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Department of Transportation and Communication Management Science

Master Thesis

Real Time Route Optimization for Hazmat Transportation: A Multi-objective Genetic Algorithm

即時性之路徑規劃於危險物品運輸 -多目標基因演算法之應用

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碩士論文

即時性之路徑規劃於危險物品運輸-多目標基因演算法之應用

Real Time Route Optimization for Hazmat Transportation: A Multi-objective Genetic Algorithm

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ABSTRACT

On July 30, 2014, a series of gas pipeline explosion accidents occurred in the Kaohsiung City, Taiwan, which caused 32 people killed and 321 others injured. After this, local government decided to substitute chemical truck for pipeline transporting hazmat, so the risk of hazmat accidents was transferred to the city road system. Therefore, the risk management of route for hazmat transporting needs to be noticed.

Hazmat transportation accidents usually followed with catastrophic losses and cause heavy impact to society and environment, especially in populous or heavy traffic area such Taiwan city. Further, the real traffic conditions are changing rapidly, which leads to many uncertainties. Despite a large number of researches discussing the route planning of hazmat transportation, most are static research. Thus, this research adopts dynamic traffic characteristics. Besides, more and more cities tend to develop smart city, which implies a growing number of real time traffic data are generated. That also could provide decision maker to generate better decisions for hazmat transportation.

This research aims to develop a model for real time route optimization of hazmat transportation based on multi-objective genetic algorithm. We consider two objectives (transportation risk and cost) involving traffic travel time and traffic volume. The proposed model is tested on realistic Kaohsiung network. Finally, the results present the optimal routes of single O-D pair, multiple O-D pairs, and sensitivity analysis. This research is expected to provide some recommendations and references for related stakeholders such as hazmat industries, government, and residents.

Keywords: Hazmat transportation, Multi-objective, Genetic algorithm, Real time, Route planning

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摘要

近年來危險物品的風險管理已成為全世界的重要課題，特別是在以工業為主的國家裡，因其危險物品之事故往往會造成環境和社會嚴重的破壞。在2014年，作為台灣石化工業重鎮的高雄市，因其管線設計不當以及疏於維護，發生嚴重的管線氣爆事件，日後考量到高雄市居民對於舊管線仍存在著安全之疑慮，故高雄市政府即宣布汰除舊有管線，則改以化學槽車來運送危險物品，雖然如此，槽車的行駛路線仍會造成民眾與車輛有一定程度的危害風險，因此，此事件突顯出危險品運輸路線設計的重要性，台灣國內也應對此課題加以關注。

相較於國外對於危險物品運輸路徑規劃之研究趨於完整，台灣國內則尚未有完善的管理部門及研究計畫，再者，過去國外文獻中所提出的模型大多以靜態路網作為試驗，故本研究於危險物品運輸之最佳路徑中考量動態元素，以因應即時的交通路網路況。另外，在未來城市趨於智慧化的形況下，透過感測器甚至是物聯網之通訊設備，將擁有更多即時性的交通數據作為監控管理，且日後也能應用於危險物品路徑規劃上做更精準之決策。

本研究建構一模型為即時性之路徑規劃於危險物品運輸，在考量運輸風險和運輸成本之目標下，納入動態元素如隨時間變動之車流量、平均旅行時間當作評估項目，並基於多目標基因演算法求解最佳路徑，結果則以高雄氣爆案周遭路網做實證，將產生之結果繪於路網中。其中，對於設定的起訖對分別以個別以及同時考慮多起迄對的方式來呈現其變化，最後，設定不同之演算法參數以比較結果之優劣。期望提供政府、居民以及業者(化工廠、煉油廠、油罐車業者)對於危險品運輸更進一步之參考與建議。

關鍵字：危險物品運輸、多目標、基因演算法、即時性、路徑規劃

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CHAPTER 1 INTRODUCTION

1.1 Research Background and Motivation

With the advance of communication technology, a growing number of real time traffic data not only redefine the risk assessment but also assist in renewing the optimal route for hazard materials (hazmat) transportation. On the other hand, it could timely mitigate risk and decrease cost simultaneously for daily hazmat transporting on roads. (Giglio et al., 2004). Because many time-varying components (the state of the road, of the weather, of the driver, of the hazardous material) are no longer suitable for conventional definitions proposed by past researches, this research needs to discuss the tough problem and focuses on real time route planning of hazmat transportation.

Nowadays, enormous quantities of hazmat are transported to create numerous chemical products for growing needs of daily commodities. But in terms of daily transporting of chemical trucks, it causes an unpredictable damage when accidents happen. In the United States, consequence of accidents caused huge damage during the past decade: an average of 59 million dollars lost on the highway per year (Hazmat Summary by Mode of Transportation, PSMSA, 2018). As for Taiwan, the related statistics is so relatively insufficient that we could not know how severe the accidents caused. But accidents of chemical trucks still happen somewhere in Taiwan to pose an unreasonable risk to our health, safety, or property. Further route planning accounts for the majority of hazmat transportation issues comparing with risk assessment and facility location/emergency planning in the industrial countries (Faghih-Roohi et al., 2016). Therefore, especially in Taiwan, which is a small island and high population density, the problem of real time optimal route for hazmat transportation cannot be

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ignored in a rapidly changing traffic condition.

On 1st August 2014, a series of gas explosions happened in the southern Taiwanese city of Kaohsiung. Not only the blasts rocked the city's roads and vehicles but also killed 32 people and injured 321 unfortunately. According to the investigation report (Control Yuan Republic of China, Taiwan, 2014), bad transportation pipeline design and careless management were the main reasons of the accident. Afterwards, due to the residents lived nearby the affected area strongly worried that the pipeline accident will be occurred again, the Kaohsiung city government to abandon the all hazmat pipeline of the disaster area. Thus, the mode of hazmat transportation was changed from pipeline transportation to chemical trucks to reduce citizens' fear. Then numerous chemical trucks were increasingly needed for remediation to original demand, whereas the citizen's safety concern shifts from pipeline transportation to the road, particularly in the route assignment of chemical truck.

In the end of 2014, Kaohsiung city government announced that the regulation of the restricted route and only allowed to pass within 6:00 a.m.-18:00 p.m. for chemical trucks. In 2017, Toxic and Chemical Substances Bureau, Environmental Protection Administration Executive Yuan, R.O.C. also regulated that the chemical trucks need to equipped GPS for control easier. As described above, the restricted route not only lacks risk assessment, but also the related academic research for endorsement. The hazmat transporting route still poses a certain level of risk. Thus, the risk management of route should be more noticed in Taiwan.

In the past, a large number of researches which related to route planning of hazmat took static components as objectives. But many components should be time-dependent and spatial characteristic in real traffic conditions. Such as driver behavior, status of chemical truck, hazmat, and route segment, could cause different traffic conditions and

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different risk/cost levels. Thus, if the components are not dynamic, the results also could not meet real conditions even though the proposed model could decide precisely optimal route. In other words, the more accurate the analytical data is, the more effective the analytical results are. Besides, more and more cities tend to develop "smart city" (Chourabi et al., 2012), which implies a growing number of real time traffic data are generated under the communication technology such as Internet of Things (IoT) (Zanella et al., 2014). For decision maker, that not only assists in more effective traffic management but also could provide more precise decisions for hazmat transportation (Liu et al., 2012).

In order to enhance safety and meet real traffic conditions, this research constructs a model based on multi-objective genetic algorithm for real time route optimization of hazmat transportation. The model considers two objectives (transportation risk and transportation cost) with dynamic components (traffic volume and travel time) because high traffic volume may bring high risk of accidents and traffic congestion may cause travel time lower over time. Further it is hard to collect the dynamic components including traffic volume and travel time in traffic network, thus it is evaluated from traffic simulation software (DynaTAIWAN) (Hu et al., 2007). The proposed model is tested on realistic Kaohsiung city network and the results of experiments are presented by different scenarios.

1.2 Research Objectives

The purpose of this research is to find optimal route of hazmat transportation with different time interval. It means that we could and simultaneously mitigate risk and decrease cost on the route assignment of chemical trucks over time. The results are expected to provide practical recommendations and references for related stakeholders

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such as hazmat carrier, government and residents for further discussion. The objectives are summarized as follows:

1. Define two objectives (transportation risk and cost) with real time traffic characteristics. Static components include population distribution, accident rate, average radius of the exposure region and so on. Dynamic components include traffic volume and travel time. We update the time-varying traffic data with particular time interval in our traffic network.
2. Develop a model based on real time multi-objective genetic algorithm and a solution algorithm to find the Pareto solutions (minimize cost and risk simultaneously). The results are divided into three parts: 1. presenting real time optimal route for single O-D pair, 2. presenting sensitivity analysis by setting different parameters of algorithm 3. presenting real time optimal routes of multiple O-D pairs.
3. Develop a strategy based on weighting objectives to find the optimal routes and to verify the results from multi-objective genetic algorithm. The reason is that although heuristic algorithm could find optimal solutions within a reasonable time, it does not guarantee the solutions are best. (Rocha & Neves, 1999)

1.3 Research Flow Chart

Figure 1.1 is the research flow chart and the following briefly describes research tasks in respectively.

1. Research Background and Motivation

   Explain the important issue of the hazmat transportation management and real time route in Taiwan. Besides, define the purpose of research and outline the research objectives.

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2. Literature Review

   Review the hazmat transportation route problem, risk assessment, multi-objective optimization and genetic algorithm. Further we reviewed the recent research about real time hazmat route problem.

3. Problem Statement

   Based on the research background and motivation, describe this issue in detail and define the clear problem in this research.

4. Model Formulation and Solution Algorithms

   We propose a model for real time route optimization of hazmat transportation. Present the real time multi-objective genetic algorithm whose core is NSGA-II and real time optimal route with two objectives including minimum transportation risk and cost. Further, present the detailed definition, formulation and solution algorithms.

5. Numerical experiments &Empirical Analysis

   Beneath the Kaohsiung City network, collect the two objectives (transportation risk, cost) with dynamic components and program the proposed model based on real time multi-objective genetic algorithm.

6. Results and Discussion

   This research presents the results of real time optimal routes and depicts the routes on the Kaohsiung City network. Last, presents the empirical study by different scenarios.

7. Conclusions and Suggestion

   Because Taiwan has rare research related to real time hazmat route problem, this research devoted to providing recommendations and references for related stakeholders based on the results of numerical experiments in this section.

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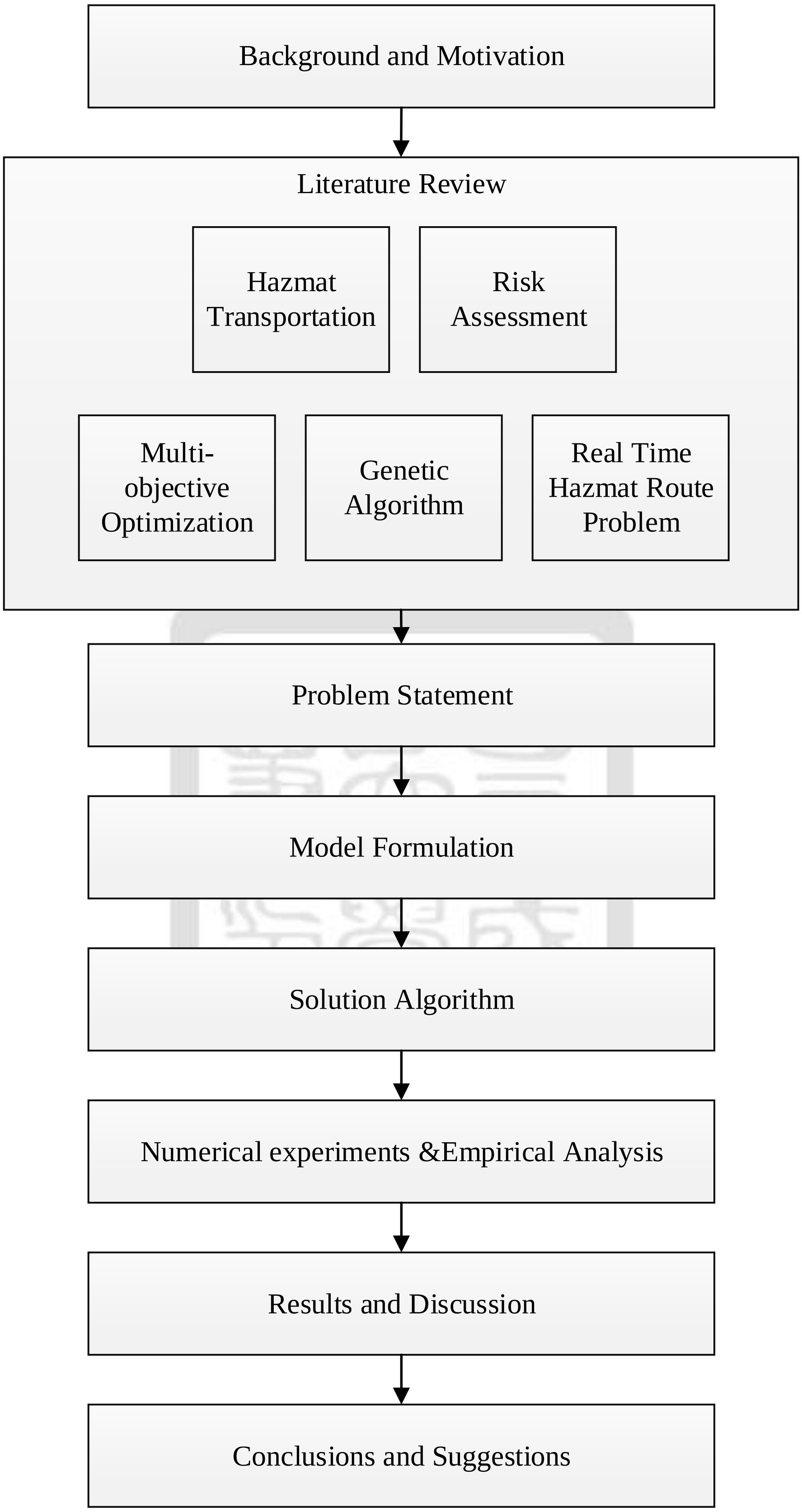

Figure 1.1 Research Flowchart

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CHAPTER 2 LITERATURE REVIEW

The purpose of this research is to develop a real time route optimization for hazmat transportation base on a multi-objective genetic algorithm. Therefore, we focus on the problem of multi-objective hazmat transportation combining with dynamic components. Each of sections are detailed summarizing as follow: Section 2.1 reviews the definitions, international regulations and accidents of hazmat transportation. Section 2.2 reviews the risk assessment for hazmat transportation. Section 2.3 reviews the multi-objective optimization approach and its application in hazmat management. Section 2.4 reviews genetic algorithm, multi-objective genetic algorithm (MOGA) and the elitist non-dominated sorting genetic algorithm Ⅱ(NSGA-II). Section 2.5 reviews real time hazmat route problem and the dynamic components. Section 2.6 summarizes Chapter 2 by providing the key point from each section.

2.1 Hazmat Transportation

With the rapid development of the logistics industry, the transportation modes of land, sea and air are closely related. Among those, also includes a considerable quantities of hazmat transportation. However, hazmat possesses explosive, flammability, toxic, corrosive infectious and radiative properties. In case hazmat accidents happen, it often brings much greater harm to health, life, property and the environment than general cargo. Thus, we must pay more attention to risk management. The following sections focus on reviewing international regulations, definitions of hazmat and practical accidents of hazmat transportation.

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2.1.1 International Regulations and Definitions

From first version of Recommendations on the Transport of Dangerous Goods (1956) publishing, the United Nations Economic and Social Council (ECOSOC), continuously revised it. In 2017, the version was updated to Twentieth revised edition. Above shows that numerous issues of hazmat still be constantly discussed and revised. The main concept of the recommendations is requirement for ensuring the safety of people, property and the environment in the light of technical progress, the advent of new substances and materials, the exigencies of modern transport systems.

In 1957, the United Nations Economic Commission for Europe (UNECE) enacted the European Agreement concerning the International Carriage of Dangerous Goods by Road (ADR) whose structure is consistent with that of the United Nations Recommendations on the Transport of Dangerous Goods. The purpose of agreement is mainly for hazmat regulations including packaging, labeling, equipment and transport. Taiwan and more than forty countries complied with this to regulate the national regulations for hazmat transportation.

As for United States, they established the Hazardous Materials Transportation Act (HMTA) in 1975 based on Title 49 of the Code of Federal Regulations (CFR). It defined hazmat as: if we cannot control the hazmat substance safely, it may cause health, safety and property to unreasonable harm in commercial transportation. The purpose of the Act is to protect and prevent the life, property and the environment from the impact of the risks posed by hazmat in interstates, states and international business. Regulation under the Act are categorized into four terms, including Procedures and Policies, Material Designations & Labeling, Packaging Requirements and Operational Rules.

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2.1.2 Hazmat Transportation Accidents in United States

Figure 2.1 and Figure 2.2 shows the accidents of hazmat transportation during the past decade. A total of 163,086 accidents have been reported to Pipeline and Hazardous Materials Safety Administration (PHMSA). Accidents of land transportation (highway) accounted for majority of percentage. Moreover, the number of accidents has gradually increased. The consequence of these accidents caused totally 594 million dollars and the average of 59 million dollars per year damage on the highway. Figure 2.3 indicates that the damage is no significant decreasing during the past decade.

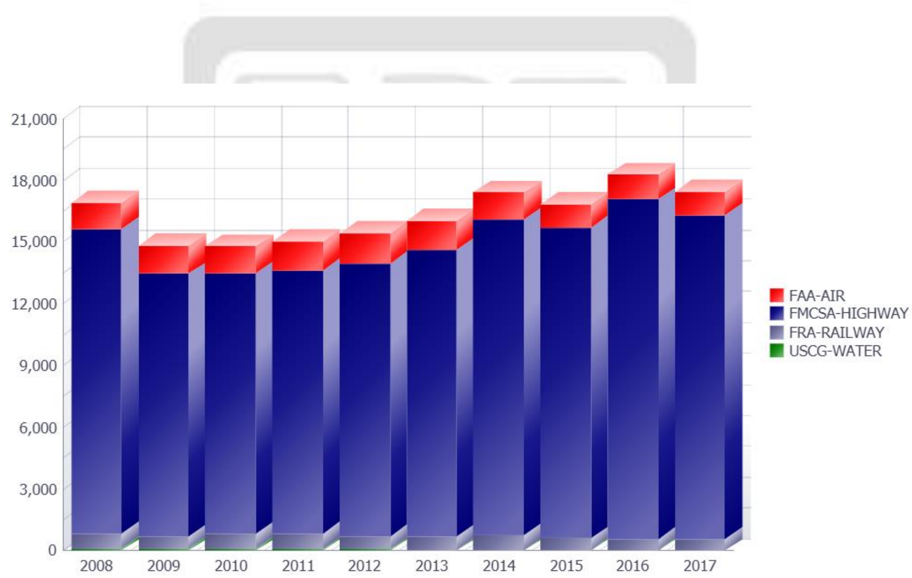

Figure 2.1 Accidents by Mode and Incident Year

Source: Pipeline and Hazardous Materials Safety Administration

(2018 Hazmat Summary by Mode of Transportation)

Mode Of Transportation	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	總計
FAA-AIR	1,278	1,356	1,295	1,401	1,460	1,441	1,327	1,130	1,203	1,161	13,052
FMCSA-HIGHWAY	14,803	12,729	12,652	12,812	13,255	13,887	15,316	15,124	16,524	15,724	142,826
FRA-RAILWAY	748	641	747	744	661	667	717	580	545	568	6,618
USCG-WATER	100	90	105	71	70	63	47	24	11	9	590
總計	16,929	14,816	14,799	15,028	15,446	16,058	17,407	16,858	18,283	17,462	163,086

Figure 2.2 Accidents By Mode and Incident Year

Source: Pipeline and Hazardous Materials Safety Administration

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(2018 Hazmat Summary by Mode of Transportation)

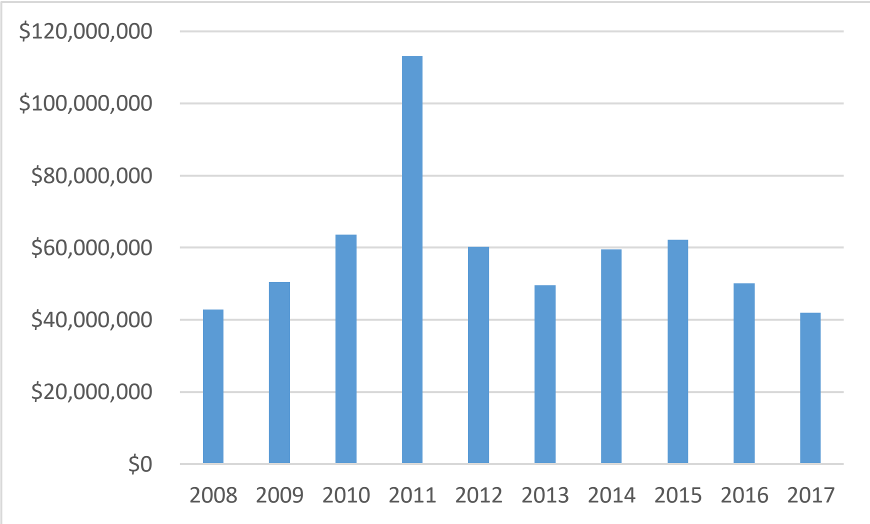

Figure 2.3 Damages on highway Incident Year

Source: Pipeline and Hazardous Materials Safety Administration

(2018 Hazmat Summary by Mode of Transportation)

2.1.3 Hazmat Transportation Accidents in Taiwan

The accidents of chemical trucks in Taiwan recently for two year shows in Appendix (Table A-1). The table shows that overturn and collision accidents of chemical truck are endless. Although the police officers and firefighters could be immediately on-site accident after receiving the emergency notification, the accident caused by the chemical truck requires more professional treatment than the general traffic accident. Moreover, the traffic chaos and impact to environmental caused by accidents are often more serious. After being transferred from pipeline transportation to chemical truck, it appears to be more important for the regulation of hazmat transportation.

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2.2 Risk Assessment for Hazmat transportation

As was mentioned in the beginning of this chapter, many academic research had devoted great effort to exploring risk assessment. Because the accident of chemical trucks might have spillage, flash fire or explosion when the collision and overturn happened, the risk always have higher impact than the normal accident in general. They also denote "danger circle" as the range of risk, because it is difficult to estimate some characteristics such as meteorological conditions and topography, the effect on humans, and the location of individuals at the time of the release. Then the danger circle is related to probability of an accident, accident rate, conditional release probability, population density, impact region and the length of the link. (Erkut & Verter, 1998) The following focus on the definitions of risk and how risk assessment applied to hazmat transportation problems.

