Chapter 2-Literature Review

2.1 Introduction

The review of the literature will briefly explore the statistical methods and the neural network methods. Then, some existing dynamic flow methods utilized to estimate the travel time will be introduced. Lastly, some incident detection algorithms will be reviewed.

2.2 Statistical Methods

Statistical methods have traditionally built a linear or a non-linear model, based on the historic traffic data, to predict the travel time on freeway or arterial streets.

H. M. Zhang[1] use the historic critical v/c ratio, occupancy from the loop detector to build up a non-linear model named "the journey Speed Model" to predict the travel time on arterial streets. The journey speed is represented as the weighted sum of the historic speed and the current speed from the detector: $\gamma \times \bar{u}_{v/c} + (1-\gamma) \times \bar{u}_{q/o}$

Where $\bar{u}_{v/c} = u_f - a\exp(\beta \frac{v}{c})$,and $\bar{u}_{q/o} = 0.379 \times \sum_i q_i / \sum_i o_i$. Where qi is the flow rate detected by the detector and *oi* is the detected occupancy for time interval *i*. u_f is the free-flow speed, a and β are model parameters and γ is a weighting factor. However, this statistical method is peculiar to the network under study and is not generic and transferable to other traffic networks for other cities.

2.3 Neural Networks

Neural networks are models designed to imitate the human brain through the use of mathematical models. Similar to statistical methods, Neural Networks are built

[1] H.M.Zhang '*A link journey speed model for arterial traffic' Research Report ,Civil and Environmental Engineering,University of California, Davis, December 1,1998.*

using previous existing data. However, neural networks can perform better than statistical methods in mapping the relationships between the travel times and the input data. In the past several years, neural networks have been successfully applied to predict short-term traffic flow and travel time. The followings are some of the applications of neural networks for travel time prediction:

1. Rilett and Park[2] used spectral basis neural networks (SNN) to forecast multiple-periods freeway corridor travel times based on the data from US 290 in Houston, Texas. In the result, the mean absolute percent error (MAPE) ranges from 5.9 percent to 15.3 percent from 5 minutes to 25 minutes. They also find that the higher the time period, the higher errors will be when using SNN to predict the travel time on freeway.
2. In another research, Rilett and Park[3] combined Artificial Intelligence (AI) clustering techniques with Artificial Neural Networks (ANN) to predict the multiple-period travel time. The ANN is also built based on the data from US 290 in Houston, Texas. The result is similar to SNN network as stated above.
3. Abdulhai, Porwal and Recker[4] used an advanced Time Delay Neural Network (TDNN) model combined with Genetic Algorithm (GA) to predict the traffic flow and density. The travel time can be computed based on the predicted traffic flow and density. Similar to the study from Rilett and Park, the TDNN works well for

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[2] Laurence R.Rilett and Dongjoo Park,*'Direct Forecasting of Freeway Corridor Travel Times Using Spectral Basis Neural Networks'* presentation at 78th Transportation Research Record Journal, Washington D.C.,1999

[3] Dongjoo Park and Laurence R. Rilett *'Forecasting Multiple-Period Freeway Link Travel Times Using Modular Neural Networks'* Paper for Presentation at the Transportation Research Board Journal, Washington D.C.,1998

[4] Baher Abdulhai, Himanshu Porwal and Will Recker, 'Short Term Freeway Traffic Flow Prediction Using Genetically-Optimized Time-Delay-Based Neural Networks', Publication Transportation Research Board Journal . Washington D.C.,1999

short periods of times but to a lesser extent for higher periods of time.

4. Ishak, S., and C. Alecsandru[5] used multiple topologies of dynamic neural network to optimize the short-term travel time prediction. They also tested and compared four different neural network architectures under different settings and traffic conditions. The four different neural networks are a) Multi-Layer Perceptron Network (MLP). b) Modular network. c) Hybrid principal component analysis (PCA) network and d) Co-Active neuro-Fuzzy Inference System (CANFIS). The results show that CANFIS network was the optimal topology.

2.4 Dynamic Flow Methods (Intersection Control Delay)

Both the Statistical methods and the neural network methods have shown good accuracy in predicting the travel time by utilizing historic traffic data. However, they can not estimate the real-time travel time based on the real-time dynamic flow on the link. Fortunately, in the past years, some methods and technologies were developed to estimate the travel time depending on the dynamic flow and the characteristics of the observed freeway or arterial street. These travel time estimation methods, including their current technologies used to obtain travel time, are reviewed in this section.

