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On the Modeling Disrupted Networks using Dynamic Traffic Assignment

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On the Modeling of Disrupted Networks using Dynamic Traffic Assignment

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Abstract

On the Modeling of Disrupted Networks using Dynamic Traffic Assignment

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A traffic network can be disrupted by work zones and incidents. Calculating diversion rate is a core issue for estimating demand changes, which is needed to select a suitable work zone configuration and work schedule. An urban network can provide multiple alternative routes, so traffic assignment is the best tool to analyze diversion rates on network level and the local level. Compared with the results from static traffic assignment, dynamic traffic assignment predicts a higher network diversion rate in the morning peak period and off-peak period, a lower local diversion rate in the morning peak period. Additionally, travelers may benefit from knowing real-time traffic condition to avoid the traffic incident areas. Deploying variable message signs (VMSs) is one possible solution. One key issue is optimizing locations of VMSs. A planning model is created to solve the problem. The objective is minimize total system travel time. The link transmission model is used to evaluate the performance of the network, and bounded rational behavior is used to represent drivers' response to VMSs. A self-adapting genetic algorithm (GA) is formulated to solve the problem. This model selects the best locations

to provide VMSs, typically places are that allow travelers to switch to alternative routes. Results show that adding more VMSs beyond a certain threshold level does not further reduce travel time.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Background

Traffic networks can be disrupted in multiple ways – for instances, traffic incidents and construction or maintenance work on the facilities. These disruptions can be classified into two categories-planned disruptions and unplanned disruptions.

Lane closures from highway work zones are an example of planned disruptions. Work zones introduce many challenges to ensuring smooth traffic operations and a safe environment for drivers and workers. Closing one or more lanes may exacerbate already present congestion problems, decrease capacity of links, increase weaving as drivers merge into the continuing lane(s), cause a significant decreasing in speed across lanes, and increase the risk of rear-end collisions, especially if a queue forms that extends upstream of signs alerting drivers to the work zone conditions. One way to improve traffic conditions in work zones is reducing traffic volume through work zones. Some drivers will naturally divert when a work zone is put into place and even more will divert if given proper guidance. Understanding total amount of travelers who remain to through work zone area is a critical issue. The diversion rate is used to represent diversion behavior in this thesis. After obtaining the diversion rate of work zone, one can establish a reasonable project schedule and choose a safe, efficient traffic management strategy to reduce congestion, make traffic operation smoothly and improve safety.

Incidents always happen randomly, so lane closures due to an incident an example of unplanned disruptions. However, if travelers have real-time traffic information, they may be able to switch routes and avoid entering the incident area. Intelligent transportation systems (ITS) have emerged as an effective solution to this problem, enabling the collection of real-time traffic information, generation of route guidance based on this information, and communication of this information to drivers. This strategy can potentially reduce travel times and improve traffic network performance. Variable message signs (VMSs) are a component of ITS which disseminate information to drivers who pass by them. Travelers can then select revised routes when they receive the information, if desired. Travelers will make this decision based on the potential travel time savings by choosing an alternate route.

1.2 MOTIVATION

Highway work zones and incidents are factors that disrupt a network, but work zones are planned factors and incidents are unplanned factors. There are different ways to improve the performance of a network based on the type of the disruption.

For a work zone, planners and contractors need to estimate change in travel demand through the work zone area, in order to select a suitable work zone configuration and a suitable schedule based on the changing. The core issue of estimating demand changes is to calculate the diversion rate. In existing literature, there are three kinds of methodologies for diversion behavior- simple user equilibrium (UE), theoretical methods, and empirical algorithms. These methods typically focus on a small area surrounding the work zone, with the work zone links and one alternative route. This setup may be appropriable in rural areas. However, in urban areas, the network generally has multiple alternative routes, and route selection is primarily driven by travel time. If people need to spend more time to travel through the work zone area, they may switch to alternative routes. Traffic assignment models assign demand of each origin-destination (OD) pair on the network based on the travel time of each route connecting this OD. If there is a work zone on the network, these models can capture time changing caused by work zone and reassign demand on the updated network. The central assumption of traffic assignment is that travelers are familiar with the condition of a network, the location of a work zone on the network, and the condition of alternative routes if the work takes several weeks and drivers have time to learn the new network conditions. There are two types of traffic assignment, static traffic assignment (STA) and dynamic traffic assignment (DTA). In STA, OD demand is time-independent, an assumption better suited to long-term planning. By contrast, in DTA, demand is time-dependent, an assumption more applicable to real-time traffic guidance.

By contrast, accidents happen randomly. In such cases, VMSs can disseminate information to drivers to provide them with the latest traffic information. VMSs are relatively inexpensive, compared to capacity expansion; however, there is still a finite budget available for deployment of VMSs, along with constraints on telecommunications and the related infrastructure – for instance, it would be impractical to place a VMS at every intersection in a traffic network. Finding the optimal locations for deploying VMSs maximizes the benefit from VMSs by using the limited budget in the most effective way. The major modeling issue regards how to represent drivers' response to VMSs. Many factors, such as the content of information provided, can affect reaction behavior. Some factors, such as personal background, are difficult to model. However, travel time is a key factor when people select their routes and this is easier to model. The content of VMSs can contain the delay caused by accidents. This delay can be used to measure how travelers response to VMSs. More people use alternate routes when delay becomes longer. Otherwise, more people are likely to keep their current routes. Using delay to describe reaction behavior is therefore better than using a fixed diversion rate. This problem can be complex, so efficient methods are needed to find a solution in a reasonable amount of time.

1.3 CONTRIBUTIONS

This thesis develops a modeling approach to estimate the diversion rate caused by a long-term work zone on an urban network. As mentioned above, there are multiple alternative routes available in urban networks. Two types of diversion rate are defined. Network level diversion, used to measure the total number of travelers that enter the work zone area, and local level diversion, used to compute the total number of drivers remaining on a work zone link. Calculating this diversion rates can identify which type of lane control strategy is best. The relationships between network level diversion rate and demand, local level diversion rate and demand, and diversion rate on both levels is studied. Engineers can use these relationships to calculate the diversion rate for a work zone in any region.

Bounded rationality is introduced to represent drivers' behavior in response to VMSs. Each driver has an individual tolerance band of delay. Drivers will only switch routes if the delay exceeds their tolerance threshold. Calculation of delay considers characteristics of the accident, and the resulting assignment framework produces more robust results than using a fixed diversion rate. This is the primary contribution relating to optimal location of VMSs. The second contribution is the application of a self-adapting genetic algorithm to solve this problem. The crossover and mutation rates in the algorithm are based on the fitness value of chromosomes. Tuning the parameters of heuristics is a difficult problem, and the self-adapting approach produces solutions faster than using fixed values for the crossover and mutation rates.

1.4 ORGANIZATION OF THESIS

The rest of the thesis is organized as follows. Chapter 2 includes reviews of previous studies on how to predict diversion rates caused by highway work zones, models and algorithms that are used to find the optimal locations of VMSs, and how to describe drivers' reaction of VMS. This chapter also introduces the link transmission model (LTM) as a simulation model to solve the optimal location of VMSs. Chapter 3 explains the modeling approach for estimating diversion rates of work zones on an urban network. Results from STA and DTA are compared with each other, and the results from DTA are also compare with video data obtained from the field. The relationships between network level diversion rate and demand, local level diversion rate and demand, and diversion rate on both levels are developed. Chapter 4 develops a model to find the optimal locations of VMSs by minimizing excepted total travel time. A self-adaptive genetic algorithm is applied to solve the model. The results of a numerical example are presented at the end of this chapter. Conclusion and possible directions of future work are presented in chapter 5.

Chapter 2: Literature Review

2.1 Introduction

Literature for computing diversion rates can be classified into simple user equilibrium, theoretical method, and empirical algorithms. Most of these models are applied on the condition which provides only one alternative route. The diversion rate from simple UE is based on the total number of travelers through a work zone link and alternative route when travel times on both routes are equal. The theoretical method applies flow fluid theory to compute diversion rate, in which a "pressure difference" impels drivers to switch to the alternative route. One type of empirical algorithms uses survey data to create logit models or regression models to represent diversion behavior. Another type of empirical algorithms uses queue length or toleration of delay to compute diversion rate.

Multiple heuristic algorithms such as genetic algorithms and tabu search have been applied on find the optimal locations of VMSs. Previous studies use a pre-set rate or logit models to represent drivers' reaction behavior. This thesis will apply bounded rationality to describe the reaction behavior. Bounded rationality has already been applied to traffic assignment in other contexts, leading to the formulation of bounded rational user equilibrium.

In the following sections, we review the methods are used to estimate diversion rate due to work zone at first. Then, we review models developed by previous studies to solve for the optimal locations of VMSs, methods to represent response behavior of

VMSs, applications of bounded rationality in the transportation area, and the link transmission model which is used to simulate traffic condition. Finally, we describe the contribution of this thesis in the context of existing literature.

2.2 Driver diversion

The QUEWZ software, first developed for Texas Department of Transportation in 1982 (1), incorporated an empirical algorithm to account for natural diversion in the 1987 version (2). There are two options related to count diversion on this algorithm. One option assumes travelers tolerate the delay caused by work zone and a threshold value is used to represent toleration. If delay is over the threshold value, travelers will switch to alternative route. Otherwise, they will still go through work zone. The default is for drivers to divert when delay exceeds 20 minutes. Another option specifies a queue length threshold. Enough vehicles divert to alternative routes in order to keep queue length below the threshold. Ullman (3) studied temporary lane closures on Texas freeways, many of them with frontage roads that provided a parallel alternate route, and found the level of diversion to be directly related to the amount by which demand exceeded capacity. The study recommended using queue length as the default diversion threshold, and adjusts the default based on average ramp spacing upstream of work zone link. Traffic volumes on work zone links are slightly lower than historical demand. Although delay and queue length stabilized at all sites, the values of these performance measures differed greatly across sites with very similar characteristics – suggesting that a one-sizefits-all diversion rate is not appropriate and that the characteristics of the network surrounding the freeway must be considered.

Like Ullman (3), Lee et al. (4) also found significant traffic volume changes on exit and entrance terminals upstream of work zones. The authors found little variations in the percent change in volume on ramps and the main lanes across several field studies in Wisconsin. Volumes on on-ramps upstream of work zones decreased in volume 20% to 40%; increased 50% to 60% on exit ramps; and decreased 10% on freeway lanes approaching the work zone. These results differ from what was found in Ullman's (3) study, again suggesting that site-specific characteristics and network characteristics play an important role.

Ullman and Dudek (5) developed a theoretical approach to predicting queue length at short-term work zones in locations where ramps are closely spaced – allowing many opportunities for diversion. The approach describes the traffic flow on work zone area as a fluid flow through a section of permeable pipe. At the beginning, the pressure inside the pipe is equal to the outside pressure. A work zone is represented as a bottle neck in the pipe, reducing the flow rate and increasing the inside pressure. The difference of pressure pushes flow through the wall of pipe. The authors apply Darcy's Law to calculate diversion flow.

A binary logit model is created by Song and Yin (6) to represent diversion behaviors at work zones. The model includes three variables – travel time, work zone location (urban or rural), and weather (normal or bad conditions). The data used to develop this model comes from a stated preference survey. Then they use two processes (open-loop and closed-loop) to calibrate a “Remaining Traffic Factor” that is used to account for diversion rate when one lane closed. The binary logit model is used to compute a parameter to adjust route travel time on both processes. The open-loop process is suitable for short-term work zone. The closed-loop process uses stochastic user equilibrium assignment, and is applicable for long-term work zone.

Qin et al. (7) analyzed the data from two state wide data management systems in Wisconsin and find that natural diversion is up to 15%. Gravity model and linear regression models are used to estimate the traffic impacts on arterials and alternative routes due to a short-term freeway lane closure. According to the models, higher signalized intersection density in alternative routes and higher speed difference between regular and lane closure conditions on arterials makes more travelers switch to alternative route. Linear models have better fitness than gravity models, because they contain the speed difference. While the authors show that such a model can be estimated, it remains a problem to determine the values of the independent variables such as speed difference before the work zone is put in place.

Chien and Yang (8) developed an analytical model to optimize the length and schedule of a work zone on a rural freeway. The diversion model assumes that travelers switch to the alternative route until its travel time is equal to the one on the work zone route. The maximum diverted traffic volume is also defined as the difference between capacity of the alternative route and the existing traffic volume on this route. They found that the diverted flow significantly depends on the difference of travel time on both routes. The diversion rate is lower with light traffic on the freeway (work zone area). Otherwise, the diversion rate becomes higher.

2.3 Finding the optimal location of VMSs

Several previous studies have focused on the problem of finding optimal locations for VMSs. Abbas and McCoy (9) are first researchers who addressed this problem. The objective of their model is to maximize the total number of vehicle that pass by VMSs. The model does not consider the diversion rate after drivers see traffic information provided by VMSs. Chiu et al (10) and Chiu & Huynh (11) combine the tabu search heuristic with dynamic traffic simulation and assignment to obtain optimal VMS location, based on minimizing total cost of VMSs. The cost of VMSs is the sum of agency and average user cost. The average user cost is the difference of average total user monetary cost between no-accident and accident condition. Simulation is used to obtain the travel times of vehicles, and an assignment process is used to assign vehicles to the network and find alternative paths that are the shortest paths based on current travel time when travelers wish to switch their routes. Chiu & Huynh also consider interactions between VMS and advanced traffic information system (ATIS). Huynh et al (12) uses the same framework with the G-D (greedy and drop) heuristic to find the near-optimal solution. The near-optimal solution includes 15% of the optimal solution that comes from exhaustive search of all potential solutions. However, the computation time is more acceptable compared with tabu search and genetic algorithm.

2.3.1 Drivers' Reaction to VMSs

An importation component of VMSs simulation is how to represent drivers' behavior when they pass by VMSs. Most of above-mentioned studies use a fixed rate to describe drivers' reaction after they pass by VMS. For instance, Chiu & Huynh (11) use 15% as VMS response rate. That means that 15% of drivers will switch their current routes to the shortest routes that from VMS location to their destinations when they pass by a VMS. The methodology of most studies that focus on response behavior of VMS (13, 14, 15, 16, 17) is based on data from stated-preference (SP) survey, revealed preference (RP) surveys, route simulators, and driving simulators. Then they create logit models based on the data to represent response behavior. The logit models include multiple significant factors such as socioeconomic characteristics, network condition and trip types. For instance, Peeta et.al (14) developed binary logit models for general case, truck drivers, non-truck drivers and based on the SP survey data from the Borman Expressway region in northwestern Indiana. All models contain socioeconomic factors (sex, age, and education level), VMS message types (message includes location of the accident only, combination of location, delay and best detour), and trust in information provided. Familiarity with alternative routes has a significant effect on truck drivers, but does not affect no-truck drivers. Peng et al (17) focused on motorist responses to VMSs on arterial surface streets. They developed an ordered logit model for the question-how often do you change your route due to arterial VMSs based on an SP survey on Milwaukee, Wisconsin. The model finds that the more often drivers pass by VMS and they consider VMSs are more useful. Full-time workers are more likely to switch their routes than part-time workers.