Erkut and Verter summarized an overview of the risk definition of the transport of hazmat, including the traditional risk, edge risk and path risk. They also define societal risk as the product of link length, accident rate, conditional release probability, population density and impact radius. (Erkut & Verter, 1998)

Erkut and Ingolfsson summarized the various classic path risk evaluation models for hazmat transportation as Table 2-1, focusing either on one of the two attributes only or on both. They illustrate that different researchers quantify hazmat transportation risk depend on different perspectives and scenarios of problem. But they all have a common objective—by finding an optimal route to maximally reduce its impact on society for the hazmat transportation. (Erkut & Ingolfsson, 2005)

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Table 2-1 Classic path risk evaluation models

Model	Risk measure	Formula
TR	Expected risk (Traditional risk)	$\min_{l \in P} \sum_{(i,j)\in A^l} p_{ij} c_{ij}$
PE	Population exposure	$\min_{l \in P} \sum_{(i,j)\in A^l} c_{ij}$
IP	Incident probability	$\min_{l \in P} \sum_{(i,j)\in A^l} p_{ij}$
PR	Perceived risk	$\min_{l \in P} \sum_{(i,j)\in A^l} p_{ij} (c_{ij})^q$
MM	Maximum risk	$\min_{l \in P} \max_{(i,j)\in A^l} c_{ij}$
MV	Mean variance	$\min_{l \in P} \sum_{(i,j)\in A^l} (p_{ij} c_{ij} + k p_{ij} (c_{ij})^2)$
DU	Disutility	$\min_{l \in P} \sum_{(i,j)\in A^l} p_{ij} (\exp(k c_{ij} - 1))$
CR	Conditional probability	$\min_{l \in P} \frac{\sum_{(i,j)\in A^l} p_{ij} c_{ij}}{\sum_{(i,j)\in A^l} p_{ij}}$

Kang et al. proposed a new measurement of risk model, value-at-risk (VaR) which was most used in financial application in the past. The model introduced a new factor of confidence level α meaning the decision maker’s risk preference. The objective of the VaR model is to set the worst risk threshold by a shipment within a certain confidence interval. That means the optimal VaR path varies under different α. In case study, they addressed single-trip optimal hazmat shipment problem by selecting the lowest VaR value. Further, they combined the VaR model with other models to list several paths (better VaR values). (Kang, Batta, & Kwon, 2014)

Kwon extended the framework to conditional value-at-risk (CVaR) models which was applied to deal with financial portfolio optimization. In VaR model, usually ignore some road segments with very small accident probability but large accident consequence. Compared with VaR, CVaR models can avoid the use of the links with

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large consequence by selecting a sufficiently large confidence level that stands for extreme risk averse attitude. Further CVaR has better mathematical and computational properties, in addition to the better behavior in long tail. (Kwon, 2011)

2.3 Multi-objective Optimization Approach

Hsu indicated that Multiple Criteria Decision Making (MCDM) includes Multiple Objective Programming (MOP) and Multiple Attribute Decision Making (MADM). The main difference could be summarized as the aspects of alternative solutions and evaluated approach. MOP obtains the non-dominated solutions via mathematical programming from infinite solutions (discrete). MADM obtains the non-dominated solutions via relative importance from limited solutions. Further, MOP could be divided into three categories as figure 2.4 which is related to informations, preference selection and pratical method. (Hsu, 2003)

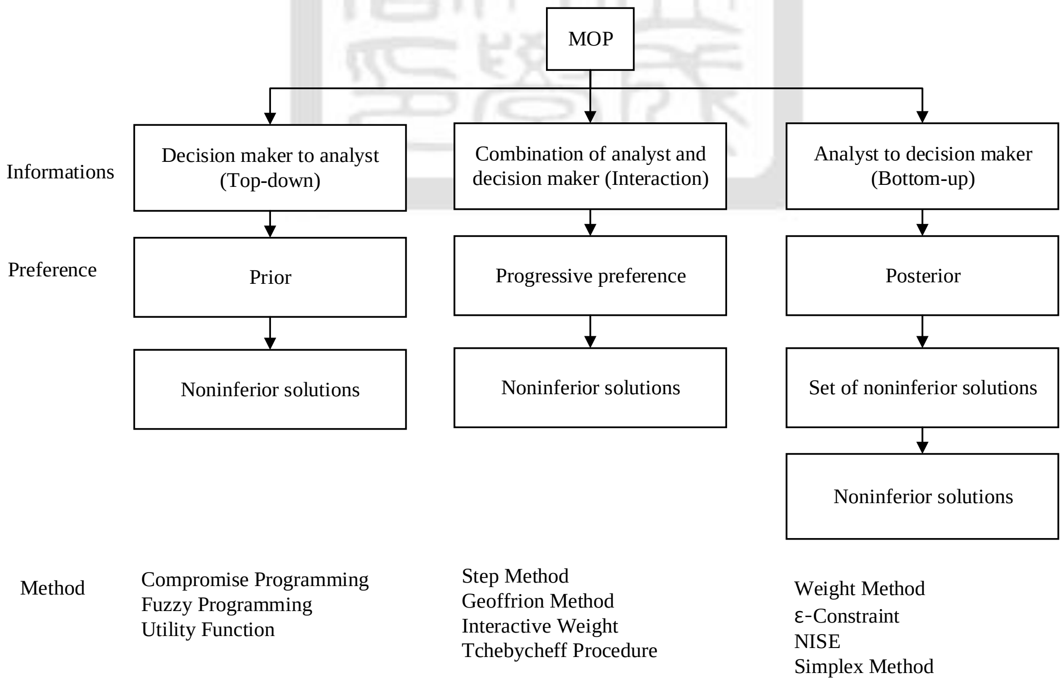

Figure 2.4 Categories of multiple objective programming

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Multi-objective optimization (also named as multi-objective programming, vector optimization, and Pareto optimization etc.) has been applied in many fields of science, including engineering, economics and logistics. In the field of transportation, most of the objectives we considered such as travel time, distance, cost, congestion for the transporting, considering the price, service level, and seamless transfer service always have conflict. Thus, the goal of multi-objective optimization is to consider more than one objective to be optimized simultaneously with mathematical optimization problems involving. The optimal solutions of multi-objective optimization need to be taken in the presence of trade-offs between two or more conflicting objectives. Besides, there exists a (possibly infinite) number of Pareto optimal solutions, and none of the objective functions can be improved in value without degrading some of the other objective values. Then the general form, some applications of the multi-objective optimization approach in hazmat and multi-objective genetic algorithm are reviewed as below.

2.3.1 General Form of Multi-objective Optimization

The model of multi-objective programming (MOP) is basically the expansion of the single objective linear programming. The difference between them is that MOP can simultaneously address two or more than two objectives, whereas single objective programming only address one objective. The concept of MOP is vector optimization, namely $\max Z = [Z_1, Z_2, \dots \dots, Z_p]$which is a set of alternative solution, not a point which obtain in the single objective programming.

Take a general mathematical form as example, there are n variables, m constraints and p objectives, the form of multi-objective programming formulated as equation (2-1) to (2-3).

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$$\max Z(X_1, X_2, \ldots\ldots, X_n) = [Z_1(X_1, X_2, \ldots\ldots, X_n), \ldots\ldots, Z_p(X_1, X_2, \ldots\ldots, X_n)] \quad (2\text{-}1)$$

$$\text{s.t.} \sum_{j=1}^{n} a_{ij} X_j \geq b_i, \ \ i = 1,2, \ldots\ldots, m \quad (2\text{-}2)$$

$$X_j \geq 0, \mathrm{j} = 1,2, \ldots\ldots, \mathrm{n} \quad (2\text{-}3)$$

$Z_1, Z_2, \ldots\ldots, Z_p$ represent p single objective function, $Z(X_1, X_2, \ldots\ldots, X_n)$ represent the objective function. Given vector Z optimization situation, obtain one or several solutions. A solution $X = (X_1, X_2, \ldots\ldots, X_n)^T$ is a vector of n decision variables which is the non-dominated solution (Pareto solution, Pareto optimal, Pareto efficient or non-inferior) of the multiple objective programming. Given the inherent resource allocation, non-dominated solution means that one feasible solution which have none of the value of objective functions can be improved without reducing any the other objective values.

For two solution x and y, x is said to dominate y if and only if equation (2-4) is satisfied in a maximum problem, which represents that solution x is no worse than solution y in all objectives, and strictly better than y in at least one variable

$$\mathrm{i} \in (1,2, \ldots, \mathrm{N}), F_i(x) \geq F_i(y), and\ j \in (1,2, \ldots, N), F_j(x) \geq F_j(y) \quad (2\text{-}4)$$

In Deb's research, Figure 2.5 presented that Pareto-optimal set is continuous curves. It could have four scenarios with two objectives. Each objective can be minimized or maximized, so the objectives combinations are min-min, min-max, max-min, and max-max. The gray region means the feasible solution region, and the black continuous curves are the Pareto optimal sets (non-dominated solutions). (Deb, 2001)

Given the same search space, in the top-left of figure 2.5, the task is to minimize both objectives f1 and f2. The black continuous curves mark the Pareto-optimal solution set. If f1 is to be minimized and f2 is to be maximized, the result of Pareto-optimal set

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is different, which is shown in the top-right of figure 2.5. Similarly, the Pareto-optimal sets for two other cases— (maximizing f1, minimizing f2) and (maximizing f1, maximizing f2)—are shown in the bottom-left and bottom-right of figure 2.5, respectively. In any case, the Pareto-optimal set always consists of solutions from a particular edge of the feasible search region.

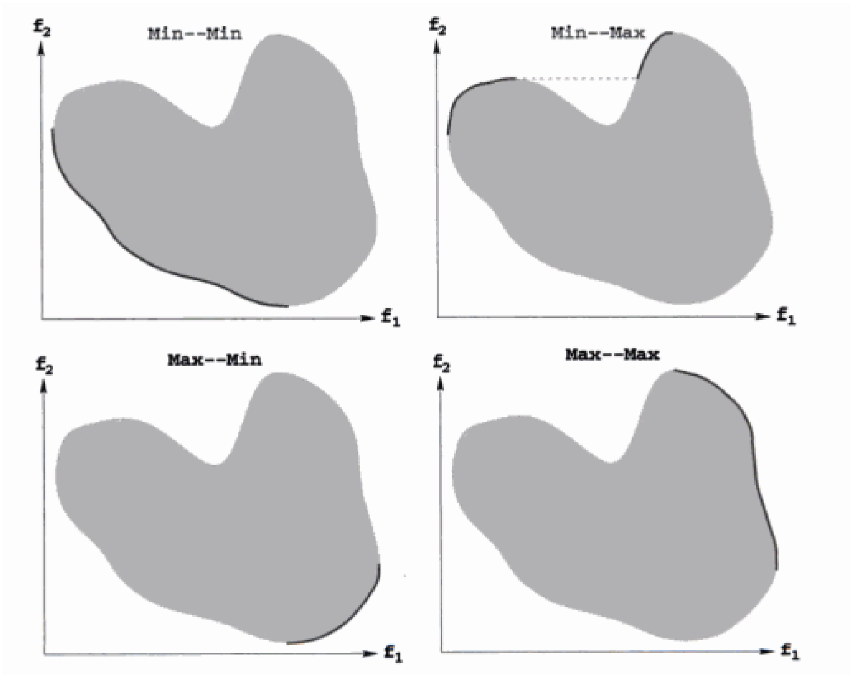

Figure 2.5 Pareto-optimal set with continuous curves (Deb, 2001)

Figure 2.6 presents the procedure of the principles in an ideal multi-objective optimization. In Step 1 (vertically downwards), multiple trade-off solutions are found (Pareto optimal). Moreover, the case of single-objective optimization is completed in this step, because the optimal solution is only one. Thus, it will not enter next step. In Step 2 (horizontally, towards the right), the higher-level information is provided to choose one of the trade-off solutions. In the case of multi-objective optimization with multiple global optimal needs to take both steps to first find all or many of the global optimal and then to choose one from them by using the higher-level information in some problems.

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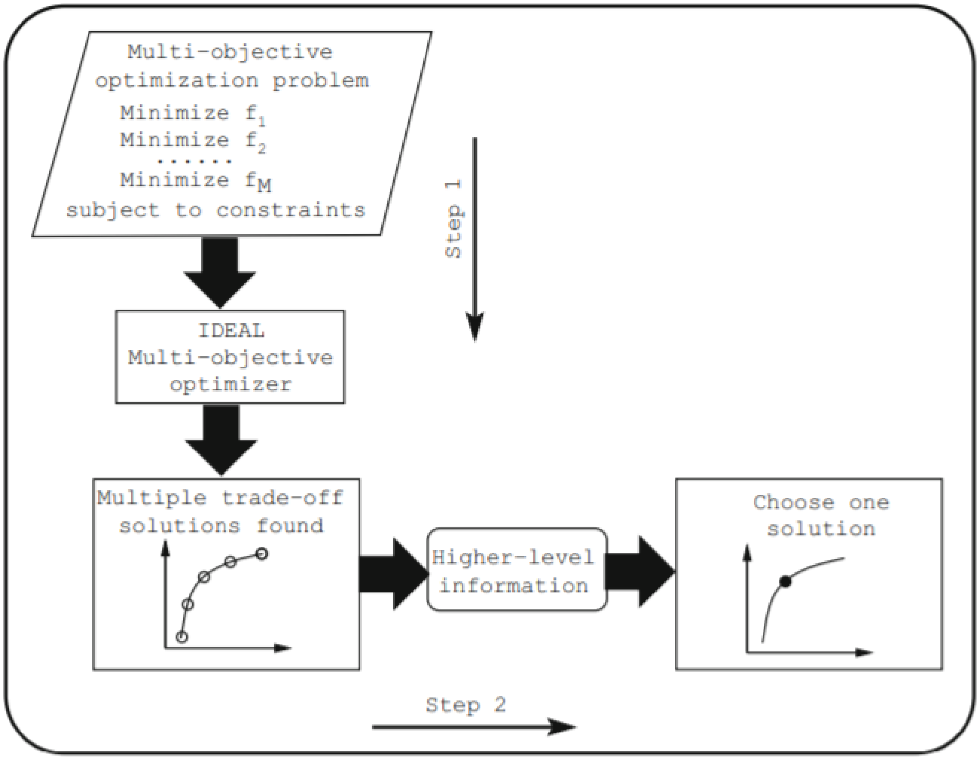

Figure 2.6 Procedure of an ideal multi-objective optimization

Source: Multi-objective optimization (Deb, 2014)

2.3.2 Application of Multiple Objective Approach in Hazmat Management

The route planning of hazmat transportation is a multi-objective problem because of different concerns from all parties. The government hopes that the transportation route could be far away to the densely populated area to eliminate citizen's fear, which means risk consideration. On the other hand, the carriers hope that transportation cost could be the least, which means cost consideration. However, the two factors often exist conflict during simultaneously adopting as consideration objectives, so it be regarded as multi-objective problem. Thus, a great number of researchers mainly concerned with minimum cost and minimum risk simultaneously, some researchers concerned with other objectives. In this section, multiple objective methodologies and objectives applied in the issues are summarized in following Table 2-2.

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Table 2-2 Multiple objective approach in hazmat route

Reference	Authors& Year	Methodology	Objectives
A multi-objective programming model for locating treatment sites and routing hazardous wastes	(Zografos & Davis, 1989)	Mathematical formulation	Risk Risk of special population categories Travel time Property damages
Multi-objective routing of hazardous materials in stochastic network	(Wijeratne et al., 1993)	Stochastic Multi-objective Shortest Path	Travel time Rates of occurrence for accidents resulting in a release of hazardous material Operating cost
A model to assess risk, equity and efficiency in facility location and transportation	(Current & Ratick, 1995)	Weighting method	Total transportation risk Total facility risk Maximum transport exposure Total operating costs
A multi-objective programming model for locating treatment sites and routing hazardous wastes	(Giannikos, 1998)	Goal programming	Total operating cost Total perceived risk Distribution of risk among population centres Equitable distribution of the disutility caused by the operation of the treatment facilities
A multi-objective geographic information system for route selection of	(Chen et al., 2008)	Multi-objective GIS	Travel time Transportation risk The exposed population

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Reference	**Authors& Year**	**Methodology**	**Objectives**
nuclear waste transport			
Multi-objective route planning for dangerous goods using compromise programming	(R. Li & Leung, 2011)	compromise programming	Travel time, accident probability, road users at risk, off-road population at risk, special population at risk and expected damage on economy
A multi-objective model for the hazardous materials transportation problem based on lane reservation.	(Zhou et al., 2012)	ε-constraint	Impact on the normal traffic Population exposure and the probability of hazardous material accident
A multi-objective mathematical model for the industrial hazardous waste location-routing problem	(Samanlioglu, 2013)	The lexicographic weighted Tchebycheff implementation	Total cost Total transportation risk related to the population exposure along transportation routes of hazardous materials and waste residues Total risk for the population around treatment and disposal centers (site risk)

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Reference	Authors& Year	Methodology	Objectives
A genetic algorithm for multi-objective dangerous goods route planning	(R. Li et al., 2013)	Genetic algorithm	Travel time, accident probability, on-road exposure risk, off-road exposure risk, people with special needs at risk, negative impact on economy, and emergency response capabilities
Optimization for Hazardous Materials Road Transportation Based on Multi-objective Method	(X. Li & Jiang, 2013)	Dijkstra Algorithm, AHP	Transportation risk Distance Cost
Cost and risk aggregation in multi-objective route planning for hazardous materials transportation—A neuro-fuzzy and artificial bee colony approach	(Pamučar et al., 2016)	Adaptive neuro fuzzy inference system, Artificial bee colony algorithm, Dijkstra's algorithm	Operating cost Emergency response Risk associated with the environment Risk of an accident The Consequences of an accident Risk associated with infrastructure Risk of terror attack/hijack
An Improved Multi-Objective Programming with Augmented ε-Constraint Method for Hazardous Waste	(Yu & Solvang, 2016)	Augmented ε-constraint method	Facility risk and transportation risk fixed facility costs, processing costs of hazardous waste, and transportation costs

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Reference	Authors& Year	Methodology	Objectives
Location-Routing Problems			
Using metaheuristic algorithms to solve a multi-objective industrial hazardous waste location-routing problem considering incompatible waste types	(Rabbani et al., 2018)	NSGA-II, Multi-Objective Particle Swarm Optimization	Total site risk Transportation cost Transportation risk

2.4 Genetic Algorithm

Multi-objective problem always considers two or more than two objectives, but most of methods still use general single-objective optimization by regarding one of them as an objective function and the other objectives as constraint. The usual process is to normalize the objectives and give weight depend on their importance in the objective function such as like weighting method. However, it is troublesome for decision makers to express their preferences for various objectives in an abstract and specific circumstance without earlier information (Zionts & Wallenius, 1976). But in Genetic Algorithm (GA) application, the decision makers do not need to decide the objectives priority, preferences and weight in main objective function.

In 1975, Holland (1975) first proposed Genetic Algorithm (GA) which is used for finding optimized solutions to deal with problems based on the theory of natural selection and evolutionary biology. It is not only a heuristic search method, but also a

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branch of Artificial Intelligent. Moreover, GA is suitable and excellent to address a wide range of real-world problems through large and complex data sets. Even more, it could find reasonable and optimal solutions within quick time. A genetic algorithm optimization framework was illustrated in Figure 2.7.

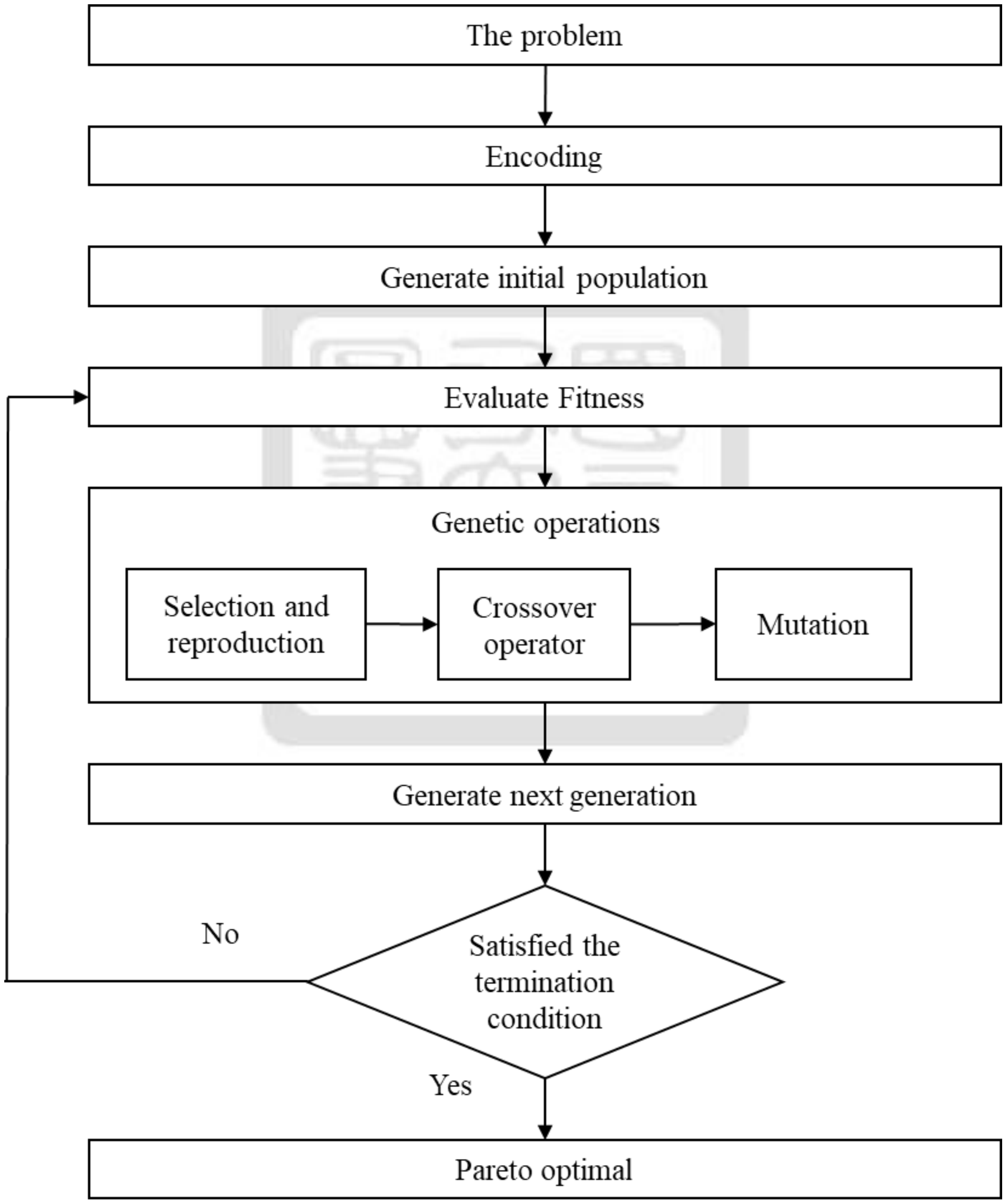

Figure 2.7 Genetic algorithm framework

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1. Encoding:

   Encoding represents that we need to transfer the problem to program language such as binary digit (0,1). Then various presenting method has been raised to evaluate it. Thus, the encoding code corresponds to genes, and genes are also the basic unit of chromosome. In other words, we encode the genes in a chromosome. Last, the final solution vector is selected by GA among the chromosomes.

