} (1-p_i)$	Erkut and Ingolfsson 2005

Note:

p_i is the incident probability along the ith link of the path comprising $n(r)$ links, and C_i is the population affected by an incident on the ith link.

2.3 Multi-objective route planning for dangerous goods transportation

2.3.1 Multi-objective optimization techniques

DG transportation is a multi-objective problem with stakeholders playing different roles and having different objectives. These objectives are generally conflicting so that a single "best" solution that can optimize every single objective is impossible (Zitzler *et al.* 2003). The solution of such problem is to search for one or a set of "compromise" solutions rendering the best possible tradeoffs for conflict resolution among different objectives. Given the multi-objective nature of the DG routing problem, multi-objective optimization (MOP) thus becomes a sound framework for analysis and decision-making.

In mathematical terms, the multi-objective optimization problem can be generally expressed as follows:

$$\min_{x} \boldsymbol{f}(\boldsymbol{x}) = \left(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x})\right)^T$$
$$s.t. \;\; \boldsymbol{x} \in \mathbf{X} \qquad (2.1)$$

where $f_i(x)$, $i = 1, 2, \ldots, m$ are objective functions, $\boldsymbol{x}$ is vector of the decision variables in the solution space **X** within which all of the points are the feasible solutions for the above MOP, and T is the transpose of the objective function vector.

Relative to single objective optimization problems, MOP solutions are optimal in the sense that the optimal achievement of one objective is often made at the expenses of the others. This kind of optimality is normally termed Pareto optimality in MOP. Non-dominated solutions, also referred to as Pareto optimal solutions, are the optimal solutions for MOP. The set of all non-dominated solutions is usually referred to as the Pareto optimal set. For a given Pareto optimal set, the corresponding objective function values in the objective space are called the Pareto front.

A wide variety of MOP solution methods have been reported in literature. Generally speaking, these methods can be categorized into the preference-based and the generating techniques. The preference-based approaches have been developed to allow decision makers to state their preferences a priori for all the objectives, such as the weighted sum approach (Steuer and Choo 1983), or interactively during the search procedure, e.g. the STEM methods (Benayoun *et al.* 1971) and through achievement functions (Wierzbicki 1980). Usually, the optimization is done by combining multiple objectives into a single overarching objective function. Each objective is assigned a scalar weight accounting for its relative importance to other objectives. By solving the combined single-objective problem, the optimal solution of the original MOP is obtained. Moreover, different solutions can be yielded by varying the weights.

The commonly used preference-based MOP methods include weighted sum approach, goal programming, compromise programming, ε-constraint method, etc. They are summarized as follows:

- *Weighted sum approach*

In this method (Steuer and Choo 1983), each objective is assigned a scalar weight that signifies its relative importance to other objectives. The original multi-objective optimization problem is then turned into optimizing a positively weighted sum of different objective functions, that is,

$$\min \sum_{i=1}^{n} w_i f_i(x), \tag{2.2}$$

where w_is are the weighting coefficients satisfying the conditions, $0 < w_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$.

Weighted sum approach is the simplest and most straightforward MOP technique. However, there are problems using this method when objectives are nonlinear or the set of feasible solutions is not convex. Even for convex multi-objective problems, a uniform variation of the weights can hardly produce an even distribution of points in the efficient set (Das and Dennis 1997). In addition, this technique generally identifies a small subset of the non-dominated solution set as it is impossible to enumerate all weights assignments.

- *Goal programming method (GP)*

Goal programming is another commonly used MOP technique. In this method, the decision-maker sets goals to be attained for each objective and attempts to minimize the deviations of the objective functions from their respective goals. The generalized goal programming method proposed by Ignizio (1976) is adapted to non-linear problems as follows:

$$\min f(x) = \left\{ \sum_{i=1}^{m} w_i \left[d_i^+ + d_i^- \right]^q \right\}^{1/q}, \quad q \ge 1 \tag{2.3}$$

$$s.t.\ \ f_i(x) + d_i^+ - d_i^- = T_i\ ,\qquad i = 1\ ,2\ \ldots\ ,m$$
$$d_i^+\ ,\ d_i^- \geq 0,\qquad i = 1,2,\ldots,m,$$

where d_i^+ and d_i^- are, respectively, the underachievement and over-achievement of the *ith* goal; *T*T_i is the goal (or target) set for the *ith* objective function; w_i, $\sum_{i=1}^{m} w_i = 1$, is the weight provided by a decision-maker, representing the relative preference / importance attached to the *ith* objective; and q is the parameter governing the deviation from the goal (Rao *et al.* 1988).

The use of deviation variables makes the handling of constraints in goal programming flexible and effective. Also this technique has a good conceptual foundation. However, since there is at least one deviation variable associated with each goal, it can be troublesome with larger problems.

- *Compromise programming method (CP)*

Compromise programming is a mathematical programming technique that is used to find a compromise solution amongst a set of conflicting objectives. In essence, the main idea of CP is to identify an ideal solution as a point where each objective achieves its optimum value simultaneously, and to search for a multi-objective solution that is closest to the ideal solution (Zeleny 1982; Ehrgott 2005). Generally, the formation of CP is expressed as:

$$\min_{x \in X}\left(\sum_{i=1}^{m} w_i (f_i(x) - f_i^*)^p\right)^{\frac{1}{p}},\qquad 0 < w_i \leq 1,\ \ \sum_{i=1}^{m} w_i = 1,\ \ \ 1 \leq p \leq \infty, \qquad (2.4)$$

where $f_i(x)$ and f_i^* are the efficient point and the ideal point, respectively; w_i is the weight accounting for the relative importance of the *ith* objective; p is the parameter governing the distance between $f_i(x)$ and f_i^*. p acts as a weight attached to the deviation of a solution from the ideal point reflecting the decision maker's perspective (Romero and Rehman 1989). Although the weights are used as the preference structure when applying CP, it has been mathematically proven that CP is superior to the weighted-sum (WS) method in locating the efficient solutions (Steuer 1986).

- *ε-constraint method*

This method optimizes one of the objective functions while the others are required to have specified upper bounds. In other words, it minimizes the single most important objective function and simultaneously maintains the maximum acceptable levels for the others (Marler and Arora 2004; Ehrgott 2005), that is:

$$\begin{aligned} &\min\ f_i(x), \quad i = 1, 2, \ldots, m \\ &s.t.\ f_j(x) \le \varepsilon_j, \quad j = 1, 2, \ldots, m \text{ and } j \ne i. \end{aligned} \tag{2.5}$$

The selections of $f_i(x)$ and ε_j are not straightforward and depend on the particular problem under consideration. In general, the higher values of ε_j 's mean a wider feasible region for the single objective optimization problem and this may in turn give a more improved solution for $f_i(x)$ at the expense of the other objective functions. As shown in the formulation, the optimization problem (2.5) can be solved for all $f_i(x)$'s (i = 1, 2, ..., m) and the optimal solution that best suits the problem can be chosen among the m solutions. But this involves laborious computational effort.

The MOP methods discussed above have been employed to solve various optimization problems. Although easy to understand, they leave more for decision makers to do if there are too many objectives or the concerned objectives are incommensurable. Moreover, these methods directly generate user-optimal solutions, and only one solution can be obtained at a time.

Different from preference-based techniques, generating approaches attempt to obtain an evenly distributed set of points along the Pareto front, thereby presenting an unbiased structure of all possible trade-offs amongst the competing objectives. Various generating methods have been developed, including weighted sum approaches with weight scanning (Steuer and Choo 1983), and a series of heuristic approaches such as simulating annealing (Suppapitnarm *et al.* 2000), evolutionary programming (Fogel *et al.* 1966), and genetic algorithms (Goldberg *et al.* 1992).

Recently, heuristic generating methods, especially genetic algorithms (GAs), have gained ever-growing acknowledgement and applications (Coello 2000, Mooney and Winstanley 2006). As a highly efficient search strategy for global optimization, GAs exhibit superior performance on solving multi-objective optimization problems that have a large and complex solution space. Moreover, being a population-based approach, a GA is able to find multiple feasible solutions in a single run (Andersson 2000). On the other hand, the main impediment of GAs is that when used in a finite population, GAs tend to converge to a single solution known as genetic drift, thus resulting in a clumping of solutions in objective space (Coello 2000). Moreover, GAs are computational expensive in terms of computation time and memory space required.

Although there are numerous generating methods, few of them can virtually sample a diversified and well-extended Pareto front for a given MOP. Some of these methods also suffer from either an exhaustive computation problem or generating too many solutions to choose from. Motivated by the challenges, Das and Dennis (1998) developed a normal boundary interaction (NBI) method, which can explore both the convex and concave parts of the Pareto front, and produce uniformly distributed solutions. Due to its reliance on equality constraints, however, NBI will converge to local optima for complex, nonlinear problems. In addition to NBI, adaptive methods have also been applied in recent studies. Kim and Weck (2005) suggested using an adaptive weighted sum method to solve the 'concave region' problem. Aiming for a good shape representation of the Pareto front, Zhang and Gao (2006) proposed an adaptive scheme that automatically updates the weights involved in a min–max method. Through a novel bilevel strategy, the tangent and normal directions of the Pareto curve are calculated, and Pareto optimum points can be obtained sequentially with a uniformly spaced distribution. Despite those attempts, the adaptive methods still require further improvement in order to achieve balances between computational efficiency and well distributed solutions.

2.3.2 Vehicle routing with multiple objectives

2.3.2.1 Generating the optimal routes

DG route planning falls into the category of vehicle routing problem, which can be viewed as an extension of the elementary shortest path problem. In graph theory, the shortest path problem is to find a path between two vertices such that the sum of the weights of its constituent edges is minimized. An example is to search for a path linking two nodes of a transportation network with minimum travel cost. There have been extensive studies on the shortest path problem in literature, which provides good insights of the state-of-the-art and various algorithms to generate the optimal solution.

(1) The single objective shortest path

The shortest path (SP) algorithms are initially developed by Bellman (1958) and Dijkstra (1959). Although various improvements have been proposed since the end of 1950s, most of the variants perform the same fundamental operations and only differ in terms of implementation issues such as network storage structure, labeling method and node selection process. As the most well-known and commonly used SP solution method, Dijkstra's algorithm can be summarized as follows:

> Denote $G = (N, A, C)$ as a directed network, where $N = \{1, 2, \ldots, n\}$, $A = \{(i, j) \mid i, j \in N\}$ and $C = \{c_{ij} \mid (i, j) \in A\}$ are the sets of nodes, arcs and arc-travel costs respectively. It is assumed that G does not comprise any cycle with negative cost, and that the costs c_{ij} are additive along the arcs. Let node s be the source node of the path, t be a sink node on that path, and $f(t)$ be the total travel cost of the currently known shortest path between s and t. The recursive step of the algorithm can be put as: finding an arc $(i, j) \in A$ so that the cost $f(i)$ of traveling from node s to node i increased with the cost c_{ij} of travelling along (i, j) is less than the present cost of travelling from s to node j: $f(i) + c_{ij} < f(j)$. If such an arc exists, then node i becomes the predecessor of node j in the shortest path and the procedure resumes, otherwise the present cost of travelling from the origin to node j is the minimum cost.

The above procedure computes a shortest path tree from one source node to all the others in the network. It can also be used for finding costs of shortest paths from a single source node to a single destination node by stopping the algorithm once the shortest path to the destination has been determined.

Cherkassky *et al.* (1996), and Zhan and Noon (1998) tested and discussed the computational efficiency of Dijkstra's algorithm and its various variants. According to their tests, a simplex implementation of Dijkstra's algorithm has complexity of $O(n^2)$, while improvements result in lower complexities to $O(na)$, or $O(a+nlog(n))$, or $O(a+nC_{max})$, where n and a are the number of nodes and arcs in the network, respectively, and C_{max} is the maximum arc cost. In addition, Zhan (1997), and Miller and Shaw (2001) addressed concerns with respect to the network representation and data processing for the use of shortest path algorithms within a geographical information system (GIS). Although there are a wide variety of SP algorithms, no algorithm is absolutely better than another since it is always possible to construct a network "which illustrates the very worst behavior of a particular algorithm" (Van Vliet 1977).

The conventional Dijkstra's shortest path algorithm works under the assumption that travel costs are additive along the links. This leads to the traditional formulation of the shortest path problem:

$$\min\left(\sum_{(i,j)\in A} c_{ij} x_{ij}\right) \tag{2.6}$$

$$s.t. \quad \sum_{(i,j)\in A} x_{ij} - \sum_{(i,j)\in A} x_{ji} = \begin{cases} 1, & if\ i = s, \\ 0, & if\ i \neq s,t, \quad \forall (i,j) \in A \\ -1, & if\ i = t, \end{cases} \tag{2.7}$$

where s and t are the origin and destination of the path, respectively. The constraints (2.7) ensure the flow of DG from origin s to destination t. The binary variable $x_{ij} = 1$ when the link from i to j belongs to the shortest path, and $x_{ij} = 0$ otherwise.

Most algorithms provided in commercial software rely on the dynamic programming theory to solve the shortest path problem. Dynamic programming for the SP problem can be regarded as a special case of Dijkstra's algorithm. The node selection rule is adapted to make use of network connectivity, leading to the recursive problem:

$$f(j) = \min_{\{i\in n \mid i=\pi(j)\}} \left(f(i) + c_{ij}\right) \tag{2.8}$$

and the labeling phase is modified to account for node-related costs. The efficiency of dynamic programming depends on Bellman's principle of optimality, that is, "any optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision" (Bellman 1957). In other words, any sub-path of the optimal route must be optimal, and minimizing the total travel cost can be achieved by recursively minimizing partial travel costs. Over the years, dynamic programming has been used successfully to solve various shortest path problems, including not only standard SP problems, but also some variants with time-varying travel costs (Chabini 1998; Miller-Hooks 2001), stochastic link attributes (Wijeratne *et al.* 1993), and non-linear cost functions (Eiger *et al.* 1985).

(2) The multi-objective shortest path (MOSP)

In the context of DG transportation, the routes must be efficient with respect to a number of criteria. While the carriers are primarily interested in minimizing transportation cost, which may be a function of travel time, travel length, route characteristics etc., public agencies are concerned with minimizing the risk incurred by population, environment and properties along the route. Both travel cost and risk may be expanded or completed with further-detailed objectives.

Replace the single cost c_{ij} of traversing link (i, j) in expression (2.6) by the multi-dimensional attribute $c(i,j) = (c_{ij}^1, c_{ij}^2, ... c_{ij}^m)$, the shortest path problem has now m objectives:

$$\min \quad f(x) = \begin{cases} f_1(x) = \sum\limits_{(i,j)\in A} c_{ij}^1 x_{ij}, \\ f_2(x) = \sum\limits_{(i,j)\in A} c_{ij}^2 x_{ij}, \\ .... \\ f_m(x) = \sum\limits_{(i,j)\in A} c_{ij}^m x_{ij}. \end{cases} \tag{2.9}$$

$$s.t. \sum_{(i,j)\in A} x_{ij} - \sum_{(i,j)\in A} x_{ji} = \begin{cases} 1, & if\ i = s, \\ 0, & if\ i \neq s,t, \quad \forall (i,j) \in A,\ x_{i,j} \in \{0,1\} \\ -1, & if\ i = t, \end{cases} \tag{2.10}$$

As introduced in section 2.3.1, for a multi-objective problem, it is usually difficult if not impossible to identify a single "best" route that can optimize every single objective in MOSP. For example, one route may minimize the number of people at risk, while another route may minimize the accident probability. Due to the multi-objective nature, there are a number of "equivalent" solutions, in the sense that none of them is better than any other with respect to all objectives. These solutions are Pareto optimal or non-dominated solutions for the concerned MOSP.

The Pareto optimal solutions can be generated using multi-objective linear programming (MOLP) techniques or dynamic programming (DP) based algorithms (Current and Marsh 1993). MOLP methods create efficient solutions within reasonable computational time (Evans 1984). However, due to the discrete nature of the variables in MOSP, and the requirement of MOLP that each objective be a linear function of the link attributes, few of MOLP methods work well for MOSP problems. The most successful MOLP example might be the branch-and-bound algorithm (Nemhauser 1994; ReVelle *et al.* 1997). However, the efficiency of such algorithm depends on the order in which the variables are examined. In the worst case, it may come down to a mere enumerative method on a network.

By making use of network connectivity to direct the search towards the optimal solution, dynamic programming methods have proven to be more effective than MOLP in dealing with MOSP problems. For the network defined in subsection 2.3.2.1, DP can be regarded as a particular case of the following generic procedure, which sets the frame for all MOSP algorithms:

- Step 1: Set initial value of $\boldsymbol{f}(t) = \left(f_1(t), f_2(t), \ldots, f_m(t)\right)$, the cost of travelling from source node s to current node t, and $\pi(t)$ the predecessor of node t.
- Step 2: Find an arc $(i, j) \in A$ such that $\boldsymbol{f}(i) + \boldsymbol{c}_{ij}$ is non-dominated. Set $\boldsymbol{f}(j) = \boldsymbol{f}(i) + \boldsymbol{c}_{ij}$ and $\pi(j) = i$, and update the set F_j of non-dominated labels for node j, by adding the new label and removing those that have become dominated.
- Step 3: Repeat step 2 until $f(i) + c_{ij}$ is dominated for every arc $(i, j) \in A$.

The above procedure can be adapted to handle various formations of cost functions (Sancho 1988), such as $f_k(j) = f_k(i) + c_{ij}^k$, $f_k(j) = f_k(i) \times c_{ij}^k$, $f_k(j) = \min\left(f_k(i), c_{ij}^k\right)$, or a combination of these. The generic MOSP algorithm appears similar to Dijkstra's single objective SP algorithm. However, the former keeps in memory all the Pareto-optimal labels, rather than keeping the best label found for each node *j*, because none of the Pareto labels can be deemed better than any other (Daellenbach and De Kluyver, 1980). Moreover, the generic MOSP algorithm retains a certain number of temporary paths based on some preference rules and defers the final choice until further information is available.

Martins (1984) demonstrated that every Pareto-optimal path from origin to destination contains only Pareto-optimal sub-paths from the origin to any intermediate node of the considered path. Hansen (1980) developed several bi-criterion shortest path algorithms, which were further generalized by Martins (1984). There has been a substantial amount of work since these pioneering articles in early 1980s. Most of these work deals with only two objectives, but claims that the solutions can easily be generalized to more than two criteria. Skriver (2000) made a summary of the bi-criterion shortest path algorithms and classifies various techniques into four categories based on the niceties of implementation: *k*-th shortest path, two-phase method, label-setting and label-correcting algorithms. The label-correcting method was found to be most efficient, which confirms the conclusions of Martins and Dos Santos (1999). Gandibleux *et al.* (2006) extended Martins' labeling algorithm by introducing a procedure that can solve the multi-objective shortest path problem with a max-min cost function. Gandibleux *et al.* argued that the number of efficient solutions would increase with the number of objectives considered and the density and size of the network.

The multi-objective shortest path problem is NP-hard (Skriver 2000), which indicates that no algorithm can guarantee to find the set of efficient solutions within polynomial computational time. Moreover, each algorithm has its merits; no algorithm outperforms any other when their performance is averaged over all possible networks (Corne and Knowles 2003).

2.3.2.2 Alternative solutions to the generation of efficient routes

MOSP problems generally have multiple Pareto optimal solutions from which decision makers can choose the most preferred or best compromise solution to implement. However, generating and presenting the entire Pareto set to decision makers may not be efficacious as they will find it difficult to make a selection due to the large number of paths. To address this issue, researchers have proposed various alternative methods. Based on the strategy used for exploring the Pareto set, these methods can be distinguished as three categories:

- methods for identifying the Pareto optimal solution set approximately;
- methods based on utility functions; and
- interactive methods.

(1) Identifying an approximation of Pareto optimal routes

Evolutionary algorithms (EAs) and genetic algorithms (GAs) have seen wide applications to various types of routing problems (Leung *et al*., 1998; Mooney and Winstanley 2006), though few works have appeared applying them directly to multi-objective shortest path problem. Davies and Lingras (2003) implemented a GA-based approach to routing shortest paths in dynamic and stochastic networks where the network information changes over time. Their experimental results show that the proposed GA could find the shortest path and alternative backup paths efficiently. Mooney and Winstanley (2006) proposed an evolutionary algorithm (EA) for multi-criteria path optimization problems. Their results indicate that the EA outperforms the modified Dijkstra approach in terms of execution time and, that the EA converges quickly to the Pareto-optimal paths. Recently, Pangilinan and Janssens (2007) explored the Strength Pareto Evolutionary Algorithm (SPEA) in generating efficient solutions to multi-objective routing problem and described its behavior in terms of diversity of solutions, computational complexity, and optimality of solutions. Base on their experimental results, the authors conclude that the evolutionary algorithm can find diverse solutions in polynomial time and can be an alternative when other methods are trapped by the tractability problem.

Although heuristic methods such as EAs and GAs have not been extensively employed in solving the multi-objective shortest path problem, one may expect this topic to flourish in the near future, as well as the general application of other heuristic algorithms such as taboo search or the ant algorithm.

(2) Generating user-optimal route using utility functions

Unlike heuristic methods which search for approximately optimal solutions without assumptions on the decision-makers' preferences, preference-based methods are developed to allow the decision makers to state their preferences *a priori* or during the search procedure and thus to avoid keeping too many solutions. To model decision-maker's preference structure, one of the commonly used methods is to construct a utility function. The function represents the utility, or disutility, associated with each possible solution and, as such, is characteristic of the decision-maker (Thurston 1991).

The most popular utility function is the weighted sum. A weight w_k is assigned to each objective f_k, reflecting the importance of this particular objective to the decision-maker. By summing all the weighted objectives, the problem is transformed to a single objective:

$$\sum_{k=1}^{m} w_k f_k, \qquad 0 < w_t \le 1, \ \sum_{t=l}^{m} w_t = 1, \tag{2.11}$$

which has the advantage of remaining linear across links. This property ensures that Bellman's principle of optimality holds with the weighted sum function. Given a set of weights (w_1 ,w_2 ,...,w_m), an optimal route can be identified using a standard shortest path algorithm. Varying the weights would yield different efficient solutions for the concerned MOSP problem (White 1982).

The utility function commonly used in compromising programming is considered to be more general (Chen *et al.* 1999; Zhang 2003), which measures the "closeness" of a feasible solution $f_k(x)$ to the ideal solution f_k^0, under the preference structure provided by a decision-maker:

$$U(p,w) = \left(\sum_{k=1}^{m} w_k (f_k(x) - f_k^0)^p \right)^{1/p}, \qquad w_k > 0, \quad 1 \le p \le \infty. \tag{2.12}$$

Paixão *et al.* (2003) proposed to use the Euclidian norm (i.e. p = 2) as a better objective function, arguing that it allows minimizing every individual objective simultaneously. As Bellman's optimality principle does not hold, Paixão *et al.*

employed a labeling algorithm similar to that of the multi-objective shortest path. Wakuta (2001) adopted a novel approach to a MOSP problem by formulating it as a Markov decision process. Instead of finding the route that optimizes a certain utility function, Wakuta explored a set of policies that facilitate moving from one node to another, which ultimately yield some Pareto-optimal paths from origin to destination.

(3) Interactive selection of the optimal route

Given that decision makers may find it difficult to state their preferences before they have an explicit conception of the actual trade-offs involved (Zionts and Wallenius 1983), interactive methods were proposed to search for efficient routes. These methods are based on a direct interaction with decision makers. During the process of interaction, decision makers indicate their preferences in various forms. The algorithms find the non-dominated solutions that best correspond to the decision maker's preferences. Since the search of the Pareto-optimal solutions is limited in the search space "bounded" by decision maker's preferences, interactive methods are computationally efficient.

Current *et al.* (1990) proposed an interactive approach to solving the bi-objective shortest path problem. This method is characterized by two phases: while the first phase aims to provide a decision maker with an approximation of the possible trade-offs, the second phase settles the constrained shortest path problem under the decision maker's preference structure. Similar approaches have been reported by Climaco and Coutinho-Rodrigues (1988), and Coutinho-Rodrigues *et al.* (1994), in which the search of Pareto-optimal paths inside the duality gap (i.e. non-convex part of the Pareto frontier) was done by using a *k*-shortest path algorithm. As shown by Coutinho-Rodrigues *et al.* (1999), interactive methods based on the *k*-shortest path algorithm are more efficient than the method proposed by Current *et al.* (1990).

Murthy and Olson (1999) presented an interactive procedure to solve the bi-criterion shortest path problems by making use of the concept of domination cones. The decision maker's implicit utility function is assumed to be quasi-concave and non-increasing. Based on decision maker's pairwise comparisons of the trade-offs between two criteria, domination cones are developed, which help reduce the number of Pareto-optimal solutions. Granat and Guerriero (2003) developed a different interactive approach to multi-objective shortest path problem. Each step requires decision-makers to define the desired attributes and some trade-off weights accounting for the preferences. The algorithm then moves from the current solution towards the target ideal path by maximizing a predefined achievement scalarizing function.

Despite the expected advantage of converging directly to the user-optimal routes, interactive methods suffer some weaknesses. For an unacquainted user (decision maker), the decisions taken at similar steps may be inconsistent, which is likely to destroy the convergence of the algorithm. Moreover, interactive methods may not outperform other techniques in terms of computation time. In practice, finding a subset of Pareto optimal paths in a given region of the objective space is usually as difficult as collecting all of them, because they are encountered during the run of a generating algorithm.

2.3.3 Optimal route planning for dangerous goods transportation

A large body of literature has addressed the problem of DG routing with the aim of optimizing several objectives. However, most studies primarily focus on the physical modeling of the problem (definition of the various objectives, analysis of the trade-offs between alternative routes) and rely on simplistic MOP solution methods to calculate the optimal route.

Saccomanno and Chan (1985) examined three different routing policies separately: minimizing the operating costs, minimizing the probability of an accident, and minimizing the expected damage resulting from an accident. Each problem was solved using a single-objective shortest path tree algorithm. The three routes obtained were found to be significantly different, indicating that HAZMAT transportation involves conflicting objectives that cannot be optimized simultaneously. Robbins (1981) reported similar findings, demonstrating that compared with the route with the shortest travel distance, the route involving minimum population can significantly reduce the number of people affected by DG incidents.

DG route planning has been a popular area of research in the United States. The Office of Highway Safety under Federal Highway Administration is responsible for the regulation of routing procedures for HAZMAT transportation. Its publication (US DOT 1994) outlines the routing process involving HAZMATs. In addition to the population exposed, this guide also identifies factors such as the existence of public facilities, e.g. schools, hospitals, fire stations and reservoirs, which may affect the decision on the choice among alternative routes whose risks may otherwise be similar. The guide also states that the evaluation of plausible burden on commerce is an essential part of the selection process. In addition, the level of service of the highway collectively affects travel time, travel speed, safety and the probability of release accidents.

In their analysis, Turnquist and List (1993) focused on the aforementioned factors including operating cost, accident rate, population exposed and the number of schools in the exposure area. They concurred that multiple objectives must be incorporated into the analysis, and argued that the existence of multiple criteria meant that it is usually impossible to identify a single best route between given origin and destination. Consequently, the focus should be on finding a set of non-inferior routes which explicitly represent the trade-offs among criteria.

In the early stage, the classic shortest path routing was applied in most DG transportation problems (Joy *et al.* 1981; Abkowitz and Cheng 1988). Batta and Chiu (1988), and Chin and Cheung (1989) suggested a similar method to find a path that minimizes the weighted sum of lengths that an obnoxious unit travels over a network within a given threshold distance from the population centers and a bandwidth along a route. Gopalan *et al.* (1990), Linder *et al.* (1991), and List and Mirchandani (1991) developed models taking into account the risk equity among the generated routes. ReVelle *et al.* (1991) used a weighted combination of cost and population exposure to find routes for transporting radioactively contaminated fuel waste. Patel and Horowitz (1994), and Karkazis and Boffey (1995) studied the effects of weather systems on the routing of dangerous goods. Erkut and Verter (1995) estimated the expected number of people that would face the consequences of a possible DG related incident.

Miller-Hooks and Mahmassani (1998) proposed a specific model for optimal routing of hazardous substances in stochastic, time-varying networks. Different catastrophe avoidance models were discussed in Erkut and Ingolfsson (2000, 2005), and most of them could be reduced to a standard shortest path problem. Kara and Verter (2004), and Erkut and Gzara (2008) developed bilevel models for the network design problem with the focus on the relationship between DG regulators and the carriers. A similar problem was also addressed by Verter and Kara (2008), however, as a path-based formulation incorporating the regulator's risk concerns and the carriers' cost concerns.

The development of Geographical Information Systems (GIS) have provided DG routing with realistic means to accurately estimate the travel cost and risk, as well as vividly visualize the proposed routes. Lepofsky and Abkowitz (1993) demonstrated that GIS can be used to integrate plume representation with population data and transport maps to more effectively estimate consequences. Using combinations of routing criteria (e.g. population exposure, accident likelihood and environmentally sensitive areas) in a single analysis with varying weights on their importance, one can examine the trade-offs among various alternatives. Zhang *et al.* (2000) used GIS to assess the risks of transporting airborne contaminants (such as ammonia and chlorine) in networks. The dispersion of the airborne contaminants was modeled using a Gaussian Plume model. The probability of an undesirable consequence (such as injury, illness, or death) was modeled as a function of contaminant concentration. The risk imposed on population was estimated as the product of this probability and the population affected. The risk value was obtained by combining concentration mathematically with the population distribution by means of traditional raster GIS overlay techniques. Brainard *et al.* (1996) employed GIS to route aqueous waste cargoes with four methods: (1) routing by shortest time only; (2) routing by motorway and dual-carriageway encouragement; (3) routing to avoid population exposure; and (4) routing to avoid accidents. The first two methods were used to identify the most probable routes used by tanker drivers to deliver their consignments. The next two methods were used to analyze risk-reducing scenarios. Huang *et al.* (2004) explored a novel approach to evaluating the risk of HAZMAT transportation by integrating GIS and genetic algorithms (GAs). GIS was used to quantify the specified routing criteria, and GA was applied to efficiently determine the weights of the factors involved in route choice. Using weighted combination of routing criteria (e.g. population exposure, accident likelihood and environmentally sensitive areas) in a single analysis, one can compute the generalized cost of the possible routes and examine the trade-offs among various alternatives.

With the advances in DG routing studies, more problems have been considered, e.g., scheduling of shipments (Nozick *et al.* 1997; Erkut and Alp 2007) and facility location (ReVelle *et al.* 1991; Helander and Melachrinoudis 1997). The scheduling problem arises when considering that link attributes may vary significantly over time. For instance, at night, travel time is usually shorter because there is less traffic, yet accident rate may be higher. The optimal routing/scheduling can be formulated as a dynamic MOSP problem, and solved using a modified shortest path algorithm under some assumptions (Chabini 1998). On the other hand, the facility location problem combined with DG routing arises when planning new dangerous facilities (e.g., a waste disposal site). In this problem, the origin and/or the destination of shipments are not fixed and DG routing is only considered as a sub-problem.

Despite the extensive research that has been done on DG routing analysis, only a few have addressed the multi-objective nature of the DG routing problem using an appropriate multi-objective optimization method. Vigorous multi-objective optimization methods are seldom employed to seek optimal routes for DG transportation based on the results of risk assessment. The weighted sum (WS) approach is most commonly used in DG route planning. Although it is the simplest and most straightforward MOP technique, this method may be problematic when objectives are nonlinear or the set of feasible solutions is not convex. Even for convex multi-objective problems, a uniform variation of the weights can hardly produce an even distribution of points in the efficient set (Das and Dennis 1997). To overcome the drawbacks of conventional MOP methods, high performance MOP methods need to be developed to optimize the routes for efficient and safe DG transportation.

2.4 Summary

The transportation of dangerous goods can significantly affect human life and the environment if accidents occur during the transportation process. Such accidents can result in traffic disruption, fatalities, injuries, emergency evacuation, property and environmental damages, etc. Therefore, safe DG transportation is of paramount importance, especially in high-density-living environments.

Decisions regarding DG transportation are difficult to make because of its catastrophic consequence and public sensitivity. This makes it important to carefully study such risks for strategic decision-making. In the context of DG transportation, risk refers to the likelihood of incurring the undesirable consequences of a possible accident. Quantitative risk assessment (QRA) methods are commonly used to assess the DG risk during transportation. The common feature of all QRA approaches is that a risk indicator is composed of the probability of some undesirable events and the possible adverse consequences. The probability estimates are usually based on the accident rates with respect to DG trucks and the frequency of release sizes given the type of accident. The estimation of the unfavorable consequences is primarily focused on the expected damage to the population, properties, and environment near the incident location, while the direct damage to individuals and vehicles travelling along the route where the incident occurs are seldom considered simultaneously. Moreover, the capability of emergency response in the event of a DG accident is rarely included into the risk estimation. To make an effective risk assessment for DG transportation in high-density living environments, it is essential to take into account all of these factors and model the associated risks appropriately.

DG transportation is a multi-objective problem with stakeholders playing different roles and having different objectives. These objectives are generally conflicting so that a single "best" solution that can optimize every single objective is impossible. The solution of such problem is to search for one or a set of "compromise" solutions rendering the best possible trade-offs for conflict resolution among different objectives. Given the multi-objective nature of the DG routing problem, multi-objective optimization thus becomes a sound framework for analysis and decision-making. Extensive research has been done on DG routing with the intent of optimizing several objectives. However, only a few have addressed the multi-objective nature of such problem using an appropriate multi-objective optimization method. Vigorous MOP methods are seldom employed to seek optimal routes for DG transportation based on the results of risk assessment. Undoubtedly, high performance optimization techniques are of utmost importance to effective DG routing, particularly in high-density environments. It is instrumental to generate several efficient routes representing the inherent trade-offs among different objectives for decision-makers to choose the one that gives the best compromise among the conflicting objectives. And this will be the major objective of this research.

CHAPTER 3: DETERMINISTIC MULTI-OBJECTIVE PATH OPTIMIZATION

This chapter and Chapter 4 introduce different multi-objective optimization methodologies proposed in this study. This chapter is focused on the deterministic multi-objective path optimization techniques, and a heuristic method will be discussed in Chapter 4. The present chapter begins with an introduction on the multi-objective shortest path problem that underlies the optimal route planning for DG transportation, followed by the concept of Pareto optimality, an important notion in the multi-objective problems. The weighted sum of objective functions is discussed since it is the simplest and most straightforward multi-objective optimization technique. In the second part of this chapter, compromising programming (CP), a mathematical programming technique for finding a compromise solution amongst a set of conflicting objectives, is described in detail, with specific discussion on the utility functions that are commonly employed in CP. The construction of criteria weights is then described, with an emphasis on the analytical hierarchy process (AHP). The procedure of multi-objective DG route planning based on compromise programming is specified. To avoid the pitfalls of preference-based techniques, an adaptive weighting method for multi-objective route planning is proposed in addition to the CP approach. In the third part of this chapter, a framework of this approach to explore the Pareto front is presented, followed by the procedure of approximating such a front. The implementation issues are also specified.

3.1 Multi-objective path optimization

3.1.1 Multi-objective shortest path problem

As one of the major components of network routing problems, the shortest path problem arises in a wide variety of practical problem settings, either as a stand-alone model or as a sub-problem in more complex problem settings. Being an extension of the conventional shortest path problem, the multi-objective shortest path problem (MOSP) is concerned with finding a set of efficient paths with respect to multiple objectives (e.g. the problem of finding efficient routes in transportation planning that simultaneously minimize travel cost, path length, and travel time). In general, the objectives in a MOSP are conflicting with each other. For example, minimizing route changes may require longer journey time; while minimizing overall journey time may lead to multiple route changes. Hence, optimizing a MOSP with respect to a single objective often results in unacceptable results with respect to the other objectives. It is therefore almost impossible to generate a perfect multi-objective solution that simultaneously optimizes each objective function. A reasonable solution to a MOSP is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by another solution.

Denote $G = (N, A, C)$ as a directed network, where $N = \{1, 2,\ldots, n\}$, $A = \{(i, j) \mid i, j \in N\}$ and $C = \{ c_{ij}^k \mid k = 1, \ldots, m \text{ and } (i, j) \in A\}$ are the sets of nodes, arcs (edges), and *m-dimensional* arc costs, respectively. Each arc belonging to A is associated with a cost vector $\boldsymbol{c}_{ij} = (c_{ij}^1, c_{ij}^2, \ldots c_{ij}^m)$. It is assumed that G does not comprise any cycles with negative cost, and that the costs c_{ij}^k are additive along the arcs. Given a source node s and a destination node t, a path R is a sequence of nodes and arcs from s to t. The cost vector $\boldsymbol{c}$ for linear functions of path R is the sum of the cost vectors of its arcs, that is $\boldsymbol{c} = \sum_{(i,j)\in A} \boldsymbol{c}_{ij}$. Multi-objective shortest path problem requires one to find a simple path between s and t such that the cost of this path is minimized over all valid paths. A simple path is a path between two fixed nodes that does not contain any loops or repeated edges. MOSP can be formulated as follows:

$$\min \ \boldsymbol{f}(x) = \begin{cases} f_1(x) = \sum_{(i,j)\in A} c_{ij}^1 x_{ij}, \\ f_2(x) = \sum_{(i,j)\in A} c_{ij}^2 x_{ij}, \\ \ldots \\ f_m(x) = \sum_{(i,j)\in A} c_{ij}^m x_{ij}. \end{cases} \tag{3.1}$$

$$s.t. \sum_{(i,j)\in A} x_{ij} - \sum_{(i,j)\in A} x_{ji} = \begin{cases} 1, & \text{if } i = s, \\ 0, & \text{if } i \neq s, t, \\ -1, & \text{if } i = t, \end{cases} \tag{3.2}$$

$$x_{ij} = \begin{cases} 1, & \text{if arc } (i, j) \text{ belongs to the shortest path,} \\ 0, & \text{otherwise,} \end{cases} \qquad \forall\, arcs\, (i, j) \in A. \tag{3.3}$$

MOSP specifies that no path will contain loops and each path considered must have the same source s and destination t. Each incoming edge of a node on a path must be matched by an outgoing edge on that path except for nodes s and t (as in equation (3.3)). All valid paths have the form $\{s, p_1, p_2, \ldots p_k, t\}$ where $p_1, p_2, \ldots p_k$ represent the nodes included in the path, except for the source s and destination t.

The transportation of DGs involves multiple stakeholders such as shippers, carriers, consignees, and government agencies; each playing a different role in safely moving DG from the origins to the destinations over a transportation network. Moreover, different stakeholders usually have different priorities and perspectives on DG transportation. The carriers are primarily interested in minimizing transportation cost, which may be a function of travel time, travel length, and route characteristics, etc.; while government agencies are concerned with minimizing the risk incurred by population, environment and properties along the route. Both travel cost and exposure risk can be expanded or completed with further-detailed objectives. Therefore, DG transportation is a typical multi-stakeholder and multi-objective problem which is generally complicated to solve.

Optimal route planning for DG transportation can be treated as a MOSP in search of efficient routes that simultaneously minimize several objectives such as travel cost and exposure risk. The concept of optimization in such a MOSP is generally different from the single-objective shortest path problem, where the task is to find a path that minimizes a single objective function, i.e. travel distance. For MOSPs involving multiple conflicting objectives, a unique solution optimizing all the objectives simultaneously is hardly a realistic possibility (Zitzler *et al.* 2003). It is therefore preferable to concentrate on finding routing paths that are near optimal, or display the best trade-offs among the objectives considered. In other words, the ultimate goal is to search for Pareto-optimal paths.

3.1.2 Pareto optimality and utility functions

3.1.2.1 Pareto optimality

Consider the following multi-objective optimization problem (MOP):

$$\min_{x} f(x) = (f_1(x), f_2(x), \ldots, f_m(x))^T$$
$$s.t. \ \ x \in \mathbf{X} \qquad (3.4)$$

where $f_i(x)$, $i = 1, 2, \ldots, m$ are objective functions, x is vector of the decision variables in the solution space **X** within which all of the points are the feasible solutions for the above MOP, and T is the transpose of the objective function vector.

Relative to single objective optimization problems, MOP solutions are optimal in the sense that in general no single solution minimizes every $f_i(x)$ at the same time. The optimal achievement of one objective is often made at the expenses of the others. This kind of optimality is normally termed Pareto optimality in MOP. Non-dominated solutions, also referred to as non-inferior or Pareto optimal solutions, are the optimal solutions for MOP. Instead of a unique solution to the problem, the solutions to a multi-objective problem are a set of Pareto points. The set of all non-dominated solutions in the solution space is referred to as the Pareto-optimal set, and for a given Pareto-optimal set, the corresponding objective function values in the objective space are called the Pareto front. Figure 3.1 presents an example of a Pareto frontier. Each point represents a feasible solution, and smaller values are preferred to larger ones. Point C is not on the Pareto frontier because it is dominated by both point A and point B. Points A and B are not strictly dominated by any other, and hence both of them are Pareto optimal solutions and lie on the frontier.

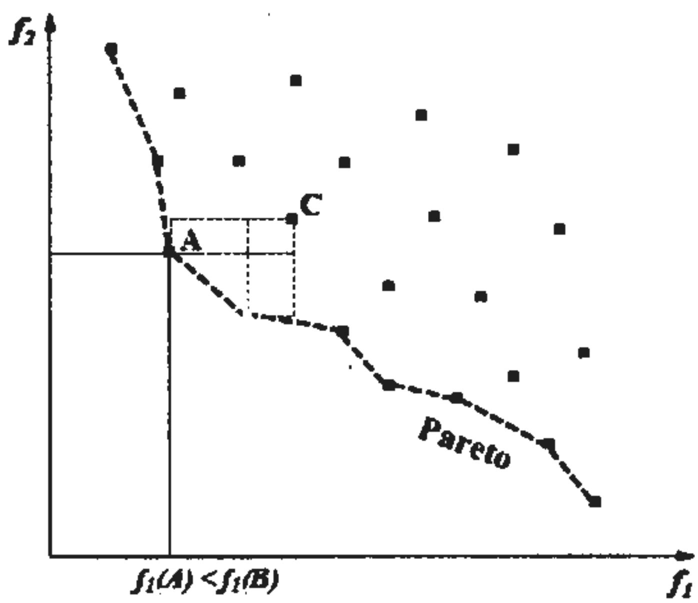


Figure 3.1 An example of Pareto frontier

Multi-objective shortest path problem is one of the core problems in the area of multi-objective optimization (Ehrgott 2005; Ehrgott and Gandibleux 2002) with numerous applications. The objectives in a MOSP are generally conflicting. Thus, unless a well-defined utility function exists, there is no single optimal solution but rather a set of non-dominated or non-inferior solutions from which a best compromise solution can be selected. Denote $R_p = (r_p^1,...,r_p^m)$ and $R_q = (r_q^1,...,r_q^m)$ as two feasible routing paths between the given origin and destination nodes, where r_p^i and r_q^i, $i = 1,...m$, are the i^{th} objective value for R_p the R_q respectively, m is the number of objective. Route R_p dominates route R_q if and only if $f_k(R_p) \le f_k(R_q)$ for $k = 1,...,m$ and $f_k(R_p) < f_k(R_q)$ for at least one objective function, which indicates that route R_p is always better than or equivalent to route R_q, and it is strictly better with respect to at least one objective. On the other hand, R_q is Pareto-optimal if it is not dominated by any other routes in the solution space, that is, for all routes R_p, $f_k(R_q) \le f_k(R_p)$ $k = 1,...,m$ and $f_k(R_q) < f_k(R_p)$ for at least one k. In addition, R_q is said to be weakly Pareto-optimal if there is no other feasible solution R_p such that $f_k(R_p) < f_k(R_q)$ for $k = 1,...,m$. It should be noted that if two routes weakly dominate each other, i.e. $f_k(R_p) \le f_k(R_q)$ and $f_k(R_q) \le f_k(R_p)$, $k = 1,...,m$, their vectors of attributes (objective function values) are equal, but nothing guarantees that they are identical.

Figure 3.2 provides a graphical interpretation of Pareto-optimal and weakly Pareto-optimal solution, as well as dominance relations. R_1, R_2, and R_3 are three optimal solutions (i.e. routing paths) to a MOSP with two objectives: R_1 = {12, 38}, R_2 = {40, 38}, R_3 = {52, 10}. The solutions R_1 and R_3 are non-dominated or Pareto-optimal, while R_2 is weakly Pareto-optimal. The other solutions are feasible, but they are dominated by R_1, R_2, and R_3.

According to the definition of Pareto optimality, moving from one Pareto optimal solution to another necessitates trade-off. A trade-off reflects the ratio of change in the values of the objective functions concerning the increment of one objective function that occurs when the value of some other objective function decreases.

Under the concept of Pareto optimality, the efficient solutions to a MOSP are equivalent: a gain in one objective is at the cost of another. The globally optimal solution to a MOSP with conflicting objectives rarely, if ever, exists. Weakly Pareto-optimal solutions, on the other hand, are also of importance for MOSP (Minami 1983). Although they do not strictly optimize any objective, they offer interesting trade-offs among the multiple objectives to decision makers, who can then keep or discard such solutions by comparing them with the genuine Pareto optimal.

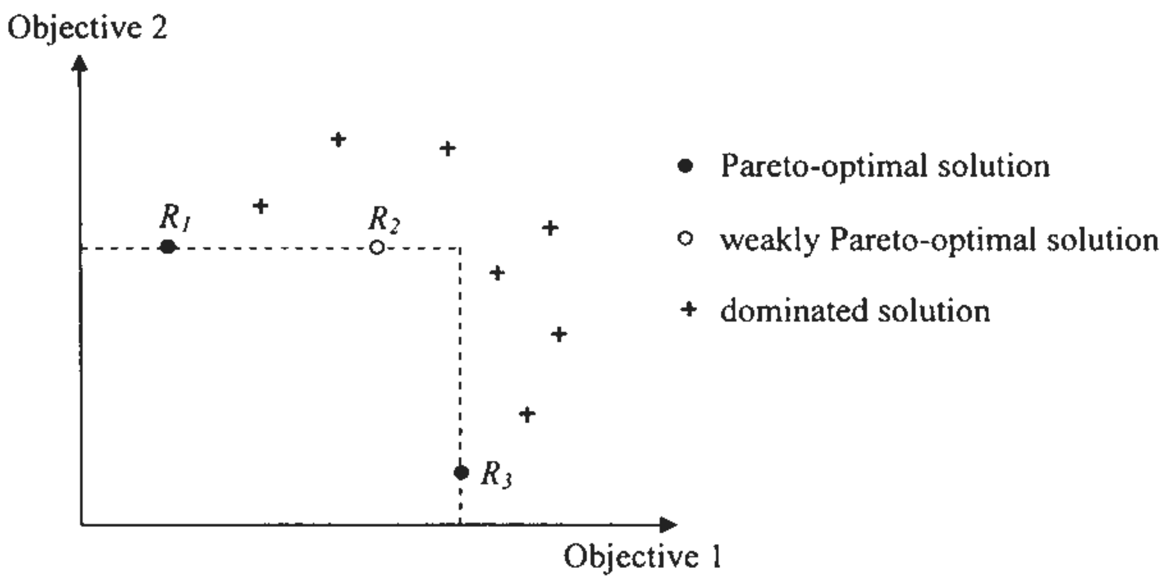


Figure 3.2 An example of Pareto-optimal and weakly Pareto-optimal solutions

3.1.2.2 Utility function

As a multi-objective optimization problem, or specifically a MOSP, route planning for DG transportation usually has several feasible solutions. These solutions render various possible trade-offs for conflict resolution among different objectives. None of them can be deemed absolutely better than another. As long as no objective is preferred to the others, all Pareto optimal paths are possible solutions to the MOSP concerned.

In practice, a decision-maker is not indifferent to all the objectives. Even if he/she does not feel comfortable ranking the objectives or stating preferences numerically (e.g. objective A is twice as important as objective B), the decision-maker is assumed to have an explicit or implicit function which reflects his /her preferences for different objectives (Henig 1985). This underlying function maps the attributes of the feasible solutions onto scalar values with the preference of each attribute determined by the decision-maker (Keeney and Raiffa 1976). According to utility theory (Thurston 1991), the overall performance of a solution can be represented by a multi-attribute utility function which incorporates consideration of attributes that cannot be directly converted to a common metric. Once the utility function is formulated, the optimization problem is formulated accordingly to optimize that utility. If the utility function properly captures how the decision-maker values a solution, an optimization of the utility would yield the best solution in respect to the decision-maker. In light of this, selecting the best route from the user's perspective comes down to optimizing the utility function over a set of feasible paths. There are generally two ways to achieve this: (1) to directly generate the solution that yields maximum utility (preference-based techniques); (2) to generate a subset of Pareto-optimal solutions, and then maximize the utility function value over this subset (generating techniques).

In general, decision making is formulated in terms of maximizing a utility function $U(x)$. In a traditional transportation problem, however, decision making is formulated in terms of minimization, i.e. to select a route with the smallest travel time. Thus, when applying the decision making theory to transportation problems, these problems are reformulated in terms of a disutility function $u(x) = -U(x)$. In other words, selecting the route with the maximum of utility U is equivalent to selecting the route with the minimum of disutility u. In this research, the word "utility function" is used in order to follow the principles of the decision making theory, but the discussion applies to disutility function as well.

As mentioned above, finding the Pareto-optimal paths can be achieved by optimizing the utility function directly, on condition that the preferences for different objectives are defined a priori by a decision-maker. The preference is used as the weight of each concerned objective. The multiple weighted objectives are meaningfully combined to form a dimensionless overarching objective function, which expresses the goodness of a particular solution. In this way, the MOSP is transformed to a single-objective shortest path problem. By solving this aggregated single-objective problem, the optimal path of the original MOSP is eventually identified. Furthermore, different Pareto-optimal paths can be yielded by varying the weights.

When solving a multi-objective optimization problem by means of preference-based techniques, the utility function is commonly used to model decision-maker's preference structure about the objectives involved. Different utility functions have been formulated. The weighted sum is probably the most popular and straightforward utility function. In this method, each objective is assigned a scalar weight accounting for its relative importance to other objectives. The original multi-objective optimization problem is then turned into optimizing a positively weighted sum of different objective functions. More complicated utility functions allow non-linear combinations of multiple objectives (Cook 1997; De Weck 2004). Most of these functions are monotonic utility functions, within which monotonically increasing or decreasing relationships between an objective and its corresponding utility are captured by larger-is-better or smaller-is-better relationships. Non-monotonic utility functions to capture periodic utilities also exist. However, those are special cases that are encountered infrequently in practice. Once the utility function for the current multi-objective problem is constructed, optimization can be conducted and the solution with maximal utility can be found. Here the weights indicating the preferences for different objectives are interpreted as control parameters. Through changing these parameters in the utility function systematically, non-dominated solutions can be found one by one.

3.1.3 A natural and self-explanatory approach – weighted sum of objective functions

Multi-objective shortest path problem can be solved using preference-based optimization techniques. Given the pre-defined preferences, different objectives are aggregated into a single objective. By solving this combined single-objective shortest problem, the Pareto-optimal paths for the original MOSP can be obtained.

There are many methods that can sum up the multiple attributes of a given route into a single scalar function. Such a function represents the utility, or disutility, associated with each possible path characterized by a decision maker. A very popular approach for converting a multi-objective problem into a single-objective problem is to minimize the positively weighted convex sum of different objectives. A coefficient, or weight, w_i is assigned to each objective f_i, reflecting the importance of this particular objective to the decision-maker. By summing all the weighted objectives, the multi-objective problem is transformed to a single objective formulation:

$$u(f(x)) = \sum_{k=1}^{m} w_k f_k(x),$$

$$s.t.\ \ w_k \geq 0,\ \ \sum_{k=1}^{m} w_k = 1. \tag{3.5}$$

Minimizing the original multiple objective functions is then equivalent to minimizing the utility function (3.5). It follows immediately that the global minimizer x^* of the above problem is a Pareto optimal point for the original multi-objective optimization problem, since if not, then there must exist a feasible x which improves at least one of the (positively weighted) objectives without downgrading other objectives and hence produces a smaller value of the weighted sum.

The weighted sum method is often considered as a naïve and simplistic approach to solving multi-objective optimization problems. However, it combines all the objectives in a single estimator where each weighting coefficient indicates the relative importance of this particular objective to the decision-maker. This renders the procedures of searching for feasible solutions much simpler. The simplicity of the weighted sum approach makes it convenient to use, especially in a situation where clarity is very important. Being natural and easily understandable, this approach can assist a decision-maker in explaining the decision process and clarifying the trade-offs in his/her decisions when confronting with dissenting views.

From the computational point of view, the weighted sum approach is very efficient in solving a multi-objective shortest path problem. Recall that the recursive step of a standard shortest path algorithm (Gallo and Pallottino 1988) can be put as follows: finding an arc $(i, j) \in A$ so that the cost $f(i)$ of traveling from the origin to node i increased with the cost c_{ij} of travelling along (i,j) is less than the present cost of travelling from the origin to node j: $f(i) + c_{ij} < f(j)$. If such an arc exists, then node i becomes the predecessor of node j in the shortest path and the procedure resumes; otherwise the present cost of travelling from the origin to node j is the minimum cost.

In case of multi-dimensional link attributes, the cost of travelling along arc (i, j) is not the value of any single attribute c_{ij}, but the m-dimensional attribute vector $\boldsymbol{c}_{ij}$, $\boldsymbol{c}_{ij} = (c_{ij}^1, c_{ij}^2, ... c_{ij}^m)$. The current Pareto-optimal paths from the origin to any node j are collected in a set F_j. The recursive step selects a node i and, for each path in F_i, compares the vector $\boldsymbol{f}(i) + \boldsymbol{c}_{ij}$ with the attributes $\boldsymbol{f}(j)$ of the paths in F_j. If this vector is eventually non-dominated, i.e., $\boldsymbol{f}(i) + \boldsymbol{c}_{ij} < \boldsymbol{f}(j)$ holds for at least one attribute, the corresponding path is added to F_j and the set of Pareto-optimal paths is updated by removing the paths from the origin to j that have become dominated.

The computational cost of the above procedure stems from the numerous comparisons that are required to determine whether the new path should be put into F_j or not. For m-dimensional attributes, such comparisons need to be performed m times for each recursive step, which is computationally expensive in terms of both time and memory. By assigning weights to each objective and combining multiple objectives into a single one through the utility function in the form of a weighted sum of objective functions, the MOSP in question collapses to a single-objective shortest path problem. As a result, the size of F_j is reduced from multiple elements (i.e. m attributes) to one single element, and the number of comparisons is limited to one at every step. The Pareto-optimal paths can then be identified by minimizing the weighted sum utility function through the conventional shortest path algorithm.

3.1.4 Limitations of the weighted sum method

The weighted sum approach has been successful in solving multi-objective shortest path problems throughout the years. Finding the Pareto-optimal paths for a MOSP is of NP-hard difficulty (Skriver and Andersen 2000), which means that no algorithm can guarantee finding the set of efficient solutions within polynomial computational time. However, it becomes easier by optimizing directly the disutility function in the weighted sum form. Through combining the weighted objectives linearly, the MOSP comes down to a single-objective problem, which is solvable in polynomial time (Cherkassky *et al.* 1996). Minimization of this disutility function yields a path that is non-dominated (Miettinen 1999). Varying the weight values, the weighted sum method can generate different Pareto-optimal paths.

However, the weighted sum method is known to have limitations in its applications (Athan and Papalambros 1996; Das and Dennis 1997). First, although there are many methods to determine the weights, such as point allocation, ranking method, and pairwise comparison, a satisfactory *a priori* selection of weights does not necessarily guarantee that the final solution be acceptable. One may have to resolve the problem with new weights. It would be more adequate to define the weights as functions of the original objectives rather than constants in order for a weighted sum formulation to model a decision-maker's preference structure accurately (Messac 1996).

The second problem with the weighted sum approach is that it is impossible to obtain points on non-convex portions of the Pareto optimal set in the objective space (Das and Dennis 1997; Messac *et al.* 2000). Due to the linear form of the scalarized objective function in the objective space, it can only be used to capture the Pareto optimal points located in the convex part of the Pareto optimum curve and will fail when such points fall within the non-convex parts of the Pareto set. In other words, not every Pareto solution can be found by solving the weighted sum utility function; there may not exist a weight w such that a given Pareto point can be found by solving the weighted sum utility function. Figure 3.3 shows the efficient set (frontier) of a bi-objective minimization problem in the objective space. The solutions obtained by solving the weighted sum utility function can be geometrically identified as the points of contact between the curve (Pareto frontier) and the tangent line of the curve that is perpendicular to the vector $\boldsymbol{w}$. This figure shows that the weighted sum approach may fail to generate the efficient solutions located on the arc between points A and B, since for some vectors $\boldsymbol{w} \geq 0$, it could achieve a smaller weighted sum value on the tangent line of the Pareto curve outside of the arc rather than at any point along that arc.

Similarly, in a MOSP, not all the Pareto-optimal paths can be generated by optimizing a weighted sum of objective functions. It is possible to find some non-dominated paths that do not minimize the sum of weighted cost for any given set of weights. Figure 3.4 shows an example.

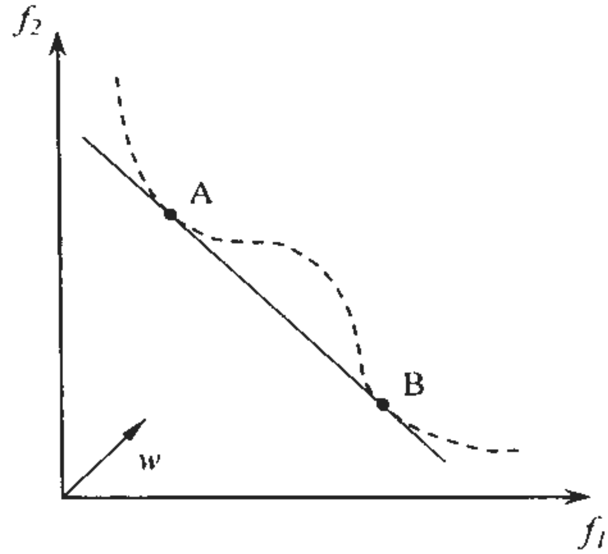


Figure 3.3 Generating Pareto-optimal solutions by the weighted sum approach

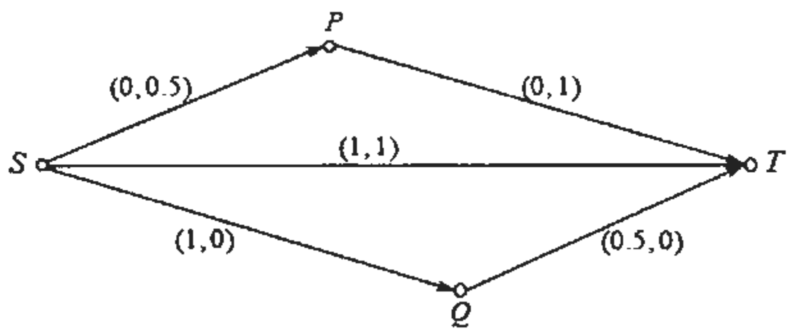


Figure 3.4 An example of a non-dominated path that does not minimize the weighted sum of objective functions for any choice of weights

From origin (*S*) to destination (*T*), there are three paths, *SPT*, *ST*, and *SQT* with attributes (i.e. objective values) of (0, 1.5), (1, 1), and (1.5, 0), respectively. None of them is worse than any other with respect to both attributes, therefore all of them are non-dominated. Denote w_1, w_2 as the weights for objectives 1 and 2, respectively. The weighted sum of attributes for the paths *SPT*, *ST*, and *SQT* are:

SPT: $0 * w_1 + 0.5 * w_2 + 0 * w_1 + 1 * w_2 = 1.5\, w_2 = 1.5(1 - w_1)$,

ST: $w_1 + w_2\ (=1)$,

SQT: $1 * w_1 + 0 * w_2 + 0.5 * w_1 + 0 * w_2 = 1.5\, w_1$.

Clearly, whatever a choice of (w_1, w_2) is made, the direct path *ST* never generates the smallest weighted sum. In other words, it is impossible to capture this path through a weighted sum approach, though it is non-dominated.

The implementation of weighted sum approach in solving MOSPs may also encounter the problem of sensitivity. For a given set of weights, minimizing the weighted sum produces one Pareto-optimal path. If users specify different priorities, the best path may change drastically. In the example of Figure 3.4, a slight change in the weights (w_1, w_2) from (0.51, 0.49) to (0.49, 0.51) would make the optimum switch from path *SPT* to path *SQT*. Hence, a slight imprecision in the statement of preferred trade-offs may lead to completely different solutions.

The final difficulty with the weighted sum approach is that this method cannot approximate the real Pareto optimum curve properly. This is because a uniform variation of the weights can hardly produce an even distribution of the Pareto optima (Das and Dennis 1997). Quite frequently, all of the points found cluster in certain parts of the Pareto set with no point in the interesting 'middle part' of the set, thereby providing little insight into the shape of the trade-off curve. This implies that depending on the structure of the problem, the linearly weighted sum does not guarantee that a desirable solution be produced as a decision-maker expects.

3.2 A preference based multi-objective optimization technique

The weighted sum approach is the simplest and most straightforward way of obtaining multiple points (solutions) on the Pareto-optimal front. However, this method often produces poorly distributed solutions along a Pareto front, and it is unable to find Pareto optimal solutions in non-convex regions. Moreover, varying the weights does not guarantee the identification of desirable solutions. Motivated by the obvious need for a more powerful approach, Zeleny (1973), Yu and Leitmann (1974), and others developed Compromise Programming (CP) – an approach based on a procedure that finds an efficient point closest to the *ideal point*, the point at which every objective under consideration simultaneously attains its minimum value. For the multi-objective optimization problems with conflicting objectives, such ideal point can never be achieved despite its existence. Nevertheless, this point can serve as a reference point for evaluating the comparative performances of the alternatives in achieving the desired objectives (Zeleny 1982). The CP method is a general formulation of multicriteria optimization. By varying the involved weighting parameters, one can get various desired Pareto optimal solutions. On the other hand, it has been mathematically proven that the CP method is advantageous over the classical weighting method (weighted sum) when the Pareto optimum closest to the ideal point in the Minkovsky metric is sought (Zhang 2003).

3.2.1 Compromise programming (CP)

Compromise Programming is a multicriteria decision technique which employs a priori information on the preference structure of the decision-maker to find a compromise solution amongst a set of conflicting objectives. It expresses the goal-seeking behavior (Yu 1985) in terms of a distance function. In order to achieve this, a reference point is taken for representing the goal to attain, and the distance to this point from any other point of the objective space is minimized.

According to Romero and Rehman (1989), compromise programming can be regarded as a natural and logical way to solve multi-objective optimization problems. As a distance-based technique, CP is marked by the following features: First, compromise programming makes use of the concept of non-dominance to select the best solution or choice of alternatives. A CP solution is deemed non-dominated in the sense that it cannot be made better off without worsening some other solutions. Second, CP considers the ideal solution as an analytical reference for optimization. The ideal solution (CP ideal) is the solution with the best, or almost the best values of the concerned criteria, rather than a target established by the decision-maker from his/her own views and judgments. Third, a CP solution is obtained by minimizing the weighted distance from each efficient point to the reference point (CP ideal) so that the decision-maker will choose the efficient alternative closest to the CP ideal. Therefore, although using preference-based weights, CP searches for an optimal solution rather than a 'satisficing' solution (Ballestero 2007). Satisficing is a decision-making strategy that attempts to meet criteria for adequacy, rather than to identify an optimal solution.

In essence, the main assumption in CP is to search for a multi-objective solution closest to the ideal solution. The concept of 'closeness' is basically related to human preferences represented by a function measuring the distance of the compromise solution from the ideal solution. CP helps decision makers to choose an optimal or the best compromise solution on the basis of a distance function generated by a combination of attribute scores. This technique is preferred by many researchers to other approaches because of the simplicity of the distance-based methods, their relationship to multi-attribute utility theory, and the availability of solution algorithms (Lakshminarayan *et al.* 1995).

The CP methods in multi-objective optimization problems differ in their choice of the distance metric and definition of the reference point. In most conventional CP models, the reference point is defined by the ideal solution point whose components are obtained by minimizing each individual objective. In some variant versions of CP methods, however, the reference point is defined by a solution whose components are slightly smaller than those of the ideal solution. Such a point is called a utopian point. The advantage of using utopian point instead of ideal point is to guarantee that there exists a positive weight vector such that a feasible MOP solution is at least weakly non-dominated (Choo and Atkins 1983). In this research, without loss of generality, the reference point is defined as the *ideal point* at which all objectives achieve their minimum values simultaneously, and decision makers would prefer the solution having a cost value as close as possible to the minimum.

The basic idea of the CP method is to define the scalarized objective function to be minimized by a metric form. Mathematically, this metric is a type of evaluation index measuring the distance between the Pareto optimum to be sought and the reference point. Such a distance can be calculated by using the *Lp*-metric. In a Cartesian plane, the distance between two points, $x^1 = \left(x_1^1, x_2^1\right)$ and $x^2 = \left(x_1^2, x_2^2\right)$, can be calculated using the Pythagorean theorem as follows:

$$d = \left[\left(x_1^2 - x_1^1\right)^2 + \left(x_2^2 - x_2^1\right)^2\right]^{1/2}$$

This concept of distance can easily be extended to an m-dimensional space, and the distance between points x with objective k becomes the Euclidean distance:

$$d = \left[\sum_{k=1}^{m}\left(x_k^2 - x_k^1\right)^2\right]^{1/2}$$

The extension of this Euclidean distance is most commonly employed in compromise programming as the distance measure. It is a member of the family of *Lp*-metric (known as Minkovsky metric) (Lakshminarayan *et al.* 1995), which is represented in its general form as:

$$L_p = \left[\sum_{k=1}^{m} w_k \left(z_k - z_k^* \right)^p \right]^{1/p}, \qquad 1 \le p \le \infty, \tag{3.6}$$

where z_k and z_k^* are the efficient point and the ideal point respectively; w_k, $\sum_{k=1}^{m} w_k = 1$, is the criterion weight in standardized form, representing the relative preference / importance attached to the k^{th} criterion. The weights are generally defined by a decision maker. They can also be developed by means of analytic hierarch process (AHP) through pairwise comparison of the criteria. An important advantage of compromise programming in practical applications is to encompass an interactive procedure allowing decision makers to specify their preferences in the optimization process by a weighting system, which is believed to facilitate the determination of the best CP solutions (Ballestero 1997).

The parameter p in (3.6) is a parameter governing the distance between an efficient point z_k and the reference point z_k^*. It acts as a weight attached to the deviation of a feasible solution from the ideal point reflecting the decision maker's perspective (Romero and Rehman 1989). The value of p ranges from one to infinity and presents the concern of the decision maker over the maximum deviation (Tecle and Yitayew 1990). The larger the value of p, the greater the concern becomes. Each value of p gives a different measure of distance. L_1 (p = 1) is the so-called street-block distance (also called Manhattan distance) that gives the maximum distance between two points. In the context of suitability evaluation for alternative routes, total compensation between objectives is assumed, indicating that a decrease of 1 unit in one objective can be totally compensated by an equivalent gain in any other objective (Pereira and Duckstein 1993). In the situation where p = 2, the *Lp*-metric represents the Euclidean distance, L_2. Each weighted deviation is accounted for in direct proportion to its size. When p becomes greater than a certain value, the largest deviation $|z_k - z_k^*|$ will dominate the evaluation, and it will reach a totally non-compensatory situation when $p = \infty$ (Zeleny 1982). Therefore, all possible distances in the space are bounded by the 'longest' distance (the L_1-metric) and the 'shortest' distance (L_∞-metric), which is also called the "*Tchebysheff*" distance.

Given p and the weight set (w_i), the preferred alternative has the minimum Lp distance value. Thus, the alternative with the lowest value for the Lp-metric will be the best compromise solution because it is the solution nearest to the ideal point.

3.2.2 Relating utility function optimization to compromise programming

In general, methods for multi-objective optimization problems can be categorized into the generating technique and the preference-based technique. The generating technique, as the name suggests, generates complete or a subset of feasible solutions for a MOP, and leaves the physical interpretation and the intensive choice of the best solution with those who can take on the responsibility. No prior knowledge of relative importance of each objective is used. By contrast, the preference-based technique has been developed to allow decision-makers to state their preferences a priori for all objectives, such as the weighted sum approaches (Steuer and Choo 1983), or interactively during the search procedure, e.g. Step Method (STEM) (Benayoun *et al.* 1971) and through achievement functions (Wierzbicki 1980). Usually, the optimization is done by aggregating different objectives into a single objective and assigning them different weights provided by the decision-maker.

As a typical preference-based method of MOP, utility functions serve to map the attributes of the feasible solutions onto a scalar value with the preference of each attribute determined by the decision-maker. By systematically changing these parameters, the utility function can seek the non-dominated solutions one after another. The utility function commonly used in CP measures the distance between a Pareto optimum (an efficient solution) and the ideal point, along with parameters accounting for the decision-maker's concern over the maximum deviation. It is considered to be more general than weighted sum (Chen *et al.* 1999; Zhang 2003). Its universal formulation is expressed as:

$$\left\| F(x) - F^{*} \right\|, \tag{3.7}$$

where the norm $\|\cdot\|$ is a mathematical measure of the distance between points, i.e. $d(f^2, f^1) = \|f^2 - f^1\|$; $F(x)$ and F^* are the efficient solution point and the ideal solution point, respectively. As mentioned above, the distance measure in CP, namely the *Lp*-metric, is closely related to the parameters p and weight set (w_k); thus, for a weighted *Lp*-metric, the utility function can be formulated as:

$$U(p,w) = \left[\sum_{k=1}^{m} w_k \left|f_k(x) - f_k^*\right|^p\right]^{1/p}, \qquad w_k \geq 0,\ \sum_{k=1}^{m} w_k = 1,\ 1 \leq p \leq \infty.$$

Observe that for every $x \in X$, $f_k(x) > f_k^*$. Thus the absolute value sign in the definition of the metrics can be dropped. Consequently, the above utility function can also be written as:

$$U(p,w) = \left[\sum_{k=1}^{m} w_k \left(f_k(x) - f_k^*\right)^p\right]^{1/p}, \qquad w_k \geq 0,\ \sum_{k=1}^{m} w_k = 1,\ 1 \leq p \leq \infty. \tag{3.8}$$

When $p = 1$, the $U(1, w)$ can be expressed as:

$$U(1,w) = \sum_{k=1}^{m} w_k \left(f_k(x) - f_k^*\right) = \sum_{k=1}^{m} w_k f_k(x) - \sum_{k=1}^{m} w_k f_k^*, \qquad w_k \geq 0,\ \sum_{k=1}^{m} w_k = 1, \tag{3.9}$$

which is equivalent to the weighted sum formulation.