2.4.1 Queue Length Estimation under Incident or Non-Incident Conditions

Shock-wave method is used to compute the queue length and the travel time under incident conditions after computing the incident response and clearance time. Two cases are provided by Dr. Hobeika[6] to compute the queue length of the incident.

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[5] Sherif Ishak and Ciprian Alescandru *'Optimizing Traffic Prediction Performance of Neural Networks under Various Topological, Input, and Traffic Condition Settings'* presentation and publication at the Transportation Research Board Journal, Washington D.C.,2003

[6] Hobeika, A. G., Dhulipala, S. "Estimation of Travel Times on Urban Freeways Under Incident Conditions" Transportation Research Record No. 1867. pg. 97, Transportation Research Board Journal, Washington D.C., 2004

a) The upstream flow is greater than the new capacity.

The backward forming shock-wave velocity upstream of bottleneck is determined as follows:

$$W_u = \frac{(\overline{q_{i_u}} \times N_{i_u} - C \times N_{i_b})/N_{i_u}}{\overline{K}_{i_u} - \overline{K}_{i_b}};\text{......}\quad\text{（Eq 2- 1）}$$

b) The upstream flow is less than the new capacity.

The forward moving shock-wave velocity upstream of bottleneck is determined as follows:

$$W_d = \frac{\left(C \times N_{i_b} - \overline{q}_{i_u} \times N_{i_u}\right)/N_{i_u}}{\overline{K}_{i_b} - \overline{K}_{i_u}} \text{......}\quad\text{（Eq 2- 2）}$$

Where, C,q, and K refer to the capacity, average flow, and average density on the link at the bottleneck and at the upstream location of the link respectively.

The queue rate(QR) is computed as follows:

$$QR = \frac{dn}{dt} = \left(\overline{q}_{i_u} \times N_{i_u} - C \times N_{i_b} - W_u \times \overline{K}_{i_u} \times N_{i_u}\right)\text{......}\quad\text{（Eq 2- 3）}$$

The number of vehicles in queue (Q) at time ($t_0 + n\Delta t$) is computed as follows:

$$Q_n = QR \times \Delta t_n \quad \text{......}\quad\text{（Eq 2- 4）}$$

where n=1,2,3,.....m;

The total vehicles in the queue from the beginning of the incident to current time is computed as follows:

$$Q_m = \sum_{n=1}^{m} Q_n \text{......}\quad\text{（Eq 2- 5）}$$

Therefore the travel time for the vehicle that just entered the queue is computed as follows:

$$\overline{tt}_{b_n} = \frac{Q_m}{C \times N_{i_b}} \quad \text{(Eq 2- 6)}$$

The shock-wave method works well in computing the number of vehicles in the queue when the incoming volume is greater than the intersection capacity. The shock-wave method is utilized in this thesis to compute the queue at the intersection which will be discussed later on in Chapter 4.

Fadhely, Kenneth, and Donald[7] in 2000 introduced and compared queue methods from SIDRA, HCM2000,TRANSYT-7F, SOAP, NCHRP 279 Guidelines, SIGNAL 97,NETSIM and Oppenlander's Method. In their study, the SIDRA and HCM2000 method have better accuracy than other methods since most of other methods will forgive the residual queue built up by the previous cycle length and some of them only report average value of the queue. Their research shows that it is important to consider the queue built up by the pervious time intervals.

2.4.2 Intersection Control Delay-HCM2000

Vehicles will stop due to the red time at the intersection which leads to additional travel time. These kind of stopped delays behind the intersection are named intersection control delay in HCM2000[8]. In HCM2000, the travel time on the link composes of two parts: a) travel time on the link at free flow speed and, b) intersection control delay.

The average control delay per vehicle that arrives in the analysis period is computed as follows:

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[7] Fadhely Viloria, Kenneth Courage, Donald Avery, 'Comparison of Queue Length Models at Signalized Intersections' for presentation for Transportation Research Board 79th annual meeting, January 2000.
[8] HCM2000, Highway Capacity Manual 2000 by Transportation Research Board

$$d = d_1(PF) + d_2 + d_3 \quad \text{(Eq 2- 7)}$$

Where:

d= control delay per vehicle (sec/veh)

d1=uniform control delay assuming uniform arrivals (sec/veh);

PF=uniform delay progression adjustment factor, which accounts for effects of signal progression;

d2=incremental delay to account for effect of random arrivals and oversaturation queues, adjusted for duration of analysis period and type of signal control; this delay component assumes that there is no initial queue.(sec/veh)

d3=initial queue delay, which accounts for delay to all vehicles in analysis period due to initial queue at start of analysis period.(sec/veh)

The uniform delay progression adjustment factor is determined by arrival type and the green ratio which is shown in Page 16-20 of HCM2000.