2. Generate Initial Population:

   A set of chromosomes construct initial population. Each chromosome is a solution to the problem that research want to solve. The constructive methods are various such as random walk and heuristic initialization. Further the size of population could cause the solving efficiency. Large size of population has higher probability and longer computing time to find the optimal solution while small size of population could converge too early for finding the optimal solution.

3. Evaluate Fitness:

   The fitness function could determine whether a chromosome has the ability to compete with other chromosomes. The fitness function gives each chromosome fitness score. In general, higher fitness score has higher probability to be selected to the next generation. Thus, excellent chromosome could be reserved.

4. Selection and Reproduction:

   There are various selection methods to select the chromosome with higher fitness scores, and the Roulette Wheel (or fitness proportional) selection is traditional selection method. This proportionally allocates each chromosome a probability of being selected depend on fitness score. Then the chromosomes with higher fitness score have more chance to be selected for reproduction.

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5. Crossover Operator:

   The phase in a genetic algorithm is core mechanism. For each chromosome could be mated by another one to generate offspring. These are created by exchanging the genes of parents among themselves until the crossover point is matched.

6. Mutation:

   During period of forming new offspring, a mutation with a low random probability happen in some of their genes. There are two goals, one is building the new solving possible to keep diversity. The other one is to reimport the lost information in the evaluated process.

7. Termination Condition:

   General termination conditions have three situation and means that reach the optimal solution.

   (1) Setting numbers of generation: This method could stop the solving process when fit the numbers of generation and control the computing time, but might not find the best optimal solution or could not converge.

   (2) Reach the target fitness score: Reaching the target fitness score setting is to find the optimal solution.

   (3) Convergence: It causes evolution to halt because precisely every fitness score of chromosomes in the population is identical meaning convergence and find the optimal solution.

2.4.1 Multi-objective Genetic Algorithm (MOGA)

Konak et al. (Konak et al., 2006) presented multi-objective GA (MOGA) and summarized a list of well-known multi-objective GA. Research focused on their components and the distinguished issues encountered while implementing multi-

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objective GA. The main goal is to compare the evaluation of different multiple objective genetic algorithm. Table 2-3 highlights a list of representative multi-objective GA with their characteristics and authors. Compared with single objective GA, multi-objective GA needs to face the conflicting problem and satisfy three claims as our literature knowledge. 1. Assess and select properly the Pareto optimal solution and reproduce to next population. 2. Keep the chromosomes set and Pareto optimal solution in diversity. 3. Construct the effective mechanism with crossover, mutation and reproduction for forming Pareto optimal solution.

Table 2-3 A list of representative multi-objective GA

Generation	Characteristics	Algorithm	Authors
I	Pareto sorting	VEGA	(Schaffer, 1985)
II	Pareto sorting and keeping diversity	MOGA	(Fonseca & Fleming, 1993)
III	Multi-objective function with weight and elitism	RWGA AWGA SPEA-II NSGA-II I-AWGA	(Ishibuchi & Murata, 1998) (Gen & Cheng, 2000) (Zitzler et al., 2001) (Deb et al., 2002) (Gen, Cheng, & Lin, 2008)

Schaffer (Schaffer, 1985) proposed the first multi-objective GA, called vector evaluated GA (VEGA). The procedure is introduced as below. Step 1, it divided population P_t into K equal sized sub-populations: $P_1, P_2, \dots, P_k$. Then, each solution in sub-population P_i is assigned a fitness value based on objective function Z_i. Step 2, combine all sub-populations. Step 3, solutions P_{t+1} are selected from these sub-populations by proportional selection for crossover and mutation. Step 4, satisfy the

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terminal condition or return to Step 1. But the final Pareto solutions from the model cannot uniformly satisfy the conflicting objectives.

Deb et al. (Deb et al., 2002) introduced the elitist non-dominated sorting genetic algorithm Ⅱ (NSGA Ⅱ) in order to modify a number of criticisms of the non-dominated sorting genetic algorithm (NSGA) (Srinivas & Deb, 1994). Compared with NSGA, there are three main improvements for more effective solutions. That is fast non-dominated sorting approach, elitism strategy and crowded comparison operation. The procedure of fitness computation and choosing are depicted as Figure 2.8.

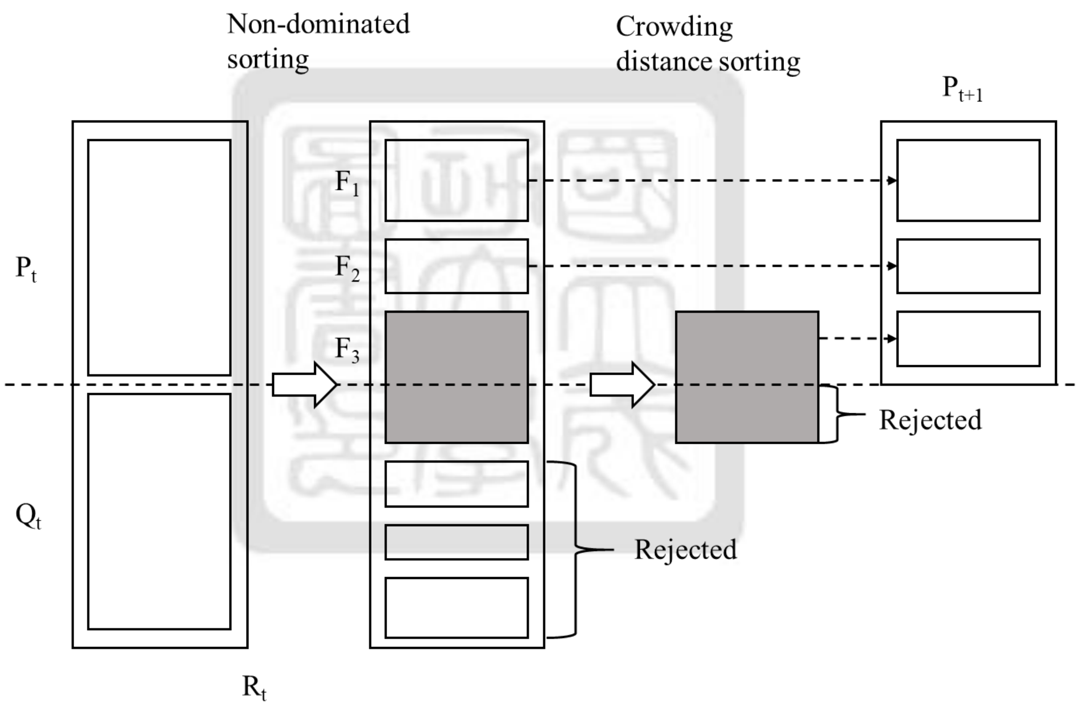

Figure 2.8 NSGA II fitness computation and select procedure

A more comprehensive steps are presented.

For t=0

Step 1: A random parent population P_0 of size N is created

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Step 2: The child population Q_0 of size *N* is created by crossover and mutation procedure from P_0

For t≥ 1

Step 3: Combine parent and children population as $R_t = P_t \cup Q_t$. R_t is size 2*N*.

Step 4: Sorting the non-dominated fronts $F_1, F_2, \ldots, F_k$ in R_t as figure 2.9

Step 5 : Calculate crowding distance of the sorted solutions in all the fronts F_i.

Step 6 : Create P_{t+1} as follows:

Case 1: If $|P_{t+1}| + |F_i| \leq$ N, then set $P_{t+1} = P_{t+1} \cup F_i$.

Case 2: If $|P_{t+1}| + |F_i| >$ N, then add the least crowded $\mathrm{N} - |P_{t+1}|$ solutions from F_i to P_{t+1}.

Step 7: Use tournament selection based on the crowding distance to select parents from P_{t+1}. Then apply crossover and mutation to P_{t+1} to create child population Q_{t+1} of size *N*.

Step 8: Set t = t + 1, and go to Step 3.

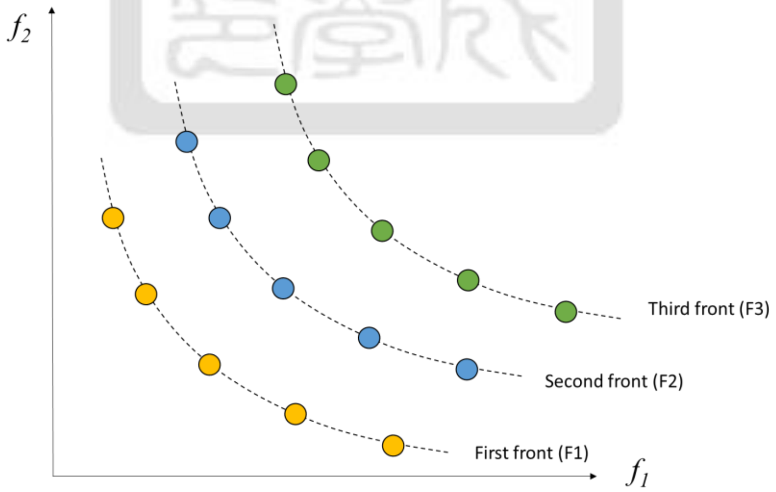

Figure 2.9 Fast non-dominated sorting approach

2.5 Real Time Hazmat Route Problem

In a real environment, many components should be dynamic including time-

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dependent and spatial characteristics. Components such as driver behavior, status of chemical truck, hazmat, and route segment, can cause different traffic conditions and different risk/cost levels. Thus, if the components are not dynamic, the results also could not meet real traffic conditions even though the proposed model could decide precisely optimal route. In other words, the more accurate the data is, the more effective the results are. Thus, due to the influence of rapidly changing traffic conditions, the real time optimal route could timely mitigate risk and decrease cost for daily hazmat transporting on roads (Giglio et al., 2004).

2.5.1 Static and Dynamic Components

More and more cities tend to develop “smart city” (Chourabi et al., 2012), which implies a growing number of real time traffic data are generated under the innovative communication technology such as sensors, 5G, IoT and communication equipment (Zanella et al., 2014). For decision maker, that not only assists in more effective traffic management but also could provide more precise decisions for hazmat transportation (Liu et al., 2012). In fact, the objectives of model include static and dynamic components. The Table 2-4 shows main factors affecting the risk and cost in hazmat transportation. Therefore, the most of sources of static components could be collected from government open platform, but the dynamic components are hardly observed because of lacking various technologies to collect. Thus, these real time traffic data are collected by traffic simulation software and past researches to closely meet real traffic conditions. (Giglio et al., 2004)

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Table 2-4 Factors affecting route risk and cost in hazmat transportation

Factors	Static components	Dynamic components
Driver	Age, training condition	Physiological state Mental state Roads familiarity
Chemical Truck	Periodic examination	Components conditions Speed
Hazmat	Type of Hazmat at start of route	Chemical and physical conditions
Route segment	Length of road Type of road Residents Prohibited route for hazmat transportation	Traffic flow Travel time Not fixed population on the route Weather condition

2.5.2 Applications of Real Time Hazmat Route Problem

Toumazis and Kwon first proposed a new method for hazmat routing on time-dependent networks based on conditional value at risk (CVaR). CVaR is generally used to deal with financial institutions for portfolio optimization, but this research considers CVaR as the main risk objective in optimization of hazmat transportation network. They also extended the static model to the dynamic model by regarding accident probabilities and accident consequences as time-dependent components. That is, the probability of the components in the links mainly depend on the traffic conditions. Further, they computed the accident probabilities based on Poisson distribution which is suitable for rare event like hazmat accidents. (Toumazis & Kwon, 2013)

Faghih-Roohi et al. also proposed a dynamic model for hazmat transportation routing and scheduling with conditional value at risk (CVaR). CVaR model was prove as a flexible, suitable, efficient method for hazmat transportation. The design of experiment in this research is to input several scenarios including different sort of

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hazmat and time schedules. First, find the lowest risk of sort of hazmat to transport, then compute the other hazmat risk and update the optimal route again. Repeat above process until every hazmat finish the transporting tasks. (Faghih-Roohi et al., 2016)

Qu et al. used a new methodology for addressing dynamic routing optimization of the chemical hazmat transportation. The process is divided into four major stages: (i) information collection and preparation; (ii) modeling and solving individual and system routing models; (iii) reactive routing optimization under uncertainties; and (iv) trade-off study for potential shipping delays. A novel mixed integer linear programming (MILP) model is developed to determine the optimal shipping path via minimizing the transportation risk, then the routing model consists two parts: the individual and system routing models. The strategy of this research considers updating the optimal route when uncertainties occur. The uncertainties refer to change of weather and the occurrence of incidents. Moreover, if some shipping time violates the time limits, optimal solutions subject to different allowable shipping time (AST) are iteratively identified, so that the relation between AST and the corresponding transportation risk can be figured out. (Qu et al., 2018)

2.6 Summary

As was mentioned in the previous sections, many models had been proposed to obtain optimal hazmat transportation route, but most of them deal with various problems by different approaches. All evaluated manner mainly considered two of the most important objectives – risk and cost, which usually have conflicting situation. Thus, they applied diverse multi-objective optimization to solve dilemma situation. Moreover, because some of multi-objective optimization have the requirement of prior preference, the weight needs to be collected by experts through analytic hierarchy

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process (AHP) or other methods.

Dréo et al. (Dréo et al., 2006) had proposed, in MOP, there are two kinds of problems which cause ineffective solutions. First is “NP-difficult” whose computing time is too long to generate effective solutions. Second is “Global and Local optimum”, that is difficult to completely ensure that the solutions are the best. Therefore, this research constructs heuristic algorithm based on multi-objective genetic algorithm. With the ability of multi-objective genetic algorithm to search the global domain, the optimal solutions could be obtained within a reasonable time. (Sivanandam & Deepa, 2008) Especially in real time optimal route for hazmat transportation, it needs also more effective algorithm to deal with the complex network. This research aims at solving the hazmat transportation risk and cost objectives simultaneously and using NSGA-II to solve the real time route problem. The detailed description of the model formulation is discussed in the next chapter.

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CHAPTER 3 RESEARCH METHODOLOGY

As described in Chapter 1, the purpose of this research is to formulate a model for real time route optimization of hazmat transportation. Use real time multi-objective genetic algorithm to deal with the route planning problem and obtain Pareto optimal which also called real time optimal route with two objectives including minimum transportation risk and cost. Chapter 3 is organized as follows. Section 3.1 presents the conceptual framework. Section 3.2 presents the problem statement and the research assumptions of this research. Section 3.3 illustrates the research framework to describe the procedure of the methodology. Section 3.4 proposes and discusses the model formulation of problem. Section 3.5 discusses the solution algorithm applied in this problem.

3.1 Conceptual Framework

Most of research takes static components as objectives to develop optimal route for hazmat transportation. But in a real world, due to the influence of rapidly changing traffic conditions, many elements should be dynamic including time-dependent and spatial characteristic. Such as driver behavior, status of chemical truck, hazmat, and route segment, could cause different traffic conditions and different risk/cost levels. Thus, this research considers two objectives (risk, cost) with dynamic components, which concerns carrier and government points of view. Based on real time multi-objective genetic algorithm, we obtain real time optimal route that timely mitigate risk and decrease cost on roads (Giglio et al., 2004). We extend static model proposed by Liao et al. to dynamic model (Liao et al., 2017). In selecting the objectives, we do not consider the emergency response capability because it is static characters. The algorithm is also changed from MOGA to Real time-MOGA. The main conceptual

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framework is formulated in Figure 3.1.

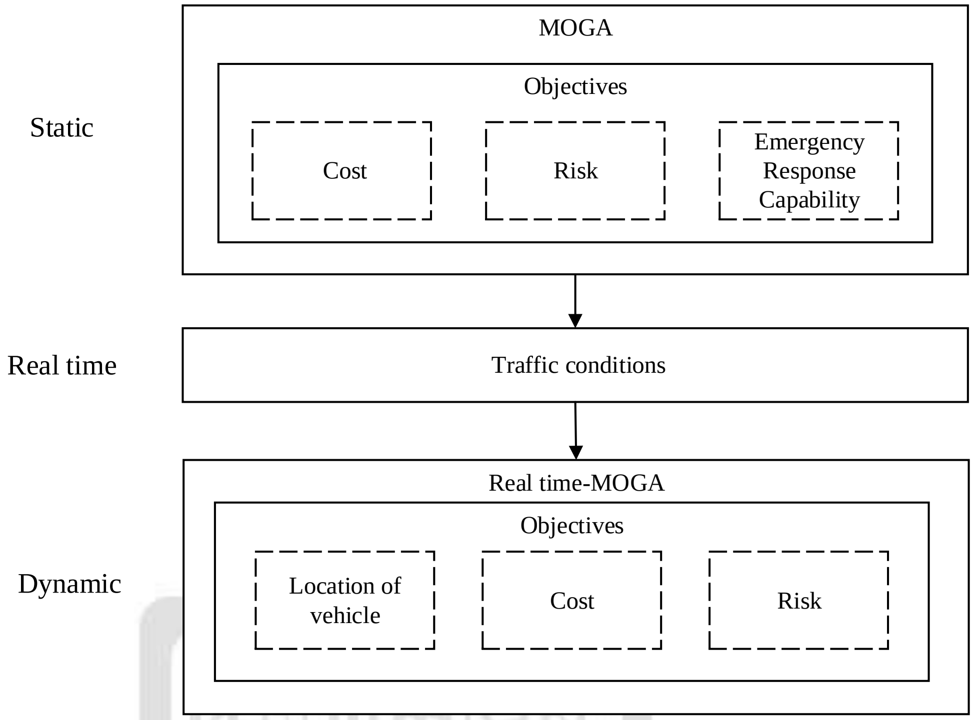

Figure 3.1 Conceptual framework

3.2 Problem Statement and Research Assumptions

In this research, we define time as *t*, which means the planning horizon is discretized into small time interval, such as one, two or five minutes. The model is formulated as follows: Given a hazmat transportation network G= (*N*; *A)*, where *N* is the set of nodes and *A* is the set of directed links. Each link (i , j) is associated with transportation risk (R_{ij}^t), and transportation cost (C_{ij}^t). In this network, for a single-trip risk and cost optimization problem, we define that the origin node is *s*, the destination is *i* and the others are intermediate nodes. Each route belongs to a solution set, which has the total transportation risk of solution l of route set p ($TR_p^{l,t}$) and the total transportation cost of solution l of route set p ($TC_p^{l,t}$). Besides, we update the vehicle location and the objectives within particular time interval to generate next round's parameter including O-D pair, risk and cost.

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According to above description, the assumptions and framework of this research are described as follows:

1. While conducting the experiment, only single hazmat with highest risk level of hazmat is considered. Moreover, the problem of fleet vehicles is not under consideration.
2. Updating optimal hazmat route depends on vehicle location and particular time interval.
3. Due to insufficient hazmat transportation data in Taiwan, we set the parameter in Poisson distribution based on the definition proposed by Toumazis and Kwon (2013).
4. Only two types of dynamic components (travel time and traffic volume) are considered in real traffic conditions. The population density of every area changes during the day is not under consideration.

3.3 Research Framework

The research framework of real time route optimization for hazmat transportation network planning is presented in Figure 3.2. The framework includes four main parts: Objectives setting, applying dynamic components in real time-MOGA, non-dominated solutions and optimal decision making. The details of each part are described as follows:

1. Objectives setting: As previous reviewed in Section 2.2, the hazmat transportation problem usually takes transportation risk and transportation cost and into consideration. Further, the risk of link is defined as "danger circle", which includes probability and consequence of an accident of the link at different time interval.

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Then, the cost is defined as operator cost, travel time and length of the link at different time interval. In this research, the objectives definition of risk, cost, vehicle location are defined as following Section 3.4.1 and be calculated on each links.

2. Applying dynamic components in real time-MOGA: For the real time optimal route of hazmat transportation, we update vehicle location, the two objectives (risk, cost) with dynamic components under particular time interval. Then we also identify the vehicle location en route to renew the O-D pair. Because we have to consider simultaneously the minimum risk and cost objectives in route planning, we proposed the real time-MOGA to deal with the dilemma situation.
3. Non-dominated solutions: We solve the non-dominated solutions (optimal route) by a real time multi-objective genetic algorithm. The core of real time-MOGA is NSGA-II. Section 2.4.1 shows the basic concept and flowchart of NSGA-II. The more detailed flow chart about real time multi-objective genetic algorithms are presented in Figure 3.5. Under the particular time interval, if the hazmat vehicle has not arrived at the final destination yet, the procedure turns back to step 2 to update the dynamic components.
4. Optimal decision making: For each single O-D pair, we pick the final transporting route form the non-dominated solution generated by the real time-MOGA as suggested hazmat transportation routes. As for multiple O-D pairs, we proposed a strategy to balance the transportation risk on our transporting network. As the result, the optimal route network for hazmat transportation has gradually been formed.