When $p = \infty$, the corresponding CP problem becomes a min-max problem, and minimizing $U(\infty, w)$ is equivalent to minimizing the maximum weighted deviation:

$$\min_{x \in X} \max_{k=1,\ldots,m} \left\{w_k (f_k(x) - f_k^*)\right\}, \qquad w_k \geq 0,\ \sum_{k=1}^{m} w_k = 1, \tag{3.10}$$

Such a method is referred to as the min-max method, or weighted Tchebycheff approach, which turns out to be very useful in generating Pareto solutions. In this research, besides the compromise programming method, an adaptive method based on the weighted Tchebycheff approach is also developed to solve the problem of multi-objective route planning for DG transportation. This will be elaborated further in section 3.3.

Recall that both the weighted sum and the min-max belong to particular cases of the utility function formulated as (3.8) with the parameter p taking the values of 1 and infinity, respectively. In other cases, i.e. $2 \leq p < \infty$, the utility function is nonlinear and does not have explicit physical meaning. However, as illustrated in Figure 3.5, the exponent p has the effect of adjusting the curvature, i.e. the convexity of the objective function. An increase of p is favorable to capture the non-convex Pareto optimum set (Zhang 2003).

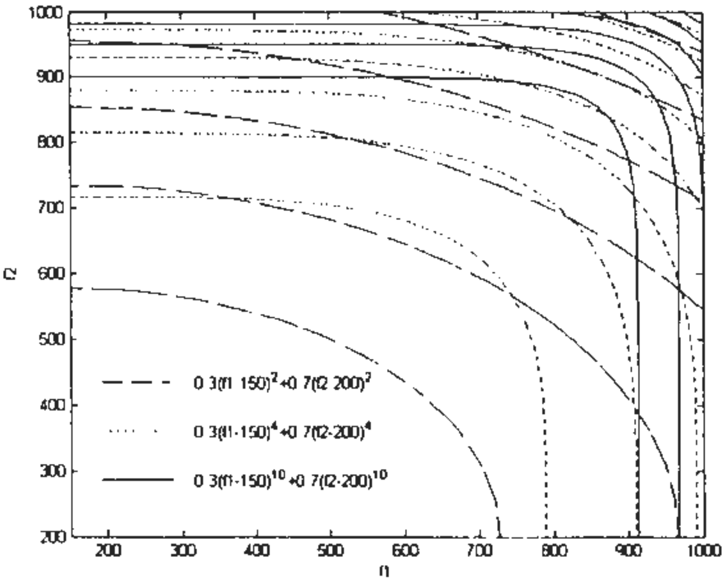


Figure 3.5 Illustration of the CP method using different exponents

Based on the utility function of (3.7), a general CP problem can be formulated as:

$$Min\ \left\|F(x) - F^{*}\right\|$$

$$s.t.\ \ x \in \mathbf{X}\ . \tag{3.11}$$

Whether an optimal solution of problem (3.11) is Pareto optimal depends on the properties of the distance measure, and hence on the properties of norm $\|\cdot\|$. A norm $\|\cdot\|$ is called monotone, if $\|f^1\| \le \|f^2\|$ holds for all f^1, $f^2 \in R^m$ with $|f_k^1| \le |f_k^2|$, $k = 1,\ldots, m$ and moreover $\|f^1\| < \|f^2\|$ if $|f_k^1| < |f_k^2|$, $k = 1,\ldots, m$. A norm $\|\cdot\|$ is called strictly monotone, if $\|f^1\| < \|f^2\|$ holds whenever $|f_k^1| \le |f_k^2|$, $k = 1,\ldots, m$ and $|f_i^1| \neq |f_i^2|$ for some j. With this definition of monotone, it is easy to prove that for an optimal solution $\hat{x}$ of (3.11), the followings hold:

i) If $\|\cdot\|$ is monotone, then $\hat{x}$ is weakly Pareto optimal. If $\hat{x}$ is a unique optimal solution of (3.11), then $\hat{x}$ is Pareto optimal.

ii) If $\|\cdot\|$ is strictly monotone, then $\hat{x}$ is Pareto optimal.

Proof:

i) Suppose $\hat{x}$ is an optimal solution of (3.11) and $\hat{x}$ is not weakly Pareto optimal. Then there is some $x' \in X$ such that $f(x') < f(\hat{x})$. Therefore $0 \le f_k(x') - f_k^* < f_k(\hat{x}) - f_k^*$ for $k = 1,...,m$ and $\left\| f(x') - f^* \right\| < \left\| f(\hat{x}) - f^* \right\|$, contradicting optimality of $\hat{x}$.

Now assume that $\hat{x}$ is a unique optimal solution of (3.11) and $\hat{x}$ is not Pareto optimal. Then there is some $x' \in X$ such that $f(x') \le f(\hat{x})$. Therefore $0 \le f_k(x') - f_k^* \le f_k(\hat{x}) - f_k^*$ for $k = 1,...,m$ with one strict inequity, and $\left\| f(x') - f^* \right\| \le \left\| f(\hat{x}) - f^* \right\|$. Given the optimality of $\hat{x}$, equality must hold, which contradicts the uniqueness of $\hat{x}$.

ii) Suppose $\hat{x}$ is an optimal solution of (3.11) and $\hat{x}$ is not Pareto optimal. Then there are $x' \in X$ and $j \in \{1,...,m\}$ such that $f_k(x') \le f_k(\hat{x})$ for $k = 1,...,m$ and $f_j(x') < f_j(\hat{x})$. Therefore $0 \le f_k(x') - f_k^* \le f_k(\hat{x}) - f_k^*$ for all $k = 1,...,m$ and $0 \le f_j(x') - f_j^* < f_i(\hat{x}) - f_j^*$. Again the contradiction

$$\left\| f(x') - f^* \right\| < \left\| f(\hat{x}) - f^* \right\|$$

follows. □

The weighted CP problem in line with the utility function (3.8) derived from the weighted *Lp*-metric can be formulated as follows for general *p*:

$$\min_{x \in X} \left(\sum_{k=l}^{m} w_k \left(f_k(x) - f_k^* \right)^p \right)^{1/p}, \qquad w_k \ge 0,\ \sum_{k=1}^{m} w_k = 1,\ 1 \le p \le \infty. \tag{3.12}$$

Without loss of generality, consider the following formulation:

$$\min_{x \in X} \beta = \left(\sum_{k=l}^{m} w_k \left(f_k(x) - f_k^* \right)^p \right), \qquad w_k \ge 0,\ \sum_{k=1}^{m} w_k = 1,\ 1 \le p \le \infty. \tag{3.13}$$

Due to the fact that f_k^* is the minimum value of each individual criterion over the feasible solution space, $f_k(x) - f_k^* > 0$. Hence, the partial derivative of the scalarized objective function β with respect to each constituent criterion is positive. According to the theorem that the solution of a scalar objective function is sufficient for Pareto optimality if the objective function increases monotonically with respect to each criterion (Stadler 1988), the solution of (3.13) is thus sufficient for Pareto optimality. The increase of a component w_k will push the solution of the related criterion $f_k(x)$ toward the ideal solution f_k^*. Therefore, varying w_k in the nominal interval of [0, 1] can generate a set of Pareto optimal solutions.

3.2.3 Weights assignment and analytic hierarchy process (AHP)

The weight w_k in the formulation of compromise programming is attributable to the decision maker's preferences accounting for the relative importance of each objective. A wide range of techniques exist for the development of weights, including point allocation, different ranking methods, and pairwise comparison. When point allocation is used to develop weights, the weights are estimated by the decision maker on a pre-determined scale, the more points an objective receives, the greater its relative importance is. The total of all objective weights must sum to 1. This method is easy to normalize. The ranking techniques, such as rank sum, reciprocal, and exponent, also provide a satisfactory approach to weight assessment. As a starting point in deriving weights, these ranking methods provide a way of simplifying multicriteria analysis. However, the ranking technique is limited by the number of objectives to be ranked. It is therefore inappropriate for a large number of objectives since it becomes very difficult to straight rank as a first step (Malczewski 1999).

Among various methods in assessing criterion weights, the analytic hierarchy process (AHP) (Saaty 1980) using the pairwise comparison technique is commonly employed. AHP works basically by developing priorities in terms of the relative importance judged on a scale of 1 to 9 (nine-point scale). The importance of each objective is individually determined and a pair-wise comparison matrix is created. The eigenvalues of this matrix are then calculated and these eigenvalues are employed as weights of the objectives. In detail, to assess weights to a set of m objectives by means of AHP, the procedure is described as follows:

Step 1: Generating the pairwise comparison matrix.

Given a pair of objectives each time, a nine-point scale value is used to specify and rate the relative performance for all the pairs. The definition of the value is shown in Table 3.1. The comparison forms a ratio matrix (Table 3.2). The upper right of the matrix is the values assigned by a decision-maker, while the lower left of the matrix is filled up with the reciprocal value corresponding to the respective element. The diagonal elements are all equal to 1 as the objective is compared with itself.

Table 3.1 Rating scale for pairwise comparison

Intensity of Importance	**Definition**
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extreme importance

Source: Saaty (1980)

Table 3.2 Pairwise comparison ratio matrix

	obj_1	obj_2	obj_3	...	obj_m
obj_1	1	w_{12}	w_{13}	...	w_{1m}
obj_2	$1/w_{12}$	1	w_{23}	...	w_{2m}
obj_3	$1/w_{13}$	$1/w_{23}$	1	...	w_{3m}
obj_m	$1/w_{1m}$	$1/w_{2m}$	$1/w_{3m}$	...	1

Step 2: Computing the objective weights.

AHP computes a weight for each objective based on the pairwise comparisons using mathematical techniques such as eigenvalue, mean transformation, or row geometric mean. In this research, the eigenvalue technique is employed for computing the weights under AHP.

2.1 Add up the values of each column of the pairwise matrix:

$$sum\_1 = 1 + 1/w_{12} + 1/w_{13} + \ldots + 1/w_{1m}$$

$$sum\_2 = w_{12} + 1 + 1/w_{23} + \ldots + 1/w_{2m}$$

...

$sum\_m = w_{1m} + w_{2m} + w_{3m} + \ldots + 1$

2.2 Recalculate each element in the matrix by dividing its current value by its corresponding column total: $w_{ij}^{'} = w_{ij} / sum\_j$ $(i, j = 1, \ldots, m)$

2.3 For each row, add up the new value of each element, and then average the sum by the number of objectives. The final output is the relative weight (w^{*}) of the objectives:

$$w_1^{*} = \sum_{j=1}^{m} w_{1j}^{'} \Big/ m$$

$$w_2^{*} = \sum_{j=1}^{m} w_{2j}^{'} \Big/ m$$

...

$$w_m^{*} = \sum_{j=1}^{m} w_{mj}^{'} \Big/ m$$

Note that due to the normalization process, the sum of these weights is equal to 1, i.e. $\sum_{i=1}^{m} w_i^{*} = 1$.

Step 3: Testing the consistency of pairwise judgment.

In AHP, after the generation of the relative weights of the objectives, the degree of inconsistency of the weights is tested by computing consistency ratio (CR) through a number of steps (Malczewski 1999).

3.1 Calculate the consistency vector (c) for each objective. The consistency vector is computed by dividing the weighted sum vector by each individual objective weight (w_j^{*}). The computation is performed row by row. The weighted sum vector is the summation of the products of weight w_j^{*} by each of the original weight w_{ij} in this particular row i, that is:

$$c_1 = \sum_{j=1}^{m} w_j^{*} w_{1j} \Big/ w_1^{*}$$

$$c_2 = \sum_{j=1}^{m} w_j^{*} w_{2j} \Big/ w_2^{*}$$

...

$$c_m = \sum_{j=1}^{m} w_j^* w_{mj} \Big/ w_m^*$$

3.2 Calculate the average of the consistency vectors (c), λ_{max}: $\lambda_{max} = \sum_{i=1}^{m} c_i \Big/ m$

3.3 Compute the consistency index (CI): $CI = (\lambda_{max} - m)/(m-1)$

3.4 Calculate the consistency ratio (CR) by dividing the consistency index (CI) by the random index (RI): $CR = CI/RI$. The value of RI varies with different number of objectives being considered, and it can be checked out from Table 3.3.

Table 3.3 Random inconsistency indices

m	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Source: Saaty (1990)

As suggested by Saaty (1990), if the resulting CR ≤ 0.1, it indicates that the weights produced through pairwise comparisons are consistent; else, if CR > 0.1, it indicates inconsistency in the weighting process. In this case, the pairwise judgment should be revised and the weights should be recomputed accordingly (Malczewski 1999).

3.2.4 Compromise-programming-based multi-objective route planning for DG transportation

Multi-objective DG route planning can be identified as an application in transportation planning. The shortest path problem is one of the typical problems in the design of transportation network. It deals with the search for a path from a source to a destination that minimizes the sum of the weighted constituent links. For the dangerous goods transportation problem, the "shortest" path could be the one with minimum population exposure risk, or lowest accident probability, or least operating cost, or the efficient combination of all such objectives.

Various solution techniques have been developed to solve the shortest path problem. Important algorithms include Dijkstra's algorithm (Dijkstra 1959), Bellman-Ford algorithm (Bellman 1958; Ford and Fulkerson 1962), A* search algorithm (Pearl

1984), Floyd-Warshall algorithm (Floyd 1962; Warshall 1962), and Prim's algorithm (Cherition and Tarjan 1976). Dijkstra's algorithm searches for the shortest paths from a single source vertex to all other vertices in a weighted, directed graph. All weights (i.e. edge-travel costs) must be non-negative. The Bellman-Ford algorithm also solves the single-source problem. However, unlike Dijkstra's algorithm, the Bellman-Ford algorithm can be used on graphs with negative edge weights, as long as the graph contains no negative cycle reachable from the source vertex (node) *s*. The A^* algorithm searches for the least-cost path from a given source node to the destination. It uses heuristic information (including the cost from the source node to the current node, and a heuristic estimate of the distance to the goal) to determine the order in which the search visits nodes in the tree, so that the search becomes more efficient. The Floyd-Warshall algorithm finds shortest paths in a weighted, directed graph with negative cost edges. A single execution of the algorithm can lead to the finding of the shortest paths between all pairs of vertices. The Prim's algorithm finds a minimum spanning tree for a connected weighted graph. The process that underlies Prim's algorithm is similar to the greedy process used in Dijkstra's algorithm.

Among various shortest path algorithms, Dijkstra's algorithm is one of the most well-known and commonly used algorithms. Starting with the source node, Dijkstra's algorithm searches for the shortest path from the source node to one additional node within the network in each subsequent iteration. The procedure requires n - 1 iterations to find the shortest path tree. The algorithm uses a set S (i.e. the set of solved nodes) to store the nodes for which the shortest path has already been established by the algorithm at the current point. At initialization, the travel cost of the source node s is set to 0, and the costs of all other nodes are assigned the value of infinity. While iterating, the algorithm assigns a new value to each node t in the network, which represents the travel cost (i.e. length) of the shortest path to node t from s through the members of S. At the end of the algorithm, the final value of node t is the ultimate travel cost of the shortest path from s to t.

The Dijkstra's algorithm is essentially a labeling method. It is based on a node selection rule which ensures that the shortest path tree is constructed by "permanently labeling" one node at a time (Zhan and Noon 1998). Once a node is permanently labeled, its optimal shortest path distance from the source node is identified. To be specific, denote $G = (N, A, C)$ as a directed network, where $N = \{1, 2, \ldots, n\}$, $A = \{(i, j) \mid i, j \in N\}$ and $C = \{c_{ij} \mid (i, j) \subset A\}$ are the sets of nodes, arcs and arc-travel costs respectively. It is assumed that G does not comprise any cycle with negative cost, and that the costs c_{ij} are additive along the arcs. It should be noted that most road networks satisfy the assumption of directed graph since each side of the road is usually dedicated to one direction only. For bidirectional graphs, undirected links can be achieved by splitting each bidirectional link into two unidirected links between the same extreme nodes. Let node s be the source node of the path, t be a sink node on that path, and $f(t)$ be the total travel cost of the currently known shortest path between s and t. Let $\varphi(t)$ be the parent node, or predecessor, of node t in the current shortest path from s to t. Let S be the set of solved nodes to which the distance from the source node s is shortest.

- Step 1: Initialization.

  Set suitable values of $f(t)$ and $\varphi(t)$ for all nodes t. For instance, $f(s) = 0$ and $f(t) = \infty$ if $t \neq s$, and $\varphi(t) = \emptyset$, $S = \{s\}$, $\forall t \in N \setminus \{s\}$.

- Step 2: Label setting.

  Find an arc $(i, j) \in A$ (node selection) such that $f(i) + c_{ij} < f(j)$ and update the shortest path tree by setting a new "label" $(f(j), \varphi(j))$ with $f(j) = f(i) + c_{ij}$ and $\varphi(j) = i$ (labeling phase). Update the set S by adding node j to S.

- Step 3: Repeat Step 2 until $f(i) + c_{ij} \geq f(j)$ for every arc $(i, j) \in A$.

The above procedure computes a shortest path tree from one source node to all the others in the network. It can also be used to find costs of shortest paths from a single source node to a single destination node by terminating the algorithm once the shortest path to the destination has been determined.

The Dijkstra's algorithm can only solve single objective shortest path problem. Route planning for DG transportation, however, involves multiple objectives with reference to operating cost, accident probability, exposure risk, and emergency response capability. Hence multi-objective shortest paths need to be determined. This is far beyond the capability of the conventional Dijkstra's algorithm, since running Dijkstra's algorithm to different objectives can only establish the corresponding paths being optimal in one particular objective. In order to address this issue, a modified Dijkstra's algorithm is proposed in this research, which incorporates compromise programming in the search for the Pareto optimal routes for DG transportation. Due to the multi-objective nature of the problem, the single cost c_{ij} of traversing link (i, j) used in Dijkstra's algorithm is replaced by the multidimensional attribute vector $c(i,j) = (c_{ij}^1, c_{ij}^2, ... c_{ij}^m)$. For the DG routing problem with m objectives, the proposed algorithm works as follows:

- Step 1: Pre-determine the value of the parameter p and a set of weights (w_1, w_2, ..., w_m) for the objectives under consideration. The weights are generated by making use of AHP through pairwise comparisons. Test the degree of inconsistency of the weights to ensure that the weights produced be consistent.

- Step 2: Initialization. Set suitable values of $f(t)$ and $\varphi(t)$ for all nodes t: $f(s) = 0$ and $f(t) = \infty$ if $t \neq s$, and $\varphi(t) = \emptyset$, $S = \{s\}$, $\forall t \in N \setminus \{s\}$.

- Step 3: For each objective k ($k = 1, 2, ..., m$), search the shortest paths (to be exact, the least cost paths) from the start point s to each node on the network by making use of Dijkstra's algorithm, and then save all least cost values $f_k^*(i)$ ($k = 1, 2, ..., m; i \in N$) in an array.

- Step 4: Find an arc $(i, j) \in A$ such that for each individual objective k ($k = 1, 2, ..., m$), $f_k'(i) = f_k(i) + c_{ij}^k$, and for all objectives under consideration, $f'(i) = \left\{ \sum_{k=1}^{m} w_k \left(f_k'(i) - f_k^*(i) \right)^p \right\}^{1/p} < f(j)$, update the shortest path tree by setting a new "label" $(f(j), \varphi(j))$ with $f(j) = f'(i)$ and $\varphi(j) = i$. Update the set S by adding node j to S.

- Step 5: Repeat step 4 until $f(i)+c_{ij} \geq f(j)$ for all objectives and every arc (i, j) that constitutes the path between the start point (source) and the end point (destination).

Step 4 is the key step of the proposed algorithm. It modifies the classic Dijkstra's algorithm by taking into account multiple objectives in the cost calculation for each link. Let (i, j) be a link, between the source s and the destination v, with node j and its immediate predecessor i, $i, j \neq s$, and $i, j \neq v$. For each individual objective k, link (i, j) bears a cost c_{ij}^k. The cost of traversing from node i to node j for objective k is calculated as: $f_k^{'}(i) = f_k(i) + c_{ij}^k$. For all objectives considered, the overall cost of traversing link (i, j) is obtained as: $f^{'}(i) = \left\{\sum_{k=1}^{m} w_k \left(f_k^{'}(i) - f_k^{*}(i)\right)^p\right\}^{1/p}$. Compare the value of $f^{'}(i)$ with the previously recorded value on node j, if $f^{'}(i) < f(j)$ (infinity in the beginning), overwrite $f(j)$ with $f^{'}(i)$; otherwise, keep $f(j)$ as the "label" of node j.

An upper bound of the running time of an algorithm is often referred to as the complexity of the algorithm. It is derived that the implementation of the modified Dijkstra's algorithm has complexity $O\left(m\left(n^2+e\right)\right)$, where m is the number of objectives considered, n and e are the number of nodes and edges (arcs), respectively, of the network G defined earlier. This is apparently a modification of the computation time for the conventional Dijkstra's algorithm. Implementing the conventional Dijkstra's algorithm to find a single objective shortest path runs in $O\left(n^2\right)$ time. With the increase of the objectives concerned, the complexity of the algorithm will increase accordingly. In the modified Dijkstra's algorithm, to evaluate the disutility for each arc, we must first solve the shortest path problem m times for each objective: it takes the time proportional to $O\left(mn^2\right)$ using the conventional Dijkstra's algorithm. Next, for each arc, we compute its disutility value, and it takes the time proportional to $O(me)$ for all arcs. Using the modified Dijkstra's algorithm in line with the utility function (3.12), we compute the multi-objective shortest path in time $O(n^2)$, and thus the total time of the proposed modified Dijkstra's algorithm for solving MOSP problem is $O(m(n^2 + e))$.

It is not difficult to prove the correctness of the proposed modified Dijkstra's algorithm because the proof is essentially the same as that of the classic Dijkstra's algorithm. In fact, with the aid of CP, the multiple weighted objectives are combined meaningfully to form a dimensionless overarching objective function. As a result, the original MOSP comes down to a single-objective shortest path problem, which can be solved by the modified Dijkstra's algorithm in polynomial time.

The proof can be obtained using proof by contradiction. Denote S as the set that consists of the vertices whose distance to the source node s is shortest; d[u] as the cost of a path from s to node u, $u \neq s$; sDist[s, u] as the cost of the "shortest" path from s to u. Before proceeding with proof, we claim some facts/lemmas first.

- Shortest paths are composed of shortest sub-paths. This is based on the notion that if there was a shorter path than any sub-path, then the shorter path should replace that sub-path to make the whole path shorter.
- If $s \rightarrow \ldots \rightarrow u \rightarrow v$ is a shortest path from s to v, then after u is added to S, d[v] = sDist[s, v] and d[v] is not changed thereafter. It takes advantage of the fact that at all times d[v] $\geq$ sDist[s, v].

After running the algorithm, we get d[u] = sDist[s, u] for all u. Once u is added to S, d[u] is not changed anymore and should be sDist[s, u].

Proof by contradiction:

Suppose that u is the first vertex added to S for which d[u] $\neq$ sDist[s, u]. Note that u cannot be s, because d[s] = 0. In addition, there should be a path from s to u; otherwise, d[u] would be infinity.

Let $s \rightarrow x \rightarrow y \rightarrow u$ be the shortest path from s to u. x is within S and y is the first vertex not within S. When x is inserted into S, d[x] = sDist[s, x]. Edge (x, y) was relaxed at that time. Hence our claim that d[y] = sDist[s, y] follows from the convergence property, and we have d[y] = sDist[s, y] $\leq$ sDist[s, u] $\leq$

d[u] (By the upper bound property). Now both y and u are in S when u is chosen, so d[u] ≤ d[y]. Consequently, the two inequalities must be equalities: d[y] = sDist[s, y] = sDist[s, u] = d[u]. Hence d[u] = sDist[s, u], which contradicts our hypothesis. Therefore, when each u is inserted, d[u] = sDist[s, u]. □

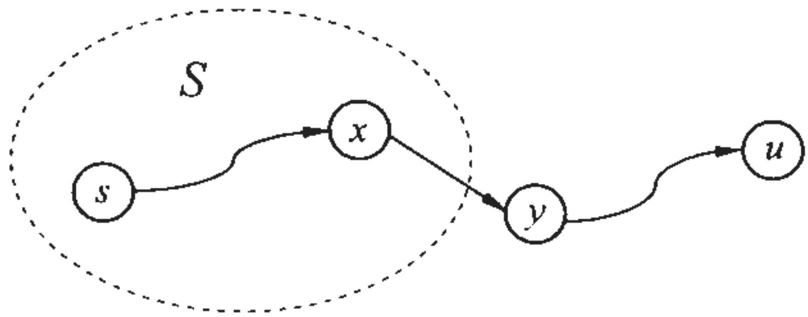


Figure 3.6 Correctness proof of the algorithm

3.3 An adaptive weighting approach to multi-objective route planning

The preference based multi-objective path optimization methods, such as weighted sum approach and compromise programming, are aimed to find the Pareto optimal paths in a pre-determined fashion. The weights accounting for the preferences for different objectives are defined a-priori by a decision-maker. In some cases, however, decision makers may find difficult to state their preferences before they have an explicit conception of the actual trade-offs involved. As Zionts and Wallenius (1976) stated, decision makers in general are accustomed to responding to the trade-off questions in the context of a concrete situation (i.e. the trade-offs that are attainable from realizable situations) rather than in the abstract. Consequently, it is often desirable to generate the efficient solutions first, and then let decision makers select the most preferred or the best compromise solution from this set. Generating the entire Pareto optimal set may not be efficacious as it becomes difficult to make a selection due to the large number of alternatives. A more effective solution is to generate a subset of non-dominated solutions that is small enough to be handled by a decision maker, and yet large enough to give an overview of all the possible trade-offs among conflicting objectives.

3.3.1 A framework to explore the Pareto front

As one of the two major solution techniques for multi-objective path optimization problems, the generating approach attempts to obtain a set of Pareto-optimal paths for a given MOSP, with the ultimate goal of sampling a well-extended and uniformly diversified Pareto front. A variety of generating methods have been developed, ranging from exact methods, such as multi-objective linear programming and dynamic programming, to a series of heuristic approaches, such as simulated annealing and tabu search. However, most of these methodologies fail to explore the non-convex part of a Pareto front that may be of interest to decision makers. Some of them also suffer from excessive complexity, requiring the solution of an exhaustive computation problem or generating too many solutions for a straightforward choice.

An alternative to both the generating techniques and preference-based techniques is to define a parametric objective function that behaves like a utility function and can generate multiple Pareto-optimal paths for multi-objective path optimization problem by varying the parameters. A careful choice of these parameters makes it possible to directly generate reasonably good paths, which provide an approximation of the set of optimal paths without too much redundancy. As a result, decision makers are presented with a small set of solutions for the final choice, and yet feel reasonably confident that the key options have not been overlooked.

Recall that the best possible outcome of a multi-objective (minimization) problem would be the ideal point F^I where each objective achieves its optimal value simultaneously, or the utopian point defined as $F^U = F^I - \varepsilon$, $\varepsilon \geq 0$ with very small components. As stated in section 3.2.1, the advantage of using utopian point is to ensure that there exists a positive weight vector such that a feasible MOP solution is at least weakly non-dominated. This will be clarified further later in this subsection. It is well-known that when the objectives involved in a MOP are conflicting with each other, it is impossible to attain either the ideal point or the utopian point. However, this point can serve as a reference point for the search of a feasible solution closest to it. This is the basic notion of CP. Based on this notion, a parametric objective function is adopted, which is commonly used in CP to measure the distance between an efficient solution point and the reference point F^0, $F^0 \in \{F^I, F^U\}$. As introduced earlier, a general formulation of the CP problem is expressed as:

$$\min \left\| F(X) - F^0 \right\| \tag{3.14}$$

Generally, the weighted metric $Lp = \|\cdot\|_p^\lambda$ with ($p \geq 1$) is adopted so that the CP problem is formulated as

$$\min \left(\sum_{k=1}^{m} \lambda_k \left(f_k(X) - f_k^0 \right)^p \right)^{1/p}, \qquad \lambda_k > 0,\ 1 \leq p \leq \infty, \tag{3.15}$$

for general p, and

$$\min \max_{k=1,\ m} \left(\lambda_k (f_k(X) - f_k^0) \right), \qquad \lambda_k > 0 \tag{3.16}$$

for $p = \infty$, where λ_k designates the k-th positive weighting coefficient. Lp is strictly monotone for $1 \leq p < \infty$ and monotone for $p = \infty$ (Ehrgott 2005).

Since the structure of the CP problem depends on the choice of the metric, we use the notation CP(p, λ). Our primary concern here is the case in which the parameter p takes the value of infinity. As introduced in subsection 3.2.2, when $p = \infty$, the CP(∞, λ) becomes a min-max problem, which minimizes the following parametric objective function:

$$U(\lambda, f) = \max_{k=1,\ m} \left(\lambda_k (f_k(X) - f_k^0) \right), \qquad \lambda_k > 0 \tag{3.17}$$

$U(\lambda, f)$ is not exactly a utility function in the sense that is defined in subsection 3.1.2 since it is not strictly increasing. For example, a route R_p with attributes $f_p = (0, 1, ..., 1)$ dominates a route R_q with attributes $f_q = (1, 1, ..., 1)$, but their maximum weighted attribute is equal most of the time. Hence, the minimum of the function (3.17) may not be strictly non-dominated. However, any non-dominated route minimizes $U(\lambda, f)$ for a given positive weight vector, λ.

The CP(∞, λ), referred to as the *weighted Tchebycheff approach*, is of significance in generating Pareto optimal solutions. Bowman (1976) shows that for every Pareto solution there exists a positive vector of weights so that the corresponding CP(∞, λ)

is solved by this Pareto point. Figure 3.7 shows the same efficient frontier that is depicted in Figure 3.3. For the given reference point U and the weight vector $\boldsymbol{w}$, the solutions of CP(∞, λ) can be geometrically identified as the points of contact between the efficient frontier and the corresponding level curve ("square wedge") of the weighted Tchebycheff metric. It is observed that varying the reference point and the weights, one may reach all the efficient points located on the arc between points A and B. Therefore, in this research, an adaptive weighting method based on the weighted Tchebycheff is developed to solve the multi-objective DG routing problem, which guarantees that a set of efficient routing paths can be generated; moreover, these solutions can provide decision-makers with an overview of the solution space and the possible trade-offs among the conflicting objectives.

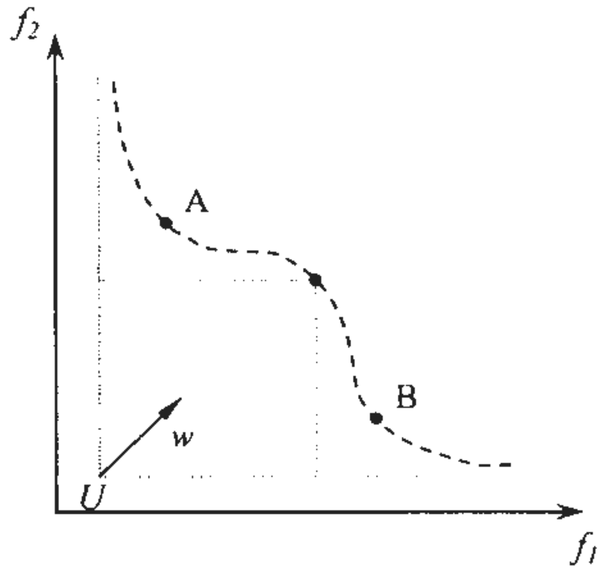


Figure 3.7 Generating Pareto-optimal solutions by the weighted Tchebycheff approach

It should be noted that, as illustrated earlier, the solutions obtained by means of the weighted Tchebycheff approach are weakly non-dominated when $F^0 = F^U$. The proof of this notion is as follows:

Proposition: A feasible solution $\hat{x} \in X$ is weakly non-dominated $\Leftrightarrow$ there exists a weight vector $\lambda > 0$ such that $\hat{x}$ is an optimal solution of the problem (3.16).

Proof:

"$\Leftarrow$" Suppose $\hat{x}$ is an optimal solution of the problem (3.16) and $\hat{x}$ is not weakly non-dominated. Then for a strictly positive weight vector $\lambda > 0$, there is some $x' \in X$ such that $0 < \lambda_k (f_k(x') - f_k^U) < \lambda_k (f_k(\hat{x}) - f_k^U)$. Divided by λ_k

we get $f_k(x') - f_k^U < f_k(\hat{x}) - f_k^U$ for all $k = 1, \ldots, m$, which contradicts the optimality of $\hat{x}$.

"⇒" The necessity property can be proved by defining appropriate weights. Let $\lambda_k = 1/(f_k(\hat{x}) - f_k^U)$, $k = 1,\ldots, m$. Since $(f_1^U,\ldots, f_m^U)$ is the utopian point, λ_k is strictly positive for all $k = 1,\ldots, m$. Suppose $\hat{x}$ is not optimal for (3.16) with these weights. Then there is a feasible $x' \in X$ such that

$$\max_{k=1,\ldots m} \lambda_k (f_k(x') - f_k^U)$$

$$= \max_{k=1,\ldots m} \frac{1}{f_k(\hat{x}) - f_k^U}(f_k(x') - f_k^U)$$

$$< \max_{k=1,\ldots m} \frac{1}{f_k(\hat{x}) - f_k^U}(f_k(\hat{x}) - f_k^U) = 1$$

and therefore

$$\lambda_k (f_k(x') - f_k^U) < 1 \ \textit{for all}\ k = 1, \ldots, m.$$

Divided by λ_k we get $f_k(x') - f_k^U < f_k(\hat{x}) - f_k^U$ for all $k = 1, \ldots, m$ and thus $f(x') < f(\hat{x})$, contradicting the fact that $\hat{x}$ is weakly non-dominated. □

In summary, any Pareto optimal solution can satisfy the min-max formulation (3.16) for a given positive vector λ; on the other hand, by solving (3.16), a weakly non-dominated solution can be obtained. Furthermore, if this optimal solution is unique, it is then Pareto-optimal. For proof of the last proposition, refer to subsection 3.2.2.

Recall that the exponent p in the formulation of compromise programming has the effect of adjusting the curvature of the objective function, and an increase of p is favorable to capture the non-convex Pareto optimum set. When $p \to \infty$, the corresponding CP problem becomes a min-max problem formulated as (3.16). Consider the function $\beta = max(\lambda_1 f_1', \lambda_2 f_2')$. A geometrical interpretation shows that in two-dimensional space, the isolines of such a function form a square wedge and that the inner part of the wedge corresponds to the set of solutions dominating the summit of the square angle (Figure 3.8). The shape of the isolines is ideally suited for the exploration of both the "convex" and "concave" parts of the Pareto front, while ensuring Pareto-optimality of the points encountered. Hence, an approximation of the Pareto front can be obtained by solving several instances of the min-max problem

$$\min \max_{k=1,\dots,m} \left(\lambda_k (f_k(x) - f_k^0)\right), \quad \lambda_k > 0\,,$$

where $(f_1^0,\dots,f_m^0)$ defines the search origin, and the reciprocal of the weight's vector $(1/\lambda_1,\ 1/\lambda_2,\ \dots,\ 1/\lambda_m\ )$ designates the search direction (Wierzbicki 1980, 1986). Figuratively, solving an instance of this problem is equivalent to exploring the Pareto front along the specific line joining the reference point and the nadir point (the anti-ideal point, which is defined in such a way that it is composed of the worst values obtained for each objective) of the current exploration region. For instance, in a two-objective case shown in Figure 3.8, when minimizing the parametric objective function's value C, the isolines of $max\left(\lambda_1 f_1', \lambda_2 f_2'\right) = C$ will move downward along the line joining the reference point U and the nadir point, and reach the Pareto front. This approach can be viewed as an example of the achievement scalarizing function (Wierzbicki 1982). The main structure of an achievement scalarizing function is based on the weighted Tchebycheff distance from the reference point to the feasible set. In other words, the maximum (unwanted) deviation from the reference point is minimized.

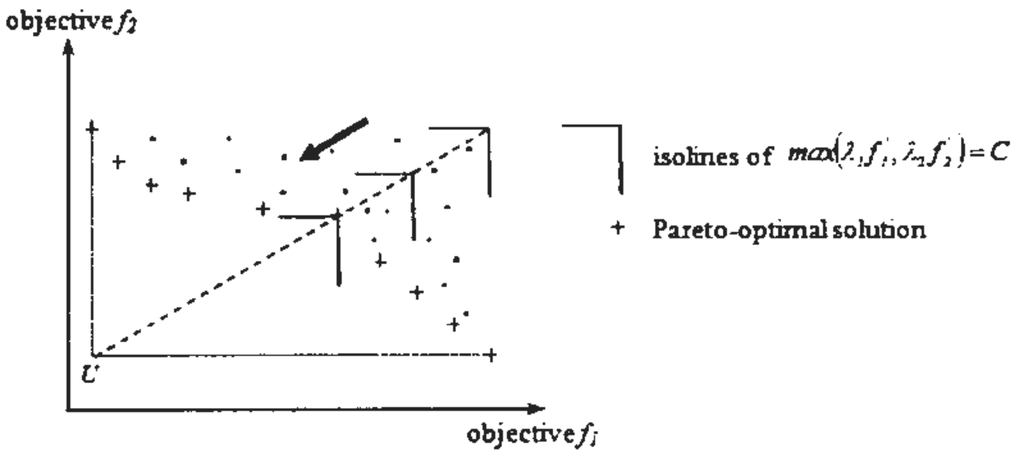


Figure 3.8 Isolines of $max\left(\lambda_1 f_1', \lambda_2 f_2'\right) = C$ used to derive both the convex and concave parts of Pareto optimal

Since it is closely related with the weight coefficients which vary with the search direction in the objective space, the proposed methodology can be considered as an adaptive weighting method. Although the weight coefficients are involved in both methods, the generation of the weights in the proposed adaptive weighting method is essentially different from that in the weighted Tchebycheff approach. The weights employed in the latter method are generally created based on a decision-maker's preferences for different objectives. In the proposed adaptive weighting method, however, the weights are calculated based on certain heuristics. No prior knowledge of relative importance of each objective is used. Through adaptively adjusting the exploration in the objective space, the weights can be generated accordingly, and a good approximation of the Pareto front can then be achieved. This will be discussed in detail in the next subsection.

3.3.2 Sampling the Pareto front

The number of Pareto-optimal solutions to the multi-objective shortest path problem may increase exponentially with the size of the network and the number of objectives (Hansen 1980). Therefore, identifying and presenting the entire Pareto optimal set is practically impossible due to its size. A practical approach is to investigate a set of solutions that represent the Pareto optimal set as well as possible so that the decision-maker can easily understand the available trade-offs and select desirable paths. The previous subsection has defined a mathematical tool to explore the objective space along a given direction. By varying the origin and direction of exploration, one can generate a good approximation of the Pareto front.

Studies show that an approximation of the Pareto front without prior knowledge of the actual one can be achieved by means of heuristic methods. In order to improve the efficiency, an adequate heuristics should seek a balance between the amount of information provided and the computational time required to obtain it. In this connection, an ideal algorithm should effectively combine exploration of the largest unexplored regions of the objective space with exploitation of the previously encountered solutions (Hughes 2003). The goodness of an algorithm can be reflected by the quality of the approximate set, which is generally measured in terms of diversity of the generated solutions, uniformity of their distribution, and cardinality (Kim *et al.* 2000). More specifically, a diverse set of efficient paths is essential to provide backup alternatives in case the designated route is affected by an unexpected event. A relatively even distribution of the solutions is beneficial to the unbiased presentation of the possible trade-offs among alternative routes. Finally, a reasonable size of the approximate set is of utmost importance. Ideally, it should be small enough to be handled by a decision maker and yet large enough to give an overview of all the possible trade-offs among conflicting objectives.

The major concern of the proposed adaptive weighting method is how to alter the weights so that a good approximation of the Pareto front can be efficiently generated with an acceptable amount of the solutions. In our solution, once a Pareto-optimal is obtained, the search space will be partitioned into smaller pieces, and the regions that are either dominated by the known optimal solutions or free of optimal solutions will be discarded. The search origin and direction are then adjusted based on the largest unexplored space that may contain efficient solutions.

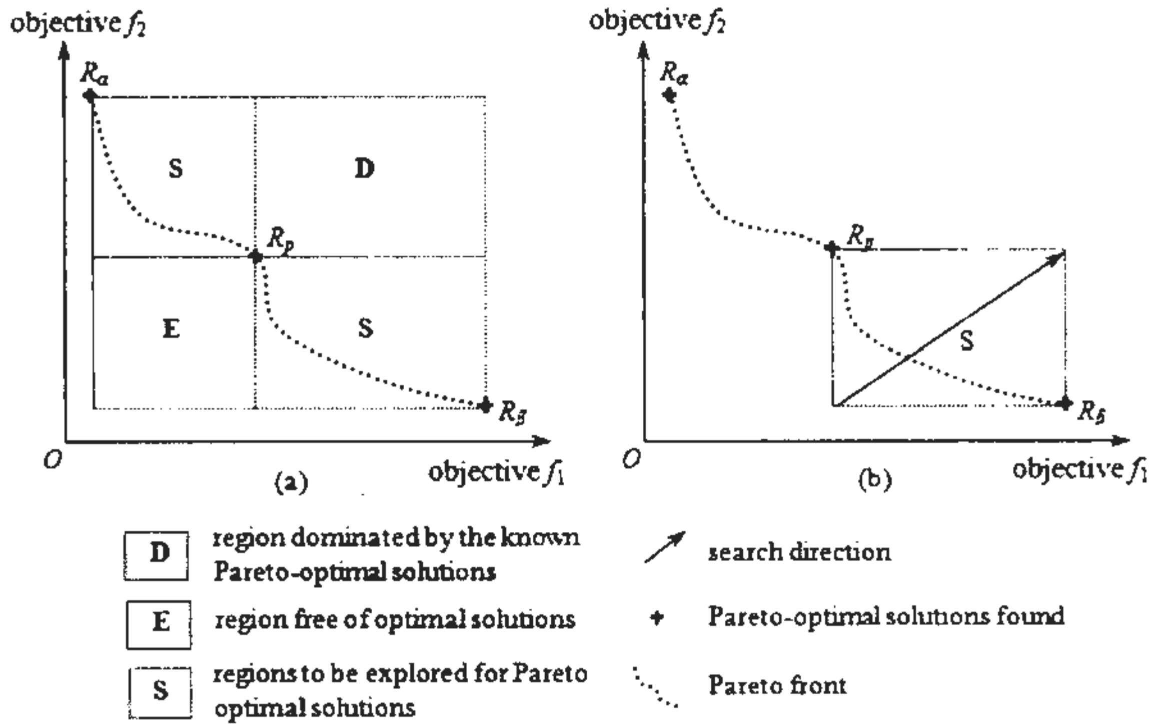


Figure 3.9 (a) Partition of the two-dimensional search space; (b) determination of the search origin and direction based on the largest unexplored sub-region

As shown in Figure 3.9 for the case of two dimensions, points R_α and R_β represent two "extreme" solutions which individually minimize each of the two objectives. When a Pareto optimal point R_p is found, the objective space can then be partitioned into three kinds of regions. Region D is dominated by a known solution R_p, hence no Pareto optimal point will exist there. Region E is obviously free of optimal solutions. Therefore, only regions S are the ones that need to be explored, with a possibility that the Pareto optimal points might be found there. Once the larger unexplored region (e.g. the lower left sub-region S) is identified, the search origin and direction of the exploration for new Pareto optimal solutions can be determined accordingly. The way of comparing the promising unexplored regions is to compare the area of each concerned region because only two objectives are being considered here. When the dimensions m is higher than 2, the notion of volume is used to compare the unexplored regions. The calculation of the exact volume of the regions can be very cumbersome when m is large. For the sake of simplicity, in this research, the volume of the unexplored region is broadly estimated as the product of difference on each individual objective value between the nadir point and the reference point of this particular region.

A list of unexplored regions is carefully maintained in implementing the proposed method. The list is sorted in descending order of volumes so that the largest unexplored region is always the next candidate to search for an additional point. Each time when a new efficient solution is found, the list will be updated subsequently. In that list, every unexplored region is described by its utopian point and nadir point, its expected volume, and the known solutions lying on its boundaries. The utopian point and the nadir point of an unexplored region are defined as the lowest point and the furthest summit of the region, respectively. The proposed procedure works as follows (Figure 3.10):

- Step 1: For each objective k, search for the optimal solution f_k, and thus define the utopian point $\boldsymbol{U}$ = ($f_1^U, f_2^U, ..., f_m^U$) and the nadir point $\boldsymbol{V}$ = ($f_1^V, f_2^V, ..., f_m^V$). Based on $\boldsymbol{U}$, $\boldsymbol{V}$, and the optimal solutions obtained for each individual objective, the region to be explored can be identified. Initialize the list of the unexplored regions.
- Step 2: Remove the largest unexplored region from the list and define the new search origin and the new searching direction $\boldsymbol{\lambda}$ based on the attributes of $\boldsymbol{U}$ and $\boldsymbol{V}$ as $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \dots \lambda_m)$, where $\lambda_k = 1/(f_k^V \quad f_k^U)$, $k = 1,\dots, m$.
- Step 3: Solve the min-max problem (3.16).
- Step 4: If the solution found is already known, resume at Step 2; else a new solution is found. Calculate the new unexplored regions lying between this

new solution and its neighbors according to their objective values, then update the list of unexplored regions and resume at Step 2.

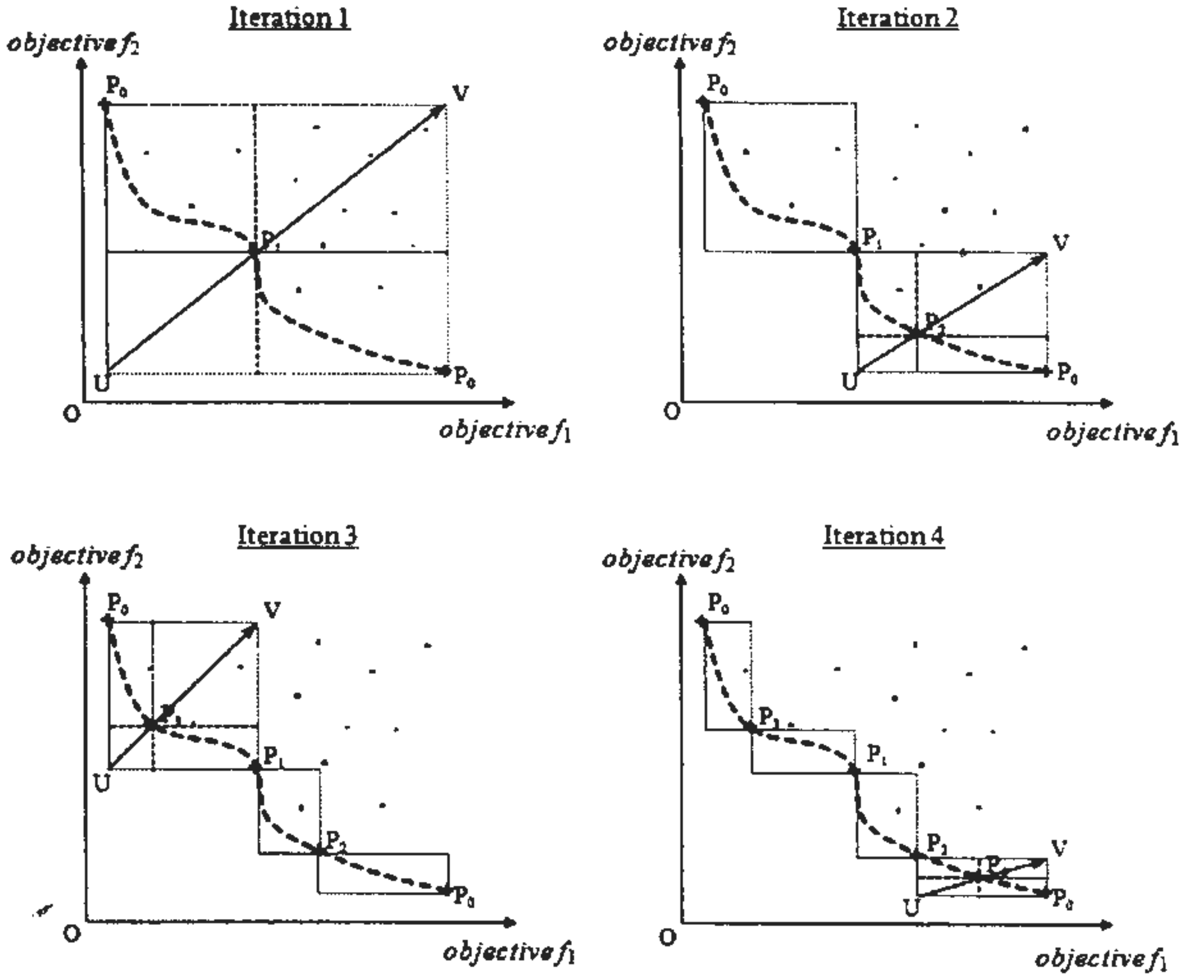


Figure 3.10 Iterative search for Pareto-optimal solutions in two-dimensional objective space

In Step 1, the utopian point $U = (f_1^U, f_2^U, ..., f_m^U)$ is computed as a result of m single objective optimizations with each objective serving as an objective function at a time. Once the utopian point is determined, the information found is then used to compute an estimate of the nadir point $V = (f_1^V, f_2^V, ..., f_m^V)$. An approximation of V is defined in such a way that for each criterion k, f_k^V represents the worst value obtained during the computation of the utopian point. It should be noted that except for the first iteration, the attributes of U and V in Step 2 need to be updated in each iteration according to the known Pareto-optimal lying on the largest unexplored region. To solve the min-max problem $min\left(\max_{k=1,\ m}\left(\lambda_k(f_k(X)-f_k^0)\right)\right)$ in Step 3, a classic labeling algorithm is employed in our case, along with proper modifications, to yield the desirable minimization solution. The algorithm stops when a subset of Pareto-optimal solutions of the desired size has been obtained or when the proportion of the remaining unexplored sub-regions is sufficiently small.

3.3.3 Implementation issues

3.3.3.1 Complexity of the algorithm

As introduced in the preceding subsection, the procedure proposed to approximate the Pareto front mainly consists in managing the list of unexplored regions. After initialization, a typical iteration of the algorithm is as follows:

First, select the largest unexplored region. Since the list of unexplored regions is sorted in descending order of volumes, the largest one is always the first element in the list. Based on the largest unexplored region, we can define the current search origin and direction, and solve the corresponding minimization problem $\min U(\lambda, f)$ to obtain a new Pareto point (solution). The minimization operation results in a complexity of $O(m(n^2 + e))$, where m is the number of concerned objectives, n and e are the number of nodes and edges (arcs), respectively, of the network G defined at the beginning of this chapter.

Next, verify that the newly found solution is not already known. This can be done by comparing this solution with N non-dominated solutions that have been found so far (exclude the extreme solutions found during the phase of initialization). Since there are m attributes which need to be compared, this operation can be accomplished in $O(Nm)$.

Subsequently, subdivide the currently explored region based on the newly found point, which can create at most m sub-regions that may contain Pareto-optimal solutions and thus need for further exploration. For each of these unexplored sub-regions, calculate the coordinates of the Nadir point and broadly estimate the unexplored volume, which result in a complexity of $O(m)$ and $O(m^2)$, respectively.

Finally, update the list of unexplored regions by inserting the newly created ones in the sequence, which requires a dichotomous search over the volumes. This is of complexity $O(m\times s\log(s))$ where s is the number of elements of the list. If N non-dominated solutions have so far been found (excluding the extreme solutions found during the phase of initialization), the list of unexplored regions will contain at most $s = N\times m-(N-1)$ elements, because each non-dominated solution defines m unexplored sub-regions in the objective space but $(N-1)$ of them are counted twice.

Note that the bounds on the complexity given in the above are broadly estimated, and thus are probably loose. Nevertheless, one may notice that among those recursive steps, the first step has absolutely higher complexity than each of the rest typical iterations. This step involves solving a non-linear integer program of NP-hard difficulty. The main computational burden in terms of run-time and memory space, therefore, comes from this step. Hence, the efficiency of the procedure proposed to approximate the Pareto front depends largely on the efficient solution of this step. In addition, it is also essential to keep the number of iterations small and to make the most of each iteration.

3.3.3.2 Solving the min-max problem

Although managing the list of unexplored regions can be onerous, it is not as computationally expensive as solving the min-max problem, $min\left(\max_{k=1,\dots,m}\left(\lambda_k(f_k(X)-f_k^0)\right)\right)$. The general min-max optimization problem in various forms has long had the attention of researchers. A number of approaches for handling the min-max problems have been reported in previous studies. The commonly used methods include the classical and augmented Lagrangians (Kim and Choi 1998; Polak and Royset 2005), the standard and improved branch-and-bound algorithms (Yamada *et al.* 1997; Jansson and Knüppel 1995), etc. However, in the case of network routing problem, both Lagrangians and branch-and-bound algorithms are unlikely to outperform the labeling algorithms in solving the shortest path problem developed from the original min-max problem, because the labeling algorithms are specifically designed to make use of the network shape. The labeling algorithms process the links in the optimal order and run faster than a standard linear programming solver (Gutiérrez and Medaglia 2008). With this consideration, the Dijkstra's algorithm, a classic node-labeling algorithm, is employed, with proper modifications, to search for the minimum of the disutility function $U(\lambda, f) = \max_{k=1,\dots,m}(\lambda_k(f_k(X) - f_k^0))$. Given the multi-objective nature of our application problem (i.e. optimal route planning for DG transportation), the cost of traversing link used in the conventional Dijkstra's algorithm is, in our case, not the value of any single criterion, but rather the largest element of the weighted "distance" between the point being explored and the reference point among all the objectives examined, that is, $c_{ij} = \max_{(i,j)\in A, k=1,\dots,m}(\lambda_k(f_k - f_k^0))$. The procedure of solving the min-max problem by means of the modified Dijkstra's algorithm is similar to that of the conventional Dijkstra's working on shortest path problem. The recursive step of the algorithm can be put as follows:

> finding an arc $(i, j) \in A$ so that the cost $f(i)$ of traveling from the origin to node i increased with the cost c_{ij} of travelling along (i, j) is less than the present cost of travelling from origin to node j: $f(i) + c_{ij} < f(j)$. If such an arc exists, then node i becomes the predecessor of node j in the shortest path and the procedure resumes, otherwise the present cost of travelling from the origin to node j is the minimum cost.

However, everything has a cost. While the labeling algorithm can solve the min-max problem more efficiently than a standard linear program solver such as branch-and-bound procedure, it causes another problem for implementation, namely the memory space requirements. Unlike the branch-and-bound algorithm, the labeling algorithm requires large amount of computer memory to store the list of temporary labels for every node. Considering the increasing capabilities of desktop computers in terms of speed and memory space, this issue, however, seems insignificant as a whole.

3.3.3.3 Estimation of the potentially Pareto-optimal volumes

The proposed adaptive approach approximates the Pareto-front by exploring the empty regions that may contain Pareto-optimal solutions. The volume of these regions indicates the amount of information that remains unknown and decreases with more efficient solutions sought, thus indicating how effective the approximation is.

The simplicity of the two-dimensional case makes one underestimate the difficulty of estimating these volumes. For example, consider a situation with three objectives as shown in Figure 3.11.

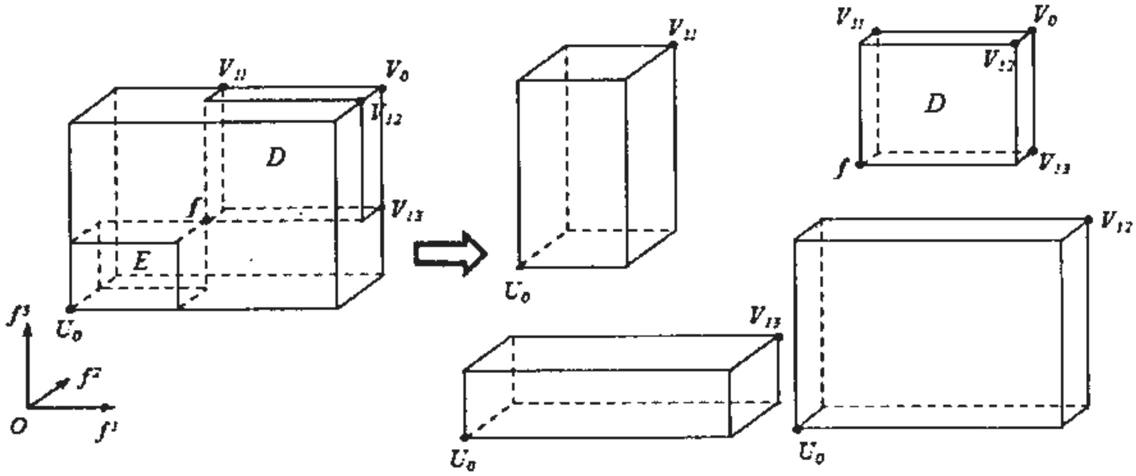


Figure 3.11 Partitioning of the three-dimensional search space

Suppose that U_0 and V_0 are the utopian point and the nadir point, respectively, of the currently explored region, the point f is a non-dominated point found based on U_0 and V_0. Region D is dominated by f and region E is free of optimal points. The remainder of the cuboid is potentially Pareto-optimal. Following the proposed procedure, there are three unexplored regions along the three faces of region D, namely the three cuboids with extreme vertex V_{11}, V_{12}, or V_{13}. Strictly speaking, these three regions are not completely unexplored as they all contain region E where no Pareto-optimal solution can be found. Therefore, the actual unexplored volumes should be calculated by deducting the volume of region E from each of them. For example, the exact volume of the unexplored region with the extreme vertex V_{11} should be calculated as:

$$\left(V_{11}^1 - U_0^1\right)\left(V_{11}^2 - U_0^2\right)\left(V_{11}^3 - U_0^3\right) - \left(f^1 - U_0^1\right)\left(f^2 - U_0^2\right)\left(f^3 - U_0^3\right) \qquad (3.18)$$

Though it is relatively easy to calculate these volumes for the first iterations, it can become extremely difficult to handle the succedent ones, especially when the number of objectives is more than 3. As mentioned earlier, the purpose of calculating the unexplored volume is to compare the relative size of the unexplored region and to identify the largest one accordingly in order to define the new search origin and direction for exploring additional Pareto point. On the other hand, at each iteration, the region free of Pareto-optimal solutions (i.e. the region of type region *E*) is included in each of the unexplored regions. Whether including or excluding its volume in the calculation of the unexplored volumes will actually not influence the comparison result of the relative size of the unexplored regions. In view of this, in the present study, each of the potentially Pareto-optimal volumes is broadly estimated as the product of difference on each individual objective value between the nadir point and the utopian point of this particular region.

3.3.3.4 Termination criteria of the algorithm

The adaptive weighting algorithm produces one solution in each iteration. More solutions can be generated through several iterations. The termination criterion of an algorithm controls the amount of solutions produced. There are two ways to define the criterion: it can either be defined as a desired number of solutions that is sufficiently small to be handled by a decision-maker, or defined as the maximum loss of information acceptable by the decision-maker. If either of the termination criteria is satisfied, the iterative process of the algorithm will be terminated. In the proposed adaptive method, the algorithm stops when a subset of Pareto-optimal solutions of the desired size has been obtained, or when the proportion of the remaining unexplored sub-regions is sufficiently small, that is, the total area of the unexplored regions is smaller than a certain percentage of the initial unexplored region.

3.4 Summary

The transportation of dangerous goods is a multi-objective problem (MOP) with stakeholders playing different roles and having different objectives. These objectives are generally conflicting so that a unique solution that can optimize every single objective is impossible. The solution of such problem is to search for one or a set of "compromise" solutions, known as Pareto optima, which render the best possible trade-offs for conflict resolution among different objectives. The simplest and also most widely used method for such MOP is to minimize a positively weighted sum of all the objectives, thus transforming the problem to a much easier single objective optimization. Traditionally, the weights represent the relative importance of each objective provided by decision-makers, and only one solution can be rendered accordingly. Although simple and straightforward, weighted sum approach suffers from some drawbacks. In particular, this method often produces poorly distributed solutions along a Pareto front. Neither can it find the Pareto optimal solutions in non-convex regions.

Motivated by the obvious need for more efficient solutions, a couple of MOP techniques are proposed in this research, namely, the compromise programming method and the adaptive weighting method. Compromise programming is a multicriteria decision technique which employs a priori information on the preference structure of the decision-maker to find a compromise solution amongst a set of conflicting objectives. CP expresses the goal-seeking behavior in terms of a distance function. In order to achieve this, a reference point is taken to represent the goal to be attained, and the distance to this point from any other point of the objective space is minimized. In this research, without loss of generality, the reference point is defined as the ideal point where each objective achieves its minimum value simultaneously, and decision makers would prefer the solution having a cost value as close as possible to the minimum. The distance between an efficient point and the reference point is calculated by using the *Lp*-metric. The weights accounting for the decision-maker's preferences for different objectives are computed by means of analytic hierarchy process.

Optimal route planning for DG transportation can be treated as a multi-objective shortest path problem. The Dijkstra's algorithm is one of the most commonly used algorithms in routing analysis, which solves the single-source shortest path problem with non-negative link cost. This algorithm, however, can only solve single objective shortest path problem, whereas DG routing involves multiple objectives, and thus multi-objective shortest paths should be derived. In order to address this issue, a modified Dijkstra's algorithm is developed in this study, which incorporates compromise programming in search for the Pareto optimal routes for DG transportation. The core of the modification is to take into account multi-objectives in the cost calculation for each link. The composite cost of a link is computed by aggregating multiple attributes into a single one through compromise programming, with the consideration of decision-makers' preference for each objective and perspective on the deviation of a feasible solution from the ideal solution. The modified Dijkstra's algorithm guarantees that the solution belongs to the set of efficient solutions.

The compromise programming model attempts to find the Pareto optima in a pre-determined fashion. The weights accounting for the preferences for different objectives are defined a-priori by a decision-maker. In some cases, however, it is difficult for decision makers to state their preferences before they have an explicit conception of the actual trade-offs involved. Consequently, it is often desirable to generate the efficient solutions first, and then let decision makers select the most preferred or the best compromise solution from this set. Identifying the entire Pareto optimal set is practically impossible due to its size. Therefore, a realistic approach is to investigate a set of solutions that represent the Pareto optimal set as well as possible. With these concerns in mind, an adaptive weighting method is developed. Rather than an unnecessarily extensive search, this method focuses the search on a particular region of the Pareto front in order to obtain a subset of the Pareto optimal solutions. A weighted maximum utility function is adopted in the method. By altering the weights adaptively according to the largest unexplored feasible region and solving the corresponding min-max problem through custom-made labeling algorithm, a relatively well-distributed set of Pareto optimal solutions can be generated efficiently. When the approximation of the Pareto front reaches a pre-specified resolution, the algorithm terminates. The proposed adaptive method is capable of generating reasonably good solutions to present the decision-maker with an unbiased overview of the possible trade-offs among the concerned objective.

The compromise programming model and the adaptive weighting approach are two MOP methods proposed in this research to solve the multi-objective DG routing problem. Both of them can be considered as the class of deterministic technique, within which the exploration in the search space is goal-directed, rather than a random search. Besides the deterministic methods, the heuristic technique, i.e.

genetic algorithm in our case, has also been explored in this research to search for efficient solutions for multi-objective DG route planning. This will be elaborated in the next chapter.

CHAPTER 4: EVOLUTIONARY MULTI-OBJECTIVE PATH OPTIMIZATION

Route planning for the transportation of dangerous goods often requires the optimization of multiple objectives that are conflicting and non-commensurable. Many approaches have been developed to generate various routing alternatives. These methods typically depend on a weighting mechanism to aggregate multiple objectives into a single one. As a result, the process becomes a single-objective optimization, and the outcome of this simplified process will largely depend on the vector of weights employed. To generate the desired solution, the exploration in the objective space is always oriented towards the expected direction. In other words, the search is goal-directed, rather than a random search. In the literature of multi-objective optimization, these optimization methods generally belong to the class of deterministic technique. The compromise programming approach and the adaptive method introduced in Chapter 3 fall within this category.

Since the 1960s there has been increasing interest in the simulation of living beings to develop powerful algorithms for difficult optimization problems. Evolutionary algorithm (EA), a probabilistic optimization technique, provides an alternative to the conventional techniques. Among all the EAs, genetic algorithm (GA) is the most widely used. GAs are a class of global search methods that are modeled after the mechanics of natural evolution within populations and species via reproduction, competition, selection, crossover breeding, and mutation. They operate with a population of possible solutions rather than a single candidate. Therefore, they are less likely to get trapped in a false local optimum. Moreover, a number of Pareto optimal solutions may be captured during one run of GA. GAs are relatively simple and easy to implement. They do not require any auxiliary information such as gradients other than the evaluation of the multiple objective functions. These merits make GAs very appealing as more reasonable candidate optimization tools for optimal route planning for the transportation of DG.

This chapter introduces the proposed GA-based approach, a heuristic method, to the multi-objective path optimization problem. First, GAs and their characteristics are briefly introduced at the beginning. Then the major components and basic structure of simple GAs are examined. Subsequently, a detailed introduction of the proposed GA-based heuristic approach to multi-objective route planning for DG transportation is presented, which includes the genetic representation scheme of candidate solutions, the initialization of population, and the evaluation of fitness. Finally, the genetic operators used in the proposed GA are discussed with specifics on the implementation issues

4.1 Genetic algorithms

4.1.1 Introduction

Evolutionary algorithm (EA), a probabilistic optimization technique which has been proposed based on Darwin's theory of natural selection, provides an alternative to conventional techniques of solving optimization problems. The class of evolutionary algorithms includes genetic algorithms (GA) (Holland 1975), genetic programming (GP) (Koza 1992), evolutionary programming (EP) (Fogel *et al.* 1966), and evolutionary strategy (ES) (Schwefel 1995). Among all the evolutionary algorithms, GA is probably the most widely used method. GA was first introduced by Holland (1975) and it has been receiving increased attention thanks to the tremendous successful applications in different disciplines, such as bioinformatics, engineering, economics, chemistry, manufacturing, mathematics, and physics (Tarafder *et al.* 2005).

A genetic algorithm is a computational model simulating the process of genetic selection and natural elimination in biologic evolution. As a highly efficient search strategy for global optimization, GA exhibits favorable performance on solving multi-objective optimization problems. Compared to traditional search algorithms, GA is able to acquire and accumulate the necessary knowledge about the search space automatically during its search process, and control the entire search process self-adaptively through the random optimization technique. Being a population-based approach, GA can find multiple feasible solutions in a single run. The ability of GA to simultaneously search different regions of the solution space makes it possible to find a diverse set of solutions for complex problems with non-linear objective functions and non-convex solutions space. In addition, most multi-objective GAs do not require users to prioritize, scale, or weigh objectives.

The basic idea of GA is to start with a population of potential solutions (represented as chromosomes) instead of a single point in the search space, and allow the population to evolve using genetic operations such as selection, crossover, and mutation until the termination criteria are satisfied. In the evolution process, GA uses a directed random search strategy: genetic operators such as crossover and mutation perform essentially a blind search, while the selection operator hopefully directs the search towards the desirable area of the solution space. This indicates that selection plays an important role in exploitation, while crossover and mutation are critical in exploration. A general principle for applying genetic algorithms to a particular real-world problem is to make a good balance between exploration and exploitation of the search space. To achieve this, all the components of the genetic algorithms, such as population size, crossover and mutation rate as well as the mechanism used for population initialization, individuals' representation, and evolution implementation, should be examined carefully. Moreover, additional heuristics may be needed to enhance the performance of the algorithm.

4.1.2 Overview of genetic algorithms

Genetic algorithm was first developed by Holland (Holland 1975). In general, GA consists of five basic components as summarized by Michalewicz (1996):

1. A genetic representation of solutions to the problem;
2. A way to create an initial population of solutions;
3. An evaluation function rating solutions in terms of fitness;
4. Genetic operators that generate new individuals;
5. Values for the parameters of genetic algorithms.

A genetic algorithm generally starts with a population of randomly generated individuals (i.e. chromosomes, each representing a potential solution to the problem) and happens in generations. In each generation, the fitness of each chromosome in the population is evaluated by a predefined function. Multiple chromosomes are stochastically selected from the current population (based on their fitness) and modified (recombined and randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. This iterative process continues until the termination criterion is satisfied. The general procedure of genetic algorithms can be summarized as follows:

```
Procedure: Genetic Algorithms
  begin
      t = 0
      generate initial population P(t)
      evaluate P(t)
      while (not termination condition) do
      begin
          t = t + 1
          select P(t) from P(t-1) based on fitness of the individuals in P(t-1)
          generate (by crossover and mutation) structures in P(t)
          evaluate P(t)
      end
  end
```

where $P(t)$ is the population at generation t. Figure 4.1 shows the simplified flowchart of a GA.

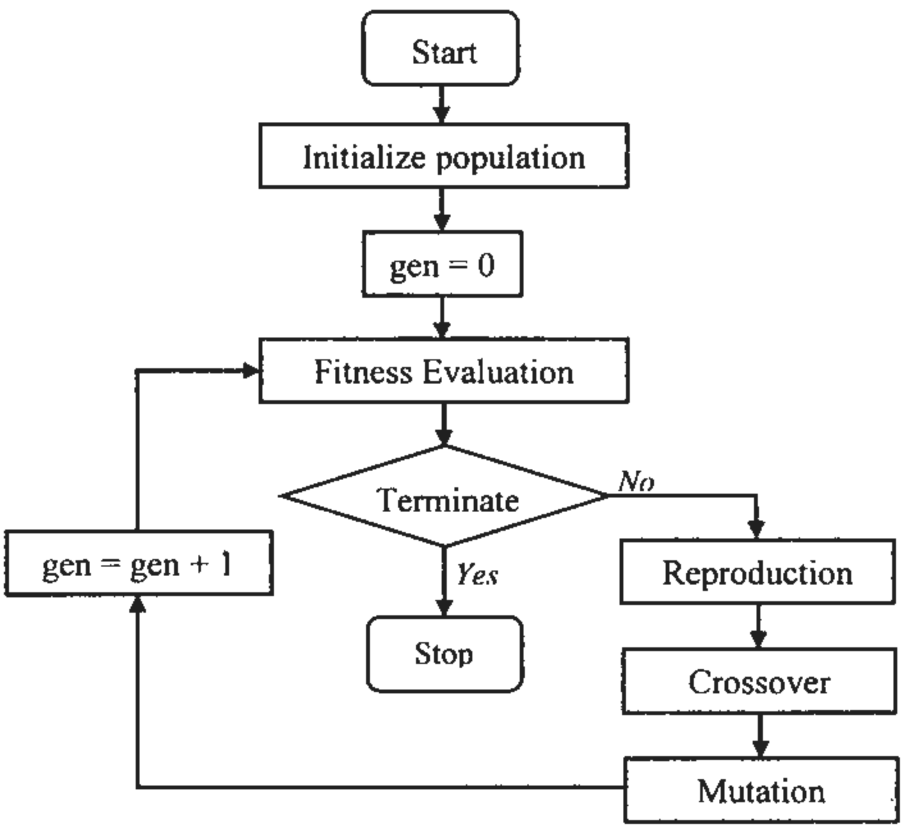


Figure 4.1 Flowchart of a genetic algorithm

Genetic representation (encoding) plays an important role in genetic algorithm. The original GA uses binary encoding. However, with the increasing utilization of GA in more complex problems, different encoding methods have been proposed, such as real-number encoding, integer or literal permutation encoding and general data structure encoding (Gen and Cheng 2000). Traditionally, the initial population is generated randomly with an attempt to cover the entire range of possible solutions (the search space). In some occasions, the solutions may be "seeded" in the areas where optimal solutions are likely to be found.