2.3.2 Bounded Rationality on Transportation Area

Bounded rationality (18) is a concept in decision making, in which the rationality of individuals is limited by the information they have, the cognitive limitations of their minds, and the finite amount of time they have to make decisions. It was first proposed by H.A. Simon and has been studied well in the economics field. The following researches in the transportation area consider bounded rationality. Mahmassani and Chang (19) introduced bounded rationality to user equilibrium traffic assignment and formulated bounded rational user equilibrium (BRUE). They use departure time of work trip to represent BRUE. If delay of departure time *i* falls into a traveler's indifference band of delay, he will still select this time on next day; otherwise, he will change departure time. Hu & Mahmassani (20), Jayakrishnan & Mahmassani (21) and Mahmassani &Liu (22) introduce bounded rationality to describe response behavior to real-time information system. If the difference of travel time between the current route and the best route is greater than a traveler's threshold, that traveler will switch his/her route; otherwise, he/she will keep his/her current route. Szeto and Lo (23) applied bounded rationality to dynamic traffic assignment and proposed tolerance-based dynamic user optimal principle which is travel time of all used paths for each OD pair is equal or within an acceptable tolerance. Lou and Yin (24) are the first to systematically explore BRUE in a static network. They provided the formulation of path-based and link-based

BRUE and properties of BRUE. Finding the best and worst case BRUE flow are formulated and solved on this paper. Because BRUE has multiple equilibria, Guo and Liu (25) developed a link-based boundedly rational day to day model whose equilibria is BRUE to evaluate the phenomenon of irreversible network change.

2.4 MODELING NETWORK

The link transmission model (LTM), proposed by Yperman (26), is used to simulate traffic flow on a network. It is a component of dynamic traffic assignment and also is a component of finding optimal locations of VMSs. The model is consistent with the hydrodynamic theory of traffic flow. The input of LTM is the demand on each route from traffic assignment algorithm and the outputs are travel time and volume of every link on each time period. The network consists of links and nodes, and there are corresponding models to compute traffic flow. This subsection introduces link models first, followed by node models and the overall process of LTM.

For each link, we need to know the number of vehicles which can enter or leave during time period *t*. LTM defines the sending flow $S_i(t)$ and receiving flow $R_i(t)$for link *i* on time period *t* to calculate this information. The model also records cumulative count of vehicles that cross the tail $N^{\uparrow}(t)$ and head $N^{\downarrow}(t)$ of link *i* on time period *t* in order to compute sending/receiving flow and link travel time.

Equations 2.1 and 2.2 are used to calculate sending and receiving flow of link *i* on time period *t*:

$$S_i(t) = min\{ N^{\uparrow}\left(t - {}^{L}/_{v_f} + \Delta t\right) - N^{\downarrow}(t), q_{\max}\Delta t\} \tag{2.1}$$

$$R_i(t) = min\{ N^{\downarrow}\left(t - {}^{L}\!/_{w_f} + \Delta t\right) + K_{j,i}L - N^{\uparrow}(t), q_{max}\Delta t\} \quad (2.2)$$

where L is the length of link i, v_f , w_f and $K_{j,i}$are the free-flow speed, shockwave speed and jam density of link i, $q_{\max}$ is the capacity of link i , and Δt is length of a time period.

According to cumulative counts of tail and head of link i, we can compute the travel time and link volume of this link. $N^{\uparrow}(t)$ and $N^{\downarrow}(t)$ of a link. An example is shown in Figure 2.1. The difference between $N^{\uparrow}(t_1)$ and $N^{\downarrow}(t_1)$ is the volume of this link on time period t_1.The following process computes link travel time and link volume on time t_1: First, find cumulative number of vehicles that enter the link on time t_1. Then find time t_2 on $N^{\downarrow}(t)$ let $N^{\uparrow}(t_1) = N^{\downarrow}(t_2)$. The difference between t_1 and t_2 is link travel time on time period t_1.

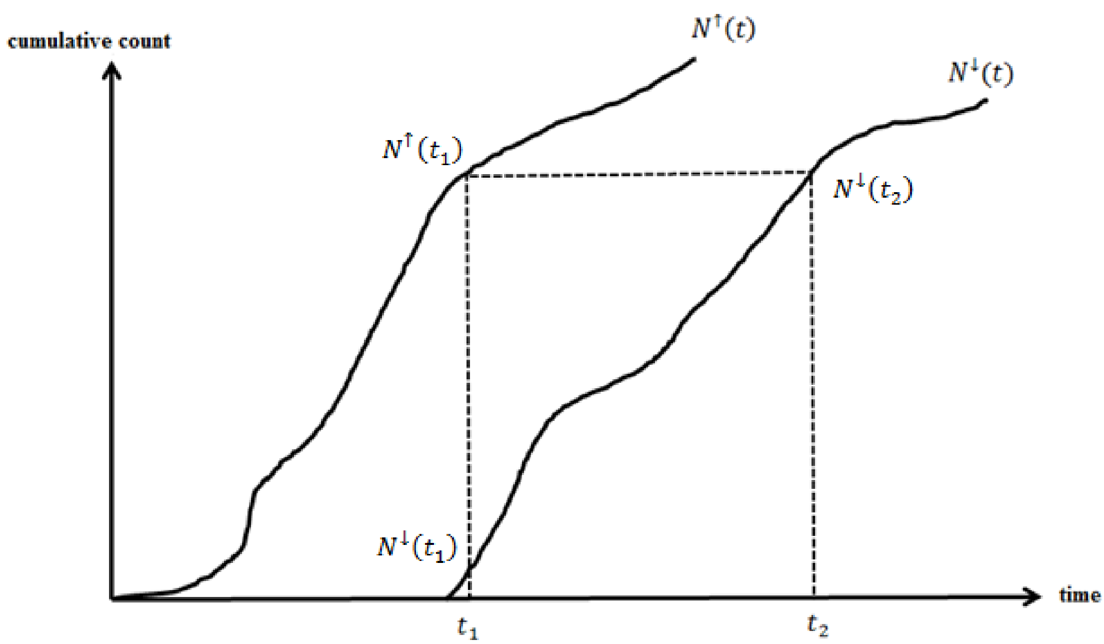

Figure 2.1: Cumulative count of vehicles on tail and head of a link

There are multiple node types. This thesis use three kinds of nodes: normal nodes, merge nodes and diverge nodes. Figure 2.2 shows the structure of each kind of node.

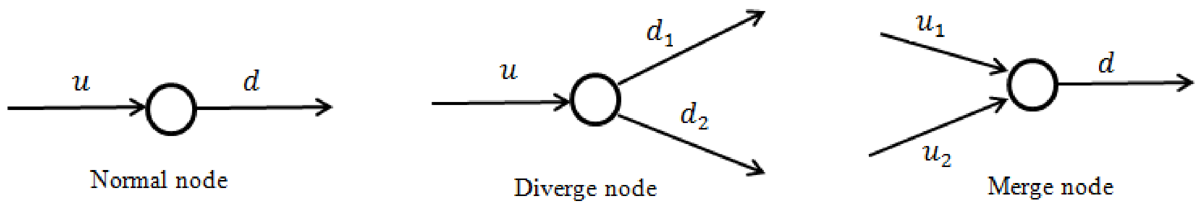

Figure 2.2: The structure of nodes

A normal node has one incoming link and one outgoing link. Let S_u and R_d be sending flow of upstream link and receiving flow of downstream link. The transition flow of normal node *i* is $q_i = min\{S_u, R_d\}$.

A diverge node has one incoming link and at least one outgoing link. Here, we use two outgoing links as an example. Let S_u, R_{d1} and R_{d2} be the sending flow of the upstream link, and the receiving flows of downstream link $d1$ and $d2$, respectively. Let P_{d1} and P_{d2} be the proportion of drivers turning into link $d1$ and $d2$, and f_{d1} and f_{d2} be the turning flow from upstream link to link $d1$ and $d2$. There are two possible cases. First, if $P_{d1}S_u \leq R_{d1}$, and $P_{d2}S_u \leq R_{d2}$, the amount of drivers turning into any link is less than receiving flow of this link, so $f_{d1} = P_{d1}S_u$ and $f_{d2} = P_{d2}S_u$. Second, if at least turning flow on at least one downstream link is greater than its receiving flow, then only some proportion of the sending flow can leave the upstream link. We introduce ϕ to represent this proportion and equation 2.3 is used to calculate it

$$\phi = min\{\frac{R_{d1}}{P_{d1}S_u}, \frac{R_{d2}}{P_{d2}S_u}\} \tag{2.3}$$

so $f_{d1} = \phi P_{d1} S_u$ and $f_{d2} = \phi P_{d2} S_u$.

A merge node has at least one incoming link and only one outgoing link. Here, we also use two incoming links as an example. Let S_{u1}, S_{u2} and R_d be the sending flows of upstream link $u1$ and $u2$ and receiving flow of downstream link, f_{u1} and f_{u2} be transition flow from upstream links $u1$ and $u2$ to downstream link. Again, there are two cases. If $S_{u1}+S_{u2} \leq R_d$, the total amount of drivers go to downstream link is less than receiving flow of this link, so $f_{u1} = S_{u1}$ and $f_{u2} = S_{u2}$. In the other case, not all of the flow from upstream links can enter the downstream link. This condition can be divided into two sub-cases: if flow from both upstream links is restricted, $f_{ui} = \frac{f_{ui}^{max}}{f_{u1}^{max}+f_{u2}^{max}} R_d$. f_{u1} and f_{u2} satisfies $f_{u1} + f_{u2} = R_d$ and $\frac{f_{u1}}{f_{u2}} = \frac{f_{u1}^{max}}{f_{u2}^{max}}$. If only one upstream link's flow is restricted, let this upstream link is link $u1$, all drivers on link $u2$ go to downstream link and the rest room of downstream link is for link $u1$, so $f_{u2} = S_{u2}$ and $f_{u1} = R_d - S_{u2}$. f_{u1} and f_{u2} satisfies $f_{u1} + f_{u2} = R_d$ and $S_{u2} < \frac{f_{u2}^{max}}{f_{u1}^{max}+f_{u2}^{max}} R_d$.

The overall LTM process involves the following three steps.

1. Check the stop criteria (no vehicles remaining on the network). If there is no vehicle on the network, calculate travel time and volume for each link on each time period, otherwise, go to step 2.
2. Determine sending and receiving flow of each link by using link model
3. Determine transition flow of each node by using node model, then vehicles transfer from upstream link to downstream link and update cumulative counts of each link, go to step 1.

2.5 SUMMARY

In this chapter, we surveyed the methods that used to compute diversion rate caused by a work zone. These algorithms focus on the work zone area which includes the work zone link and one or two alternative routes. A work zone on urban network is more complex than this condition. Traffic assignment tools can assign demand on a network and can capture time changing caused by work zone, so they are used in this thesis to calculate the diversion rate. In order to understand diversion behavior more deeply, two kinds of diversion rate are used on this study: network level diversion and local level diversion. This study also developed relationships between network level diversion rate and demand, between local level diversion rate and demand, and between diversion rate on both levels.

Heuristic algorithms that can be used to find the optimal locations of VMSs and are reviewed in section 2.3, along with algorithms for modeling driver behavior. This thesis uses bounded rationality to describe drivers' reaction behavior. This concept represents the principle of route choice and also captures the characteristics of accidents. The self-adapting genetic algorithm is introduced to solve the problem. The crossover and mutation rate are adjusted automatically based on fitness of chromosomes. It can reduce the algorithm's running time compared to fixed parameter values.

Chapter 3: Diversion Behavior for Work Zone

3.1 INTRODUCTION

As described in section 2.2, there are three kinds of methodologies- simple user equilibrium, theoretical methods and empirical algorithms. These methods focus on a work zone area which only includes the work zone link and one alternative route. While this condition is suitable on rural areas, in urban areas, the network typically has multiple alternative routes. Dynamic traffic assignment (DTA) and static traffic assignment (STA) models assign travelers on a network using the user equilibrium principle, which assumes travelers are familiar with the condition of a network. If a work zone lasts for several weeks, drivers will learn to anticipate possible delays, and readjust to a new equilibrium. Therefore, DTA and STA tools are able to analysis diversion behavior for long-term work zones on an urban network.

This study uses VISTA (Visual Interactive System for Transport Algorithms) as the DTA tool and TransCAD as the STA tool, so this chapter will first introduce these tools briefly. Then, we describe how to use DTA and STA to calculate the diversion rate for long term work zone areas. The results from DTA and STA are compared with each other and the results also compared with video data from the field. The difference between DTA and STA will be presented. Finally, a sensitivity analysis will be undertaken using DTA, to see the impact the roadway volume-to-capacity ratio on the diversion rate under different demand level.

3.2 INTRODUCTION OF DTA AND STA TOOLS

VISTA (27) is a simulation-based dynamic traffic assignment software. It can perform dynamic user equilibrium based on the cell transmission model (CTM) with extensions for signalized intersections (28).

The cell transmission model was developed by Daganzo (29, 30). It is a discrete version of the Lighthill-Whitham-Richards (LWR) hydrodynamic traffic flow model. Each network link is divided into several cells, and the number of vehicles in each cell will be tracked on every iteration (six seconds is used in VISTA).

The *sending flow* of a cell is the number of vehicles that can leave the cell if there is no downstream restriction, and the *receiving flow* is the number of vehicles that can enter if there is an infinite source. The maximum number of vehicles in each cell, and the maximum flow that can be sent from one cell to next are determined from the capacity, and density of each network link and the length of each cell. The most important feature of CTM is that the total number of vehicles in each cell cannot exceed finite limits. Instead, queues will be formed, which is the advantage of CTM over STA.