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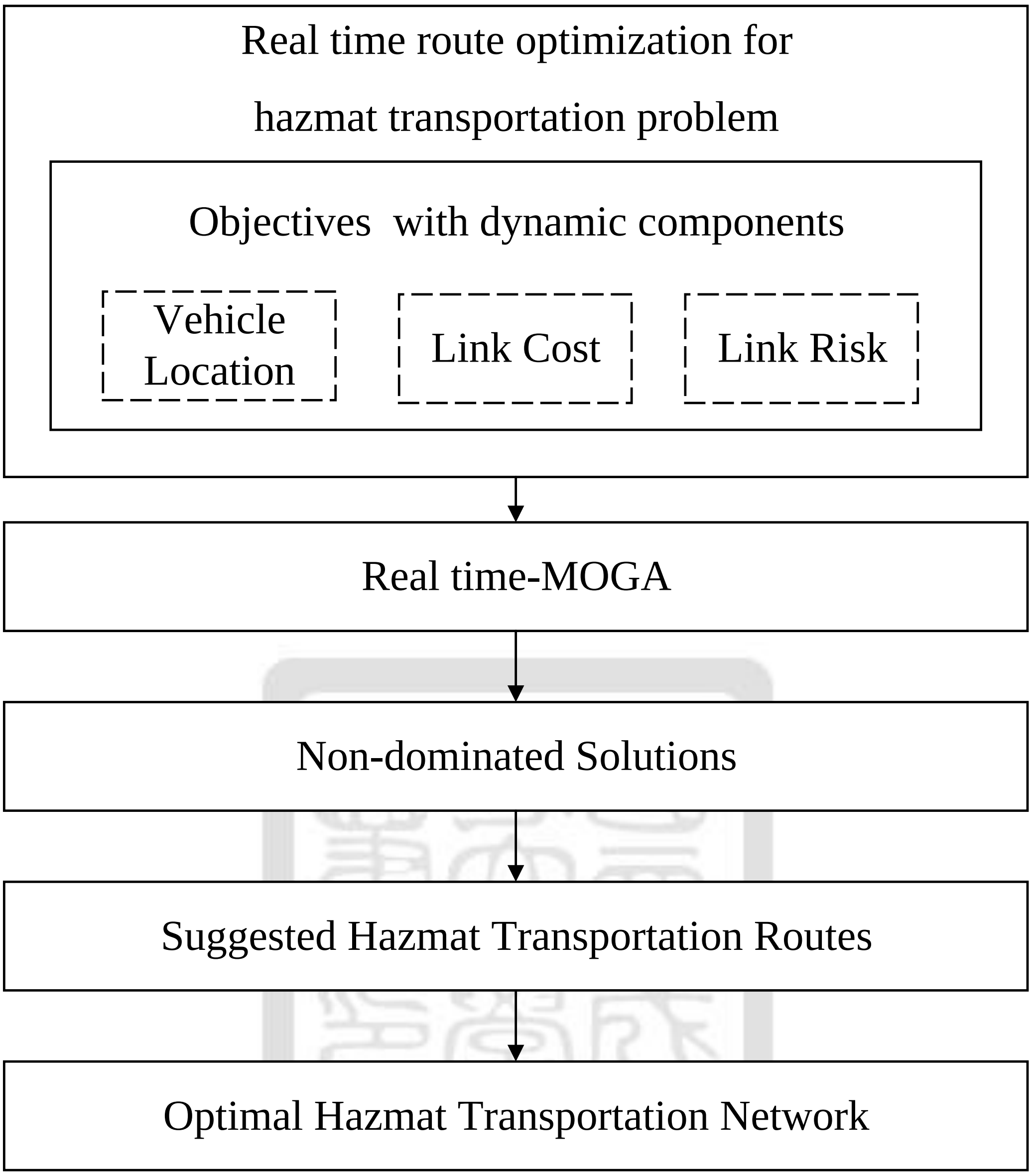

Figure 3.2 Research framework

3.4 Model Formulation

This section shows descriptions and definitions of criteria. This research develops real time multi-objective genetic algorithm models with two conflicting objectives including minimum total cost, minimum total risk. The definitions of risk and cost in each link are discussed in Section 3.4.1. The summary of notations and model formulations are listed in Section 3.4.2.

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3.4.1 Definition of Criteria

Particular time interval and vehicle location

We set time *t* as particular time interval of hazmat transporting. Two conditions are addressed. First, if the next node of vehicle location at time *t* is not destination, we need to update optimal route with real time-MOGA as Figure 3.3. Second, if the next node of vehicle location at time *t* is destination, we do not need to update optimal route as Figure 3.4. When vehicle arrive destination, we terminate the procedure of hazmat transporting.

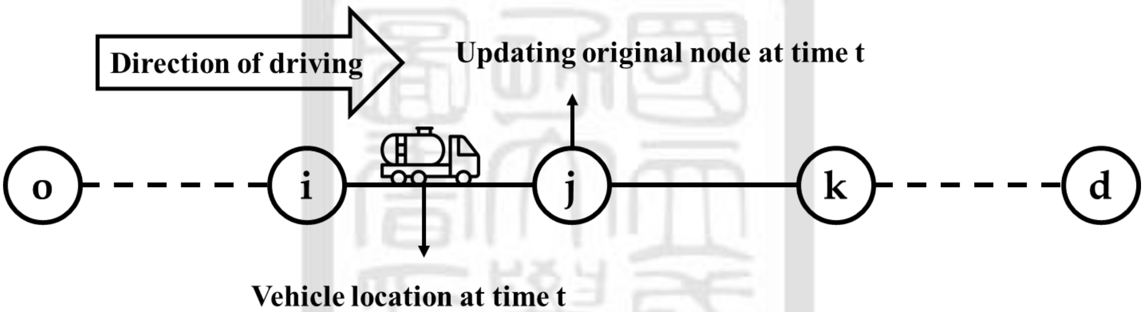

Figure 3.3 Condition of updating optimal route

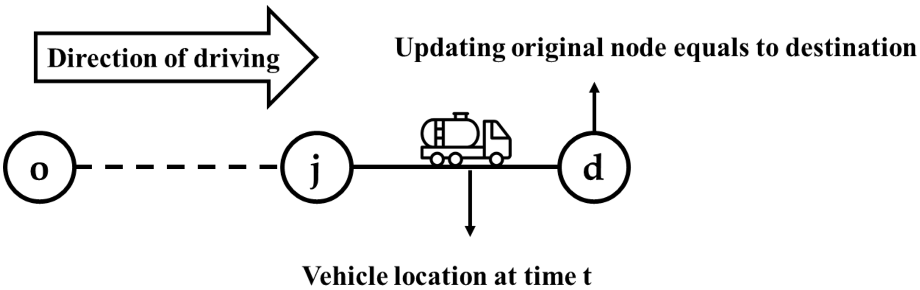

Figure 3.4 Condition of terminating updating optimal route

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Link cost

For each link on the network, this research adds *t* as the time characteristic which depends on vehicle location and defined transportation cost as travel time (C_{ij}^{t}). Compared with past static researches, we select the travel time evaluated by link length and travel velocity as the operating cost as equation (3-1). Then with particular time interval, the travel velocity is obtained by the result of traffic simulation software (DynaTAIWAN), and the link length is measured by Google Map. The link cost is evaluated as follow:

Time-dependent link cost C_{ij}^{t} = *Time-dependent link travel time* =

Link length (L_{ij}) / *Time-dependent link travel velocity* (V_{ij}^{t}) $\quad (\forall i, j \in A,\ \forall t)$, (3-1)

The definition of transportation cost for link (i, j) includes link length and travel velocity of link at time interval *t*.

Link risk

In Section 2.2, various risk models had been proposed to assess the risk on the hazmat transporting route. In this research, we adopt the concept of risk assessment proposed by Erkut and Verter (Erkut & Verter, 1998) and the accident probability and accident consequences proposed by (Toumazis & Kwon, 2013). For each link on the network, the time-dependent accident probability (P_{ij}^{t}) was defined as a Poisson distribution whose parameter is presented as u_{ij}^{t}. Parameter u_{ij}^{t} can be measured based on the information derived from road conditions such as accident rates, length of link and hourly traffic volume with particular time interval. As for time-dependent link accident consequences can be measured based on radius of the exposure region, population density in the neighborhood of link, length of link and hourly traffic volume with particular time interval. Radius of the exposure region is estimated by hazard modeling program, ALOHA 5.4.4. As mentioned above, the main reason we adopt

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hourly traffic volume as time-dependent parameter is that we would like to avoid large-scale vehicle exposure when accident happens. The link risk is evaluated as follow:

Time-dependent link risk $(R_{ij}^{t}) =$ $(\forall i, j \in A,\ \forall t),$ (3-2)

Time-dependent link accident probability (P_{ij}^{t})

**Time-dependent link accident consequences* (AC_{ij}^{t})

$u_{ij}^{t} =$ $(\forall i, j \in A,\ \forall t),$ (3-3)

*(Hazmat accident rate per mile/vehicle) * (Length of link)* (Hourly traffic volume at time t)*

$= (3.19922 * 10^{-7}) * L_{ij} * TV_{ij}^{t}$

$n_{ij}^{t} \sim Poisson\ (u_{ij}^{t})$ $(\forall i, j \in A,\ \forall t),$ (3-4)

$P_{ij}^{t} = 1 - pr\{No\ accident\ occurs\}$ $(\forall i, j \in A,\ \forall t),$ (3-5)

$$= 1 - \frac{\left(u_{ij}^{t}\right)^{n_{ij}^{t}}}{n_{ij}^{t}!} * e^{-u_{ij}^{t}}\ ,\ n_{ij}^{t} = 0$$

Time-dependent link accident consequences $(AC_{ij}^{t}) =$ $(\forall i, j \in A,\ \forall t),$ (3-6)

$$w_1 * \left(\pi * r_{ij}^{2} * D_{ij}\right) + w_2 * \frac{(2 * r_{ij} * TV_{ij}^{t})}{L_{ij}}$$

The definition of transportation risk for link (i, j) includes accident probabilities and accident consequences of link at time interval *t*. Equation (3-3) is the Poisson parameter evaluated by accident rate, length of link and traffic volume at time interval *t*. Equation (3-4) represents that the accident probabilities is subjected to Poisson distribution. Equation (3-5) is the definition of accident consequences evaluated by average radius of the hazmat exposure region, population density, length of link and traffic volume at time interval *t*. Note here that the hazmat accident rate per mile/vehicle is based on Comparative Risks of Hazardous Materials and Non-Hazardous Materials Truck Shipment Accidents/Incidents (2001) from Federal Motor Carrier Safety Administration.

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3.4.2 Formulation

This section discusses the model formulation of the real time multi-objective hazmat transportation routing problem. Two objectives are considered including cost and risk with particular time interval. The notations of the formulation are listed in Table 3-1.

Table 3-1 Notations of the model formulation

Notation	**Definition**
Set	
$G = (N, A)$	A set of nodes N and a set of links A build up the network.
M	The set of intermediate nodes.
Decision variables	
X_{ij}^{t}	If link (i,j) is selected into the route, X_{ij}^{t}=1 at time interval t Otherwise, X_{ij}^{t}=0 (time: t)
Parameters	
TR_{p}^{lt}	The total transportation risk of alternative p of route l at time interval t
TC_{p}^{lt}	The total transportation cost of alternative p of route l at time interval t
R_{ij}^{t}	The risk of link (i, j) at time interval t
C_{ij}^{t}	The cost of link (i, j) at time interval t
$\overline{R_{ij}^{t}}$	Standardization of the risk of link (i, j) at time interval t
$\overline{C_{ij}^{t}}$	Standardization of the cost of link (i, j) at time interval t
V_{ij}^{t}	The travel velocity of link (i, j) at time interval t
L_{ij}	The length of link (i, j)

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P_{ij}^t	Accident probabilities on link (*i, j*) at time interval *t*
AC_{ij}^t	The accident consequences of link (*i, j*) at time interval *t*
u_{ij}^t	The parameter in Poisson distribution
n_{ij}^t	The number of hazmat accidents of link (*i, j*) at time interval *t*
TV_{ij}^t	The hourly traffic volume of link (*i, j*) at time interval *t*
r_{ij}	The average radius of the exposure region on link (*i, j*)
D_{ij}	The population density in the neighborhood of arc (*i, j*)
AR_{ij}	The hazmat accident rate of link (*i, j*)
w_1	The weight of population density
w_2	The weight of traffic volume

Objective function	
Risk	
Min $TR_p^{lt} = \sum_{i \in N} \sum_{j \in N} \overline{R_{ij}^t} \times X_{ij}^t$	(3-7)
Cost	
Min $TC_p^{lt} = \sum_{i \in N} \sum_{j \in N} \overline{C_{ij}^t} \times X_{ij}^t$	(3-8)
Subject to	
$\overline{C_{ij}^t} = \frac{C_{ij}^t}{Max(C_{ij}^t)}$	(3-9)
$\overline{R_{ij}^t} = \frac{R_{ij}^t}{Max(R_{ij}^t)}$	(3-10)
$\sum_j X_{ij}^t - \sum_j X_{ji}^t = \begin{cases} 1 & \forall i \in s \\ -1 & \forall i \in i \\ 0 & otherwise \end{cases}$	(3-11)
$X_{ij}^t \geq 1 \quad \forall (i,j) \in A$	(3-12)

Two objectives are described in equation (3-7) and (3-8). Equation (3-7) minimize

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the total transportation risk of solution l of route p at time t. Equation (3-8) minimize the total transportation cost of solution l of route p at time t. In order to address different unit simultaneously, it is needed to standardize the two considered objectives and presented in (3-9) and (3-10). Each link of calculation value divided by the maximum of all of the links is the chosen standardized procedure. Last equations (3-11) and (3-12) are flow conservation equations. Then based on the descriptions and definitions of transportation risk and transportation cost in this section, the solution algorithm is built in the next section.

3.5 Solution Algorithm

This section shows the overall model for real time route optimization for hazmat transportation. We adopt a real time multi-objective genetic algorithm with two conflicting objectives including minimum total transportation risk and cost. Then consider the time characteristic, so we update the two objectives and vehicle location under particular time interval. The procedure of model framework is presented as Figure 3.5.

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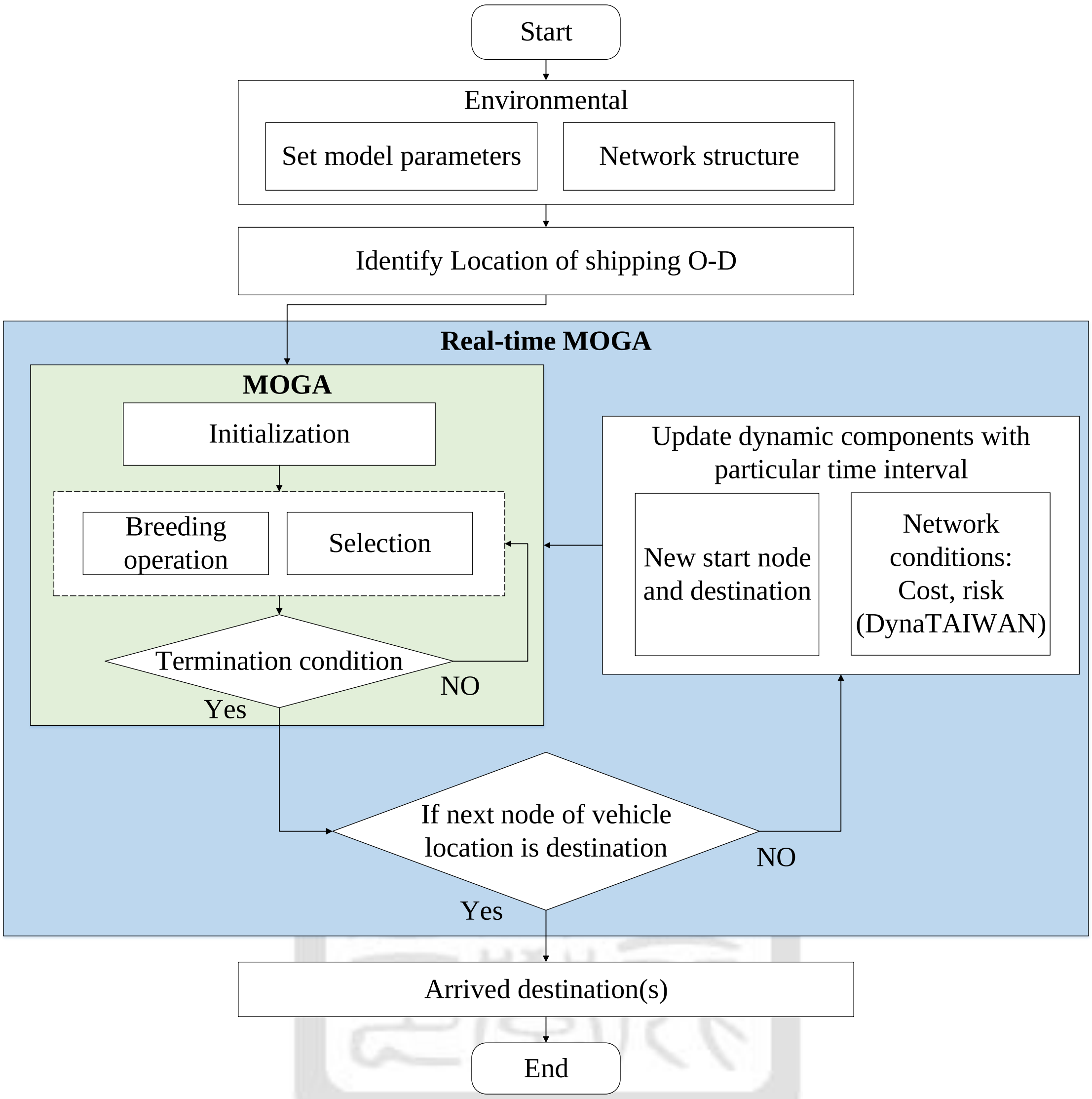

Figure 3.5 Model framework

First, we set up an experimental network, model parameters, and the O-D pair. Second, execute the multi-objective genetic algorithm with two objectives to obtain Pareto optimal solutions (optimal route). Third, we identify the optimal route and get vehicle location at particular time interval. If the next node of vehicle location is not destination, we update the dynamic components and new start node at particular time interval. Last, execute the second step until next node is destination. The detailed procedure of real-time MOGA is formulated in Section 3.5.1 and Section 3.5.2. Last, if

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the vehicle has not arrived the destination yet, trigger the particular time interval to return to second step. If the vehicle has arrived the destination, the procedure is terminated.

3.5.1 Procedure of Genetic Algorithm

This section provides basic procedure of genetic algorithm including encoding, generating initial population, fitness evaluation and offspring. Step1: Encoding of problem is depicted as Figure 3.6. Each of populations, we define the basic unit of chromosome as alternative routes and the genes in each chromosome as nodes. Step2: Generating initial population is depicted as Figure 3.7, we use the shortest path algorithm (Dijkstra algorithm) (Dijkstra, 1959) and random walk to generate initial population (P_0^t) with *n* alternative routes at time *t*. (Note that the network does not include negative edges) Step3: Fitness evaluation is depicted as Figure 3.7, the total transportation risk ($TR_p^{l,t}$) and cost ($TC_p^{l,t}$) of each alternative route are fitness evaluation.

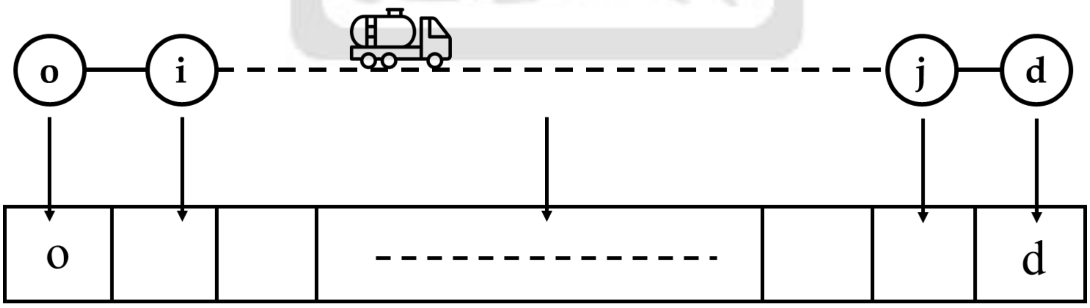

Figure 3.6 Encoding procedure

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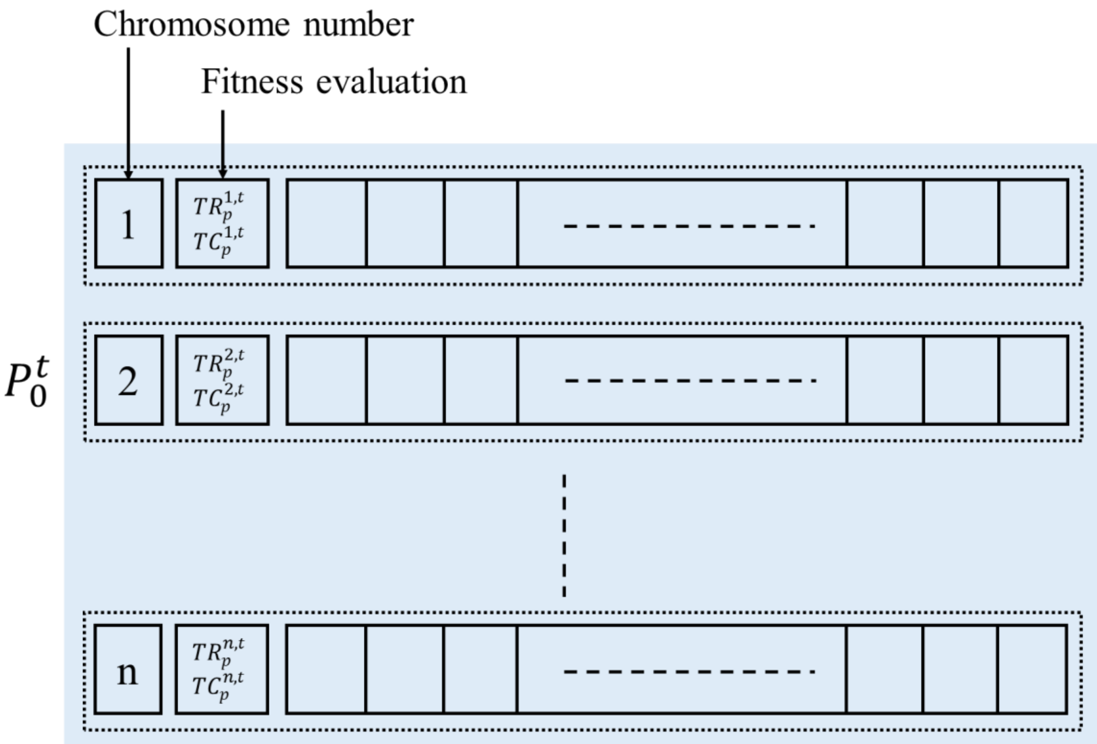

Figure 3.7 Generating initial population and fitness evaluation procedure

Step4: Generating of offspring is divided into three part: selection, crossover operator and mutation. 1. Selection follows the procedure NSGA-II. That is discussed in Section 3.5.2. 2. The crossover operator is that randomly pick two chromosomes up and crossover the routes at same genes (nodes) depending on setting the crossover rate, which is depicted as Figure 3.8. The mutation is that select a node randomly in the route besides origin and destination. Using shortest path algorithm to renew the route after the selected node, which is depicted as Figure 3.9.