To evolve to the next generation, genetic operators (i.e., selection, crossover, and mutation) are employed to recombine the solutions in the previous generation to form a new generation. Selection (reproduction) is a process in which the individuals are selected based on their fitness and copied to the next generation. Selection is intended to improve the average quality of the population by giving the high-quality chromosomes better chances of being copied into the next generation (Goldberg 1989; Hue 1997). The selection thereby focuses the exploration on promising regions in the solution space. Selection should work to impose a balance between selection pressure and population diversity. The selection pressure is defined as the ratio of the probability of selection of the best chromosome in the population to that of an average chromosome. The convergence rate of GA is largely determined by the magnitude of the selection pressure. A low selection pressure leads to low convergence rate, and the GA will take unnecessarily longer time to find the optimal solution. On the other hand, a high selection pressure results in the population's reaching equilibrium very quickly, but with inevitable sacrifices in genetic diversity (i.e., convergence to a suboptimal solution). Therefore, the proper selection schemes are of importance to the implementation of a GA. Many selection methods have been proposed. The selection schemes commonly used in the current practice include roulette wheel selection (Holland 1975), ranking selection (Baker 1985), tournament selection (Goldberg *et al.* 1992), and Genitor (or "steady state") selection (Whitley 1989; Syswerda 1989).

Crossover is a process of combining two parental chromosomes and generating new offsprings that are different from their parents. After the selection (reproduction) process, the population is enriched with better individuals. Reproduction makes clones of good chromosomes but does not create new ones. A crossover operator is applied to create better offsprings. The simplest genetic algorithm uses single-point crossover in which only one crossover point is randomly selected to break a chromosome into two segments. By exchanging corresponding segments of two parents, new offsprings are then produced. Figure 4.2 illustrates the single-point crossover operation.

Parent 1	0 1 0 0 1 ¦ 0 0 0 1 0
Parent 2	0 0 0 1 1 ¦ 1 0 0 0 1

⇩

Offspring 1	0 1 0 0 1 ¦ 1 0 0 0 1
Offspring 2	0 0 0 1 1 ¦ 0 0 0 1 0

Figure 4.2 Single-point crossover

In addition to the single-point crossover, more complicated crossover operations have also been proposed, such as multi-point crossover (De Jong and Spears 1992) and uniform crossover (Ackley 1987). They are all based on the same principle of exchanging corresponding segment(s) of two parents to produce offsprings. Figure 4.3 illustrates a two-point crossover operation. The dotted lines indicate the crossover points. Thus the contents between these points are exchanged between the parents to produce new offsprings for mating in the next generation.

Parent 1	1 1 0 ¦ 0 1 0 ¦ 1 0 0 1
Parent 2	0 0 1 ¦ 0 0 1 ¦ 1 1 0 0

⇩

Offspring 1	1 1 0 ¦ 0 0 1 ¦ 1 0 0 1
Offspring 2	0 0 1 ¦ 0 1 0 ¦ 1 1 0 0

Figure 4.3 Two-point crossover

In Figure 4.4, the offsprings are produced using the uniform crossover approach. Each gene in the offspring is created by copying the corresponding gene from one or the other parent chosen according to a crossover mask of the same length as the chromosomes. A crossover mask is randomly generated for each pair of parents. The offsprings, therefore, contain a mixture of genes from each parent.

Parent 1	1 0 1 0 0 0 1 1 1 0
Parent 2	0 0 1 1 0 1 0 0 1 0
Mask	0 1 1 0 0 1 1 0 0 0
Offspring 1	0 0 1 1 0 0 1 0 1 0
Offspring 2	1 0 1 0 0 1 0 1 1 0

Figure 4.4 Uniform crossover

Mutation plays a role in alterations of genetic materials and randomly disturbing genetic information. It is considered as a background operator to maintain genetic diversity in the population. Mutation introduces new genetic structures in the population by randomly modifying some of its building blocks. It assists the search in escaping from local optima and maintains diversity in the population. The mutation operation is essentially done by altering the value of a randomly selected position in a string. Figure 4.5 illustrates a chromosome before and after mutation at two mutation points indicated by the double arrows.

Parent	0 0 1 0 1 0 0 0 1 0
Offspring	0 0 0 0 1 0 0 1 1 0

Figure 4.5 Mutation operation

An important parameter in mutation operation is the mutation probability, which decides how frequently parts of chromosome are mutated. Compared to crossover probability (which is usually between 0.6 and 1), mutation probability is usually set fairly low (e.g. 0.01). If it is set to high, the search will turn into a primitive random search.

Termination is the criterion by which the genetic algorithm decides whether to continue or to stop the search. The termination criteria can be specified as the permissible maximum number of generations or an acceptable approximated solution. The evolution process can also be terminated when the best individual found has remained unchanged over a specified number of consecutive generations. Generally, the last criterion applies as convergence slows to the optimal solution (Louis 1993).

4.2 A GA-based approach to multi-objective path optimization problem

While the basic structure of a genetic algorithm is universally followed in all applications to solve an optimization problem, experience has shown that the success of GA is largely dependent on the specifics of how it is applied. To this end, the essence of a customized genetic algorithm for the multi-objective route planning for the transportation of dangerous goods is detailed in this section.

4.2.1 Genetic representation

Genetic representation (encoding) of a solution to the problem in the context of a chromosome structure is a critical step in a genetic algorithm. Various encoding methods have been developed for different types of problems. According to the type of symbols used as the alleles of a gene, the encoding methods can be classified as: binary encoding; real number encoding; integer or literal permutation encoding; and general data structure encoding (Gen and Cheng 2000). Binary encoding is commonly used because it is simple to create and manipulate. In addition, single-point crossover and mutation can be conducted without modification to a range of problems (Davis 1991). However, for many problems in the real world, it is hard or even impossible to represent solutions using binary encoding. Other representation schemes are better suited for these problems. For example, real number encoding outperforms binary encoding for function optimizations and constrained optimizations (Eshelman and Schaffer 1993, Michalewicz 1996, Walters and Smith 1995), while integer or literal permutation encoding is deemed best for combinatorial optimization problems, which searches for a best permutation or combination of objectives subject to constraints (Cheng *et al.* 1999; Zhu 2003; Wang *et al.* 2008).

Genetic algorithms have seen wide applications in solving various transportation problems such as shortest path problem, vehicle routing problem, traveling salesman problem, network flow problem, etc. When solving these problems by genetic algorithms, the integer-string representation is most commonly used for chromosome encoding. The candidate solution is usually represented as a string (chromosome) of K distinct integers, where K is the number of nodes the candidate route comprises. Each gene in the chromosome is the integer node number. The sequence of the genes indicates the order of the nodes through which the routing path passes. For example, the integer string of 1 – 2 – 6 – 3 – 7 – 8 – 4 – 9 – 5 – 10 represents a route between nodes 1 and 10 shown in Figure 4.6.

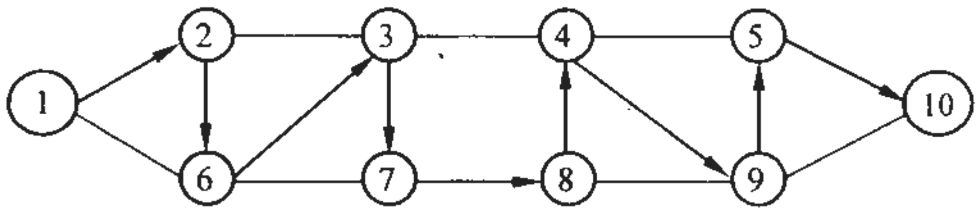


Figure 4.6 Example of a route and its integer encoding

The same encoding scheme is adopted in the proposed genetic algorithm to represent potential routing solutions. In this method, a feasible route is represented as a variable-length chromosome, which consists of an ordered sequence of positive integers representing the IDs of nodes through which the route passes. Each gene of the chromosome represents a node in a route. The first gene is always reserved for the source node. The length of the chromosome is variable, depending on the number of nodes that form the route. Every chromosome starts with a source node and ends with a destination node, connecting links that stretches from the origin to the destination along a constrained network. An example of genetic representation for a route from node S to node T is shown in Figure 4.7. The chromosome is encoded as a list of nodes along the constructed route, $\{S - P_1 - P_2 - \ldots - P_{n-1} - P_n - T\}$. The first gene encodes the source node S, and the second gene encodes the node randomly or heuristically selected from the network, which is connected with node S. This procedure continues iteratively for the succeeding nodes until a simple path to the destination node T is created. It should be noted that a valid chromosome is loop-free, that is, no duplicated integers should be included in the sequence. The existence of loops may cause problems when routing. Neither can the consistency of routing be guaranteed in the presence of loops.

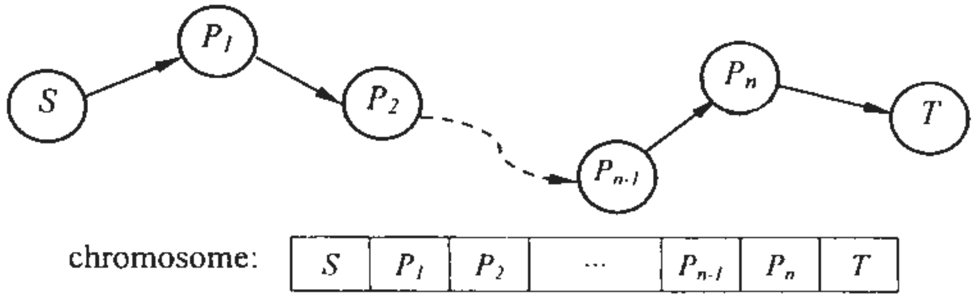


Figure 4.7 Example of a routing path and its encoding scheme

4.2.2 Population initialization

A genetic algorithm normally starts with an initial population. In general, there are two issues to be considered for population initialization of GA: the initial population size and the procedure to initialize the population (Goldberg 1989; Hue 1997). It is generally agreed that the population size should increase significantly with the complexity of the problem in order to generate good solutions. While a large population might increase the diversity of solutions, it demands excessive costs in terms of both memory and time (Goldberg 1989; Harik *et al.* 1999). Recent studies have shown, however, that satisfactory results can be obtained with a much smaller population size using an additional elitism strategy and adaptive grid-type technique to accelerate the convergence and to keep the diversity in Pareto front (Coello and Pulido 2001). As would be expected, deciding adequate population size is crucial for the efficiency of a GA. In this study, the size of the initial population is defined as an empirical parameter, and its value is set after a number of experimental tests. The determination of population size aims at striking a balance between the extra computational efforts and the diversity of rendered solutions.

Population initialization is a crucial task in genetic algorithms because it can affect the convergence speed as well as the quality of the final solution. In general, there are two ways to generate initial population. The first one is random initialization. In the absence of a priori information about solution, random generation is most commonly used to create initial population. Baker and Ayechew (2003) argue that randomly generated population (over a more structured approach) 'provides a more diverse population that converges to a near optimal solution quickly.' The other way to initialize population is heuristic initialization. A good knowledge of the problem always contributes to the problem-solving process. Upon its availability, heuristic initialization can be performed by "seeding" solutions in areas where optimal solutions are likely to be found. Seeding the initial population may improve initial quality and provide a better starting point for the genetic algorithm. It has been observed that the mean fitness of heuristic initialization is generally higher than that of random initialization so that it may help the GAs to find solutions faster (Zhang and Armstrong 2008).

Random initialization benefits the diversity of population; however, it may take longer time for the GAs to find satisfactory solutions. On the other hand, heuristic initialization provides a better starting point for a GA, which may facilitate the convergence of the algorithm. Using a purely heuristic method would, however, merely produce a number of solutions all identical to each other, which would be undesirable in terms of the evolutionary theory. In this regard, we experiment with both techniques to initialize a group of individuals (candidate routes) in the population. The initiation procedure starts with an origin and randomly chooses a valid node based on the connectivity information of the network. The encoding process keeps selecting a valid node that can be connected to the last node of the current route and has not been included in the route so far, until a destination is reached. However, applying random walk only can result in poor performance when working on larger sized network, for example, consuming an excessive amount of CPU time to form extremely long chromosomes. To solve this problem, heuristics are introduced into the initialization process. A hybrid approach that contains the seeds generated by Dijkstra's shortest path algorithm is employed in this study. The seeds include the routes produced by Dijkstra's algorithm on each single objective, as well as those generated by combining two or more objectives using unbiased preferences (i.e., equal weight) on each objective. The objectives to be combined and the number of these objectives are chosen at random, while the duplicated combination is prevented. The heuristic initialization will contribute 20% individuals in the initial population, and the remaining individuals are provided by random walk.

By incorporating random initialization with heuristic initialization, we may achieve a higher quality of initial population than random generation while still preserving population diversity to certain extent.

4.2.3 Fitness evaluation

The fitness function in a single-objective GA is typically the objective function of the indicated optimization problem (Goldberg 1989; Leung *et al.* 1998). It is used to measure the quality of the individuals (chromosomes) in a population. The fitness function has a higher value when the fitness characteristic of the chromosome is better than others. Moreover, it introduces a criterion for the selection of chromosomes. The definition of the fitness function is therefore very critical (Hue 1997).

Different from single-objective GAs, in a multi-objective scenario, the fitness value of a solution should reflect its optimality in each of the objectives. The fitness value of a solution depends not only on the values from a single objective function, but also on its optimality within the entire population. Therefore, a Pareto optimum concept is adopted. In the proposed GA, a Max-Min fitness function (Balling *et al.* 1999) is employed to measure the Pareto optimality of each route in a particular generation:

$$Fitness^i = 1 - \max_{j \neq i}\left(\min_{k=1,2,\ldots m}\left(\frac{f_k^i - f_k^j}{f_k^{\max} - f_k^{\min}}\right)\right) \quad (4.1)$$

where $Fitness^i$ is the fitness of the ith route in the generation, f_k^i and f_k^j are the values of the kth objective for the ith and jth routes in the generation, respectively. The scaling factors $f_k^{\max}$ and $f_k^{\min}$ are maximum and minimum values, respectively, of the kth objective in the generation.

In equation (4.1), the min is taken over all the objectives from 1 to m, and the max is taken over all routes in the generation from 1 to n (i.e. population size) except route i. Hence, the Max-Min fitness function here can be easily implemented as three nested loops. The outer loop over i ranges from 1 to n. The middle loop over j ranges from 1 to $n-1$. The inner loop over k ranges from 1 to m. Thus, the total number of comparisons is $m \times n \times (n-1)$.

The Max-Min fitness function is derived from the definition of dominance. Any chromosome whose Max-Min fitness value is less than 1 is a dominated route; it is otherwise a non-dominated route if the value of $Fitness^i$ is greater than one. This is because $Fitness^i > 1$ indicates that the latter part of the right-hand side of equation (4.1) is negative, i.e. $\max_{j \neq i}\left(\min_{k=1,2\ldots m}\left(\frac{f_k^i - f_k^j}{f_k^{\max} - f_k^{\min}}\right)\right) < 0$, which means route i outperforms the others on at least one objective. A chromosome is weakly-dominated if its Max-Min fitness is one, which means that it is either a dominated route or a duplicate non-dominated route. The Max-Min fitness of a solution can identify not only whether a solution is dominated or not (with respect to the rest of the population), but also whether it is clustered with other solutions, i.e., diversity information. When the fitness is maximized, it rewards diversity and penalizes clustering of non-dominated solutions (Balling 2003). As a result, no additional clustering or niching technique is needed with the Max-Min fitness function.

For multi-objective DG routing problem, a route is a "non-dominated route" if it is feasible and there is no other feasible solution in the generation which has better values for all the objectives considered. According to equation (4.1), the fitness of Pareto-optimal routes will be between 1 and 2, whereas the fitness of dominated routes will be between 0 and 1. A "clustered route" is a route whose objective values are close to those of other candidates in the generation. According to equation (4.1), the Max-Min fitnesses of clustered non-dominated routes are greater than and close to 1, whereas the Max-Min fitnesses of non-clustered non-dominated plans are greater than and far from 1. Thus, the Max-Min fitness function given by equation (4.1) penalizes both dominance and clustering. Maximizing the Max-Min fitness function will yield a diverse set of non-dominated routes.

4.2.4 Genetic operations

4.2.4.1 Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual chromosomes (solutions) are selected through a fitness-based process, where fitter chromosomes are typically more likely to be selected. There are two basic types of selection scheme commonly used in current practice: proportionate selection and ordinal-based selection (Goldberg 1989; Hue 1997).

Proportionate selection selects chromosomes based on their fitness values relative to that of the others in the population. It is generally more sensitive to the selection pressure. Therefore, a scaling mechanism in the form of function transforming the raw fitness into scaled fitness is often used, which redistributes the fitness range of the population in order to adapt to the selection pressure. Fitness scaling aims to maintain a reasonable differential between relative fitness ratings of chromosomes, and to prevent too-rapid takeover by some "super" chromosomes to meet the requirement to limit competition early but to stimulate it later (Gen and Cheng 2000).

The best known proportionate selection technique is the roulette wheel selection (Figure 4.8). The principle of roulette selection is a search through a roulette wheel with the slots in the wheel proportionate to the chromosome's fitness values. The value of a chromosome is set by dividing its fitness by the sum of the fitness in the population. Each chromosome is assigned a slice of the roulette wheel, with the size of the slice being proportional to the chromosome's fitness. The wheel is spun N times, where N is the number of chromosomes in the population. On each spin, the chromosome under the wheel's marker is selected as a parent for the next generation. Due to the randomness of the selection, fit chromosomes are not guaranteed to be selected for, but have a higher probability of selection. For this reason, elitism is a common practice in GA selection to ensure that the best chromosomes are selected and copied directly to the next generation.

Ordinal-based selection schemes select chromosomes based on their rank rather than fitness within the population. The chromosomes are ranked according to their fitness values. The selection pressure depends on the relative ranking of the population. Similar to proportionate selection schemes, ordinal-based selection suffers when the selection pressure is inadequate (i.e., low or high), in other words, a low selection pressure leads to low convergence rate, while a high selection pressure may result in loss of genetic diversity or convergence to local rather than global optima. Examples of ordinal-based selection type include tournament selection, (μ, λ) selection, truncation selection, and linear ranking selection.

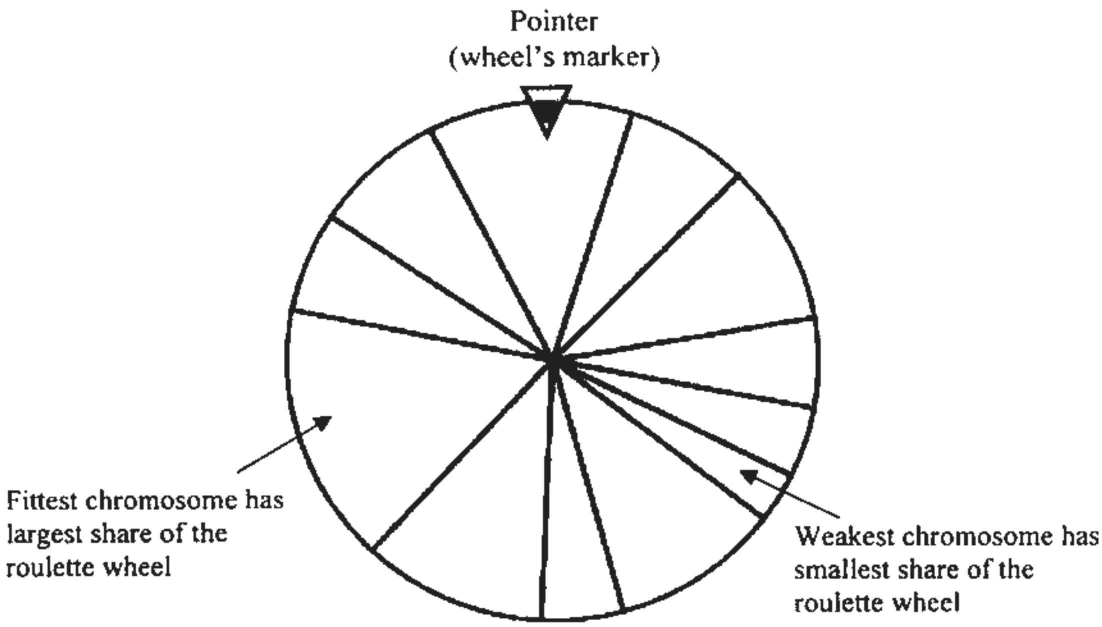


Figure 4.8 Roulette wheel selection

Tournament selection (Goldberg *et al.* 1992) is one of the most widely used ordinal-based selection schemes. In tournament selection, a specified number of chromosomes, *s* (tournament size), is selected from the current population. The best individual out of the *s* chromosomes is selected for further genetic operation. The selection of *s* chromosomes can be performed either with or without replacement. The difference is that in a selection with replacement, the chromosomes selected for the current tournament are candidates for other tournaments; while in a selection without replacement, the chromosomes once selected are not candidates for other tournaments. In GA literature, tournament selection without replacement has received considerable analytical attention, and has been successfully used in a wide variety of GAs. Tournament selection without replacement works by means of choosing non-overlapping random sets of *s* chromosomes from the population, running tournaments among them, and selecting the winner of the tournament from each set to serve as a parent for the next generation. The mating pool comprising the tournament winners has higher average population fitness. The fitness difference provides the selection pressure, which drives GAs toward improved population fitness of the succeeding generations. Unlike the roulette wheel selection, the selection pressure in the tournament selection strategy is easily adjusted by changing the tournament size. The selection pressure increases as the tournament size becomes larger (Hue 1997; Harik *et al.* 1999). The tournament selection technique is simple and efficient. The main advantage of this mechanism is that it does not require implementation of any ranking or scaling method; instead, only the relative differences of fitness values between the selected individuals are needed.

In the proposed GA, the tournament selection without replacement is employed to generate a new population for the next generation. Tournament selection is implemented with a tournament size of three. Each time three chromosomes (routes) are randomly selected from the current generation, and are involved in the tournament. The chromosome with the highest fitness value (i.e., the best Pareto-optimal route) is selected and put into the mating pool. This process will repeat N' times until the mating pool is filled. The N' chromosomes in the mating pool will then be undergoing genetic operations such as crossover and mutation to produce succeeding population. Note that the value of N' is not the same as that of the population size N, rather, N' is a bit smaller than N. The rest ($N - N'$) chromosomes in the immediate succeeding generation will be derived through the elitism strategy (which will be explained in the next paragraph). Tournament selection without replacement is perceived as an effort to keep the selection noise as low as possible (Goldberg *et al.* 1992). Hence, in each generation, once a chromosome has been selected in the tournament selection, it will be removed from the population in order to ensure that the same chromosome would not be chosen twice as a parent.

As a common practice in most GAs, the selection operation employed in the proposed GA also incorporates an elite retaining strategy. Elitism is the process of preserving previous high performance chromosomes from one generation to the next. This is usually achieved by simply copying the fittest chromosomes directly into the new generation. Elitism has long been considered an effective method for improving the efficiency of a GA (De Jong 1975). Various studies have shown that inclusion of an elitist element can considerably improve the performance of the algorithms, because it ensures that the best solutions found would not be lost (Zitzler *et al.* 2000;

Deb *et al.* 2000). In this study, elite retaining is carried out before the actual tournament selection starts. The elitism is chosen at 10%, meaning that 10% of the best individuals whose Max-Min fitness values are the highest in the current generation are copied directly into the next generation without modification.

4.2.4.2 Crossover

The crossover operator, one of the distinctive characteristics of GAs, plays a vital role in the search process. It is considered one of the essential components for the good performance of a GA.

Crossover is the process of combining two parent solutions and producing offsprings from them. It is applied with an expectation that a better offspring is created. Crossover proceeds in three steps:

i. The selection operator randomly selects a pair of parent chromosomes for the mating;
ii. A cross-site is then selected at random along the length of the mated chromosomes;
iii. Finally, the position values are swapped between the two chromosomes following the cross-site.

For a selected pair of chromosomes, a random number between zero and one is generated. If the random number falls below the crossover probability, then these two chromosomes will be recombined. Crossover is achieved by simply choosing at random a crossover point (cross-site), copying everything before this point from one parent and then, copying everything after the crossover point from the other parent. Besides the single-point crossover, more complicated crossover algorithms have also been devised, which often involve more than one cut point. An advantage of having more crossover points is that the problem space may be searched more thoroughly. However, adding additional crossover points is more likely to disrupt the building blocks of chromosomes during the process of crossover operation, and consequently degrade the performance of the GA (Sivanandam and Deepa 2008).

In routing problems like multi-objective route planning addressed in this research, crossover essentially plays the role of producing offsprings (i.e. new routes) by cutting the two chosen chromosomes (parents) and exchanging each partial route of the parent chromosomes. Each offspring represents only one route. One partial route connects the source node to the intermediate node where crossover is conducted (i.e. cross-site), and the other partial route connects the intermediate node to the destination node. The crossover between two dominant parents chosen by the selection gives higher probability of producing offsprings possessing the dominant traits.

In view of this, one-point crossover is employed in the proposed GA. Unlike the conventional one-point crossover operating on two chromosomes of the same length, in the proposed crossover scheme, the two chromosomes (routes) chosen for crossover can have different lengths, that is, the number of nodes that form each parent (route) can be different from each other. The only condition is that the two parent chromosomes have at least one gene (node) in common except for the source and destination nodes. This common node is the crossover point/cross-site where crossover is accomplished. The crossover point can be at different positions on each parent chromosome. For example, it may be on the 23rd node in one parent, but on the 15th node in the other. If more than one common gene is found, the proposed GA will randomly choose one of them as the crossover point. Figure 4.9 shows an example of the crossover procedure. Two routes, $\{S - P_1 - P_3 - P_6 - P_4 - P_7 - T\}$ and $\{S - P_2 - P_3 - P_4 - P_5 - T\}$, are selected by tournament selection as parent 1 and parent 2, respectively, for mating. P_3 is detected as the node which is commonly included in both routes. It is then used as the crossover point of each chromosome. Each route is "broken" into two partial routes on the crossover point: $\{S - P_1 - P_3\}$ and $\{P_6 - P_4 - P_7 - T\}$ from parent 1, and $\{S - P_2 - P_3\}$ and $\{P_4 - P_5 - T\}$ from parent 2. Two corresponding partial routes are subsequently exchanged: for example, $\{P_6 - P_4 - P_7 - T\}$ from parent 1 is exchanged with $\{P_4 - P_5 - T\}$ from parent 2. The partial routes are then assembled: $\{S - P_1 - P_3\}$ from parent 1 is connected with $\{P_4 - P_5 - T\}$ from parent 2, while $\{S - P_2 - P_3\}$ from parent 2 is connected with $\{P_6 - P_4 - P_7 - T\}$ from parent 1. Two new routes are produced eventually, they are: $\{S - P_1 - P_3 - P_4 - P_5 - T\}$ and $\{S - P_2 - P_3 - P_6 - P_4 - P_7 - T\}$.

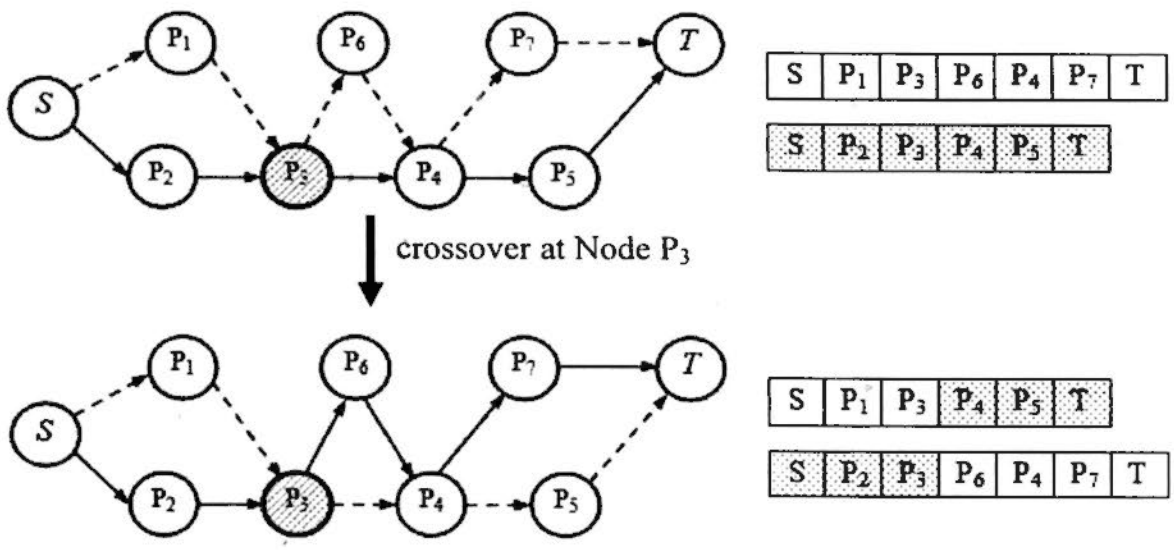


Figure 4.9 An example of single-point crossover

The crossover procedures may generate loops in routes. A route with one or more loops in it is regarded as an infeasible route, since it is commonly agreed that the solution to the shortest path problem should not include any loop. To cure infeasible chromosomes, a repair function is applied in the proposed GA to eliminate undesired loops in each infeasible chromosome. The proposed repair function detects a loop in a route by searching for duplicated nodes. The loop is then eliminated by deleting the duplicated nodes. For example, the route {S – P_1 – P_2 – P_8 – P_{14} – P_{13} – P_8 – P_{14} – P_{19} – P_{24} – T} produced by crossover is an infeasible route since a loop {P_8 – P_{14} – P_{13} – P_8} can be detected in it. By deleting one of two node P_8, a valid route { S – P_1 – P_2 – P_8 – P_{14} – P_{19} – P_{24} – T} is generated accordingly.

4.2.4.3 Mutation

Similar to the role of crossover, mutation is also critical to the success of GAs. If crossover is supposed to exploit the current solution to find better ones, mutation is supposed to help explore the whole search space (Sivanandam and Deepa 2008). Mutation is viewed as a background operator to maintain genetic diversity in the population. It plays the role of altering genetic materials as well as for randomly disturbing genetic information. Mutation introduces random changes to a chromosome and thus maintains or increases population diversity. It diversifies the search directions and avoids the convergence of the algorithm to local optima.

After crossover, the newly generated chromosomes are subjected to mutation. However, not all but part of the chromosomes will take part in the mutation procedure. Whether a chromosome will be mutated is determined by the probability of mutation (i.e. mutation rate). For a chosen chromosome, a random number between zero and one is generated. If the random number falls below the rate of mutation, then this particular individual will be mutated. There are many different types of mutation, such as flip bit mutation, boundary mutation, uniform mutation, non-uniform mutation, and Gaussian mutation. Unlike the flip mutation which can only be used for binary genes, the other four mutation operators can only be used for integer and float genes. The flip bit mutation simply inverts the value of the chosen gene (0 goes to 1 and 1 goes to 0). The boundary mutation replaces the value of the chosen gene with either the upper or lower bound for that gene (chosen randomly). The uniform mutation replaces the value of the chosen gene with a uniform random value selected between the user-specified upper and lower bounds for that gene. The non-uniform mutation increases the probability that the amount of the mutation will be close to 0 as the generation number increases. This mutation operator keeps the population from stagnating in the early stages of the evolution, while allows the algorithm to fine tune the solution in the later stages of evolution. The Gaussian mutation adds a unit Gaussian distributed random value to the chosen gene. The new gene value is clipped if it falls outside the user-specified lower or upper bounds for that gene.

The mutation method used in this study is somewhat different from the aforementioned mutation schemes. In the proposed GA, the mutation operation generates an alternative partial route from the mutation point (i.e. the node in the route which is chosen to be mutated) to the destination node. First, a gene (i.e. a node) in a chosen chromosome is randomly selected as the mutation point. A partial route starting from this mutation point to the destination is subsequently generated by means of a similar procedure used for population initialization, incorporating heuristics with random walk. The produced partial route is then combined with the surviving portion of the parent route, i.e. the partial route stretching from the origin to the mutation point in the parent's chromosome, to form a new route. Note that the nodes that are already included in the partial route from the origin to the mutation point should not be introduced into the partial route from the mutation point to the destination, except for origin, destination, and mutation point. The underlying reason is that the same node cannot be included in one route twice; otherwise, it incurs loops in the route, which in turn results in the route infeasible. Recall that the crossover operation may generate invalid routes that contain loop(s). This problem, however, will not happen to the mutation operation. The chromosome obtained by mutation is certainly feasible, because during the mutation process, once a node is chosen, it will be excluded from the candidate nodes forming the rest of the route. Hence no loop will be included in the generated routes.

Figure 4.10 indicates how a new chromosome is created by mutation operation. Let $\{S - P_1 - P_2 - P_5 - P_6 - T\}$ be the parent chromosome that is selected to mutate. As can be seen from Figure 4.10, there also exist other routes between the source node S and the destination node T. In order to perform a mutation, a gene (i.e. node P_1) is randomly selected first from the chosen chromosome. P_1 is the mutation point. One of the nodes directly connected to node P_1, for example, P_4, is chosen at random as the first node of the alternative partial route. The remaining procedure follows that in the initializing process to create the partial route stretching from P_1 to the destination T, $\{P_1 - P_4 - P_2 - P_3 - T\}$. Finally, this partial route is combined with the partial route starting from the source S to the mutation point P_1, $\{S - P_1\}$, and the new route between S and T, $\{S - P_1 - P_4 - P_2 - P_3 - T\}$ is eventually formed.

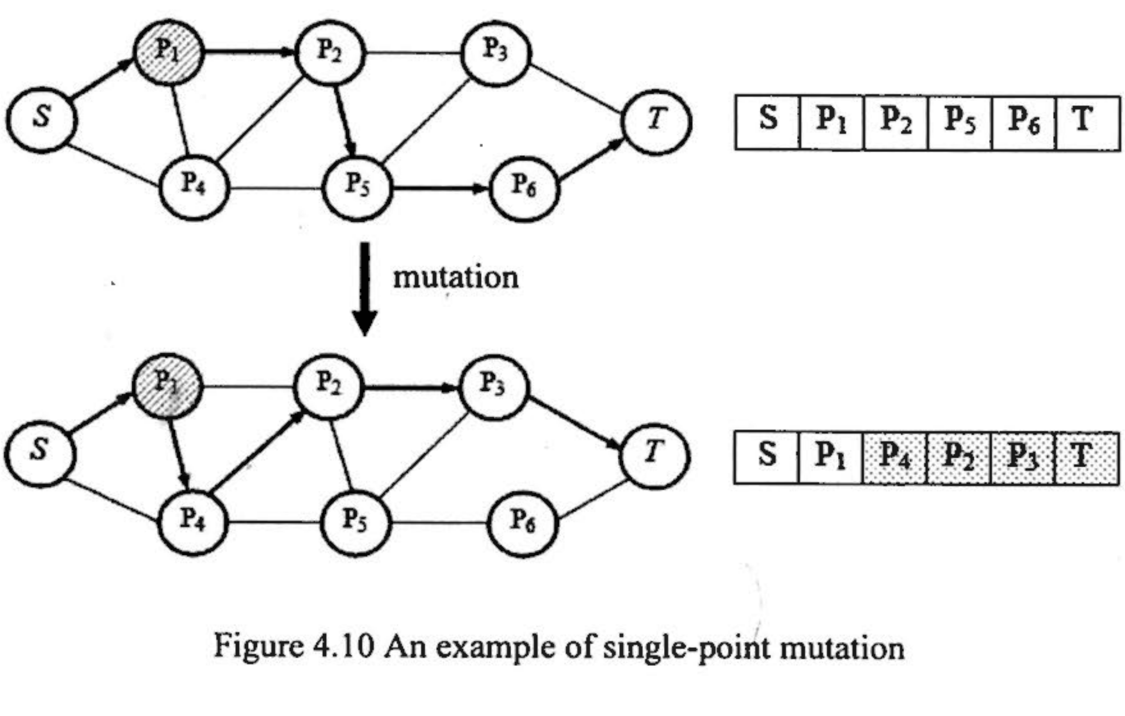


Figure 4.10 An example of single-point mutation

4.2.5 Termination criteria

Termination is the criterion by which the genetic algorithm decides whether to continue or stop the search. Each of the enabled termination criterion is checked after each generation to decide whether it is the time to stop. The termination conditions that are most commonly used include:

- The maximum number of generations has been reached.
- A specified time has elapsed. It should be noted that if the maximum number of generation has been reached before the specified time has elapsed, the search process will terminate.
- There is no change to the population's best fitness for a specified number of generations. Note that the process will end if the maximum number of generation has been reached before the specified number of generation without changes has been obtained.
- There is no improvement in the objective function for a specified number consecutive generation.
- Combinations of the above.

The proposed GA is controlled by two termination criteria. One criterion is that a specified number of generations have evolved. The other is that the mean of the fitness in the entire population has remained unchanged, or changes within a very small range, over a specified number of consecutive generations. If either of the two termination criteria is satisfied, the iterative process of the GA is terminated.

4.2.6 The proposed genetic algorithm

With the above detailed introduction of each component, the proposed genetic algorithm tailored for multi-objective route planning for the transportation of DG are described algorithmically as follows. The block diagram of the proposed GA is shown in Figure 4.11.

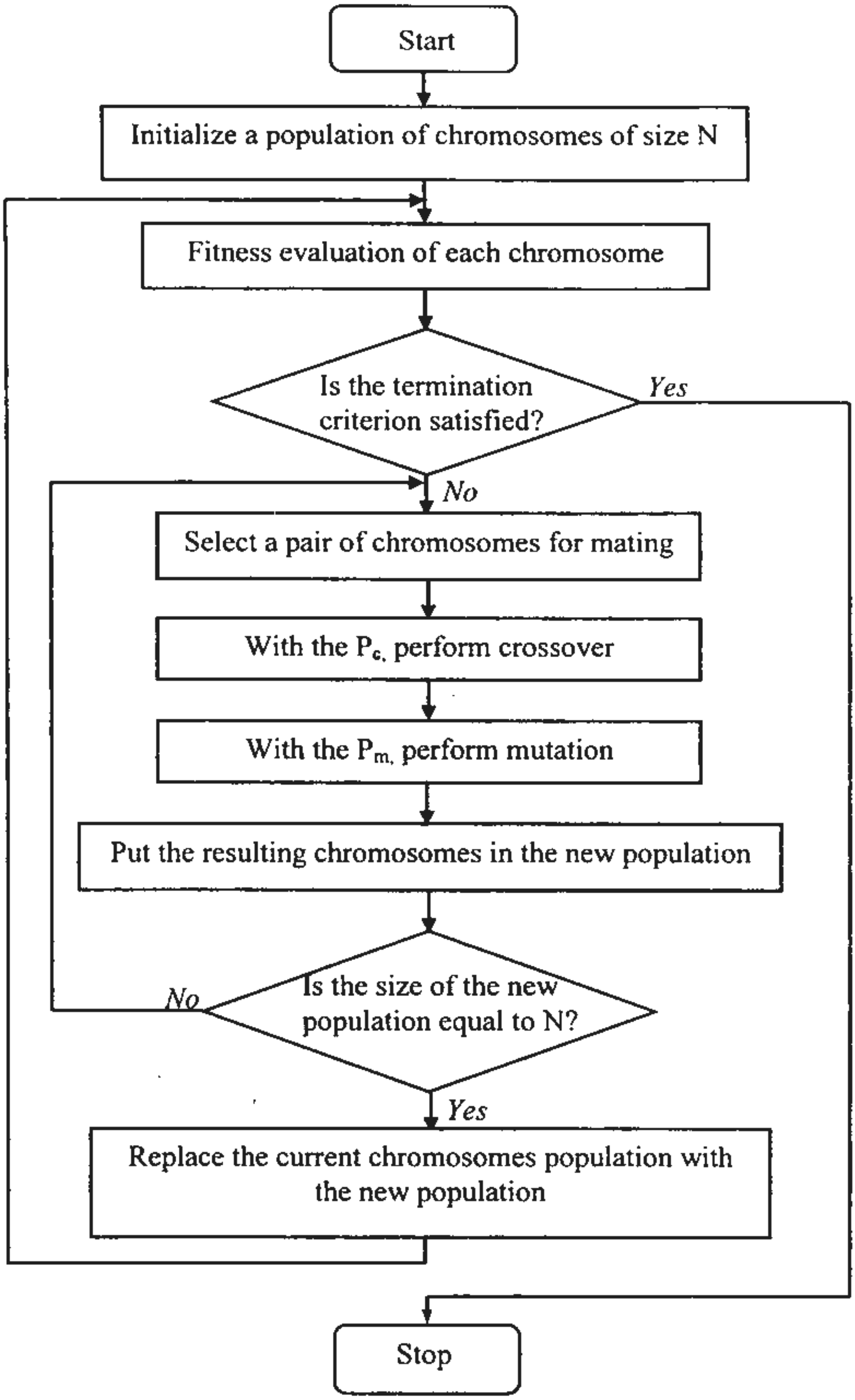


Figure 4.11 The flowchart of the multi-objective routing genetic algorithm

Step 1. Population Initialization:

1.1 Specify the population size N_{pop}, tournament size s, elitism size N_{elite}, crossover probability P_c, mutation probability P_m, and the evolution termination criteria.

1.2 Based on the proposed chromosome representation, generate N_{pop} chromosome (candidate route) to form the initial population $POP(0)$:

$$POP(0) = \{CHR_1(0), CHR_2(0), \ldots CHR_{Npop}(0)\}.$$

A hybrid approach is used to initialize population $POP(0)$, which incorporates random walk with heuristic initialization containing the seeds generated by Dijkstra's shortest path algorithm. Each chromosome is represented in the same encoding scheme as shown in Figure 4.7.

1.3 Set $k = 0$.

Step 2. Fitness evaluation:

Compute the fitness $Fitness(CHR_i(k))$ of individual $CHR_i(k)$, $i = 1\ldots N_{pop}$, according to the formula (4.1). Sort the fitnesses in the descending order so that the fittest individual is always on the top.

Step 3. Population evolution:

3.1 Elitist strategy.

Select N_{elite} elites from the current population, $N_{elite} = N_{pop} * 10\%$. Copy these individuals directly into the next generation without modification.

3.2 Selection.

(1) Pick three individuals at random from current generation.

(2) Compare the fitness values of these 3 individuals. Select the one with the highest Max-Min value as one parent chromosome, say $CHR_i(k)$.

(3) Remove the selected individual from the current population so that it would not be picked again as a candidate for other tournaments.

(4) Repeat (1) to (3) to select another parent chromosome, say $CHR_j(k)$, $i \neq j$.

3.3 Crossover.

(1) Identify the crossover point.

Compare the genes of $CHR_i(k)$ and $CHR_j(k)$. If no common genes (common nodes except for the source and destination nodes) can be found, put one of them back into the mating pool, and then pick another individual. If more than one gene is found in common, randomly choose one common gene, and the locus of this gene becomes the crossover point.

(2) Perform the crossover operation on $CHR_i(k)$ and $CHR_j(k)$ with probability P_c, and yield the intermediate individuals $OSP'_i(k)$ and $OSP'_j(k)$.

Break $CHR_i(k)$ and $CHR_j(k)$ into two parts, respectively, on the crossover point. Connect the upper part of $CHR_i(k)$ with the lower part of $CHR_j(k)$ to yield the offspring $OSP'_i(k)$. Similarly, connect the upper part of $CHR_j(k)$ with the lower part of $CHR_i(k)$ to yield another offspring $OSP'_j(k)$. The upper part of an individual represents the portion of the chromosome stretching from the first gene (source node) to the intermediate gene at the crossover point, and the lower part represents the portion stretching from the intermediate gene at the crossover point to the last gene (destination node).

(3) Repair infeasible route if necessary. Detect loops in the offspring $OSP'_i(k)$ by searching for duplicate nodes. The loop is then eliminated by deleting genes between duplicate nodes. Repeat the same operation on the offspring $OSP'_j(k)$.

3.4 Mutation.

(1) Identify the mutation point.

Randomly choose a gene (node) from $OSP'_i(k)$, and the locus of gene becomes the mutation point.

(2) Mutate $OSP'_i(k)$ with probability P_m to yield the offspring $OSP_i(k)$.

Take 1.2 of Step 1 to generate the new lower part of the chromosome $OSP'_i(k)$ stretching from the intermediate gene at the mutation point to the last gene. Assemble this portion with the surviving portion of $OSP'_i(k)$, the offspring $OSP_i(k)$ is then generated.

(3) Repeat (1) and (2) to yield the offspring $OSP_j(k)$.

3.5 Construction of new population.

Repeat 3.2 to 3.4 until ($N_{pop} - N_{elite}$) individuals have been produced. Together with N_{elite} elites copied directly from the current population, a new population with its size of N_{pop} is constructed.

$$POP(k+1) = \{CHR_1(k+1), CHR_2(k+1), \ldots CHR_{Npop}(k+1)\}.$$

Replace the current population with this new one.

Step 4. Termination check:

If $POP(k + 1)$ satisfies the pre-specified evolution termination criteria, the algorithm terminates; otherwise, go to Step 2 with $k = k + 1$.

4.2.7 Implementation issues

4.2.7.1 Complexity of the genetic algorithm

Compared with the compromise programming and the adaptive weighting method, the proposed genetic algorithm has relatively higher complexity. To start, the population initialization takes time proportional to $O(N_{pop}n^2)$ to create N_{pop} initial candidates by either random walk or seeding (i.e. heuristic initialization) using Dijkstra's algorithm, where N_{pop} is the population size, n is the number of nodes of the network G defined in Chapter 3. After initialization, a typical iteration of the algorithm comprises four operations: fitness evaluation, selection, crossover, and mutation. Implementing the Max-Min fitness function to evaluate the fitness of each individual in the current generation runs in $O(mN_{pop}^2)$, where m is the number of objectives considered. Given that $(N_{pop} - N_{elite})$ individuals need to be selected and the size of tournament selection is 3, the selection operation can be accomplished in $O(3(N_{pop} - N_{elite}))$, where N_{elite} is the elitism size. To decide whether a crossover operation needs to be conducted on a pair of selected individuals, a random number between zero and one is generated for each pair. At the worst, all the random numbers fall below the crossover probability. Consequently, the crossover operation has to be performed on every pair of chromosomes, which results in a complexity of $O(N_{pop} - N_{elite})$. Similarly, the mutation operation results in a complexity of $O((N_{pop} - N_{elite})n^2)$ at the worst when each selected individual needs to be mutated. Consequently, the overall complexity for the initialization and N iteration is approximately $O(N_{pop}n^2 + N(mN_{pop}^2 + (N_{pop} - N_{elite})(n^2 + 4)))$.

4.2.7.2 Global fitness

When the algorithm stops, a set, of (approximate) solutions for the DG routing problem will be obtained. Moreover, M generations of population of solutions will be generated. Decision makers may be interested in examining how well the genetic algorithm can improve Pareto optimality from generation to generation. However, the fitness function in formula (4.1) is designed to compare the fitnesses between solutions within a generation, thereofore it cannot be used to compare the fitnesses between solutions in different generations as the scaling factors f_k^{max} and f_k^{min} in different generations might be different. To solve this problem, a "global generation" is created, which includes (M * N_{pop}) feasible solutions from M generations lumped together. The "global fitness" for each of the (M * N_{pop}) solutions in the global generation can be calculated according to formula (4.1). Based on global fitnesses, the ''global Pareto set'' for the global generation can be generated.

4.3 Summary

GAs are a particular type of evolutionary algorithm initially developed by Holland (1975) in the early 1970s. A GA is a computing model that aims to minimize (or maximize) an objective function by simulating the mechanism of genetic selection and natural elimination in biological evolution. It is a computationally simple yet robust and powerful way to search for optimal and near-optimal solutions for optimization problems. As a highly efficient search strategy for global optimization, GAs exhibit superior performance on solving multi-objective optimization problems that have a large and complex solution space. Moreover, being a population-based approach, a GA is able to find multiple feasible solutions in a single run.

GAs operate on a population of candidate solutions encoded as a finite bit string – chromosome. It usually starts with an initial population of candidate solutions that are randomly or heuristically generated. These candidates are retained and ranked according to their quality measures by a fitness function, which screens out unqualified solutions. Genetic operations, such as selection, crossover, and mutation, are then performed on those qualified solutions to generate new candidate solutions for the next generation. These processes are carried out repeatedly until certain convergence condition is met.

The unique features of GAs facilitate their application in multi-objective route planning for the transportation of DGs. This chapter details a genetic algorithm for multi-objective DG routing analysis. Variable-length chromosomes (representing routes) and their genes (representing nodes) are used to encode the problem. A chromosome consists of sequences of positive integers representing the IDs of nodes through which a route passes. Each valid chromosome starts with a source node and ends with a destination node. No duplicated integers are included. A hybrid approach is used to initialize the population, which incorporates random walk with heuristic initialization containing the seeds generated by Dijkstra's shortest path algorithm. The incorporation of heuristics into random initialization enables the production of a better initial population while maintaining its diversity. A Max-Min fitness function derived from the definition of dominance is employed to maximize the difference between any two routes, which ultimately results in a diverse set of non-dominated solutions. The tournament selection without replacement is used to select candidates for breeding a new generation. An elite retaining strategy is incorporated, copying the fittest individuals directly into the next generation without modification, which prevents the loss of the best solutions found in each generation. The crossover operation exchanges partial chromosomes (i.e. partial-routes) at location independent crossover point. A repair function is applied to cure the infeasible chromosomes produced from crossover by eliminating undesired loops in these chromosomes. Through crossover, the algorithm searches the solution space in a very effective manner. The mutation operation introduces new partial chromosomes (partial-routes), which, in essence, maintains the diversity of population, thereby avoiding local traps. Selection, crossover, and mutation together provide a search capability that leads to improved quality of solutions and enhanced convergence rate.

The present and the preceding chapters have introduced different methodologies for the multi-objective path optimization problem. While Chapter 3 focuses on the deterministic optimization techniques, present chapter concentrates on the heuristic method. Applications of these approaches in optimal route planning for dangerous goods transportation is demonstrated in Chapter 5.

CHAPTER 5: CASE STUDY ON HONG KONG ROAD NETWORK

The previous chapters have presented conceptual and numerical optimization tools for the generation of multi-objective shortest paths with specific attention given to the transportation of dangerous goods on the road. As an application example, this chapter focuses on the problem of routing the road tankers conveying liquefied petroleum gas (LPG) in Hong Kong, a high-density living environment. A set of routing criteria fitting the context of the high-density living, in particular, Hong Kong, is identified. With the aid of GIS, each criterion is quantified under the rules suggested by the authoritative organizations. The three MOP methodologies proposed in this research are employed individually to generate various efficient solutions for optimal route planning for transporting LPG between Tsing Yi LPG terminal and the designated LPG filling stations located in Kowloon and the New Territories. The composition of risks in each solution is examined and the actual trade-offs involved are interpreted. Particular issues with respect to the implementation of each method are specified. The execution efficiency and application condition of each method are also discussed.

5.1 Overview

The transportation of dangerous goods can significantly affect the human and natural environment if accidents occur during the transportation process. Hong Kong is a large city with high population density and narrow streets. Due to the land constraints, vehicles carrying DG inevitably have to pass through densely populated areas or their vicinities. Therefore, safe DG transportation is of paramount importance. Routing of such vehicles should consider not only the operating cost, but also the safety of travelers in the network, the population potentially exposed, as well as the possible damage inflicted to the surrounding properties and facilities in the event of a DG incident. It is thus necessary to model the risks associated with the transportation of DGs and to design appropriate routes presenting inherent trade-offs between costs and risks.

Everyday, there are different types of dangerous goods transported on the roads in Hong Kong. As one of the most commonly transported DGs in Hong Kong, liquefied petroleum gas (LPG) was chosen as the DG example for this case study. LPG is non-toxic and is not harmful to soil or water. Tests conducted by the U.S. Environmental Agency show that LPG vehicles produce 30 ~ 90% less carbon monoxide than gasoline engines and about 50% fewer toxins and other smog producing emissions. Since LPG is harmless to the environment, it is considered as a type of clean energy. At present, almost 100% of taxis and more than 60% of light buses in Hong Kong run on LPG. Albeit harmless, LPG is potentially dangerous. It is highly inflammable like all petroleum fuels. Small quantities of LPG can give rise to large volumes of gas/air mixture as approximately 2% of the vapour in air will form a flammable mixture; if this situation occurs in a confined space and the mixture ignites, an explosion will result. LPG vapour is heavier than air, which has important safety implications. Any leakage will sink to the ground and accumulate in low-lying areas and may be difficult to disperse. The vapour can remain for some time if the air is relatively still, and if ignition occurs at a remote point the resulting flame may travel back to the sources of the leak. In addition to the risk of fire/explosion, LPG is also dangerous as it vaporizes and cools rapidly, and can therefore inflict severe cold burns if spilt on the skin. Moreover, it has an anaesthetic effect when mixed in high concentrations with air; the greater the concentration, the greater the risk of suffocation.

Given the dangerous nature of LPG, safe LPG transportation is of even greater importance for high-density living environment like Hong Kong in which population and socioeconomic activities are densely distributed over the transportation network. Route planning plays a crucial role in the prevention or minimization of possible catastrophic consequences on human life and the environment. However, study on such a problem in Hong Kong has seldom been reported so far. Hence there is an urgent need to carry out risk assessment and optimal route planning for LPG transportation in Hong Kong.

LPG is imported into Hong Kong by sea and stored at Tsing Yi LPG Terminals. It is then distributed throughout Hong Kong in cylinders and bulk road tankers. As Figure

5.1 shows, there are currently a total of 56 LPG filling stations in Hong Kong. Among them, 12 are dedicated LPG filling stations of which 9 are located in Kowloon and the New Territories. In addition, there are 44 non-dedicated LPG filling stations (i.e. LPG gas refilling stations). Currently, there are no designated routes for LPG cylinders and road tankers in Hong Kong. However, under the Road Tunnels (Government) Regulations, they are forbidden to pass through any tunnels in Hong Kong. The existing regulations specify the forbidden spots or road sections rather than the approved routes. Given a set of alternate routes between an origin and a destination, there are no quantitative means for the evaluation of the suitability of possible routes at the present moment. In the case study, a set of criteria were formulated for risk assessment, and the proposed methodologies were then employed to search the Pareto-optimal routes for transporting LPG from Tsing Yi LPG Terminal to the 9 dedicated LPG filling stations located in Kowloon and the New Territories. Note that for illustration purpose, the results of Tsing Yi terminal to Kowloon Bay and Tai Po station are presented in this chapter. Other choices of destination were tested and gave comparable results. However, in order to keep this chapter to a reasonable size, they are not reported below, but detailed in the appendix. It should also be noted that the present study mainly focuses on routing from Tsing Yi terminal to the dedicated LPG filling stations located in Kowloon and the New Territories. Stations located in Hong Kong Island were not taken into account in present study, because the transportation mode of LPG from Tsing Yi Terminal to Hong Kong Island is different from those of Tsing Yi to Kowloon and the New Territories. Since it is forbidden to pass through any tunnels in Hong Kong, a LPG tanker cannot run from Tsing Yi to Hong Kong Island directly, rather, it has to be transported from Tsing Yi to the Kwun Tong Dangerous Goods Vehicle Ferry Pier, then ferried to the North Point Ferry Pier, and finally delivered to LPG filling stations in Hong Kong Island. Due to the existence of multi-mode of transportation, the risk assessment for LPG transportation from Tsing Yi to Hong Kong Island will be quite different, more factors need to be considered; in addition, the risk of transfer also needs to be taken into account. Because of those reasons, this case study only concentrates on routing from Tsing Yi to Kowloon and the New Territories.

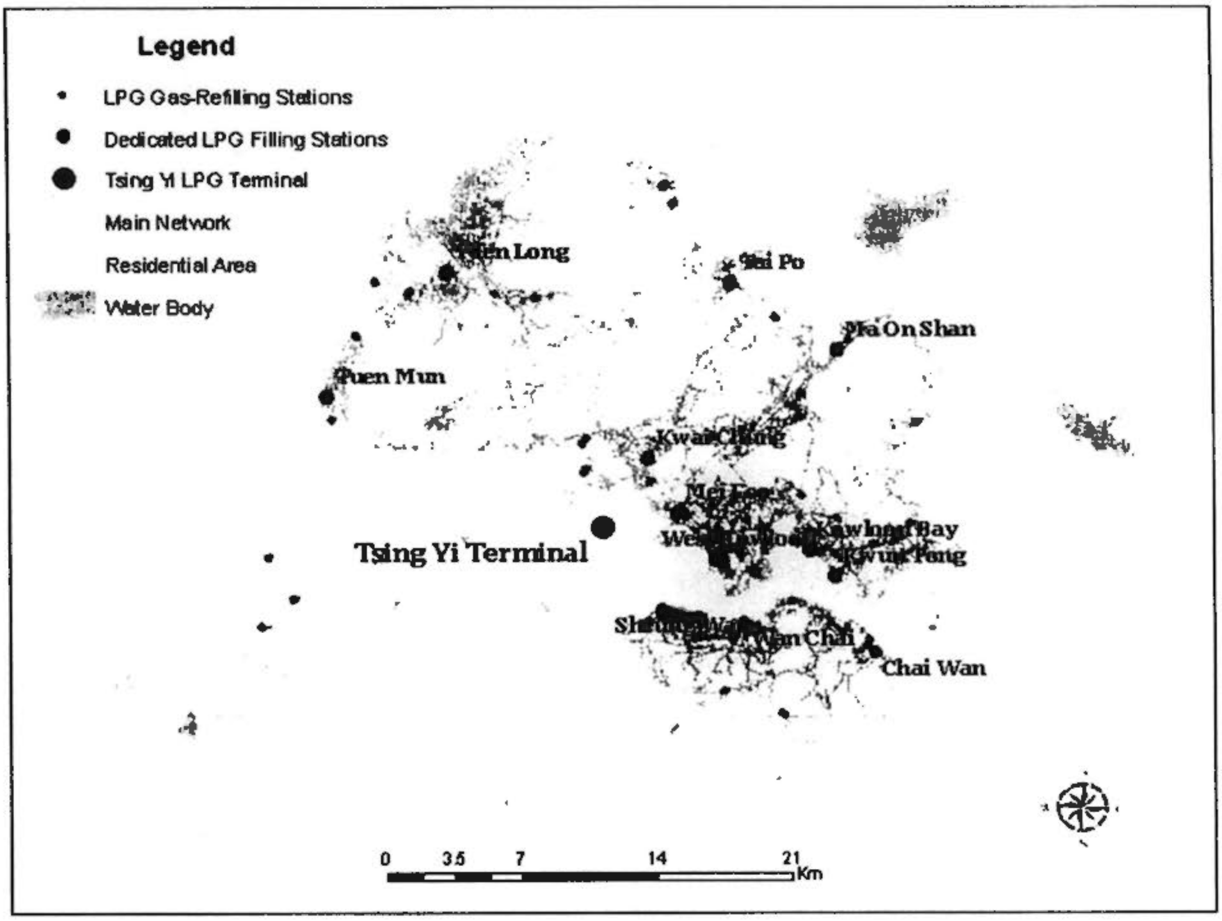


Figure 5.1 LPG supply and distribution in Hong Kong (*Source*: Electrical and Mechanical Services Department, Hong Kong)

In the present case, the problem of routing dangerous shipments is essentially spatial, therefore a Geographical Information System (GIS) is appropriate to manage and display the set of geospatial data. GIS provides functions to perform topological operations and database queries in a natural and straightforward manner. The GIS platform adopted for this case study is ArcGIS 9.2, a GIS software package developed by Environmental System Research Institute, Inc. (ESRI), which runs on a desktop computer and allows for customization. The data used in the case study were mostly collected in 2008 from different sources, such as the Transport Department, the Planning Department, and the Census and Statistics Department. The data include several layers representing the territorial and administrative boundaries, the land use, transportation infrastructures, and a comprehensive inventory of all the buildings and points of interest. The road network is highly detailed with 40,150 links used to represent the 4,392.25 km of roads, and a description of the link attributes (e.g. road type, speed limit, traffic flow, traffic accident rate). The database provides adequate information to locate industrial, commercial and residential buildings along a road, to estimate the impact area in the event of a DG accident, or to calculate the response time from the nearest emergency response unit for instance. Thus, it forms a solid foundation for subsequent risk assessment and route planning.

5.2 Relevant concepts, procedures and measurements

5.2.1 Identification of routing criteria

The routing criteria considered by traditional routing procedures usually include costs (like transport time, transport distance), safety (for the purpose of preventing accident), and exposure to the public and natural environment. To minimize the risk of exposure, in particular, the highly populated areas, places of high commercial value, ecologically sensitive regions, etc. should be avoided.

US Federal Highway Administration (US DOT 1994) suggests that, when determining routes for any class of DG, the following factors should inevitably be considered: population density, type of highway, type and quantity of DG, emergency response capabilities, exposure and other risk factors, accident history, terrain consideration, effect on commerce, delays in transportation, and climatic conditions. These factors are, however, not universal. Routing criteria need to be tailored to the local situation. Since high-density living is of a particular concern in our study, the exposure risk considered in this study should contain not only road users at risk, but also off-road population exposure, as well as population with special needs at risk. The special populations are the groups (e.g., students and the elderly) that may be particularly sensitive to DG releases, and are, therefore, difficult to evacuate in the event of a DG accident. The risk of special population exposure is as important as those of the other two kinds of population exposure in DG route planning (US DOT 1994). In addition, the emergency response capability is also included in the route analysis, with a view that timely action by emergency responders can considerably reduce the magnitude of the consequences associated with a DG release, and is, therefore, of significance in a high-density living environment.

By considering costs, safety, and exposure, the following attributes are identified as the routing criteria for Hong Kong:

- expected travel time
- probability of an incident with release of LPG
- expected road users at risk
- expected off-road population at risk
- expected people with special needs at risk
- expected negative impact on economy: industrial, commercial and transport facilities at risk
- emergency response capabilities

Note that the factor with reference to environmentally sensitive areas is not included as a routing criterion. This is because LPG is non-toxic and free of lead, and is thus not harmful to the natural environment. Nevertheless, LPG is still potentially dangerous due to its high inflammability. It also should be noted that the optimization methodologies proposed in this research are limited in that all attributes be additive along paths. As a result, most of the attributes in this research are expected values, which are additive under the assumption that accident probabilities are independent from one link to another. This simplification, which is in fact commonly adopted in most prevailing literature, enables using the conventional labeling algorithm such as Dijkstra's algorithm with moderate, rather than drastic, modification to solve the routing problems. However, more elaborate attribute definitions should be considered in further improvements of the optimization tools.

5.2.2 Quantification of the objectives – analysis using GIS

The use of GIS in vehicle routing problems presents a variety of advantages over the conventional methods. GIS has powerful spatial data processing and analytic capabilities, which facilitate the determination of the impact area and the search for particular features. In addition, GIS provides efficient database management capabilities that can handle attribute data. Attribute queries are easy and relatively accurate. The present study uses ArcGIS as the GIS platform to support route analysis. After identifying the routing criteria, GIS is used to quantify each criterion.

Given the identified criteria, up to seven different objectives are included in the routing analysis. These objectives can be classified into three major categories: operating costs, risk estimates and emergency response capabilities. It should be pointed out that due to the inevitable use of simplified approximations, the numerical values of these objectives may not be exact but they can simply illustrate the actual figures.

5.2.2.1 Operating costs

The cost of operating a vehicle usually involves many factors ranging from fuel consumption, maintenance, to insurance and amortization costs, which, under different accounting policies, may yield different definitions of cost. It is generally recognized that the main part of the operating costs increase with the running of the vehicle, and that the costs from other sources are either negligible or constitute a fixed charge. In the case of DG transportation, although the insurance cost is not supposed to be negligible (Verter and Erkut 1997), it is usually assumed in most literature that the operating costs mainly depend on trip length and travel time. Wijeratne *et al.* (1993) suggested using the following formula to estimate the operating costs for the transportation of DGs:

$$\text{operating cost} = \alpha \times \text{expected travel time} + \beta \times \text{trip length}, \qquad (5.1)$$

where α and β are numerical parameters that can be fitted through regression analysis (Wijeratne *et al.* took α = 21.67 US$/hr and β = 0.714 US$/miles). In the above formula, both the expected travel time and trip length are included as two objective functions in the analysis. In practice, however, the expected travel time and trip length are strongly correlated positively: the shorter the route, the earlier the vehicle will reach destination. Since the optimal routes for both objectives will probably be similar, the objectives are redundant and the estimation of the route length can thus be removed from the routing analysis. For simplicity, this study assumes that the operating costs are an increasing function of the travel time only, and the travel time is directly designated as one objective in the minimization problem. In the absence of actual travel time profiles for the Hong Kong road network, the expected travel time of each link (i.e. road segment) is estimated as a function of length of road segment and functional speed:

$$\text{expected travel time} = \text{length of road segment} / \text{functional speed}, \quad (5.2)$$

where functional speed is the traffic speed limit, which varies with different types of road.

5.2.2.2 Risk estimates

Numerous models have been proposed to measure the risk of transporting dangerous goods along a route (subsection 2.2.3). The common feature of all approaches is that a risk indicator is composed of the probability of some undesirable events and the possible adverse consequences. Here, the risk is specified by the following constituent components: accident probability, exposed population along the route (including both road users and off-road population), people with special needs at risk, and economic activities under threat.

Let p_i be the probability of an accident with release of DG along the i-th link of route r, which comprises $n(r)$ links, and C_i be the consequence of such accident. Under some reasonable assumptions, notably that $p_i << 1$ for every link, the expected consequence of an accident along route r can be defined as:

$$E_r(C) = \sum_{i=1}^{n(r)} p_i \prod_{j=1}^{i-1} (1 - p_j) C_i \approx \sum_{i=1}^{n(r)} p_i C_i , \quad (5.3)$$

where C_i's are successively the road users at risk along link i, the off-road population at risk along link i, the special population at risk along link i, and the expected damage on the economy along link i.

The probability $P(X)$ of a possible outcome X of a DG accident is usually calculated from a sequence of other probabilities, since there is no adequate historical record from which to estimate the distribution of $P(X)$ directly. Suppose that the adverse outcome X is conditional on a release R, which is in turn conditional on an accident A, using Bayesian theorem, we then obtain the probability of outcome X resulting from an accident A, $P(X)$, as:

$$P(X) = P(A) \times P(R \mid A) \times P(X \mid A, R), \quad (5.4)$$

where $P(A)$ is the probability of traffic accident A occurring on a road segment, $P(R \mid A)$ and $P(X \mid A, R)$ are both conditional probabilities. $P(R \mid A)$ is the probability of occurrence of release accident R given traffic accident A, while $P(X \mid A, R)$ is the probability of outcome X given release accident R resulted from accident A. Each of these three probabilities can be estimated separately. For instance, $P(A)$ can be estimated by multiplying the historical rate of accidents per truck-kilometer on a segment by the length of the segment in kilometers; $P(R|A)$ can be estimated by calculating the historical percentage of accident that gave rise to a release; and $P(X|A,R)$ can be estimated by calculating the historical percentage of release accidents that had the adverse outcome X (Chow *et al.* 1990; Erkut *et al.* 2007).

It should be pointed out that the focus of the present study is primarily on the multi-objective DG routing, elaborated risk assessment is not the scope of our study. Given this consideration, the risk associated with LPG transportation is broadly estimated in the case study; and then based on risk estimation, multi-objective route planning is subsequently conducted to search efficient routes for transporting LPG from Tsing Yi LPG terminal to the designated LPG filling stations. In this respect, the present study uses a relative risk approach rather than absolute risk model. The risk values calculated by this method are not meaningful as absolute numbers; instead, it represents the relative difference in the risks among alternatives that are used to differentiate routes.

(1) Accident probability

The probability of an accident with release is calculated as the product of Truck Accident Rate (per km), Conditional Probability of Release, and Length of link (in km). That is,

$$\text{Accident Probability} = \text{Truck Accident Rate (per km)} \times \text{Conditional Probability of Release} \times \text{Length of link (in km)}. \quad (5.5)$$

The truck accident rate and the conditional release probability in formula (5.5) are road type related. Given the number of total accidents and the number of accidents involving trucks occurred in one year, the truck accident rate can be broadly estimated in proportion to traffic accident rate. According to the road traffic accident statistics of HK in year 2008, the truck accident rate for each road is about 6% of the value of traffic accident. In the absence of specific statistics for Hong Kong, numerical values of the conditional probability of release were taken from Harwood *et al.* (1993), and they were adapted to the Hong Kong road network based on local traffic conditions (Table 5.1).

Table 5.1 Conditional release probability adopted in the present study for estimating the probability of a DG incident

Road type	Designation in Harwood *et al.* 1993	Conditional release probability
Expressway	Urban freeway	0.062
Major road	Urban multilane divided	0.062
Secondary road	Urban two-lane	0.069

Source: Harwood *et al.* (1993)

One may argue that the conditional release probability varies with road traffic, weather conditions, time of day, and numerous other parameters. However, deficiencies and inconsistencies in a truck accident database preclude more elaborate models (Lepofsky *et al.* 1993). Similar single-value probability models have been widely used in many studies in the field of DG transportation and have been well accepted by scholars and practitioners in absence of anything better (Turnquist and List 1993; Ashtakala and Eno 1996).