TransCAD, developed by Caliper Corporation, is a transportation planning software combined with GIS. One function of TransCAD is doing static traffic assignment. It provides multiple assignment methods – all or nothing, incremental assignment, capacity restraint, user equilibrium and system optimum. The Bureau of Public Roads (BPR) function is used to compute link cost, with user-set values of the parameters α and β. The convergence criterion is based on maximum absolute change in link flows between iterations. When maximum absolute change is smaller than the preset threshold, the algorithm will stop. This study chooses standard BPR functions to describe link performance and uses user equilibrium assignment as the assignment method.

3.3 METHODS FOR ESTIMATING DIVERSION RATE

This study focuses on work zones on an urban network. Under this condition, there are multiple alternative routes available upstream of the work zone, and at least one alternative route is available when people reach the work zone link. An example is shown in Figure 3.1. Area A is the upstream area of the work zone and it provides multiple alternative routes to travelers. Travelers switching to other routes on this area affects the performance of the whole network. Area B is the work zone area. When travelers enter area B, there is still one alternative route that is the last option to avoid the work zone. We want to understand diversion behavior in both areas A and B. Therefore, diversion rates on two levels are defined. Network level diversion represents how many travelers avoid entering the work zone area, and choosing other arterial streets/expressways. It can describe the change of demand in the work zone area. Another type of diversion rate focuses on local level (the work zone area). It can be used to find the percentage of travelers who keep their original route through the work zone link when they choose to enter the work zone area. Agencies and contractors can use this type of diversion rate to provide appropriate guidance as to the number of lanes to close.

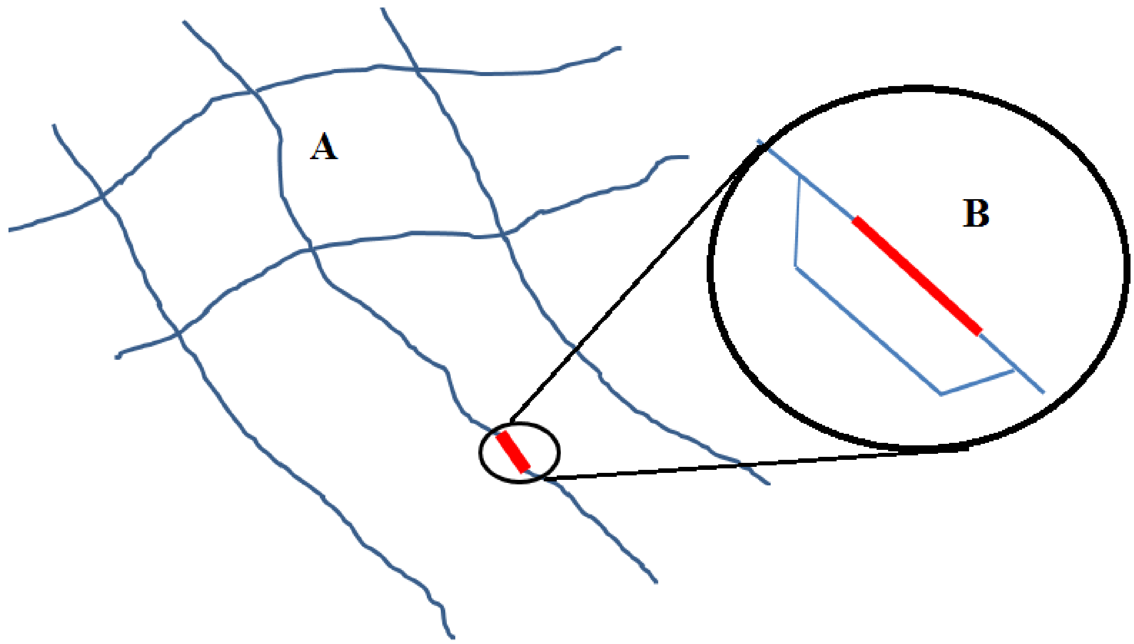

Figure 3.1: Example of a work zone on urban network

Figure 3.2 illustrates the topology of the work zone area links. Link 2 is the work zone link.

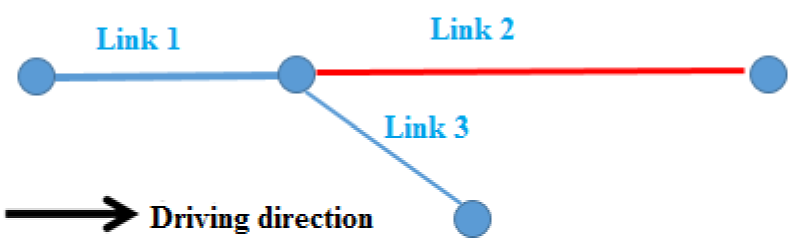

Figure 3.2: Topology of the work zone area links

If people choose alternative routes on area A, they will not enter link 1. Therefore, the change in volume on link 1 represents the diversion rate on the network level. The change in volume on links 2 and 3 indicate the diversion rate on the local level.

Equation 3.1 is used to compute network level diversion:

$$D_i = \frac{V_{regular,i} - V_{workzone,i}}{V_{regular,i}} \tag{3.1}$$

where D_i is the diversion rate on link 1, $V_{regular,i}$ is the volume on link *i* under regular condition (no-work zone) and $V_{workzone,i}$ is the volume on link *i* under work zone condition.

Equation 3.2 is used to compute diversion rate on local level:

$$D_i = R_{regular,i} - R_{workzone,i} \tag{3.2}$$

D_i is the diversion rate on link 2 or link 3, $R_{regular,i}$ is the ratio of the volume on link *i* to the volume on link 1 under regular condition (no-work zone) and $R_{workzone,i}$ is this ratio under work zone conditions.

The process of calculating diversion rates using DTA and STA tools has three steps:

1. Run DTA/STA model on a network under normal condition (no work zone). When the network reaches equilibrium, we record the volume on links that relate to the diversion rate.

2. Add a work zone on the network, we run the models with the same demand again. When the network reaches the equilibrium condition, we record volume on links.
3. Use equations 3.1 and 3.2 to compute two types of diversion rate according to the results from steps 1 and 2.

3.4 Comparing STA and DTA results

This study uses the work zone on IH-35 in Austin as the case study. Figure 3.3 shows the work zone location and the links whose flow may be impacted by the work zone condition. The network used on traffic assignment tools is same as the one is shown on figure 3.3.

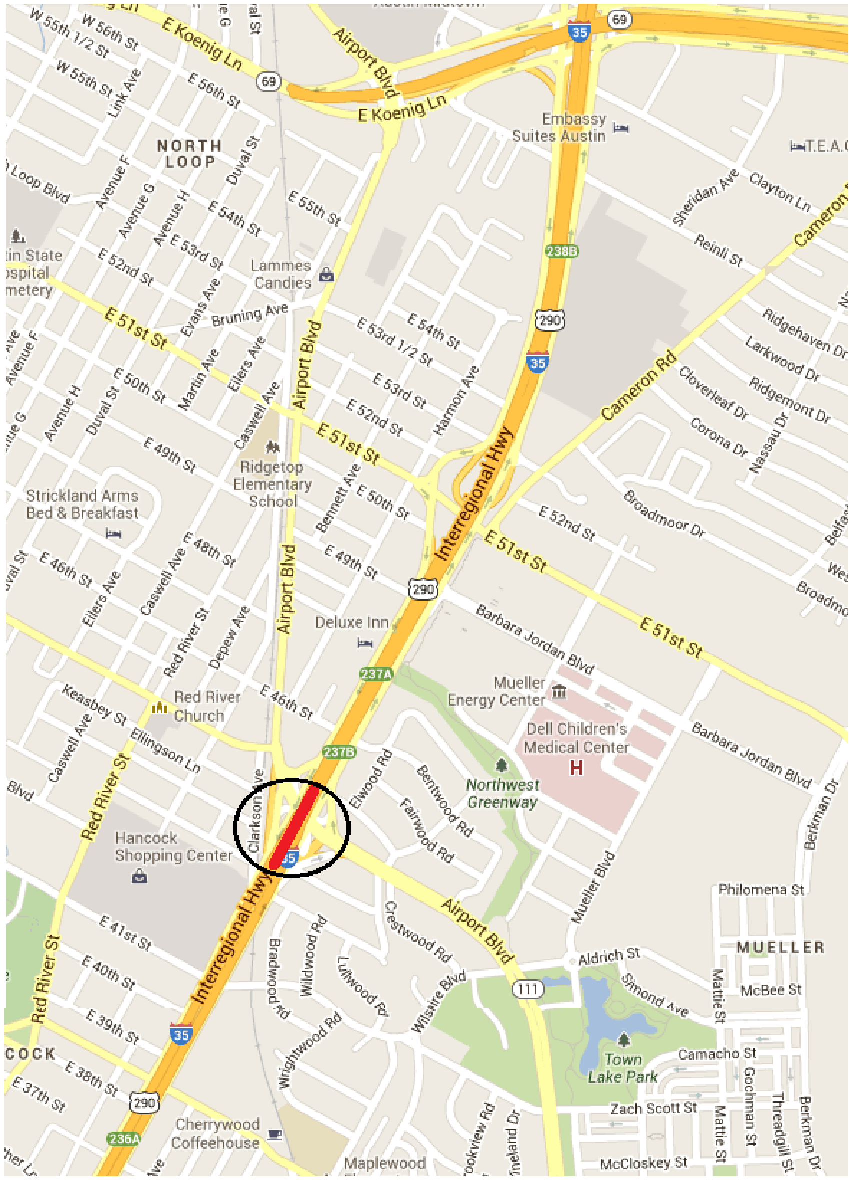

Figure 3.3: Location of the work zone

The work zone area lies downstream of the intersection of Airport Blvd and IH-35 south bound in the downtown area of the city of Austin. Upstream of the work zone area, the IH-35 lanes are separated into two groups, the lower deck and the higher deck. The work zone is located on the lower deck which is the red line on Figure 3.3. During work zone operations, the work zone area (the lower deck) is fully closed.

For clarity, we use figure 3.4 to illustrate the topology of the work zone area links. Links 1 and 2 lie upstream of the work zone. Links 3 and 4 denote the lower and upper deck of IH-35. Link 3 is the work zone. Link 5 is the off-ramp of IH-35. Travelers can use it to avoid the work zone and enter frontage road which is parallel to I-35 or other alternative routes. We use the diversion rate on link 1 to represent diversion rate on the network level. Diversion rate on link 2 is used to describe diversion rate on local level. DTA uses time-dependent demand and it has warm up and clearing periods which are the periods that begin to load vehicles on the network and let all vehicles leave the network. So we calculate diversion rate from DTA based on the stable condition which excludes warm up and cooling down periods.

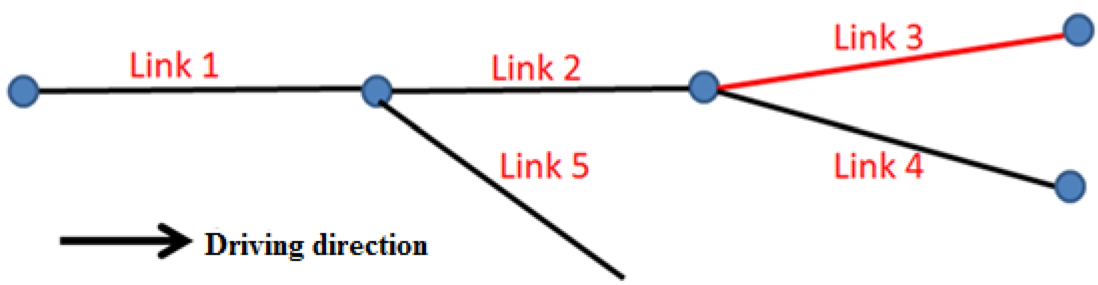

Figure 3.4: The topology of the work zone area

The results from STA and DTA are shown as follow. There are two scenarios in the case study, the morning peak period (7 am to 9 am) and the off peak period (9 pm to 6 am). The demand profile (31) is shown in figure 3.5. Only morning peak demand is already provided by the regional network. Off-peak period demand is obtained based on the demand profile and morning peak period. This method obtains a scale factor representing the ratio of off peak period demand to morning peak period, then uses this factor to multiply morning demand to obtain the off-peak demand. Equation 3.3 is used to compute this factor.

$$f = {P_{off\ peak}}/{P_{morning\ peak}} \tag{3.3}$$

where f is the scale factor, $P_{off\ peak}$ or $P_{morning\ peak}$ is the percentage of total demand on off peak period or morning peak period over the whole day.

According to assignment results, the selected stable condition on morning period is from 8 am to 9 am. The volume in the off-peak period has two phases. The first which called as phase 1 is from 9 pm to 12 am (congested) and the other which called as phase 2 is from 12 am to 6 am (uncongested). The condition on phase 2 is uncongested. The selected stable condition on phase 1 is from 9:30 pm to 10:30 pm and the one on phase 2 is from 2 am to 3 am.

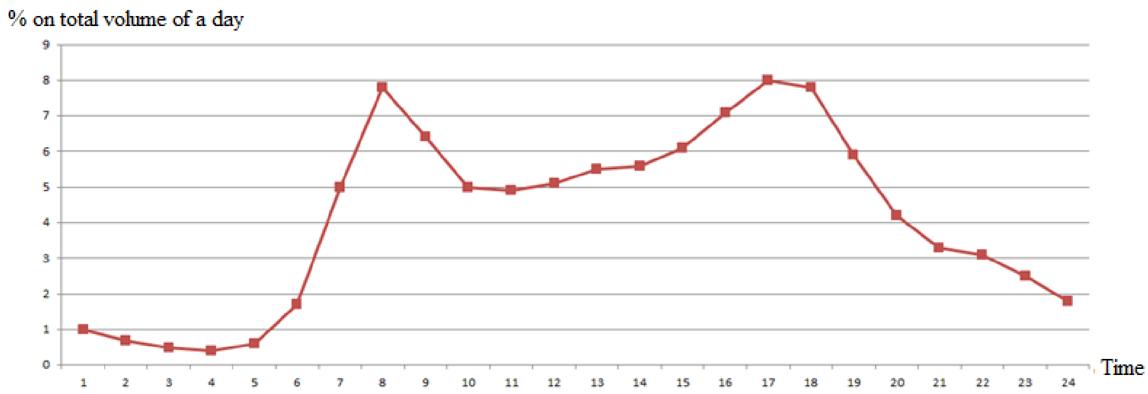

Figure 3.5: Demand profile of a day

Tables 3.1 and 3.3 show flow assignment results from STA for morning peak and off peak period, respectively. Tables 3.2 and 3.4 show the results from DTA for morning peak and off peak period, respectively.