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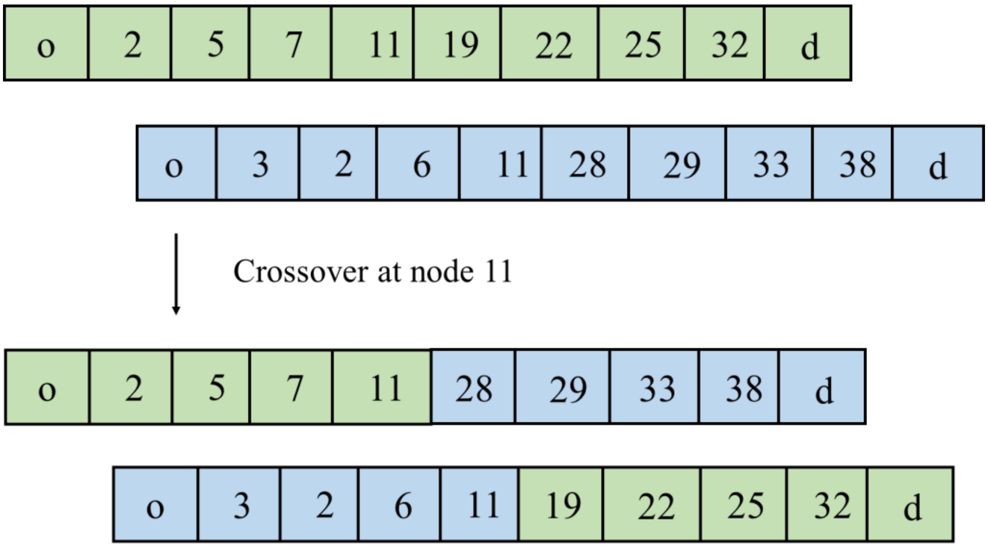

Figure 3.8 Crossover operator procedure

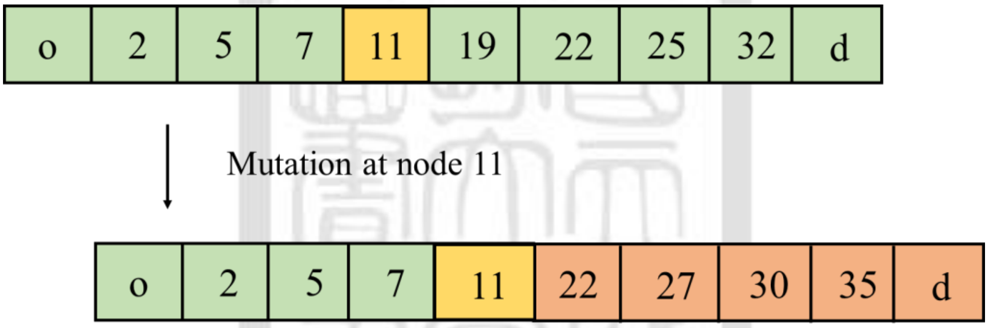

Figure 3.9 Mutation procedure

3.5.2 Procedure of NSGA-II

As mentioned in Section 3.5.1, NSGA Ⅱ (Non-dominated Sorting Genetic Algorithm Ⅱ) is one of multi-objective genetic algorithm. Using fast dominated sorting approach and crowding distance to select and duplicate the next generation is main characteristic. Thus, this section introduces the characteristic and solution procedure of NSGA-II.

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Fast non-dominated soring

Fast non-dominated soring is a method to sort all of the solutions (alternative routes) in population into respective front, whose procedure is showed in Figure 3.10. Then Figure 3.11 is a two-objective example. Each solution includes total transportation risk and cost of. The solutions (number 1) in 1st front (Pareto front) means that it cannot find any solution to dominate this solution, that is, no solutions exist in the space between the solution intersecting the x and y axis. If there are n solutions in the space, the ranking number of solutions is *n+1*. For example, the number 3 in Figure 3.11 means the solution belong to the third front. This solution is dominated by 2 solutions. Hence, the formulation of fast non-dominated sorting is presented as follow:

$$r_2(x,t) = 1 + nq(x,t) \tag{3-13}$$

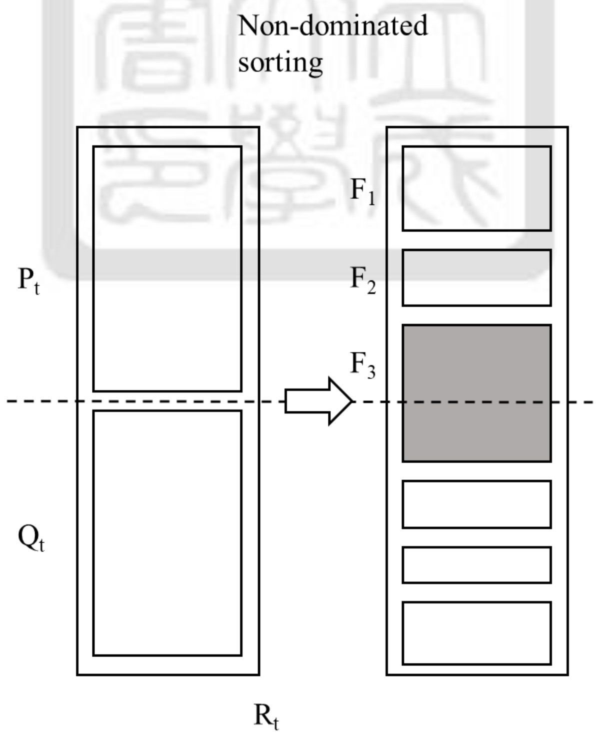

Figure 3.10 Procedure of fast non-dominated soring

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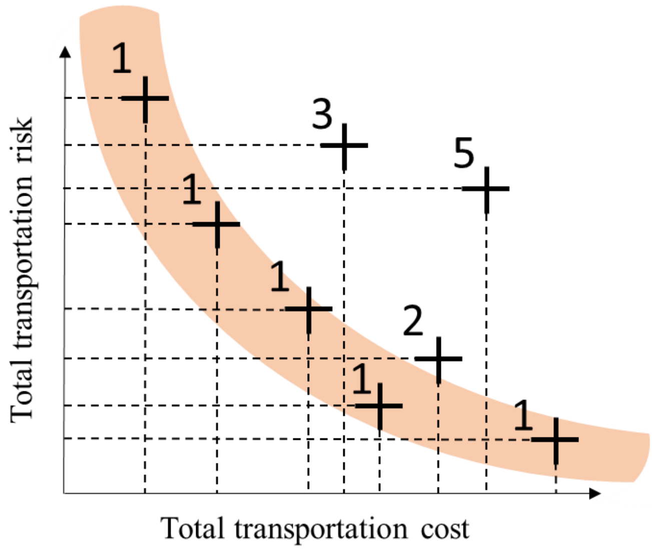

Figure 3.11 Example of fast non-dominated sorting

Crowding distance

According to the ranking number of solutions, the solutions in the 1st front is better than other solutions of front. Thus, the smaller ranking number of solutions represents that the solution is better. Then the solutions from first non-dominated front F_1 and the set F_2 are chosen to fill next population until select N (population size) solutions. When the quantities of solutions from the selected front third F_3 are more than the needs of next population, we use crowding distance to sort the solutions in descending order and choose the best solutions to fill the next population. The procedure of crowding distance is depicted in Figure 3.12.

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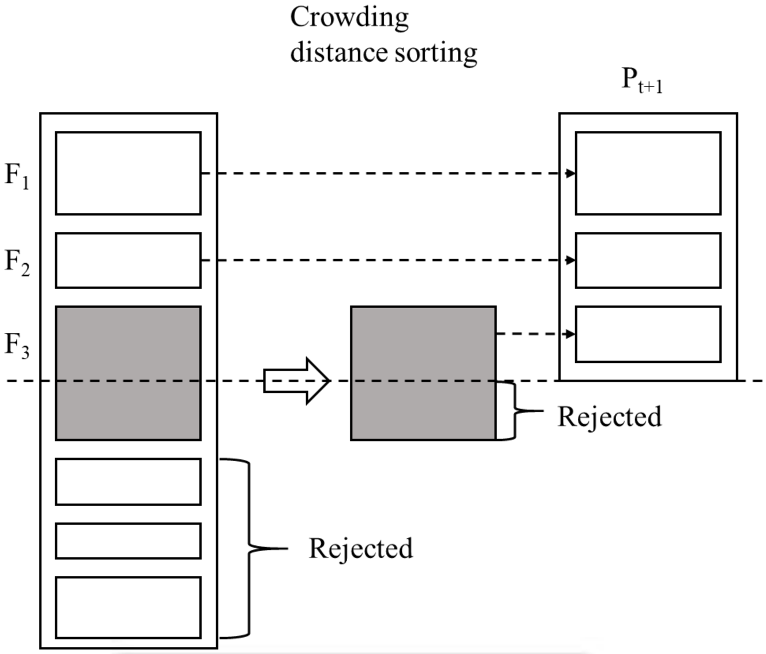

Figure 3.12 Procedure of crowding distance

The selection process is that let $l = |F_j|$ represents the quantities of solutions in front F_j and $x_{[i,k]}$ represents the ith solution in the sorting list with respect to the objectives function k. Set $cd_k(x_{[1,k]}) = \infty$ and $cd_k(x_{[l,k]}) = \infty$. Equation (3-14) means taking the near solution values in the same front to minus then dividing by the difference of maximum and minimum objective value of k objective ($i = 2, \dots, l-1$). Equation (3-15) means to find the total value of crowding distance, that is, sum all $cd_k(x)$ from different objective k.

$$cd_k(x_{[i,k]}) = \frac{z_k(x_{[i+1,k]}) - z_k(x_{[i-1,k]})}{z_k^{max} - z_k^{min}} \quad ,\forall k \ , i=2,3,\dots l-1 \tag{3-14}$$

$$cd(x) = \textstyle\sum_k cd_k(x) \quad ,\forall \text{ k} \tag{3-15}$$

Figure 3.13 is example of crowding distance; the two objectives k are total transportation risk and cost. We calculate the solution i in second front F_2, minus the near solutions' objective value $x_{[i+1,k]}$ and $x_{[i-1,k]}$ respectively then divided by the maximum minuses minimum in that objective. Sum the all $cd_k(x)$ from different objective k. Then calculate the total crowding distance value of each solution in selected

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front.

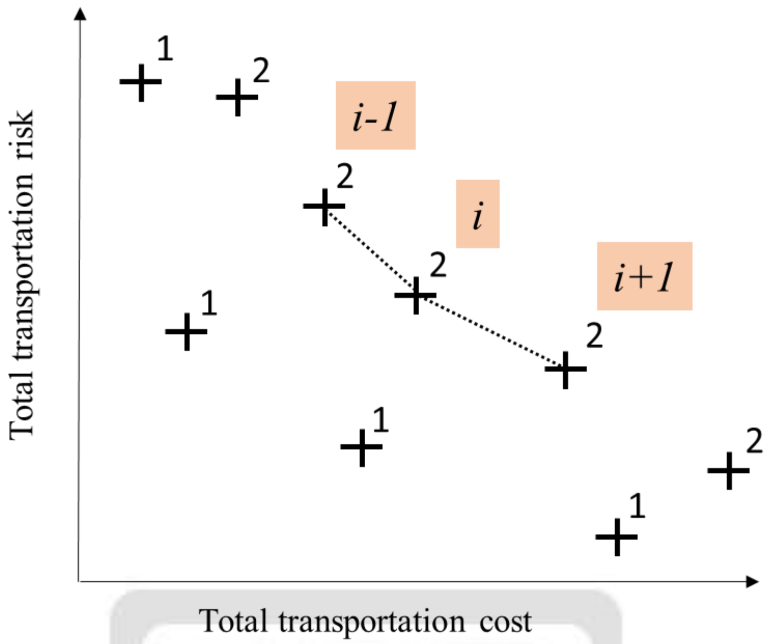

Figure 3.13 Example of crowding distance

In crowding distance operator, small crowding distance value means the solution is close to near solutions. We select the solutions with large crowding distance value in selected front to fill next population N for keeping the diversity and uniform distribution.

Solution Process of NSGA-II

In real-time MOGA, we use NSGA II to minimize two objectives simultaneously and obtain Pareto solutions. Figure 3.14 shows the solution process of NSGA-II and steps are presented as below in detail.

For t=0

Step 1: Set the parameters of algorithm: population size N, crossover rate P_c, mutation rate P_m, generation size and the origin-destination node of route, the initial population $P_{i=0}$ based on shortest path algorithm and random walk.

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Step 2: Generate offspring population Q_i of size *N* through crossover and mutation procedure from parent population P_i. Further only the population P_1 is generated by step 2, the other population P_i are generated by all steps.

For t≥ 1

Step 3: Combine the Q_0 with P_i, which called R_0, presented as $R_i = P_i \cup Q_i(2\mathrm{N})$.

Step 4: Form the next population P_{i+1} (N solutions) from R_i based on fast non-dominated sorting approach and crowding distance.

Step 5: If fit the setting generation, stop the procedure. If not, go to Step 2.

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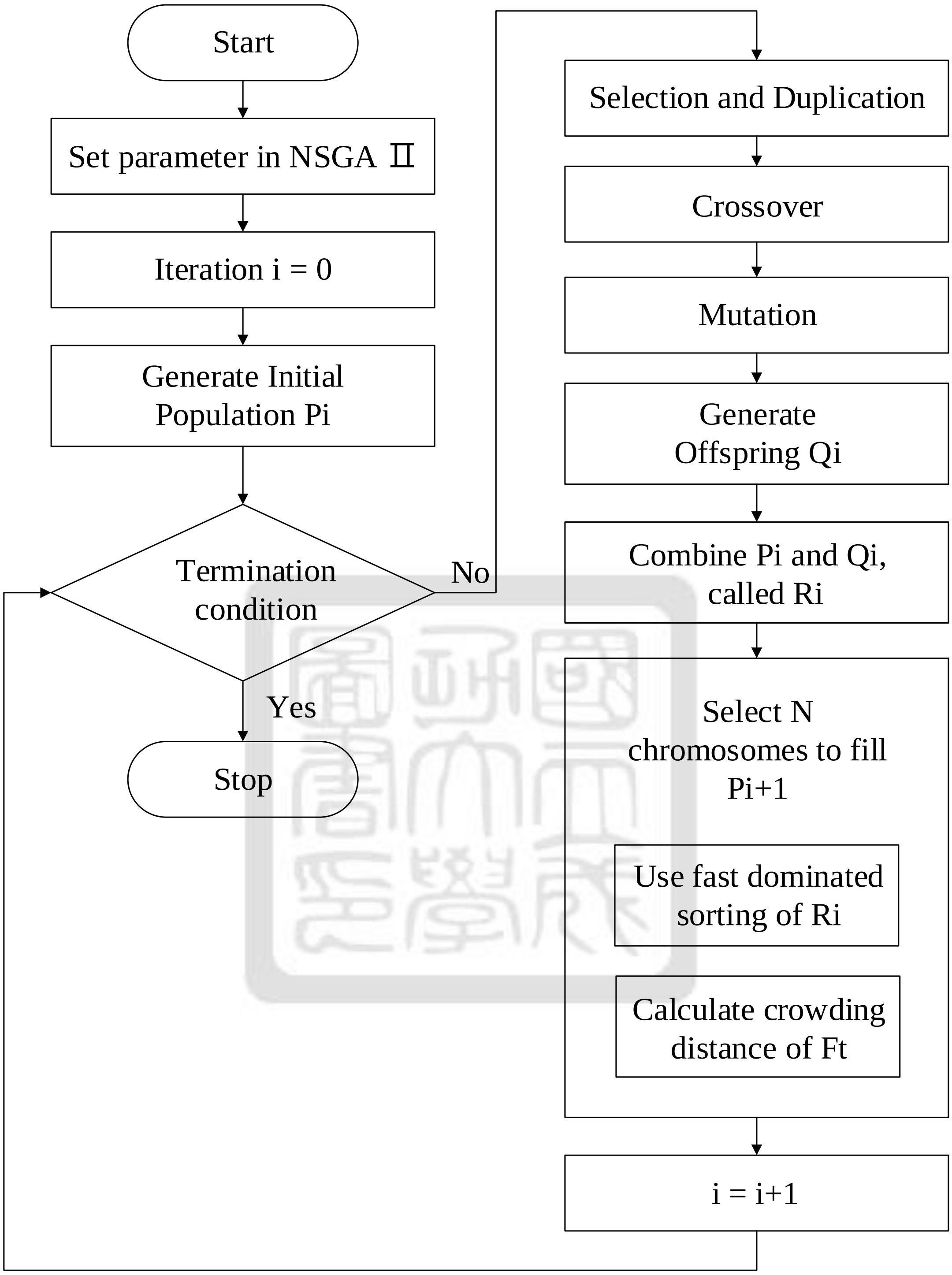

Figure 3.14 Solution process of NSGA-II

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CHAPTER 4 EMPIRICAL STUDY

In order to develop a real time route optimization for hazmat transportation based on a multi-objective genetic algorithm, this chapter describes the empirical experiment on Kaohsiung network and presents the proposed algorithm. Section 4.1 illustrates the basic data of experimental network. Section 4.2 illustrates program flowchart of real time NSGA-II. Section 4.3 presents the results of analysis. 4.4 summarizes the results of empirical experiments.

4.1 Data Description

After the gas explosions in 2014, numerous chemical trucks were increasingly needed for remediation to original demand. Besides, many industrial parks are located in Kaohsiung City, which is showed in Figure 4.1. In the end of 2014, the regulation of the restricted route (red dotted line) to chemical trucks, which was announced by Kaohsiung city government. Moreover, the routes of chemical trucks are forbidden in specific sections and only allowed to pass within 6:00 a.m.-18:00 p.m. It is worth mention that there are not any restrictions in the region which has high population density (red frame with dotted line). For the reason, the proposed model is tested on the Kaohsiung network with realistic network characteristic and regulation which is showed in Figure 4.2. The network includes 5 districts (Cianjin district, Xinxing district, Lingya district, Qianzhen district and Fengshan district) which are presented as every blue frame with dotted line. There are 7 demand zones, 133 nodes and 466 links. The red line in the network is the link which damaged in gas explosion in 2014. The yellow nodes mean the preset O-D pairs in the experiment. It represents the possible distribution or storage nodes of hazmat. The design of 6 O-D pairs is showed in Table 4.1, including preset start node and destination node.

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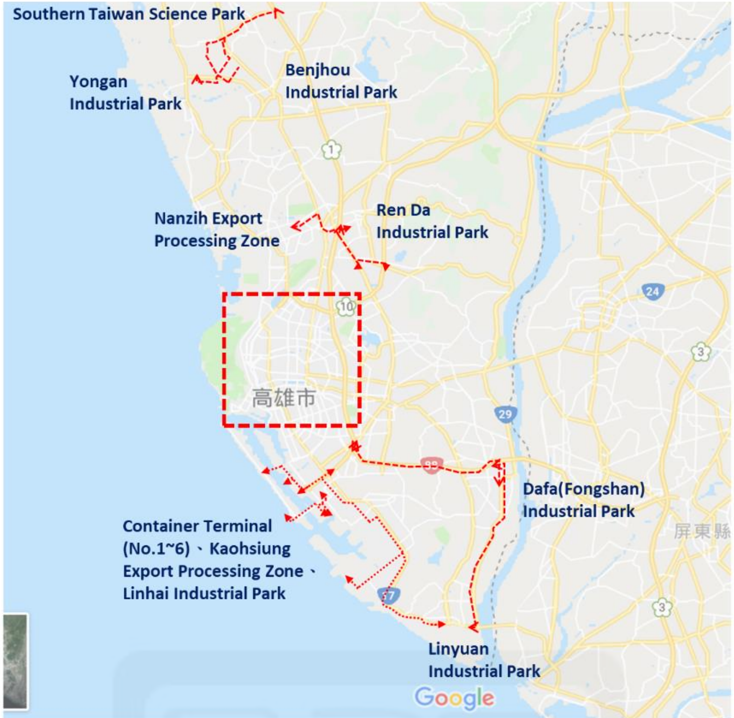

Figure 4.1 Restricted route to chemical trucks in 2014

Source: Kaohsiung city government, Google Maps

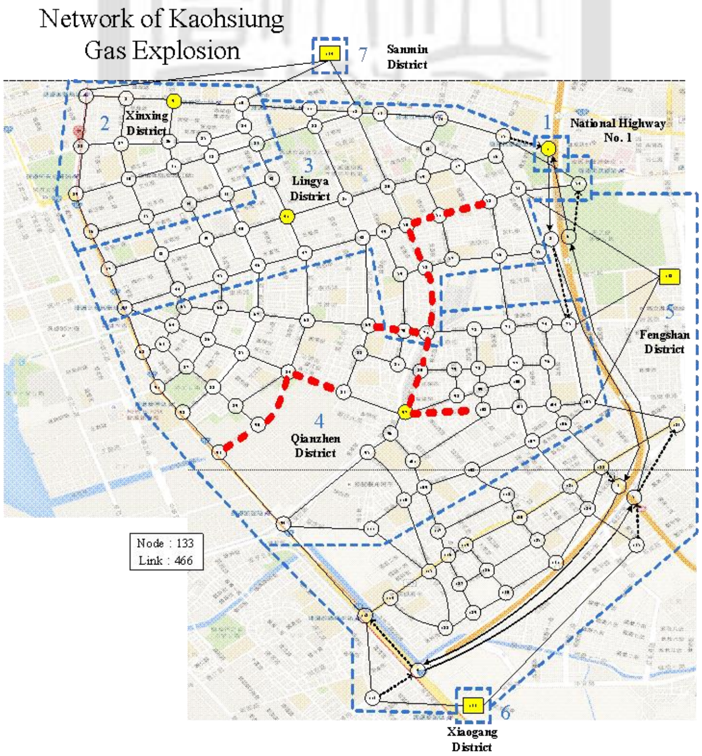

Figure 4.2 Kaohsiung network (Liao et al., 2017)

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Table 4-1 O-D pairs design

	O-D 1	O-D 2	O-D 3	O-D 4	O-D 5	O-D 6
Start node	1	1	133	133	122	1
Destination node	9	97	41	97	41	134

4.1.1 Basic Data of Experimental Network

A briefly list of collected data and their sources are shown in Table 4-2. The data applied in the algorithm are retrieved from statistical data of government department, open data on the internet and traffic simulation software.

Table 4-2 Data sources

Objective	**Data**	**Source**
Cost	Link travel time	DynaTAIWAN
Risk	Population	Civil Affairs Bureau of Kaohsiung City Government
	District area	Internet statistical data from Sheethub
	Accident rate	(Toumazis & Kwon, 2013)
	Length of link	Google Map
	Hourly traffic volume	DynaTAIWAN
	Impact radius	Hazard modeling program, ALOHA (Version 5.4.7, 2016)

There are two real time data (link travel time and hourly traffic volume) in the network. These are simulated by traffic simulation software (DynaTAIWAN). In this research, we collect the real time data with particular time interval (per 5 minute). However, at some time interval, some links without traffic volume will cause the links

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risk to be zero. But for these links, the population density still needs to be considered, so we set that the minimum traffic volume is equal to 1.

4.1.2 Hazmat Impact Radius

In order to calculate the affected area when accidents happen, we adopt the hazmat impact radius as measurement method. This research uses a hazard modeling program, ALOHA (Version 5.4.7, 2016), which is a software that allows us enter details about a realistic environment. It also could estimate threat zones associated with different types of hazardous chemical releases.

Thus, we chose the chemical named propylene as our hazmat to be transport because propylene is one of the most important and basic chemicals in the petrochemical industry, but it also could cause disastrous consequences if leak out. We set the simulation parameters with meteorology data, temperature and wind data are the average data in Kaohsiung, and assume the worst situation, Boiling Liquid Expanding Vapor Explosions, happened when accident, other parameters are presented in Figure 4.3.