Uniform delay (d1) is caused by cyclic interruption of service caused by the red phase at a signalized intersection assuming uniform arrivals, stable flow, and no initial queue. Part of the observed group of vehicles will stop and queue because of the red light. It is computed as follows:

$$d1 = \frac{\frac{CL}{2} \times (1 - \frac{g}{CL})^2}{(1 - (\min(1, \frac{V}{C}) \times \frac{g}{CL})} \quad \text{(Eq 2- 8)}$$

Where

CL= cycle length(s)

g = effective green time.(s);

C= capacity of the intersection. (vph);

V=volume (vph);

Incremental delay (d2) is composed of two parts: a) random delay due to nonuniform arrivals and temporary cycle failures and b) oversaturation delay caused by sustained periods of over saturation. The d2 is computed as follows:

$$d2 = 900 \times CL \times [(\frac{V}{C} - 1) + \sqrt{(\frac{V}{C} - 1)^2 + \frac{8kl\frac{V}{C}}{C \times CL}}] \text{.......................................（Eq 2- 9）}$$

Where

T=duration of analysis period,(h)

k=incremental delay factor that is dependent on controller settings;

l = Upstream filtering/metering adjustment factor;

The k and l can be determined in relative table in HCM2000. But normally, for the pretimed signal, k is 0.5.

The initial delay in HCM2000 (d3) is experienced by the vehicles waiting for the initial queue to clear the intersection. The initial delay (d3) in HCM2000 composes of three situations: a) Initial queue delay with initial queue clearing during analysis time period T, b) Initial queue delay with initial queue decreasing during analysis time period T and c) initial queue delay with initial queue increasing during time period T.

Therefore, d3 is computed as follows:

$$d3 = \frac{1800Q_b(1+u)t}{CT} \text{..（Eq 2- 10）}$$

Where

Q_b =initial queue at the start of period T(veh);

T=duration of analysis period(h);

t=duration of unmet demand in T(h), and

u= delay parameter.

t=0 if Q_b =0,else $t = \min\left\{T, \frac{Q_b}{C\left[1-\min(1,\frac{V}{C})\right]}\right\}$ ....（Eq 2- 11）

u=0 if t<T, else $u = 1 - \frac{CT}{Q_b\left[1-\min(1,\frac{V}{C})\right]}$ ....（Eq 2- 12）

The general formula for the initial queue clearing time is computed as follows:

$$T_c = \max(\left(T, \frac{Q_b}{C} + T \times \frac{V}{C}\right) \quad \text{（Eq 2- 13）}$$

When there is an initial delay, the uniform delay in HCM2000 is revised to:

$$d1 = d_s \times \frac{t}{T} + d_u \times PF \times \frac{(T-t)}{T} \quad \text{（Eq 2- 14）}$$

Where

d_s =saturated delay (d1 evaluated for V/C=1), and

d_u =undersaturated delay (d1 evaluated for actual V/C value)

Table 2-1 shows the equation selection of delay model variables by cases in HCM2000.

Table 2-1 Selection of Delay Model Variables by Cases

Case No.	V/C	Qb	d1	d2	t	u	d3	Tc
1	⩽1	0	Eq 2-13	Eq 2-14	0	0	0	T
2	>1	0	Eq 2-13	Eq 2-14	0	0	0	TX
3	⩽1	>0	Eq 2-19	Eq 2-14	Eq 2-16	0	Eq 2-15	T
4	⩽1	>0	Eq 2-19	Eq 2-14	T	Eq 2-17	Eq 2-15	Eq 2-18
5	>1	>0	Eq 2-19	Eq 2-14	T	1	Eq 2-15	Eq 2-18

The intersection control delay method in HCM2000 works well and is widely acceptable due to its stopped delay algorithms. Tsekeris and Skabardonis[9](2004) compared the performance of the method in HCM2000 with the spot speed model(SSM) and BPR methods on arterial networks. In their study, method in HCM2000 demonstrated the most promising modeling approaches. Meanwhile, the SSM and BPR methods are almost fully insensitive to the change in signal timing phase which is questionable. The sensitive test also shows that SSM and BPR are not reliable on the application of travel time estimation on arterial networks.