Morning peak average hourly demand by STA				
	Normal		Work zone	
Link ID	Total	Per-lane	Total	Per-lane
1	18940	4735	14912	3728
2	17296	4324	11160	2790
5	1647	1647	3755	3755

Table 3.1: Results from STA-TransCAD for morning peak period

Morning peak average hourly demand by DTA				
	Normal		Work zone	
Link ID	Total	Per-lane	Total	Per-lane
1	6472	1618	3500	875
2	5860	1465	2800	700
5	612	612	697	697

Table 3.2: Results from DTA-VISTA for morning peak period

Off -peak average hourly demand by STA				
	Normal		Work zone	
Link ID	Total	Per-lane	Total	Per-lane
1	2488	622	2372	593
2	2196	549	1852	463
5	292	292	520	520

Table 3.3: Results from STA-TransCAD for off peak period

Off-peak average hourly demand by DTA								
Phase 1					Phase 2			
	Normal		Work zone		Normal		Work zone	
Link ID	total	per lane	total	per lane	total	per lane	total	per lane
1	6616	1654	3958	990	2352	588	2110	528
2	5281	1320	2748	687	2243	561	1490	373
5	1335	1335	1210	1210	109	109	620	620

Table 3.4: Results from DTA-VISTA for off peak period

Based on the flow assignment results, we obtain the diversion rates for both scenarios. Tables 3.5 and 3.6 show the diversion rates on morning peak and off peak period, respectively.

	Link ID	STA	DTA
Network level	1	21%	46%
Local level	2	16%	11%

Table 3.5: Diversion comparison during morning peak period

	Link ID	STA	DTA	
			Phase 1	Phase 2
Network level	1	9%	40%	10%
Local level	2	10%	10%	25%

Table 3.6: Diversion comparison during off peak period

From table 3.5, we find that during the peak hour, the diversion rate on network level from STA is smaller than the one from DTA. This reflected by the comparison on link 1. Notice that, when there is a work zone, DTA tells us that more people will try to avoid entering the work zone area. Fewer people will enter link 1. The work zone area has less congestion, so fewer people will switch to alternative route. Therefore, diversion rates on local level from DTA are smaller than the ones from STA. Actually, the result from DTA is more reasonable because, for a long term work zone, many vehicles will transfer to other routes at the network level instead of passing through work zone area because people know the congestion will be happened on the work zone area. Meanwhile, because DTA cannot allow link volumes to exceed the capacity of this link, DTA is more likely to assign travelers to other alternative routes than STA when downstream is congested. So the total number of vehicles that get in to the work zone area provided by DTA will drop dramatically. Table 3.6 reflects a similar trend on network level diversion. DTA allows more vehicles to use alternative routes on both phases' network level. Demand in phase 1 is much higher than that in phase 2, so the work zone area becomes more congested in phase 1 if all travelers pass through it. For this reason, the diversion rate in phase 1 is higher than on phase 2. Diversion rates on local level from DTA are higher than or equal to the ones from STA. Because more people already choose alternative routes on network level. During off peak hours, when there is a work zone on the main lanes, drivers know that they do not need to worry about congestion on local streets. Therefore, most vehicles would prefer to leave the highway and divert to local streets because they know that they can avoid passing through the more "dangerous" work zone area without suffering congestion.

We will compare the results from DTA with field data in the following way. Video data provided by Texas Department of Transportation shows traffic in the work zone area. It records the volumes on link 1, 2 and 5 from 9 pm to 11 pm on three days on regular condition and first two days on work zone condition. This study uses the volumes of links on two days on work zone condition and one day on regular condition to analyze. Tables 3.7 and 3.8 show the link volumes on work zone condition and regular condition. Diversion rates on both days are described on table 3.9.

	First day of work zone			Second day of work zone		
Time	Link 1	Link 2	Link 5	Link 1	Link 2	Link 5
9:00-10:00	2353	2053	300	2087	1966	121
10:00-11:00	1113	1001	112	2077	1956	121

Table 3.7: Link volumes on work zone condition

Time	Link 1	Link 2	Link 5
9:00-10:00	4000	3725	275
10:00-11:00	3109	2883	226

Table 3.8: Link volumes on regular condition

	First day of work zone		Second day of work zone	
	Network level	Local level	Network level	Local level
Time	Link 1	Link 2	Link 1	Link 2
9:00-10:00	41%	6%	37%	-1%
10:00-11:00	64%	3%	33%	-1%

Table 3.9: Diversion rates on both days

According the results, diversion rates on both levels of first day are higher than the ones of second day. People overreact when it is the first day of work zone project. When drivers see the work zone signs, they think the work zone area becomes congested. So people are more likely to choose alternative routes to avoid the congestion. On the second day, people already know there is a work zone on this area and the level of congestion is not very high when they start their trips. Some travelers can accept the delay caused by work zone, so the diversion rates on network level is decreased. The volume on link 2 does not exceed the capacity of this link, so people still keep their original routes and the diversion rate on link 2 is very close to zero.

The diversion behavior on the second day is same as the one for a long term work zone project, so we will compare the result of second day and the one from DTA. The link volume on the period that from 9 pm to 11 pm and diversion rate provided by DTA are shown in tables 3.10 and 3.11.

	Regular condition			Work zone condition		
Time	Link 1	Link 2	Link 5	Link 1	Link 2	Link 5
9:00-10:00	5738	5378	360	4655	3071	1584
10:00-11:00	5419	5147	272	4672	3093	1579

Table 3.10: Link volumes from 9 pm to 11 pm provided by DTA

	Network level	Local level
Time	Link 1	Link 2
9:00-10:00	19%	28%
10:00-11:00	14%	29%

Table 3.11: Diversion rates from 9 pm to 11 pm provided by DTA

According to the tables, the trend of diversion rate provided by DTA is similar with the real data. Along with decreasing demand, the diversion rate on network level is also lower. Fewer people want to pass through the work zone area and the level of congestion on work zone area is less. So more people want to keep their original routes and diversion rate on network level is smaller. The route choice behavior of DTA model involves choosing the shortest path from the origin to the destination. Even the work zone area is uncongested, but as long as travel times on alternate route are less than travel time on work zone link, people will choose alternative route rather than pass through work zone link. Empirically, people will accept a little longer travel time and will keep their original routes when there is no congestion or less congestion on work zone link. These reasons explain why the local level diversion rates from DTA and field observations do not match exactly.

3.5 DIVERSION RATE SENSITIVITY ANALYSIS

The diversion rate can be affected by many factors. Demand on work zone areas is one of the most important factor and is easy to quantify. When network demand increases, more people want to enter the work zone area and congestion increases. Travelers are then more likely to use alternative routes. Alternately, if the work zone area becomes less congested, more travelers will keep their original routes. This study uses VISTA to simulate traffic conditions on the network used in section 3.4 under different demand levels to create the relationship between diversion rate and the change of demand based on the result from VISTA.

The process of obtaining simulation results is as follows. It has three steps:

1. Simulate traffic condition on the work zone area under regular and work zone condition on the same demand level.
2. Find total volume on link 1, 2 during simulation period under both condition and calculate diversion rates based on equation 3.1 and 3.2.
3. Repeats step 1 and 2 for each demand level.

Diversion behavior is different under different demand levels. Therefore, we analyze the traffic condition from uncongested to congested. The network reaches the most congested condition during the peak period. Demand in the morning period is consider as the 100% level. The traffic conditions under demand levels from 10% to 90% will also be considered. The diversion rates on both levels under different demand level are shown on Table 3.12. Scatter diagrams of diversion rate on network level and local level are shown on figure 3.6 and 3.7.

Demand level	Network level	Local level
	Link 1	Link 2
10%	3.89%	23.51%
20%	5.14%	23.06%
30%	7.15%	27.48%
40%	19.00%	25.25%
50%	27.40%	11.30%
60%	32.80%	10.46%
70%	22.23%	13.69%
80%	20.66%	14.70%
90%	18.17%	13.13%
100%	50.87%	7.04%

Table 3.12: Diversion rates on each demand level

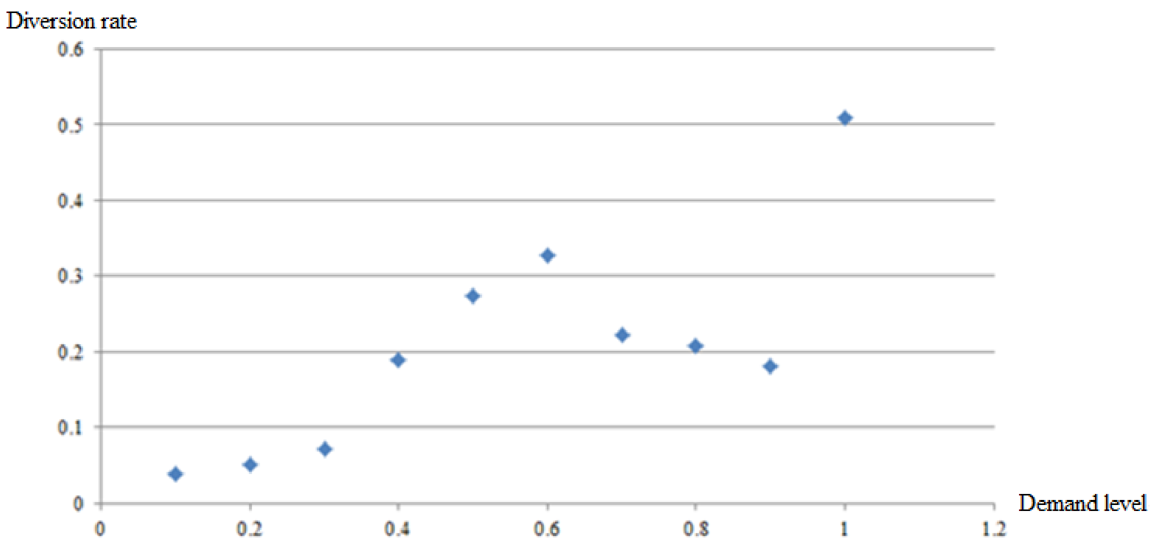

Figure 3.6: Scatter diagram of diversion rate on network level

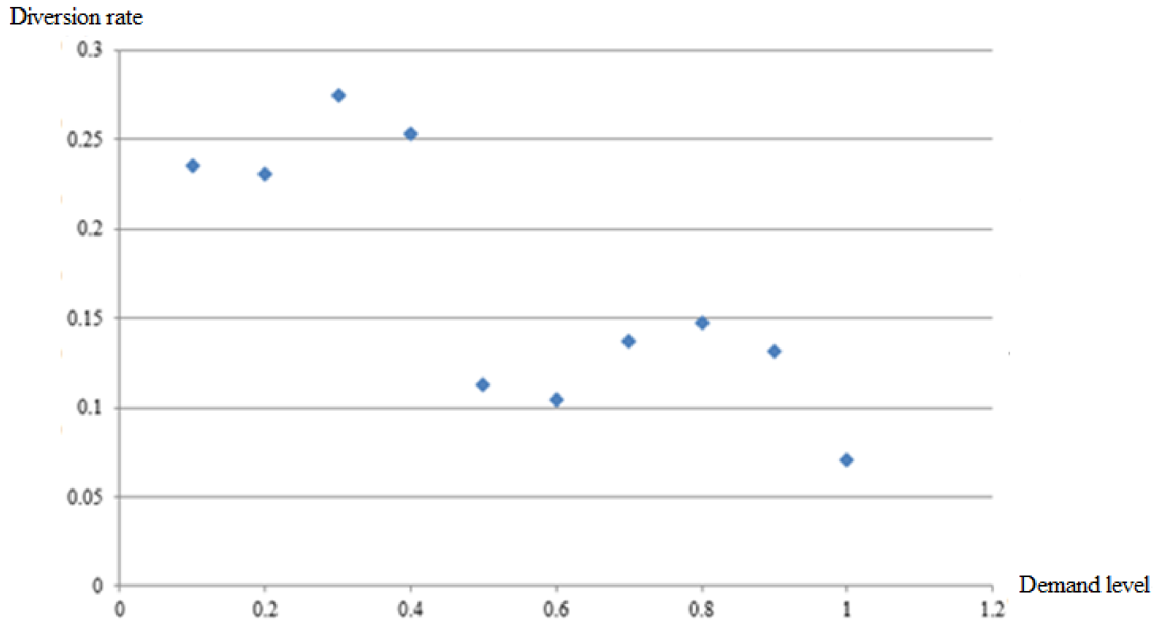

Figure 3.7: Scatter diagram of diversion rate on local level

According to this result, when demand increases, more people are likely to choose alternative routes on network level. The work zone area becomes more congested along with number of person who enter the work zone area is increased. Meanwhile, a queue will occur in this area. When people see there is a queue, they will think delay of travel time on this area surpasses their tolerance and decide to use alternate routes. In addition, this work zone is a long term project, and people already know there will be congestion on this area during this period. There is a different trend happen on diversion rate on the local level. Diversion rate on local level will be decreased when demand is increased. More people do not enter the work zone area, so volume on work zone links will be decreased. The delay of travel time will become shorter, respectively. People are more likely to accept the delay and to keep their original routes. This is the reason that diversion rate on local level decreases.

In addition, the relationship between diversion rate on network level and on local level will be analyzed. Figure 3.8 shows the scatter diagram of diversion rate on network level vs. the one on local level.