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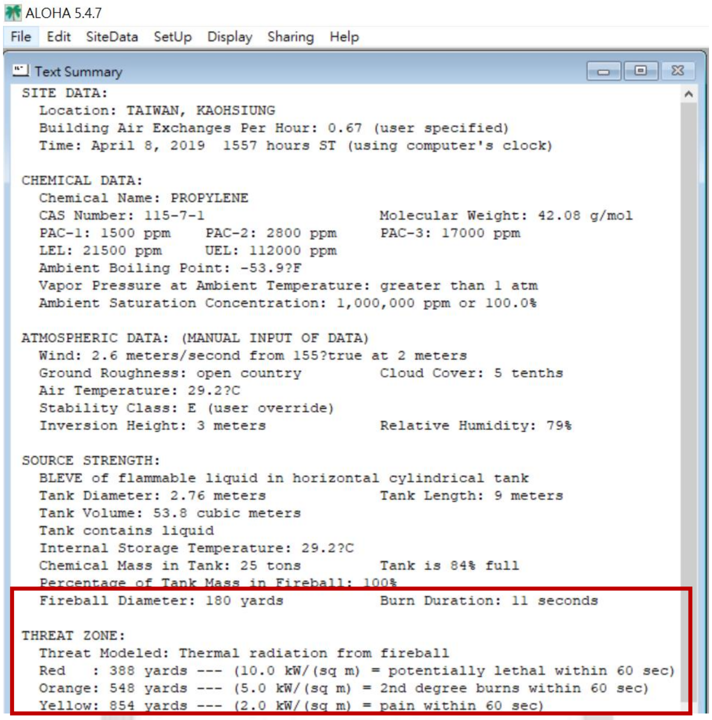

Figure 4.3 ALOHA 5.4.7 simulation setting and results

Through simulation, the detailed results also could be found from Figure 4.3 with red frame. The fireball diameter is 180 yards, is equal to 0.16 km. The threat zone could be divided into three levels due to the thermal radiation from fireball. The most serious is potentially lethal within 60 sec. Second is 2nd degree burns within 60 sec. Last is to get pain within 60 sec. The schematic diagram is shown in Figure 4.4, and the detailed radiation is shown in Table 4-3. In order to minimize the possible impact to the network, we adopt the maximum threat zone, 854 yards (0.78km), as our impact radius when accident happens.

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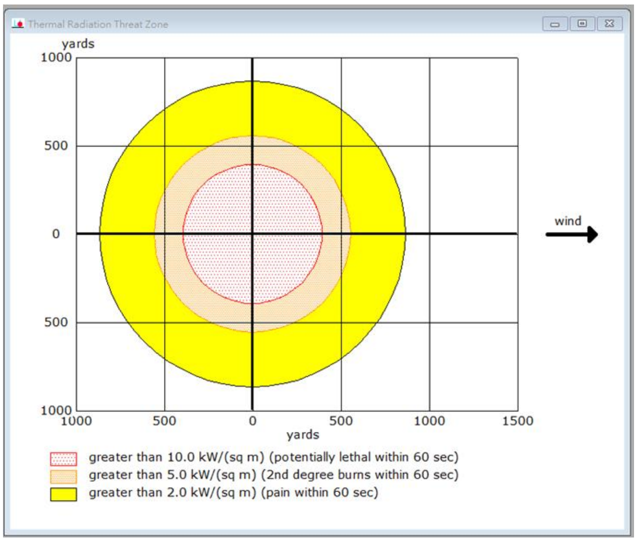

Figure 4.4 Thermal Radiation Threat Zone (Output from ALOHA)

Table 4-3 Thermal radiation from fireball

Theat zone	Thermal radiation (yards)	Thermal radiation (km)
Fireball Diameter	180	0.16
Potentially lethal	388	0.35
2nd degree burns	548	0.5
Pain	854	**0.78**

4.1.3 Population Density

This research adopts village as the basic unit when calculate population density. According to the statistics data from the Civil Affairs Bureau of Kaohsiung City Government, we could collect the population data of each village in 2018. Links' length is measured by google map, and villages' area is obtained through open data integrated by Sheethub. Because the partition of each village is trivial, it causes a link might pass through several villages, we use the average population density when this situation happens:

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$$\textit{Population density on link } j = \frac{\sum_i \text{village population}}{\sum_i \text{village area}} \textit{ (people per km-sq)}, \qquad (4\text{-}1)$$

where i represent the villages link j pass through, j represent the links in network. Table 4-4 shows the example of calculating population density in each link. The population density is equal to the total population divided by the total area.

Table 4-4 The population density in each link

Origin	Destination	Passed villages	Population	Area	Population density
1	2	Weiwu Vil. + Xinqiang Vil.	8825	1.0495	8408.75
2	3	Xinqiang Vil. + Xinfu Vil. + Xintai Vil. + Lauye Vil. + Zhonglun Vil.	27149	2.354193	11532.19
2	75	Xinqiang Vil.	6395	0.967553	6609.46
3	4	Zhonglun Vil. + Bauan Vil. + Nancheng Vil. + Mingzheng Vil.	24348	4.847163	5023.14
4	5	Zhonglun Vil.+ Bauan Vil.+ Nancheng Vil.+ Mingzheng Vil.	24348	4.847163	5023.14
4	112	Mingzheng Vil.+ Fuxing Vil.	13062	1.88025	6946.95

4.2 Program Flowchart

In order to solve the problem of real time hazmat transporting, the proposed algorithm (Real time NSGA-II) was coded in Python and tested on a Windows 10 machine (Intel Core i5-7200U/ 2.70 GHz processer with 8GB RAM).

The Figure 4.5 shows the program flowchart and the explanation is described as follow:

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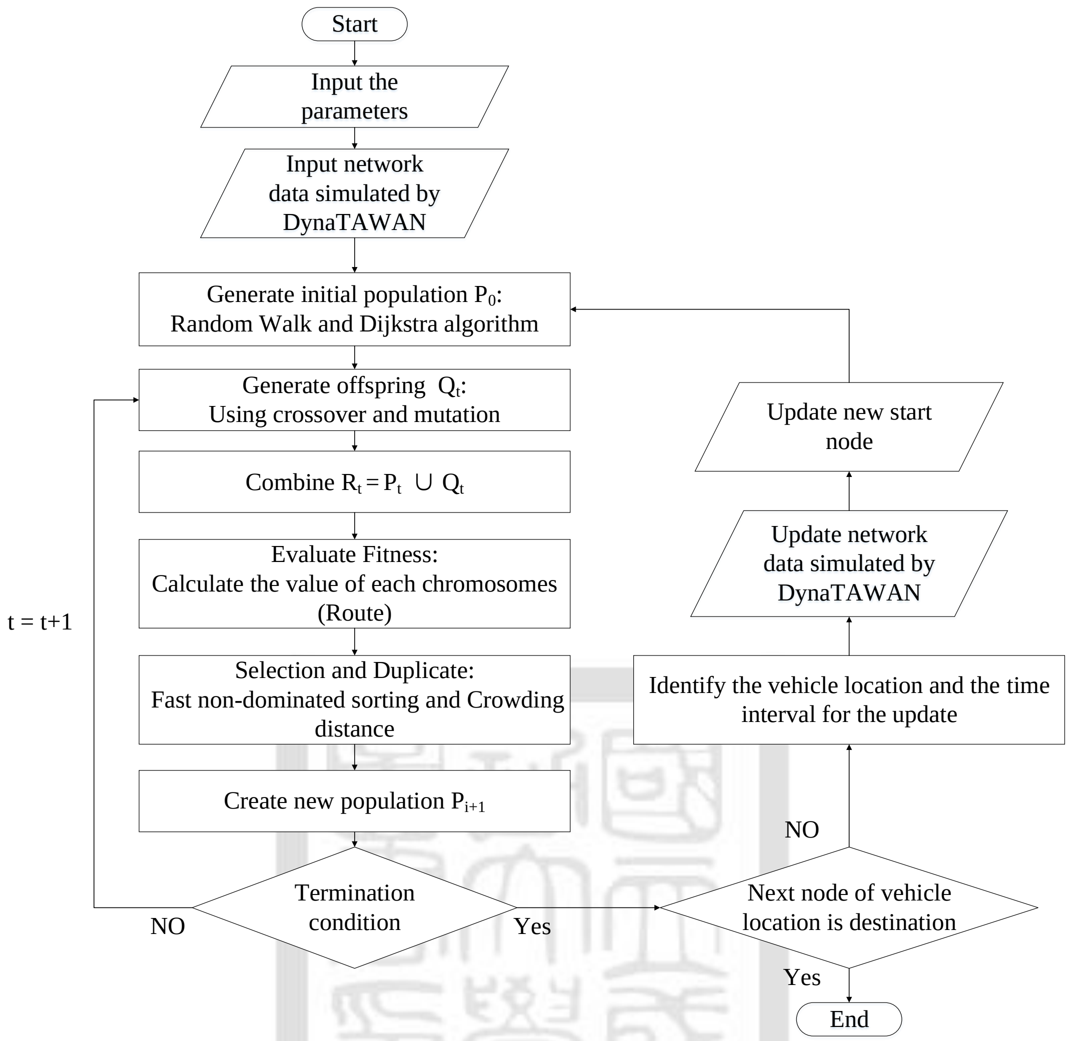

Figure 4.5 Program flowchart

The input of program parameters includes network data from DynaTAIWAN, crossover rate, mutation rate, termination condition, population size, and the proportion of initial population. In terms of initial population, if we only apply random walk to generate chromosomes (routes), it may lead to poor performance, on a large network especially. It means that could result in taking too much time to generate unusual chromosomes route. Thus, according to Li et al. (2013), the heuristic initialization based on Dijkstra's algorithm is applied to generate 20% chromosomes of initial population. Because this research considers two objectives, there are two types of shortest routes produced by the algorithm based on cost and risk network respectively. In other words,

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the number of shortest routes is six in first generation (The shortest routes based on cost and risk account for fifty percentage respectively). By this way, it not only could preserve population diversity to a certain extent, but also result in higher quality of the initial population simultaneously. The random walk and Dijkstra algorithm are described as follow:

Random Walk:

Given the O-D nodes, we start from the origin node and search connected node through the input network. Then, randomly choose the connected node as next node until arrive the destination node. The process is suitable for each node. But it might form the loop of route or no connected node in search process, so we put restriction on choosing a node which has already chosen in the route.

Dijkstra algorithm:

Step 1: Assign to every node a tentative distance value. Set distance value of initial node to zero and distance value of all other node to infinity.

Step 2: Generate a set of visited nodes with just the initial node and unvisited set with all node without initial node.

Step 3: For the initial node or current node, consider all its unvisited neighbors and calculate the distance (distance to the current node and distance from current node to the neighbor). If the calculated distance is less than their current tentative distance, replace it with this new distance.

Step 4: When we are done considering neighbors of the current node, put the current node into visited set and remove it from unvisited set.

Step 5: If the destination node has been put into visited set, the algorithm has finished. If not, go to step 6.

Step 6: Set the unvisited node marked with smallest tentative distance as the next

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current node and go back to step 3.

After the procedure of initialization, we generate the optimal solutions (routes) by crossover, mutation, selection and duplicate. The detailed process is depicted in Section 3.5. Because size of the optimal solutions (routes) are same preset population size, we pick the route with highest occurrence in the optimal solutions (routes) as transporting route. Then we calculate the total travel time of the transporting route and examine the next node of driving route at particular time interval. If the next node is destination, the program has finished. If not, we update the network and the new start node at particular time interval. Finally, it is to generate new route by NSGA-II with these updated parameters until next node of driving route is destination.

4.3 Results of Analysis

4.3.1 Sensitivity Analysis

In order to prove that the Pareto solutions by NSGA-II are the best, the sensitivity analysis is proposed to test preset parameter specification based on Li et al. (2013). We take O-D 3 for example, Table 4-5 and Table 4-6 show the Pareto solutions with different parameters including crossover rate, mutation rate, and Generation. The cost and risk of average values in each test are calculated by the values of chromosomes in last generation. The difference of two tables is that if initial population includes the routes generated by Dijkstra algorithm. We could find that even though the all standard deviations could converge into approximate zero, the all averages indeed have different results. Thus, we also compare the all averages in Figure 4.6, Figure 4.7, and Figure 4.8.

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Table 4-5 Pareto solutions with different parameters and Dijkstra algorithm

With Dijkstra algorithm				
Crossover rate	Objectives	Average	Standard deviation	Time (s)
0.1	Cost	3.650	0.044	6
	Risk	0.944	0.036	
0.3	Cost	3.612	0.028	6.9
	Risk	0.949	0.021	
0.5	Cost	3.616	0.016	6.1
	Risk	0.946	0.009	
0.7	Cost	3.611	0.281	6.2
	Risk	0.986	0.060	
0.8	Cost	3.607	0.022	6.1
	Risk	0.952	0.018	
0.9	Cost	4.201	0.768	6.5
	Risk	0.928	0.105	
Mutation rate	Objectives	Average	Standard deviation	Time (s)
0.001	Cost	4.340	0.785	1.7
	Risk	0.918	0.110	
0.005	Cost	4.189	0.777	2.9
	Risk	0.937	0.110	
0.01	Cost	4.131	0.773	3.5
	Risk	0.949	0.111	
0.03	Cost	4.288	0.787	3.1
	Risk	0.926	0.111	

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0.05	Cost	3.616	0.016	6
	Risk	0.946	0.009	
0.1	Cost	4.340	0.785	10.4
	Risk	0.918	0.110	
Generation	Objectives	Average	Standard deviation	Time (s)
30	Cost	4.131	0.773	3.3
	Risk	0.949	0.111	
50	Cost	4.297	0.761	4.1
	Risk	0.920	0.109	
100	Cost	3.652	0.032	6
	Risk	0.949	0.030	
200	Cost	4.131	0.773	10.9
	Risk	0.949	0.111	
500	Cost	3.660	0.013	25.8
	Risk	0.922	0.007	
1000	Cost	3.611	0.000	48.7
	Risk	0.949	0.000	

Table 4-6 Pareto solutions with different parameters and no Dijkstra algorithm

With no Dijkstra algorithm				
Crossover rate	Objectives	Average	Standard deviation	Time (s)
0.1	Cost	4.833	0.108	6.5
	Risk	1.007	0.002	
0.3	Cost	4.672	0.268	5.7
	Risk	1.067	0.009	

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0.5	Cost	4.453	0.377	6.3
	Risk	1.235	0.067	
0.7	Cost	4.203	0.047	5.7
	Risk	1.532	0.008	
0.8	Cost	4.506	0.005	6.3
	Risk	1.252	0.016	
0.9	Cost	4.384	0.087	6.2
	Risk	1.049	0.012	
Mutation rate	Objectives	Average	Standard deviation	Time (s)
0.001	Cost	4.632	0.181	2.8
	Risk	1.593	0.135	
0.005	Cost	4.471	0.295	3.7
	Risk	1.706	0.091	
0.01	Cost	4.330	0.109	5.2
	Risk	1.537	0.020	
0.03	Cost	4.523	0.082	5.7
	Risk	0.988	0.015	
0.05	Cost	4.069	0.019	6.2
	Risk	1.067	0.013	
0.1	Cost	3.938	0.013	11.8
	Risk	0.952	0.007	
Generation	Objectives	Average	Standard deviation	Time (s)
30	Cost	4.512	0.185	3.3
	Risk	1.173	0.129	

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50	Cost	4.313	0.025	4.6
	Risk	1.010	0.111	
100	Cost	4.506	0.005	5.9
	Risk	1.252	0.016	
200	Cost	5.677	0.260	9.2
	Risk	1.107	0.036	
500	Cost	4.017	0.000	21.9
	Risk	1.026	0.000	
1000	Cost	3.812	0.000	37.2
	Risk	1.063	0.000	

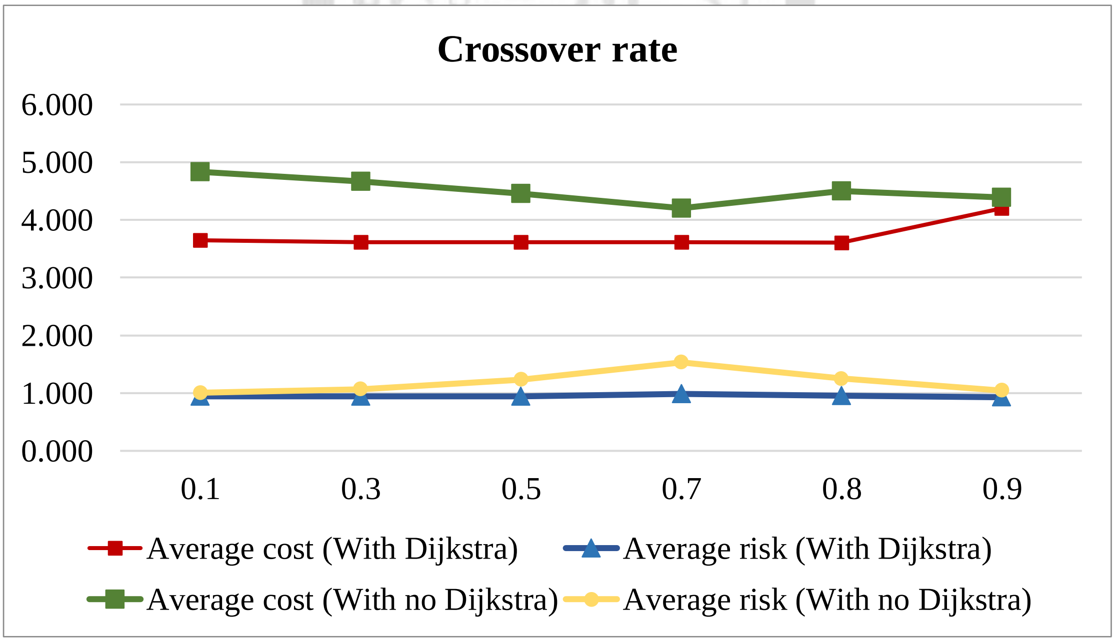

Figure 4.6 Averages for different crossover rate

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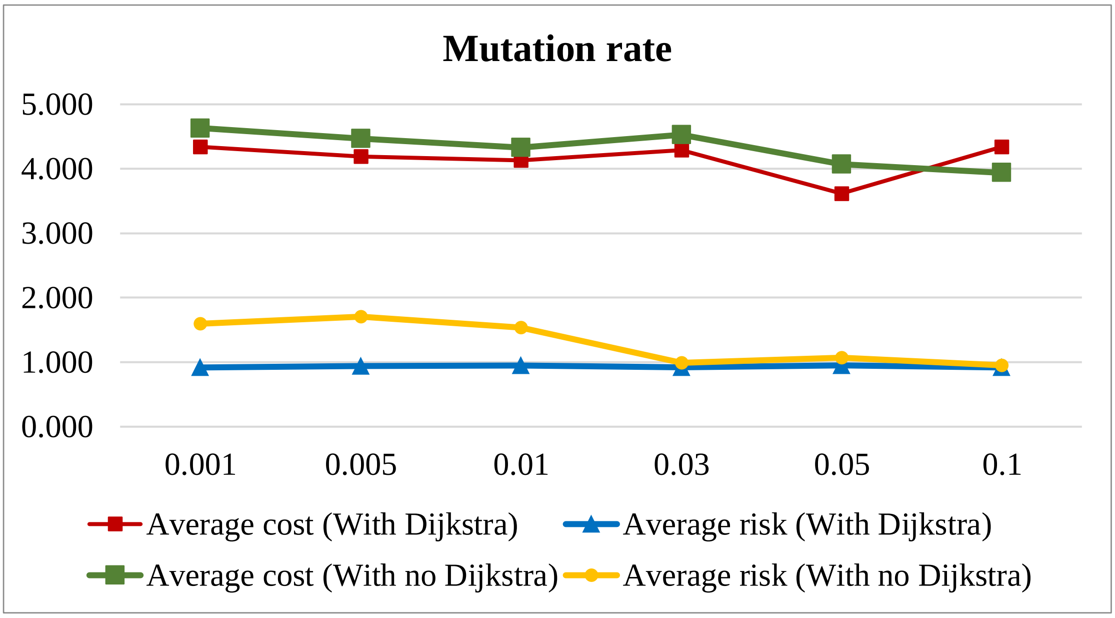

Figure 4.7 Averages for different mutation rate

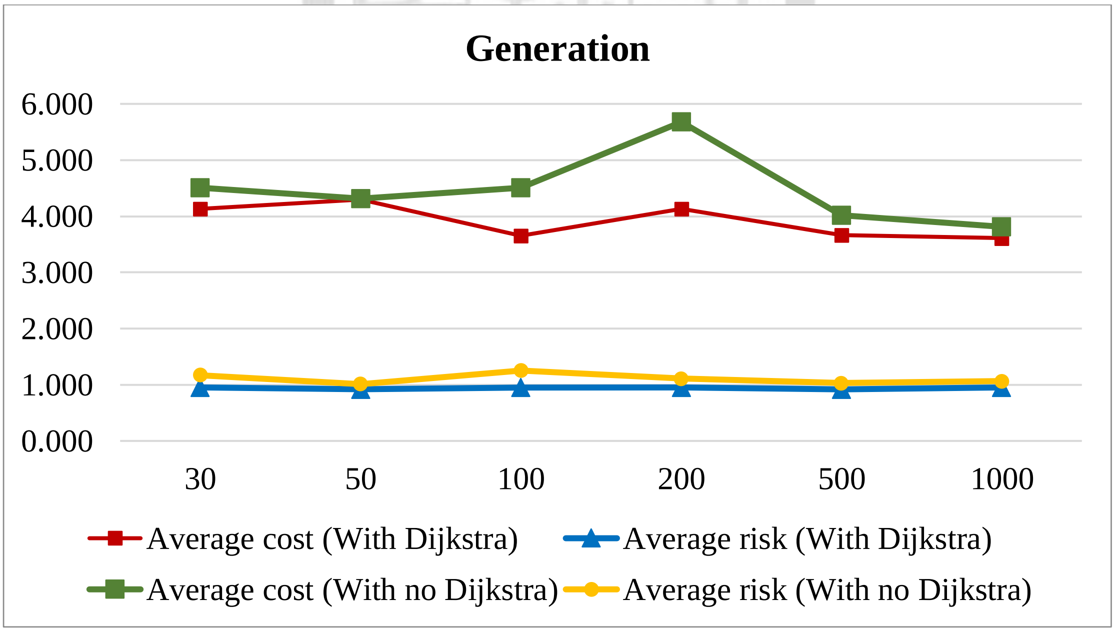

Figure 4.8 Averages for different generation

In Figure 4.6, Figure 4.7, and Figure 4.8, we could discover two information. First, it proves the Pareto solutions with parameter specification based on Li et al. (2013) are relatively better. Second, it will hardly generate convergent solutions with no Dijkstra's algorithm. Thus, if the initial population including Dijkstra's algorithm, we indeed find better and convergent solutions within a short time.