(2) Road users at risk

Road users at risk (i.e. on-road exposure) refer to the travelers on the roadway near the truck carrying DG, which is obviously associated with traffic volume. As a measure of on-road exposure, vehicle-minutes, as suggested by Nozick *et al.* (1997), is used for all vehicles within a distance x from the truck. That is, as the truck moves along a link, vehicles potentially exposed to the risk of fire and/or explosion hazard are those that are traveling in the same direction as the truck, and are less than distance x (e.g. 800 meters) behind it, as well as those vehicles traveling in the opposite-direction lanes at distance x or less ahead of the truck. The reason vehicle-minutes, rather than just vehicles, is used as a measure of the exposure is because we want to reflect both how many vehicles are within a specified distance of the DG truck, and for how long. Suppose a truck carrying DG is crossing a road link. Based on the information such as traffic volume in terms of average annually daily traffic

(AADT), length of the link, functional speed, on-road exposure for one link is estimated as follows:

- per lane traffic volume = AADT / number of lanes
- per lane traffic density = per lane traffic volume / functional speed = AADT / number of lanes / functional speed
- exposure window behind the truck = 0.8 kilometers (assumed)
- vehicles in exposure window (x) = per lane traffic density × number of lanes × exposure window = (AADT / number of lanes / functional speed) × number of lanes × 0.8 = AADT / functional speed × 0.8
- time to traverse link = length of the link / functional speed
- vehicle exposure = vehicles in exposure window × time to traverse link × 2 = (AADT / functional speed × 0.8) × (length of the link / functional speed) × 2 = AADT × length of the link × 1.6 / functional speed^2

As mentioned earlier, vehicles potentially exposed to the risk include not only those traveling in the same direction as the DG truck within a distance x, but also the vehicles traveling in the opposite-direction. Hence, a factor of 2 is employed in the calculation of vehicle exposure. The above calculations are repeated till the values of vehicle-minutes of exposure for all links in the network have been obtained. Note that vehicles more than 800m ahead of the truck traveling in the same direction, or behind the truck traveling in the opposite direction, are not included in the on-road exposure risk estimation because in the event of an incident, they are already moving away from the truck.

(3) Off-road population at risk

Off-road population refers to the population residing or working some distance away from the road. This factor measures the average population at risk in case of accident on a link, under the assumption that the probability of an accident is constant along the entire length of the link. If an accident occurs within a link, then the expected number of people exposed is the population within a given radius of the accident location. The length of the radius depends on the type of DG. Given that the location of future accidents is unknown and that they are expected to occur with a probability that is uniformly distributed over the link, the expected number of people at risk can be approximated as the population within the impact area (a buffer) formed by a series of equally spaced circles centering the link.

In ArcGIS, a buffer zone is created to simulate the potential impact area. The potential impact zone for petrochemicals is typically taken at 800 meters in all directions (US DOT 1994). Therefore, a buffer of 800m width is generated for each road segment. The off-road population exposure along a road segment is calculated from the exact number of buildings (residential, commercial and offices) within the potential impact zone. Through ArcGIS, the appropriate attributes are queried and the respective risk values are calculated. It should be noted that here the estimated off-road exposure does not account for the decreasing probability of fatalities as people live further from the road where the release occurs. Considering that an elaborate assessment for the effects of a release of dangerous goods in the urban environment is beyond the scope of this research, the present study simply assumes that a release would equally affect an impact area that is isotropic and the dimension of which depends on the type of material spilled (US DOT 1994).

(4) Special population at risk & expected damage on the economy

The additional risk components, such as special population at risk and negative impact on economy, are estimated using the framework suggested by US DOT (1994). An indicator for special population exposure is derived based on the location of schools, hospitals, and day care centers for the elderly. The value of such indicator is calculated from the number of schools, hospitals, and elderly centers that falls within the impact zone of the network.

As for the expected damage on the economy due to a DG transport incident, it is again calculated as the product of accident probability with the number of industrial, commercial and transportation facilities potentially at risk, assuming that a facility within the impact zone will be out of service until the area has been cleaned up. If land-use prices were available, it would also be possible to include a measure of the expected property damage caused by an accident.

5.2.2.3Emergency response capabilities

Emergency response capabilities can be a critical consideration in evaluating the consequences of a traffic accident involving the release of DGs. Timely action by emergency responders can significantly reduce the magnitude of the consequences associated with a DG release. The time required for emergency personnel to get to the accident site is important for establishing control of the immediate area and determining the nature of the hazard. The number of emergency response units or teams (e.g. fire, police, and emergency medical) that are within a certain response window along segments of a route could be counted and rated on a scale, which could then be applied to reduce the consequence term in the risk calculation.

In this case study, the factor of the emergency response capabilities is estimated using the framework suggested in the US DOT guidelines for DG routing (US DOT 1994). Several elements are taken into account: the proximity of the emergency response units to each road segment; the number of trained and equipped firefighting units; the number of police cars and; the number of ambulances (from the Ambulance Depots) available within a specific response window (6 minutes in an urban area and 9 minutes in a suburban area, Hong Kong Fire Services Review 2007) from any point along a given route. The count of those numbers is divided by the route length and is then translated into a rating on a scale from 1.0 (low) to 1.5 (high). The relative risk for each route can then be divided by the response capability factor. Obviously, the higher the rate, the lower the risk score. This estimation assumes that the closest unit will respond whether or not the incident is within its area of jurisdiction. Further, it assumes homogeneity in response training and capability across all fire response units because consistent information on these important details is not available.

5.3 Compromise-programming-based route planning

As a natural and logic way to solve multi-objective optimization problems, compromise programming employs a priori information on the preference structure of the decision-maker to find a compromise solution amongst a set of conflicting objectives. Therefore, a proper determination of the two parameters, the weight w_i

and the exponent p, in line with decision-makers' preference is essential to the efficient implementation of the compromise programming method.

5.3.1 Determination of parameters in compromise programming

5.3.1.1 Weight (w_i)

It is usually recognized that determination of weights is one of the most difficult exercises in analyzing problems involving multiple objectives, especially those employing a linear or convex combination operation. The weight w_i in the *Lp*-metric is attributable to the decision maker's preferences, and signifies the relative importance of each criterion. Many methods can be used to assess criterion weights. Present study employs the Analytic Hierarchy Process (AHP) (Saaty 1990) to construct the weights. AHP works basically by developing priorities in terms of the relative importance judged on a scale of 1 to 9. The importance of each criterion is individually determined and a pair-wise comparison matrix is created. Subsequently, the eigenvalues of this matrix are calculated and these eigenvalues are employed as weights of the criteria.

In this case study, criteria weights are constructed using the following procedures and principles. First, a pair-wise comparison matrix is employed to determine the relative importance of each decision criterion in comparison to the others. Considering that the population exposure is the key factor in determining the consequences of a DG release in risk analysis, the three criteria closely related to such a factor, namely the off-road population exposed (PR), the road users (UR), and the special population at risk (SR), should therefore have higher weights than the others. PR, UR, and SR are thus given the same weight, but two times more important than that of accident probability (AP), expected damage on economy (DE), and emergency response capability (ER), and three times more than that for travel time (TT) (Table 5.2). Furthermore, AP, DE, and ER are weighted twice more than that of operating cost, and are given an equal weight. It should be noted that such weighing principle can be taken as a basis, and different weighing schemes can be implemented in accordance with decision-makers' preferences. Such procedures result in composite weights (Table 5.2) with a consistency ratio of 0.002, which is completely acceptable under the principle described in Saaty (1990).

Table 5.2 Pair-wise comparison matrix for deriving priorities of criteria

	TT	AP	PR	SR	DE	UR	ER	Comparison weight
Travel time (TT)	1	1/2	1/3	1/3	1/2	1/3	1/2	0.061
Accident probability (AP)	2	1	1/2	1/2	1	1/2	1	0.107
Off-road population at risk (PR)	3	2	1	1	2	1	2	0.206
Special population at risk (SR)	3	2	1	1	2	1	2	0.206
Expected damage on economy (DE)	2	1	1/2	1/2	1	1/2	1	0.107
Road users at risk (UR)	3	2	1	1	2	1	2	0.206
Emergency response capability (ER)	2	1	1/2	1/2	1	1/2	1	0.107

5.3.1.2 Exponent p

Romero and Rehman (1989) pointed out that the parameter p in the weighted Lp-metric of a compromise programming model acts as a weight attached to the magnitude of deviation between the value of a given alternative and that of the ideal point. The value of p ranges from one to infinity and presents the concern of the decision maker over the maximum deviation. The larger the value of p, the greater the concern becomes. It is a general practice in solving compromise programming problems to use the following values for the parameter p (Thinh and Hedel 2004):

- $p = 1$ (the Manhattan norm),
- $p = 2$ (the Euclidean norm), and
- $p = \infty$ (the maximum norm, corresponding to the "*Tchebysheff*" distance).

For other values of p, since the corresponding utility function is non-linear and has no explicit physical meaning, they are seldom applied in a compromise programming model for solving practical problems.

In this case study, without loss of generality, the Manhattan distance (full trade-off), the Euclidean distance (partial compensation), and the "*Tchebysheff*" distance (the non-compensatory position) are employed to solve the DG routing problem.

5.3.2 Single-objective optimization results and interpretations

To examine the effectiveness of the proposed methodology, two scenarios were developed for testing. Both scenarios are to select optimal routes from Tsing Yi LPG terminal to the dedicated LPG filling stations located in Kowloon and the New Territories.

The first scenario considers each objective individually, which corresponds to a series of single objective optimal route planning problems. This can be treated as the special case of multi-objective optimization by assigning unit weight to a certain criterion (the one that is considered to be absolutely the most important by a decision maker), and 0 to the others. Under this scenario, the parameter p is set to 1. Given 7 objectives and 9 different LPG stations, a total of 63 routes are generated. The optimal routes between Tsing Yi and Kowloon Bay and those between Tsing Yi and Tai Po are shown in Figure 5.2 and 5.3, respectively, for illustration purposes.

As a summarizing statistic of the optimal routes for the 9 origin-destination (OD) pairs (i.e., Tsing Yi terminal to each of the 9 dedicated LPG stations), Table 5.3 contains the average and standard deviation of the objective-function values under each of the 7 individual objectives, whereas Table 5.4 contains the minimum and maximum of the routes. The rows in the tables correspond to the optimal solutions, and the columns to the objectives. Note that for each link, the scores on these criteria must be normalized to unify the units of measurement of the criteria. The reason for normalization is that the data sets (attribute values of the quantified criteria) contain a mixture of measurements made on different scales and in different units. The criterion of on-road population exposure risk, r_i, is normalized as a score, z_i, as: $z_i = (r_i - min) / (max - min)$, where *min* and *max* represent the minimum and maximum value of this criterion, respectively, over all edges of the road network. The other criteria are normalized in a similar manner. It is observed that in Table 5.4, for each objective, the lower bounds (minima) in each row are more or less the same. The reason is that these minima are all derived from the Tsing Yi – Kwai Chong pair or from the Tsing Yi – Mei Foo pair. These two stations are very close to the Tsing Yi terminal. Due to the rather short distance and the road network structure, the optimal routes for these two O-D pairs with respect to different objectives do not vary significantly. For the other O-D pairs, however, there are few instances of high similarity between the routes selected by different objectives.

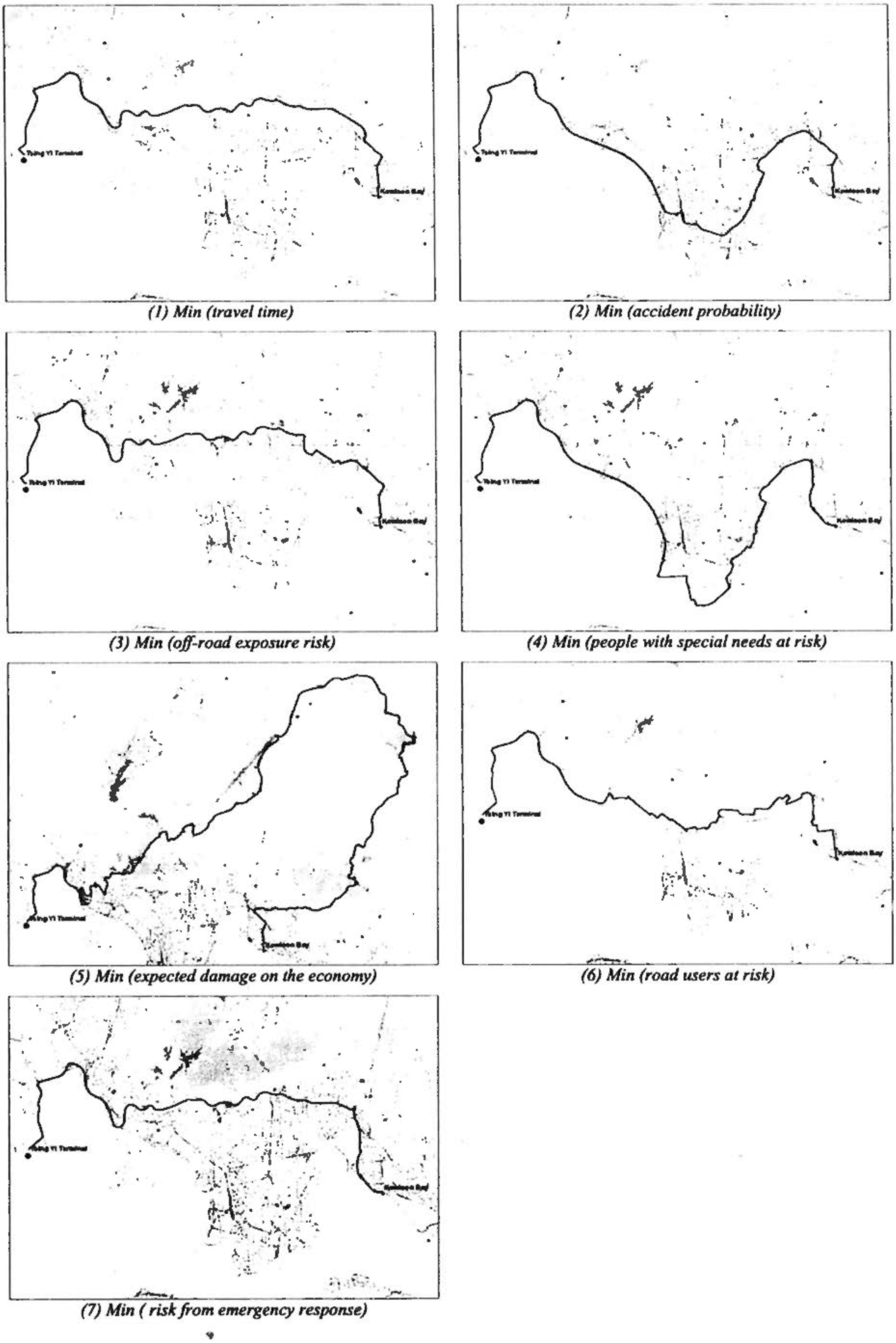
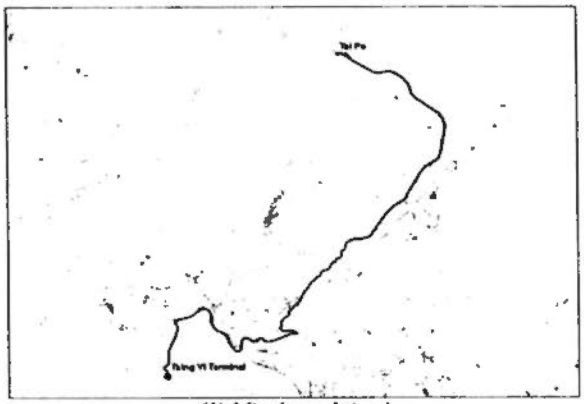
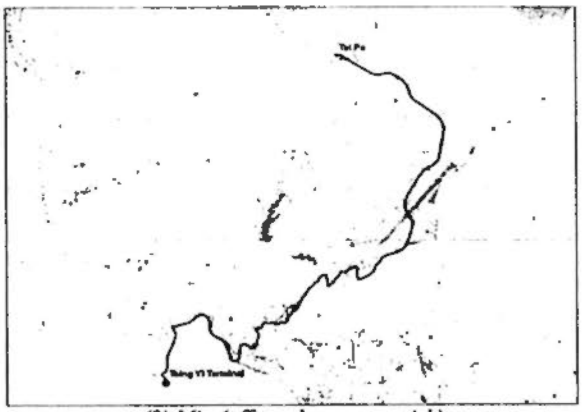


Figure 5.2 Seven single-objective optimal routes from Tsing Yi LPG terminal to Kowloon Bay LPG filling station



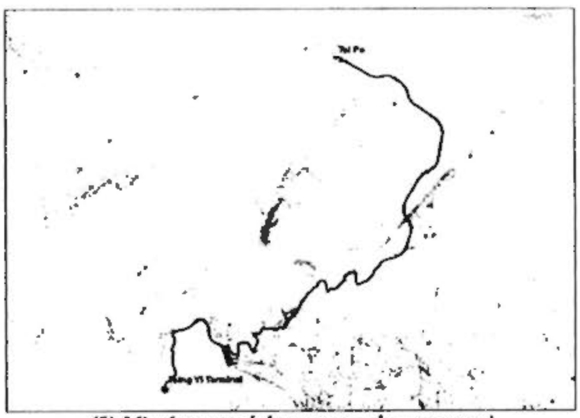
(1) Min (travel time)

(2) Min (accident probability)



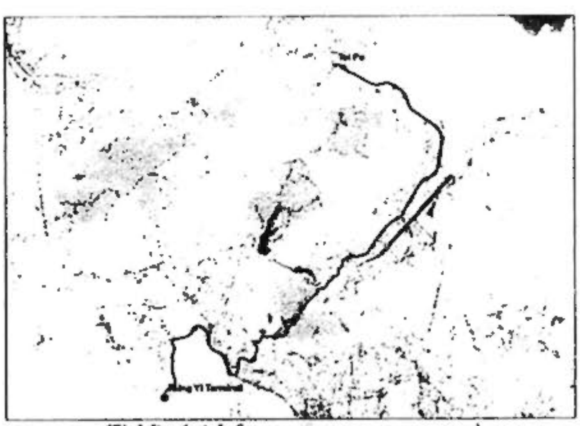
(3) Min (off-road exposure risk)

(4) Min (people with special needs at risk)



(5) Min (expected damage on the economy)

(6) Min (road users at risk)



(7) Min (risk from emergency response)

Figure 5.3 Seven single-objective optimal routes from Tsing Yi LPG terminal to Tai Po LPG filling station

Table 5.3 Averages and standard deviations (in parentheses) of normalized optimal objective-function values of the 9 O-D pairs under each objective

optimal solution \ objective	travel time (normalized units)	accident probability (normalized units)	off-road population at risk (normalized units)	special population at risk (normalized units)	expected damage on economy (normalized units)	road users at risk (normalized units)	emergency response capabilities (normalized units)
1. Min (travel time)	2.57 (1.16)	2.12 (0.96)	0.68 (0.46)	1.55 (1.00)	0.96 (0.57)	4.03 (2.25)	1.75 (0.92)
2. Min (accident probability)	3.12 (1.95)	1.81 (0.79)	0.78 (0.74)	1.15 (0.64)	0.77 (0.59)	3.36 (1.76)	1.71 (0.92)
3. Min (off-road population exposure)	2.69 (1.26)	2.02 (0.94)	0.49 (0.34)	1.35 (0.92)	0.74 (0.55)	3.23 (1.62)	1.75 (0.95)
4. Min (population with special needs at risk)	3.89 (2.55)	3.09 (2.21)	0.89 (0.88)	0.97 (0.57)	1.02 (0.99)	3.15 (1.66)	2.56 (1.51)
5. Min (expected damage on economy)	4.04 (2.66)	3.48 (3.05)	0.58 (0.47)	1.59 (1.34)	0.59 (0.33)	3.82 (2.46)	3.02 (2.73)
6. Min (road users at risk)	3.23 (1.68)	2.78 (1.55)	1.31 (1.48)	2.08 (1.75)	1.31 (1.02)	2.16 (0.97)	2.64 (1.58)
7. Min (risk from emergency response)	2.65 (1.21)	2.00 (0.92)	0.54 (0.36)	1.39 (0.88)	0.80 (0.56)	3.52 (1.67)	1.27 (0.67)

Table 5.4 Minima and Maxima of normalized optimal objective-function values of the 9 O-D pairs under each objective

optimal solution \ objective	travel time (normalized units)	accident probability (normalized units)	off-road population at risk (normalized units)	special population at risk (normalized units)	expected damage on economy (normalized units)	road users at risk (normalized units)	emergency response capabilities (normalized units)
1. Min (travel time)	1.05 – 4.31	0.88 – 3.23	0.08 – 1.47	0.33 – 3.01	0.31 – 1.89	1.12 – 6.91	0.67 – 2.73
2. Min (accident probability)	1.02 – 7.12	0.81 – 2.95	0.08 – 2.08	0.33 – 2.02	0.26 – 1.99	1.12 – 5.56	0.67 – 2.88
3. Min (off-road population exposure)	1.02 – 4.52	0.81 – 3.10	0.08 – 1.02	0.33 – 2.81	0.26 – 1.83	1.12 – 4.80	0.67 – 2.98
4. Min (population with special needs at risk)	1.02 – 8.01	0.81 – 6.44	0.08 – 2.42	0.33 – 1.89	0.26 – 2.89	1.12 – 5.11	0.67 – 4.60
5. Min (expected damage on economy)	1.02 – 8.42	0.81 – 8.13	0.08 – 1.38	0.34 – 4.13	0.26 – 1.17	1.08 – 7.71	0.55 – 7.69
6. Min (road users at risk)	1.07 – 5.63	0.86 – 4.80	0.08 – 3.88	0.34 – 4.99	0.31 – 3.07	1.08 – 3.88	0.56 – 4.42
7. Min (risk from emergency response)	1.08 – 4.36	0.86 – 3.20	0.08 – 1.10	0.35 – 2.75	0.31 – 1.90	1.29 – 5.52	0.38 – 2.19

As depicted in Figures 5.2 and 5.3, the single objective optimization solutions are rather different from each other. The differences in attribute values are clearly revealed in Tables 5.3 and 5.4. These tables show that the optimal solution obtained under one single objective gives non-optimal solutions under other objectives. In fact, in most instances there are significant trade-offs among the optimal solutions with respect to these criteria.

The minimum travel time solution has the shortest travel time because most of its links are part of the expressways and trunk roads. This, on the other hand, makes the on-road exposure risk (road users at risk) the largest for the Tsing Yi – Tai Po pair, and the second largest for the Tsing Yi – Kowloon Bay. Since it passes through several densely populated areas, the off-road population exposure risk is also made relatively high. Consequently, the societal risk, which is the sum of the three parts relevant to public safety, namely on-road population exposure risk, off-road population at risk, and the population with special needs at risk, under this solution is, for the Tsing Yi – Tai Po pair, the largest among all 7 single objective optimization solutions, and for the Tsing Yi – Kowloon Bay pair, the third largest. This indicates that by minimizing travel time, the public safety is jeopardized simultaneously.

The minimum off-road exposure solution has the minimal off-road exposure risk, and the third smallest on-road exposure risk. It serves the second best on public safety among all the solutions, and performs very well under the other criteria. In the context of overall cost, i.e. the sum of the costs and all sorts of risks, this solution is reasonably good but still fails to strike the best compromise among various objectives.

The minimum economic damage solution minimizes the expected negative impacts on the economy in the event of an accident. It makes a big detour from Tsing Yi terminal to Kowloon Bay station, in an effort to avoid densely commercialized areas. This leads to the longest travel distance and the highest accident probability, and the overall cost with it is also extremely high. From the perspective of operating cost, this solution is probably unacceptable to the DG transport operators, neither is it desirable from the perspective of safety. For the Tsing Yi – Tai Po pair, however, the performance of this solution is satisfactory.

The minimum on-road exposure risk solution exhibits good performance in minimizing the risk of on-road population exposure, since most of its links mainly follow secondary road with relatively lighter traffic. However, this results in running a very high risk of off-road exposure. In addition, due to the proximity of special populations, the risk of special population exposure is doubled accordingly. Meanwhile, the expected damage on the economy with this solution is the largest among all solutions.

The above analysis demonstrates that the existence of multiple criteria makes it difficult if not impossible to identify a single "best" solution for all criteria. The optimal solution under one objective is generally attained at the expenses of the others. To strike a good balance among the objectives, the focus should then be on finding a set of "compromise" solutions containing trade-offs among the objectives for decision making. The follow-up experiments were performed under this principle. We employed different numbers of criteria and adopted different values for parameters w_i and p to generate Pareto-optimal solutions under these scenarios by means of compromise programming, and analyzed the trade-offs among the solutions.

5.3.3 Multi-objective optimization results and interpretations

In general, the number of solutions for MOP problems increases with the number of objectives considered. Given multiple objectives, there could be a large number of solutions when selecting optimal routes based on various combinations of different objectives for each origin-destination pair. For illustration purpose, the Tsing Ti – Kowloon Bay and Tsing Ti – Tai Po pairs are chosen to provide some insight into the trade-offs among different MOP solutions.

First, the three factors pertinent to public safety (i.e., road users at risk, off-road population at risk, and people with special needs at risk) are considered to generate the multi-objective DG routes. Solutions obtained well represent the Government's major concern in DG routing. Second, the criterion of operating cost, e.g. travel time, is added for the purpose of striking a balance between economy and safety. Third, all 7 criteria are considered with (1) equal weights, and (2) different weights obtained by the pair-wise comparison method. Three scenarios are explored in this series of studies: $p = 1$ (full tradeoff), $p = 2$ (partial compensation), and $p = \infty$ (the non-compensatory position). With the increase of the number of objectives, the MOP routing solutions also increase. Although many more routes could be generated by tuning the values of the parameters w_i and p, 12 of them are selected. Their attributes are shown in Table 5.5 and Table 5.6. It should be noted that all values in these tables are unit free due to data normalization.

The single objective optimization solutions are the "extreme" solutions each obtained from individually minimizing one of the 7 criteria. Table 5.5 and Table 5.6 make a general comparison among the single objective optimization solutions and compromise solutions. Solutions 1 to 7 are single objective ones, while 8 to 19 are compromise solutions under different scenarios. All of these solutions are Pareto-optimal. Given any two of them, one is better than the other with respect to at least one objective, and vice versa.

In order to facilitate decision-makers to select an appropriate routing decision, the solutions are graphically displayed in Figure 5.4 (for Tsing Ti – Kowloon Bay) and Figure 5.5 (for Tsing Ti – Tai Po) for efficient comparison. Each row of Table 5.5 and Table 5.6 is shown as a piecewise linear curve representing each Pareto-optimal solution. Points in each curve correspond to the scaled values of the 7 objectives.

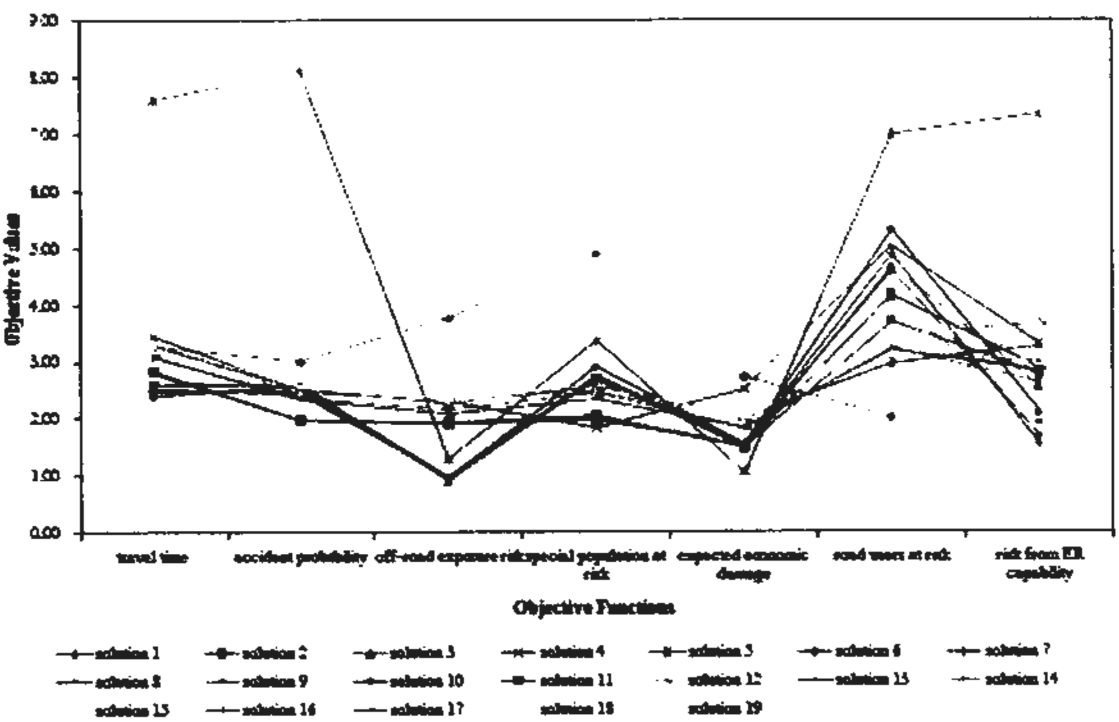


Figure 5.4 The objective function values for different optimizations (Tsing Yi – Kowloon Bay)

Table 5.5 Normalized objective function values of the optimal solutions obtained by the compromise programming for the Tsing Yi – Kowloon Bay pair (1 ~ 7 are single objective optimization solutions, 8 ~ 19 are MOP solutions)

optimal solution \ objective	travel time (normalized units)	accident probability (normalized units)	off-road population at risk (normalized units)	special population at risk (normalized units)	expected damage on economy (normalized units)	road users at risk (normalized units)	emergency response capabilities (normalized units)	societal risk (normalized units)	total risk (normalized units)	overall cost (normalized units)
1. Min (travel time)	2.413	2.593	0.982	2.921	1.546	5.333	2.109	9.235	13.375	17.896
2. Min (accident probability)	2.819	1.968	1.913	1.983	1.507	4.180	2.881	8.076	11.551	17.251
3. Min (off-road population exposure)	2.598	2.575	0.902	2.725	1.482	4.671	2.550	8.297	12.355	17.503
4. Min (population with special needs at risk)	3.458	2.529	2.287	1.833	2.528	5.015	3.320	9.136	14.192	20.970
5. Min (expected damage on economy)	7.604	8.129	1.284	3.369	1.062	7.004	7.348	11.657	20.847	35.799
6. Min (road users at risk)	3.279	3.004	3.758	4.899	2.727	2.023	3.685	10.680	16.411	23.375
7. Min (risk from emergency response)	2.535	2.465	0.965	2.691	1.546	4.883	1.552	8.540	12.551	16.638
8. focusing on societal risk (p=1)	3.098	2.349	2.073	2.353	1.828	3.218	2.846	7.644	11.820	17.765
9. focusing on both travel time and societal risk (p=1)	2.656	2.554	0.974	2.769	1.542	4.089	1.947	7.833	11.929	16.531
10. equally weighing of all 7 criteria (p=1)	2.489	2.469	0.965	2.690	1.542	4.587	1.691	8.242	12.253	16.433
11. weighing criteria by AHP (p=1)	2.836	1.985	1.941	2.045	1.516	3.713	2.767	7.699	11.200	16.803
12. focusing on societal risk (p=2)	3.293	2.532	2.277	2.574	2.011	2.960	3.288	7.811	12.354	18.935
13. focusing on both travel time and societal risk (p=2)	3.291	2.535	2.270	2.577	2.008	2.968	3.283	7.815	12.358	18.932
14. equally weighing of all 7 criteria (p=2)	3.090	2.367	2.149	2.463	1.851	3.246	2.626	7.859	12.077	17.793
15. weighing criteria by AHP (p=2)	3.290	2.536	2.285	2.545	2.019	3.042	3.015	7.872	12.427	18.732
16. focusing on societal risk (p=∞)	3.264	2.453	2.315	2.491	1.945	3.437	3.661	8.243	12.642	19.566
17. focusing on both travel time and societal risk (p=∞)	3.261	2.454	2.313	2.493	1.941	3.438	3.658	8.244	12.640	19.558
18. equally weighing of all 7 criteria (p=∞)	3.378	2.565	2.381	2.586	2.026	3.412	2.940	8.379	12.970	19.289
19. weighing criteria by AHP (p=∞)	3.270	2.448	2.311	2.481	1.938	3.453	3.633	8.246	12.632	19.534

Note:

1) societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.
2) total risk : the value of this attribute is calculated as the sum of the societal risk and normalized accident probability and expected damage on the economy.
3) overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk

Table 5.6 Normalized objective function values of the optimal solutions obtained by the compromise programming for the Tsing Yi – Tai Po pair (1 ~ 7 are single objective optimization solutions, 8 ~ 19 are MOP solutions)

optimal solution \ objective	travel time (normalized units)	accident probability (normalized units)	off-road population at risk (normalized units)	special population at risk (normalized units)	expected damage on economy (normalized units)	road users at risk (normalized units)	emergency response capabilities (normalized units)	societal risk (normalized units)	total risk (normalized units)	overall cost (normalized units)
1. Min (travel time)	3.698	2.966	0.754	1.801	1.086	6.549	2.655	9.103	13.155	19.508
2. Min (accident probability)	7.121	2.736	0.861	1.484	0.663	5.555	2.421	7.901	11.300	20.842
3. Min (off-road population exposure)	4.025	3.080	0.419	1.459	0.602	4.580	2.717	6.458	10.140	16.882
4. Min (population with special needs at risk)	6.292	5.619	0.665	0.800	0.667	3.727	3.407	5.193	11.479	21.178
5. Min (expected damage on economy)	4.417	3.465	0.429	1.695	0.506	4.627	3.178	6.751	10.721	18.316
6. Min (road users at risk)	5.257	4.802	1.017	1.672	1.349	3.192	3.865	5.881	12.032	21.155
7. Min (risk from emergency response)	3.923	3.067	0.537	1.456	0.695	5.521	2.188	7.514	11.276	17.386
8. focusing on societal risk (p=1)	5.429	4.844	0.698	1.206	0.958	3.241	3.346	5.145	10.947	19.723
9. focusing on both travel time and societal risk (p=1)	3.907	2.986	0.489	1.486	0.664	4.413	2.542	6.388	10.039	16.488
10. equally weighing of all 7 criteria (p=1)	3.905	2.982	0.493	1.489	0.665	4.414	2.492	6.396	10.044	16.441
11. weighing criteria by AHP (p=1)	3.996	3.091	0.419	1.473	0.604	4.472	2.600	6.365	10.059	16.655
12. focusing on societal risk (p=2)	5.429	4.845	0.698	1.198	0.959	3.279	3.289	5.175	10.979	19.697
13. focusing on both travel time and societal risk (p=2)	4.013	3.107	0.419	1.457	0.599	4.420	2.802	6.297	10.003	16.818
14. equally weighing of all 7 criteria (p=2)	3.923	2.992	0.490	1.491	0.668	4.430	2.514	6.411	10.070	16.508
15. weighing criteria by AHP (p=2)	3.930	3.087	0.487	1.484	0.675	4.415	2.528	6.386	10.149	16.607
16. focusing on societal risk (p=∞)	5.429	4.845	0.698	1.198	0.959	3.279	3.289	5.175	10.979	19.697
17. focusing on both travel time and societal risk (p=∞)	4.011	3.103	0.422	1.454	0.595	4.441	2.813	6.318	10.016	16.840
18. equally weighing of all 7 criteria (p=∞)	4.013	3.097	0.420	1.478	0.607	4.486	2.602	6.384	10.088	16.703
19. weighing criteria by AHP (p=∞)	5.443	4.849	0.700	1.204	0.964	3.297	3.203	5.201	11.014	19.661

Note:

1) societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.
2) total risk : the value of this attribute is calculated as the sum of the societal risk and normalized accident probability and expected damage on the economy.
3) overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk

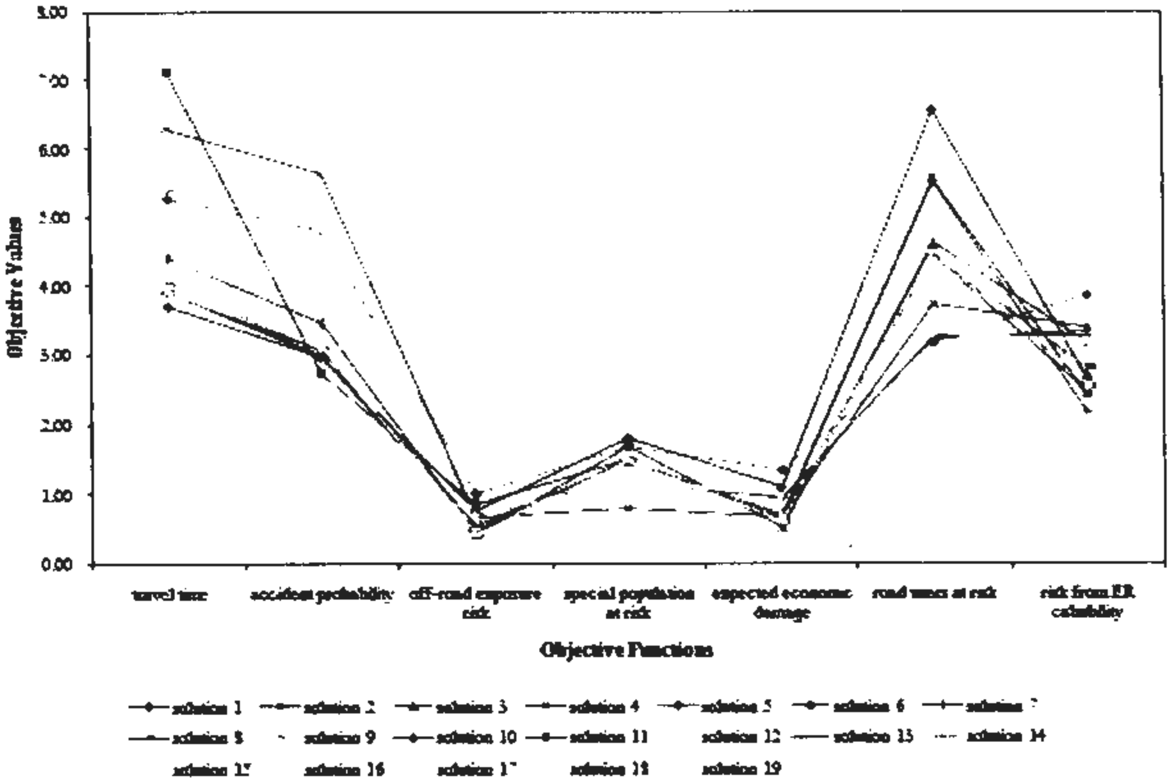


Figure 5.5 The objective function values for different optimizations (Tsing Yi - Tai Po)

Clearly, there does not exist any curve that laid below all the others. If such a curve existed, the Pareto solution represented would be better than any other with respect to all the objectives.

To enrich the comparison, we use in Figure 5.6 and Figure 5.7 one stacked bar for every row of Table 5.5 and Table 5.6, respectively. Each bar consists of seven sections, one for each objective. In this case, we are also able to order the Pareto solutions by simply ordering the bars by their heights, that is, by the sum of the seven scaled objective values.

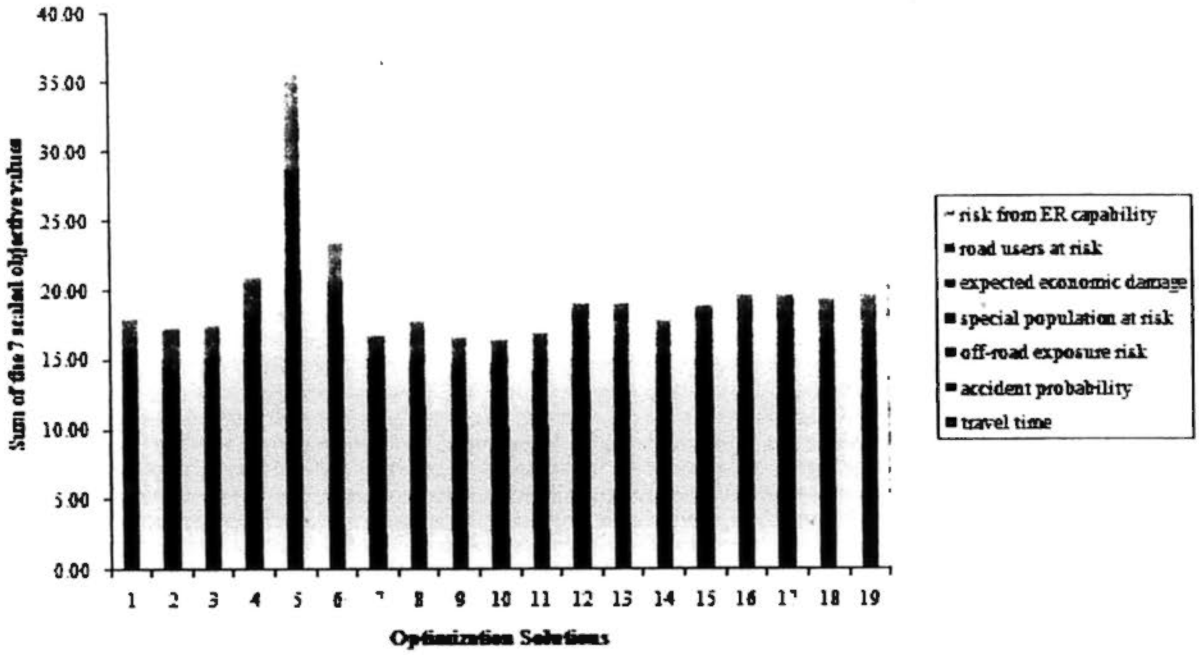


Figure 5.6 Sum of the 7 scaled objective values for different optimizations (Tsing Yi – Kowloon Bay)

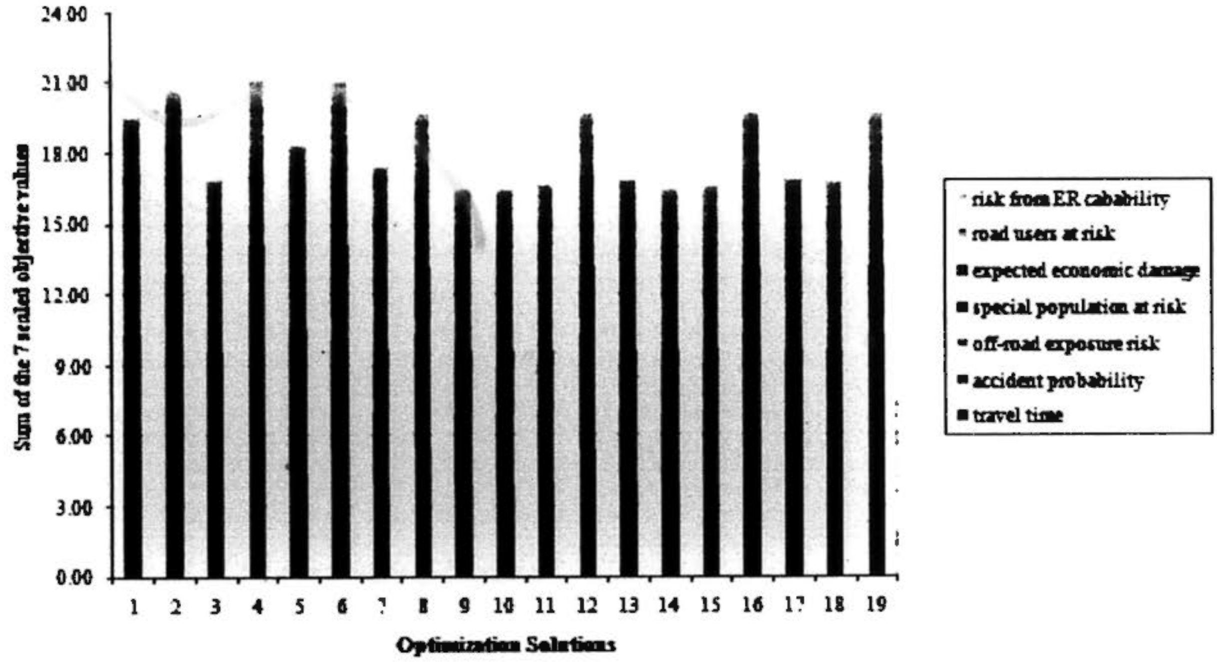


Figure 5.7 Sum of the 7 scaled objective values for different optimizations (Tsing Yi – Tai Po)

Based on the optimization results, we have the following observations:

1) The minimization of the single objective function gives rise to a significant achievement of the chosen criterion, whilst heavily compromising the others. This has been discussed in detail in subsection 5.3.2.

2) The multi-objective solutions represent a good compromise among the competing objectives, as evidenced by comparison of the results obtained with various combinations of different objective functions in the compromise programming problem.

Solution 8 focuses on the importance of public safety. The three factors with reference to societal risk, namely population exposure risk, including both on-road and off-road, as well as special population at risk are considered impartially. This solution serves best on safety, yet it is not equally desirable from the perspective of expected damage on the economy in the event of a DG incident, which increases by over 60% than the minimum obtained under the single-objective solution 5.

Based on solution 8, solution 9 considers public safety together with travel time, which makes improvement on the objectives with respect to travel time, off-road population exposure, the possible damage on the economy, and the emergency response capability. As trade-offs, for the Tsing Yi – Kowloon Bay pair, solution 9 downgrades by 9%, 17%, and 27% over solution 8 on accident probability, special population at risk, and road users at risk, respectively. Larger trade-offs are observed for the Tsing Yi – Tai Po pair, where solution 9 downgrades by 23% and 36% over solution 8 on special population at risk and road users at risk, respectively. Nevertheless, for both O-D pairs, the objective values between these two solutions do not differ as significantly as those among single objective optimization solutions.

Solution 10 is obtained by taking all 7 criteria into consideration with unbiased preferences (i.e. equally weighted on each objective). For both Tsing Yi – Kowloon Bay and Tsing Yi – Tai Po, this solution increases by about 5% than solution 1 (which is the shortest path) in travel time, and offers different trade-offs with other objectives: 50% ~ 80% more population with special needs at risk (compared to the minimum achieved in solution 5), but smaller trade-offs with the minimum solutions obtained under other single-objective minimization problems. The societal risk of this solution is lower than that of most single objective solutions, though it is not the lowest among all the 18 solutions. In the context of overall cost, solution 10 is the best.

Similar to solution 10, solution 11 also takes all criteria into account in the process of route planning. The only difference is that the latter assigns dissimilar weights to different objectives. The weights indicate relative importance of each criterion, and are generated by means of pair-wise comparison (see Table 5.2). Compared with solution 10, for both O-D pairs, solution 11 has relatively lower special population exposure risk and expected damage on the economy; it also enhances the emergency response capability. This is, however, at the cost of the lower achievements of the other objectives.

Solutions 12 to 15 correspond to solutions 8 to 11 respectively, replacing $U(1,w)$ with $U(2,w)$ as the utility function. Solutions 16 to 19 also correspond to 8 to 11 respectively, yet the utility function is changed to $U(\infty,w)$. From Table 5.5 and Table 5.6, it is not difficult to find that while these substitutes are worse off on some objectives, they make improvement on the others at the same time. Yet, the objective function values vary within a small range.

The results presented and the behaviors shown in Figures 5.4 to 5.7 reveal the diversity of DG routing solutions under the multi-objective approach, which confirms the effectiveness of the proposed methodology.

5.4 Optimal routing by adaptive weighting approach

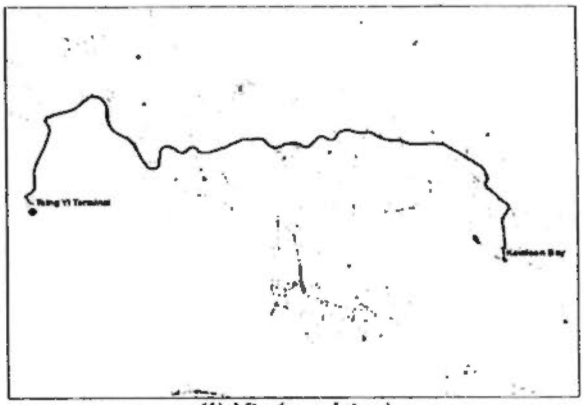
The same routing problem between Tsing Yi LPG terminal and the dedicated LPG filling stations were analyzed using the proposed adaptive weighting method introduced in Chapter 3. Recall that this method consists in approximating the Pareto front with a few suitable solutions to help the decision-makers select the most satisfied routes without generating all of them.

5.4.1 Optimal routing results and interpretations

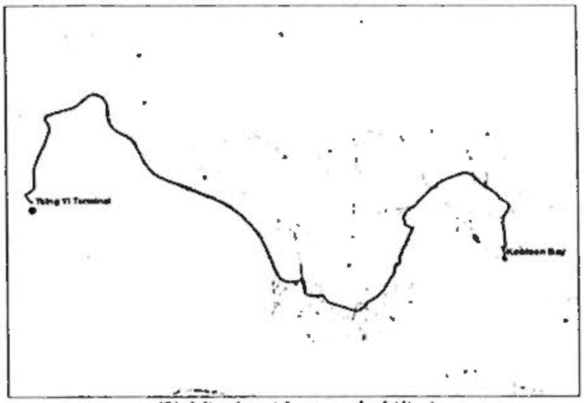
As indicated in Chapter 3, the implementation of the proposed adaptive method is based on the result of *m* single objective optimizations with each objective at a time serving as an objective function. Therefore, as an initial condition, a set of extreme solutions minimizing each of the objectives individually are generated first. After that, the adaptive method is used to search for optimal routes with respect to multiple objectives. To examine the effectiveness of the method, three scenarios were developed for testing. First, public safety, which involves the factors of road users at risk, off-road population at risk, and people with special needs at risk, is considered to generate the optimal routes. Clearly, the obtained solutions effectively address the government's major concerns in DG routing. Second, the criterion of operating cost, e.g. travel time, is added with the intention of striking a balance between economy and safety. Third, all 7 criteria are considered simultaneously. With the increase of the number of objectives, the number of Pareto optimal solutions also increases. The reason is that a Pareto-optimal solution for two objectives is also Pareto-optimal when considering one or more additional objectives in conjunction with these two objectives. Thus, the set of non-dominated solutions for all the objectives contains at least all the non-dominated solutions for any choice of two, three, four, or more objectives. Out of the numerous routes, 12 are selected. For illustration purposes, the resulting optimal routes from Tsing Yi LPG terminal to each of the two dedicated LPG filling stations, i.e. Kowloon Bay and Tai Po, are presented below to provide some insight into the trade-offs among different solutions. Their attributes are shown in Table 5.7 and Table 5.8, respectively. The rows correspond to the optimal solutions, and the columns to the objectives. Note that all the values in these tables are unit free due to data normalization.

5.4.1.1 The Tsing Yi – Kowloon Bay pair

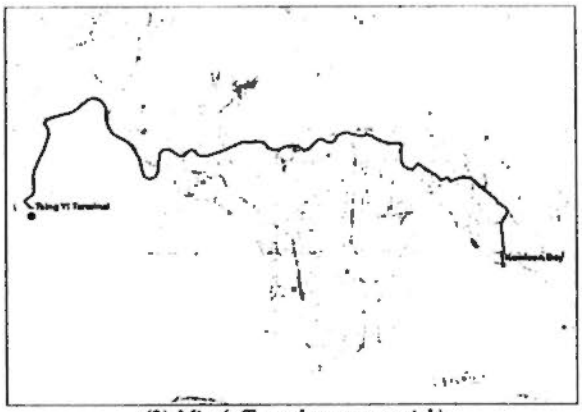
Solutions 1 to 7 are "extreme" solutions, each of which individually minimizes one of the seven objectives. These solutions provide information on the initially unexplored region. Although these routes have been presented in Figure 5.2, they are also displayed in Figure 5.8 in conjunction with MOP solutions for the purpose of comparison. Table 5.7 reveals that there are significant trade-offs among the Pareto-optimal solutions with respect to different criteria.



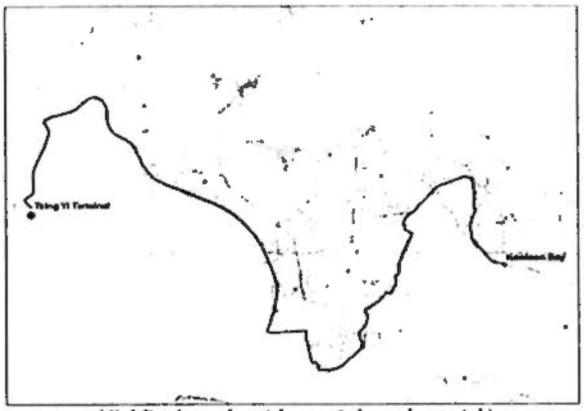
(1) Min (travel time)



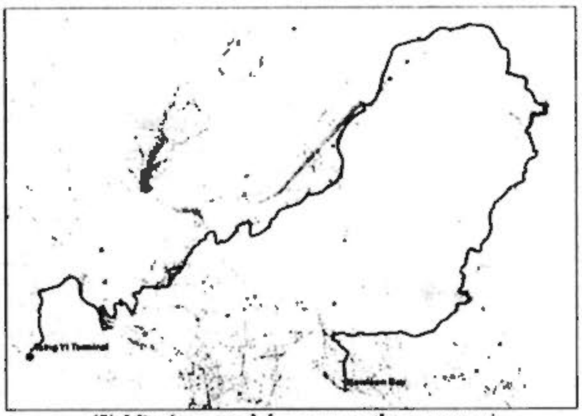
(2) Min (accident probability)



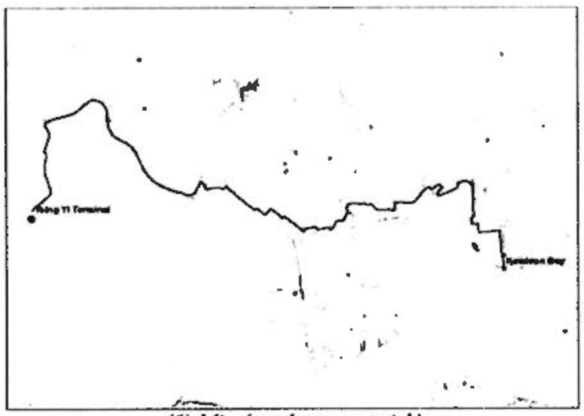
(3) Min (off-road exposure risk)



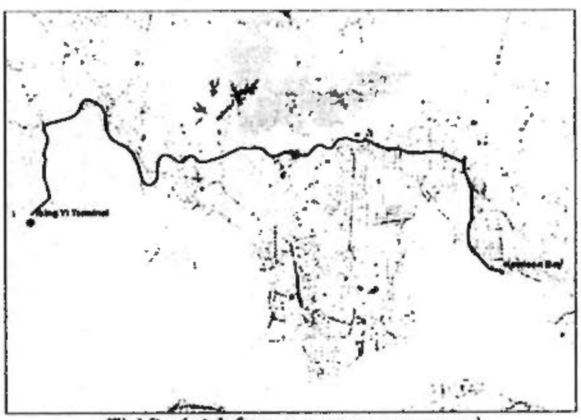
(4) Min (people with special needs at risk)



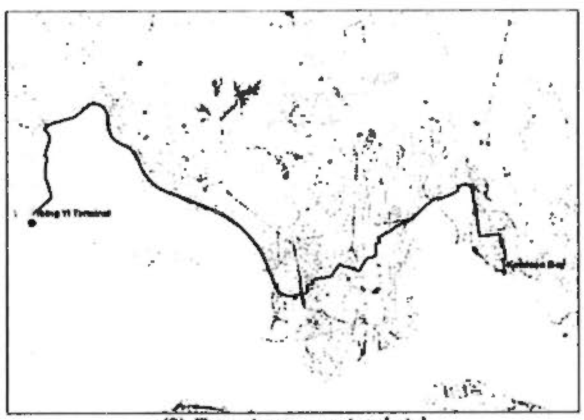
(5) Min (expected damage on the economy)



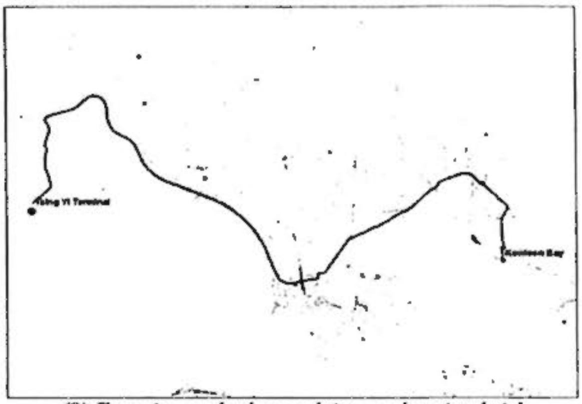
(6) Min (road users at risk)



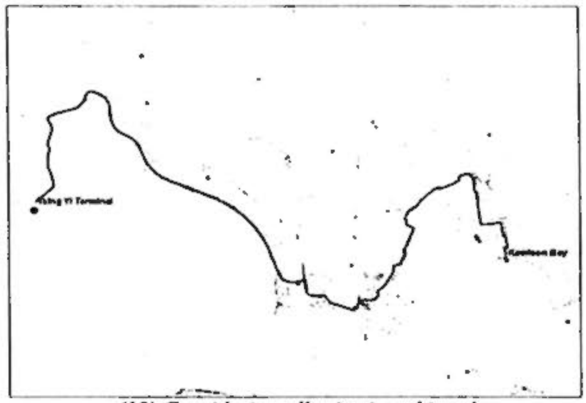
(7) Min (risk from emergency response)



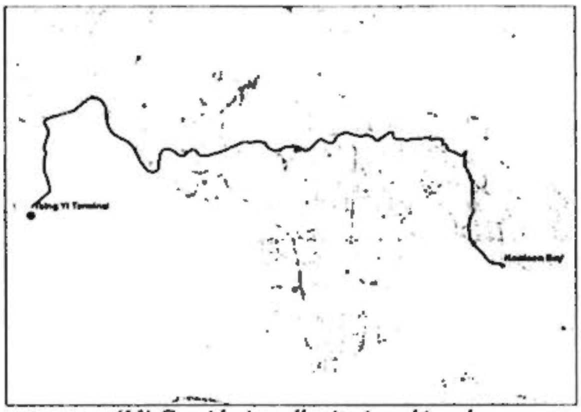
(8) Focusing on societal risk



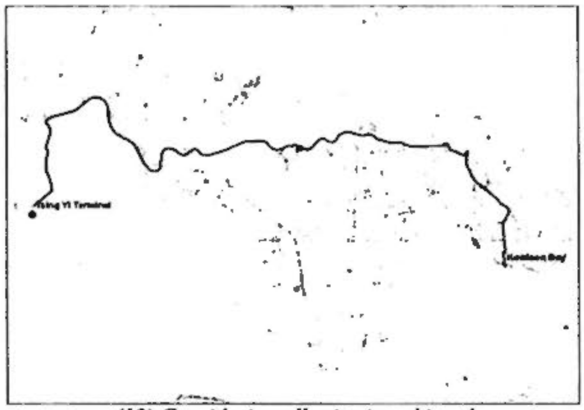
(9) Focusing on both travel time and societal risk



(10) Considering all criteria unbiased



(11) Considering all criteria unbiased



(12) Considering all criteria unbiased

Figure 5.8 Efficient routes from Tsing Yi terminal to Kowloon Bay LPG filling station generated by the adaptive weighting method

Table 5.7 Normalized objective function values of the optimal solutions obtained by the adaptive weighting method for the Tsing Yi – Kowloon Bay pair (1 ~ 7 are "extreme" solutions, 8 ~ 12 are MOSP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	2.413	2.593	0.982	2.921	1.546	5.333	2.109	9.235	13.375	17.896
2. Min (accident probability)	2.819	1.968	1.913	1.983	1.507	4.180	2.881	8.076	11.551	17.251
3. Min (off-road population exposure)	2.598	2.575	0.902	2.725	1.482	4.671	2.550	8.297	12.355	17.503
4. Min (population with special needs at risk)	3.458	2.529	2.287	1.833	2.528	5.015	3.320	9.136	14.192	20.970
5. Min (expected damage on the economy)	7.604	8.129	1.284	3.369	1.062	7.004	7.348	11.657	20.847	35.799
6. Min (road users at risk)	3.279	3.004	3.758	4.899	2.727	2.023	3.685	10.680	16.411	23.375
7. Min (risk from emergency response)	2.535	2.465	0.965	2.691	1.546	4.883	1.552	8.540	12.551	16.638
8. Focusing on societal risk	2.901	2.373	2.526	3.410	1.989	2.744	2.760	8.679	13.042	18.702
9. Focusing on both travel time and societal risk	2.632	2.043	2.303	3.058	1.735	3.707	2.544	9.069	12.847	18.023
10. Considering all criteria unbiased	3.144	2.419	2.265	2.602	1.934	3.124	2.823	7.990	12.343	18.311
11. Considering all criteria unbiased	2.656	2.554	0.974	2.769	1.542	4.089	1.947	7.833	11.929	16.531
12. Considering all criteria unbiased	2.520	2.560	0.969	2.874	1.488	4.659	2.195	8.502	12.551	17.266

Note:

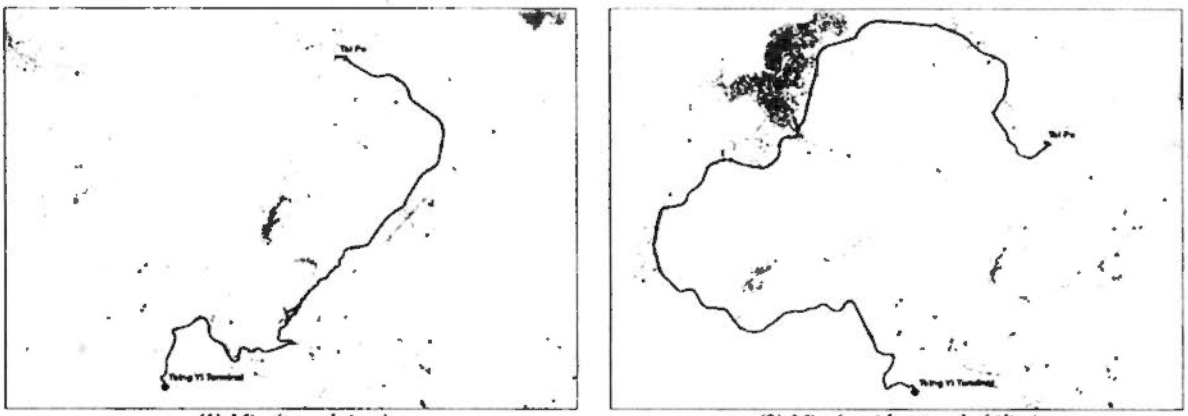
1) societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.
2) total risk : the value of this attribute is calculated as the sum of the societal risk and normalized accident probability and expected damage on economy.
3) overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk.

Solution 1 has the shortest travel time because most of its links are part of expressways and trunk roads. Solution 2 has the lowest accident probability, and is the best among all extreme solutions in terms of public safety. Solution 3 has the least off-road exposure risk. Solution 4 is the best with regard to the risk of population with special needs exposed. Solution 5 minimizes the expected negative impacts on the economy in the event of an accident, by incorporating a large detour from Tsing Yi to Kowlooon Bay to avoid densely commercialized areas. This solution requires a longer travel distance and has a higher accident probability than all other solutions identified. It also performs very poorly in terms of road users' safety and emergency response capabilities. Because of its high operating costs, this solution would probably be unacceptable to DG transport operators, and it also leaves a lot to be desired from the perspective of safety. Solution 6 has minimum on-road exposure risk since most of its links mainly follow secondary roads with relatively light traffic. However, this results in running very high risks of off-road exposure and special population exposure, and the largest expected damage to the economy. Solution 7 performs the best on emergency response.

Individual minimization of each of the seven objectives gives rise to a significant achievement of the chosen objective, while heavily compromising the others. By contrast, the multi-objective solutions represent a good compromise among the competing objectives, as evidenced by a comparison of solutions 8 to 12 given in Figure 5.8. Solution 8 focuses on the importance of public safety by considering on-road exposure, off-road exposure, and special population at risk impartially. This solution serves best on safety, yet it is not equally desirable from the perspective of expected damage on the economy in the event of a DG incident, which is over 70% greater than the minimum obtained under solution 5. Solution 9 incorporates operating cost (travel time) with public safety. Compared with solution 8, this solution improves about 8% ~ 13% on most objectives; on the other hand, it also downgrades by 35% over solution 8 on on-road exposure risk. Obviously, the improvement in operating cost and some other objectives comes at the cost of sacrificing the road users' safety, though such trade-offs are not as substantial as those among the "extreme" solutions. Solutions 10 to 12 are obtained by taking all 7 criteria into consideration simultaneously. Similar to solutions 8 and 9, these three MOP solutions present various trade-offs among different objectives. Compared to the "extreme" solutions, however, these trade-offs are much milder. It should be noted that although each of the last three solutions is created by impartially considering all 7 criteria, they are somewhat geometrically different from each other, which indicates that the proposed adaptive method is capable of generating a set of diverse non-dominated solutions for the DG routing problem.

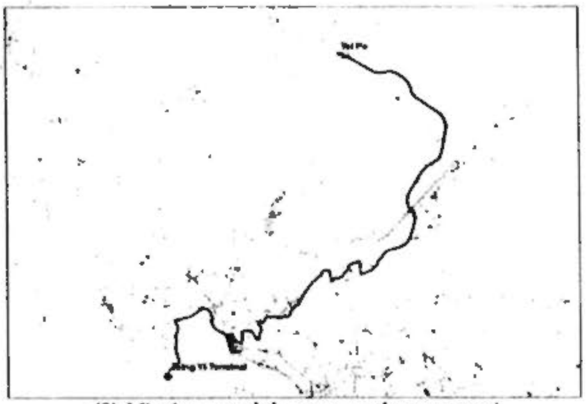
5.4.1.2 The Tsing Yi – Tai Po pair

Twelve of the optimal routes for the Tsing Yi – Tai Po pair generated by the proposed adaptive method are presented in Figure 5.9, among which the first 7 solutions are "extreme" ones, and the last 5 are MOP solutions. Table 5.8 summarizes their attributes and reveals the differences in their attribute values.

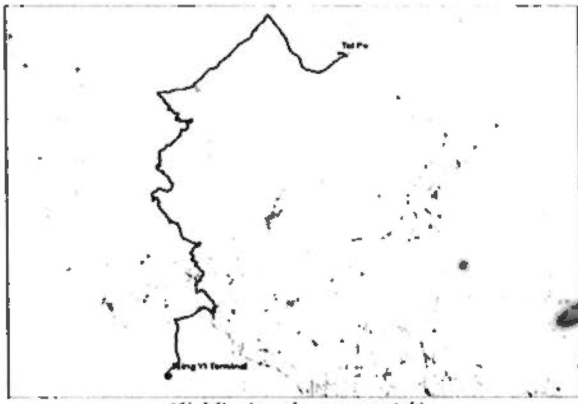


(1) Min (travel time) *(2) Min (accident probability)*

(3) Min (off-road exposure risk) *(4) Min (people with special needs at risk)*



(5) Min (expected damage on the economy)



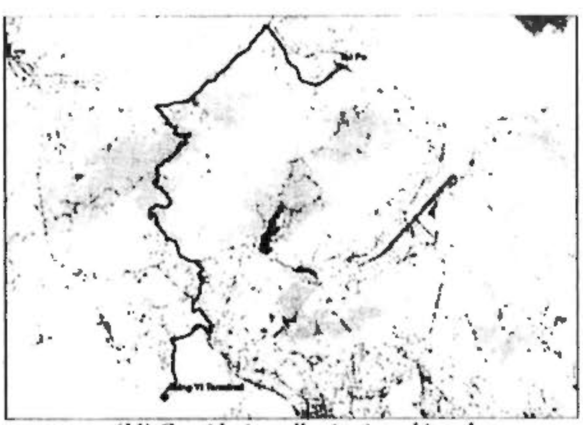
(6) Min (road users at risk)

(7) Min (risk from emergency response)

(8) Focusing on societal risk

(9) Focusing on both travel time and societal risk

(10) Considering all criteria unbiased



(11) Considering all criteria unbiased

(12) Considering all criteria unbiased

Figure 5.9 Efficient routes from Tsing Yi terminal to Tai Po LPG filling station generated by the adaptive weighting method

Table 5.8 Normalized objective function values of the optimal solutions obtained by the adaptive weighting method for the Tsing Yi – Tai Po pair (1 ~ 7 are "extreme" solutions, 8 ~ 12 are MOSP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	3.698	2.966	0.754	1.801	1.086	6.549	2.655	9.103	13.155	19.508
2. Min (accident probability)	7.121	2.736	0.861	1.484	0.663	5.555	2.421	7.901	11.300	20.842
3. Min (off-road population exposure)	4.025	3.080	0.419	1.459	0.602	4.580	2.717	6.458	10.140	16.882
4. Min (population with special needs at risk)	6.292	5.619	0.665	0.800	0.667	3.727	3.407	5.193	11.479	21.178
5. Min (expected damage on the economy)	4.417	3.465	0.429	1.695	0.506	4.627	3.178	6.751	10.721	18.316
6. Min (road users at risk)	5.257	4.802	1.017	1.672	1.349	3.192	3.865	5.881	12.032	21.155
7. Min (risk from emergency response)	3.923	3.067	0.537	1.456	0.695	5.521	2.188	7.514	11.276	17.386
8. Focusing on societal risk	5.429	4.845	0.698	1.198	0.959	3.279	3.289	5.175	10.979	19.697
9. Focusing on both travel time and societal risk	5.065	4.555	0.885	1.471	1.039	3.356	3.521	5.712	11.305	19.891
10. Considering all criteria unbiased	3.923	2.992	0.490	1.491	0.668	4.430	2.514	6.411	10.070	16.508
11. Considering all criteria unbiased	5.193	4.726	0.909	1.594	1.147	3.334	3.866	5.837	11.711	20.770
12. Considering all criteria unbiased	3.743	2.844	0.476	1.323	0.657	5.138	2.452	6.936	10.437	16.632

Note:

1) societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.

2) total risk : the value of this attribute is calculated as the sum of the societal risk and normalized accident probability and expected damage on economy.

3) overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk.

Solution 1 is the fastest route. However, the risks of special population exposure and on-road exposure with this solution are very high, resulting in the maximum societal risk of any of the alternatives. In solution 2, while the accident probability is minimized, the large detour from Tsing Yi to Tai Po following the links with low accident rate leads to the longest travel time. Solution 3 has minimum off-road exposure risk. Solution 4 is the best with regard to the risk of exposure of populations with special needs. However, it also has the highest accident probability, more than 100% greater than the minimum obtained by solution 2. Solution 5 minimizes the expected damage to the economy in the event of an accident. Solution 6 minimizes the on-road exposure risk by following secondary roads with lighter traffic, at the cost of the highest risk of off-road exposure. Moreover, should a DG accident occur, the expected damage on the economy of this solution will be more than doubled comparing to the minimum obtained in solution 5. Solution 7 is the most desirable from the perspective of emergency response capabilities.