The intersection control delay method in HCM2000 is widely implemented to estimate the intersection control delay at signalized intersections for a relatively long time analysis period such as 15 minutes or above. However, if the travel time estimation is updated for every cycle length, the computation of initial delay of d3 in HCM2000 for each cycle length is questionable. For example, let us assume that there is no incoming vehicle in the analysis time period, and only one vehicle is in the initial queue. According to Equation 2-16, t is equal to $\frac{Q_b}{C}$ which represents the time the initial queue would clear the intersection, which in this example would be 1/C, which is a very small number. However, the clearing time of the initial queue is relative to the signal phase of the intersection. If the analysis time period starts at red time, then t should be greater than the waiting time for the red time phase which in many cases is around 30 secs. and consequently is much greater than 1/C. But, if the analysis time period starts at the beginning of the green time, t will be smaller than

[9] Theodore Tsekeris and Alexander Skabardonis '*On-line Performance Measurement Models For Urban Arterial Networks*' presentation and publication for Transportation Research Board 83rd Annual Meeting.Washington D.C. January 2004.

1/C. Therefore, the methodology in HCM2000 is not good for estimating the travel time for a short time period update.

2.4.3 Using Loop Detectors and Probes to estimate the travel time

In 1996, Ashish Sen[10] used vehicle probes and the loop detector to estimate the travel time on arterials.

In their study, a number of probe vehicles were driven over the study route. The probes can measure link travel time even during congestion. However, the probe method experienced two main difficulties: a) data input is small due to the low proportion of probes within the total number of vehicle population (The higher proportion of probes will lead to a huge funding problem), b) The travel time estimated by probe is not statistically independent. The reason is that a vehicle arriving at the intersection at the end of red time will experience less stopped delay than the one arriving at the intersection at the start of red time.

In their paper, they addressed these shortcomings by introducing the use of loop detectors to estimate the travel time. The loop detector is usually installed fairly close to the stop line of the intersection in order to help control traffic signal. As a result, the queue will easily build over the loop detector. Hence, the reading of the loop detector to obtain the number of vehicles and the speed will not be reliable and can not reflect the queue length and how many vehicles are arriving at the intersection. If the detector is placed far from the stop line where the queue never extends over the detector, the travel time estimation requires the information about intersection capacity and the

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[10] Ashish Sen, Siim Soot, Joseph Ligas and Xin Tian,*'Arterial Link Travel Time Estimation: Probes, Detectors and Assignment-type Models'* Technical Report Number 50, National Institute of Statistical Sciences July,1996.

phases of the cycle length. Their paper concludes that a short reporting time of the loop detector is required to get a better estimation of travel time.

2.4.4 Using GPS Probe and Loop Detector Data Fusion for Travel Time Estimation.

Choi and Chung(2001)[11] fused the travel time detected by GPS and loop detector to enhance the accuracy of the estimation procedure. The voting technique, fuzzy regression and Bayesian pooling method are utilized in this fusion procedure. Figure 2-1 shows the process of its fusion algorithm.