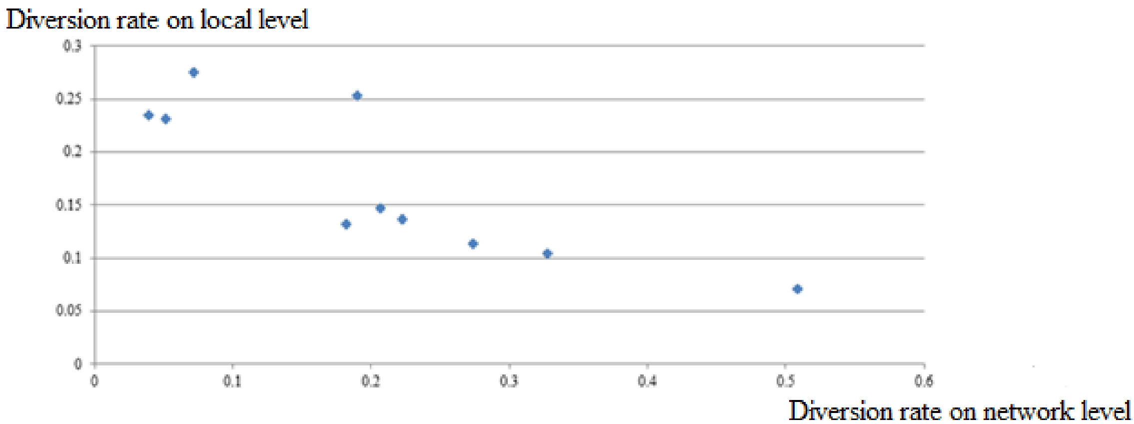

Figure 3.8: Scatter diagram of network level vs. local level diversion rate

Based on figure 3.8, the diversion rate on the local level falls off when diversion rate on network level is increased. More and more people switch to alternative routes on network level and fewer people enter the work zone area, so the ratio of volume and capacity on work zone area goes down and this area becomes less congestion. People will still on their current routes, and diversion rate on local level is decreased respectively.

The above analysis provides a general description of the relationships obtained from simulation in this location. However, this analysis requires the construction of an appropriate network and deployment of a simulation tool. To provide useful results even when such tools and networks do not exist, we perform a regression analysis to describe the general trends observed.

Equation 3.4 is used to represent the relationship between demand level and diversion rate on network level. Table 3.13 shows the summary of the model and figure 3.9 shows the line of this model on the scatter diagram.

$$D_{network\ level} = 0.362x + 0.008 \tag{3.4}$$

where x is the demand level.

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.77	0.592	0.541	0.0963367

Table 3.13: The summary of the model 3.4

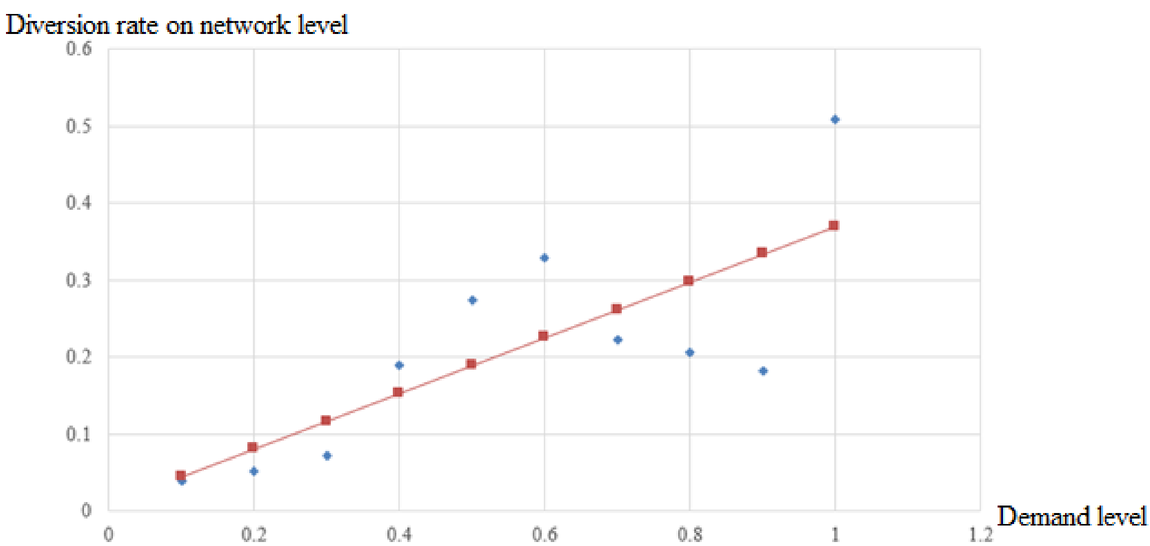

Figure 3.9: The line of model 3.4 on the scatter diagram

Equation 3.5 is used to represent the relationship between demand level and diversion rate on local level. Table 3.14 shows the summary of the model and figure 3.10 shows the line of this model on the scatter diagram.

$$D_{local\ level} = -0.192x + 0.275 \tag{3.5}$$

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.812	0.659	0.616	0.0444138

Table 3.14: The summary of the model 3.5

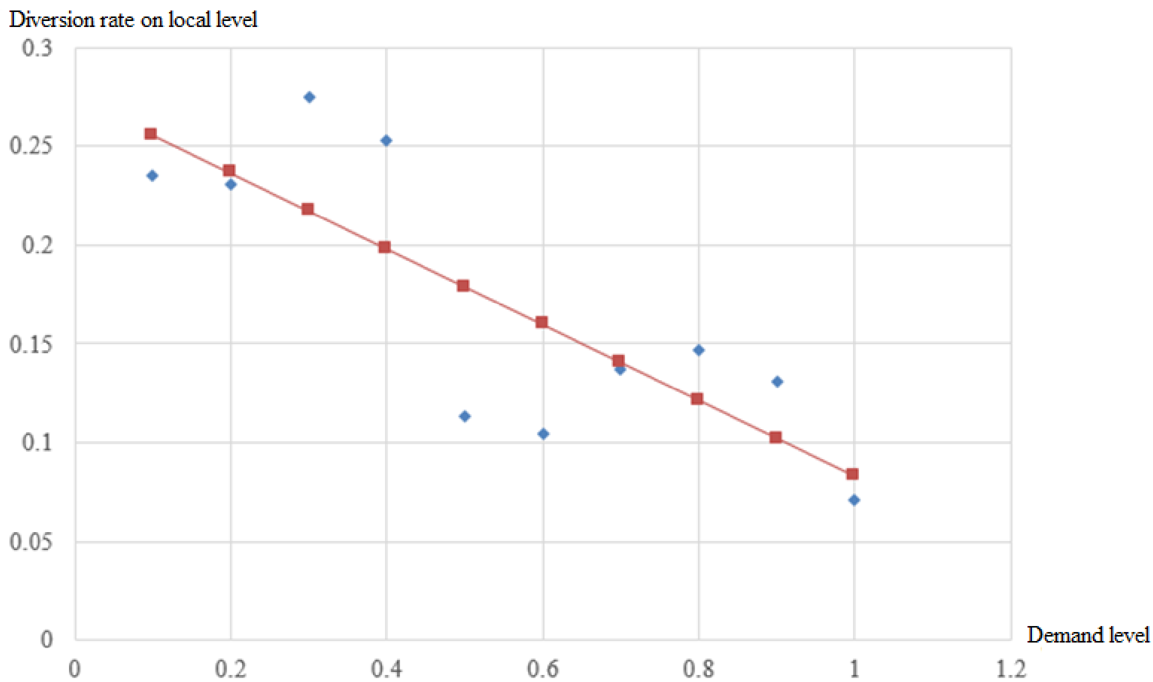

Figure 3.10: The line of model 3.5 on the scatter diagram

Equation 3.6 is used to represent the relationship between diversion rate on network level and the one on local level. Table 3.15 shows the summary of the model and figure 3.11 shows the line of this model on the scatter diagram.

$$D_{local\ level} = -0.424x + 0.258 \quad (3.6)$$

where x is the network level diversion rate.

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.842	0.709	0.672	0.0410428

Table 3.15: The summary of the model 3.6

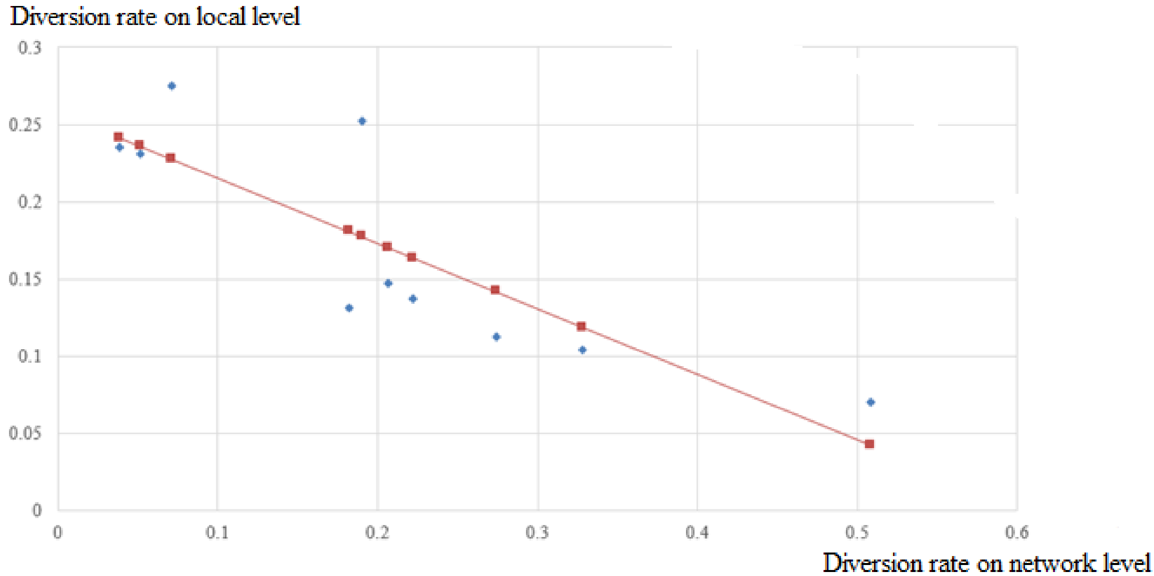

Figure 3.11: The line of model 3.6 on the scatter diagram

Based on the results, R-values of all models are close to or greater than 0.8. Slopes of model 3.4 and 3.5 are positive. There is a strong positive linear relationship between diversion rate on network level / on local level and demand level. Model 3.6 has the negative slope, so diversion rate on network level has a strong negative linear relationship with the one on local level.

3.6 Conclusion

In this chapter, we build a modeling approach for analyzing diversion behavior for long term work zone on an urban network. Diversion rates on the network level and local level are used to describe how many people switch to alternative routes on both levels. Because there are multiple routes on an urban network, traffic assignment tools are more suitable than the methods used in previous studies. The STA tool-TransCAD and the DTA tool-VISTA are used to obtain the traffic condition of the network along with diversion rates on both levels. According to the results, diversion rates on network level from STA on morning peak and off peak period are smaller than the ones from DTA. DTA allows more travelers to use alternative routes and the work zone links become less congested. So diversion rate on local level from DTA is smaller than the one from STA on morning peak period. The off-peak period has a contrary tendency, where the diversion rate on local level from DTA is greater than the one from STA. Because the work zone area becomes less congested and fewer people switch to alternative route on network level, more people will use alternative routes on local level. Compared with video data from the field, DTA can capture diversion behavior on the network level. DTA assumes all people use the shortest path, while in reality people are willing to accept a slightly more delay. Therefore, DTA overestimates the diversion rate on local level. Finally, we analyze diversion behavior under different level of demand that from uncongested to congested. Diversion rate on network level has positive relationship with demand changing, while diversion rate on local level has negative relationship with demand changing and diversion rate on network level.

Chapter4: Finding Optimal Location of Variable Message Signs

4.1 INTRODUCTION

Variable message signs (VMSs) provide real-time traffic information to drivers who pass by them, such as the travel time to major destinations. Drivers can then make suitable decisions based on the information given. Deploying VMSs at every intersection is unnecessary and is impossible because of the budget limitations. Therefore, it is important to find the optimal locations of VMSs given a limited budget, in order to maximize the performance of the network is useful for public agencies. A model is developed in this section to solve the problem.

Section 4.2 introduces the model in detail. A self-adapting genetic algorithm is used to solve the model and is described in section 4.3. The model uses the link transmission model (LTM) to represent the condition of a traffic network. Bounded rationality is introduced to represent drivers' behavior when they go through VMSs. Implementations of the dynamic traffic assignment and VMS function are introduced in section 4.4. A numerical example will be represented in section 4.5 and conclusions will be summarized in section 4.6.

4.2 THE MODEL FOR FINDING OPTIMAL LOCATION OF VMSS

Before introducing the model, we first describe some concepts which are used in the model. A dynamic transportation network $G = (N, A)$is given, and a set of vehicles V on this network will be assigned. Assume that the origin, destination, and departure time of each vehicle is known. Let R be the set of routes in G, and let $\psi(j, V, G)$ be a function representing the DTA model (LTM is used in this study), identifying the route chosen by vehicle j at dynamic user equilibrium. The solution represents the “base case” where there is no incident, and it is provided by an equilibrium assignment algorithm which will be described on section 4.3.

An accident $\theta = (\theta_l, \theta_c, \theta_t)$ occurs at link θ_l, reducing its capacity to θ_c for a duration θ_t. Accident occurrence is considered a random process whose distribution can be estimated from field data. This thesis assumes accident occurrence follows the normal distribution, that is, $N(\mu, \sigma^2)$. The μ and σ^2 come from the networks that used to solve the problem.

VMSs on this model provide the location of an incident, and the delay that caused by the incident. The delay is the difference of travel time on incident area between “no accident” condition and accident conditions. The incident area includes the incident link and the link that immediately upstream of the incident link. Each VMS has its own activated area. If an accident happens on activated area of a VMS, this VMS will show information of the accident to drivers who go through it. Figure 4.1 is a schematic drawing that illustrates the activated area of VMS_i. Activated distance is used to describe the size of activated area. Activated distance is three intersections or exits on the downstream from the location of VMS_i.

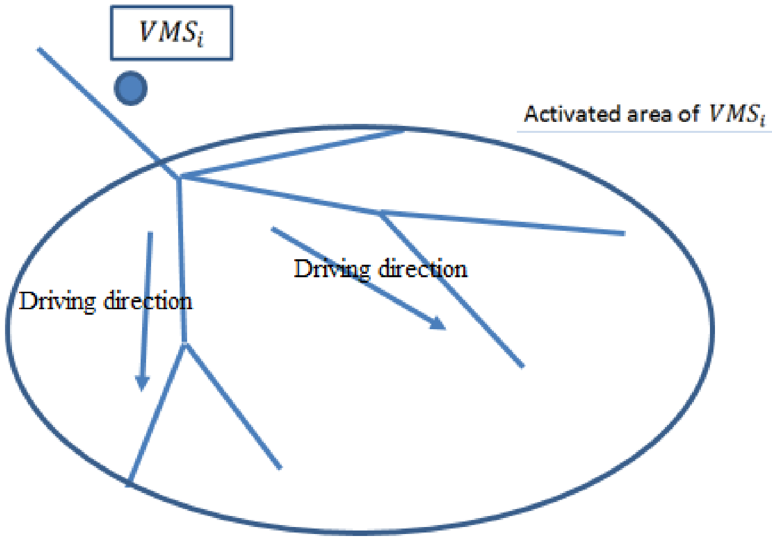

Figure 4.1: The activated area of VMS_i

Bounded rational behavior is used to describe how drivers respond to VMSs. Consider vehicle k. This vehicle has its own tolerance threshold of delay td_k. There are three cases: first, the vehicle either does not pass by any VMS signs, or no VMSs on the vehicle's route are activated, and its route is unchanged. When the vehicle passes at least one activated VMS, the vehicle will change its route to the shortest path that based on the current link travel times from the head node of the link where the activated VMS is located, to its final destination if the delay caused by the incident exceeds td_k. On the other hand, if the delay is less than td_k, the driver does not feel that the increase is significant enough to switch his/her route and keeps the current route.