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4.3.2 Single O-D Pair

Based on Li et al. (2013), we execute real time NSGA-Ⅱ with following parameter specification to generate the two-objectives Pareto solutions: Population size (N): 30, crossover rate: 0.8, mutation rate: 0.05, termination condition: 100 generation.

Given 6 O-D pairs and the network with same time interval, the output of this algorithm is the latest population which arrives our termination condition. The optimal routes of each pair considering two objectives is listed in Table 4-7.

Table 4-7 Optimal Routes of Origin-Destination Pair

OD	CPU Time(s)	#	Link	Cost	Risk	Hyper-volume
1	5.7	1	[1, 2, 75, 74, 73, 72, 71, 70, 69, 68, 67, 46, 40, 33, 32, 25, 26, 9]	3.463	0.475	81.059
		2	[1, 2, 75, 74, 73, 56, 52, 17, 18, 13, 12, 11, 10, 9]	3.486	0.329	83.766
2	2.9	1	[1, 2, 75, 74, 76, 77, 100, 99, 98, 97],	2.027	0.253	81.427
		2	[1, 2, 75, 74, 73, 72, 78, 99, 98, 97]	2.047	0.229	82.200
		3	[1, 2, 75, 74, 73, 72, 71, 80, 97]	2.128	0.229	81.854
3	5.7	1	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 58, 50, 20, 21, 41]	3.664	0.92	84.617
		2	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 69, 68, 47,	3.492	1.048	83.790

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			41]			
		3	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 59, 49, 48, 21, 41]	3.611	0.949	84.456
		4	[133, 113, 4, 112, 114, 128, 129, 130, 131, 124, 122, 106, 104, 76, 74, 73, 72, 71, 58, 50, 20, 21, 41]	5.061	0.821	82.949
4	2.6	1	[133, 135, 124, 121, 122, 106, 104, 103, 102, 99, 98, 97]	2.345	0.772	84.841
		2	[133, 113, 4, 112, 114, 128, 129, 130, 131, 124, 122, 106, 104, 103, 102, 97]	3.511	0.758	82.052
		3	[133, 135, 124, 121, 107, 103, 102, 99, 98, 97]	2.152	0.83	84.675
		4	[133, 135, 124, 121, 122, 106, 104, 103, 102, 97]	2.261	0.777	84.997
		5	[133, 135, 124, 121, 107, 103, 102, 97]	2.064	0.835	84.839
		6	[133, 113, 4, 112, 114, 128, 129, 130, 131, 124, 122, 106, 104, 103, 102, 99, 98, 97]	3.599	0.753	81.884
5	4.1	1	[122, 106, 104, 76, 74, 73, 72, 71, 70, 69, 68, 47, 41]	2.425	0.281	81.596
		2	[122, 106, 104, 76, 74, 73, 72, 71, 58, 50, 20, 21, 41]	2.597	0.153	85.100

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		3	[122, 106, 104, 76, 74, 73, 72, 71, 70, 59, 49, 48, 21, 41]	2.544	0.182	84.362
6	5.6	1	[1, 2, 75, 55, 56, 52, 17, 18, 13, 12, 134]	3.299	0.351	81.041
		2	[1, 2, 75, 74, 73, 56, 52, 17, 18, 13, 12, 134]	3.314	0.317	81.872

Among the latest population for each pair, it all could be divided into two situations. First, the routes generated from Dijkstra's algorithm actually are the optimal route. Thus, it exists in each iteration and presents in latest population. The situation happens in O-D 1 and O-D 6. Second, the algorithm could find the optimal routes except for the routes generated from Dijkstra's algorithm. Among these routes, the one of values of cost and risk is smaller than the value of routes generated from Dijkstra's algorithm. It is optimal trade-off solutions. The situation happens in O-D 2,3,4, and 5.

In order to choose one optimal driving route from latest population, the selection process is that if there are trade-off solutions, we choose one of these as optimal route because it could reflect the spirit of multi-objective most. If not, we choose one of routes from Dijkstra's algorithm. Then, the comparative method, called hypervolume proposed by Zitzler and Thiele (Zitzler and Thiele, 1999) is applied to compare the solutions. However, we estimate the hypervolume by normalizing in same unit set point (10,10) as reference point. The larger the hypervolume, the better is the solution.

As for improvement rate for each pair, we present it in Figure 4.9. The improvement rate represents an average of cost and risk in each iteration.

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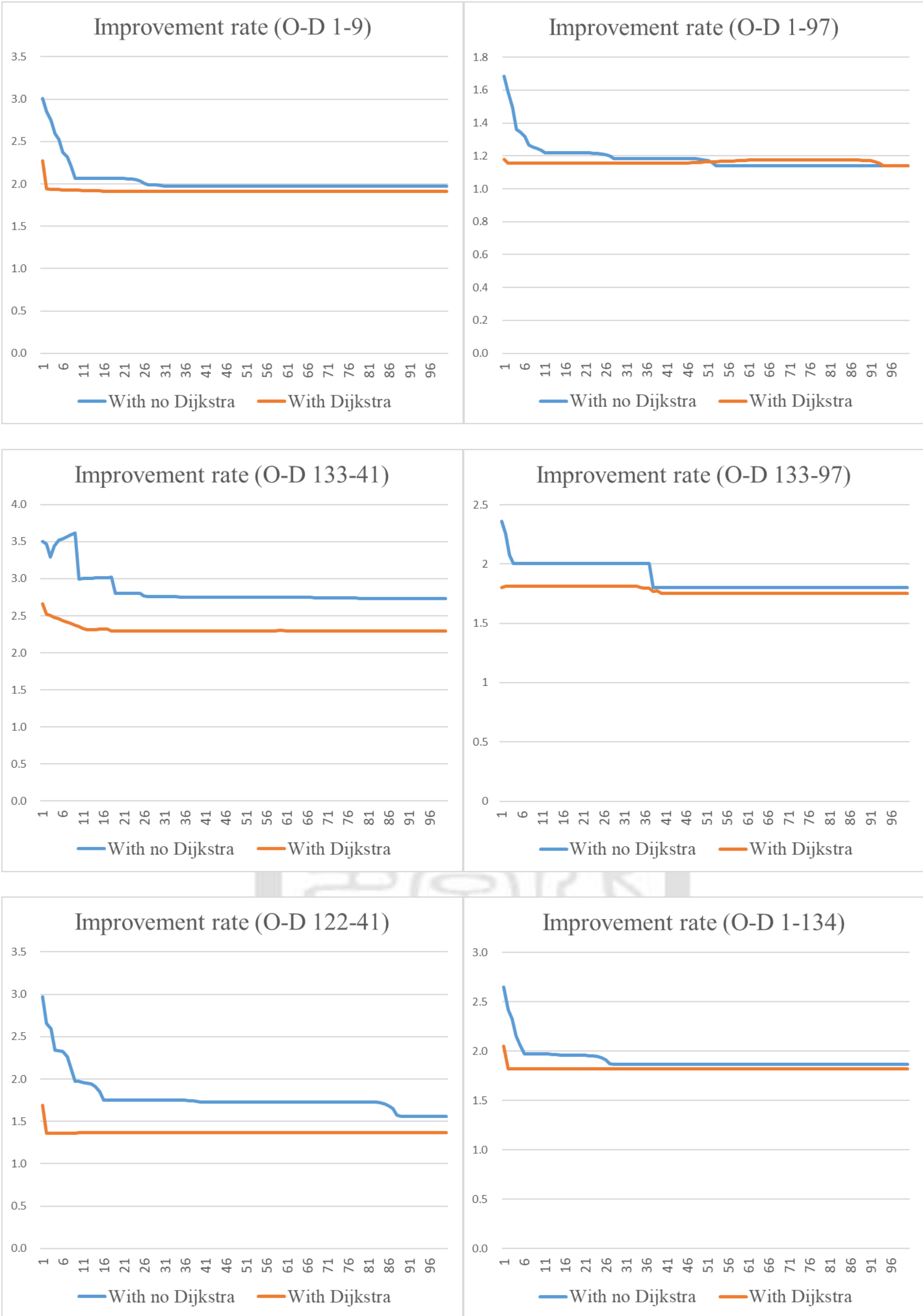

Figure 4.9 Improvement rate for each pair

The blue line means initial population does not include 20 % routes generated from Dijkstra's algorithm. On the contrary, the orange line includes that. We found that the

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initial population including routes from Dijkstra's algorithm could find better solutions. Moreover, the initial population not including routes from Dijkstra's algorithm could generate worse latest population. Thus, its value of cost and risk all are higher than the minimum cost and risk from Dijkstra's algorithm.

Based on the comparative method, we choose one optimal driving route and update it with particular time interval. Then we evaluate travel time of driving route and update the new start node at next time interval. Therefore, for each O-D pair, the optimal routes in each time interval presented by real time NSGA-Ⅱ are listed in Table 4-8.

Table 4-8 Real Time Optimal Routes of Origin-Destination Pair

OD	Time	Link	Cost	Risk
1	T= 5	[1, 2, 75, 74, 73, 56, 52, 17, 18, 13, 12, 11, 10, 9]	3.4858	0.3299
	T= 10	[74, 73, 56, 52, 17, 18, 13, 12, 11, 10, 9]	1.5235	0.1422
	T= 15	[17, 18, 13, 12, 11, 10, 9]	0.7333	0.0866
	T= 20	[10, 9]	0.1196	0.0003
2	T= 5	[1, 2, 75, 74, 73, 72, 78, 99, 98, 97]	2.0456	0.2293
	T= 10	[74, 73, 72, 71, 80, 97]	0.5803	0.0315
3	T= 5	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 58, 50, 20, 21, 41]	3.6635	0.9207
	T= 10	[107, 106, 104, 76, 74, 73, 72, 71, 58, 50, 49, 48, 21, 41]	1.5451	0.1578
	T= 15	[73, 72, 71, 70, 69, 68, 47, 41]	0.8058	0.0470
	T= 20	[47, 41]	0.0807	0.0019
4	T= 5	[133, 135, 124, 122, 106, 104, 103, 102, 97]	2.2570	0.7770
	T= 10	[122, 106, 104, 103, 102, 99, 98, 97]	0.7795	0.1100
	T= 15	[98, 97]	0.0975	0.0003
5	T= 5	[122, 106, 104, 76, 74, 73, 72, 71, 70, 59, 49, 48, 21, 41]	2.5455	0.1824

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	T= 10	[72, 71, 70, 59, 49, 48, 21, 41]	0.8758	0.0979
	T= 15	[21, 41]	0.0997	0.0002
6	T= 5	[1, 2, 75, 74, 73, 56, 52, 17, 18, 13, 12, 134]	3.3147	0.3178
	T= 10	[74, 73, 56, 52, 17, 18, 13, 12, 134]	1.4241	0.1601
	T= 15	[17, 18, 13, 12, 134]	0.6290	0.0769

For O-D 1 to O-D 6, we could find the optimal routes with different time interval. The red numbers in routes represent new start node. We terminate the program when new start node is termination node. It means that we do not need to update the driving route. In Table 4-9, we take O-D 3 to demonstrate and compare the changes with different time interval (T=5 and T=10).

Table 4-9 Comparison of different links in O-D 3

	T=5			T=10		
Link 1	Volume	Cost	Risk	Volume	Cost	Risk
107→103	178	0.99	1.05	270	0.99	1.69
103→100	146	0.81	0.69	186	0.90	0.91
100→77	97	0.37	0.21	97	0.37	0.21
77→73	198	1.05	0.44	170	1.01	0.36
73→72	81	0.75	0.09	69	0.75	0.07
72→71	75	1.08	0.17	100	1.08	0.24
71→58	164	1.74	0.42	149	1.74	0.38
58→50	151	1.23	1.15	159	1.23	1.22
50→20	123	1.17	0.37	153	1.17	0.48
20→21	7	0.55	0.02	1	0.52	0.00
21→41	27	0.77	0.17	10	0.73	0.06
Total	1247	10.50	4.80	1364	10.48	5.62
	T=5			T=10		
Link 2	Volume	Cost	Risk	Volume	Cost	Risk
107→106	219	0.85	1.14	52	0.54	0.24
106→104	54	0.54	0.16	90	0.54	0.27
104→76	71	0.93	0.66	76	0.98	0.71
76→74	146	1.01	0.30	122	1.09	0.24
74→73	66	0.81	0.09	46	0.81	0.06
73→72	81	0.75	0.09	69	0.75	0.07

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72→71	75	1.08	0.17	100	1.08	0.24
71→58	164	1.74	0.42	149	1.74	0.38
58→50	151	1.23	1.15	159	1.23	1.22
50→49	9	0.39	0.03	1	0.29	0.00
49→48	15	0.26	0.05	1	0.23	0.00
48→21	244	1.12	1.10	163	0.91	0.68
21→41	27	0.77	0.17	10	0.73	0.06
Total	1322	11.47	5.53	1038	10.91	4.17

We examine the difference between two routes which are chose in two time interval. Table 4-9 shows that the total traffic volume and total risk of route (Link 1) are relatively low at 5th time interval even though the cost is a little higher. On the contrary, the ones of route (Link 2) are relatively low at 10th time interval. Furthermore, we compare the results of two routes (no updated route and updated route). The no updated route is [133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 58, 50, 20, 21, 41]. The total transportation cost and risk are 16.934, 25.030 (unstandardized value) respectively. The updated route is [133, 135, 124, 121, 107, 106, 104, 76, 74, 73, 72, 71, 70, 69, 68, 47, 41]. The total transportation cost and risk are 15.995, 23.144 (unstandardized value) respectively. The degree of improvement in percentage for cost and risk is 6% and 8%. Thus, real time route optimization for hazmat transportation indeed bring lower risk and cost.

Figure 4.10 shows a part of program command of real time NSGA-II. The rest is an infinite iteration for finding destination.

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```python
from NSGAII import NSGAII
from read_network_dict import read_network_dict
from route_minutes import evaluation_minutes
from pick_update_route import pick_update_route
from evaluation import evaluation_value
import copy

# Need to input crossover_rate
crossover_rate = 0.8
# input mutation_rate
mutation_rate = 0.05
# input the termination generation
termination_generation = 100
# input the population size and the structure of initail population
number_of_random = 24
dijkstra_cost = 3
dijkstra_risk = 3
# input the start node and termination node
start = 1
termination = 9
update_interval = 5

def real_time_NSGAII(
    graph_raw,
    graph_standerize,
    crossover_rate,
    mutation_rate,
    termination_generation,
    number_of_random,
    dijkstra_cost,
    dijkstra_risk,
    start,
    termination,
    update_interval):