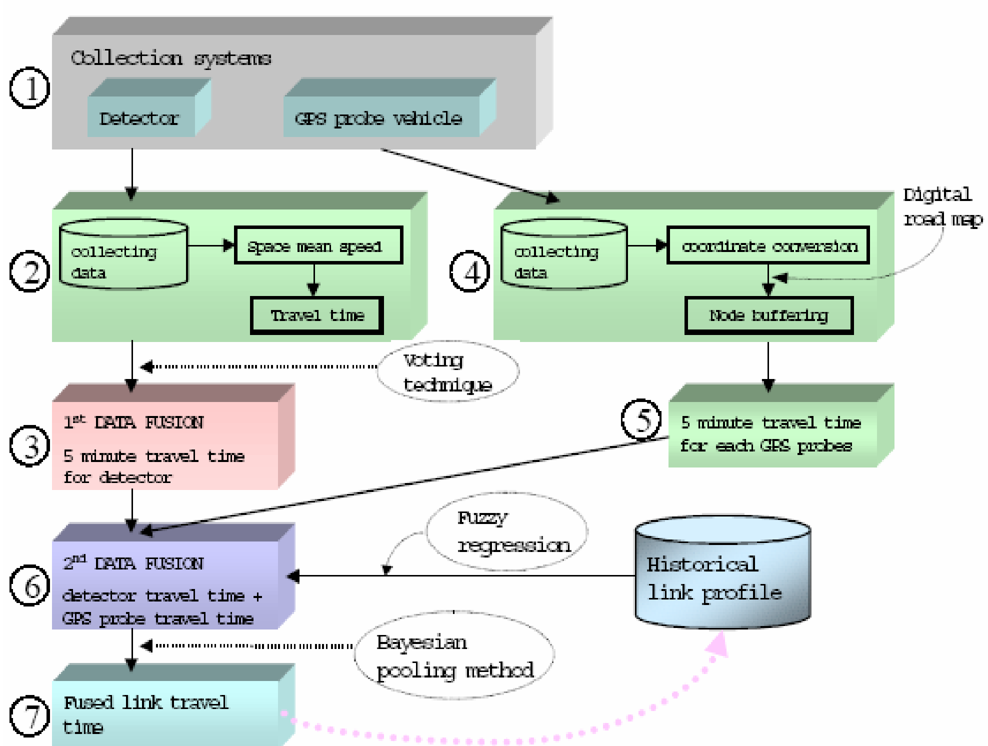

Figure 2-1 Process of Fusion Algorithm[13]

The evaluation of their study shows that this data fusion procedure can provide a

[11] Keechoo Choi and Youn-Shik Chung 'Travel Time Estimation Algorithm Using GPS Probe and Loop Detector Data Fusion', Paper No. 01-0374, Transportation Research Board 80th Annual Meeting.Washington D.C. January 2001.

more realistic link travel time. However, they used the link length divided by the detected speed as the link travel time which is not reliable on arterial streets, because it omits the intersection control delay.

2.4.5. Optimal Detector Location for Estimating Link Travel Speed in Urban Arterial Roads

As discussed in the aforementioned Ashish Sen's paper, the loop detector installed at the intersection will result in an unreliable detected speed. Hence, it can not provide good travel time estimation. Sungho Oh, Bin Ran and Keechoo Choi[12](2003) performed a study to find the best location of a detector to estimate the travel time on a relatively long urban link. They have utilized CORSIM in their study and they found that the optimal detector location was mostly related to link length and green time. In their study, the link length varied from 2000 to 7000 ft, the traffic volume varied from 500veh/h to 6000 vehicle/h. The green time varied from 20 to 50 secs., and the speed limit varied from 35 to 45mph. Finally, they compared the link average speed in the CORSIM output with the detected speed by the loop detector. In their conclusion, they found the optimal location of the detector to be 200ft from the intersection for links approximately 2000ft in length irrespective of the intersection green time. However, the optimal location of the loop detector with longer link lengths varies with the green times at the intersection.

However, I feel that the above conclusions are not reasonable for the following

[12] Sungho Oh, Bin Ran and Keechoo Choi,*'Optimal Detector Location for Estimating Link Travel Speed in Urban Arterial Roads'*, Presentation and Publication in Transportation Research Broad Washington D.C. January 2003. .

reason. The detector location at 200ft from intersection will easily experience a queue over it under very high incoming volume. Normally, the average headway plus the average vehicle length is 19 ft. Hence, 200 ft can only store 11 vehicles in the queue which can be easily exceeded in heavy traffic situation. However, this paper was helpful to us to locate the detector far enough from the intersection in order to avoid the situation where intersection queues will reach the loop detector. This will assure that the detector will provide the normal link running speed before the vehicles enter the queue or the intersection.

2.4.6 Various Applications to Estimate the Travel Time

'ITS Orange Book'[13](2004) introduced the application of several technologies to estimate and predict travel times in networks.

a) Percent of Probe vehicles

The study from University of Southampton Transportation Research (United Kingdom) shows that getting traffic information from a higher proportion of vehicles may not lead to an increase in estimated accuracy of travel times. Information from 26 percent of vehicles has the perfect performance. Their research provides a good guideline to select observed proportion of vehicles when using probe to estimate the travel time.

b) VERDI(Germany)

Vehicle Relayed Dynamic Information (VERDI) uses the GSM network to

[13] 'Predictive Travel Time' in 'ITS Orange Book 2004' Sponsored by PBS&J, and Carleton University. 2004.

communicate the probe vehicles with the control centers and determines their positions via GPS. It successfully combines the GPS and GSM technology to get the real time traffic information. However, it is still confronted with the problem that individual vehicle travel time is different if it arrives at the intersection during the green or the red time phase.

c) Houston Real-time vs. Historical

The Houston TranStar Automatic Vehicle identification (AVI) traffic monitoring system collects the travel time information on the freeway and HOV lanes in Houston area. The travel time information in real time is displayed on the website including the historical travel times .

d) Key route drive times-Chicago.