Now, we introduce the model. It is described by equations 4.2.

$$min \quad E_\theta[\sum_k T_{acc}(k,\theta)] \tag{4.2a}$$

$$s.t. \quad \sum_i \sum_q L_{i,q} = I \tag{4.2b}$$

$$\theta = (\theta_l, \theta_c, \theta_t) \tag{4.2c}$$

$$T_{acc}(k, \theta) = \psi'(j, V, G, \theta) \tag{4.2d}$$

Equation (4.2a) is the objective function. The objective is minimizing total excepted travel time (TETT). It is the average total travel time under all incident scenarios. In practice, we cannot test all scenarios and a sampling approach is used instead. Equation 4.3 is used to calculate total number of incident scenarios n required.

$$n = \frac{z_{\alpha/2}^2 \sigma^2}{\Delta^2} \tag{4.3}$$

where $z_{\alpha/2}$ is reliability coefficient, σ is standard deviation, and Δ is permissible error. Let $T_{acc}(k, \theta)$ is the travel time of vehicle k under accident θ provided by the DTA model $\psi'(j, V, G, \theta)$. It provided by a dynamic traffic network. This study uses LTM to represent a traffic network. Equation (4.2b) is the budget constraint. I is the total number of VMSs will be deployed on the network. The decision variable $L_{i,q}$ represents whether VMS_i locates on link q or not. When $L_{i,q} = 1$, it means VMS_i locates on link q. When $L_{i,q} = 0$, it means VMS_i does not locate on link q.

4.3 Solution Algorithm

According to section 4.2, condition of the network is provided by LTM. It is difficult to represent by mathematical formula. So we need to find a heuristic method to solve the problem. The decision variables are binary variables, so genetic algorithm (GA) is a suitable method. Recently, simple GA has been applied to find the optimal location of VMSs successfully (9). The overall process of simple GA is shown on figure 4.2.

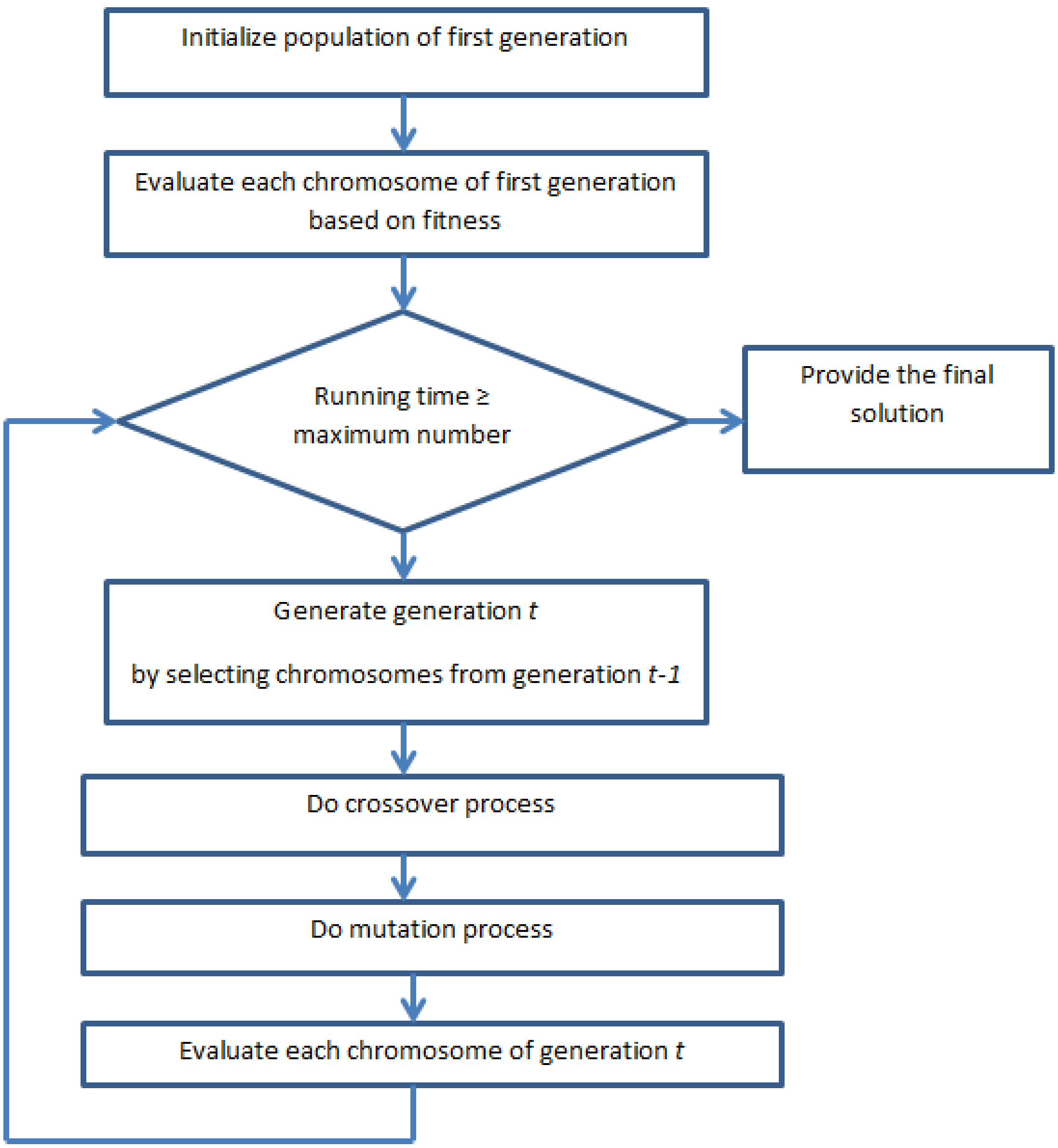

Figure 4.2: The process of simple GA

At the beginning, GA generates several initial chromosomes. Each chromosome represents a potential solution of the problem. The set of chromosomes is called as population in GA and the size of population *S* is fixed. After creating the first generation, the algorithm calculates the fitness of each chromosome. The fitness represents the performance of a chromosome. If a chromosome is close to the solution of the problem, the fitness of this chromosome is higher; otherwise, the fitness is lower. If termination condition such as maximum running time is reached is met, the algorithm returns the final solution; otherwise, it repeats the following process which has four steps. The first step is generating generation *t* from generation *t*-1 based on fitness. A chromosome which has greater fitness has more probability to copy to next generation. Then algorithm does crossover processes, choosing two chromosomes and generating crossover rates for these chromosomes randomly. If crossover rate of chromosome is less than crossover rate, do these chromosomes exchange genes that after a point. After the crossover process, a mutation process is performed, choosing a chromosome and generating the mutation rate of this chromosome randomly. If mutation rate of this chromosome is less than the chosen mutation rate, select a gene in this chromosome randomly. If the current value of this gene is 1, the new value is 0; otherwise, the new value is 1. Now, the algorithm generates generation *t*. Finally, each chromosome of this generation will be evaluated- calculate the fitness of each chromosome.

However, the rate of crossover and mutation on simple GA are fixed. These rates have appreciable effects on the performance of GA. If crossover rate is too high, the structure of chromosomes that has greater fitness value be destroyed quickly; if it is too low, the searching process will be very slow. The same thing is true with the mutation rate: if mutation rate is too small, it is difficult to generate truly new individuals; if too high, GA simply becomes a random search algorithm. Tuning these parameters usually requires a great deal of trial-and-error work; however, the self-adapting GA changes these parameters as the algorithm proceeds, based on the fitness values of each chromosome. So we use self-adapting GA to find the optimal locations of VMSs.

The solution of this problem is the locations of VMSs. Here, we use integer coding, in which each gene represents ID of a link that there is a VMS locates on it. The total number of genes on a chromosome meets the budget constraint 4.2b. Link IDs are sorted from smallest to largest. The structure of a gene is shown on figure 4.3.

ID of link l_1	ID of link l_2	......	ID of link l_I
gene 1			gene I

Figure 4.3: The structure of a chromosome

Equation 4.4 is used to calculate the fitness of each chromosome.

$$fit_i = -TETT_i \tag{4.4}$$

Where $TETT_i$ is the total expected travel time for the solution that chromosome *i* represents, as described in section 4.1.

The following steps describe how the self-adapting GA is applied to the VMS location problem:

1. Generate chromosomes for the first generation, and set initial values for algorithm parameters.
2. For each chromosome in generation *i*, obtain its fitness value by performing multiple DTA simulations under different accident condition, and calculating the objective function 4.2a, multiplying by –1 because lower values of the objective function correspond to higher fitness.
3. Generate initial chromosomes of generation i+1 based on roulette wheel algorithm. The process of the roulette wheel algorithm is:

   For each chromosome j of generation *i:* This study uses equation 4.5 to calculate probability of copying chromosome *j* of generation i+1 to the next generation $P_s(C_{i,j})$

   $$P_s\left(C_{i,j}\right) = \frac{\mathrm{e}^{-f(C_{i,j})}}{\sum_{\mathrm{j}} \mathrm{e}^{-f(C_{i,j})}} \tag{4.5}$$

   where $f(C_{i,j})$ is fitness value of chromosome *j* on generation *i.*

   Then generate a random number r $(r \in (0{,}1))$. If $r < P_s\left(C_{i,j}\right)$, $C_{i,j}$ is selected for the next generation i+1, otherwise, $C_{i,j}$ is not copied to the next generation.
4. All chromosomes take part in crossover process. The algorithm chooses chromosome l and $l + S/2$ $(l \in (1, S/2))$ to do single-point crossover. S is total number of chromosomes. The crossover rate of each chromosome and crossover factor (probability of doing crossover) are based on the higher

fitness value of the two chromosomes. The algorithm uses equation 4.6 to calculate them.

$$P_{cross,C_{i,l}} = \begin{cases} P_{cross}\left(1 - \frac{f_{i,avg} - f(C_{i,l})}{f_{i,avg} - f_{i,min}}\right) & f_{i,avg} \le f(C_{i,l}) \\ P_{cross} & otherwise \end{cases} \tag{4.6}$$

where $f_{i,avg}$the average of fitness is value on generation i, $f_{i,min}$ is the minimum fitness value on generation i, P_{cross} is pre-set crossover factor.

5. Choose chromosome q randomly, use equation 4.7 to calculate mutation rate of this chromosome.

$$P_{m,q} = \begin{cases} P_m\left(1 - \frac{f_{i,avg} - f(C_{i,q})}{f_{i,avg} - f_{i,min}}\right) & f_{avg} \le f(C_{i,q}) \\ P_m & otherwise \end{cases} \tag{4.7}$$

where P_m is pre-set mutation factor, other parameter are same as equation 4.7.

6. If the running time reaches ten thousand generations, the algorithm stops and the current best solution as the final optimal solution. Otherwise, the algorithm go back to step 3.

After two chromosomes participate in crossover, it is possible that a chromosome may contain the same location ID more than once. To avoid this possibility, the algorithm uses the following process to ensure feasibility. After chromosomes are generated, each chromosome is sorted from smallest to largest based on location ID. Suppose selected two chromosomes ($C_i$and C_j) do crossover. Let P be the crossover point and $G_{i,P}$ is the location ID of gene P on chromosome i. If $G_{i,P-1} < G_{j,P}$ and $G_{j,P-1} < G_{i,P}$, do crossover; if $G_{i,P-1} > G_{j,P}$,do crossover when $G_{i,q}$, $q \in (0, P-1)$ and $G_{j,m}, m \in (P, N)$ do not have same location ID, otherwise, $C_i$and C_j do not crossover; do the same if $G_{j,P-1} > G_{i,P}$. The following is an example to show crossover process.

C_i is 2,4,5,10 and C_j is 3,6,9,12. If the crossover point *P* is 2, $G_{i,P-1}: 2 < G_{j,P}: 6$ and $G_{j,P-1}: 3 < G_{i,P}: 4$, so do crossover. After crossover, C_i is 2,6,9,12 and C_j is 3,4,5,10. If the crossover point *P* is 3, $G_{i,P-1}: 4 < G_{j,P}: 9$ and $G_{j,P-1}: 6 > G_{i,P}: 5$, so we need to check whether $G_{i,q}$, $q \in (3,4)$ and $G_{j,m}, m \in (1,2)$ have same link ID. They do not share link ID, so do crossover. After crossover, C_i is 2,4,9,12 and C_j is 3,6,5,10.

When doing the mutation process, the mutation point *P* generated randomly. Then the algorithm chooses an ID between $G_{i,P}$ and $G_{i,P+1}$ when the difference between $G_{i,P}$ and $G_{i,P+1}$ is greater than 1, otherwise, the algorithm does not do mutation. Because C_i is sorted, the selected id is unique. The following is an example to show mutation process.

C_i is 2,3,5,10. If the mutation point *P* is 1, the difference $G_{i,1}$ and $G_{i,2}$ (2 and 3) is 1, the algorithm does not perform mutation. If the mutation point *P* is 3, the difference $G_{i,3}$ and $G_{i,4}$ (5 and 10) is 5, the algorithm generates a random number between 5 and 10, say 6, to replace 5.

4.4 IMPLEMENTATION

According to section 4.3, the fitness of each chromosome comes from simulating accidents on a dynamic traffic network. Before simulate traffic condition under accident condition, the network need to reach user equilibrium condition and the route of each vehicle whose origin route includes the accident link is known. After obtaining the equilibrium condition, we will simulate VMS and drivers' behavior under the accident condition. At the end, we obtain total system travel time under incidents from simulation model that is fitness of a chromosome. There is not any existing program that can provide this information directly, so this study develops a dynamic traffic network based on the LTM model. This section focuses on how to build a dynamic traffic network and compute the fitness of a chromosome. How to build the dynamic traffic network is described on subsection 4.4.1. Then subsection 4.4.2 shows how to calculate the fitness of each chromosome.