Solutions 8 to12 are a subset of "compromise" solutions containing trade-offs among the considered objectives. Solution 8 takes into account the road users at risk, off-road population at risk, and people with special needs at risk for the generation of optimal routes for DG shipments. While effectively addresses the government's major concerns in DG routing, solution 8 is not equally desirable from the perspective of accident probability, which is over 70% higher than the minimum obtained under solution 2. Solution 9 incorporates operating cost with public safety, which produces a shorter travel time and a lower accident probability than solution 8. On the other hand, this solution results in deterioration ranging from 2% to 21% over solution 8 on the other objectives. Solutions 10 to 12 are obtained by taking all the criteria into consideration. Like the two previously mentioned MOP solutions, these three solutions involve various trade-offs among different objectives, which, however, are not as significant as those reflected in the "extreme" solutions.

5.4.2 Assessing the theoretical validity of the model

The results presented in subsection 5.4.1 are satisfactory in the sense that the proposed adaptive weighting method proved effective in generating a small number of efficient routes under multiple conflicting objectives. However, further analyses are needed to assess the theoretical validity of the proposed algorithm; in other words, to confirm that the paths generated do provide an overview of the possible routing options. A couple of aspects of the resulting paths are examined for this purpose. The first criterion is to estimate the goodness of the approximation, which can be measured by the proportion of the objective space that is covered by the approximate set of solutions. In practice, this notion is controlled by the size of the unexplored regions remaining for exploration. Recall that the termination criterion of the algorithm can be defined as either a desired number of solutions specified by a decision-maker; or the maximum loss of information acceptable by the decision-maker. In the calculation process, once the former criterion is met, the algorithm terminates with showing the proportion of remaining unexplored regions for decision-makers' reference. In case the second criterion is satisfied earlier, it is observed that when the algorithm stops, the size of the unexplored regions accounts for less than 20% of the whole objective space.

Another criterion is to examine the efficiency of the proposed adaptive method by estimating the dissimilarity of the generated routes, which is of importance in routing DG shipments. A dissimilarity index is calculated for every pair of routes selected. It is between zero and one, where zero indicates perfect similarity and one indicates perfect dissimilarity. To compute a dissimilarity index for two routes R_i and R_j, we process the arc lists of the two routes. If these two routes share no common arcs, then the dissimilarity index for this pair is one. At the other extreme, if the two routes are identical, then the index is equal to zero. If R_i and R_j have some common arcs, but not identical, then the dissimilarity index quantifies the dissimilarity between them. The dissimilarity of two routes R_i and R_j is defined as the symmetrical function (Akgün *et al.* 2000):

$$D(R_i, R_j) = 1 - \left(\frac{L(R_i \cap R_j)}{2L(R_i)} + \frac{L(R_i \cap R_j)}{2L(R_j)} \right), \tag{5.6}$$

where $R_i \cap R_j$ denotes the portion of common arcs between the route pair R_i and R_j, and $L(\cdot)$ denotes the length of quantity under brackets. This index reflects the difference between unit value and the arithmetic average of two ratios: the intersection length divided by the length of route R_i, and the intersection length divided by the length of route R_j.

The results of the Tsing Yi – Kowloon Bay and Tsing Yi – Tai Po pairs are displayed in Table 5.9 and Table 5.10, respectively. For the Tsing Yi – Kowloon Bay pair, there are very few instances of high similarities between the generated optimal routes. The minimum and maximum dissimilarities are 22.7% and 87.8% respectively, while the average dissimilarity is 63.7% with a standard deviation of 17.5%. There are more cases of mild to high similarity for the Tsing Yi – Tai Po pair, and there are also more cases of high dissimilarity, with the dissimilarity index higher than 98%. The average dissimilarity is 65.8% with a standard deviation of 31.5%, while the minimum and maximum dissimilarities are 8.4% and 99.4%, respectively. Considering the rather short lengths of the routes, these results compare advantageously with those reported by Akgün *et al.* (2000).

The cases of other O-D pairs exhibit similar performance except for the Tsing Yi – Mei Foo and Tsing Yi – Kwai Chung pairs. Due to the rather short distance and the limited route selection between these two stations in the road network, the generated optimal routes do not vary much. As a result, the average dissimilarity is comparatively lower than those of the Tsing Yi – Kowloon Bay and Tsing Yi – Tai Po pairs. However, this is not due to the algorithm itself, but rather because of the influence of the existing network structure. Overall, the adaptive weighting method exhibits more powerful applicability to more complex road network with longer travel distance.

Table 5.9 Dissimilarity value of every pair of routes for the Tsing Yi – Kowloon Bay pair
(The lower-left part of the matrix is identical to the transpose of the upper-right corner.)

solution	Dissimilarity with solution…(%)												mean (%)
	1	2	3	4	5	6	7	8	9	10	11	12	
1	0.0	59.5	23.4	72.1	75.7	76.1	41.7	74.5	69.6	78.8	41.5	22.7	57.78
2		0.0	57.7	40.2	79.5	72.1	85.2	48.2	39.4	39.7	79.1	68.7	60.85
3			0.0	69.9	77.5	76.6	46.6	74.9	63.8	79.3	48.4	32.5	59.13
4				0.0	87.8	76.1	73.3	59.4	55.1	56.4	69.0	80.5	67.25
5					0.0	78.7	83.6	77.5	73.3	81.1	77.7	69.5	78.36
6						0.0	76.4	50.7	61.1	56.1	70.3	67.7	69.26
7							0.0	76.2	75.7	73.5	22.7	30.2	63.22
8								0.0	28.3	27.7	70.0	66.0	61.03
9									0.0	42.8	69.3	58.9	59.58
10										0.0	74.5	70.7	64.11
11											0.0	25.1	59.66
12												0.0	52.88

Table 5.10 Dissimilarity value of every pair of routes for the Tsing Yi – Tai Po pair
(The lower-left part of the matrix is identical to the transpose of the upper-right corner.)

solution	Dissimilarity with solution…(%)												mean (%)
	1	2	3	4	5	6	7	8	9	10	11	12	
1	0.0	99.1	36.2	98.9	45.9	87.4	30.6	87.7	87.3	32.8	89.5	18.9	64.95
2		0.0	98.3	73.2	99.0	88.9	99.4	89.3	88.8	98.9	88.9	98.9	92.97
3			0.0	98.0	18.4	86.9	35.6	87.3	86.8	29.0	88.9	29.8	63.20
4				0.0	98.8	43.0	99.3	32.7	42.3	98.8	42.7	98.7	75.14
5					0.0	82.2	39.5	82.6	81.9	30.6	84.0	29.2	62.92
6						0.0	87.7	21.9	11.5	85.5	8.4	83.0	62.40
7							0.0	85.8	85.3	20.3	82.8	13.7	61.83
8								0.0	20.3	85.8	22.6	83.4	63.58
9									0.0	85.3	11.4	82.8	62.16
10										0.0	80.6	14.2	60.16
11											0.0	85.1	62.26
12												0.0	57.99

5.5 Genetic-algorithm-based route optimization

5.5.1 Parameter settings in the proposed genetic algorithm

The same routing problem between Tsing Yi LPG terminal and the dedicated LPG filling stations were analyzed using the proposed genetic algorithm described in Chapter 4. The GA was coded in C++ and tested on a Windows XP machine (Pentium 4 /3.0-GHz processor with 2GB RAM). To examine the effectiveness of the proposed GA, four scenarios were explored: (1) considering each objective individually, corresponding to a series of single objective route planning; (2) searching for optimal routes with particular concern on public safety, i.e., to take into account the factors of road users at risk, off-road population at risk, and people with special needs at risk simultaneously in routing analysis; (3) to strike a balance between economy and safety by considering the operating cost in conjunction with the three factors considered in test (2); and (4) optimizing all 7 criteria simultaneously. For each test, the GA was run with a population size of 30. A hybrid approach that incorporates random walk with heuristic initialization containing the "seeds" generated by Dijkstra's shortest path algorithm was used to initialize the population. Random walk and heuristic initialization contribute 80% and 20% individuals, respectively, in the initial population. The Max-Min fitness function is employed to maximize the difference between any two paths. The tournament selection incorporating the elite retaining strategy is employed to generate a new population for the next generation. The crossover operation exchanges partial chromosomes (i.e. partial-paths) at location independent crossover point. The mutation operation introduces new partial chromosomes (partial-paths). The algorithm terminates if the change in the mean fitness of the population is less than 1% over 30 successive generations, or when 100 total iterations have been reached.

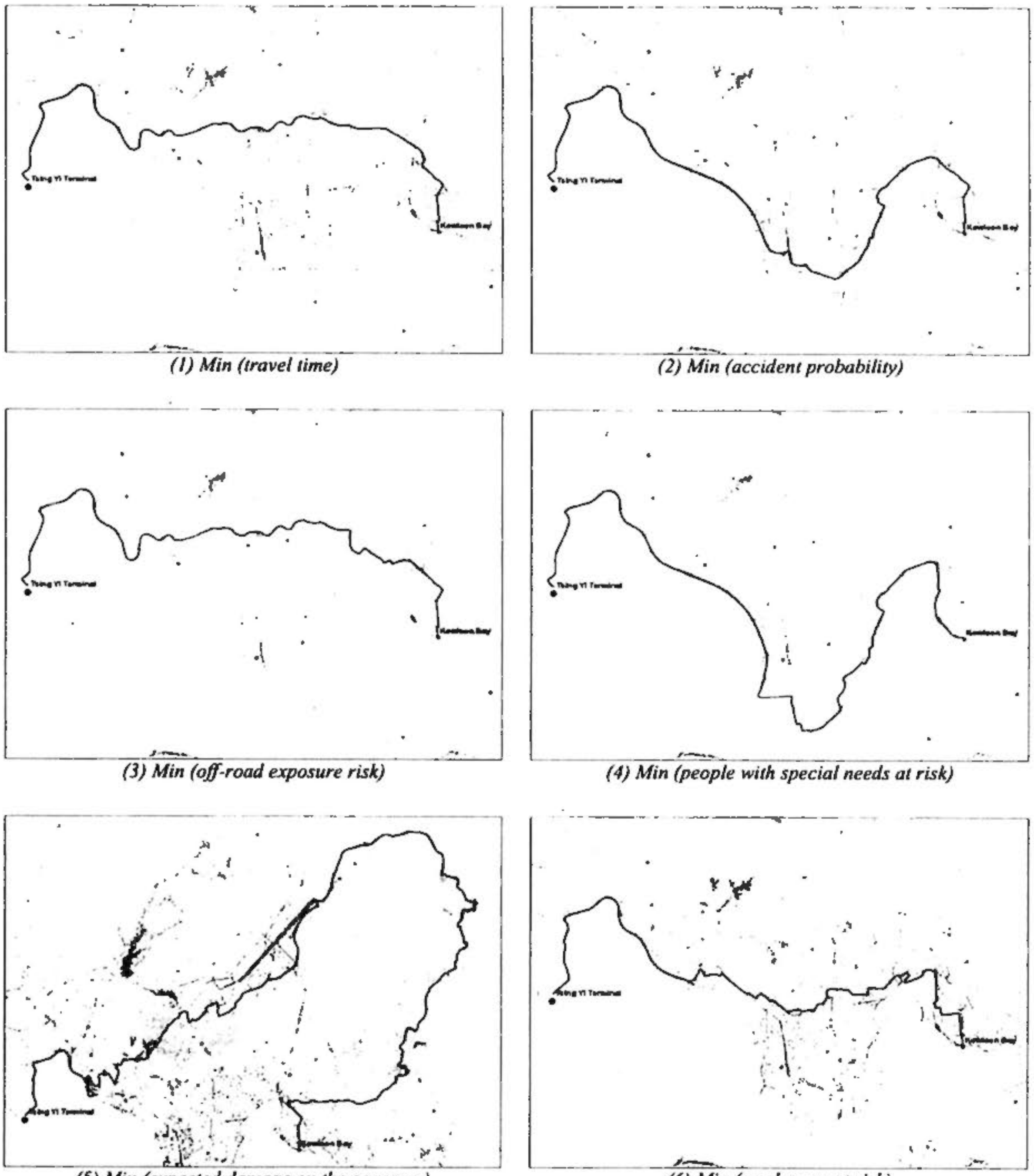
A significant problem in designing a GA is the determination of the proper values for the control parameters, such as generations, population size (i.e. number of candidates), crossover probability P_c, mutation probability P_m, termination conditions, etc. There is no formal theoretical methodology for this problem because different combinations lead to different characteristic behavior of the GA. Traditionally, parameter determination is achieved through exhaustive experimental work (Eiben *et al.* 1999). Based on the experimental tests performed in this study and reported in the literature, the final settings of the control parameters used in the proposed GA for this case study were defined as follows:

- population size: 30
- crossover probability: $P_c = 0.8$
- mutation probability: $P_m = 0.05$
- number of elites: 3
- tournament size: 3
- number of generations: 100

Note that the uniformity of the solution set is a significant issue that cannot be ignored. If every member in a solution set is exactly the same as that of another set, these two solution sets are considered uniform. Recall that given a set of criteria weights, the deterministic MOP methods such as compromise programming produces a unique solution no matter how many times the same procedure is repeated. The genetic algorithm, however, does not guarantee the uniformity in the solution set. Due to the intrinsic randomness of the GA, the solution set produced in a single run is very likely different from the set generated in another run even under the same parameter settings. Thus, in this case study, tests for each of the four scenarios were made several times in order to avoid exceptional cases.

5.5.2 Routing results and interpretations

Since genetic algorithms operate with a population of solutions, the result of the proposed GA for each of the four scenarios is not a single route but a set of routes bearing dissimilar proportions of cost and risk. Among these routes, not all but some of them are non-inferior with respect to each other. They are efficient solutions for the DG routing problem. Given the predefined population size, for each origin-destination pair, about $4 \times 30 = 120$ solutions were generated for all tests. Despite a large set of solutions, the set of Pareto-optimal routes is not very diversified since many routes overlap. For illustration purposes, 14 distinct Pareto-optimal routes from Tsing Yi LPG terminal to Kowloon Bay station are selected and presented below to provide some insight into the trade-offs among different solutions. The same number of efficient routes for the Tsing Yi – Tai Po pair is presented in Figure 5.11. Tables 5.11 and 5.12 summarize the attributes of the corresponding routes for these two O-D pairs, respectively. The rows correspond to the optimal solutions, and the columns to the objectives. Note that all the values in these tables are unit free due to data normalization.



(1) Min (travel time)

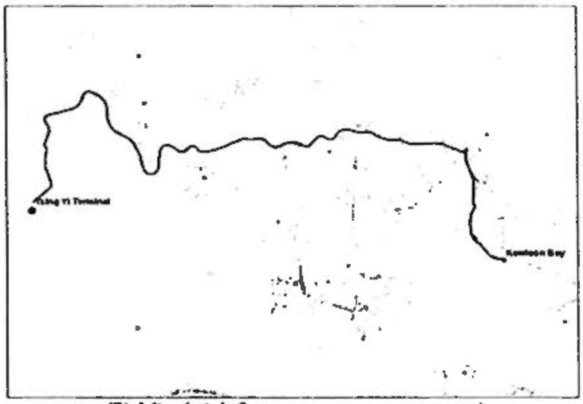
(2) Min (accident probability)

(3) Min (off-road exposure risk)

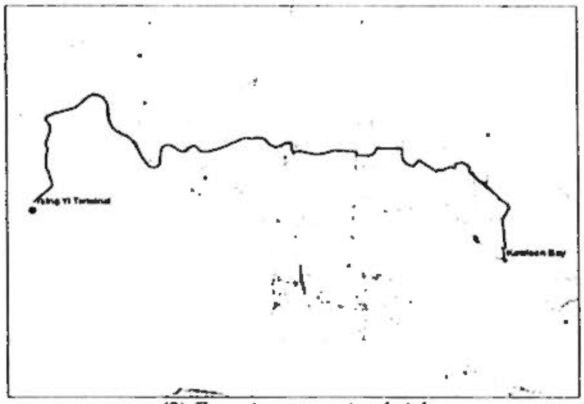
(4) Min (people with special needs at risk)

(5) Min (expected damage on the economy)

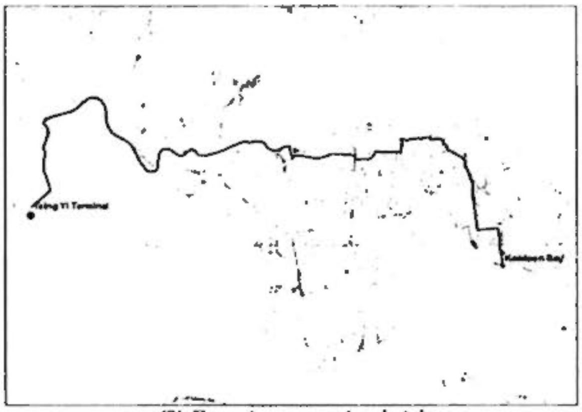
(6) Min (road users at risk)



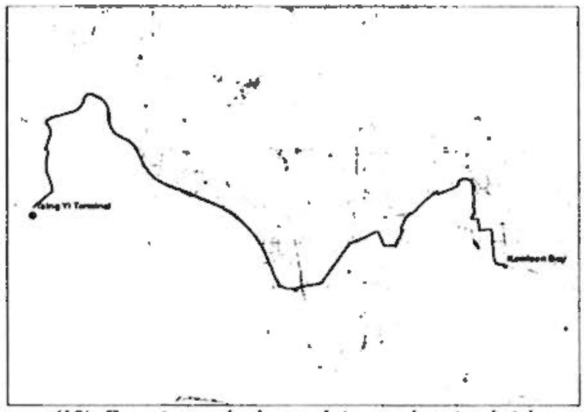
(7) Min (risk from emergency response)



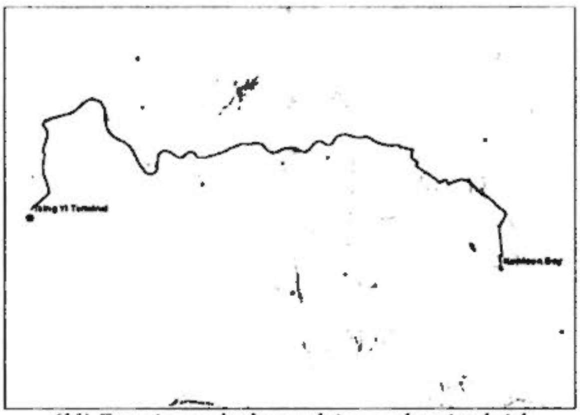
(8) Focusing on societal risk



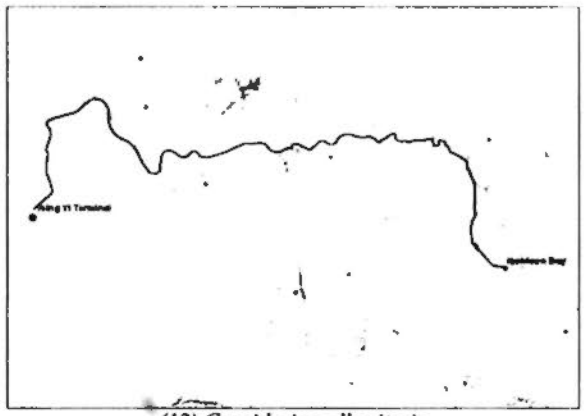
(9) Focusing on societal risk



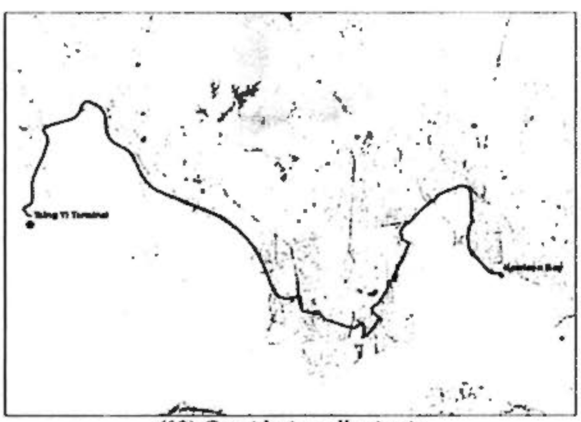
(10) Focusing on both travel time and societal risk



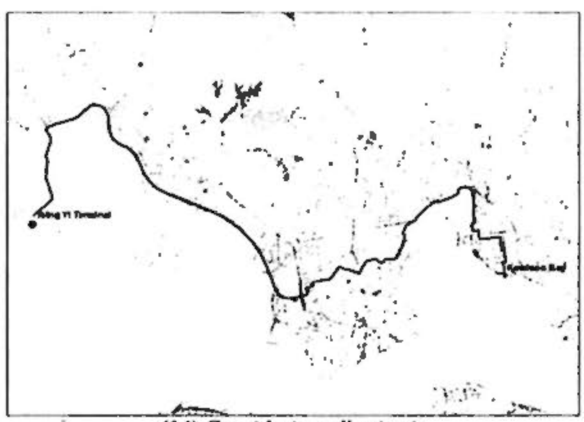
(11) Focusing on both travel time and societal risk



(12) Considering all criteria

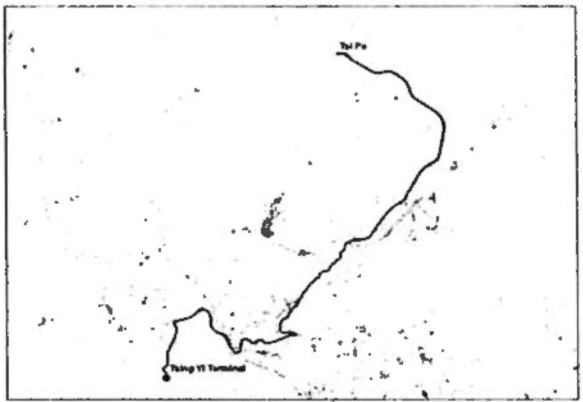


(13) Considering all criteria



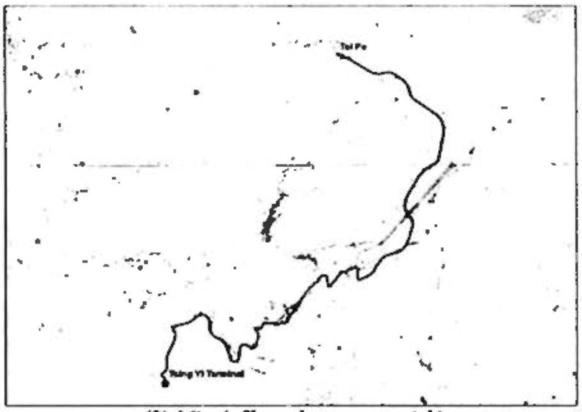
(14) Considering all criteria

Figure 5.10 Efficient routes from Tsing Yi terminal to Kowloon Bay LPG filling station generated by the genetic algorithm



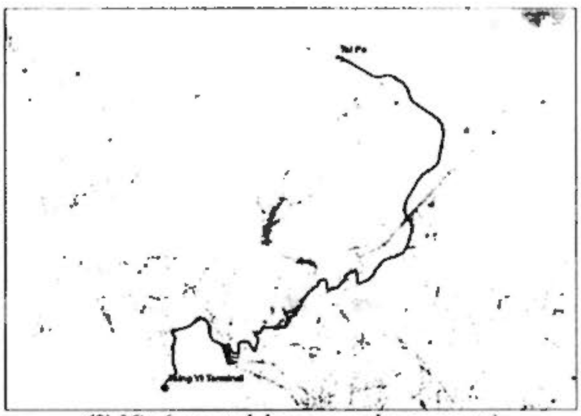
(1) Min (travel time)

(2) Min (accident probability)

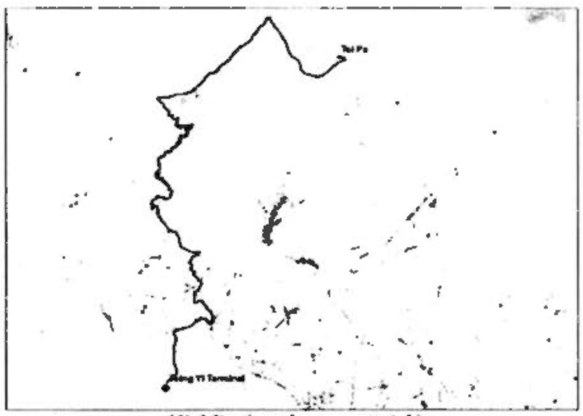


(3) Min (off-road exposure risk)

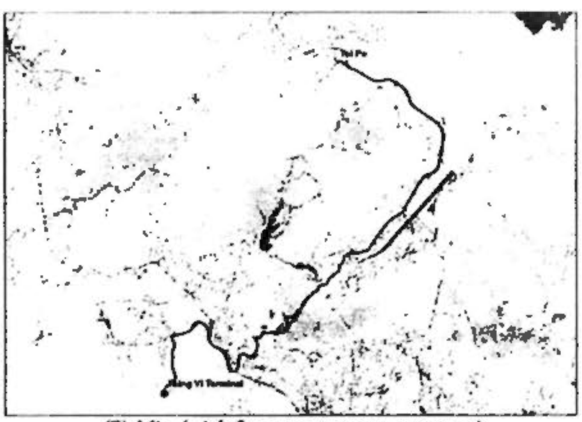
(4) Min (people with special needs at risk)



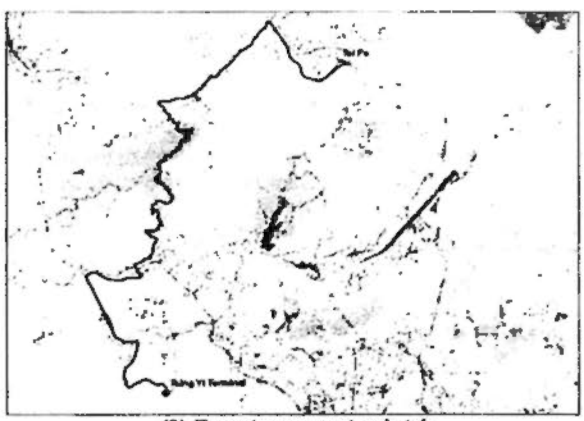
(5) Min (expected damage on the economy)



(6) Min (road users at risk)

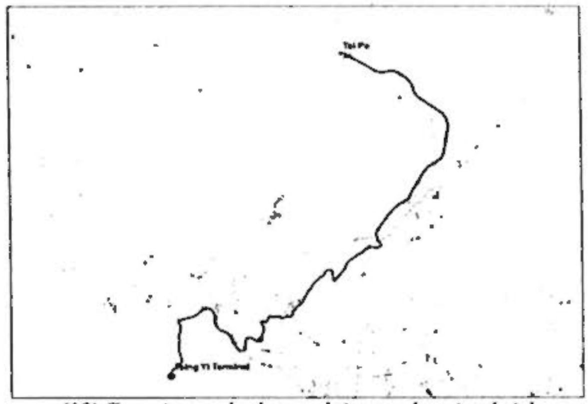


(7) Min (risk from emergency response)



(8) Focusing on societal risk

(9) Focusing on societal risk

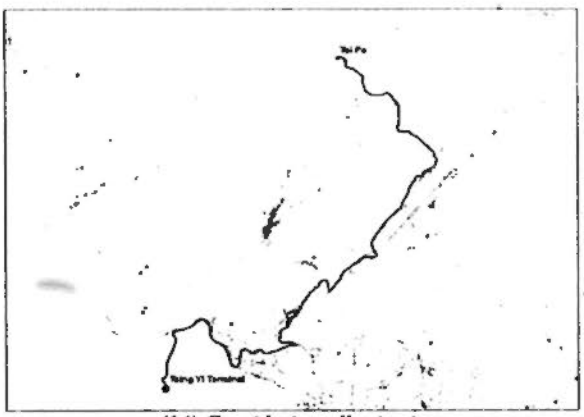


(10) Focusing on both travel time and societal risk

(11) Focusing on both travel time and societal risk

(12) Considering all criteria

(13) Considering all criteria



(14) Considering all criteria

Figure 5.11 Efficient routes from Tsing Yi terminal to Tai Po LPG filling station generated by the genetic algorithm

Table 5.11 Normalized objective function values of the optimal solutions obtained by the genetic algorithm for the Tsing Yi – Kowloon Bay pair (1 ~ 7 are "extreme" solutions, 8 ~ 14 are MOSP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	2.413	2.593	0.982	2.921	1.546	5.333	2.109	9.235	13.375	17.896
2. Min (accident probability)	2.819	1.968	1.913	1.983	1.507	4.180	2.881	8.076	11.551	17.251
3. Min (off-road population exposure)	2.598	2.575	0.902	2.725	1.482	4.671	2.550	8.297	12.355	17.503
4. Min (population with special needs at risk)	3.458	2.529	2.287	1.833	2.528	5.015	3.320	9.136	14.192	20.970
5. Min (expected damage on the economy)	7.604	8.129	1.284	3.369	1.062	7.004	7.348	11.657	20.847	35.799
6. Min (road users at risk)	3.279	3.004	3.758	4.899	2.727	2.023	3.685	10.680	16.411	23.375
7. Min (risk from emergency response)	2.535	2.465	0.965	2.691	1.546	4.883	1.552	8.540	12.551	16.638
8. Focusing on societal risk	2.832	2.709	1.067	3.342	1.626	3.251	3.012	7.660	11.995	17.840
9. Focusing on societal risk	2.821	2.684	1.044	2.933	1.597	3.865	2.177	7.842	12.124	17.122
10. Focusing on both travel time and societal risk	2.523	2.557	0.905	2.686	1.488	4.549	2.462	8.140	12.185	17.170
11. Focusing on both travel time and societal risk	2.429	2.802	1.149	3.483	1.958	3.640	2.413	8.272	13.031	17.874
12. Considering all criteria unbiased	3.316	2.538	2.312	2.582	2.015	3.099	2.856	7.993	12.546	18.717
13. Considering all criteria unbiased	3.164	2.240	2.230	2.253	1.857	3.602	2.655	8.085	12.182	18.001
14. Considering all criteria unbiased	2.980	2.455	2.621	3.281	2.096	2.534	2.871	8.436	12.987	18.838

Note:

1) societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.
2) total risk : the value of this attribute is calculated as the sum of the societal risk and normalized accident probability and expected damage on economy.
3) overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk.

Table 5.12 Normalized objective function values of the optimal solutions obtained by the genetic algorithm for the Tsing Yi – Tai Po pair (1 ~ 7 are "extreme" solutions, 8 ~ 14 are MOSP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	3.698	2.966	0.754	1.801	1.086	6.549	2.655	9.103	13.155	19.508
2. Min (accident probability)	7.121	2.736	0.861	1.484	0.663	5.555	2.421	7.901	11.300	20.842
3. Min (off-road population exposure)	4.025	3.080	0.419	1.459	0.602	4.580	2.717	6.458	10.140	16.882
4. Min (population with special needs at risk)	6.292	5.619	0.665	0.800	0.667	3.727	3.407	5.193	11.479	21.178
5. Min (expected damage on the economy)	4.417	3.465	0.429	1.695	0.506	4.627	3.178	6.751	10.721	18.316
6. Min (road users at risk)	5.257	4.802	1.017	1.672	1.349	3.192	3.865	5.881	12.032	21.155
7. Min (risk from emergency response)	3.923	3.067	0.537	1.456	0.695	5.521	2.188	7.514	11.276	17.386
8. Focusing on societal risk	5.655	5.612	0.665	0.800	0.667	3.701	3.363	5.166	11.445	20.464
9. Focusing on societal risk	5.429	4.845	0.698	1.198	0.959	3.279	3.289	5.175	10.979	19.697
10. Focusing on both travel time and societal risk	4.088	3.142	0.420	1.470	0.606	4.543	2.660	6.432	10.181	16.929
11. Focusing on both travel time and societal risk	3.907	2.986	0.489	1.486	0.664	4.413	2.542	6.388	10.039	16.488
12. Considering all criteria unbiased	5.193	4.726	0.909	1.594	1.147	3.334	3.866	5.837	11.711	20.770
13. Considering all criteria unbiased	3.789	2.839	0.476	1.325	0.659	5.225	2.395	7.026	10.524	16.707
14. Considering all criteria unbiased	3.691	3.681	0.716	1.671	0.849	5.648	3.148	8.034	12.564	19.403

Note:

1) societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.
2) total risk : the value of this attribute is calculated as the sum of the societal risk and normalized accident probability and expected damage on economy.
3) overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk.

Consider the application with respect to single objective optimization. For each O-D pair, it is found that in almost all tests, the resulting routes by the proposed GA (i.e., solutions 1 to 7) are exactly the same as the extreme ones generated by the compromise programming approach. This shows that the proposed GA is competent in handling single objective optimization problems, a special case of multi-objective optimization with particular focus on a certain objective. The interpretation of these solutions is not given here since the composition of risk and cost in each solution and the significant trade-offs among the optimal solutions with respect to different objectives have already been examined and discussed in the previous sections.

Solutions 8 to 14 are examples of the multi-objective solutions. Compared to the routes produced by single objective optimization, these solutions exhibit a good compromise among the competing objectives. Solutions 8 and 9 are obtained by minimizing the risks of on-road exposure, off-road exposure, and the special population exposure simultaneously. Solutions 10 and 11 incorporate operating cost with public safety, and solutions 12 to 14 are generated by taking all seven criteria into account simultaneously. To examine the trade-offs among the objectives in each MOP solution, we analyzed these Pareto-optimal routes for each of the two O-D pairs separately.

According to Table 5.11, it is found that for the pair of Tsing Yi – Kowloon Bay, solutions 8 and 9 have minimum societal risk, since both of them primarily focus on the importance of public safety. However, they are not equally desirable from the perspective of the expected damage on the economy in the event of a DG accident, which increases, for both solutions, by over 50% than the minimum obtained under the single-objective solution 5. As far as the capability of emergency response is concerned, solution 8 is the worst among the seven reported MOP solutions, with 90% higher risk in this factor than the minimum obtained in solution 7. However, compared to single-objective solutions 4 to 6 (which bear more or less similar value on the factor of emergency response with solution 8), the performance of solution 8 is clearly much better than those three on most criteria. Solution 10 considers public safety together with travel time and does make improvement on most of the objectives except the on-road exposure risk, which downgrades by 40% and 18% over solutions 8 and 9, respectively. Having the same focus of concern as solution 10, solution 11 takes the shortest travel time among all the MOP solutions reported in Table 5.11. Moreover, this solution outperforms solution 10 in regard to road users' safety and the emergency response capability. However, in the context of off-road exposure risk, population with special needs at risk, and expected damage on the economy in the event of a DG incident, solution 11 is not as favorable as solution 10. Solutions 12 to 14 take all criteria into consideration in the process of route planning. Like solutions 8 to 11, these three MOP solutions involve various trade-offs among the competing objectives. Overall speaking, for the Tsing Yi – Kowloon Bay pair, considering all criteria simultaneously results in lower accident probability and smaller exposure risk of special population and road users. This is, however, at the expense of travel time, off-road population exposure, expected damage on the economy, as well as a decrease in the emergency response capabilities. Nevertheless, the trade-offs among the objectives are not as significant as those reflected in the "extreme" solutions.

The MOP solutions for the Tsing Yi – Tai Po pair present a similar picture to that of Tsing Yi – Kowloon Bay. Solutions 8 and 9 serve best on public safety with the lowest societal risk among all 14 solutions reported in Table 5.12. However, this is achieved at the cost of longer travel time and higher accident probability since both routes pass through Lam Kam Road and Route Twisk, whose road conditions are undesirable. Solutions 10 and 11 incorporate operating cost with public safety, which shortens travel time and significantly reduces accident probability compared to solutions 8 and 9. On the other hand, solution 10 downgrades by about 80% and 20% over solutions 8 and 9 on special population risk and on-road exposure risk, respectively. As for solution 11, the performance on these two objectives downgrades by 23% and 36%, respectively, compared with the abovementioned two solutions. In terms of overall cost, solution 11 is reasonably good with well-proportioned compromise among various objectives. The rest three, solutions 12 to 14, are obtained by considering all seven criteria with unbiased preferences, among which solution 13 gives better performance than solution 11 on all objectives except the safety of road users, which increases by more than 18% of on-road exposure risk than solution 11. Solutions 12 and 14 involve various compromises among different objectives, and present higher overall cost than solution 13. However, compared with the single-objective solutions, they are acceptable with milder trade-offs among the competing objectives.

5.5.3 Assessing the quality of the proposed GA approach

As an efficient search strategy for global optimization, a genetic algorithm demonstrates favorable performance on solving multi-objective optimization problems. The optimal routing problem in network analysis can be solved with GA through efficient encoding, construction of fitness function, and various genetic operations.

In this case study, we have demonstrated that the GA-based route optimization for the transportation of DG in the road network of Hong Kong is subject to their satisfaction of multiple objectives in terms of cost and risk. The solution is a set of routes that are non-inferior with respect to each other. Owing to the employment of a Max-Min fitness function derived from the definition of dominance to measure the Pareto optimality of each route in a particular generation, the multiple objectives to be optimized have not been combined into a single one and hence the general nature of the solution is maintained. Moreover, the Max-Min fitness function maximizes the difference between any two routes, which ultimately results in a diverse set of non-dominated routes. This has been illustrated by the resulting solutions described in subsection 5.5.2.

The computational experiments reveal the behavior of the proposed GA as applied to the multi-objective DG routing problem in terms of diversity and optimality of solutions, and computational complexity. After examining the solutions against all seven criteria unbiasedly in routing analysis for the Tsing Yi -- Kowloon Bay pair, Figure 5.12 shows that the number of non-dominated solutions generally increases as the number of generation increases, though the number of efficient routes fluctuates in the process of iteration. This is not beyond our expectation. Due to the intrinsic randomness of the genetic algorithm, in particular, the randomness in the crossover and mutation operations, a route that is non-dominated in the previous generation is very likely to become dominated in the next generation after genetic operations as it evolves to a different one, and vice versa. This inevitably leads to the change of proportion of efficient solutions in each generation. On the other hand, the application of tournament selection and elite retaining strategy helps to improve the average quality of the population by giving the high-quality individuals a better chance to be copied into the next generation. Consequently, the number of Pareto-optimal routes, as a whole, gradually increases with the evolution of population.

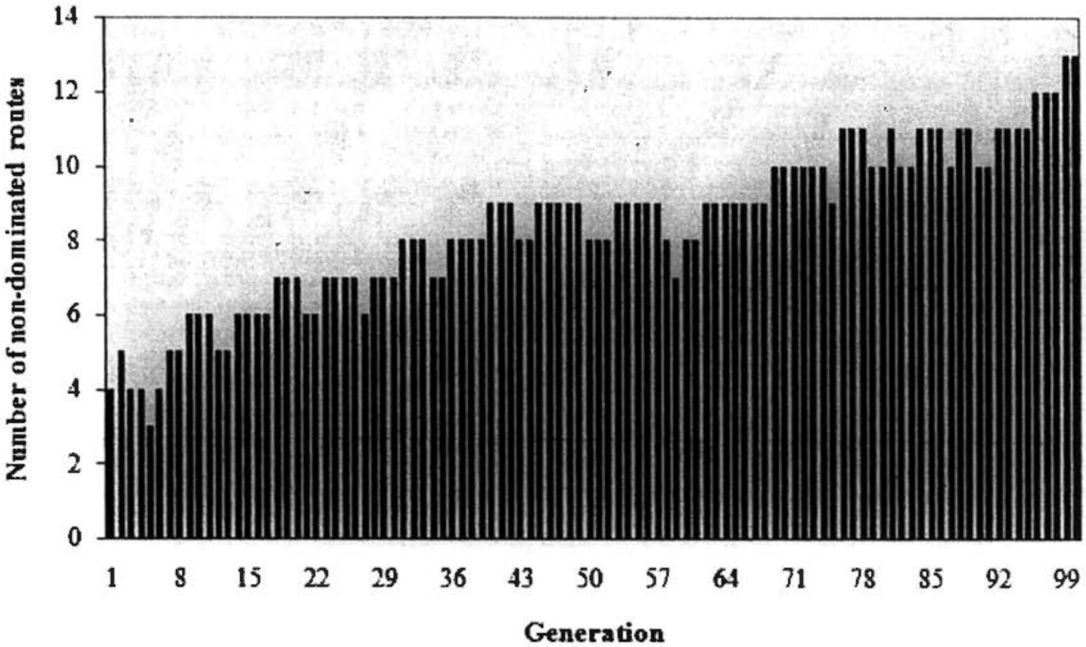


Figure 5.12 The number of non-dominated routes increases with the generations (test on the Tsing Yi –Kowloon Bay pair with unbiased consideration of all criteria)

Figure 5.12 exhibits an upward movement in the number of Pareto-optimal routes in the evolution process. However, it does not reveal exactly how Pareto optimality of solutions in different generation changes. To assess the quality of the proposed GA approach more appropriately, we attempted to examine how well the genetic algorithm improves Pareto optimality from generation to generation. However, the Max-Min fitness function used in the proposed GA is designed to compare the fitnesses between solutions within a generation, and one cannot compare the fitnesses between solutions in different generations. To solve this problem, we created a "global generation", which includes 30 × 100 = 3000 feasible routes from the 100 generations lumped together. We then calculated the "global fitness" for each of the 3000 solutions in the global generation according to the same Max-Min fitness function used before. Based on global fitnesses, we identified the ''global Pareto set'' for the global generation. Of the 3000 routes in the global generation, there are 47 distinct routes in the global Pareto set. We averaged the value of global fitness over the 30 individuals in each generation and plotted this average in Figure 5.13.

We also plotted the number of routes in each generation that are members of the global Pareto set. This plot clearly shows that the proposed GA improves global Pareto optimality from generation to generation, which confirms the effectiveness and efficiency of the proposed GA.

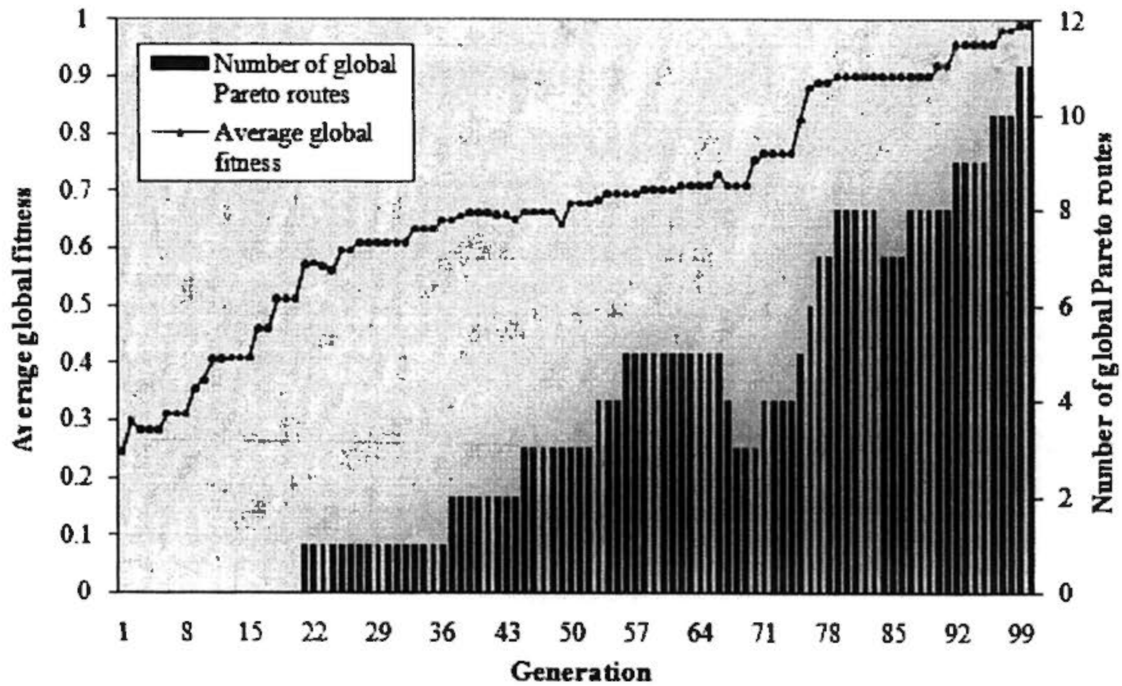


Figure 5.13 Improvement of global Pareto optimality from generation to generation

In terms of the diversity of solutions, Figure 5.14 shows a plot of 9 efficient solutions, which is a subset of the 47 distinct global Pareto-optimal routes for the pair of Tsing Yi – Kowloon Bay when considering all seven criteria unbiasedly in routing analysis. The plot of optimal routes provides information on how good an algorithm is in finding a diverse set of solutions for problems involving multiple objectives. A good spread of solutions over a range implies that the algorithm is good in finding diverse solutions (*Pangilinan and Janssens 2007)*. Figure 5.14 shows that the solutions obtained by the proposed GA are well spread over the range for all the objectives under consideration. Also, the figure reveals that the proposed GA finds non-dominated routes with appropriate compromise among the competing objectives. It is found that for any two of these MOP solutions, an improvement in one objective does not significantly downgrade others, which indicates a good balance is achieved among the objectives between different solutions. Such solutions are desirable for a MOP problem like DG route planning.

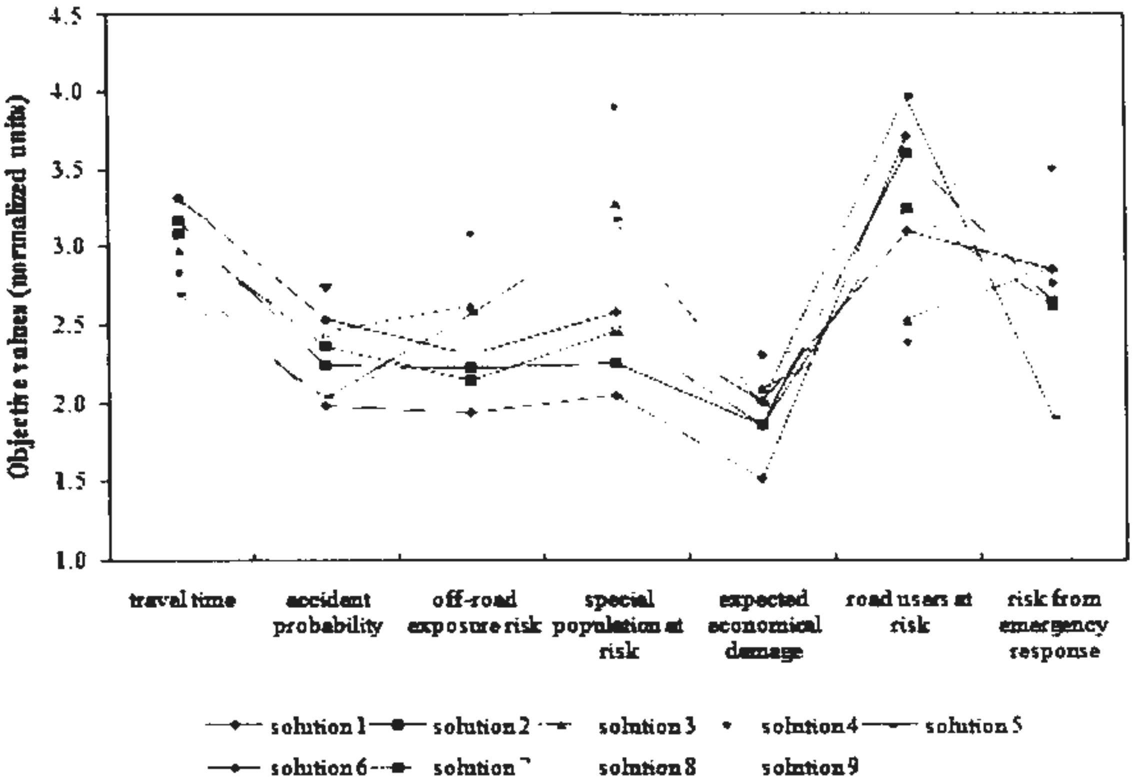


Figure 5.14 A plot for a subset of the global Pareto optimal routes

Another aspect on evaluating the proposed GA is the closeness of its solutions to the Pareto-optimal solutions. For Tsing Yi – Kowloon Bay pair, it is found that some solutions produced by the GA coincide with those generated by the compromising programming or the adaptive weighting method. It has been proved that solutions created by the CP and the adaptive methods for a MOP problem are Pareto-optimal or weakly Pareto-optimal. The agreement in the solutions of the GA with the other two methods indicates that the GA has potential of finding (approximately) efficient solutions. On the other hand, in the absence of the complete set of Pareto-optimal routes for the DG routing problem under consideration, it is difficult to evaluate the GA in terms of proximity to the Pareto front. Nevertheless, as shown in Figures 5.12 and 5.13, the GA generates more efficient routes as the number of generations increases, which means that through evolution, the non-dominated solutions are improved and move gradually to the location of the Pareto-optimal solutions. While there is no assurance that the non-dominated solutions converge to the Pareto front or the maximal set of efficient paths, the GA finds a subset of diverse and favorable non-dominated solutions with good compromise among the objectives at each generation, and improves the solution set as the number of generation increases.

With regard to computational complexity, the proposed GA is a polynomial time algorithm with respect to the number of nodes and arcs of a network. Although the CPU runtime is longer than the other two methods, unlike exhaustive algorithms, the GA does not suffer from intractability and memory problems, even with a large network size in this case study. In this regard, the proposed GA is considered to be computationally effective.

The above analysis and assessment of the proposed GA were made on the basis of the results of Tsing Yi – Kowloon Bay. In fact, similar conclusions could be arrived from the analysis of routing results of other O-D pairs, though the degree in the diversity of solutions and the optimality of solutions may be different. The present study illustrates that the GA approach is effective in solving a multi-objective optimization problem such as DG route planning. Moreover, the advantage of the GA will become more significant when dealing with more complex combinatorial optimization problems with larger solution space.

5.6 Summary and discussion

In the preceding sections, the same routing problems between Tsing Yi LPG terminal and the dedicated LPG filling stations were analyzed using three different MOP methods, namely the compromise programming approach, adaptive weighting method, and GA-based approach. The compromise programming procedure allows decision-makers to exercise their preference structures in pursuing satisfactory solutions rendering good compromises among different objectives. The adaptive weighting method approximates the Pareto front with a few suitable solutions to help decision-makers select the most satisfied routes without generating all of them. The genetic algorithm based approach uses a set of specifically designed genetic operators to efficiently capture a wide range of Pareto-optimal and near-optimal solutions, from which a decision-maker can choose the most preferred or best compromise solution as the one to implement. Although the mechanisms of the three MOP methods are different from one another, they have all been proved effective in generating efficient solutions for multi-objective route planning for LPG transportation on the road network of Hong Kong.

When considering each objective individually, no matter which method is used, the generated optimal routes in terms of a particular objective are rather different from each other. The minimization of one single objective function gives rise to a significant achievement of the chosen criterion, whilst heavily compromising the others. In other words, the trade-offs among different objectives are rather significant. This manifests the conflicting nature of the multiple objectives in the DG routing problem, which, therefore, reveals the necessity of the search for compromise solutions rendering the best possible tradeoffs among different objectives for DG route planning.

When various objectives are taken into account for DG route planning, it gives a different picture from single objective DG routing. Compared with the extreme solutions, the multi-objective solutions present a good compromise among the competing objectives, though they do not strictly correspond to a minimum of any objectives. It is observed that for MOP solutions, when one or more objectives are improved, other objectives are worsen off at the same time. However, the values of the objective functions vary within a smaller range compared with those in the single objective solutions. In other words, the compromise among the competing objectives becomes much milder. On the other hand, the diversity of the routing solutions still remains, though the differences among the routing solutions appear to be smaller. Taken together, albeit with limited scope, the computational experiments demonstrate the validity of the methodologies proposed in this research.

The Pareto-optimal routes for some origin-destination pairs, such as the Tsing Yi – Mei Foo and Tsing Yi – Kwai Chung pairs, are found to be alike in a number of cases. These optimal routes exhibit high similarity not only under different combinations of various objectives, but also under different MOP methods. The possible reason is that the distance between the origin and the destination is so short that the route selection in the road network is limited. On the other hand, the similarity also appears in the MOP solutions for the Tsing Yi – Tuen Mun pair, although in relatively fewer cases. Clearly, distance should not be the underlying reason because Tsing Yi is much more distant from Tuen Mun than that from Mei Foo and Kwai Chung. In theory, greater spatial extensiveness diversifies the choices in route selection. However, the structure of the existing road network limits such a choice. It is found that between Tsing Yi and Tuen Mun, there exists a corridor which is the only access from the origin to the destination: Tsing Yi LPG terminal→ Tsing Yi road → Cheung Tsing Highway → Tsing Long Highway → Tuen Mun Road. Vehicles have to pass through this corridor before they reach Tuen Mun LPG station. In addition, the forbidden passage of DG vehicles through any tunnels in Hong Kong further narrows down route selection. Under the joint effect of these factors, the variation in the routes between Tsing Yi terminal and Tuen Mun station is very limited. Most of these routes comprise the same sections but in different ways. For the other O-D pairs, however, the optimal routes under different objectives differ significantly, which confirms the validity of the proposed methodologies in generating a set of diverse solutions.

In present case study, identical solutions are obtained by different methods sometimes. For example, solutions 12 and 14 through compromise programming for the Tsing Yi – Tai Po pair are the same as solutions 8 and 10, respectively, through the adaptive method. There are even more identical cases found in the solutions generated by the proposed GA. As a population-based method, GA produces a set of solutions in each single run. Although not all the solutions are guaranteed to be Pareto-optimal, a few efficient routes (i.e. the ones that are Pareto-optimal or near Pareto-optimal) can be found from the solution set. Among these efficient routes, occasionally, one or more solutions are found to be the same as, or very close to, the routes generated by the compromise programming method or the adaptive weighting method. Given that the solutions by each of the three methods for these two O-D pairs exhibit great varieties, the identicalness in the optimal solutions is unlikely caused by the network structure. Rather, it confirms the validity of the methods. CP is a preference-based method, and the weights employed in CP are predetermined according to decision-makers' preferences for each objective. The generated solutions are Pareto-optimal, which reflect the trade-offs among different objectives rendered under the weighting structure. The adaptive method and the genetic algorithm fall into the category of generating technique. No prior knowledge of relative importance of each objective is used. The "weights" in the adaptive weighting method are created by the system automatically based on the largest unexplored solution space. The solution produced by this approach is weakly Pareto-optimal, or Pareto-optimal if it is unique. Working with population of solutions, GAs have been proved well suited for finding a set of approximately efficient solutions. In this case study, some solutions created by the proposed GA have been found to be very close to, or even the same as, the ones produced by the compromise programming method and the adaptive method. The occurrence of such identicalness in the solutions of the three methods indicate that the adaptive method and the genetic algorithm are competent for generating a set of efficient solutions for the multi-objective DG routing problem; moreover, the optimal ones representing certain preferences for different objectives are very likely to be found within this set.

The experimental results over the Hong Kong road network using the proposed methodologies have demonstrated various compositions of risk and cost in the routing solutions. In this study, the overall cost of a solution is defined as the summation of operating cost, various risks, and the capability of emergency response. Clearly, the principal contributor of the overall cost for different solutions is different from each other. For example, for one solution, the overall cost may mainly depend on the exposure risk; while for another solution, the operation cost contributes the most; and in the third case, the contribution of the emergency response capability is the most significant. The variety in the cost and risk composition reveals the distinct emphasis in different solutions. In addition, it is also observed that under the current system of evaluation for the cost and risk, except for the extreme solutions, the first three contributors to the overall cost are on-road exposure risk, travel time, and emergency response capability, respectively. This applies to most solutions for all origin-destination pairs addressed in the case study.

It should be noted that mathematically optimal does not necessarily mean practically optimal. A route being optimal in the context of a particular objective or a combination of several objectives may be of insignificance in practice. Take Tsing Yi – Tai Po as an example. When the major concern is to minimize the population with special needs at risk, or to minimize the on-road exposure risk, the resulting routes will always pass through Route Twisk, no matter which method is adopted. Such solutions are, however, infeasible in practice. Route Twisk is the only link to Tai Mo Shan Road, the road leading to Tai Mo Shan, the highest peak in Hong Kong. It is narrow, sloping, and tortuous. Although the traffic volume on this road is quite low, Route Twisk is rarely taken by the vehicles carrying dangerous goods due to its undesirable road condition. This indicates that despite being mathematically optimal, any solution with Route Twisk as a component leaves a lot to be desired from the viewpoint of feasibility. The Tsing Yi – Tai Po case suggests that for multi-objective problems, although various MOP solutions can be generated by means of different optimization procedures, the obtained solutions need to be examined carefully on both the optimality and rationality to ensure their feasibility.

In this research, three methods have been proposed for the problem of multi-objective DG route planning. Each of them has its respective characteristics and is applicable to different situations. When decision-makers have explicit preferences among objectives and are prone to deciding the criteria weights on their own, they can use compromise programming approach to conduct DG route planning. In other cases, they can choose generating methods such as the adaptive weighting method or the genetic algorithm. Both methods search for optimal routes with no requirement on prior knowledge of the relative importance of the concerned objectives. However, they have different working principles. The adaptive method is a deterministic approach based on compromise programming. In this method, the exploration in the objective space is always adaptively adjusted to point to the desired direction. In other words, the search is goal-directed, rather than random search. The genetic algorithm is a heuristic method. Compared to traditional search algorithms, GA is able to automatically acquire and accumulate the necessary knowledge about the search space, and self-adaptively control the entire search process through random optimization technique. Moreover, it is able to find multiple feasible solutions in a single run. Compared to the adaptive method, GA is more suitable for solving the combinatorial optimization problems with non-linear objective functions, or when little is known about the search space.

In terms of complexity, the compromise programming based approach outperforms the other two, and the genetic algorithm has the highest complexity. This can be reflected by the CPU time running for generating efficient solutions using different methodologies. Table 5.13 shows the computation time for single-objective, three-objective, and seven-objective DG routing problems for the Tsing Yi – Kowloon Bay pair. The time is in the unit of seconds. For the genetic algorithm, the computation time is averaged on the basis of ten runs. As illustrated in Table 5.13, the computation time of the genetic algorithm is the longest, followed by the adaptive method. The compromise programming is the fastest. On the other hand, however, the genetic algorithm excels the compromise programming in the generation of multiple solutions in a single run. The ability of GA to simultaneously search different regions of the solution space makes it possible to find a diverse set of solutions for the MOP problem, while compromise programming only generates a single solution each time. In comparison, the adaptive weighting method produces one solution at each iteration, and the same procedures repeat several times till the desired size of solutions are obtained.

Table 5.13 The computation time (in seconds) for single-objective, three-objective, and seven-objective DG routing problems for Tsing Yi – Kowloon Bay

	compromise programming	adaptive weighting method	genetic algorithm
single-objective problem	23.4	–	113.6
three-objective problem	74.7	124.5	397.6
seven-objective problem	153.0	229.5	823.1

It must be noted that the purpose of exploring different MOP techniques for the problem of DG routing is to provide decision-makers with more options and more flexibilities in solving the multi-criteria decision-making problem. It does not intend to draw a conclusion on which method is better than others. In fact, each approach has its advantage and applicable conditions, no method may outperform other "competitors" in all aspects.

In this case study, some constraints on the road network, such as the turn restriction on certain intersections and the traffic directions designated for the involved road segments, have not been considered due to the problem of data availability. Such road segments and intersections are then assumed to be unrestricted. Hence, the experimental results obtained under this assumption may not be one hundred percent realistic. The possible way to avoid such a problem is to secure the data and set corresponding constraints on the network.

Finally, it is worth pointing out that the road network in Hong Kong is relatively simple. A number of corridors in the network are actually the only routes between some locations. Thus, the simplicity of the road network may not be able to fully demonstrate the efficacy of the proposed framework and methodologies. It is, however, conceivable that the performance of the approach can be better illustrated when it is applied to cities with more complicated road networks in future applications.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

This study aims to contribute to the literature of dangerous goods transportation by constructing a general framework applicable to multi-objective route planning for the conveyance of DGs in a high-density living environment. In this chapter, the research findings and methodological contributions of current study are summarized. In light of the study results and limitations, some recommendations are provided for future research.

6.1 Summary of the study

This research has addressed the problem of optimal route planning for the transportation of dangerous goods on a road network. The main focus is on the development of vigorous multi-objective optimization methods to seek optimal routes for DG transportation in a high-density living environment, on the basis of multi-criteria risk assessment. A general framework for dangerous goods route planning for high-density living has been constructed. This framework can assist stakeholders in evaluating the way vehicles carrying DG are being routed on the road network, and can also provide decision-makers with efficient options if the current routes need to be adjusted.

Three distinct multi-objective optimization methods have been developed to properly manage the multiple objectives involved in DG route planning. High performance algorithms have been devised to facilitate the implementation of these methods. Multi-objective DG routing can be treated as an extension of the traditional shortest path problem, for which the Dijkstra's algorithm is the most commonly used. In order to make the best use of Dijkstra's algorithm and efficiently address the multi-objective nature of the DG routing problem, a modified Dijkstra's algorithm incorporating compromise programming (CP) has been developed to generalize multi-attributes in the calculation of the cost value for each link. The least cost path can then be identified based on the composite cost in each link. The main assumption in compromise programming is to search for a feasible solution closest to the ideal one in which each objective achieves its minimum value simultaneously. The degree of closeness is measured by the L_p-metric. Two CP-based methods have been proposed in this research to accomplish the modification of the Dijkstra's shortest path algorithm. They are: (1) a standard compromise programming method, and (2) an adaptive weighting method. The standard compromise programming approach is a typical preference-based method. The overall performance of a solution is represented by a utility function which incorporates multiple attributes with the weights accounting for decision-makers' preferences for different objectives. This method allows decision-makers to exercise different preference structures in pursuing the compromise solutions. It offers flexibility in addressing the multiple aspects of DG route planning. The solutions depict the trade-offs in achieving various objectives. This is especially critical when the efficient solutions form a non-convex frontier, in which case the conventional MOP technique such as the weighted sum approach may fail.

In the case that decision-makers find difficult to state their preferences for each objective before they have an explicit conception of the actual trade-offs involved, it is more desirable to generate the efficient solutions first, and then let the decision-makers select the most preferred or best compromise solutions from this set. This is the notion of generating method. The adaptive weighting approach proposed in this study falls into this category. A parametric objective function (i.e. the weighted min-max function) that behaves like a utility function is constructed. Properly approximating the Pareto front with a few suitable solutions is achieved by systematically varying the origin and direction of exploration. In this method, once a Pareto-optimal is obtained, the search space will be partitioned into smaller pieces, and the regions that are either dominated by the known optimal solutions or free of optimal solutions will be discarded. The search origin and direction are then adjusted based on the largest unexplored space that may contain efficient solutions. Considering that in the case of network routing problem, conventional minimax solutions such as the branch-and-bound procedure are unlikely to outperform the labeling algorithms which are specially designed to make use of the network shape and can process the links in the optimal order, the Dijkstra's algorithm along with appropriate modifications is employed to solve the min-max utility function. The cost of traversing link in the modified Dijkstra's algorithm takes into account all the objectives examined, rather than a particular objective. Compared with the compromise programming approach, the adaptive method requires no prior knowledge of relative importance of each objective, yet it can provide an unbiased approximation of the Pareto front.

Both the compromise programming approach and the adaptive weighting method depend on a weighting mechanism to collapse multiple objectives into a single objective function. To generate the desired solution, the exploration in the objective space is always oriented towards the expected direction. In other words, the search is goal-directed, rather than a random search. In the literature of multi-objective optimization, these optimization methods are generally categorized as the class of deterministic technique. By contrast, the genetic algorithm, a probabilistic optimization technique, provides a powerful alternative to the conventional solutions for difficult optimization problems. GAs are a class of global search methods that are modeled after the mechanics of natural evolution within populations and species via reproduction, competition, selection, crossover breeding, and mutation. They operate with a population of possible solutions rather than a single candidate. Therefore, they are less likely to get trapped in a false local optimum. Moreover, several Pareto optimal solutions may be captured during one run of GA. In the proposed GA-based method, a feasible routing path is represented as a variable-length chromosome whose elements represent the nodes included in it. The initial population is generated using random walk incorporated with the seeds generated by Dijkstra's algorithm. The incorporation of heuristics into random initialization is able to produce a better initial population while maintaining its diversity. The Max-Min fitness function is employed to maximize the difference between any two paths, which ultimately results in a diverse set of non-dominated solutions. The tournament selection incorporating the elite retaining strategy is employed to generate a new population for the next generation. The crossover operation exchanges partial chromosomes (partial-paths) and the mutation operation introduces new partial chromosomes. Crossover and mutation together provide a search capability that results in an improvement of solution quality and convergence rate.

Given the multiple objectives in the process of DG route planning, a set of criteria fitting the context of high-density living has been identified, covering most aspects associated with DG transportation such as travel time, accident probability, exposure risk, and emergency response capabilities. Since high-density living is of a particular concern in our study, the exposure risk considered here contains not only road users at risk, but also off-road population exposure, as well as population with special needs at risk. In addition, the emergency response capability, which is significant for high-density living, is also included in DG routing analysis, with a view that timely action by emergency responders can considerably reduce the magnitude of the consequences associated with a DG release. As another type of exposure risk, the possible damage inflicted to the surrounding properties and facilities in the event of a DG incident is also addressed.

Based on the identified routing criteria, up to seven objectives are included in the routing analysis, which can be classified into three major categories: operating cost, risk estimates, and emergency response capabilities. A risk model with respect to various risks has been designed to assess the risk associated with DG transportation. The risk assessment is conducted within a geographic information system (GIS), which exploits the powerful spatial data processing and analytic capabilities of GIS.

To validate the proposed methodologies, a case study has been carried out on the transportation of liquefied petroleum gas in the road network of Hong Kong. It attempts to generate optimal routes from Tsing Yi LPG terminal to the dedicated LPG filling stations located in Kowloon and the New Territories. To examine the effectiveness of these methodologies, four scenarios are tested for each method: (1) considering each objective individually, which corresponds to a series of single objective optimal routing problems; (2) routing with primary focus on public safety, namely road users at risk, off-road population at risk, and people with special needs at risk. Solutions obtained effectively address the government's major concerns in DG routing; (3) taking the operating cost into account in conjunction with the public safety with the intention of striking a balance between economy and safety; (4) considering all the criteria simultaneously in routing. The proposed methodologies have been implemented on a GIS platform – ArcGIS. The computational experiments demonstrate the robustness and flexibility of this platform as a tool to quantify the routing criteria through spatial analyses and database management, to perform the shortest path calculation, and to visualize the resulting solutions. A diverse set of routes have been generated under each method, presenting various trade-offs among different objectives.

6.2 Research contribution

Safe DG transportation is of even greater importance for high-density living in which population and socioeconomic activities are densely distributed over the transportation network. Risk assessment and route planning play a crucial role in the prevention or minimization of possible catastrophic consequences on human life and the environment. However, effort has seldom been made to analyze such problem in the literature. Hence there is an urgent need to carry out risk assessment and optimal route planning for DG transportation in high-density environment. This study has established a general framework for optimal DG routing in such an environment, within which non-convexity and non-linearity can be handled, risk assessment applicable to high-density living can be made, and the best compromise solution can be obtained along the Pareto front stipulating various trade-offs among the conflicting objectives. The results obtained from this research will positively contribute to the research and applications in the field of DG transportation. The contributions of this research to the literature of DG transportation can be summarized as follows.

First, this study has established a conceptual framework for optimal route planning for DG transportation in high-density living environment. To properly address the special concern on high-density living, in the risk assessment and the routing analysis, a high value has been put on various types of exposure risk, including not only the off-road population at risk, but also the road users exposed to the DG vehicles, as well as the population with special needs at risk, given that this group of people may be particularly sensitive to DG releases and are difficult to evacuate. Considering that prompt and efficient response is critical to the minimization of possible catastrophic consequences on human life and the environment in the event of a DG accident, the emergency response capability has also been counted as a factor in risk assessment and routing analysis. To the best of our knowledge, although there is a wealth of literature on the DG transportation problem, most of it only focuses on risk analysis by various risk models. Lesser effort has been made on route planning for DG transportation under conflicting objectives, particularly in high-density environment. This study sheds a light on this gap.

Second, DG transportation is a multi-criteria and multi-objective problem which is generally complicated to solve. High performance multi-objective optimization methods are of paramount importance to effective route planning for DG transportation. It is instrumental to generate a set of efficient routes representing the inherent trade-offs among different objectives for decision-makers to choose the one that gives the best compromise among the conflicting objectives. This study has developed three novel methods to facilitate the generation of a set of optimal solutions, instead of a single pseudo optimal solution, on the Pareto front including non-convex (non-supported) points for the choice of compromise solution rendering the best trade-offs among conflicting objectives. The associated high performance algorithms guarantee speedy convergence via global and local searches. The methodologies proposed in this study gives full consideration to decision-makers' inclination and capability in determining the weights for different criteria. The diversity of methodologies provides decision-makers more flexibility in choosing applicable MOP methods for DG routing.

In the previous studies, optimal route planning for DG transportation was achieved by either considering each individual objective separately, or linearly combining multiple concerned objectives by a weighed sum approach, and reducing the original problem to a standard shortest path problem. Consequently, the non-convexity consisted in solution space and the non-linearity existed in some objective functions cannot be properly handled. The methodologies proposed in this study have effectively addressed this problem. Compromise programming has been mathematically proven superior to the weighted sum method in locating non-convex points on the Pareto front (Steuer 1986). The proposed adaptive weighting method is suited for the exploration of both the "convex" and "concave" parts of the Pareto front, while ensuring Pareto-optimality of the points encountered. The ability of the genetic algorithm to simultaneously search different regions of the solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex and discontinuous spaces. Avoiding the linear form of scalarized objective functions in the objective space enables the proposed methods to efficiently handle difficult optimization problems with non-linear objective functions.

This research can benefit safe DG transportation in practical applications, particularly in high-density cities. A real-life application in optimal route planning for the transportation of liquefied petroleum gas in Hong Kong has been carried out in this study. The implementation of the proposed methodologies enables the avoidance of the pitfalls of preference-based techniques and the burden of generating a complete set of possible solutions, and provides decision-makers with an overview of the solution space and the possible trade-offs among the conflicting objectives. The application study has illustrated the adaptation of the proposed framework in a GIS environment.

Finally, different types of dangerous goods possess different characteristics whose risk assessments and routings call for a wide spectrum of technical knowledge and practical considerations. This research concentrates mainly on the transportation of petrochemical-type of DG – liquefied petroleum gas. The framework can, however, be extended for further research on more complicated problems involving the transportation of multiple DGs over a transportation network in high-density environment.