Traditional loop detectors are used to provide the travel time on key routes in the area around Chicago. The travel time and congestion levels are displayed on a real-time map as shown in Figure 2-2

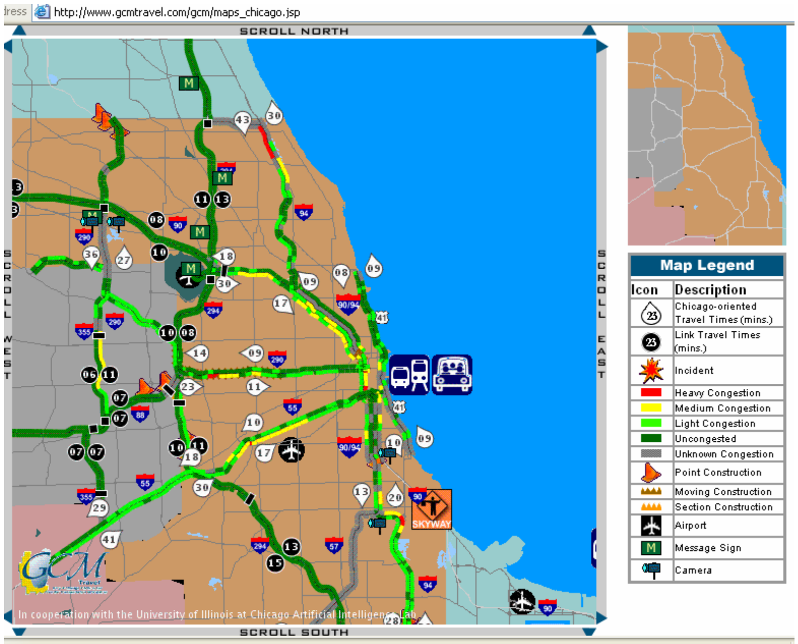

Figure 2-2 Snapshot of Traffic Situation from Website[14]

The website also provides travel times of corridors in table format as shown in Figure 2-3.

Travel Time Report Updated: 11/08/04 09:31 AM

Edens SB					
Congestion	From	To	Travel Time (minutes)	Distance (miles)	Speed (mph)
	DEERFIELD	DEMPSTER	20.3	11.2	31.3
	LAKE COOK	MONTROSE	24.7	14.8	35.8
	DEERFIELD	WILLOW	16.5	6.7	22.4
	DEERFIELD	TOUHY	23.1	13.7	33.6
	DEERFIELD	WILSON	27.2	17.4	38.0
	LAKE COOK	WILLOW	14.0	4.1	15.7
	LAKE COOK	DEMPSTER	17.8	8.6	26.8
	LAKE COOK	TOUHY	20.5	11.1	31.3
	LAKE COOK	WILSON	24.7	14.8	35.8
	LAKE COOK (VIA EDENS)	I-290/CIRCLE (VIA KENNEDY)	39.6	23.0	33.6
	DEMPSTER	MONTROSE	7.2	6.5	53.7
End of Reports (Edens SB)					

Edens NB					
Congestion	From	To	Travel Time (minutes)	Distance (miles)	Speed (mph)
	I-290/CIRCLE (VIA KENNEDY)	LAKE COOK (VIA EDENS)	27.5	22.8	49.2
	MONTROSE	DEMPSTER	7.1	6.9	55.0
	MONTROSE	DEMPSTER	6.8	6.6	55.0
	MONTROSE	TOUHY	3.8	3.6	55.0
	MONTROSE	WILLOW	11.6	10.9	55.0
	MONTROSE	LAKE COOK	17.3	14.7	49.2
	MONTROSE	DEERFIELD	20.7	17.8	49.2
End of Reports (Edens NB)					

Figure 2-3 Travel Time Table[15]

14 Source from 'http://www.gcmtravel.com/gcm/maps_chicago.jsp'
15 Source from 'http://www.gcmtravel.com/gcm/traveltimes.jsp?handler=travel_times_action'

This application indicates that the loop detector has the advantage to provide the real time travel time on a large traffic network due to wide implementation. However, this travel time computation is only based on the length of the link divided by the detected speed. It works well in freeway but it will ignore the intersection control delay on arterial streets with signalized intersections.