4.4.1 Implementing the Dynamic Traffic Network

The dynamic traffic network has two components: simulation model and dynamic traffic assignment (DTA) algorithm. The structure of network is shown on Figure 4.4. First, the DTA process is run. During this process, the LTM-based network will be built, the shortest path for each OD pair will be found, and an initial assignment will be performed. During the first iteration, the stop criterion is ignored. In later iterations , if the stopping condition is satisfied, the network is considered to have reached equilibrium and the algorithm terminates. Otherwise, the equilibrium condition is unmet, and we continue to find the time-depended shortest paths and shift vehicles from longer path to the shortest path for each OD pair. According to updated path flow, we will renew traffic condition of the network and then go back to check the stop criteria. After complete DTA process, the network reaches equilibrium condition and the route of each vehicle is already assigned. Then we can use simulate traffic condition under incidents and compute total system travel time. The following will introduce each sub-process in detail. Traffic simulation parts use link transmission model to describe the condition of a traffic network, as described in Section 2.4.

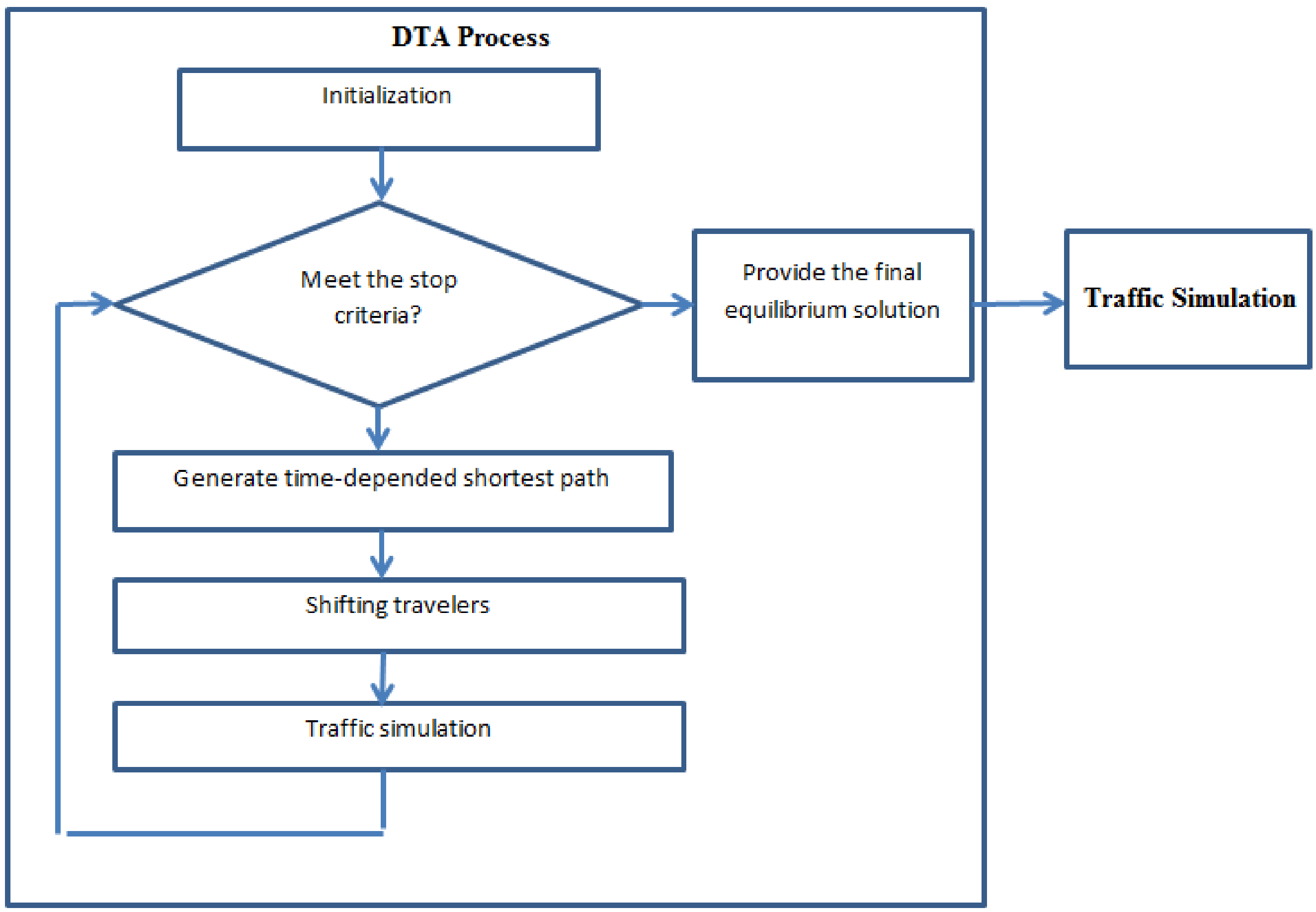

Figure 4.4: The structure of an dynamic traffic network

4.4.1.1 Initialization

There are three steps in the initialization process. First, an LTM-based network is constructed. Second, the shortest path is found for each OD pair. Finally, "all-or-nothing" assignment is performed.

When building an LTM network, the original information of the network comes from the corresponding static network. Links of an LTM-based dynamic network not only store the information that static networks used, like the head, tail and length of each link, but also record information related to vehicles which includes sending and receiving flow on each simulation period, a queue which is used to store vehicles on this link and cumulative accounts of vehicles that cross head and tail of this link. The major difference is building nodes of dynamic networks. There are two types of nodes on a static network: regular nodes and origins/destinations. According to section 2.4, a dynamic network has three kinds of regular nodes - normal nodes, merge nodes and diverge nodes. Based on link information, we obtain input and output degree of each node. Both degrees of normal nodes are one, the input and output degree of merge node are two and one, and the input and output degree of diverge node are one and two. So each node type will be defined and input and output queues will be created to storage vehicles based on degrees. When a regular node used to represent an intersection has two input degree and two output degree, it is divided into two regular nodes: a merge node and a diverge node. An artificial link connects both regular nodes. Figure 4.5 shows the process.

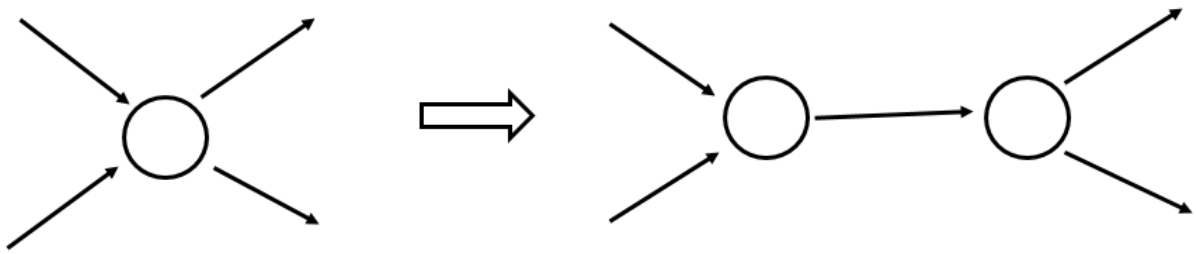

Figure 4.5: The process of splitting a node with two input degree and two output degree

Origins and destinations of a dynamic network are separate from regular nodes. However, regular nodes of a static network can represent origins and destinations. According to OD information, we can find the regular node that connects with each origin/destination. Then, we create an artificial link that connects the regular node and the origin/destination. The capacity of this link is infinite, and free-flow speed on this link id higher than regular links.

After building the network, we find the shortest path for each OD pair. There is no vehicle on the network, cost of each link is free-flow travel time. The algorithm will be described in the following section. Finally, doing “all-or-nothing” assignment-demand of each OD pair will be assigned on the shortest path that belongs to this OD pair. Then we can update the travel time of each link based on the assignment.

4.4.1.2 Stopping Criteria

The average excess cost (AEC) is used to determine whether the current solution close to equilibrium or not in the network. When it is equal to 0, each traveler on the shortest paths and the current condition reaches equilibrium. When it is greater than 0, at least one traveler is not on the shortest path. The smaller AEC value, the closer the current solution is to the equilibrium solution. Equation 4.8 is used to calculate it.

$$\frac{\sum_{(i,j)}\sum_{p}(t_{p,(i,j)}-t_{s,(i,j)})d_{p,(i,j)}}{\sum_{(i,j)}\sum_{p}d_{p,(i,j)}} \tag{4.8}$$

Where $t_{p,(i,j)}$ is travel time of path *p* of OD pair (i , *j*), $t_{s,(i,j)}$ is travel time of the shortest path *s* on OD pair (i , *j*) and $d_{p,(i,j)}$ is demand on path *p* of OD pair (i , *j*),

4.4.1.3 Finding Time-dependent Shortest Path

This section introduces how to find time-dependent shortest paths (TDSPs) from each origin to all destinations that connect with this origin on every simulation period. We assume the shortest paths do not change during each simulation period q and departure time of the shortest paths is the start time of S_q. This study uses the modified Dijkstra's algorithm to find TDSP for each OD pair depart on S_q .

Before describing the algorithm, we first introduce three assumptions:

1. Each link's travel time obeys the first-in, first-out property: if vehicle *i* enters link q at time *t* and vehicle *j* enters link q at time $t < t'$, leaving time of vehicle *i* must leave no later than vehicle *j*.
2. Vehicles are not allowed to wait at any node.
3. The network is strongly connected, that is, there is at least one path connecting each origin and destination for each simulation period.

The following describes this algorithm in detail.

Given: origin *s*, depart time S_q, the network *N (G, A)*

Provide: the shortest paths to all destinations that connect with *s*

Four datasets need to be maintained: label set: the label of node *i* (L_i) records the travel time of the shortest path from *s* to node *i*. The predecessor of node *i* (P_i) records the second to last node of the shortest path from *s* to node *i*. The unset list includes the nodes that the algorithm hasn't found the shortest paths yet. The destination set contains all destinations that are connected with *s*.

The process of the algorithm is as follows:

Initialization: set $L_s = 0$ and $L_i = \infty$ for all $i \neq s$, $P_s = -1$ and $P_i = \emptyset$ for all $i \neq s$, all nodes in unsetting list and all destinations in destination set.

Repeat the following steps until the destination set is empty.

1. Select the node *j* with the smallest label from label set, removes it from the label set and unset list.
2. If node *j* is also in destination set, remove it from this set.
3. For each link (*j*, *k*) that departs from node *j*,

    if $C_j + \tau_{jk}(C_j) < C_k$, then $C_k = C_j + \tau_{jk}(C_j)$ and $P_k = j$

    where $\tau_{jk}(C_j)$ is travel time on link (*j*, *k*) when enter time is C_j

After completing step 3, go back to check whether the destination set is empty or not. When the set is empty, TDSP for all destinations are founded.

4.4.1.4 Shifting Travelers

After finding the shortest path for each OD pair on iteration i, travelers will switch to the shortest paths from their current, longer paths to make the flow on the network closer to the equilibrium condition. This section describes how to select the number of travelers changing their routes. This method is called the method of successive averages (MSA).

The MSA process has two steps:

1. Using the shortest paths of each period, which are already known, perform “all-or-nothing” assignment. This means assigning all travelers of OD pair *j* on the shortest path of this OD pair. The result which is path flow matrix of the network of this assignment is called the target matrix H^*.
2. Equation 4.9 is used to update path flow matrix.

$$H_{i+1} = (1 - \lambda_i)H_i + \lambda_i H^* \tag{4.9}$$

where $H_{i+1}$is path flow matrix of iteration $i+1$ (next iteration), H_i is path flow matrix of iteration *i* (current iteration), λ_i is step size of iteration *i* and $\lambda_i \in [0,1]$. Equation 4.10 is used to calculate λ_i.

$$\lambda_i = \frac{1}{i} \tag{4.10}$$

4.4.2 Implementing VMS

VMSs are modeled by adding attributes on links. Each link has three attributes related to VMS: VMS-located, activate-VMS, and delay. These attributes are only accessed by traffic simulation under accident condition. If there is a VMS located on link *i*, VMS-located of link *i* is true. Otherwise, it is false. When an accident happen, each VMS checks whether it becomes activated or not. If VMS on link *i* is activated, the attribute "activate-VMS" is true and the delay attribute represents the increased travel time caused by the accident. Each vehicle has the attribute "threshold" to describe tolerance of delay. If link *i* has an activated VMS, one of two cases will happen when updating vehicles on link *i*. One is that vehicles respond to the VMS and update their routes, based on the shortest path from the current link to their destination based on current condition when delay is greater than their threshold of delay. Another case is when vehicles do not respond to the VMS and still use their original routes, when delay is less than their threshold of delay.

4.5 NUMERICAL EXAMPLE

A hypothetical network which shown in figure 4.6 used in the case study. Figure 4.7 shows the LTM network based on the original network. The model finds the optimal VMS locations based on the LTM network. The bold links are real links from the original network. The dashed lines are connectors. Table 4.1 describes the characteristics of horizontal and vertical real links. Demand on the network during 2 hours period. The OD table is shown in table 4.2. There are 3 VMSs will be installed in the network. Drivers' tolerance of delay is 5 minutes.