6.3 Recommendations for future research

As outlined in the preceding section, this study has made a positive contribution to the field of dangerous goods transportation. However, further efforts are required to extend both the methodology and the substance of this research, such as practical and reliable estimation of the risk of DG transportation; exploration of efficient approach to the DG routing problem with multiple origins and destinations; strategic handling of the constraints involved in DG route planning; uncertainty analysis; as well as real-time routing.

When modeling the risk of transporting DG along a route, the risk indicator is usually composed of the probabilities of occurrence of some undesirable events and their possible adverse consequences (Erkut *et al.* 2007). The probability of an accident in a link of a route depends on various factors such as the long-run accident rate, length of the link, road type, and traffic condition. In addition, the estimated probabilities based on individual factors might be inconsistent and sometimes even conflicting. Therefore, it is necessary to find a way to combine the pieces of evidence/probabilities to estimate the composite probability for the link. Actually, certain level of subjectivity usually exists in the estimation process, particularly when public perceived probability is involved. The present study employs the Bayesian approach to estimate the probability of an accident with release of DG. A Bayesian method, commonly used in the literature (Chow *et al.* 1990; Glickman 1991), requires decision-makers to estimate prior and conditional probabilities and cannot differentiate uncertainty from ignorance. By contrast, the Dempster-Shafer theory of evidence (Shafer 1976; Wu *et al.* 2002; Florea *et al.* 2009) does not require an assumption regarding the probability of the individual constituents. It allows combining evidence from different sources and arrives at a degree of belief (represented by a belief function) that takes into account all the available evidence. These features make D-S theory potentially valuable for risk evaluation when obtaining a precise measurement from experiments is impossible, or when knowledge is obtained from expert elicitation. In future research, the feasibility of the D-S theory in estimating the accident probability under conflicting evidence needs to be explored. In particular, to overcome the limitation of the original combination rule in the D-S theory, adaptive robust combination rules need to be constructed to give a more practical and reliable way to estimate the probability of an accident in a link of a route to be used in the estimation of risk of DG transportation.

Similar to most of the existing research in DG routing, the present study focuses on selecting the routes for a given origin-destination pair. However, a comprehensive DG transportation planning framework should consider DG transportation over the transport network with multiple designated origins and destinations, particularly when multiple DGs are involved. Selecting optimal routes for each O-D pair may result in overloading certain links of the transport network and, consequently, in poor overall system performance. Given that relatively little attention has been received in the literature, the research with respect to this kind of DG routing problem should be carried out in future. The DG routing problem with multiple origins and destinations can be formulated as a multiple destination routing (MDR) problem which searches for a minimal risk tree in a given transportation network. The key to solve a MDR problem is to find all relevant intermediate nodes linking the source and destination nodes. Leung *et al.* (1998) have proposed a novel genetic algorithm to solve the unconstrained MDR problem which out-performs the common heuristic algorithms (Tanaka and Huang 1993). The method needs to be further improved so that convergence can be guaranteed and computational complexity can be further reduced, which is essential in solving the DG routing problem with multiple origins and destinations.

The issue of constraints, such as the equity and capacity constraints in the underlying network, should also be addressed in further research. The multiple origin-destinations DG routing problem with basic constraints can be formulated as:

$$\min \sum_{e \in T} c(e) \qquad (6.1)$$

s.t. T satisfies constraint set S

where e is an edge (which corresponds to a link in a network) in sub-tree T of the weighted graph (the transportation network) G = (V, E, C) with node set V, edge set E, and weighted function $c: E \rightarrow R$, where $c(e)$ is the risk/cost imposed on the edge $e \in E$. Numerous solution methods for constrained optimization problems have been reported, such as penalty function method (Yeniay 2005), Lagrange multiplier method (Bertsekas 1982), and gradient projection method (Dick 2009). Novel strategy needs to be explored to properly handle the constraints imposed on DG route planning.

The traffic conditions and other risk factors in DG transportation networks (e.g., incident probabilities, population exposure, and the effects of release of DG) involve considerable uncertainty, which increases the difficulty of routing decision. Stochastic programming that handles such uncertainty via mean-risk (Markowitz 1987; Ogryczak and Ruszczynski 2002) and stochastic dominance (Levy 1992) is commonly employed to solve the problem. Due to the low probability but high consequence nature of DG transportation, it might be more profitable and practical to handle uncertainty by imposing fuzzy restriction on the variability of risks within the fuzzy optimization framework. By this approach, the variability of risk is formulated as fuzzy numbers in the objectives and constraints so that flexible route planning under uncertainty can be materialized. The multi-objective DG routing problem can then be formulated as a fuzzy optimization problem involving multiple objectives (Leung 1988a, b, c) and subsequently solved by fuzzy optimization methods extended on the genetic algorithm (Leung *et al.* 1998; Leung 2010).

Finally, Most of DG transportation risk factors are both time-dependent and stochastic in nature (Miller-Hooks and Mahmassani 1998; Erkut and Ingolfsson 2000), i.e., they are random variables with probability distribution that vary with time. However, the vast majority of existing routing models are static and deterministic. Therefore, dynamic and stochastic models that consider stochasticity in a time-dependent environment should be developed to generate more rational and appropriate routing solutions for DG shipments. Meanwhile, advances in information and communication technologies enable the driver and dispatch center to obtain and exchange real-time information, and as a result, to monitor and adjust the route of vehicles accordingly. Such advance renders real-time DG routing an intriguing research topic, under which the routing decision is subject to changes en-route due to real-time updates of the traffic data, and efficient re-optimization procedures are developed to seek adaptive routing strategies in response to the updated network condition.

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Publications Co-Authored During the PhD Study

Articles accepted for publication

Li, R.R. & Leung, Y. (2010) Multiobjective route planning for dangerous goods using compromise programming, *Journal of Geographical Systems* (accepted).

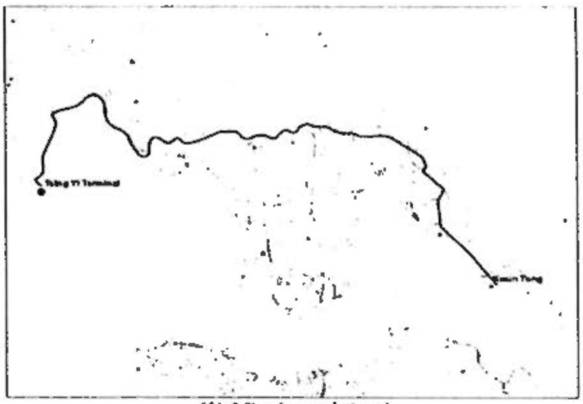
Articles under preparation

1. An adaptive weighting method for multi-objective path optimization problems
2. On the use of genetic algorithm to solve dangerous goods routing problem

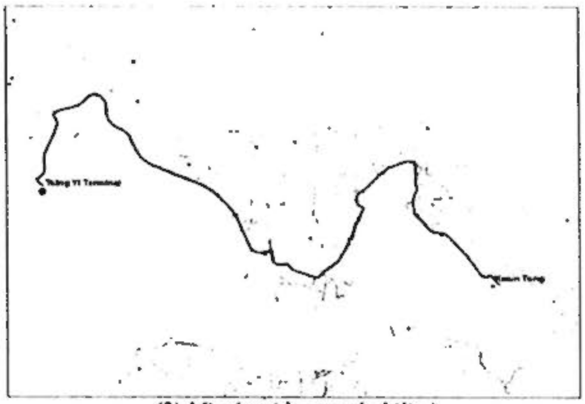
Appendix A: Supplemental Maps of Optimal Route Planning for the LPG Transportation in the Road Network of Hong Kong

In this research, three optimization methods have been developed to seek optimal routes for DG transportation with conflicting objectives, i.e., the compromise programming approach, the adaptive weighting method, and the genetic algorithm. With the support of geographical information systems (GIS), a case study was carried out in the transportation of liquefied petroleum gas (LPG) in the road network of Hong Kong. In particular, the routing problems between Tsing Yi LPG terminal and the dedicated LPG filling stations located in Kowloon and the New Territories were analyzed using the proposed MOP methodologies. To examine the effectiveness of these methods, two scenarios were developed for testing, namely, the optimal routing in terms of single objective, and the multi-objective route planning. The aforementioned three methods were successively used in each application to search for efficient routes for transporting LPG from Tsing Yi to each of the nine dedicated LPG filling stations: Kowloon Bay, Kwai Chung, Kwun Tong, Mei Foo, West Kowloon, Ma On Shan, Tai Po, Tuen Mun, and Yuen Long. For such a multi-objective routing problem, the solutions obtained by each of the three MOP methods for most of the origin-destination pairs are diverse sets of routes presenting various trade-offs among different objectives, which has been illustrated in Chapter 5.

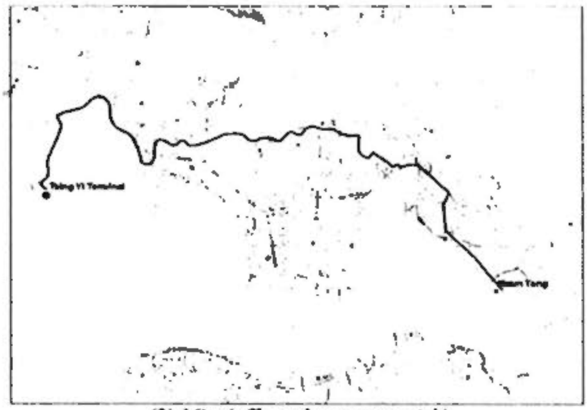
Due to space limitation, Chapter 5 only reports the sample results of the Tsing Yi - Kowloon Bay and Tsing Yi – Tai Po pairs. To maintain the integrity of the experimental results, and to further demonstrate the effectiveness of the proposed methodologies, supplemental results of the rest 7 O-D pairs are collectively presented in appendices. The maps of the efficient routes for each O-D pair are displayed in this appendix, and the corresponding attribute values of the routes are summarized in Appendix B. Note that not all routes generated by three MOP methods are displayed due to the enormous number of routes. Moreover, the set of Pareto-optimal routes for some O-D pairs (e.g., Tsing Yi – Mei Foo, Tsing Yi – Kwai Chung) do not exhibit much diversity since many routes overlap. Similar to the technique of expression adopted in Chapter 5, only a subset of efficient routes is presented for each O-D pair. Specifically, routes 1 ~ 7 are the single objective optimization solutions, 8 ~ 19 are the optimal solutions obtained by the compromise programming method, 20 ~ 24 are a subset of efficient routes generated by the adaptive weighting method, and 25 ~ 31 are the examples of the results of the genetic algorithm. Figures in odd number after "A." (e.g. Figure A.1 and Figure A.3) show the single-objective optimal routes from Tsing Yi LPG terminal to each of the dedicated LPG filling stations, while the ones in even number after "A." (e.g. Figure A.2 and Figure A.4) display multi-objective routes to the corresponding LPG stations generated by the proposed MOP methods.



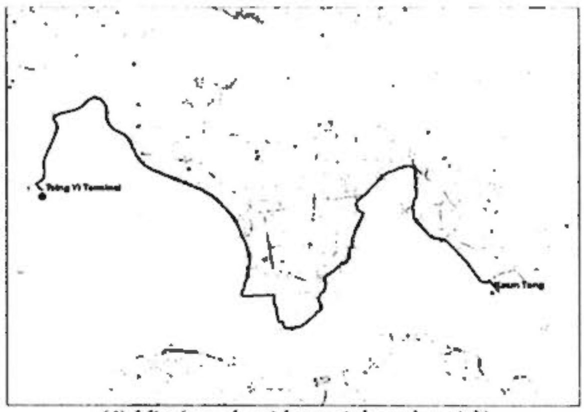
(1) Min (travel time)



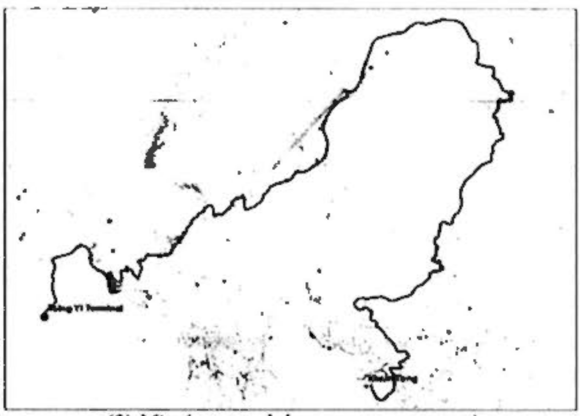
(2) Min (accident probability)



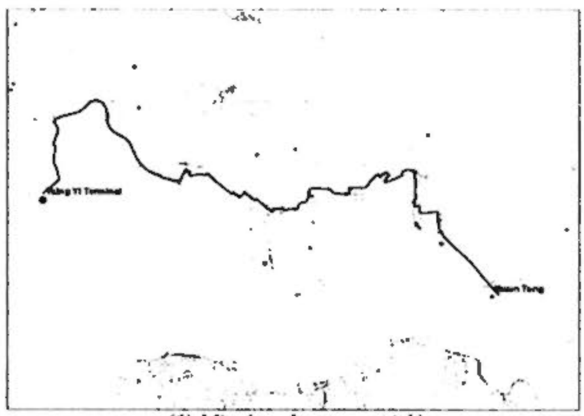
(3) Min (off-road exposure risk)



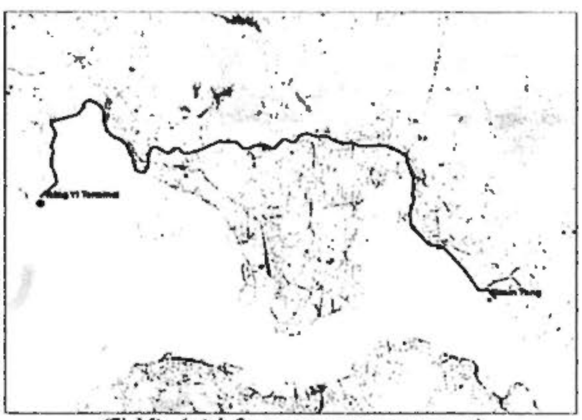
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

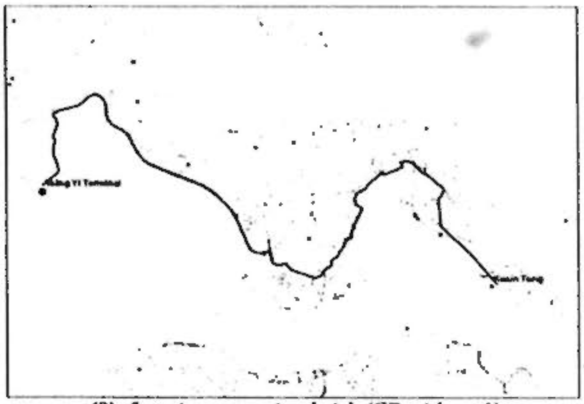


(6) Min (road users at risk)

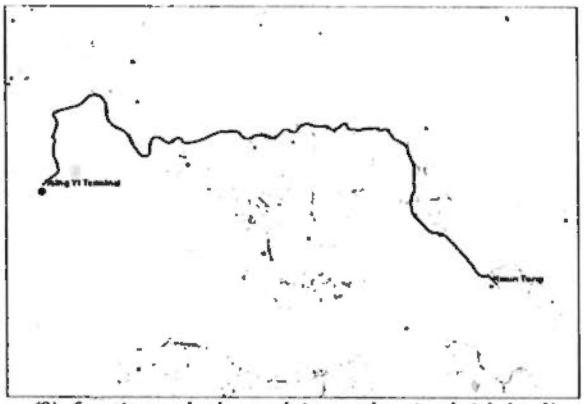


(7) Min (risk from emergency response)

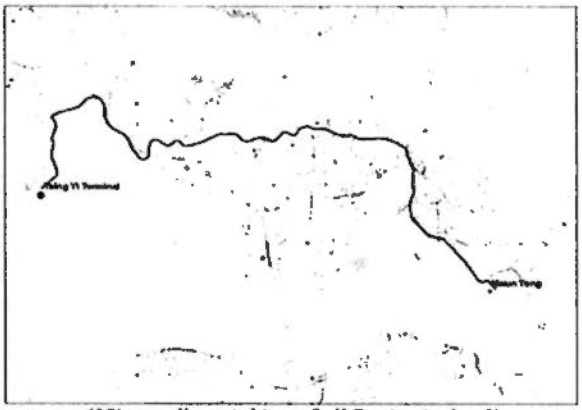
Figure A.1 Single-objective optimal routes from Tsing Yi LPG terminal to Kwun Tong LPG filling station



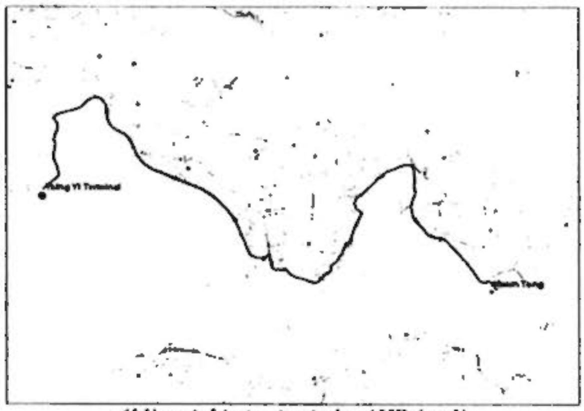
(8) focusing on societal risk (CP with p=1)



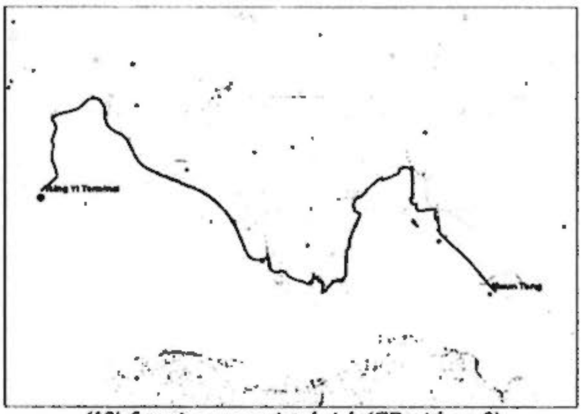
(9) focusing on both travel time and societal risk (p=1)



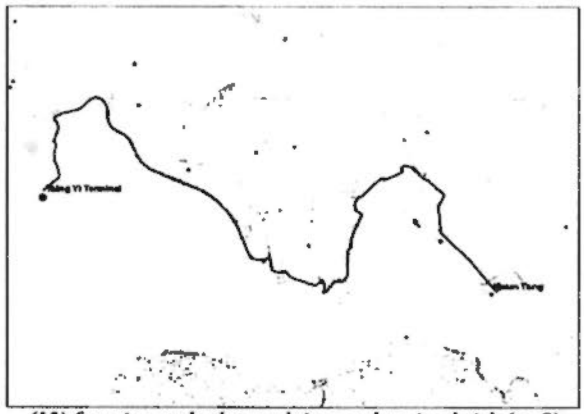
(10) equally weighing of all 7 criteria (p=1)



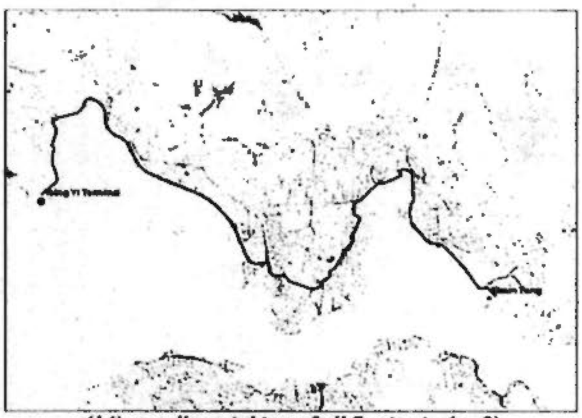
(11) weighing criteria by AHP (p=1)



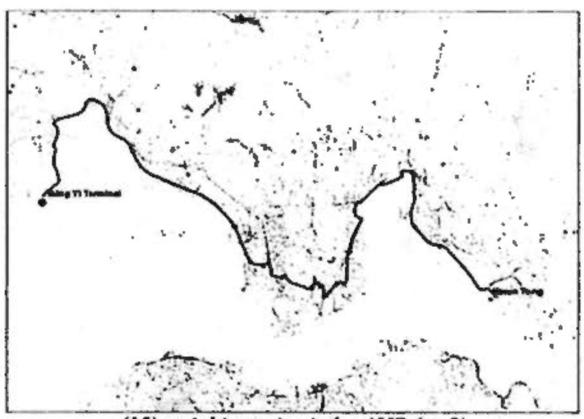
(12) focusing on societal risk (CP with p=2)



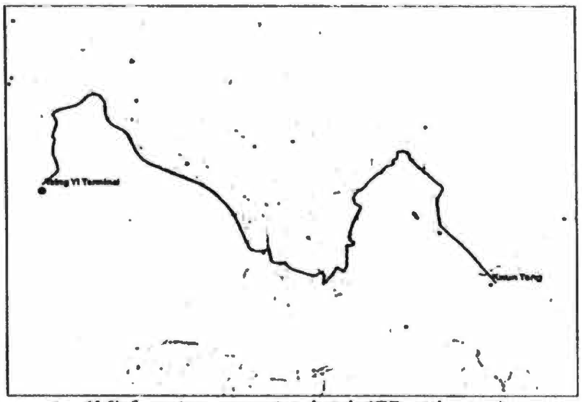
(13) focusing on both travel time and societal risk (p=2)



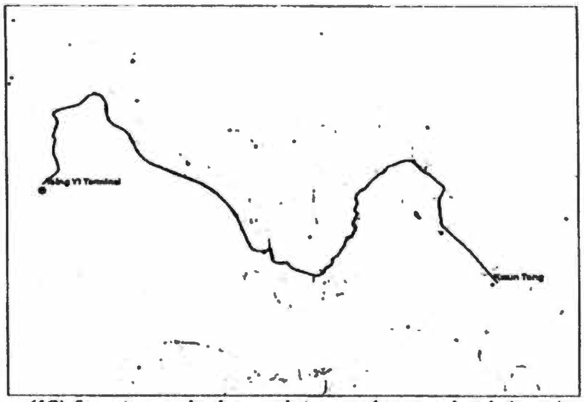
(14) equally weighing of all 7 criteria (p=2)



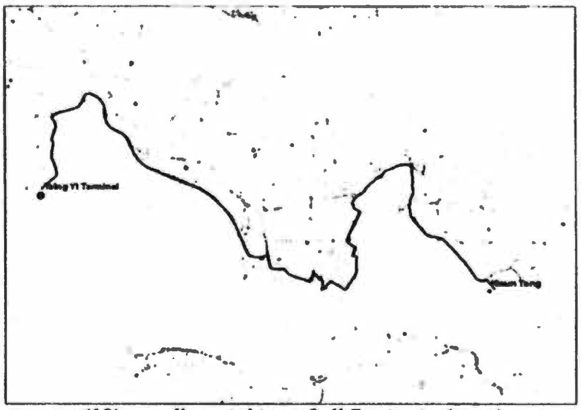
(15) weighing criteria by AHP (p=2)



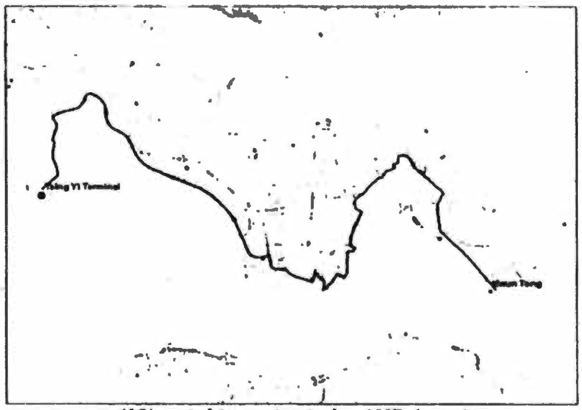
(16) focusing on societal risk (CP with p=∞)



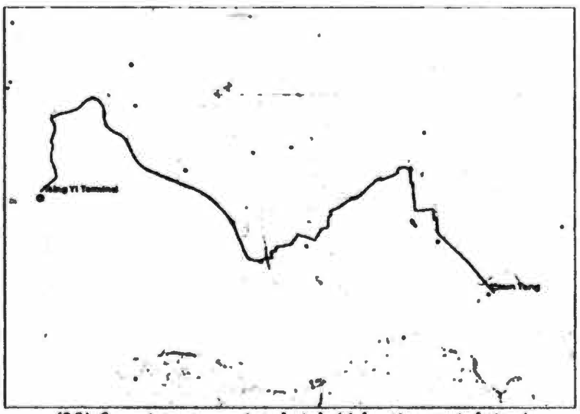
(17) focusing on both travel time and societal risk (p=∞)



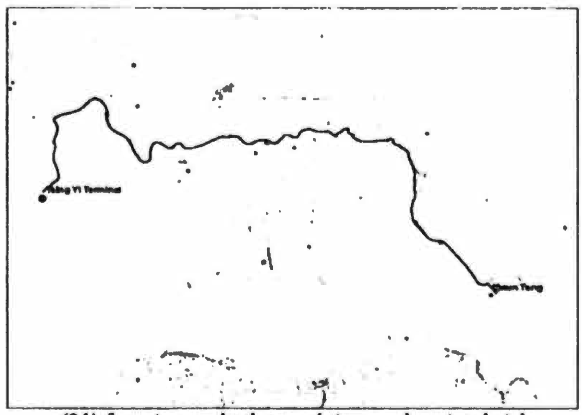
(18) equally weighing of all 7 criteria (p=∞)



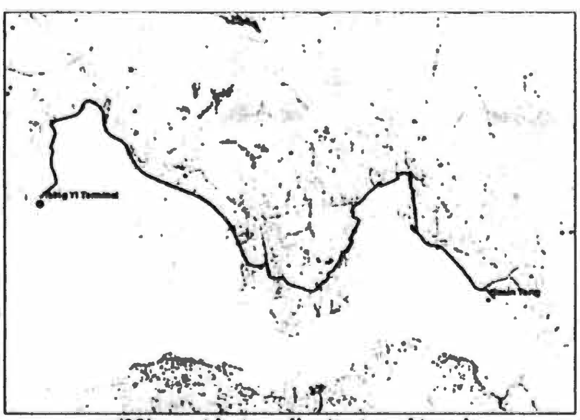
(19) weighing criteria by AHP (p=∞)



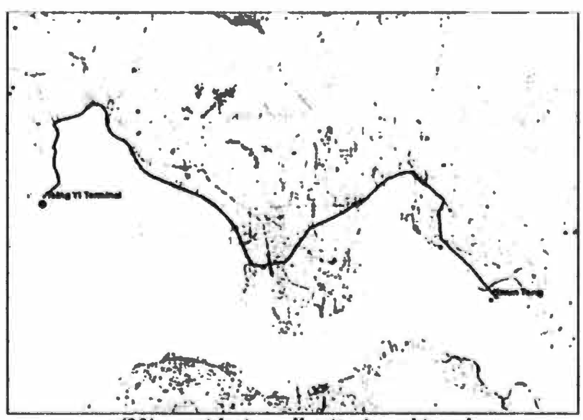
(20) focusing on societal risk (Adaptive weighting)



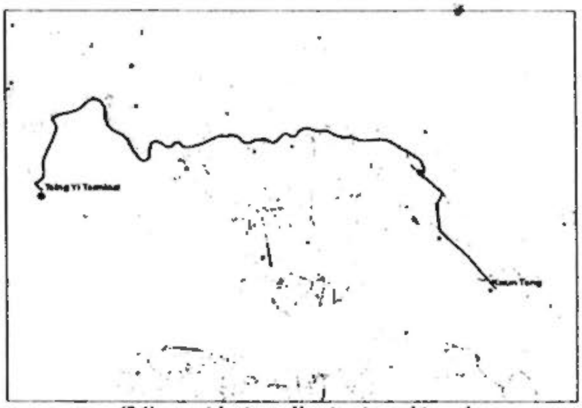
(21) focusing on both travel time and societal risk



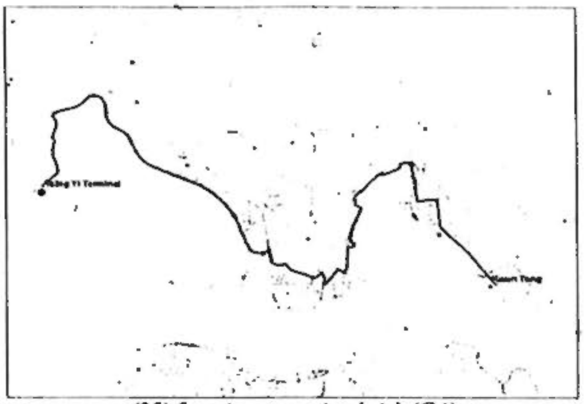
(22) considering all criteria unbiased



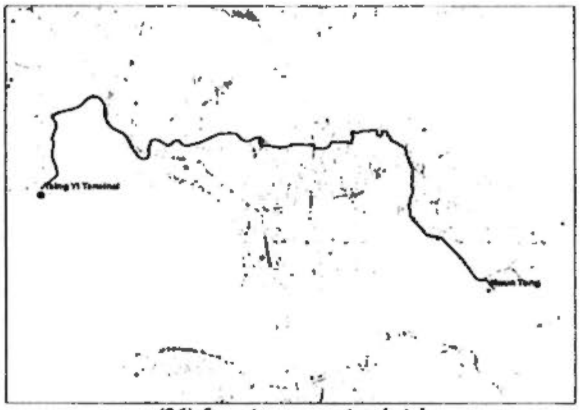
(23) considering all criteria unbiased



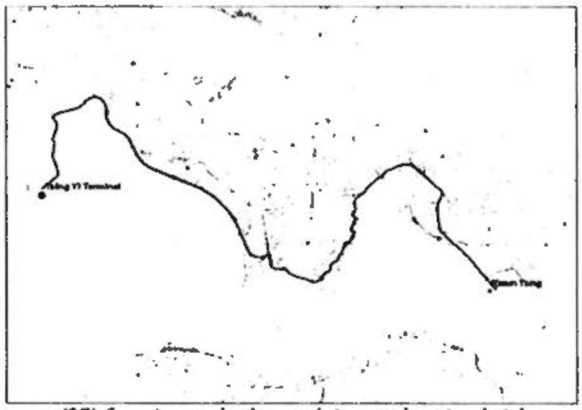
(24) considering all criteria unbiased



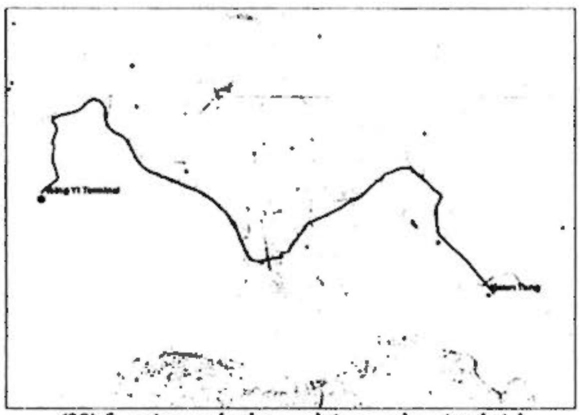
(25) focusing on societal risk (GA)



(26) focusing on societal risk



(27) focusing on both travel time and societal risk



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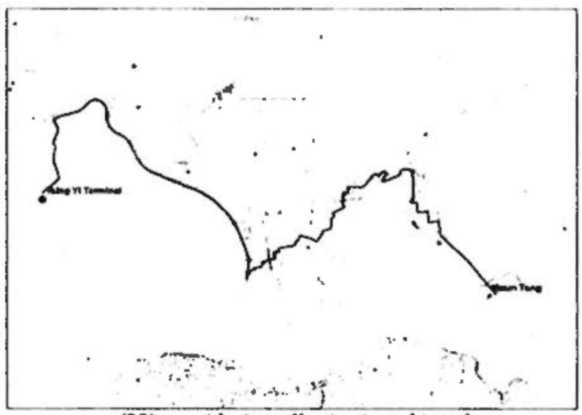
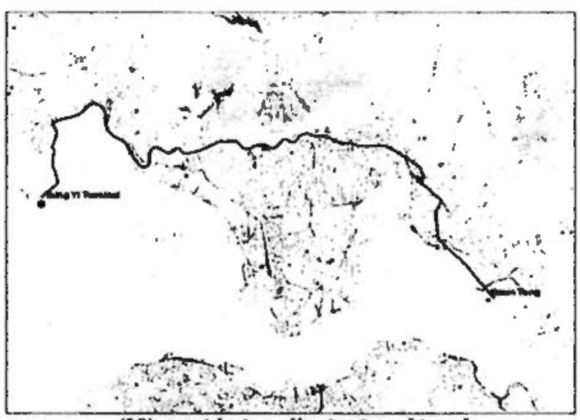
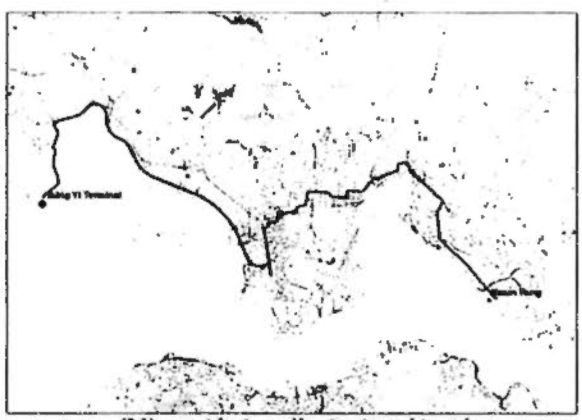


(29) considering all criteria unbiased

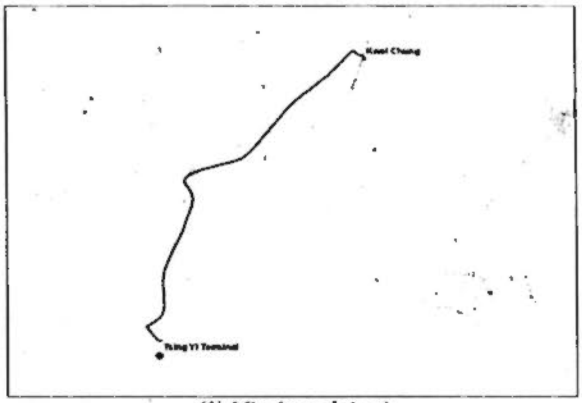


(30) considering all criteria unbiased

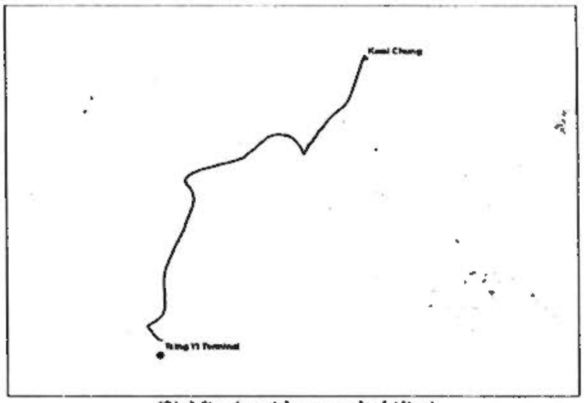


(31) considering all criteria unbiased

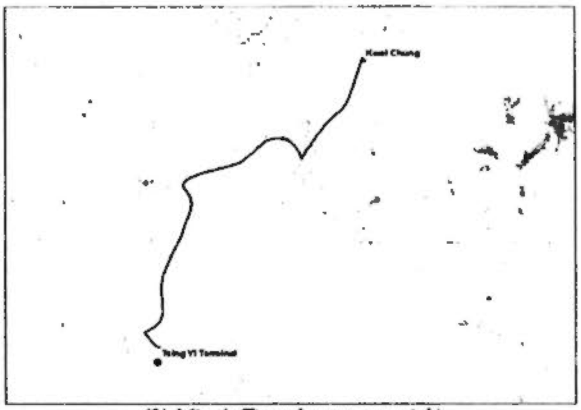
Figure A.2 Efficient routes from Tsing Yi terminal to Kwun Tong LPG filling station generated by the proposed MOP methods



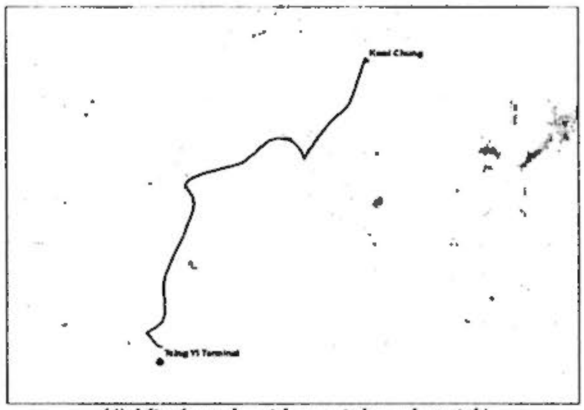
(1) Min (travel time)



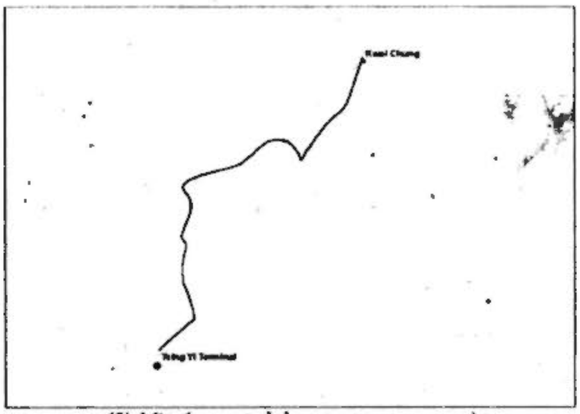
(2) Min (accident probability)



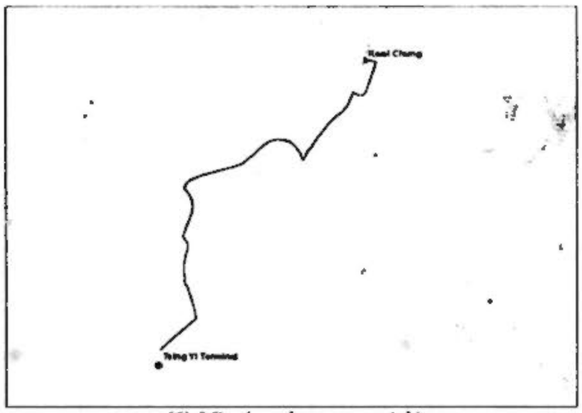
(3) Min (off-road exposure risk)



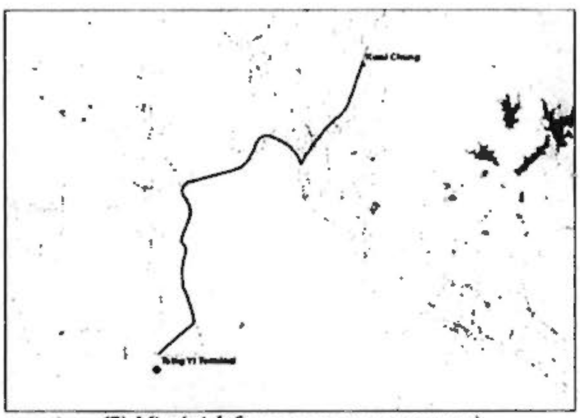
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

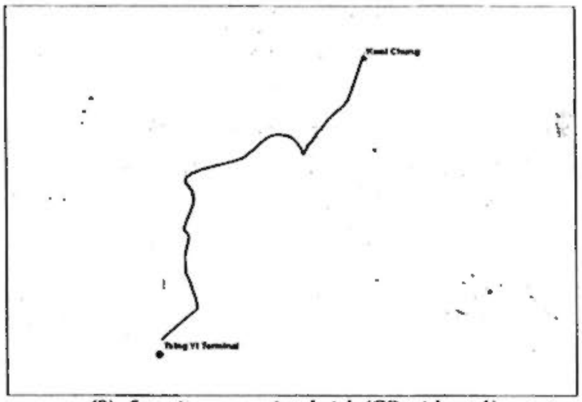


(6) Min (road users at risk)

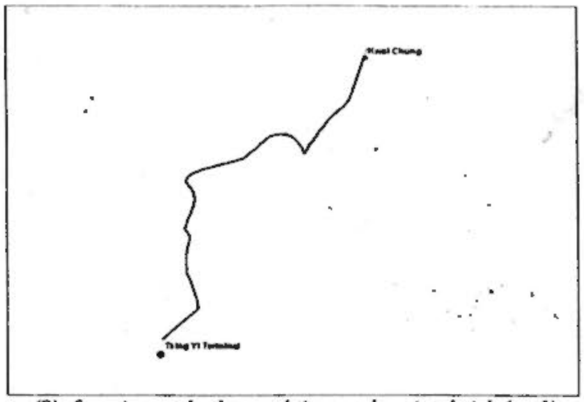


(7) Min (risk from emergency response)

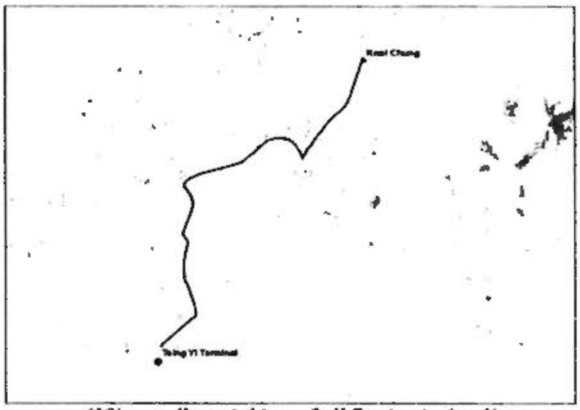
Figure A.3 Single-objective optimal routes from Tsing Yi LPG terminal to Kwai Chung LPG filling station



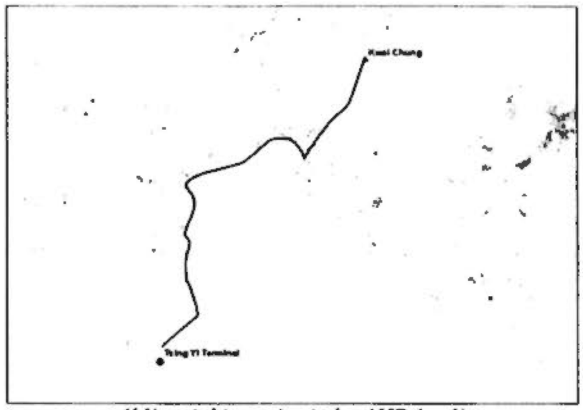
(8) focusing on societal risk (CP with p=1)



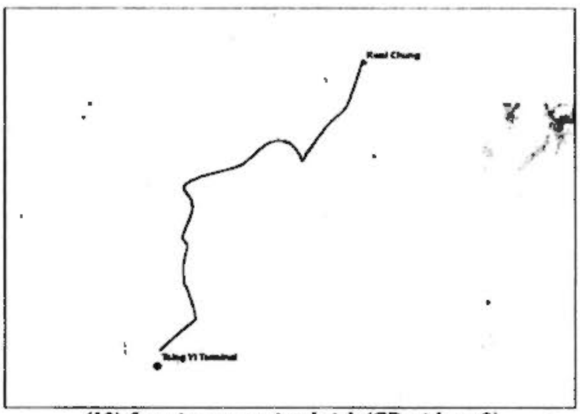
(9) focusing on both travel time and societal risk (p=1)



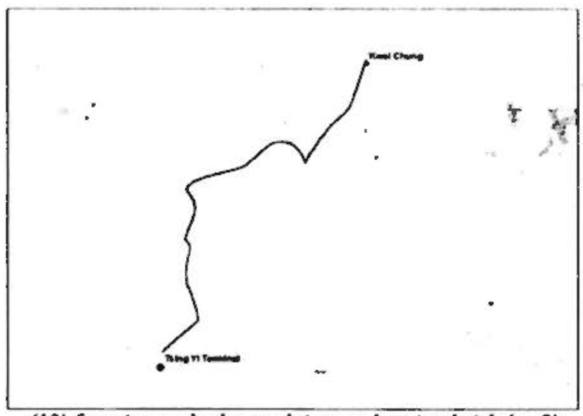
(10) equally weighing of all 7 criteria (p=1)



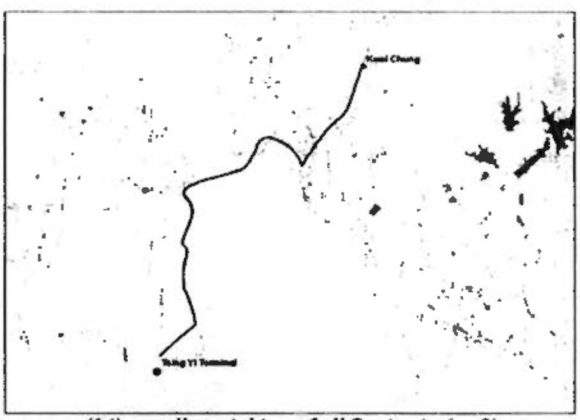
(11) weighing criteria by AHP (p=1)



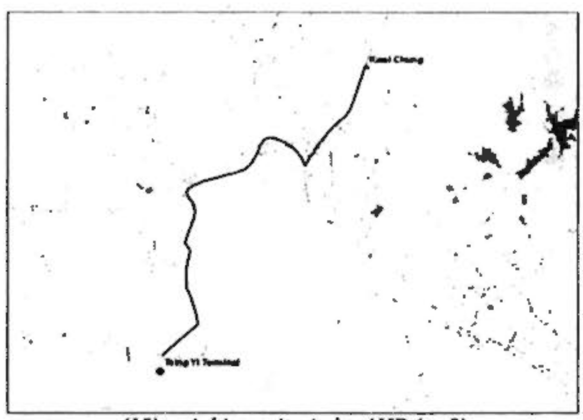
(12) focusing on societal risk (CP with p=2)



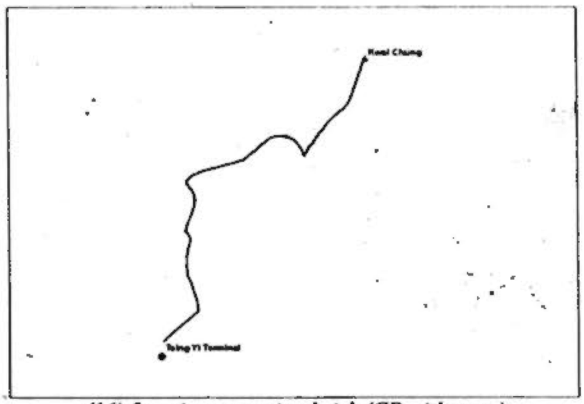
(13) focusing on both travel time and societal risk (p=2)



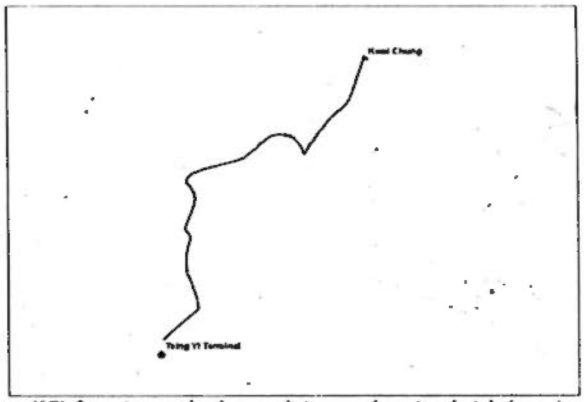
(14) equally weighing of all 7 criteria (p=2)



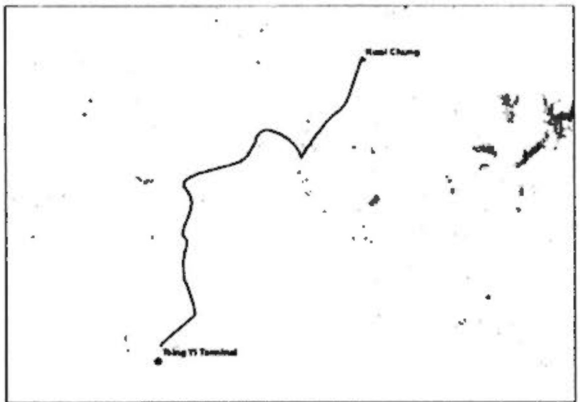
(15) weighing criteria by AHP (p=2)



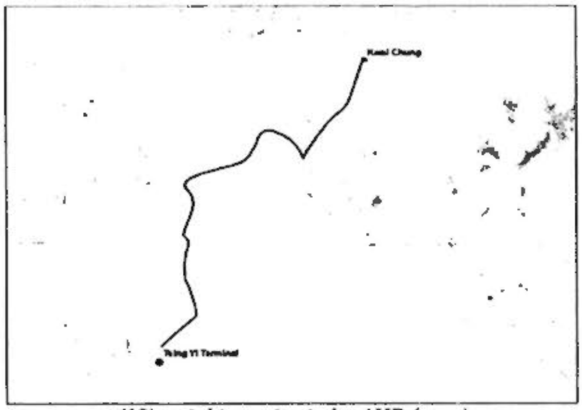
(16) focusing on societal risk (CP with p=∞)



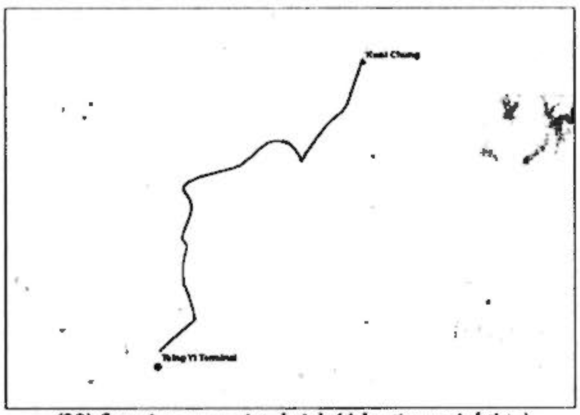
(17) focusing on both travel time and societal risk (p=∞)



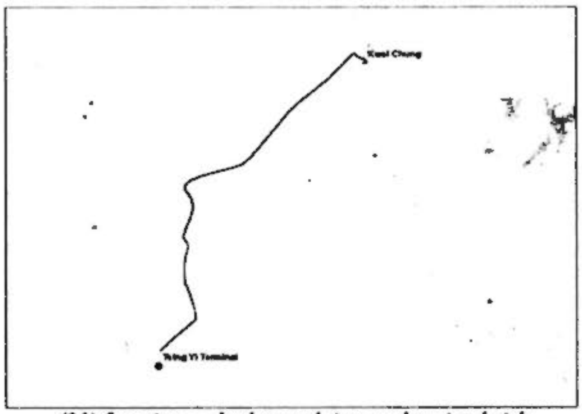
(18) equally weighing of all 7 criteria (p=∞)



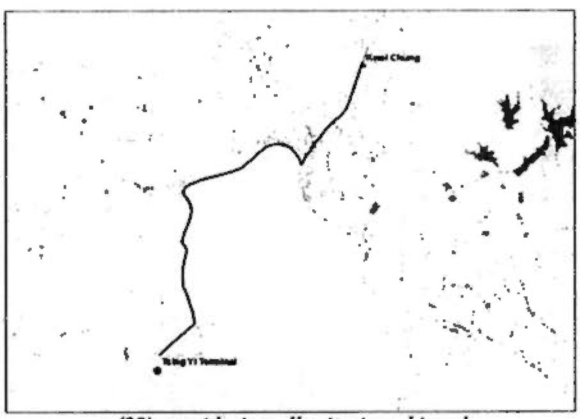
(19) weighing criteria by AHP (p=∞)



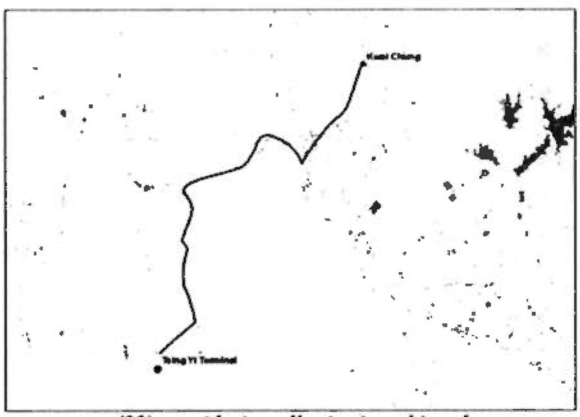
(20) focusing on societal risk (Adaptive weighting)



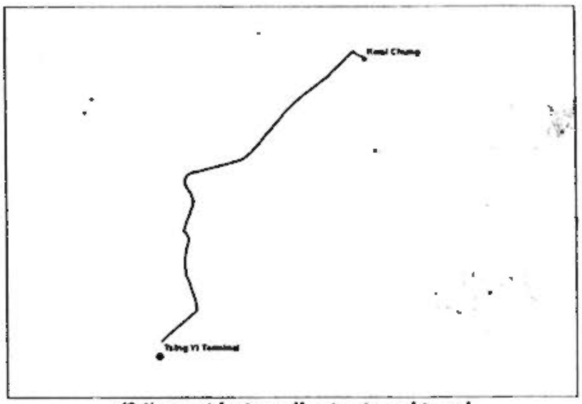
(21) focusing on both travel time and societal risk



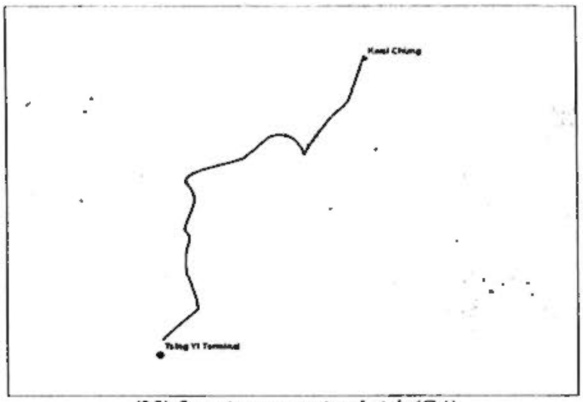
(22) considering all criteria unbiased



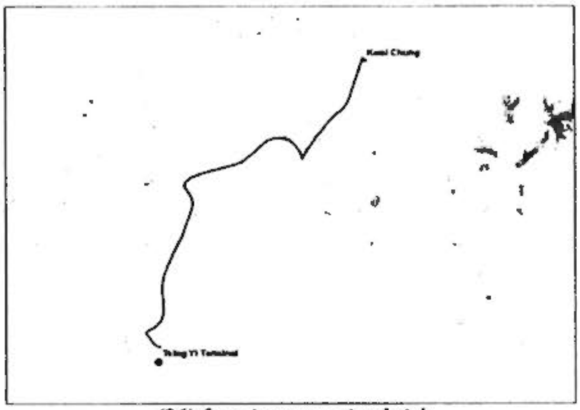
(23) considering all criteria unbiased



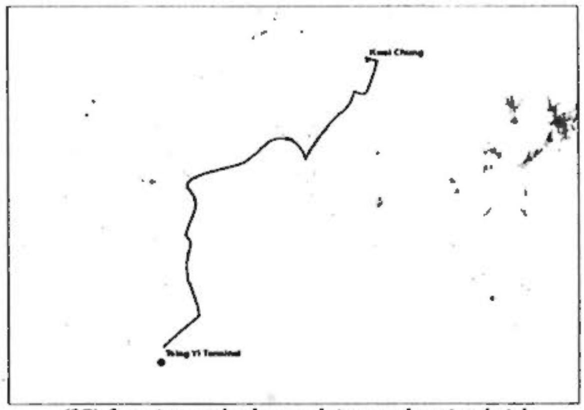
(24) considering all criteria unbiased



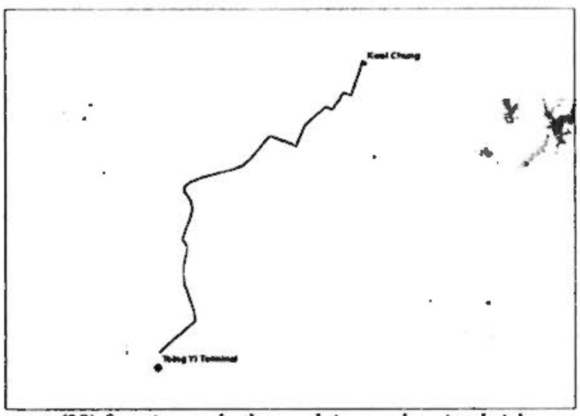
(25) focusing on societal risk (GA)



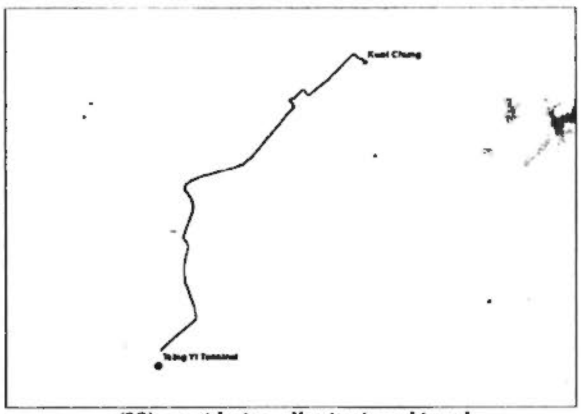
(26) focusing on societal risk



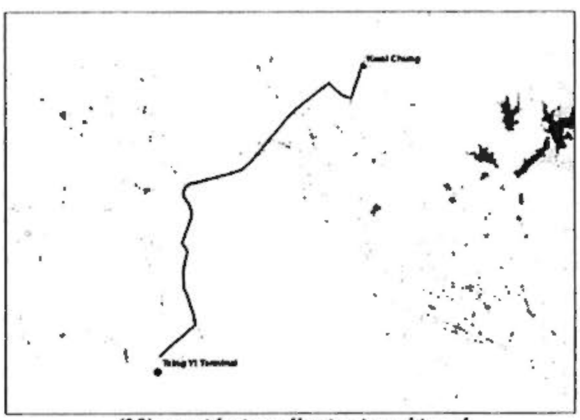
(27) focusing on both travel time and societal risk



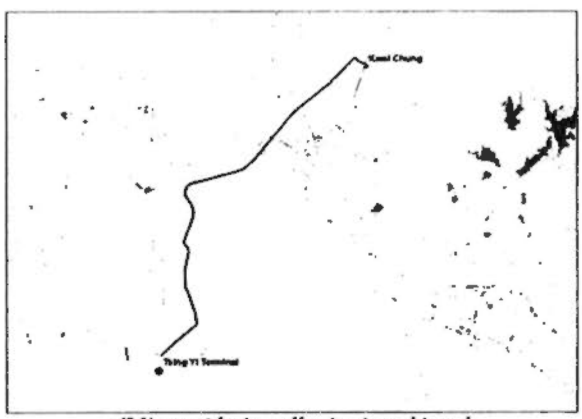
(28) focusing on both travel time and societal risk



(29) considering all criteria unbiased

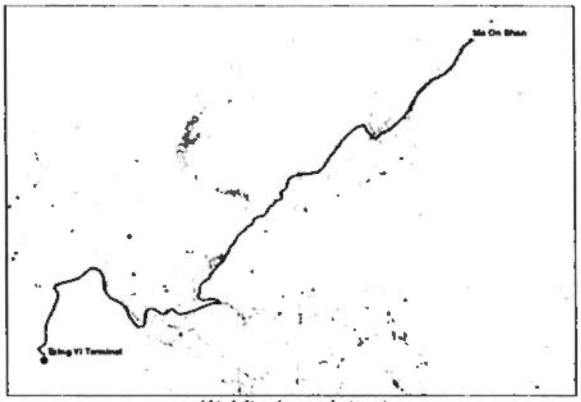


(30) considering all criteria unbiased

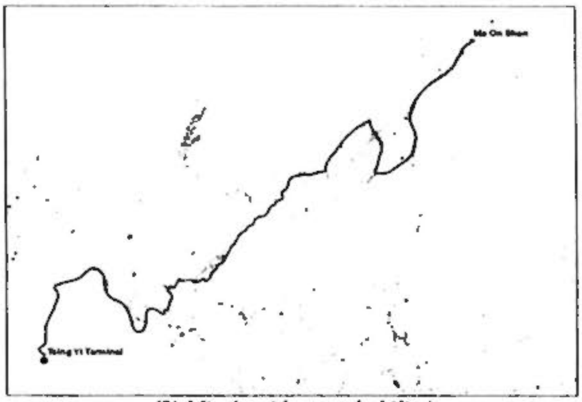


(31) considering all criteria unbiased

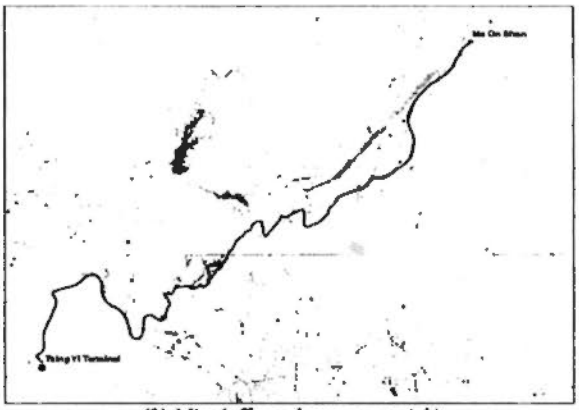
Figure A.4 Efficient routes from Tsing Yi terminal to Kwai Chung LPG filling station generated by the proposed MOP methods



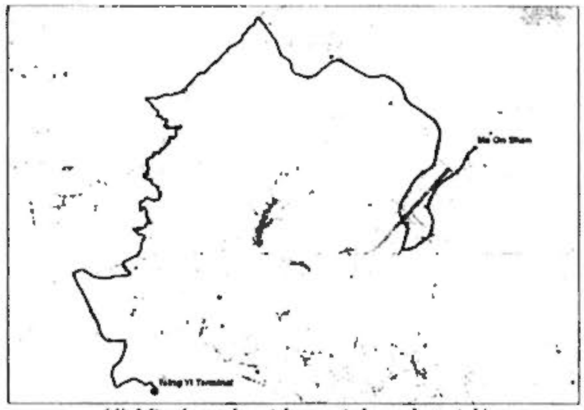
(1) Min (travel time)



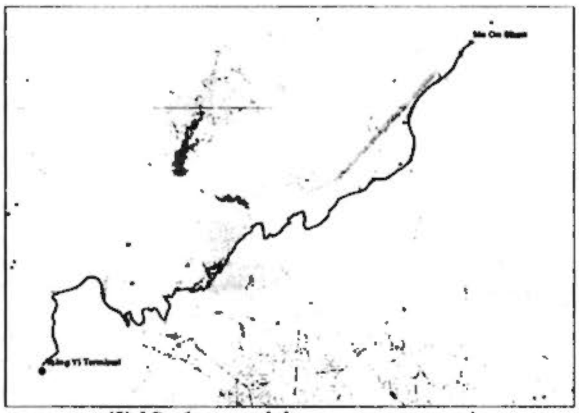
(2) Min (accident probability)



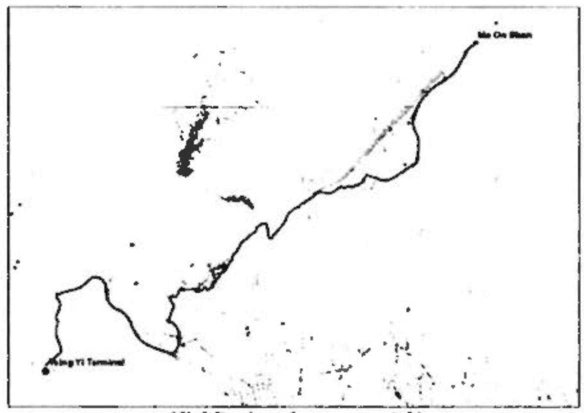
(3) Min (off-road exposure risk)



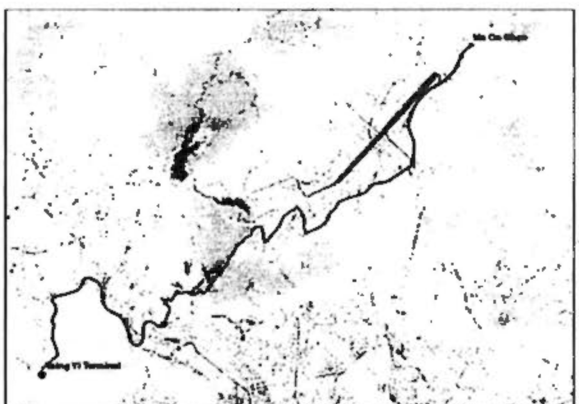
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

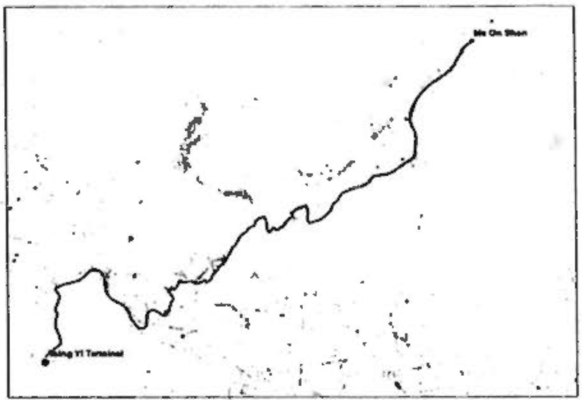


(6) Min (road users at risk)

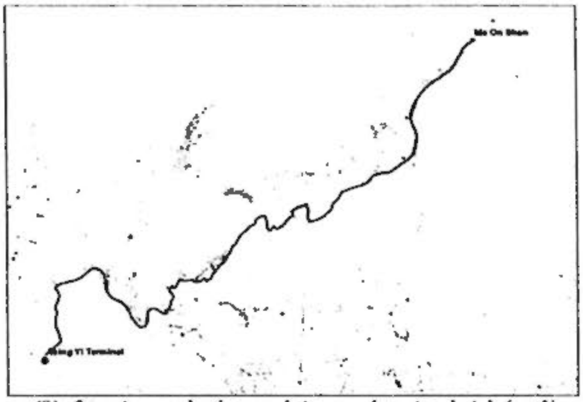


(7) Min (risk from emergency response)

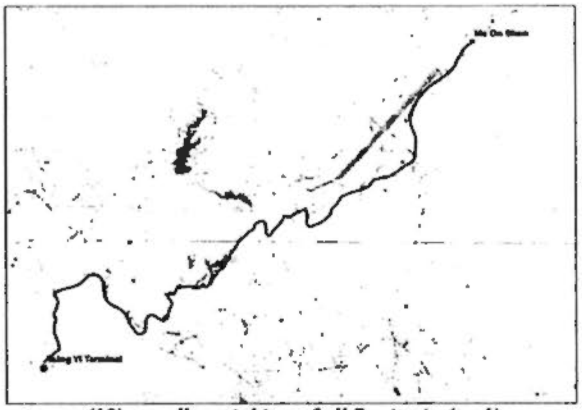
Figure A.5 Single-objective optimal routes from Tsing Yi LPG terminal to Ma On Shan LPG filling station



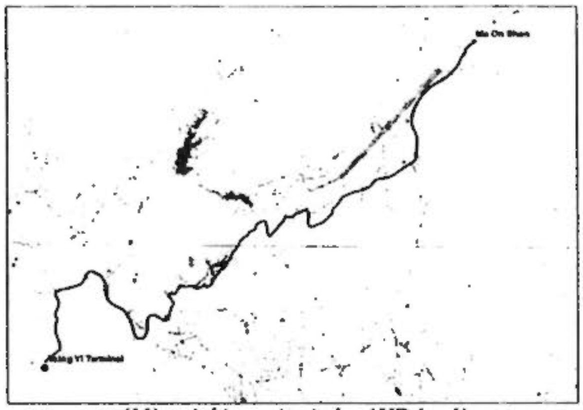
(8) focusing on societal risk (CP with p=1)



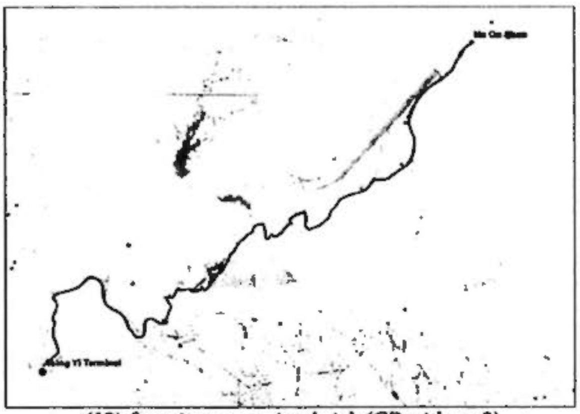
(9) focusing on both travel time and societal risk (p=1)



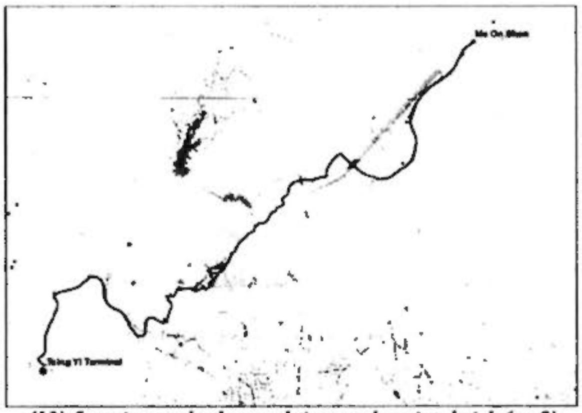
(10) equally weighing of all 7 criteria (p=1)



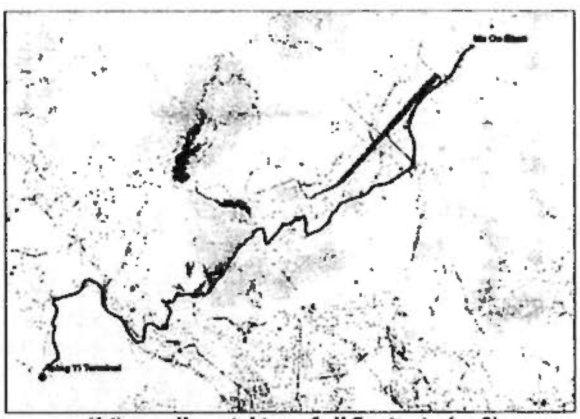
(11) weighing criteria by AHP (p=1)



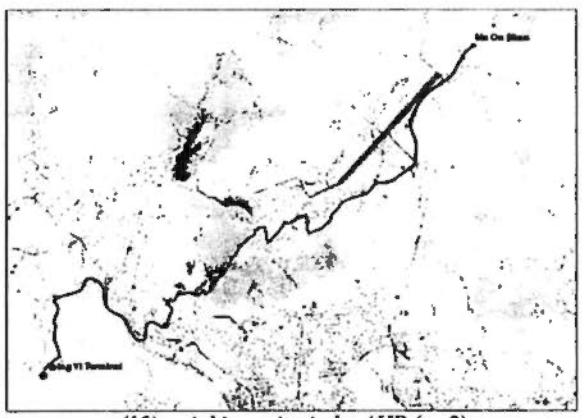
(12) focusing on societal risk (CP with p=2)