    graph_copy = copy.deepcopy(graph_raw[0]) #copy the original graph
    graph_standerize_copy = graph_standerize[0].copy()  #copy the standerized graph
    result = NSGAII(graph_standerize_copy,
        crossover_rate,
        mutation_rate,
        termination_generation,
        number_of_random,
        dijkstra_cost,
        dijkstra_risk,
        start,
        termination)
    #generate the Pareto solutions
    result2 = pick_update_route(result[2],result[0],result[1])
    #input the 1.Pareto solutions, 2. The value of Pareto solutions, 3. dijkstra_route
    #output the optimal route, the value of optimal route by hypervolume
    evaluation_value_route= []
    evaluation_value_route.append(result2[0])
    print('T= 5',result2[0], evaluation_value(graph_standerize_copy, evaluation_value_route))
    # evaluate the optimal route
```

Figure 4.10 Program command of real time NSGA-II

4.3.3 Multiple O-D Pairs

Given a multiple O-D pairs, even though we could get the optimal routes of each pair at particular time interval, the driving route of hazmat trucks causes risk to some extent. Figure 4.11 shows the optimal routes of each pair at t=5 time interval. Except

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for highway, on-ramp, and off-ramp, we discover that link [75, 74] and link [74, 73] is used more than three times. It reflects these links have relatively higher pressure.

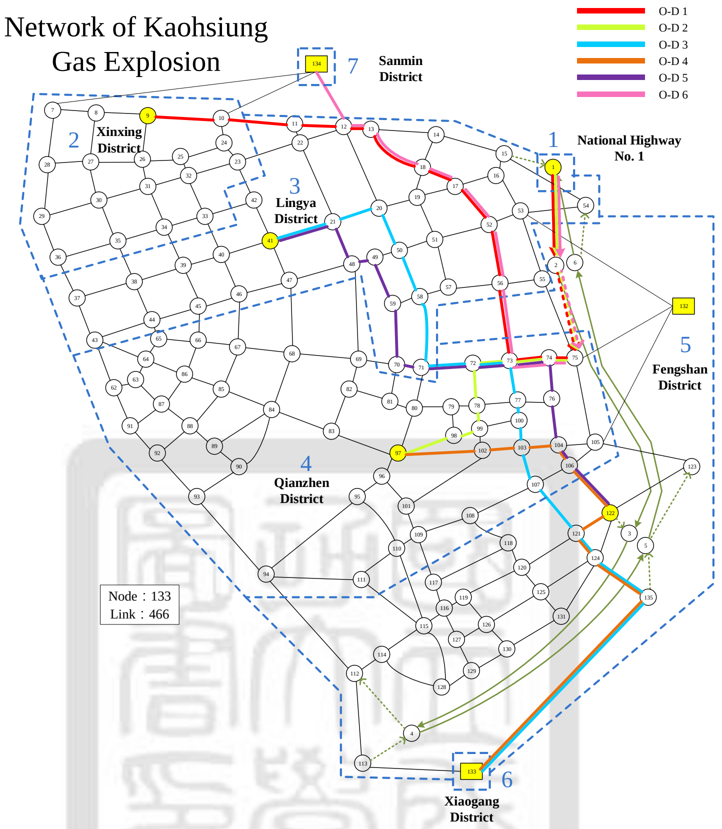

Figure 4.11 Optimal routes of each pair (t=5 time interval)

Thus, in order to avoid this situation and achieve risk equality, we execute a method and Figure 4.12 shows the flowchart. Step1: we input or renew the multiple O-D pairs, the sequence, the network data at particular time interval in advance. Step2: Pick one of O-D pairs based on the sequence and execute the NSGA-II to obtain an optimal route. Then we multiply the accident probability of used links by α and set α as infinite number at the same time interval. In other words, the hazmat trucks are prohibited from driving in the links which is used. It is worth mention that if the risk of links from the same node all have been multiplied by infinite number, we reset the risk of links. By this way, if the demand of chemical trucks for transporting hazmat increase,

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we could propose a solution to solve this problem. Step3: Once one of O-D pairs have not been processed at particular time interval, it goes to Step2. If all O-D pairs have been processed and all chemical trucks arrive at the destination(s), the program is finished. If not, it goes to Step1 until all chemical trucks arrive at the destination(s).

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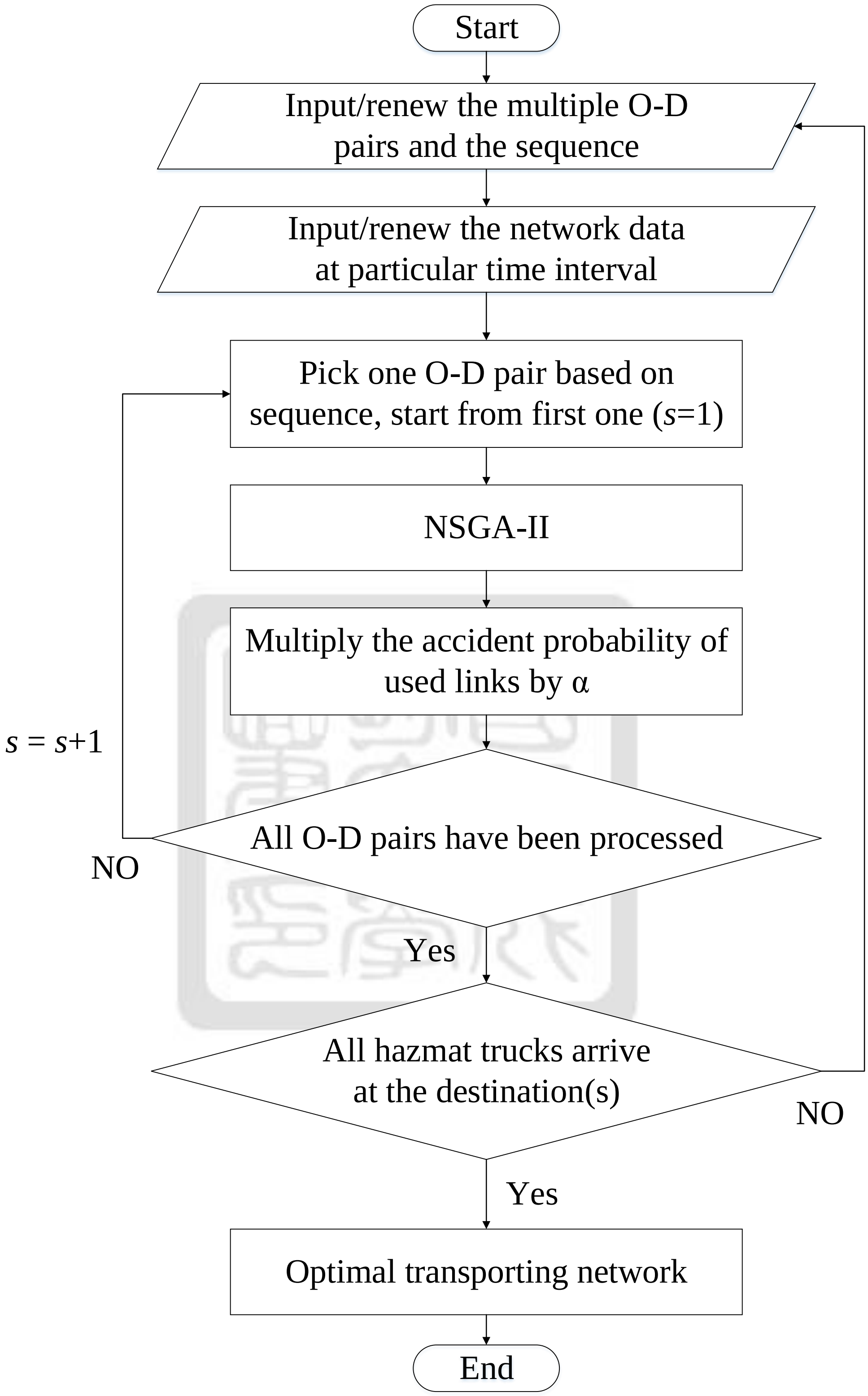

Figure 4.12 The program-processing procedure for multiple O-D pairs

Table 4-10 shows the routes of each pair at different time interval. It presents the multiple O-D pairs and there are no links which is used more than once except for

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highway, on-ramp, and off-ramp.

Table 4-10 Optimal routes of each pair at different time interval

Update time (minute)	O-D	Link	Cost	Risk
5	O-D1	[1, 2, 75, 74, 73, 56, 52, 17, 18, 13, 12, 11, 10, 9]	3.486	0.330
	O-D2	[1, 2, 75, 105, 104, 103, 102, 99, 98, 97]	2.367	0.342
	O-D3	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 58, 50, 20, 21, 41]	3.664	0.921
	O-D4	[133, 113, 4, 112, 114, 115, 111, 110, 109, 101, 96, 97]	2.600	0.885
	O-D5	[122, 124, 125, 126, 119, 116, 115, 111, 94, 93, 90, 89, 88, 87, 63, 64, 65, 66, 45, 46, 40, 41]	3.697	0.252
	O-D6	[1, 2, 75, 55, 53, 52, 51, 19, 20, 12, 134]	3.543	0.419
10	O-D1	[74, 73, 56, 52, 17, 18, 13, 12, 11, 10, 9]	2.331	0.143
	O-D2	[105, 104, 103, 102, 99, 98, 97]	0.856	0.071
	O-D3	[107, 106, 104, 76, 77, 73, 72, 71, 58, 50, 49, 48, 21, 41]	2.482	0.230
	O-D4	[112, 114, 115, 110, 109, 101, 96, 97]	1.338	0.276
	O-D5	[111, 94, 93, 90, 84, 85, 86, 66, 45, 46, 47, 41]	2.369	0.285

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	O-D6	[55, 53, 52, 51, 50, 20, 12, 134]	2.093	0.213
15	O-D1	[17, 52, 51, 50, 49, 48, 47, 41, 42, 23, 32, 25, 26, 9]	2.203	0.404
	O-D2	Arrived	0.000	0.000
	O-D3	[72, 71, 58, 50, 20, 21, 41]	1.414	0.085
	O-D4	[96, 97]	0.120	0.027
	O-D5	[90, 84, 68, 47, 46, 40, 41]	1.539	0.411
	O-D6	[50, 51, 19, 20, 12, 134]	1.299	0.112
20	O-D1	[23, 24, 10, 9]	0.372	0.034
	O-D2	Arrived	0.000	0.000
	O-D3	[20, 21, 41]	0.286	0.007
	O-D4	Arrived	0.000	0.000
	O-D5	Arrived	0.000	0.000
	O-D6	Arrived	0.000	0.000
Highway, on-ramp, and off-ramp are link [15,1],[1,2],[2,75],[2,3],[122,3],[3,4],[4,112],[113,4],[4,5],[5,123],[135,5],[5,6],[6,54],[6,1]				

Figure 4.13 presents that the optimal network for transporting hazmat at t=5, t=10, t=15, and t=20 time interval. By this method, we clearly find that link [75, 74] and link [74, 73] are used once at t=5 time interval and others are the same situation. By the way, because some links are two-way roads, such as link [109,110] and link [110,111], the two-way roads are all used and are marked by two colors.

Thus, given multiple O-D pairs, we not only could change the routes to avoid the links with high risk at different time interval but also disperse the pressure on same link.

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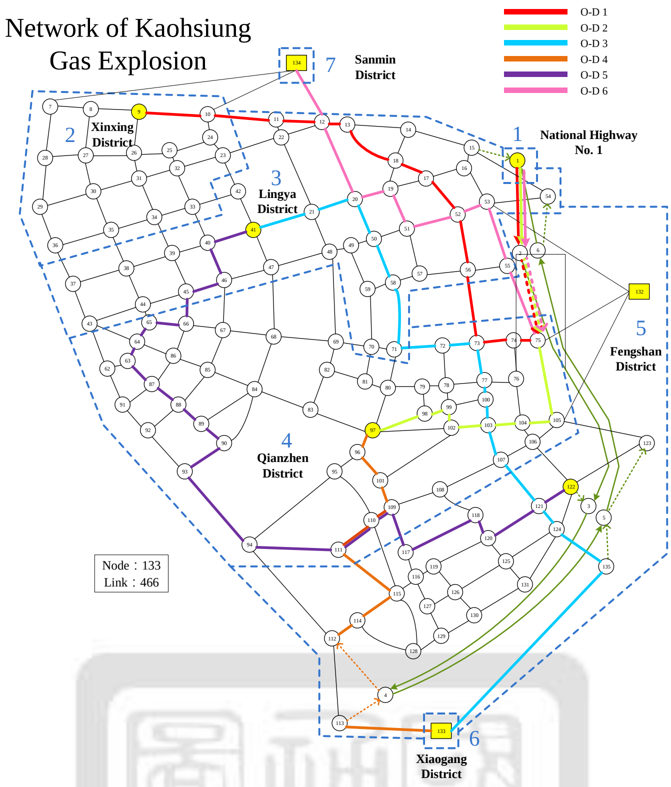
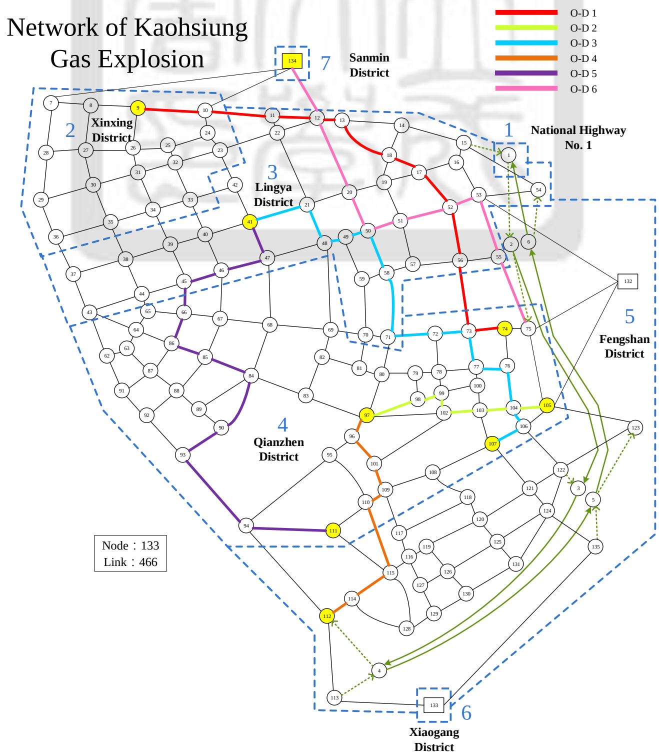


(a)



(b)

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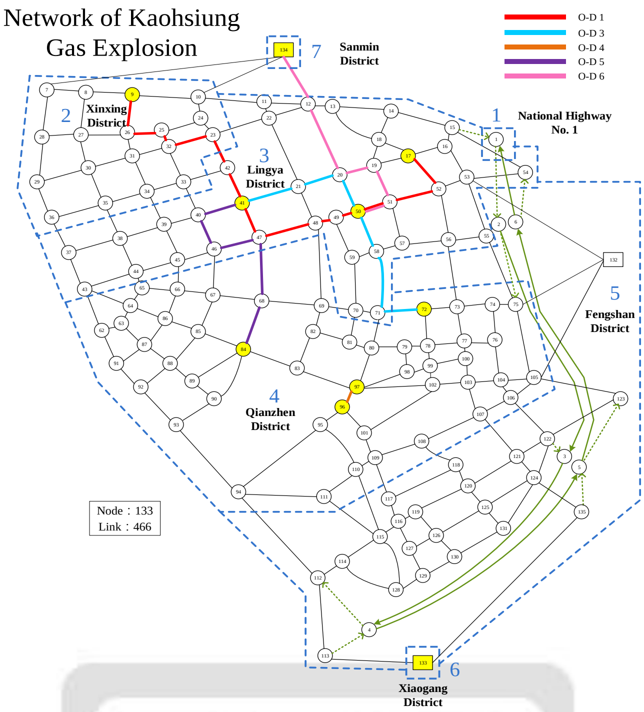
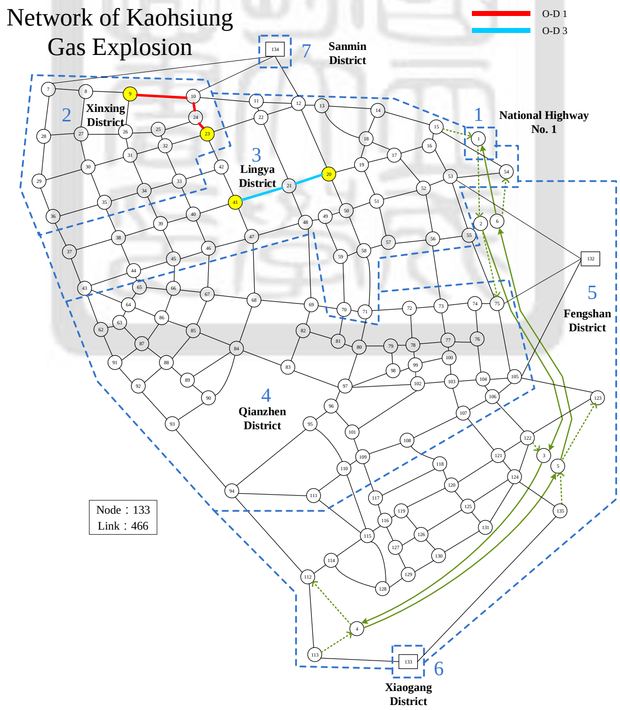


(c)



(d)

Figure 4.13 Optimal routes of each pair (No links which is used more than once): (a) t =5 time interval, (b) t =10 time interval, (c) t=15 time interval, and (d) 20th time interval

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4.3.4 Weighting Objectives

In the process of optimization, we execute standardized procedure in order to address different unit simultaneously. After that, we adopt NSGA-II to solve our problem. Although this method does not need to have prior preference, scale, or weight objectives previously, we would like to test and observe whether there are different results by weighting (W_c and W_r) two objectives and solving it. Therefore, a number of weighting combinations will be conducted to transform into a single objective problem.

Objective function:

$$\text{Min } \sum_{i\in N}\sum_{i\in N}\overline{R_{ij}^{t}}\times X_{ij}^{t}\times W_c+\sum_{i\in N}\sum_{i\in N}\overline{C_{ij}^{t}}\times X_{ij}^{t}\times W_r \tag{3-21}$$

The objective function is presented in equation (3-21). Then, we execute Dijkstra algorithm to find the optimal solutions and compare with the results from NSGA-II. Figure 4.14 shows the flowchart of the process of two methods.

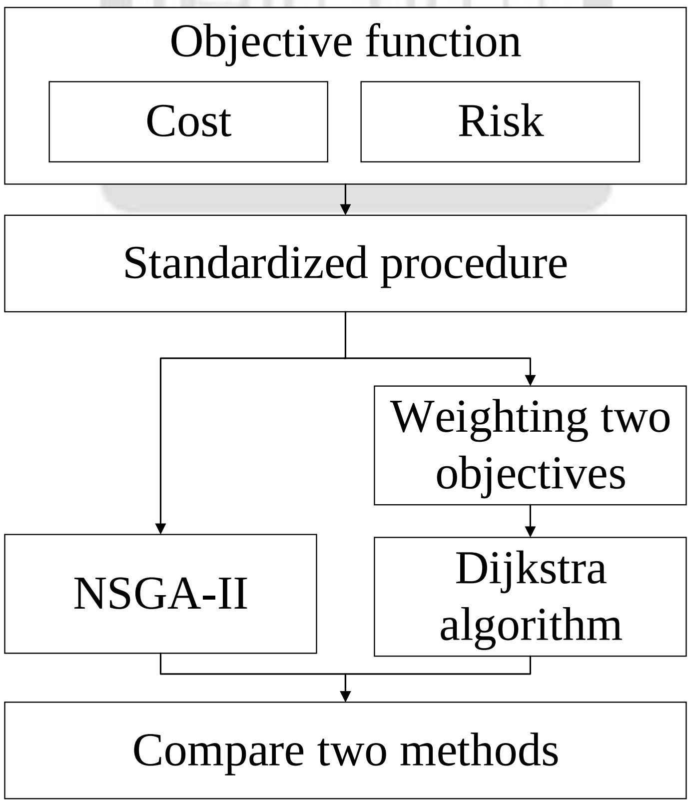

Figure 4.14 Process of two methods.

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Table 4-11 NSGA-II vs. Weighting Method (O-D 2)

O-D 2								
Methods	W_c	W_r	#	Routes	Cost	Risk	Hyper-volume	CPU time (s)
NSGA-II	None		#1	[1, 2, 75, 74, 76, 77, 100, 99, 98, 97]	2.027	0.253	81.427	2.9
			#2	[1, 2, 75, 74, 73, 72, 78, 99, 98, 97]	2.047	0.229	82.200	
			#3	[1, 2, 75, 74, 73, 72, 71, 80, 97]	2.128	0.229	81.854	
Weighting Method	0.1	0.9	#4	[1, 2, 75, 74, 73, 72, 78, 99, 98, 97]	2.047	0.229	82.200	0.2
	0.2	0.8	#5		2.047	0.229	82.200	
	0.3	0.7	#6		2.047	0.229	82.200	
	0.4	0.6	#7		2.047	0.229	82.200	
	0.5	0.5	#8		2.047	0.229	82.200	
	0.6	0.4	#9	[1, 2, 75, 74, 76, 77, 100, 99, 98, 97]	2.027	0.253	81.427	
	0.7	0.3	#10		2.027	0.253	81.427	
	0.8	0.2	#11		2.027	0.253	81.427	
	0.9	0.1	#12		2.027	0.253	81.427	

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Table 4-12 NSGA-II vs. Weighting Method (O-D 3)

O-D 3								
Methods	W_c	W_r	#	Routes	Cost	Risk	Hyper-volume	CPU time (s)
NSGA-II	None		#1	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 58, 50, 20, 21, 41]	3.664	0.920	84.617	5.7
			#2	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 69, 68, 47, 41]	3.492	1.048	83.790	
			#3	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 59, 49, 48, 21, 41]	3.611	0.949	84.456	
			#4	[133, 113, 4, 112, 114, 128, 129, 130, 131, 124, 122, 106, 104, 76, 74, 73,	5.061	0.821	82.949	

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				72, 71, 58, 50, 20, 21, 41]				
Weighting method	0.1	0.9	#5	[133, 135, 124, 122, 106, 104, 76, 74, 73, 72, 71, 58, 50, 20, 21, 41]	3.808	0.841	85.058	0.3
	0.2	0.8	#6		3.808	0.841	85.058	
	0.3	0.7	#7		3.808	0.841	85.058	
	0.4	0.6	#8	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 59, 49, 48, 21, 41]	3.611	0.949	84.456	
	0.5	0.5	#9	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 69, 68, 47, 41]	3.492	1.048	83.790	
	0.6	0.4	#10	[133, 135, 124, 121, 107, 103, 100, 77, 73, 72, 71, 70, 69, 68, 47, 41]	3.492	1.048	83.790	
	0.7	0.3	#11		3.492	1.048	83.790	
	0.8	0.2	#12		3.492	1.048	83.790	
	0.9	0.1	#13		3.492	1.048	83.790	

In Table 4-11 and Table 4-12, we take O-D 2 and O-D 3 for example and compare the results of two methods. We discovered and verified two situations. (1) We could find that the optimal solution (#5) obtained by the weighting method ($W_c = 0.5, W_r =$

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0.5) is the same as the optimal solution (#8) obtained by NSGA-II. Additionally, because the value of hypervolume of this solution is higher than the others in O-D 2, it proves again that no other solution is better than this optimal solution. (2) In second example (O-D 3), we could find that the solutions (#5, #6 and #7) obtained by the weighting method ($W_c = 0.1, W_r = 0.9$) ($W_c = 0.2, W_r = 0.8$) ($W_c = 0.3, W_r = 0.7$) are better than the optimal solution (#1) obtained by NSGA-II based on the two values of hypervolume. This means that even though genetic algorithm could find optimal solutions within a reasonable time, it does not guarantee the solutions are best. (Rocha & Neves, 1999) The main reason is premature convergence to solutions coding local optima of the objective function. Thus, diversity of each iterations is the key point with the use of genetic algorithm.

4.4 Summary

In the empirical experiments, we present different situations on Kaohsiung City to solve the route optimization for hazmat transportation. It includes the problem of real time single pair and real time multiple O-D pairs. In process of generating real time network data, a traffic simulation software (DynaTAIWAN) is applied.

In the results, we discover and prove that if initial population includes the routes generated by Dijkstra algorithm, NSGA Ⅱ could generate better solutions and get convergent solutions within a short time. Among these solutions, we choose one as driving route based on the comparative method, called hypervolume proposed by Zitzler and Thiele (Zitzler & Thiele, 1999). Then we could update the route at different time interval according to travel time of driving route and the new start node.

Moreover, we compare the solution obtained by NSGA-II to the solution obtained by weighting method and prove two things. 1. If no other solution is better than the

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solution generated from NSGA-II, we prove this solution is best. 2. If the solution is better than the solution generated from NSGA-II, it shows the heuristic algorithm falls into local optimum. Thus, we could examine the results by the weighting method.

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CHAPTER 5 CONCLUSIONS AND SUGGESTIONS

This research develops a real time multi-objective genetic algorithm to design transportation routes for hazmat routing problem. From the results of experiments, the conclusions and suggestions are summarized in Section 5.1 and Section 5.2 respectively.

5.1 Conclusions

This research identifies the important issues of hazmat transportation and deals with it on realistic network. Based on the empirical analysis, the conclusions of this research are summarized as follows:

1. When we face the problem of real time route optimization for hazmat transportation, two things are worth it to mention. First, compared with other optimization methods, genetic algorithm does not need to have prior preference, scale, or weight objectives. Second, with the ability of multi-objective genetic algorithm to search the global domain, the optimal solutions could be obtained within a reasonable time. (Sivanandam & Deepa, 2008) Especially in real time optimal route for hazmat transportation, it is indeed an effective algorithm to deal with.
2. This research constructs Kaohsiung City network and adopts real time NSGA-II to find the Pareto solutions at particular time interval. We consider two objectives including risk and cost. Among these, traffic volume and travel time simulated by DynaTAIWAN are the main time-dependent components.
3. The results present that if initial population includes the routes generated by Dijkstra algorithm, the real time NSGA-II could generate better solutions. Given multiple O-D pairs, we could generate optimal transporting network with no links which is used more than once. It not only could update the route at particular time

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interval but also alleviate risk on the network.

5.2 Suggestions

The suggestions for future study on real time route optimization for hazmat transportation problem are summarized as follows:

1. In the process of generating the routes of multiple O-D pairs, this research adopts that first come, first served. The O-D pairs are sequenced in order of preset order. Although this strategy could generate a good solution, it is not guaranteed to be the best. The reason is computing time. The computing time of generating a route of multiple O-D pairs takes approximately 280 seconds, but there are 720 permutations of the six O-D pairs. If we would like to get the best permutations which is minimum total cost and risk, it takes approximately 201,600 seconds. That means that we could not update the each of pair immediately. Thus, in order to get better solutions, another method should be applied.
2. When we use the genetic algorithm to find Pareto solutions, we could face the problem of premature convergence. There are some of the techniques used to prevent this situation. (1) Adaptive mutation rate. (2) Random offspring generation. (3) Social disasters technique. The main operator of these techniques is to increase the diversity of population and prevent ineffective process. (Rocha & Neves, 1999)
3. In the future, if real time network data could be collected by innovative communication technology such as sensors, 5G, IoT, it could substitute for the assumed network data. For Kaohsiung city government or decision maker, that not only assists in more effective traffic management but also could provide more precise decisions for hazmat transportation. Thus, we could actively avoid large-scale accidents instead of passive control for chemical trucks' driving route.

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APPENDIX

Table A-1 Incident of chemical trucks in Taiwan (2017-2019)

Date	Accident	Treatment	Impact		
			Injury/ Fatality	Congestion	Pollution
2017/05/27	A chemical truck carried Methyl acrylate caused lots of gas leaked in Daliao District.	The police and firefighters cordoned off the accident and sprinkle water to dilute the smell. The Environmental Protection Agency fined the operator ten thousand according to the air pollution law.	injury：1		●
2017/08/25	A chemical truck carried Styrene overturned and caused 4,50 kilogram of styrene leakage in Renda Industrial Park.	The police and firefighters cordoned off the accident instantly. The operator also called staff and equipment to stop leakage and follow-up accidents.	injury：1	●	●
2017/11/21	A chemical truck carried	Manufacturers putted sand and	injury：1	●	●

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Date	Accident	Treatment	Impact		
			Injury/ Fatality	Congestion	Pollution
	emulsion overturned and caused leakage in Linyuan District.	sawdust on emulsion to remove it and some flowed into the gutter.			
2018/01/31	A CPC chemical truck carried Methanol overturned due to less carefully turning.	The police and firefighters sprayed water and cordoned off the accident first.	injury：1		●
2018/03/26	A chemical truck carried sulfuric acid overturned because turning angle was too great in Luzhu District.	The fire department sent 26 firefighters, 10 fire engines and cordoned off the on-site accident.	injury：1		●
2018/07/17	A chemical truck hit on BMW at 72 County Road.	Firefighters rescued and sent their to hospital.	injury：3	●	
2018/07/22	A chemical truck carried phenol and diesel overturned	Firefighters brought LN2, chemical sorbent pad and sawdust to cover the	fatality：1	●	●

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Date	Accident	Treatment	Impact		
			Injury/ Fatality	Congestion	Pollution
	and had leakage in Tai Western Coast Expressway.	phenol lest much more leakage.			
2018/09/27	A chemical truck carried Propene overturned and had leakage in National Freeway No. 1.	Firefighters rescued the driver and sprinkled water to protect from explosion.	fatality：1	●	●
2018/12/05	A chemical truck carried Acetic acid overturned and had leakage.	Firefighters rescued the driver and sprinkled water to protect from explosion.	fatality：1	●	●
2019/01/09	A chemical truck carried Sulfuric acid	Firefighters rescued the accident which	None	●	●

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Date	Accident	Treatment	Impact		
			Injury/ Fatality	Congestion	Pollution
	was burned with unknown reason and caused leakage.	lasts more than one hour.			
2019/01/17	A chemical truck carried Sulphur had leakage in National Freeway No. 1.	Firefighters sprinkled water to protect from explosion.	injury：1	●	●
2019/01/24	A chemical truck carried Sodium hydroxide bumped hillside and caused leakage.	The staff of the Environmental Protection Bureau prevent pollution from flowing into the river.	fatality：1		●

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Date	Accident	Treatment	Impact		
			Injury/ Fatality	Congestion	Pollution
2019/02/23	A chemical truck carried Calcium chloride bumped three trucks and had leakage.	Firefighters rescued the accident and prevented from more leakage.	injury：1	●	●
2019/03/12	A chemical truck carried Styrene had a collision with front vehicle.	Firefighters closed the some lanes in National Freeway No. 1.	None	●	
2019/03/21	A chemical truck carried Isoprene overturned.	Firefighters closed the expressway and removed the truck.	injury：1	●	

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