Link type	Length	Free-flow speed	Back-wave speed	Capacity	Jam density
Horizontal	0.5 mile	30mph	15mph	6000vph	150veh/mile
Vertical	0.5 mile	40mph	15mph	10800vph	300veh/mile

Table 4.1: The characteristics of real links

Origin	Destination	Demand
1	6	6000
1	9	6400
4	3	4800
4	9	6000
7	3	4800
7	6	5600

Table 4.2: Demand on the network

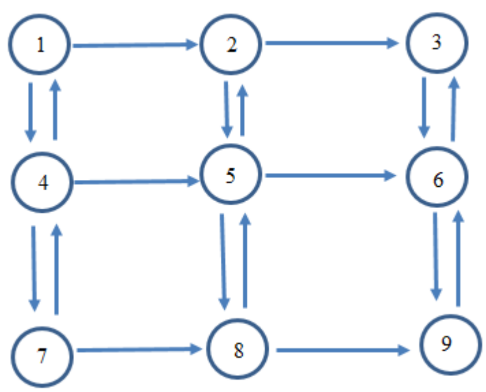

Figure 4.6: Structure of the hypothetical network

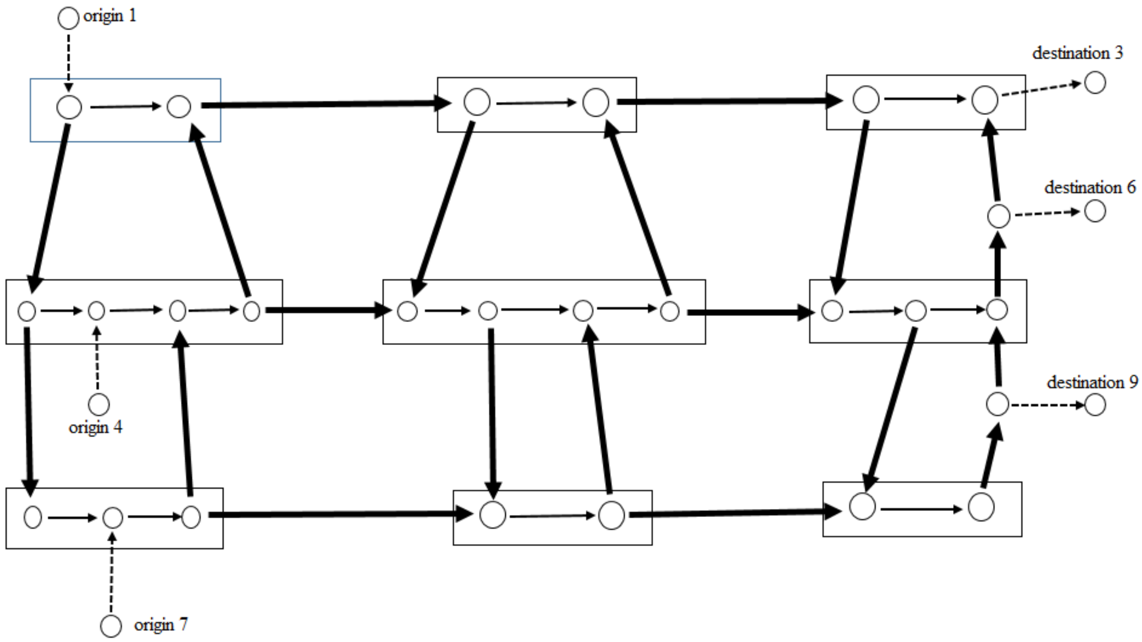

Figure 4.7: The LTM network based on the original network

Three incidents used to evaluate the performance of VMSs on the network. The characteristics of incidents are capacity reduction of 0.6, duration of 2 hours. We assume incidents only happen on the real links. The parameters of self-adapting genetic algorithm are as follows: the total number of chromosomes is 20, the total number of genes on a chromosome is 3, the pre-set crossover rate is 0.8 , the pre-set mutation rate is 0.001 and total iteration is 1000.

The three best locations are shown in figure 4.8 using stars. All VMSs are installed on the second horizontal segment (from top to bottom). These are the most commonly used links on this segment. This segment connects with other two segments. Installing VMSs on this segment, travelers can get more opportunities to avoid the accidents.

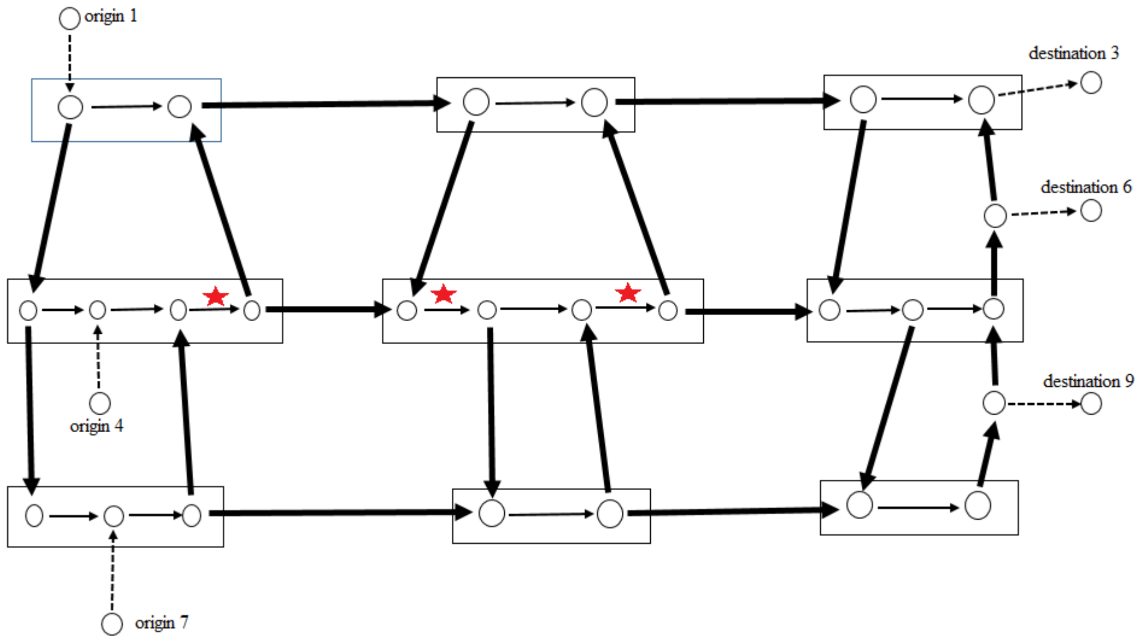

Figure 4.8: The optimal VMS locations

For comparison, the simple genetic algorithm is also used to solve the problem. The parameters of this algorithm are the same as the one of self-adapting genetic algorithm. The performances of both algorithms are shown on figure 4.9. According to the result, the simple genetic algorithm uses five more iterations to obtain the optimal solution.

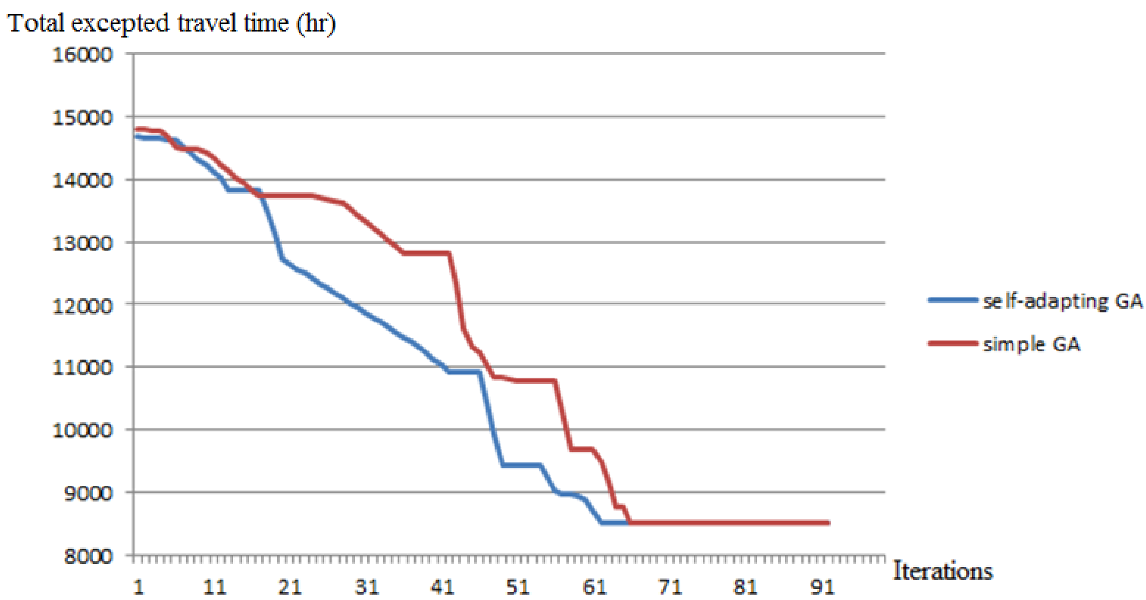

Figure 4.9: The performance of algorithms

The relationship between the total number of VMSs and the benefit from VMS is shown in figure 4.10. There is a significant decrease in the total excepted travel time from installing two VMSs to three VMSs. When total number of VMSs increases, the marginal benefit from each VMS become less. After a certain threshold, most drivers encounter by a VMS, so adding more VMSs on the network may not significantly decrease the total excepted travel time.

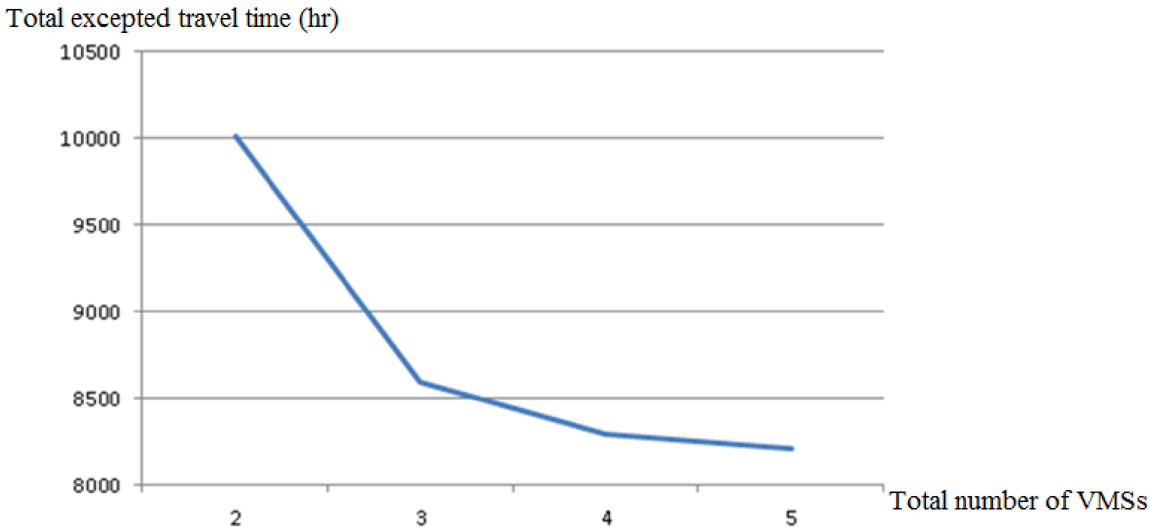

Figure 4.10: The relationship between total number of VMS and the benefit from VMS

4.6 SUMMARY

In this section, we created a planning model to find optimal VMS locations. The objective of the model is minimizing the total excepted travel time. The link transmission model used to evaluate the condition of the network under each accident scenario. Bounded rationality is used to represent reaction behavior of VMS. When the delay caused by an accident is greater than a driver's tolerance of delay, they will use the alternative route that is the shortest path from his current location to the destination. According to the results in this chapter, the best VMS locations tend to be the places which allow people to choose among alternative routes. When the total number of VMS reach a certain level, the additional benefit from adding more VMS become less. The running time from simple generic algorithm is little longer than self-adapting generic algorithm. Because the case study uses a small network, both algorithms should be compared on a large network in future research.

Chapter 5: Conclusion

This thesis presents two applications of dynamic traffic assignment for modeling disrupted networks. The first involves applying traffic assignment software programs to estimate the diversion rate caused by work zone on an urban network, a planned disruption. The second application is optimizing locations of variable message signs (VMSs) for unplanned disruptions, by using simulation-based dynamic traffic assignment program.

Multiple alternative routes are available on an urban network when there is a work zone on the network. The existing methods only focus on the work zone link and one alternative route. In chapter 3, this thesis develops an approach to compute the diversion rate for work zones on an urban network by using static traffic assignment (STA) and dynamic traffic assignment (DTA) software. Diversion rate is classified into network level and local level. Diversion rate on network level indicates total number of travelers remaining through the work zone area and diversion rate on local level indicates total number of travelers remaining through the work zone link. A work zone on southbound of IH-35 close to Airport Blvd, Austin, TX is used to analyze the results. According to the results, STA and DTA can capture travel time changing caused by the work zone and let people avoid traveling through the work zone area or the work zone link. DTA is more sensitive on travel time than STA. Total number of people that use alternative routes from DTA is greater than the one from STA when the work zone area or the work zone link becomes congested. When demand on work zone area is greater, the network level diversion rate from DTA is higher than STA. When demand on work zone area decreases, network level diversion rate from DTA becomes smaller and local level diversion rate from DTA is increased. When comparing the result from traffic assignment with the real data, traffic assignment can capture the tendency of network level diversion rate and overestimates local level diversion rate on off-peak period. Because people accept a little longer delay on real world, but traffic assignment only assign people on the shortest paths. This thesis also finds there is a positive relationship between diversion rate on network level and demand. When demand in the work zone area is increased, the network level diversion rate also increases. The local level diversion rate and demand has a negative relationship, as do the network level diversion rate and local level diversion rate. When the demand on work zone area or network level diversion rate is increased, the local level diversion rate becomes smaller. Traffic assignment software programs cannot represent the conditions of work zones in detail. However, microscopic simulator can do this. Traffic assignment software programs can combine with microscopic simulators to examine how lane control strategies like early merge, later merge, and signal control affect the diversion rate under different level of demand. People can select a suitable strategy based on the result. Also, the diversion rate will be different under different level of demand. If the relationship between volume-capacity ratio and diversion rate under different level of demand is provided, people can use it to estimate diversion rate.

In chapter 4, a planning model is developed to find the optimal locations of VMSs. The objective is minimizing total expect travel time. Several accident scenarios are simulated, using the link transmission model to calculate the objective value. The total number of scenarios is based on sampling theory. The self-adapting genetic algorithm is used to solve the model. The crossover rate and mutation rate are adjusted automatically based on the fitness of chromosomes. An important factor that affects route selection when people know an accident happened is the delay. Bounded rationality, which use tolerance of delay, is introduced to describe reaction behavior of VMSs. When the tolerance threshold increases, total number of travelers who switch their routes is decreased and more travelers tolerate the delay. This is better than using a fixed rate to describe response behavior. Based on the result, the optimal VMS locations are the positions where people have opportunities to use alternative routes to avoid the accident. When the total number of VMS reaches a certain level, adding more VMS cannot bring additional benefit. The performance of a self-adapting algorithm is slightly better than simple genetic algorithm based on the small network. Different drivers have different tolerance bands, so we need classify drivers into several classes and build bands for each class. Furthermore, the model should be tested on a large network. All of these make valuable topics for future research.

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