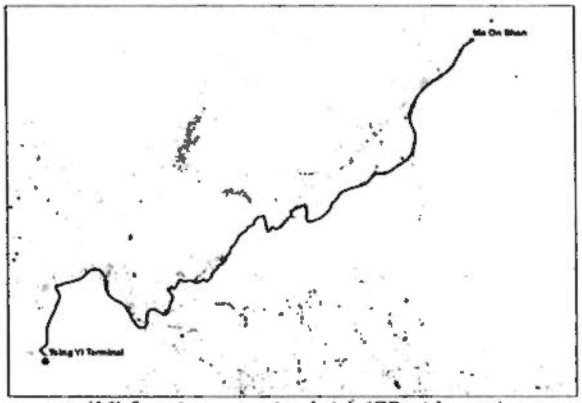
(13) focusing on both travel time and societal risk (p=2)



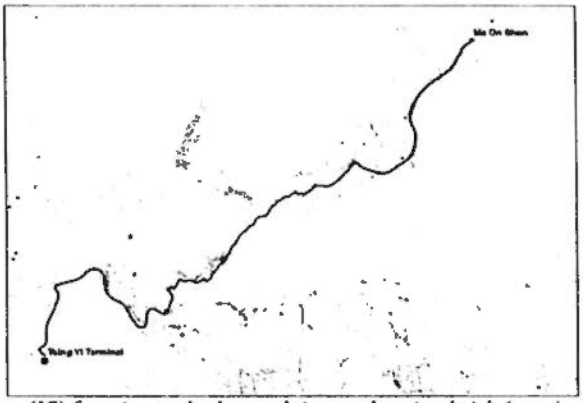
(14) equally weighing of all 7 criteria (p=2)



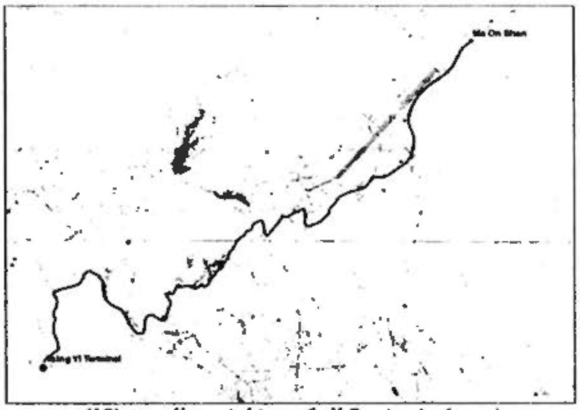
(15) weighing criteria by AHP (p=2)



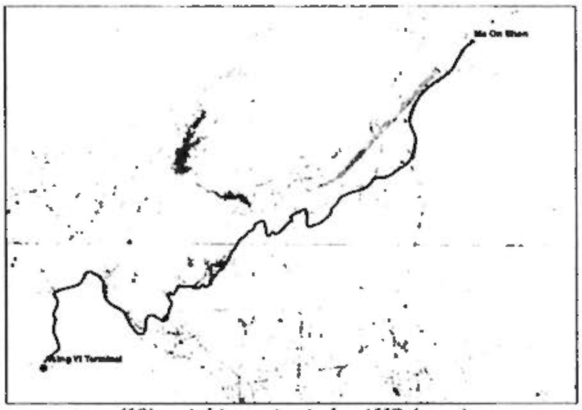
(16) focusing on societal risk (CP with p=∞)



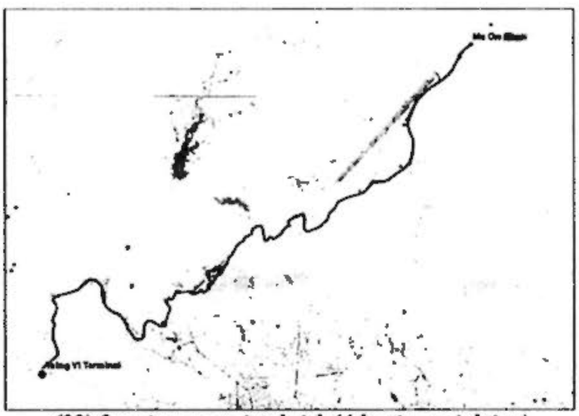
(17) focusing on both travel time and societal risk (p=∞)



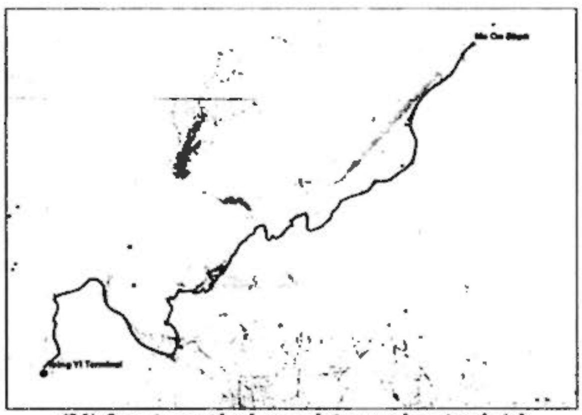
(18) equally weighing of all 7 criteria (p=∞)



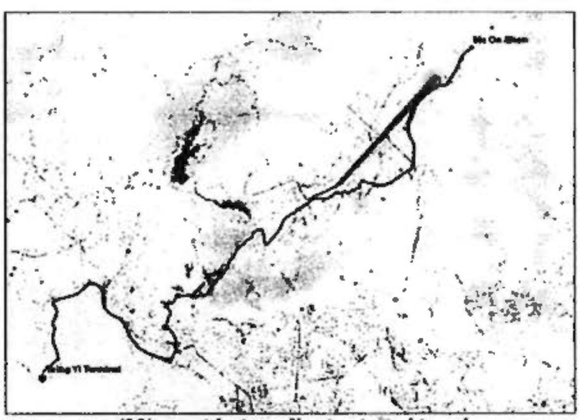
(19) weighing criteria by AHP (p=∞)



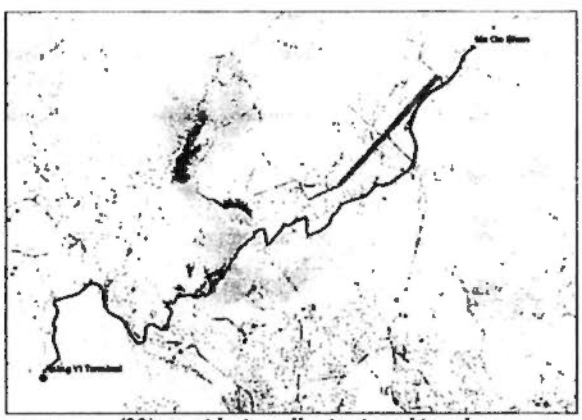
(20) focusing on societal risk (Adaptive weighting)



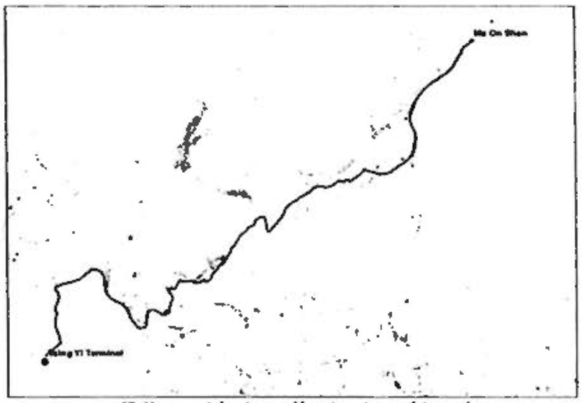
(21) focusing on both travel time and societal risk



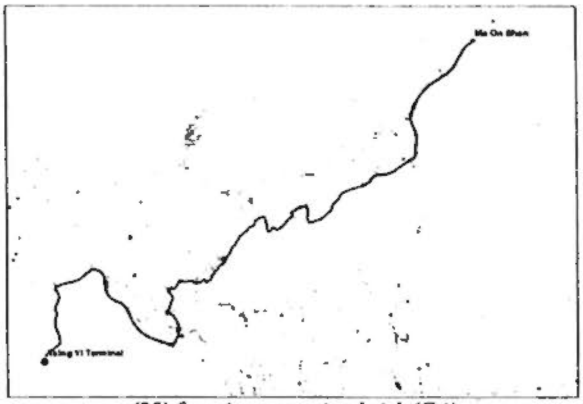
(22) considering all criteria unbiased



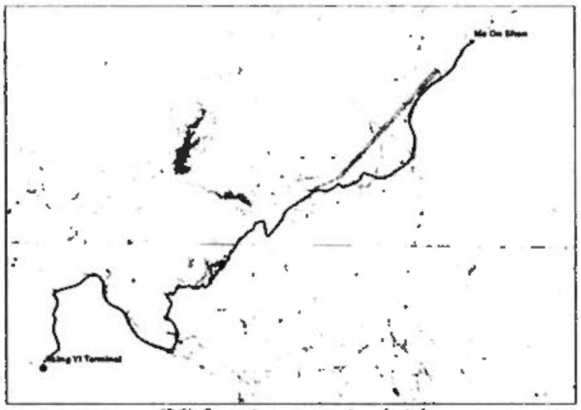
(23) considering all criteria unbiased



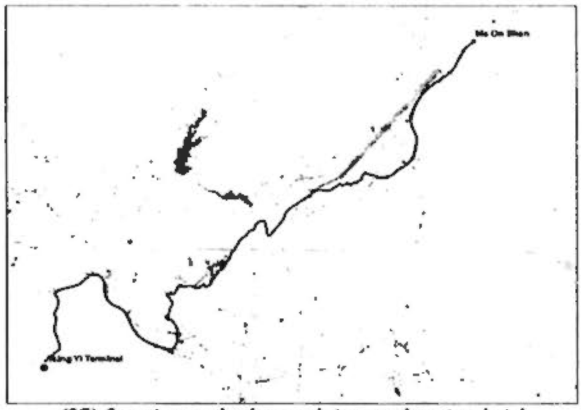
(24) considering all criteria unbiased



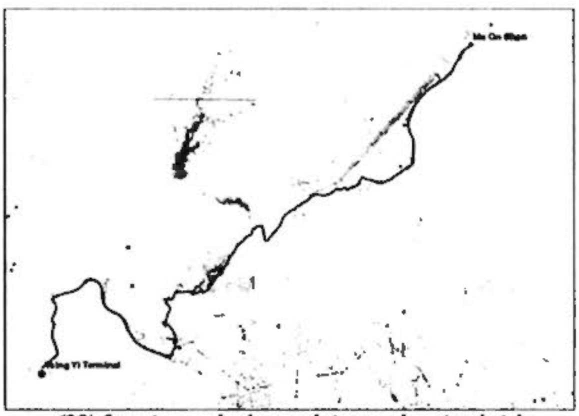
(25) focusing on societal risk (GA)



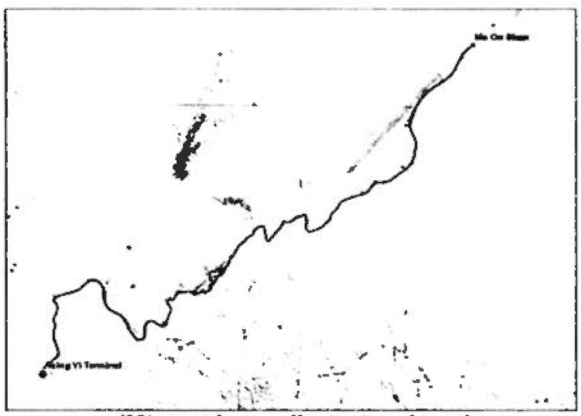
(26) focusing on societal risk



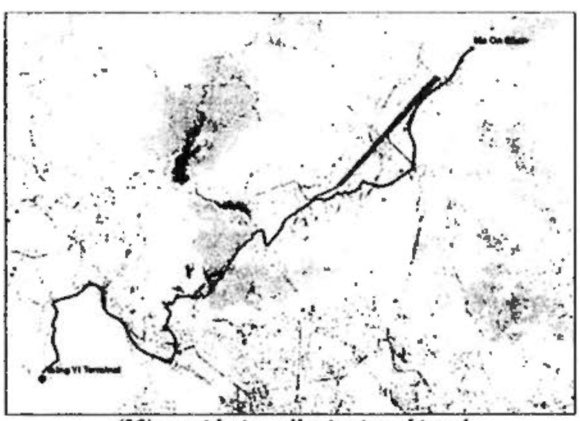
(27) focusing on both travel time and societal risk



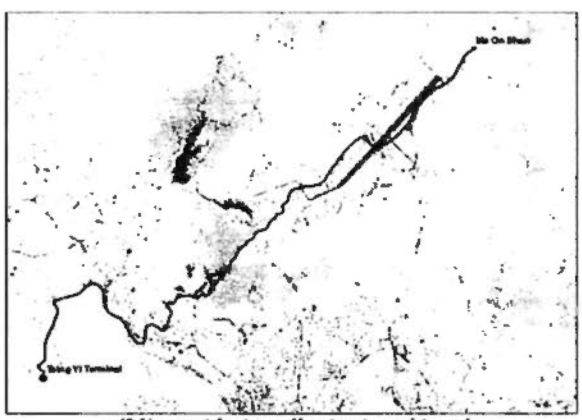
(28) focusing on both travel time and societal risk



(29) considering all criteria unbiased

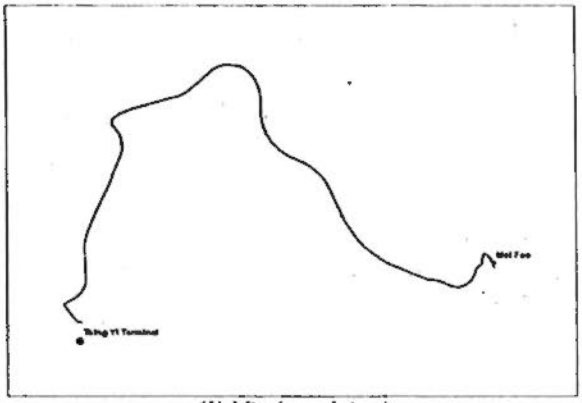


(30) considering all criteria unbiased

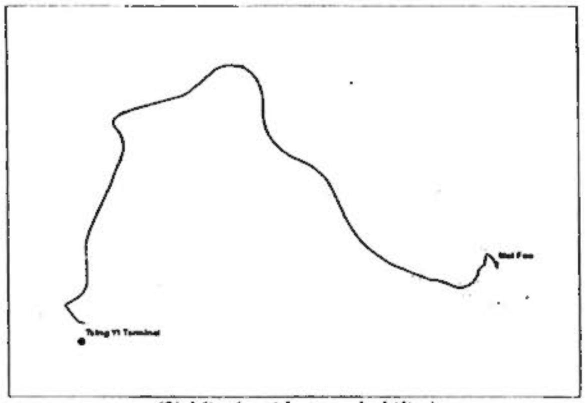


(31) considering all criteria unbiased

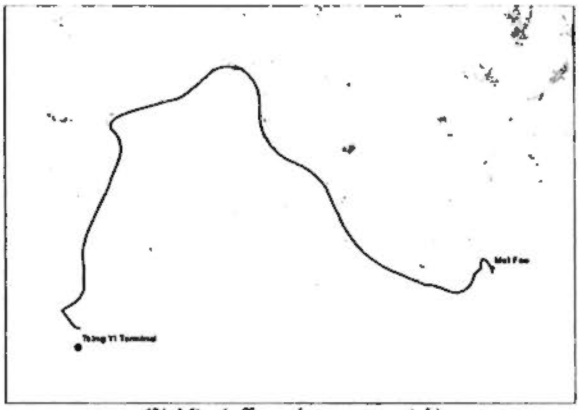
Figure A.6 Efficient routes from Tsing Yi terminal to Ma On Shan LPG filling station generated by the proposed MOP methods



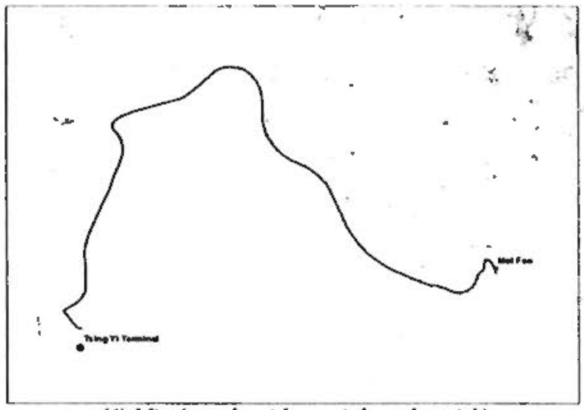
(1) Min (travel time)



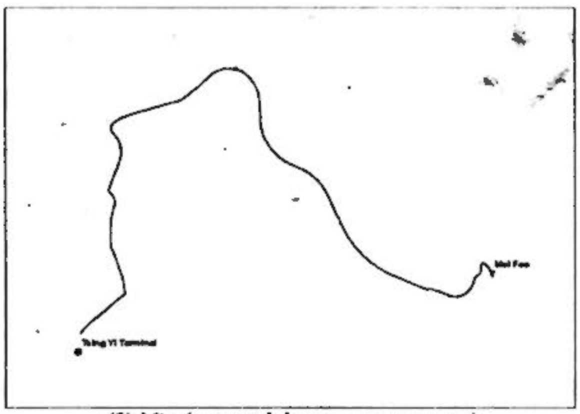
(2) Min (accident probability)



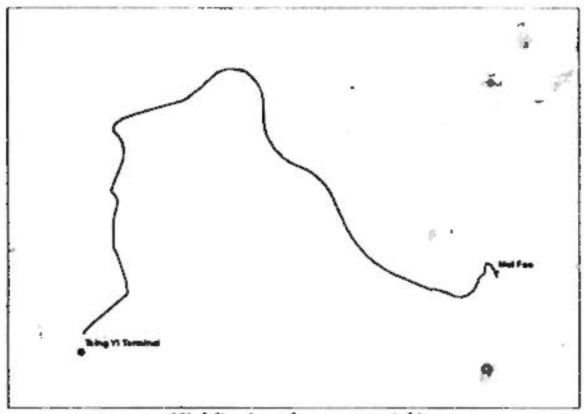
(3) Min (off-road exposure risk)



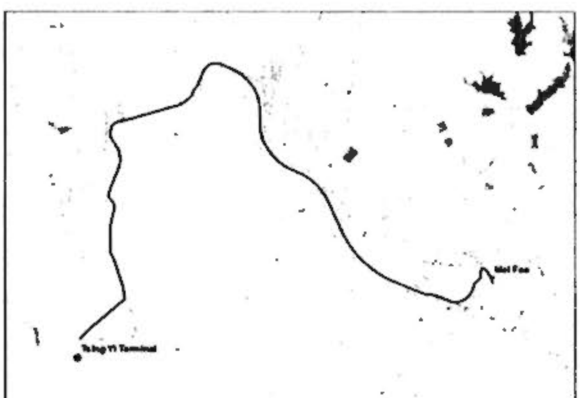
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

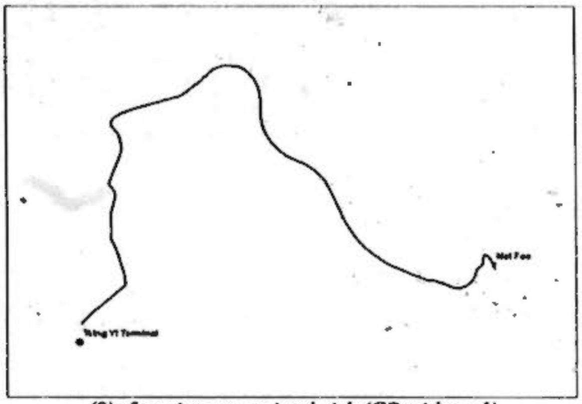


(6) Min (road users at risk)

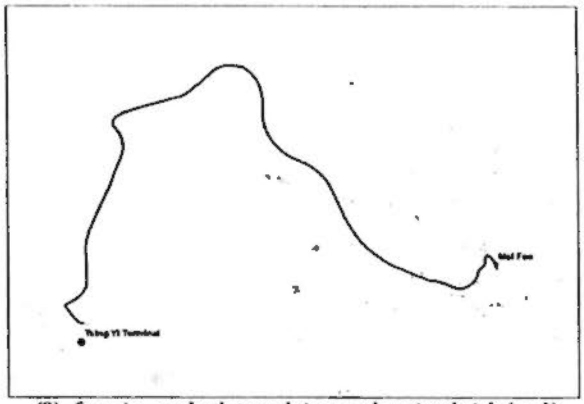


(7) Min (risk from emergency response)

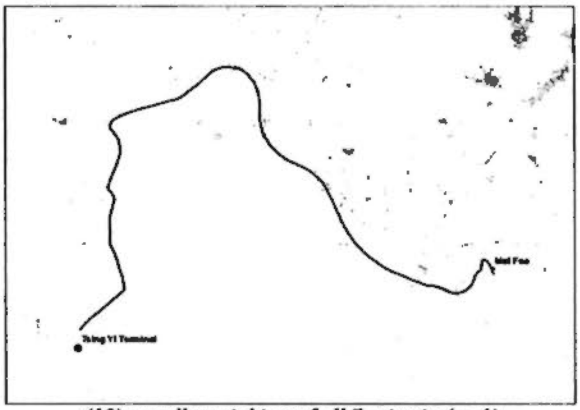
Figure A.7 Single-objective optimal routes from Tsing Yi LPG terminal to Mei Foo LPG filling station



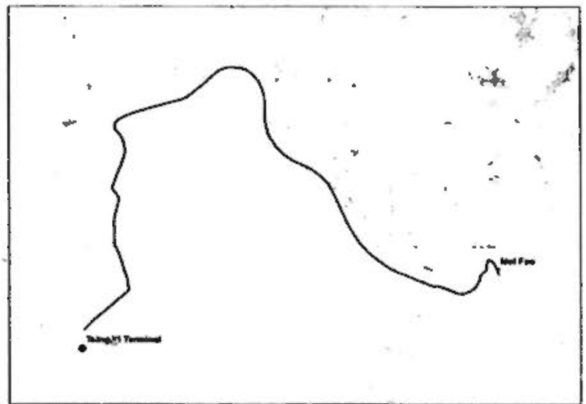
(8) focusing on societal risk (CP with p=1)



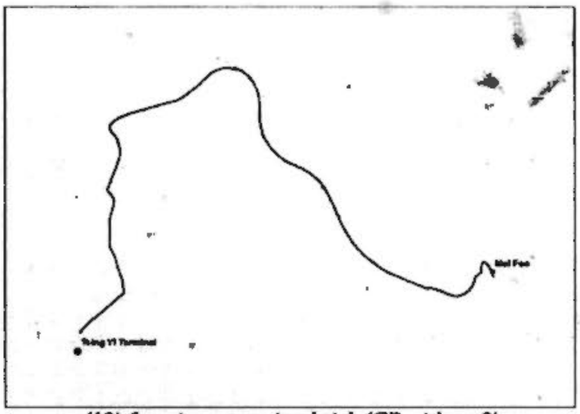
(9) focusing on both travel time and societal risk (p=1)



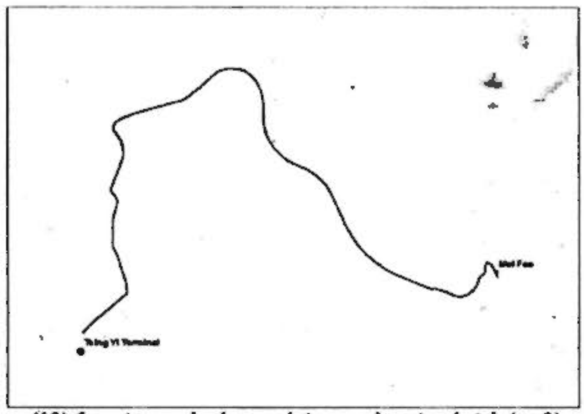
(10) equally weighing of all 7 criteria (p=1)



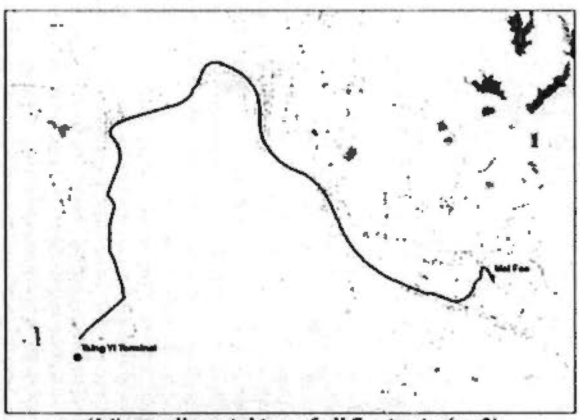
(11) weighing criteria by AHP (p=1)



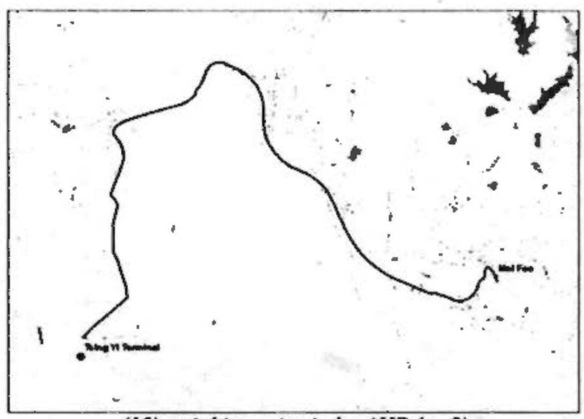
(12) focusing on societal risk (CP with p=2)



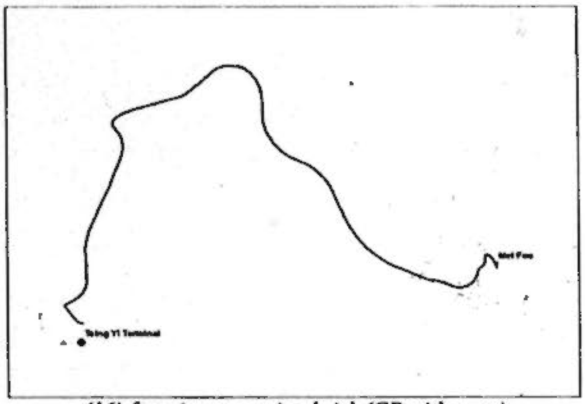
(13) focusing on both travel time and societal risk (p=2)



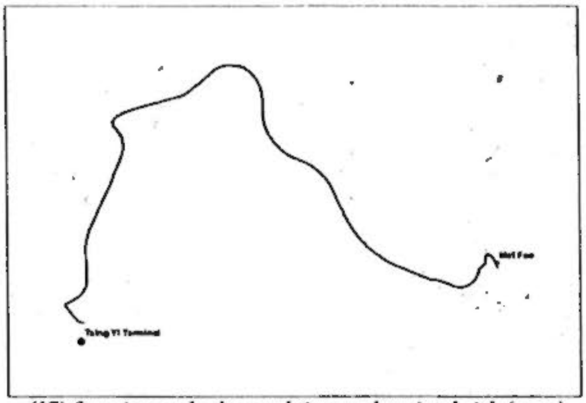
(14) equally weighing of all 7 criteria (p=2)



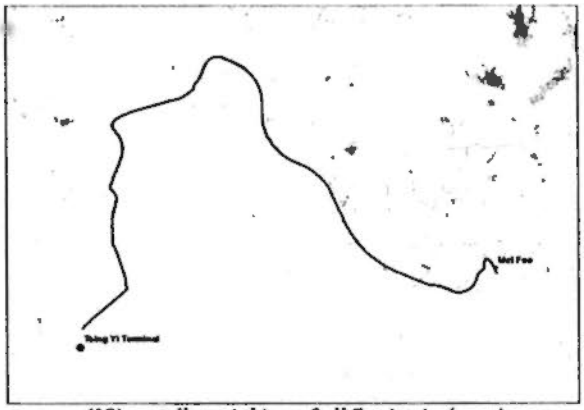
(15) weighing criteria by AHP (p=2)



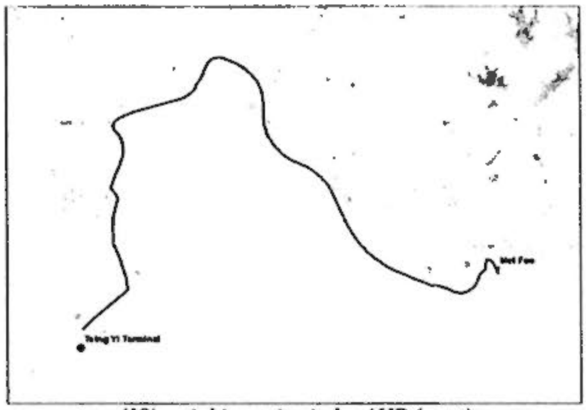
(16) focusing on societal risk (CP with p=∞)



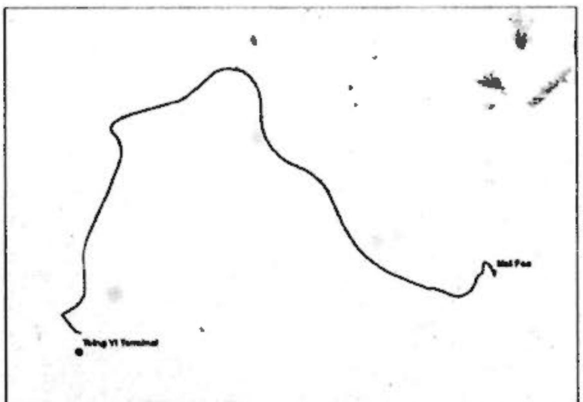
(17) focusing on both travel time and societal risk (p=∞)



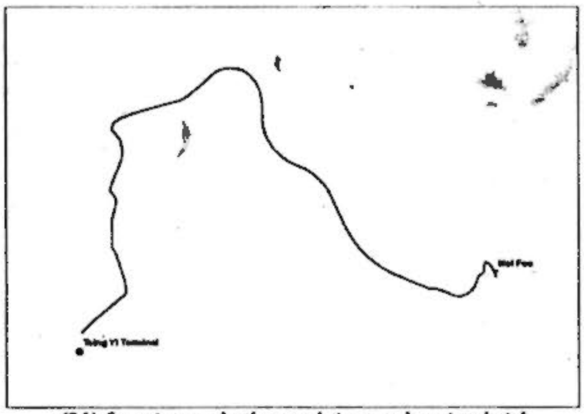
(18) equally weighing of all 7 criteria (p=∞)



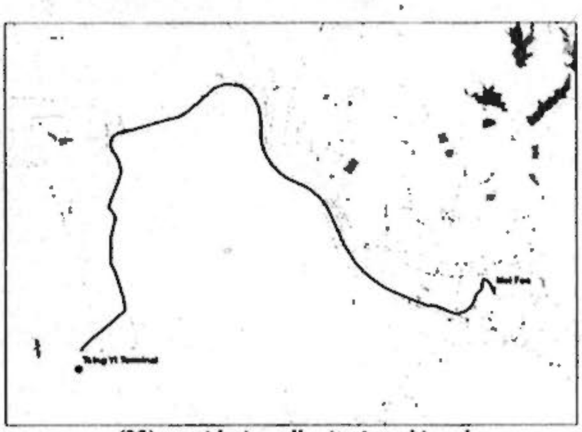
(19) weighing criteria by AHP (p=∞)



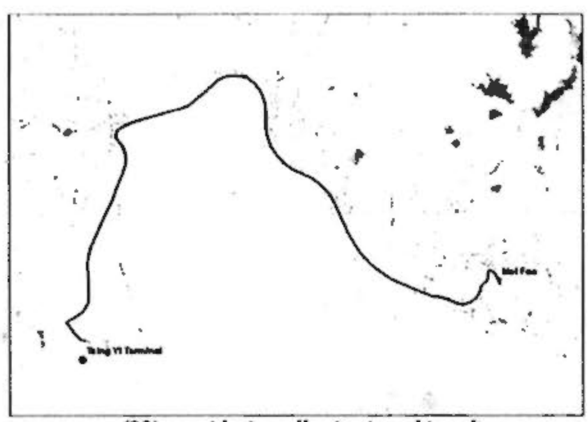
(20) focusing on societal risk (Adaptive weighting)



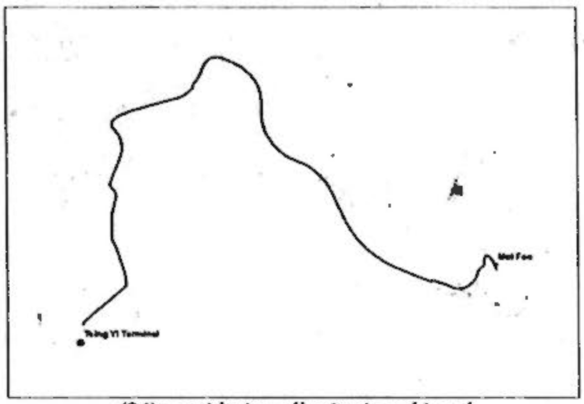
(21) focusing on both travel time and societal risk



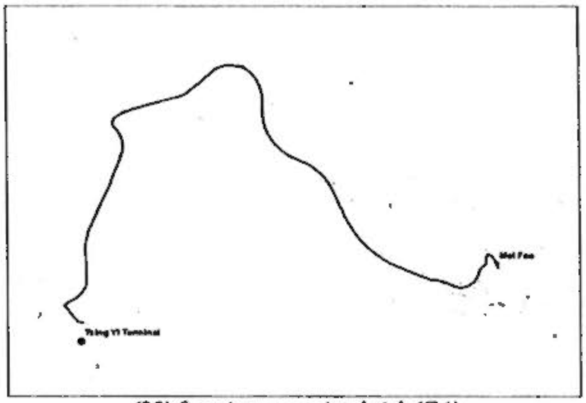
(22) considering all criteria unbiased



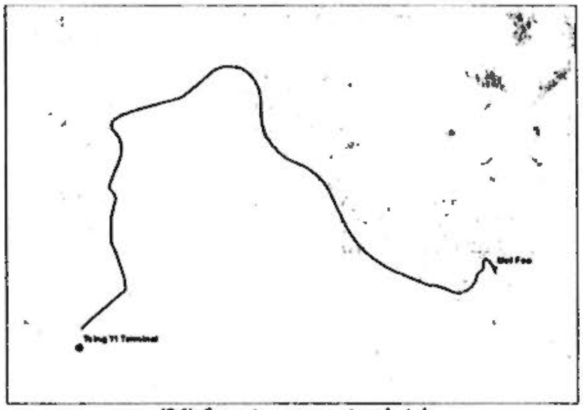
(23) considering all criteria unbiased



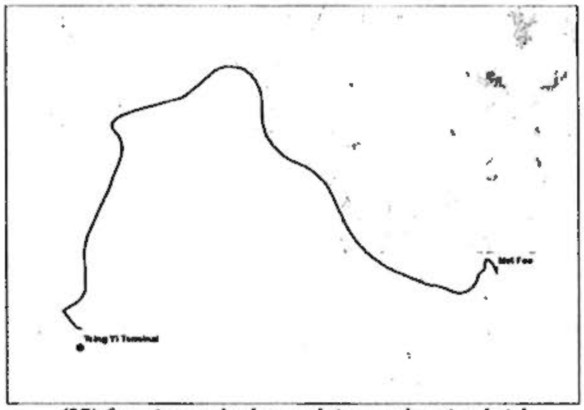
(24) considering all criteria unbiased



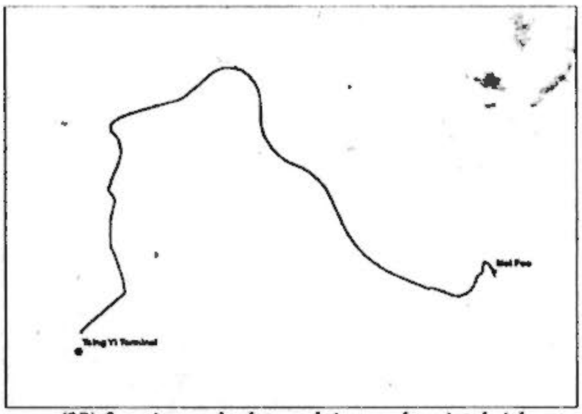
(25) focusing on societal risk (GA)



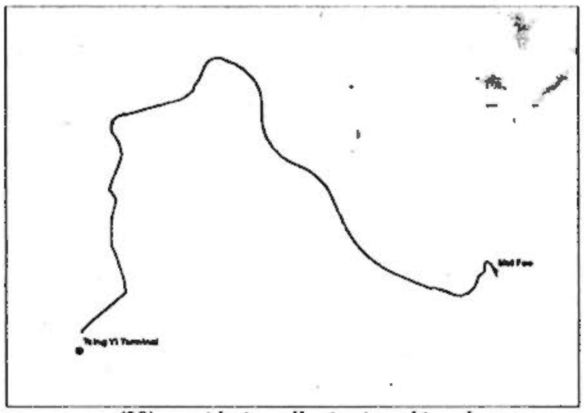
(26) focusing on societal risk



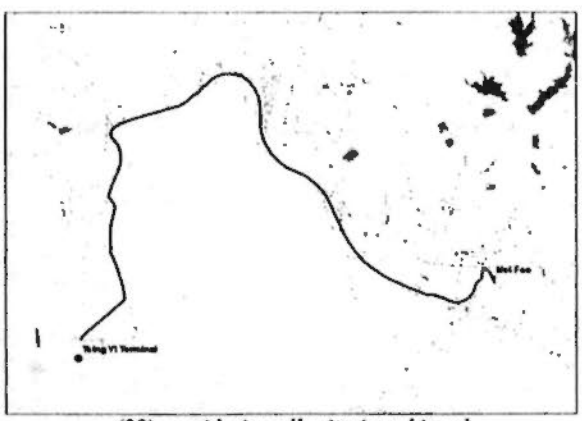
(27) focusing on both travel time and societal risk



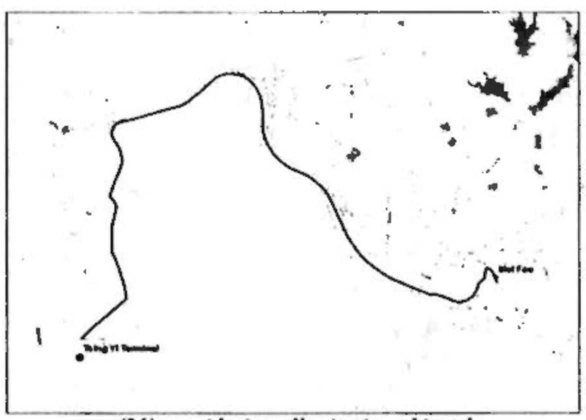
(28) focusing on both travel time and societal risk



(29) considering all criteria unbiased

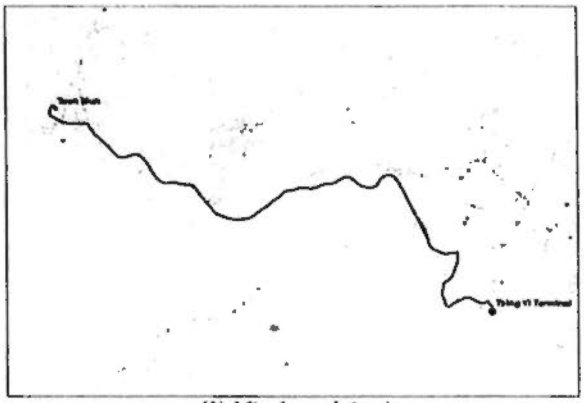


(30) considering all criteria unbiased

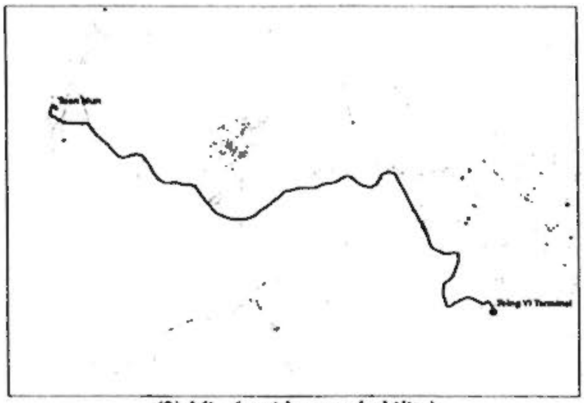


(31) considering all criteria unbiased

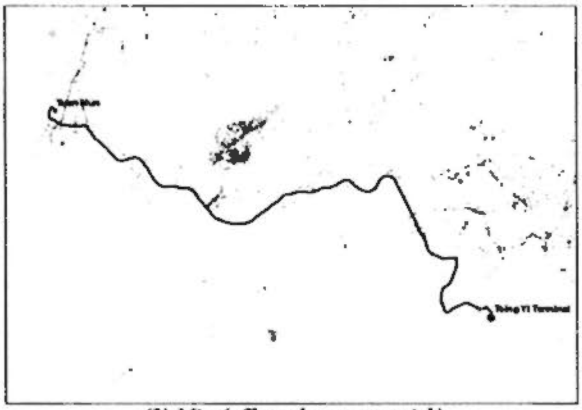
Figure A.8 Efficient routes from Tsing Yi terminal to Mei Foo LPG filling station generated by the proposed MOP methods



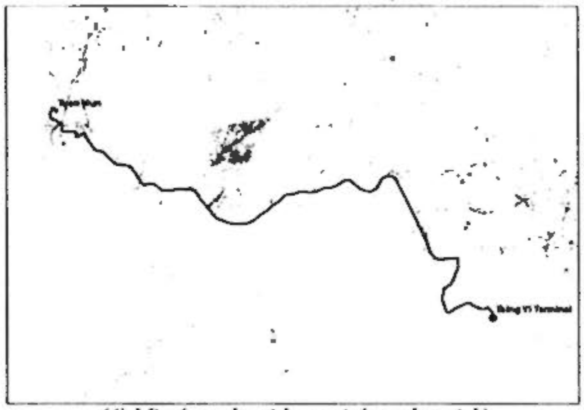
(1) Min (travel time)



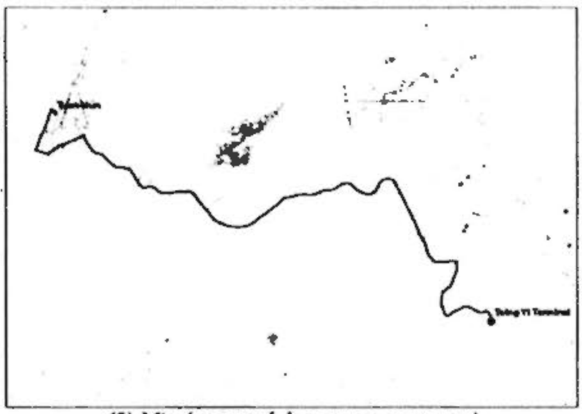
(2) Min (accident probability)



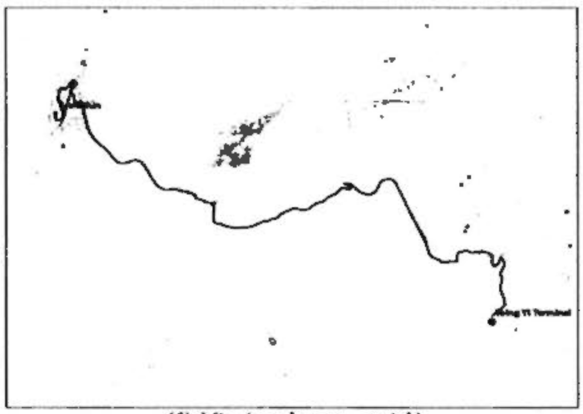
(3) Min (off-road exposure risk)



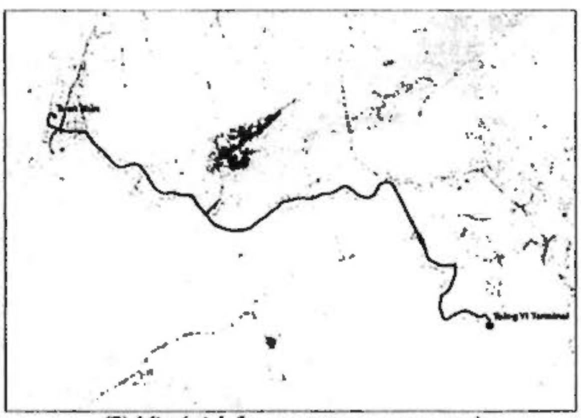
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

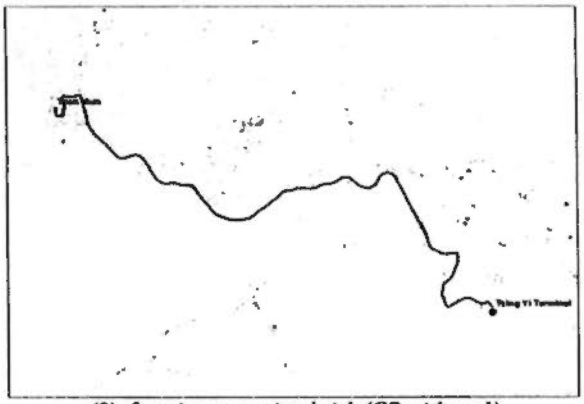


(6) Min (road users at risk)

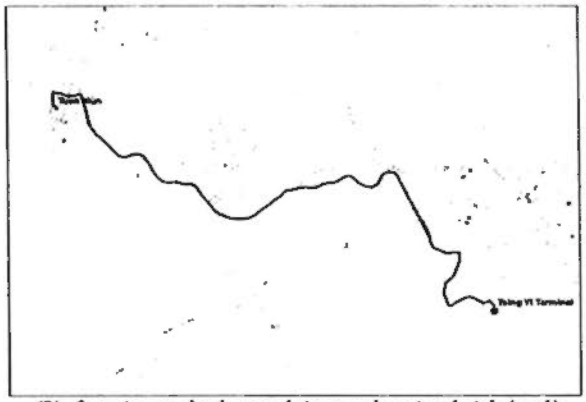


(7) Min (risk from emergency response)

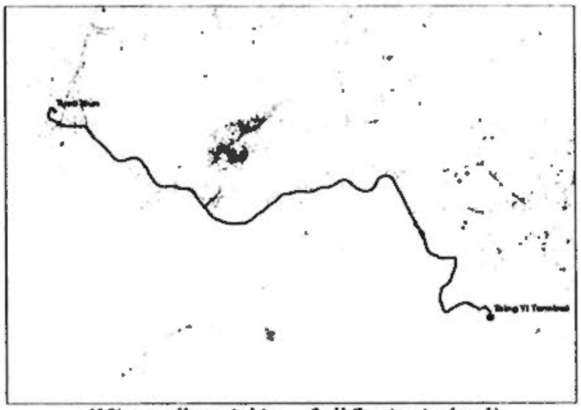
Figure A.9 Single-objective optimal routes from Tsing Yi LPG terminal to Tuen Mun LPG filling station



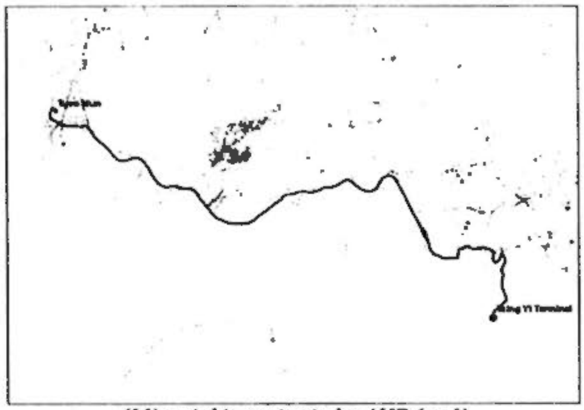
(8) focusing on societal risk (CP with p=1)



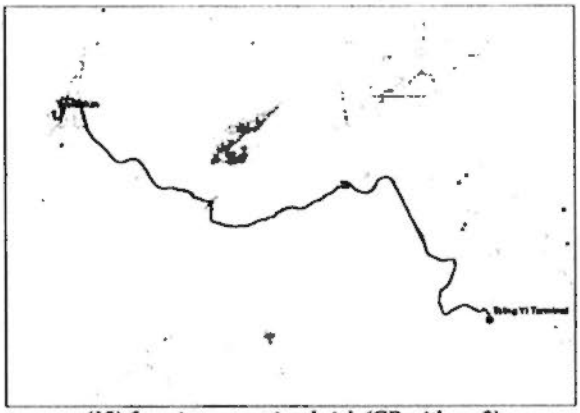
(9) focusing on both travel time and societal risk (p=1)



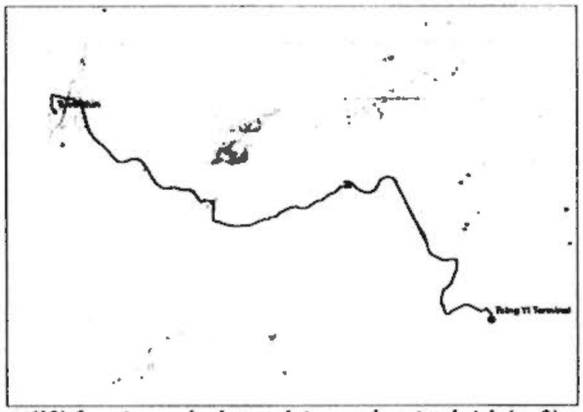
(10) equally weighing of all 7 criteria (p=1)



(11) weighing criteria by AHP (p=1)

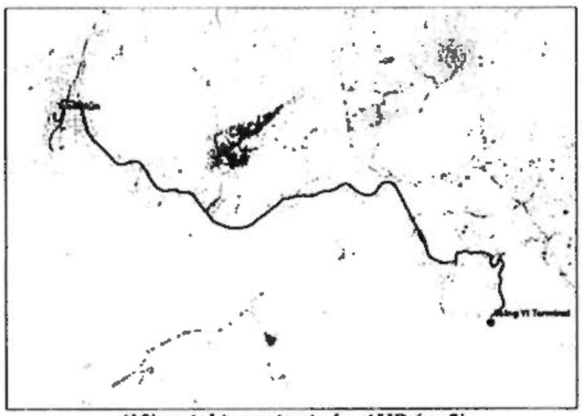


(12) focusing on societal risk (CP with p=2)

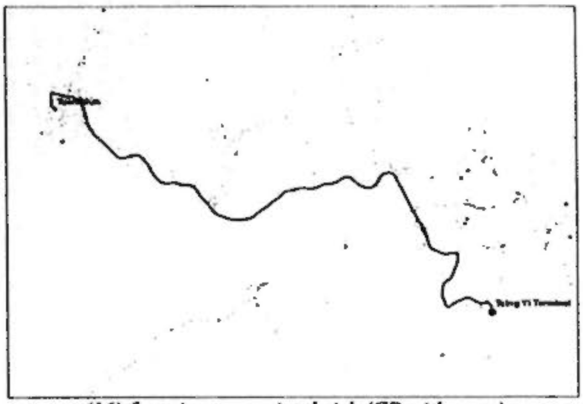


(13) focusing on both travel time and societal risk (p=2)

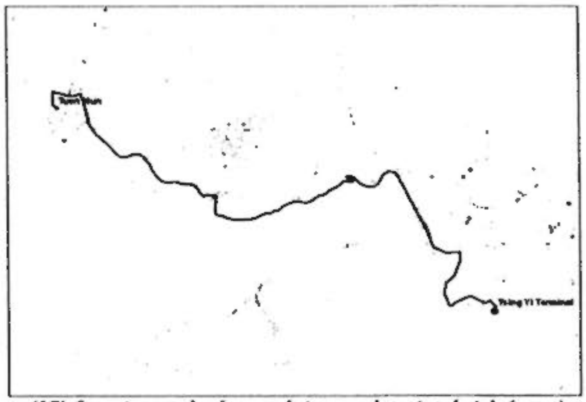
(14) equally weighing of all 7 criteria (p=2)



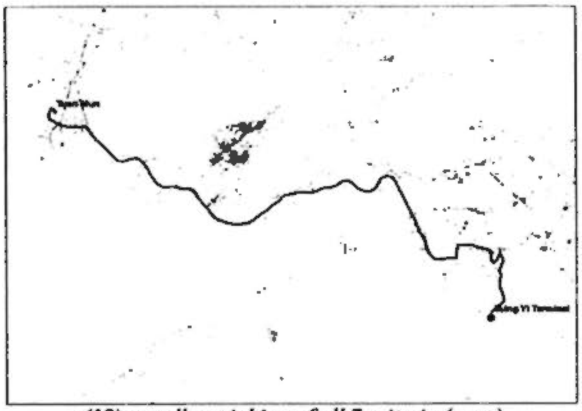
(15) weighing criteria by AHP (p=2)



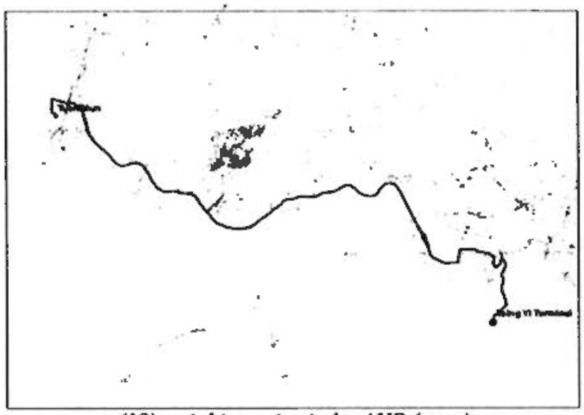
(16) focusing on societal risk (CP with p=∞)



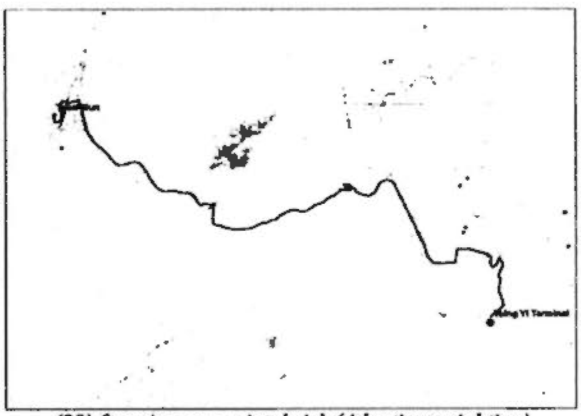
(17) focusing on both travel time and societal risk (p=∞)



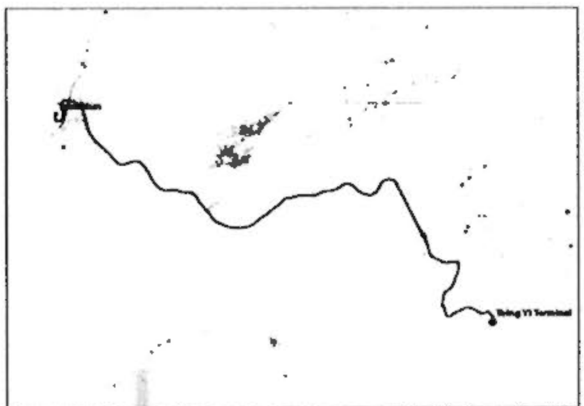
(18) equally weighing of all 7 criteria (p=∞)



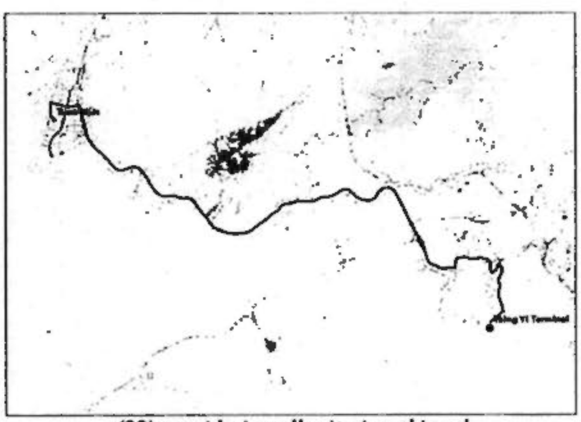
(19) weighing criteria by AHP (p=∞)



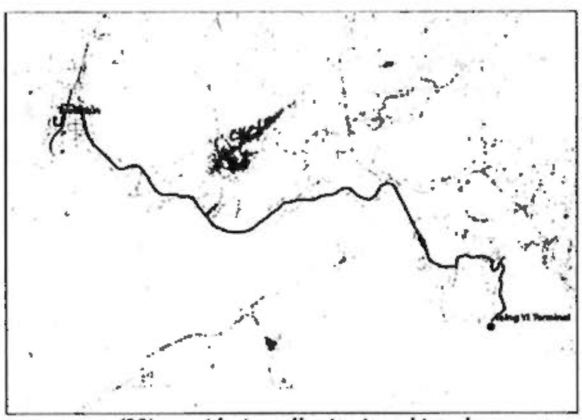
(20) focusing on societal risk (Adaptive weighting)



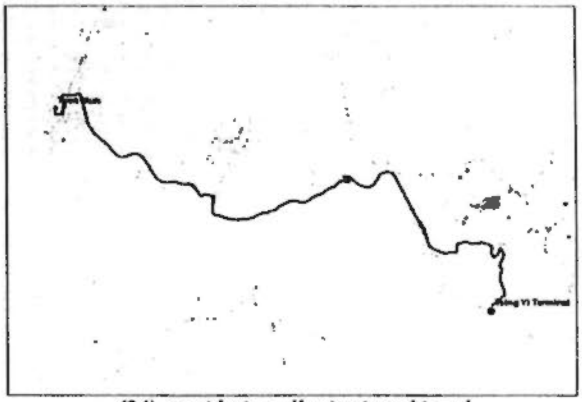
(21) focusing on both travel time and societal risk



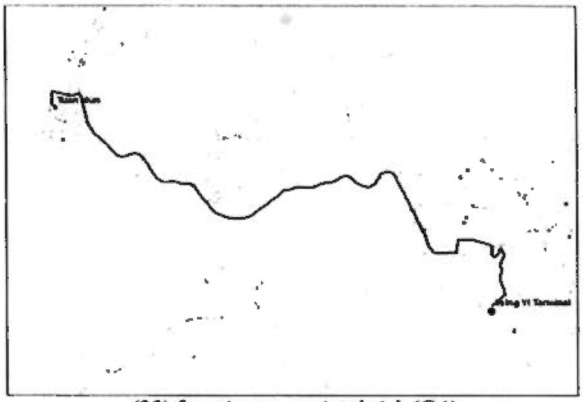
(22) considering all criteria unbiased



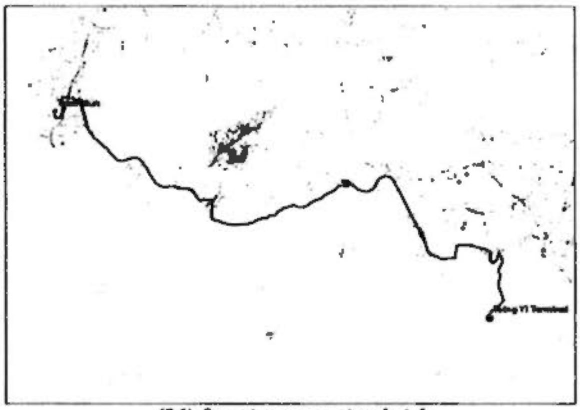
(23) considering all criteria unbiased



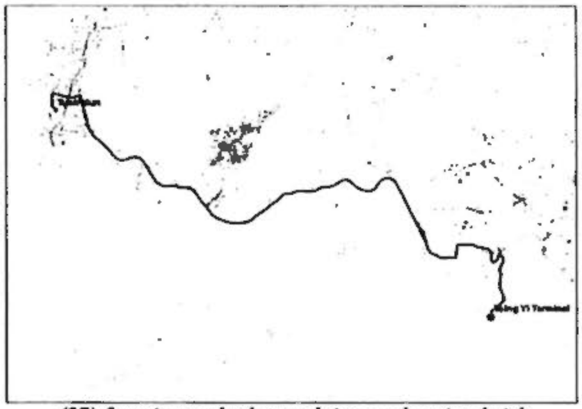
(24) considering all criteria unbiased



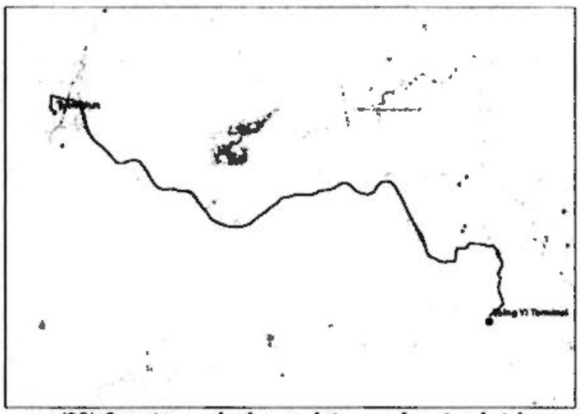
(25) focusing on societal risk (GA)



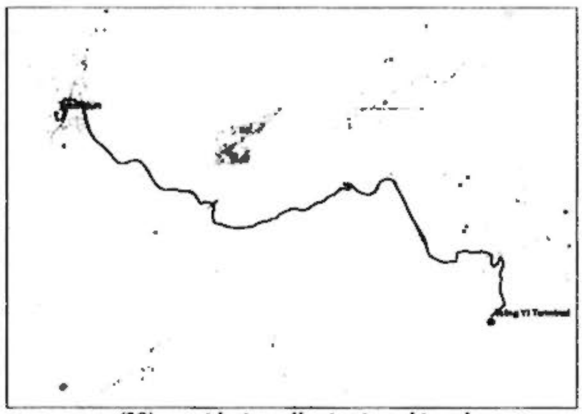
(26) focusing on societal risk



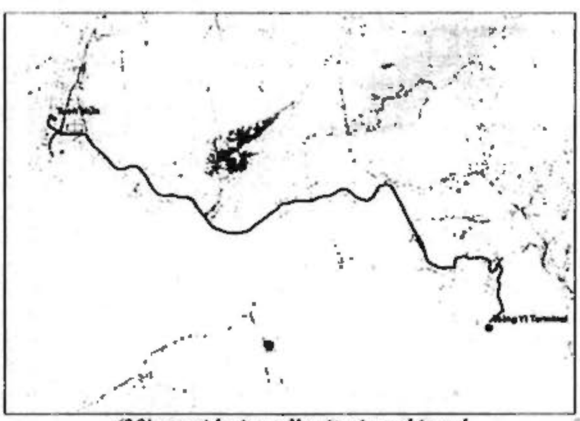
(27) focusing on both travel time and societal risk



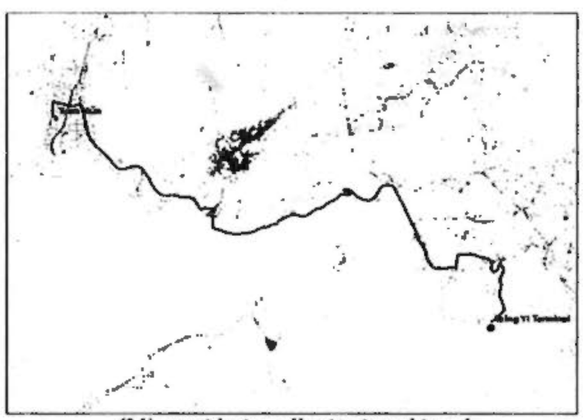
(28) focusing on both travel time and societal risk



(29) considering all criteria unbiased

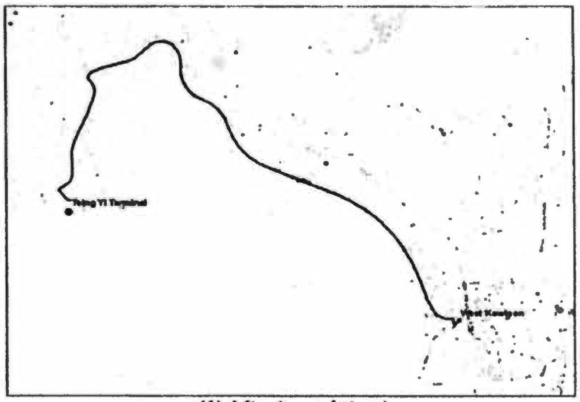


(30) considering all criteria unbiased

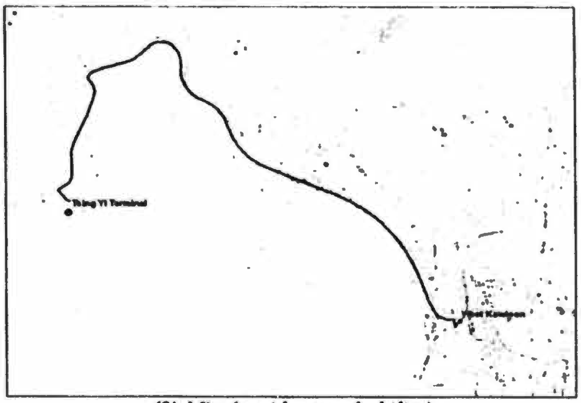


(31) considering all criteria unbiased

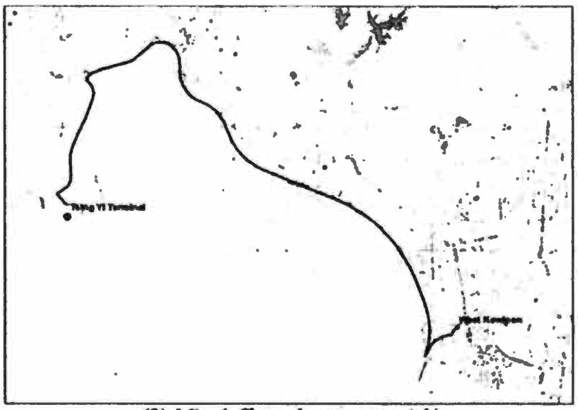
Figure A.10 Efficient routes from Tsing Yi terminal to Tuen Mun LPG filling station generated by the proposed MOP methods



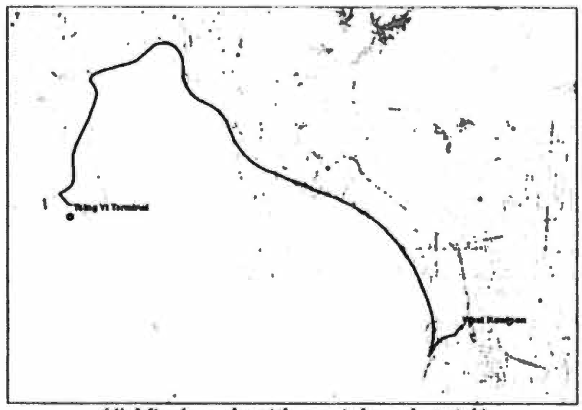
(1) Min (travel time)



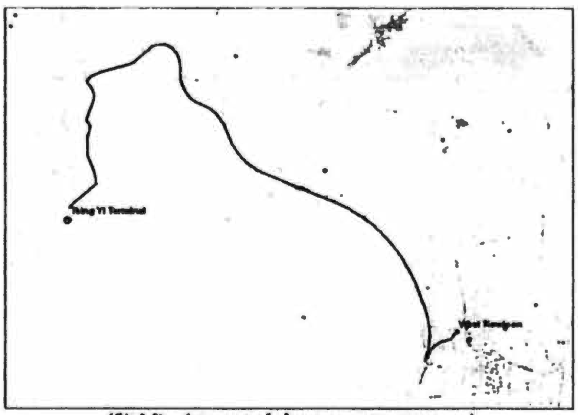
(2) Min (accident probability)



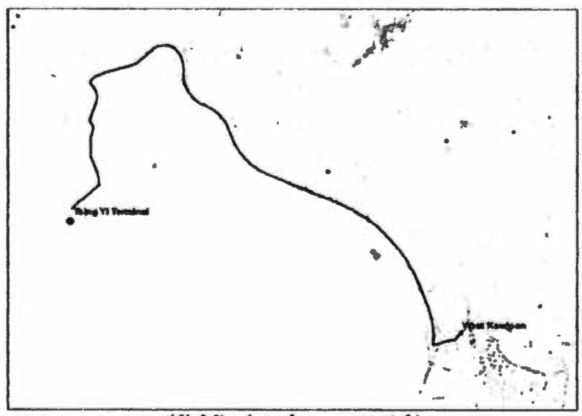
(3) Min (off-road exposure risk)



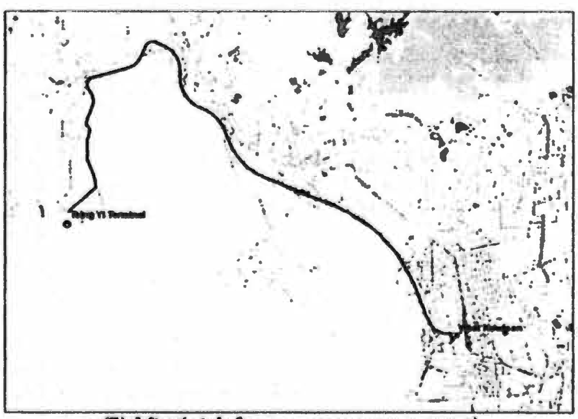
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

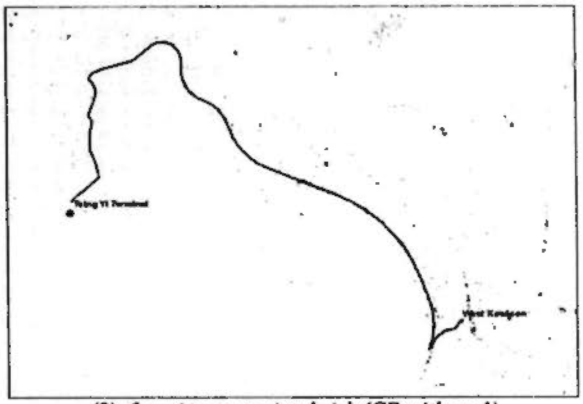


(6) Min (road users at risk)

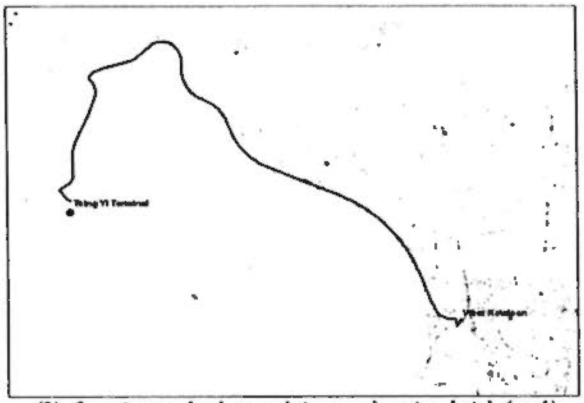


(7) Min (risk from emergency response)

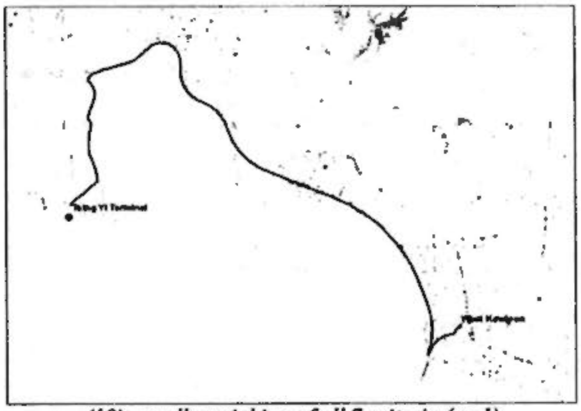
Figure A.11 Single-objective optimal routes from Tsing Yi LPG terminal to West Kowloon LPG filling station



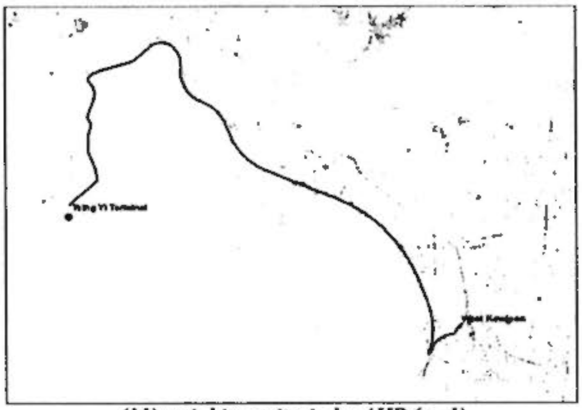
(8) focusing on societal risk (CP with p=1)



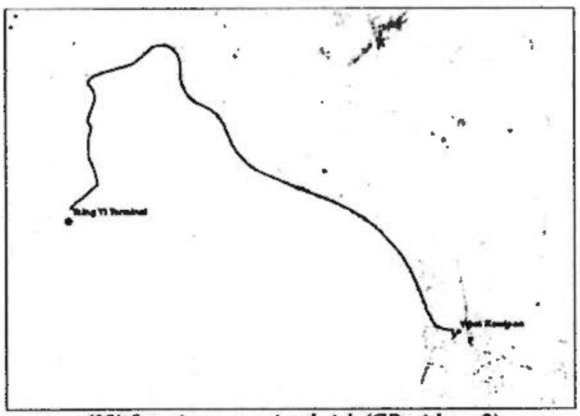
(9) focusing on both travel time and societal risk (p=1)



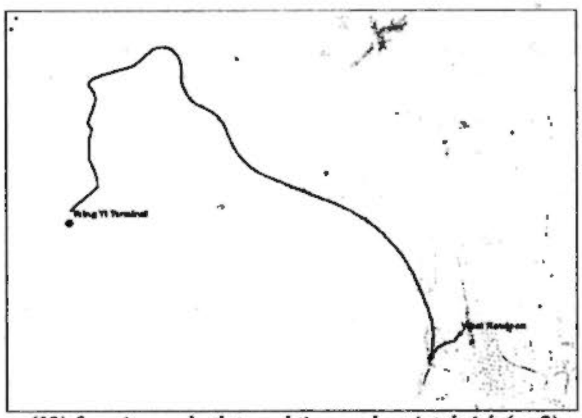
(10) equally weighing of all 7 criteria (p=1)



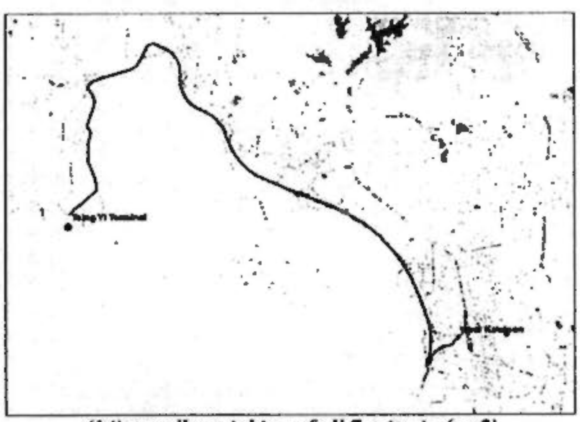
(11) weighing criteria by AHP (p=1)



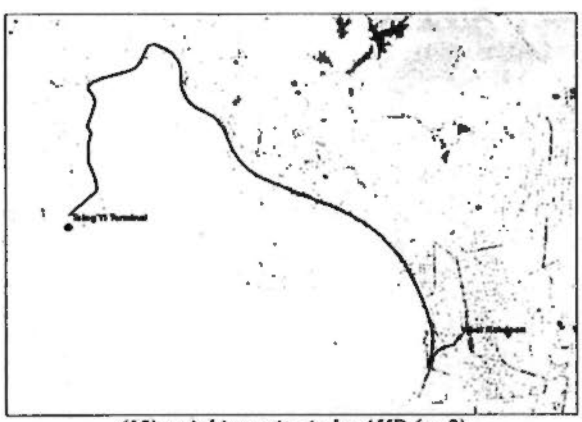
(12) focusing on societal risk (CP with p=2)



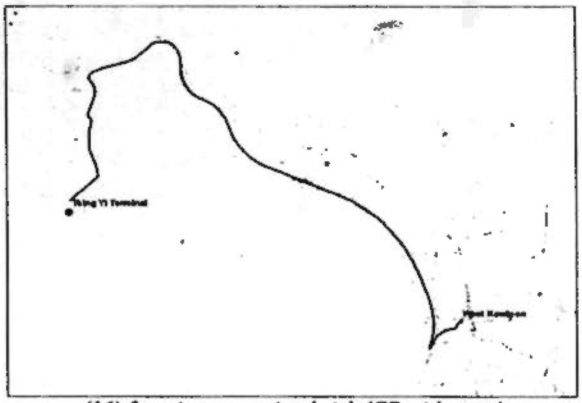
(13) focusing on both travel time and societal risk (p=2)



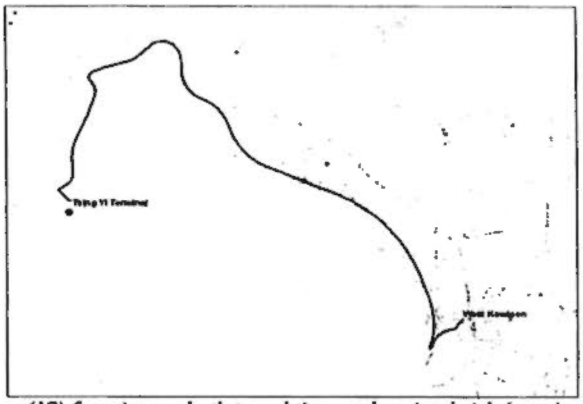
(14) equally weighing of all 7 criteria (p=2)



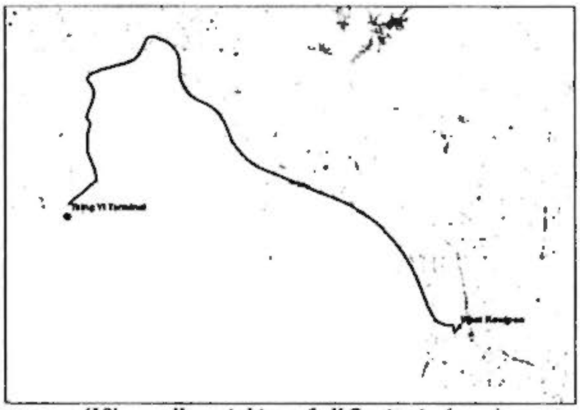
(15) weighing criteria by AHP (p=2)



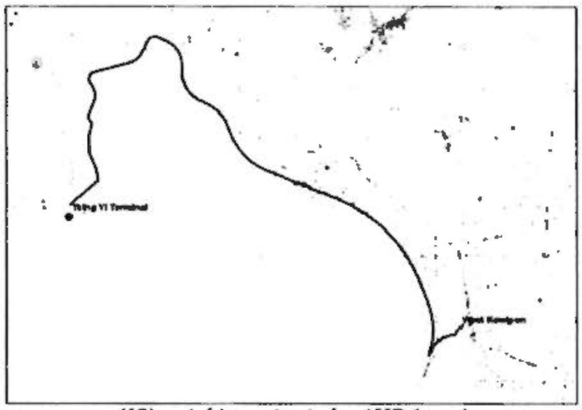
(16) focusing on societal risk (CP with p=∞)



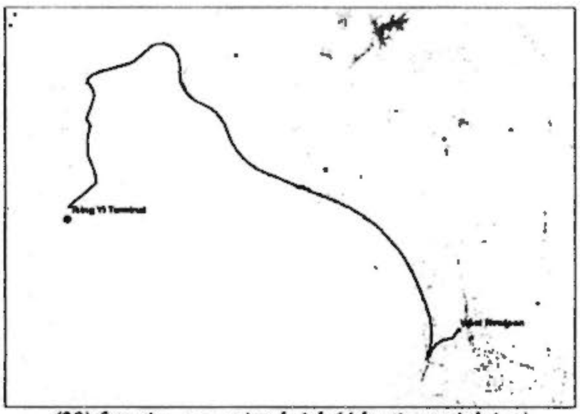
(17) focusing on both travel time and societal risk (p=∞)



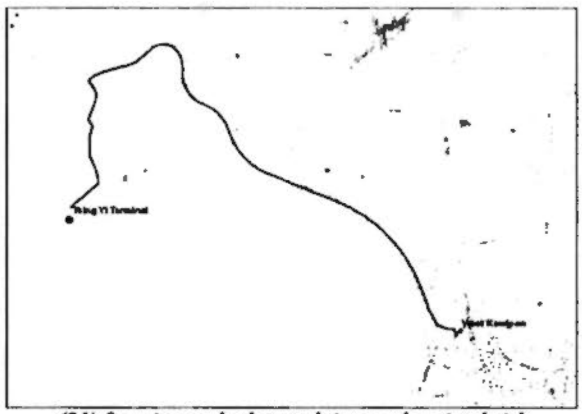
(18) equally weighing of all 7 criteria (p=∞)



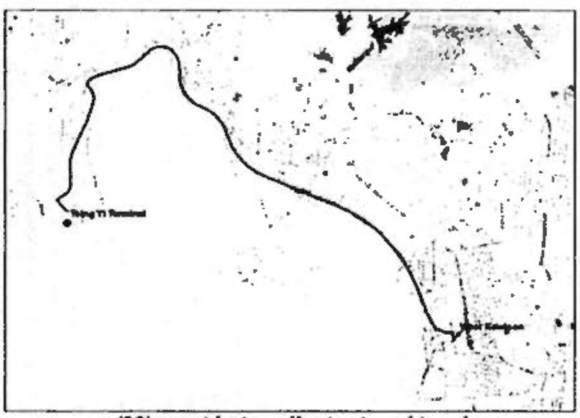
(19) weighing criteria by AHP (p=∞)



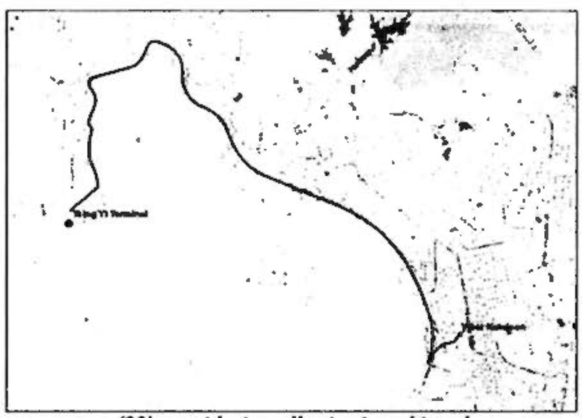
(20) focusing on societal risk (Adaptive weighting)



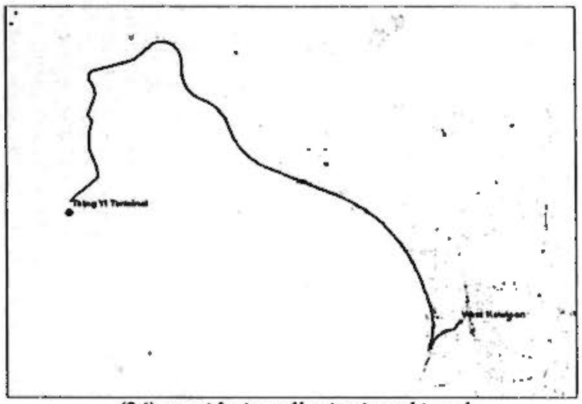
(21) focusing on both travel time and societal risk



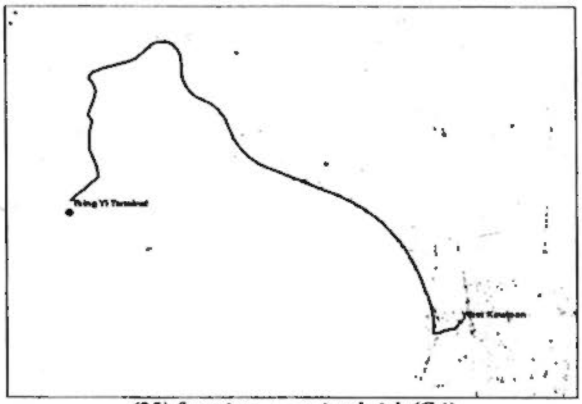
(22) considering all criteria unbiased



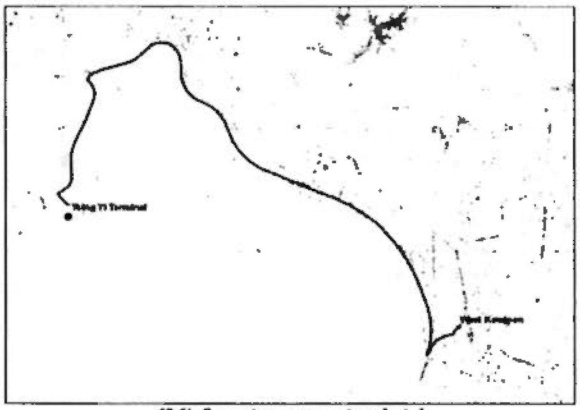
(23) considering all criteria unbiased



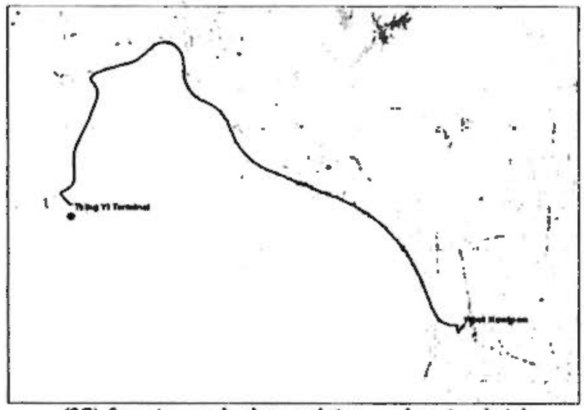
(24) considering all criteria unbiased



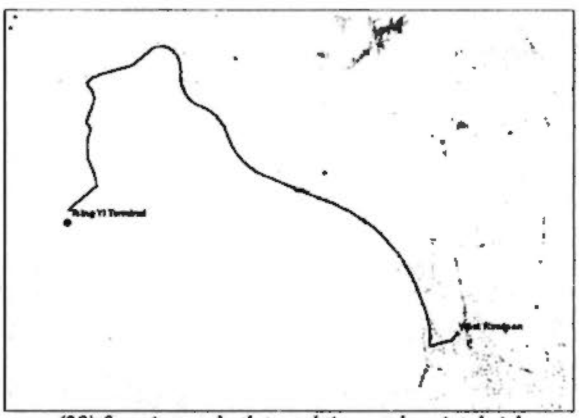
(25) focusing on societal risk (GA)



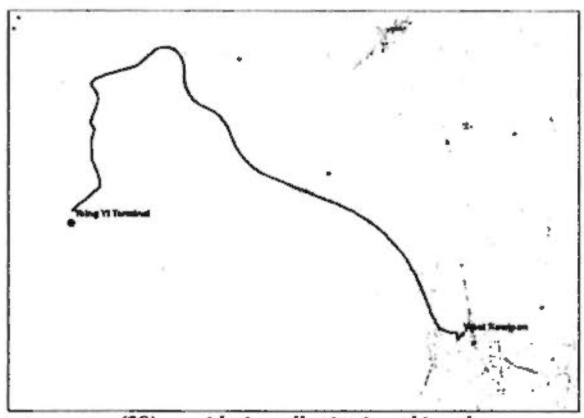
(26) focusing on societal risk



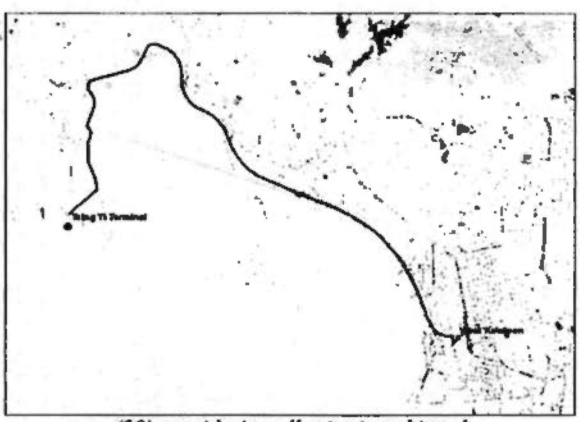
(27) focusing on both travel time and societal risk



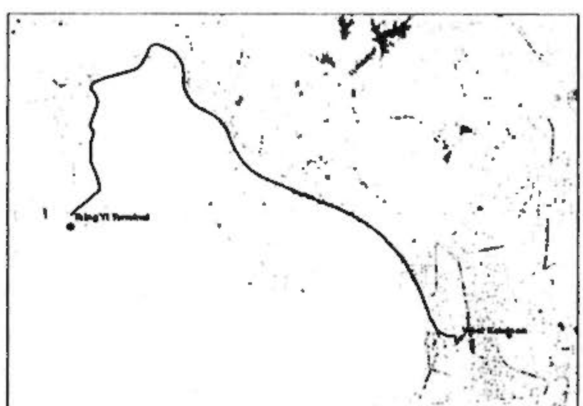
(28) focusing on both travel time and societal risk



(29) considering all criteria unbiased



(30) considering all criteria unbiased



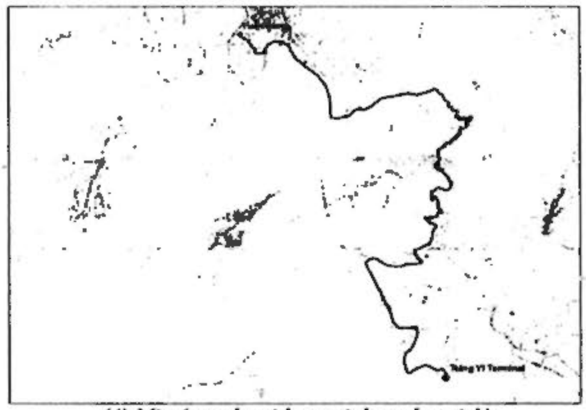
(31) considering all criteria unbiased

Figure A.12 Efficient routes from Tsing Yi terminal to West Kowloon LPG filling station generated by the proposed MOP methods

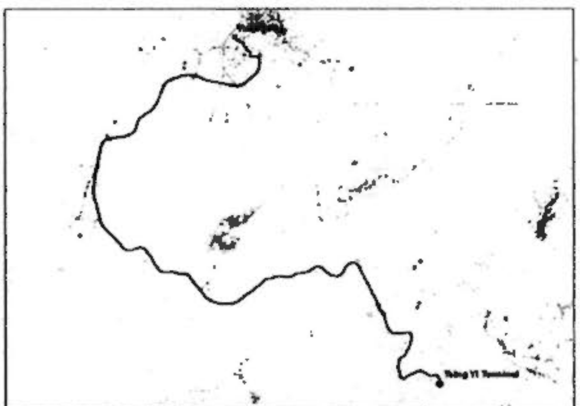
(1) Min (travel time)

(2) Min (accident probability)

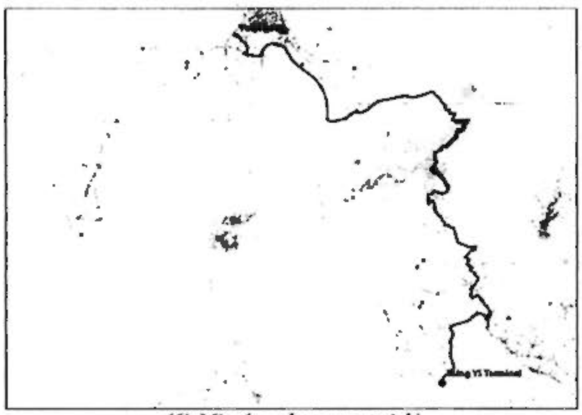
(3) Min (off-road exposure risk)



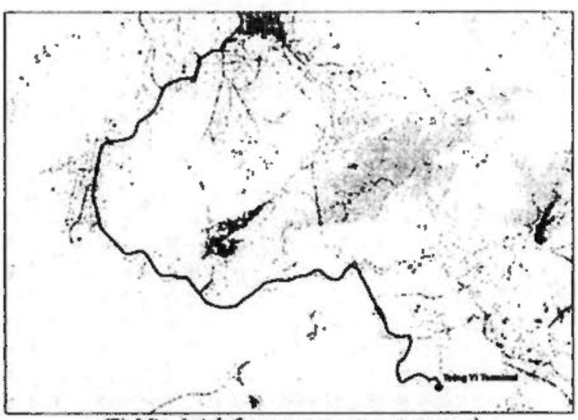
(4) Min (people with special need at risk)



(5) Min (expected damage on economy)

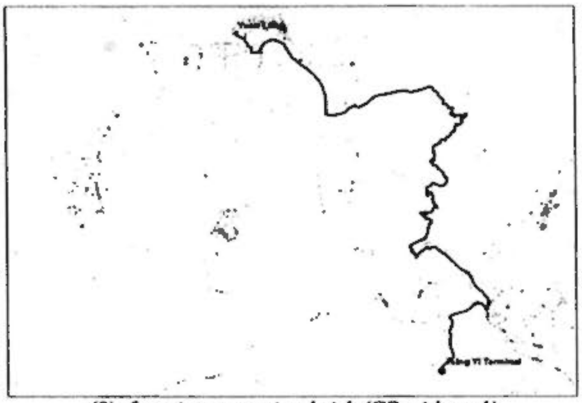


(6) Min (road users at risk)

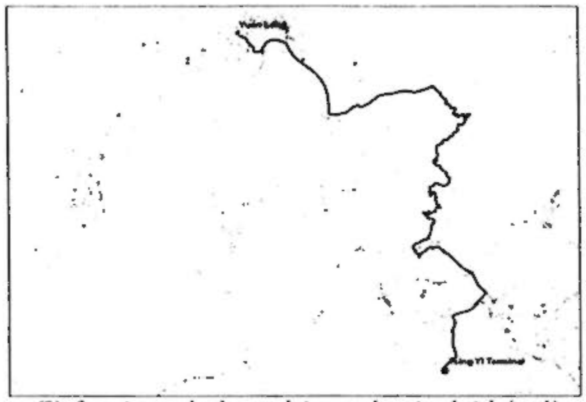


(7) Min (risk from emergency response)

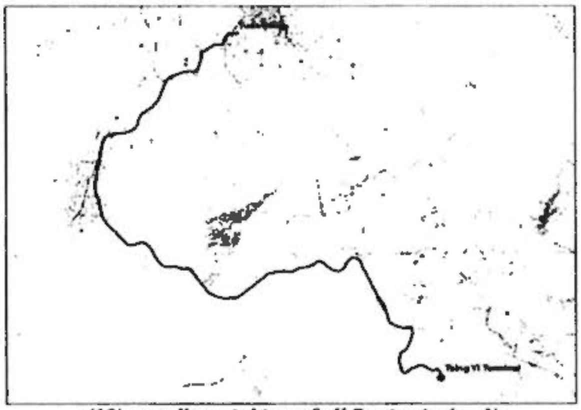
Figure A.13 Single-objective optimal routes from Tsing Yi LPG terminal to Yuen Long LPG filling station



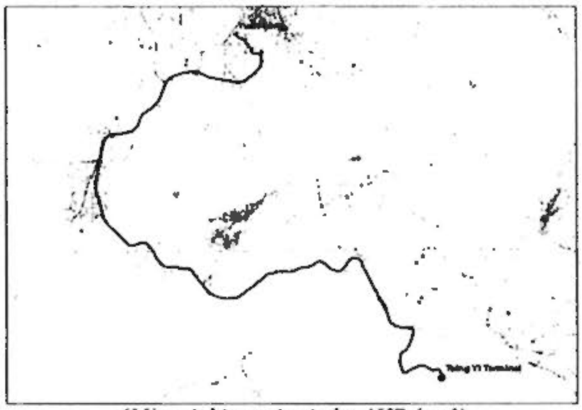
(8) focusing on societal risk (CP with p=1)



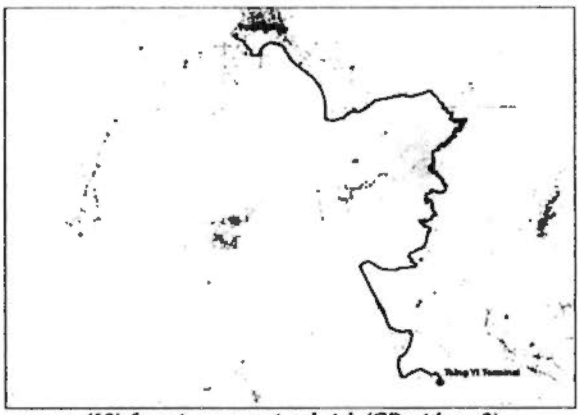
(9) focusing on both travel time and societal risk (p=1)



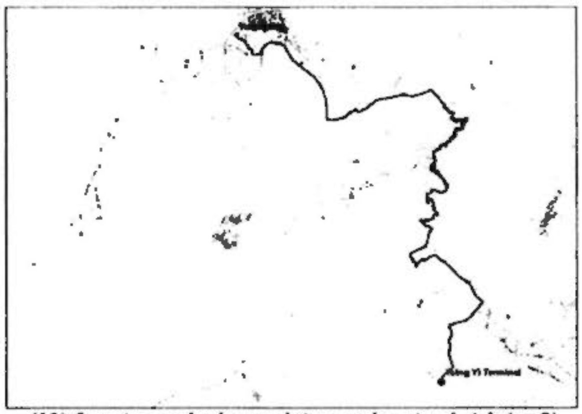
(10) equally weighing of all 7 criteria (p=1)



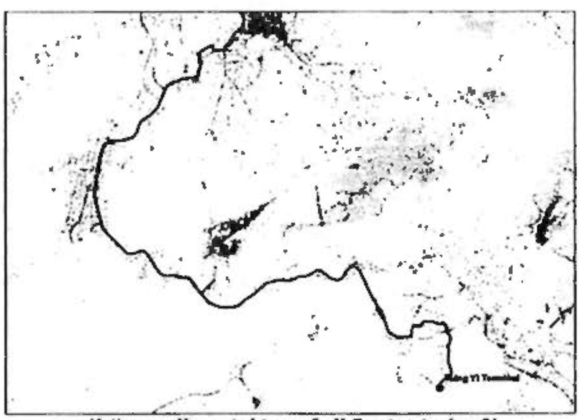
(11) weighing criteria by AHP (p=1)



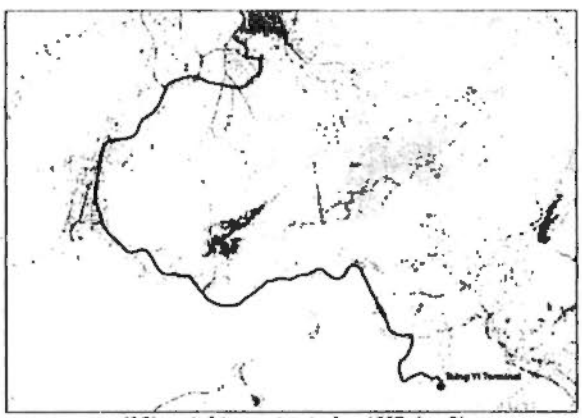
(12) focusing on societal risk (CP with p=2)



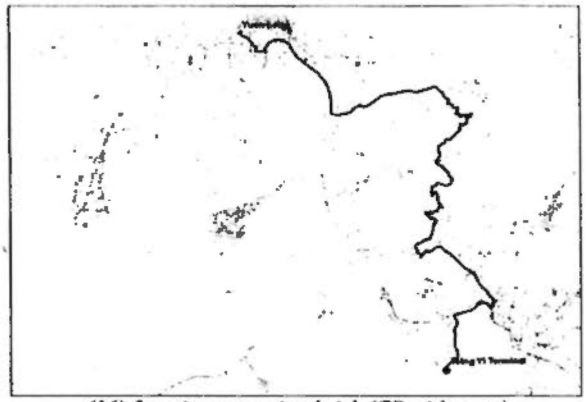
(13) focusing on both travel time and societal risk (p=2)



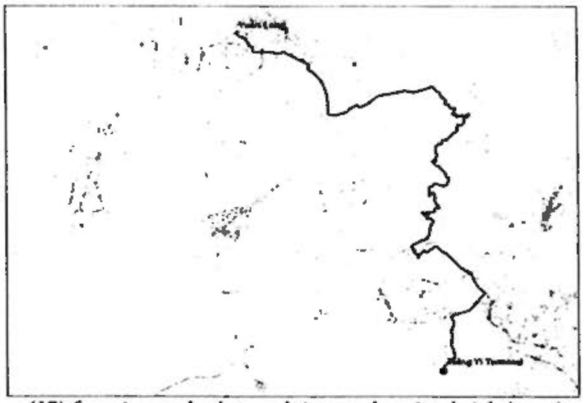
(14) equally weighing of all 7 criteria (p=2)



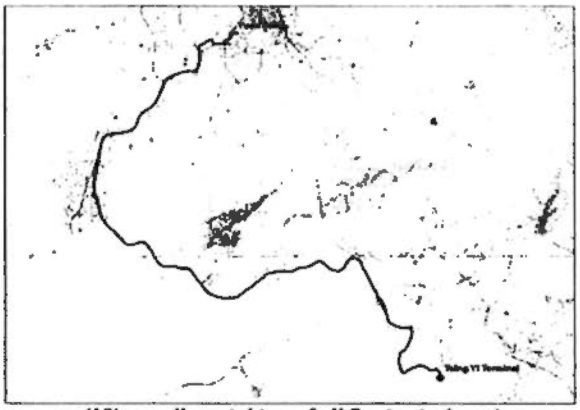
(15) weighing criteria by AHP (p=2)



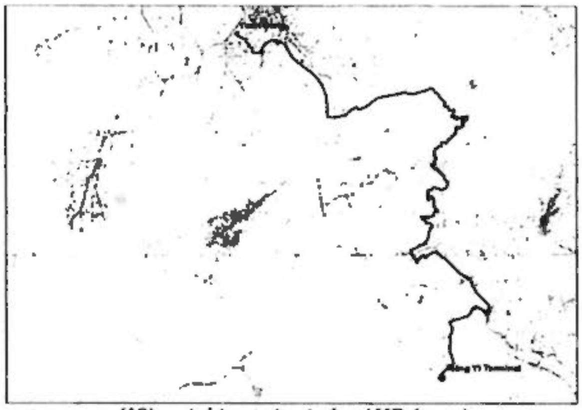
(16) focusing on societal risk (CP with p=∞)



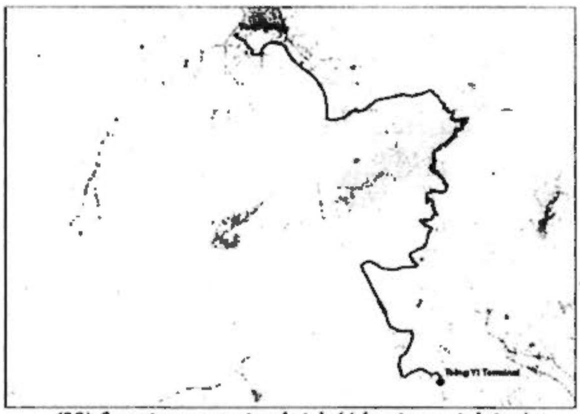
(17) focusing on both travel time and societal risk (p=∞)



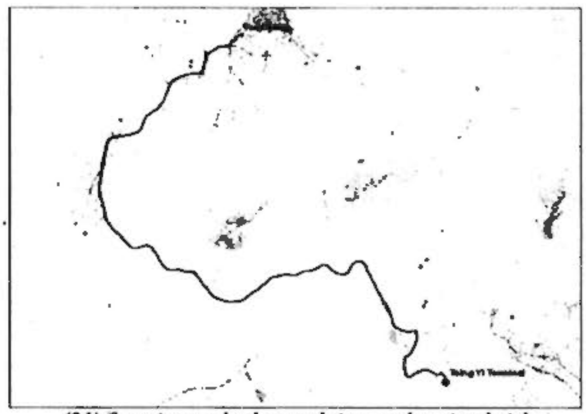
(18) equally weighing of all 7 criteria (p=∞)



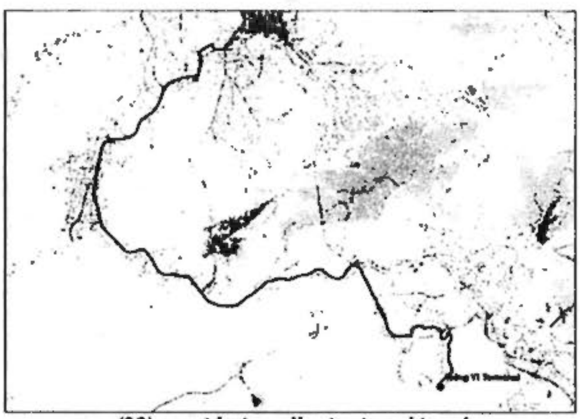
(19) weighing criteria by AHP (p=∞)



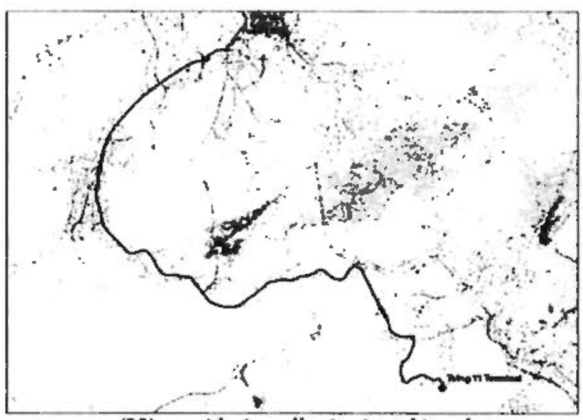
(20) focusing on societal risk (Adaptive weighting)



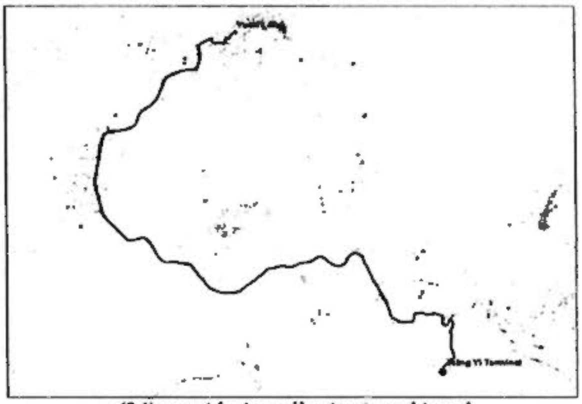
(21) focusing on both travel time and societal risk



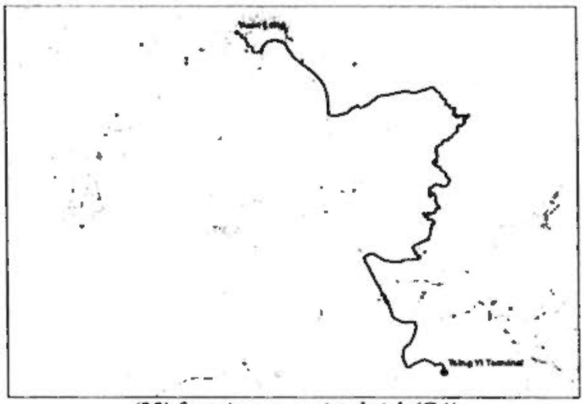
(22) considering all criteria unbiased



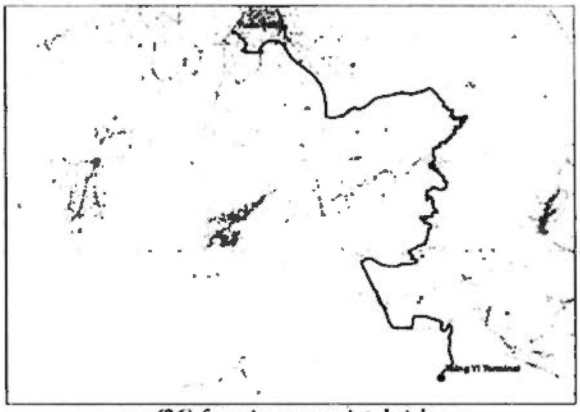
(23) considering all criteria unbiased



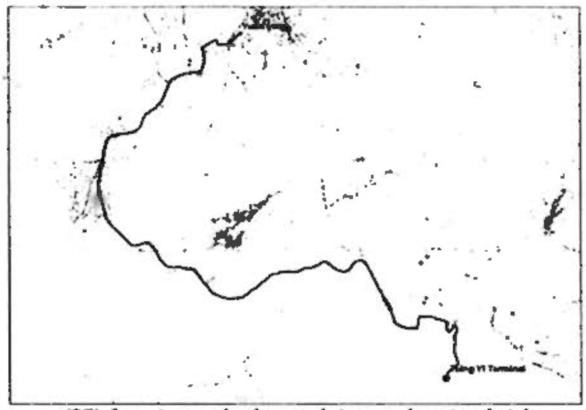
(24) considering all criteria unbiased



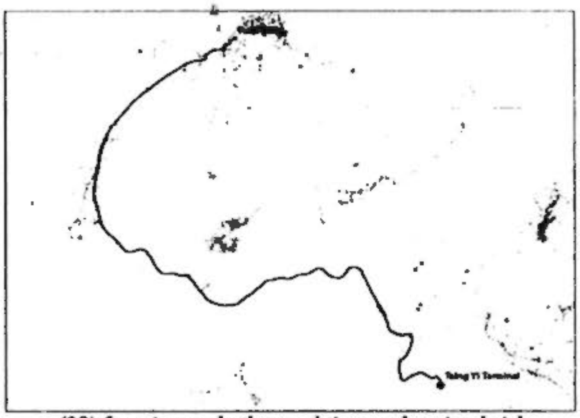
(25) focusing on societal risk (GA)



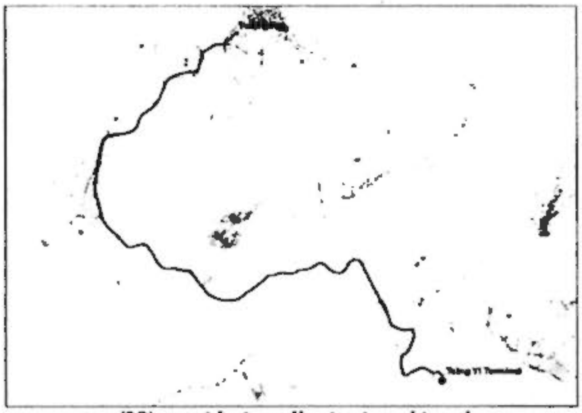
(26) focusing on societal risk



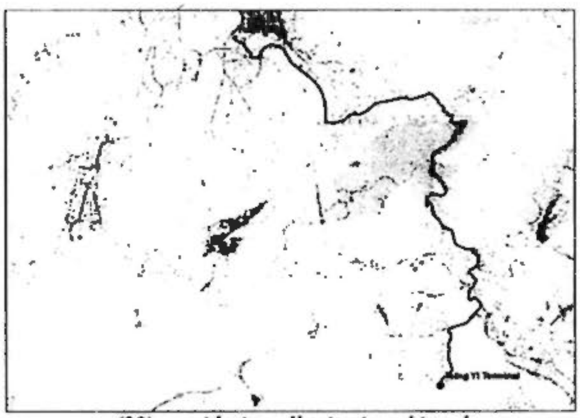
(27) focusing on both travel time and societal risk



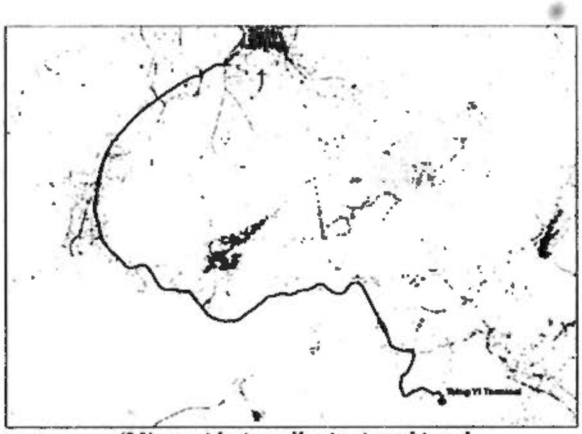
(28) focusing on both travel time and societal risk



(29) considering all criteria unbiased



(30) considering all criteria unbiased



(31) considering all criteria unbiased

Figure A.14 Efficient routes from Tsing Yi terminal to Yuen Long LPG filling station generated by the proposed MOP methods

Appendix B: Supplemental Tables of Optimal Route Planning for the LPG Transportation in the Road Network of Hong Kong

The tables presented in this appendix summarize the attribute values of the optimal routes for each O-D pair exhibited in Appendix A. It should be noted that the values for each attribute in these tables are all in normalized units. The last three attributes, i.e., societal risk, total risk, and overall cost, are defined as follows:

- societal risk: the value of this attribute is calculated as the sum of the normalized off-road population exposure risk, special population at risk, and road users at risk.
- total risk: the value of this attribute is calculated as the sum of the societal risk, normalized accident probability, and expected damage on the economy.
- overall cost: the value of this attribute is calculated as the sum of normalized travel time and total risk.

Table B.1 Normalized objective function values of optimal solutions for the Tsing Yi – Kwun Tong pair (1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	2.653	2.711	1.104	3.010	1.894	5.462	2.534	9.576	14.181	19.368
2. Min (accident probability)	3.063	2.056	2.084	2.019	1.986	4.396	2.465	8.499	12.541	18.069
3. Min (off-road population exposure)	2.838	2.693	1.024	2.814	1.830	4.801	2.976	8.638	13.161	18.975
4. Min (population with special needs at risk)	3.656	2.611	2.423	1.886	2.889	5.112	3.457	9.421	14.921	22.035
5. Min (expected damage on the economy)	8.424	8.932	1.379	4.130	1.172	7.707	7.685	13.216	23.320	39.429
6. Min (road users at risk)	3.519	3.121	3.880	4.988	3.074	2.153	4.110	11.021	17.217	24.846
7. Min (risk from emergency response)	2.725	2.544	1.099	2.747	1.900	4.998	1.611	8.844	13.288	17.625
8. focusing on societal risk (CP with p=1)	3.170	2.210	2.137	2.252	1.963	3.607	3.307	7.996	12.169	18.646
9. focusing on both travel time and societal risk (CP with p=1)	2.853	2.635	1.110	2.822	1.904	4.220	2.059	8.152	12.690	17.602
10. equally weighing of all 7 criteria (CP with p=1)	2.677	2.547	1.098	2.745	1.897	4.736	1.725	8.580	13.023	17.425
11. weighing criteria by AHP (CP with p=1)	3.079	2.074	2.111	2.081	1.995	3.929	2.352	8.121	12.190	17.621
12. focusing on societal risk (CP with p=2)	3.533	2.650	2.399	2.663	2.359	3.090	3.713	8.152	13.160	20.407
13. focusing on both travel time and societal risk (CP with p=2)	3.368	2.413	2.338	2.402	2.158	3.406	3.689	8.147	12.718	19.776
14. equally weighing of all 7 criteria (CP with p=2)	3.189	2.222	2.259	2.273	2.126	3.706	2.409	8.238	12.586	18.184
15. weighing criteria by AHP (CP with p=2)	3.389	2.391	2.395	2.355	2.294	3.502	2.798	8.252	12.936	19.123

16. focusing on societal risk (CP with p=∞)	3.504	2.571	2.437	2.580	2.293	3.567	4.086	8.584	13.448	21.038
17. focusing on both travel time and societal risk (CP with p=∞)	3.124	2.314	2.381	2.509	2.033	3.810	3.269	8.700	13.047	19.440
18. equally weighing of all 7 criteria (CP with p=∞)	3.457	2.417	2.447	2.257	2.285	3.798	2.716	8.502	13.203	19.377
19. weighing criteria by AHP (CP with p=∞)	3.510	2.565	2.433	2.570	2.285	3.583	4.058	8.587	13.438	21.006
20. focusing on societal risk (Adaptive weighting method)	3.141	2.491	2.648	3.499	2.336	2.874	3.185	9.020	13.848	20.174
21. focusing on both travel time and societal risk (Adaptive weighting method)	2.799	2.633	1.122	2.836	1.933	4.460	1.922	8.417	12.982	17.704
22. considering all criteria unbiased (Adaptive weighting method)	3.369	2.522	2.411	2.547	2.358	3.479	2.739	8.437	13.317	19.425
23. considering all criteria unbiased (Adaptive weighting method)	2.838	2.101	2.386	3.062	2.014	3.968	2.979	9.416	13.531	19.348
24. considering all criteria unbiased (Adaptive weighting method)	2.681	2.750	1.115	3.064	1.815	5.233	2.591	9.412	13.977	19.249
25. focusing on societal risk (GA)	3.513	2.611	2.459	2.642	2.330	3.534	3.670	8.634	13.576	20.759
26. focusing on societal risk (GA)	3.126	2.782	1.284	3.536	2.020	3.771	2.526	8.590	13.393	19.045
27. focusing on both travel time and societal risk (GA)	3.125	2.315	2.380	2.511	2.030	3.824	3.322	8.715	13.059	19.505
28. focusing on both travel time and societal risk (GA)	2.872	2.160	2.425	3.148	2.082	3.837	2.969	9.410	13.653	19.494
29. considering all criteria unbiased (GA)	3.486	2.795	3.013	4.069	2.570	2.550	3.715	9.632	14.997	22.198
30. considering all criteria unbiased (GA)	2.721	2.780	1.122	3.111	1.823	5.163	2.507	9.396	13.999	19.227
31. considering all criteria unbiased (GA)	3.352	2.525	3.546	4.282	2.756	2.469	4.078	10.297	15.578	23.009

Table B.2 Normalized objective function values of optimal solutions for the Tsing Yi – Kwai Chung pair (1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	0.942	0.936	0.108	0.558	0.344	1.453	0.788	2.119	3.399	5.129
2. Min (accident probability)	1.021	0.812	0.085	0.432	0.260	1.161	0.669	1.678	2.750	4.440
3. Min (off-road population exposure)	1.021	0.812	0.085	0.432	0.260	1.161	0.669	1.678	2.750	4.440
4. Min (population with special needs at risk)	1.021	0.812	0.085	0.432	0.260	1.161	0.669	1.678	2.750	4.440
5. Min (expected damage on the economy)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
6. Min (road users at risk)	1.071	0.864	0.101	0.495	0.308	1.089	0.667	1.686	2.857	4.596
7. Min (risk from emergency response)	1.083	0.863	0.136	0.621	0.399	1.636	0.384	2.394	3.656	5.124
8. focusing on societal risk (CP with p=1)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
9. focusing on both travel time and societal risk (CP with p=1)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
10. equally weighing of all 7 criteria (CP with p=1)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
11. weighing criteria by AHP (CP with p=1)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
12. focusing on societal risk (CP with p=2)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
13. focusing on both travel time and societal risk (CP with p=2)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
14. equally weighing of all 7 criteria (CP with p=2)	1.038	0.819	0.086	0.448	0.263	1.137	0.525	1.671	2.753	4.316
15. weighing criteria by AHP (CP with p=2)	1.038	0.819	0.086	0.448	0.263	1.137	0.525	1.671	2.753	4.316

16. focusing on societal risk (CP with p=∞)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
17. focusing on both travel time and societal risk (CP with p=∞)	1.022	0.813	0.085	0.443	0.260	1.121	0 553	1.649	2.722	4.296
18. equally weighing of all 7 criteria (CP with p=∞)	1.038	0.819	0.086	0.448	0.263	1.137	0.525	1.671	2.753	4.316
19. weighing criteria by AHP (CP with p=∞)	1.038	0.819	0.086	0.448	0.263	1.137	0.525	1.671	2.753	4.316
20. focusing on societal risk (Adaptive weighting method)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
21. focusing on both travel time and societal risk (Adaptive weighting method)	0.943	0.937	0.108	0.569	0.344	1.413	0.672	2.090	3 371	4.985
22. considering all criteria unbiased (Adaptive weighting method)	1.022	0.813	0.085	0.443	0.260	1.121	0.553	1.649	2.722	4.296
23. considering all criteria unbiased (Adaptive weighting method)	1.038	0.819	0.086	0.448	0.263	1.137	0.525	1.671	2.753	4.316
24. considering all criteria unbiased (Adaptive weighting method)	0.945	0.939	0.108	0.570	0.345	1.605	0.615	2.283	3.568	5.128
25. focusing on societal risk (GA)	1.022	0.813	0.085	0.443	0.260	1.121	0 553	1.649	2 722	4.296
26. focusing on societal risk (GA)	1.021	0.812	0.085	0.432	0.260	1.161	0.669	1.678	2.750	4.440
27. focusing on both travel time and societal risk (GA)	1.071	0.864	0.101	0.495	0.308	1.089	0.667	1.686	2.857	4.596
28. focusing on both travel time and societal risk (GA)	0 994	0.987	0.115	0.548	0.362	1 246	0.884	1.909	3.258	5.136
29. considering all criteria unbiased (GA)	0.975	0.961	0.112	0.594	0.357	1.326	0.813	2.033	3.351	5.139
30. considering all criteria unbiased (GA)	0.987	0.980	0.123	0.647	0.390	1.676	0.588	2.446	3.816	5.392
31. considering all criteria unbiased (GA)	0.945	0.939	0.108	0.570	0.345	1.605	0.615	2.283	3.568	5.128

Table B.3 Normalized objective function values of optimal solutions for the Tsing Yi – Ma On Shan pair (1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	3.446	3.230	0.773	2.156	1.174	6.910	2.503	9.839	14.244	20.193
2. Min (accident probability)	3.793	2.945	0.465	1.489	0.702	5.078	2.568	7.032	10.680	17.042
3. Min (off-road population exposure)	3.581	3.104	0.399	1.527	0.607	4.159	2.417	6.084	9.795	15.794
4. Min (population with special needs at risk)	8.007	6.438	0.739	1.127	0.772	4.749	4.601	6.614	13.824	26.432
5. Min (expected damage on the economy)	3.972	3.489	0.409	1.763	0.511	4.205	2.879	6.377	10.377	17.228
6. Min (road users at risk)	3.747	3.235	0.503	1.817	0.862	3.881	2.672	6.200	10.297	16.717
7. Min (risk from emergency response)	3.626	3.198	0.436	1.682	0.642	4.503	1.979	6.621	10.461	16.067
8. focusing on societal risk (CP with p=1)	3.573	3.142	0.402	1.537	0.608	3.977	2.413	5.916	9.666	15.652
9. focusing on both travel time and societal risk (CP with p=1)	3.564	3.139	0.401	1.534	0.606	3.986	2.444	5.921	9.666	15.674
10. equally weighing of all 7 criteria (CP with p=1)	3.555	3.126	0.401	1.553	0.613	4.026	2.211	5.981	9.720	15.486
11. weighing criteria by AHP (CP with p=1)	3.586	3.159	0.404	1.574	0.618	4.416	2.038	6.394	10.171	15.795
12. focusing on societal risk (CP with p=2)	3.568	3.131	0.399	1.525	0.605	3.998	2.503	5.922	9.658	15.730
13. focusing on both travel time and societal risk (CP with p=2)	3.540	3.110	0.497	1.844	0.740	4.494	2.534	6.835	10.685	16.758
14. equally weighing of all 7 criteria (CP with p=2)	3.571	3.131	0.402	1.558	0.616	4.043	2.184	6.004	9.751	15.506
15. weighing criteria by AHP (CP with p=2)	3.578	3.125	0.401	1.553	0.615	4.057	2.213	6.011	9.751	15.543

16. focusing on societal risk (CP with p=∞)	3.567	3.130	0.400	1.514	0.604	4.039	2.619	5.952	9.687	15.873
17. focusing on both travel time and societal risk (CP with p=∞)	3.542	3.059	0.509	1.631	0.717	5.179	2.566	7.319	11.094	17.202
18. equally weighing of all 7 criteria (CP with p=∞)	3.569	3.121	0.400	1.545	0.612	4.065	2.303	6.010	9.743	15.615
19. weighing criteria by AHP (CP with p=∞)	3.585	3.137	0.401	1.530	0.608	4.015	2.475	5.945	9.690	15.750
20. focusing on societal risk (Adaptive weighting method)	3.568	3.131	0.400	1.525	0.604	3.998	2.503	5.923	9.658	15.730
21. focusing on both travel time and societal risk (Adaptive weighting method)	3.728	3.191	0.428	1.596	0.770	3.949	2.784	5.972	9.933	16.446
22. considering all criteria unbiased (Adaptive weighting method)	3.787	3.297	0.507	1.847	0.867	3.888	2.612	6.242	10.406	16.805
23. considering all criteria unbiased (Adaptive weighting method)	3.536	3.151	0.401	1.567	0.611	4.161	2.270	6.129	9.891	15.697
24. considering all criteria unbiased (Adaptive weighting method)	3.559	3.154	0.471	1.724	0.692	3.960	2.421	6.155	10.001	15.981
25. focusing on societal risk (GA)	3.733	3.202	0.430	1.608	0.774	3.927	2.694	5.965	9.941	16.368
26. focusing on societal risk (GA)	3.730	3.224	0.499	1.802	0.857	3.908	2.703	6.210	10.291	16.724
27. focusing on both travel time and societal risk (GA)	3.735	3.230	0.501	1.810	0.859	3.889	2.732	6.201	10.290	16.757
28. focusing on both travel time and societal risk (GA)	3.747	3.235	0.503	1.817	0.862	3.881	2.672	6.200	10.297	16.717
29. considering all criteria unbiased (GA)	3.553	3.116	0.399	1.541	0.609	4.048	2.330	5.988	9.712	15.595
30. considering all criteria unbiased (GA)	3.744	3.234	0.504	1.818	0.862	3.881	2.642	6.203	10.299	16.686
31. considering all criteria unbiased (GA)	3.488	3.148	0.501	1.716	0.750	5.555	2.357	7.771	11.669	17.515

Table B.4 Normalized objective function values of optimal solutions for the Tsing Yi – Mei Foo pair (1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
2. Min (accident probability)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
3. Min (off-road population exposure)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
4. Min (population with special needs at risk)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
5. Min (expected damage on the economy)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
6. Min (road users at risk)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
7. Min (risk from emergency response)	1.169	0.894	0.081	0.350	0.314	1.289	0.476	1.721	2.928	4.572
8. focusing on societal risk (CP with p=1)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
9. focusing on both travel time and societal risk (CP with p=1)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
10. equally weighing of all 7 criteria (CP with p=1)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
11. weighing criteria by AHP (CP with p=1)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
12. focusing on societal risk (CP with p=2)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
13. focusing on both travel time and societal risk (CP with p=2)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
14. equally weighing of all 7 criteria (CP with p=2)	1.166	0.891	0.081	0.349	0.312	1.097	0.533	1.527	2.731	4.429
15. weighing criteria by AHP (CP with p=2)	1.166	0.891	0.081	0.349	0.312	1.097	0.533	1.527	2.731	4.429

16. focusing on societal risk (CP with $p=\infty$)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
17. focusing on both travel time and societal risk (CP with $p=\infty$)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
18. equally weighing of all 7 criteria (CP with $p=\infty$)	1.166	0.891	0.081	0.349	0.312	1.097	0.533	1.527	2.731	4.429
19. weighing criteria by AHP (CP with $p=\infty$)	1.166	0.891	0.081	0.349	0.312	1.097	0.533	1.527	2.731	4.429
20. focusing on societal risk (Adaptive weighting method)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
21. focusing on both travel time and societal risk (Adaptive weighting method)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
22. considering all criteria unbiased (Adaptive weighting method)	1.152	0.888	0.080	0.346	0.310	1.272	0.504	1.698	2.896	4.553
23. considering all criteria unbiased (Adaptive weighting method)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
24. considering all criteria unbiased (Adaptive weighting method)	1.166	0.891	0.081	0.349	0.312	1.097	0.533	1.527	2.731	4.429
25. focusing on societal risk (GA)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
26. focusing on societal risk (GA)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
27. focusing on both travel time and societal risk (GA)	1.149	0.885	0.080	0.334	0.309	1.121	0.677	1.534	2.728	4.553
28. focusing on both travel time and societal risk (GA)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
29. considering all criteria unbiased (GA)	1.169	0.894	0.081	0.350	0.314	1.289	0.476	1.721	2.928	4.572
30. considering all criteria unbiased (GA)	1.150	0.886	0.080	0.345	0.309	1.080	0.560	1.505	2.699	4.410
31. considering all criteria unbiased (GA)	1.152	0.888	0.080	0.346	0.310	1.272	0.504	1.698	2.896	4.553

Table B.5 Normalized objective function values of optimal solutions for the Tsing Yi – Tuen Mun pair (1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	2.934	1.776	0.295	1.048	0.338	3.228	1.042	4.571	6.685	10.661
2. Min (accident probability)	2.942	1.767	0.295	1.048	0.338	3.199	1.012	4.542	6.647	10.601
3. Min (off-road population exposure)	2.986	1.784	0.293	1.048	0.338	3.214	1.101	4.555	6.677	10.764
4. Min (population with special needs at risk)	3.296	2.415	0.327	0.927	0.328	3.182	2.266	4.436	7.178	12.740
5. Min (expected damage on the economy)	3.488	2.538	0.318	0.974	0.316	3.150	2.327	4.441	7.296	13.111
6. Min (road users at risk)	3.918	3.307	0.630	2.124	0.914	2.321	3.042	5.075	9.297	16.257
7. Min (risk from emergency response)	2.955	1.780	0.300	1.076	0.354	3.240	1.010	4.615	6.749	10.715
8. focusing on societal risk (CP with p=1)	3.067	1.806	0.359	1.124	0.489	2.813	1.190	4.297	6.592	10.850
9. focusing on both travel time and societal risk (CP with p=1)	3.042	1.780	0.357	1.012	0.481	2.931	1.260	4.301	6.561	10.863
10. equally weighing of all 7 criteria (CP with p=1)	2.942	1.767	0.295	1.048	0.338	3.199	1.012	4.542	6.647	10.601
11. weighing criteria by AHP (CP with p=1)	3.092	1.917	0.319	1.435	0.393	2.901	1.303	4.655	6.964	11.359
12. focusing on societal risk (CP with p=2)	3.472	2.862	0.490	1.293	0.561	2.624	2.022	4.407	7.830	13.325
13. focusing on both travel time and societal risk (CP with p=2)	3.414	2.755	0.474	1.176	0.548	2.749	2.032	4.399	7.701	13.147
14. equally weighing of all 7 criteria (CP with p=2)	3.067	1.848	0.370	1.208	0.508	2.776	1.279	4.354	6.710	11.056
15. weighing criteria by AHP (CP with p=2)	3.208	2.007	0.394	1.595	0.562	2.507	1.600	4.497	7.066	11.873

16. focusing on societal risk (CP with p=∞)	3.043	1.822	0.367	1.096	0.499	2.894	1.348	4.357	6.679	11.069
17. focusing on both travel time and societal risk (CP with p=∞)	3.413	2.713	0.464	1.092	0.529	2.786	1.943	4.342	7.584	12.941
18. equally weighing of all 7 criteria (CP with p=∞)	3.128	1.950	0.320	1.447	0.392	2.920	1.608	4.687	7.029	11.765
19. weighing criteria by AHP (CP with p=∞)	3.191	1.987	0.389	1.457	0.542	2.643	1.871	4.490	7.018	12.081
20. focusing on societal risk (Adaptive weighting method)	3.604	2.902	0.487	1.566	0.580	2.415	2.411	4.468	7.950	13.965
21. focusing on both travel time and societal risk (Adaptive weighting method)	3.067	1.848	0.370	1.208	0.508	2.776	1.279	4.354	6.710	11.056
22. considering all criteria unbiased (Adaptive weighting method)	3.183	1.939	0.382	1.399	0.535	2.663	1.580	4.444	6.917	11.680
23. considering all criteria unbiased (Adaptive weighting method)	3.217	1.998	0.394	1.595	0.562	2.478	1.570	4.467	7.027	11.814
24. considering all criteria unbiased (Adaptive weighting method)	3.588	2.888	0.490	1.591	0.592	2.371	2.165	4.452	7.933	13.685
25. focusing on societal risk (GA)	3.207	1.943	0.378	1.373	0.523	2.678	1.797	4.430	6.896	11.900
26. focusing on societal risk (GA)	3.596	2.937	0.498	1.646	0.599	2.361	2.426	4.505	8.042	14.064
27. focusing on both travel time and societal risk (GA)	3.190	1.945	0.378	1.374	0.523	2.681	1.783	4.433	6.901	11.874
28. focusing on both travel time and societal risk (GA)	3.175	1.972	0.392	1.485	0.548	2.652	1.927	4.529	7.050	12.151
29. considering all criteria unbiased (GA)	3.588	2.930	0.501	1.675	0.611	2.333	2.253	4.509	8.050	13.891
30. considering all criteria unbiased (GA)	3.622	3.011	0.515	1.680	0.615	2.326	2.313	4.521	8.148	14.082
31. considering all criteria unbiased (GA)	3.580	2.876	0.485	1.453	0.572	2.531	2.509	4.469	7.917	14.006

Table B.6 Normalized objective function values of optimal solutions for the Tsing Yi – West Kowloon pair (1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	1.441	0.951	0.487	0.507	0.497	1.268	0.793	2.262	3.710	5.944
2. Min (accident probability)	1.441	0.951	0.487	0.507	0.497	1.268	0.793	2.262	3.710	5.944
3. Min (off-road population exposure)	1.500	0.958	0.481	0.503	0.487	1.207	0.794	2.191	3.637	5.931
4. Min (population with special needs at risk)	1.500	0.958	0.481	0.503	0.487	1.207	0.794	2.191	3.637	5.931
5. Min (expected damage on the economy)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
6. Min (road users at risk)	1.534	1.012	0.513	0.546	0.521	1.164	0.707	2.223	3.755	5.996
7. Min (risk from emergency response)	1.461	0.960	0.488	0.524	0.502	1.437	0.592	2.449	3.910	5.963
8. focusing on societal risk (CP with p=1)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
9. focusing on both travel time and societal risk (CP with p=1)	1.441	0.951	0.487	0.507	0.497	1.268	0.793	2.262	3.710	5.944
10. equally weighing of all 7 criteria (CP with p=1)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
11. weighing criteria by AHP (CP with p=1)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
12. focusing on societal risk (CP with p=2)	1.442	0.952	0.487	0.518	0.497	1.228	0.676	2.233	3.682	5.800
13. focusing on both travel time and societal risk (CP with p=2)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
14. equally weighing of all 7 criteria (CP with p=2)	1.517	0.965	0.482	0.519	0.491	1.183	0.650	2.184	3.640	5.807
15. weighing criteria by AHP (CP with p=2)	1.517	0.965	0.482	0.519	0.491	1.183	0.650	2.184	3.640	5.807

16. focusing on societal risk (CP with p=∞)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
17. focusing on both travel time and societal risk (CP with p=∞)	1.500	0.958	0.481	0.503	0.487	1.207	0.794	2.191	3.637	5.931
18. equally weighing of all 7 criteria (CP with p=∞)	1.458	0.957	0.488	0.523	0.500	1.244	0.649	2.255	3.713	5.820
19. weighing criteria by AHP (CP with p=∞)	1.520	0.967	0.482	0.520	0.492	1.375	0.594	2.378	3.837	5.950
20. focusing on societal risk (Adaptive weighting method)	1.501	0.960	0.481	0.514	0.487	1.166	0.678	2.162	3.608	5.787
21. focusing on both travel time and societal risk (Adaptive weighting method)	1.442	0.952	0.487	0.518	0.497	1.228	0.676	2.233	3.682	5.800
22. considering all criteria unbiased (Adaptive weighting method)	1.441	0.951	0.487	0.507	0.497	1.268	0.793	2.262	3.710	5.944
23. considering all criteria unbiased (Adaptive weighting method)	1.520	0.967	0.482	0.520	0.492	1.375	0.594	2.378	3.837	5.950
24. considering all criteria unbiased (Adaptive weighting method)	1.503	0.962	0.481	0.515	0.488	1.359	0.621	2.355	3.805	5.930
25. focusing on societal risk (GA)	1.534	1.012	0.513	0.546	0.521	1.164	0.707	2.223	3.755	5.996
26. focusing on societal risk (GA)	1.500	0.958	0.481	0.503	0.487	1.207	0.794	2.191	3.637	5.931
27. focusing on both travel time and societal risk (GA)	1.441	0.951	0.487	0.507	0.497	1.268	0.793	2.262	3.710	5.944
28. focusing on both travel time and societal risk (GA)	1.534	1.012	0.513	0.546	0.521	1.164	0.707	2.223	3.755	5.996
29. considering all criteria unbiased (GA)	1.442	0.952	0.487	0.518	0.497	1.228	0.676	2.233	3.682	5.800
30. considering all criteria unbiased (GA)	1.461	0.960	0.488	0.524	0.502	1.437	0.592	2.449	3.910	5.963
31. considering all criteria unbiased (GA)	1.458	0.957	0.488	0.523	0.500	1.244	0.649	2.255	3.713	5.820

Table B.7 Normalized objective function values of optimal solutions for the Tsing Yi – Yuen Long pair
(1 ~ 7 are single objective optimization solutions, 8 ~ 31 are MOP solutions)

solution	travel time	accident probability	off-road exposure risk	population with special needs at risk	damage on economy	road users at risk	emergency response capabilities	societal risk	total risk	overall cost
1. Min (travel time)	4.255	2.856	1.437	1.425	1.224	4.631	2.696	7.494	11.574	18.525
2. Min (accident probability)	4.744	2.143	0.774	1.050	0.695	4.283	1.935	6.107	8.945	15.624
3. Min (off-road population exposure)	4.521	2.324	0 760	1.307	0.774	4 196	1.849	6.264	9 361	15.731
4. Min (population with special needs at risk)	6.595	5.530	0.910	0.891	0.931	3.075	3.846	4.877	11.338	21.778
5. Min (expected damage on the economy)	4.753	2.150	0.774	1.050	0.695	4.308	2.008	6.131	8.977	15.737
6. Min (road users at risk)	5.632	4.785	1.329	1.829	1.705	2.519	4.421	5.677	12.168	22.220
7. Min (risk from emergency response)	4.360	2.253	0.820	1.365	0.817	4.146	1.639	6.331	9.400	15.400
8. focusing on societal risk (CP with p=1)	5.732	4.755	0.943	1.297	1.222	2.589	3.785	4.829	10.806	20.323
9. focusing on both travel time and societal risk (CP with p=1)	5.577	4.800	0.949	1.292	1.245	2.699	3.725	4.940	10.984	20.285
10. equally weighing of all 7 criteria (CP with p=1)	4.353	2.246	0.809	1.349	0.808	4.143	1.640	6.302	9.355	15 349
11. weighing criteria by AHP (CP with p=1)	4.744	2.143	0.774	1.050	0.695	4.283	1.935	6.107	8.945	15.624
12. focusing on societal risk (CP with p=2)	6.586	5.523	0.910	0.891	0.931	3 049	3.802	4.850	11.304	21.693
13. focusing on both travel time and societal risk (CP with p=2)	5.577	4.800	0.950	1.284	1.246	2.736	3.667	4 969	11.015	20.259
14. equally weighing of all 7 criteria (CP with p=2)	4.569	2.463	0.868	1.807	0.879	3.756	2.394	6.431	9.773	16.735
15. weighing criteria by AHP (CP with p=2)	4.766	2.491	0.984	1 438	0 873	4.013	2.289	6 434	9 798	16.853

16. focusing on societal risk (CP with $p=\infty$)	5.732	4.755	0.944	1.288	1.223	2.627	3.727	4.859	10.838	20.297
17. focusing on both travel time and societal risk (CP with $p=\infty$)	5.505	5.119	1.063	1.390	1.307	3.173	3.874	5.626	12.053	21.432
18. equally weighing of all 7 criteria (CP with $p=\infty$)	4.496	2.432	0.879	1.609	0.897	3.998	2.052	6.485	9.814	16.362
19. weighing criteria by AHP (CP with $p=\infty$)	5.746	4.760	0.945	1.295	1.228	2.645	3.642	4.885	10.873	20.261
20. focusing on societal risk (Adaptive weighting method)	6.586	5.523	0.910	0.891	0.931	3.049	3.802	4.850	11.304	21.693
21. focusing on both travel time and societal risk (Adaptive weighting method)	4.340	2.233	0.804	1.345	0.792	4.051	1.814	6.200	9.225	15.379
22. considering all criteria unbiased (Adaptive weighting method)	4.586	2.478	0.868	1.805	0.884	3.755	2.179	6.429	9.791	16.556
23. considering all criteria unbiased (Adaptive weighting method)	4.286	2.870	1.453	1.462	1.234	4.593	2.725	7.508	11.612	18.622
24. considering all criteria unbiased (Adaptive weighting method)	4.577	2.471	0.868	1.805	0.884	3.729	2.135	6.402	9.758	16.470
25. focusing on societal risk (GA)	6.617	5.553	0.931	0.916	0.965	3.046	3.802	4.892	11.410	21.829
26. focusing on societal risk (GA)	6.824	5.758	0.998	1.319	1.066	2.775	4.456	5.092	11.915	23.195
27. focusing on both travel time and societal risk (GA)	4.576	2.487	0.865	1.780	0.873	3.776	2.368	6.421	9.780	16.724
28. focusing on both travel time and societal risk (GA)	4.277	2.879	1.453	1.462	1.234	4.622	2.754	7.537	11.650	18.682
29. considering all criteria unbiased (GA)	4.340	2.233	0.804	1.345	0.792	4.051	1.814	6.200	9.225	15.379
30. considering all criteria unbiased (GA)	4.255	2.856	1.437	1.425	1.224	4.631	2.696	7.494	11.574	18.525
31. considering all criteria unbiased (GA)	5.349	4.702	1.181	1.698	1.466	2.693	4.301	[illegible]572	11.740	21.391