2.5 Incident Detection Algorithm on Arterial Streets

In estimating the travel time in real time, it is important to know when an incident has occurred on an arterial link and when it will be cleared. Since the travel time estimation under incident situation is part of this thesis, the related literatures in this area have been reviewed.

Han and May (1989)[16] developed a base method to detect the incident on an arterial street. Four types of data are used in this method, which are the historical incident-free data, the recorded incident data, the off-line simulated data, and the on-line experimental data. A simplified decision tree, as shown in Figure 2-4, describes the detection of a non-recurring incident based on the computed parameters obtained from the collected data.

[16] Han, L.D. and May, A.D. (1989) *Automatic Detection of Traffic Operational Problems on Urban Arterials*, Institute of Transportation Studies, Research Report UCB-ITS-RR-89-15, University of California at Berkeley,July 1989.

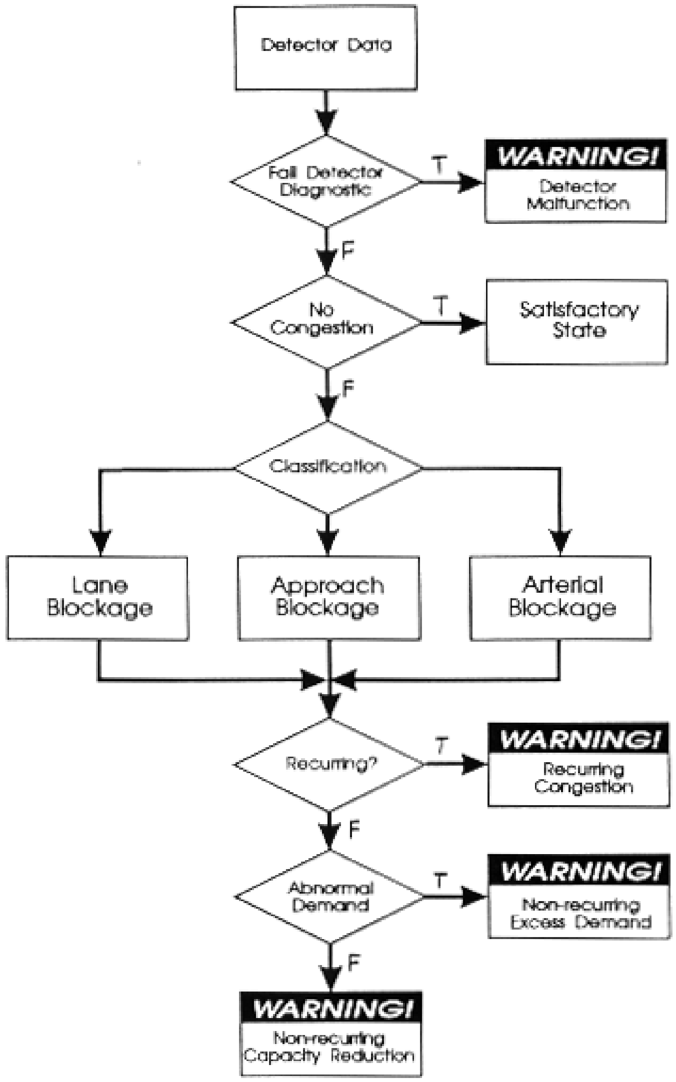

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Figure 2-4 : Simplified Decision Tree Source: Han and May (1989)

Han and May's method only used data from roadway sensors, without including data from traffic signal parameters. In addition, the location of the detector should be far away from the intersection.

In 1995, Frank S. Koppelman and Shih-Hsun Tsai[17] developed a method to detect the incident on arterial streets using point detectors. This method computes deviations

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[17] Frank S. Koppelman and Shih-Hsun Tsai,' Revised Incident Detection Algorithms for Release 2.0 and Re-calibration of Arte rial Fixed Detector Incident Detection Parameters 'Technology report from 'http://ais.its-program.anl.gov/advance/reports/travel.time.software.html' August 3,1995.

and ratios of current and historic volume and occupancy data from point detectors. Based on the deviations and ratios, the discriminant score is computed which is used to determine incident presence in the proximity of each detector and identify the roadway links which are affected if a particular detector shows an incident. The decision tree is shown in Figure 2-5

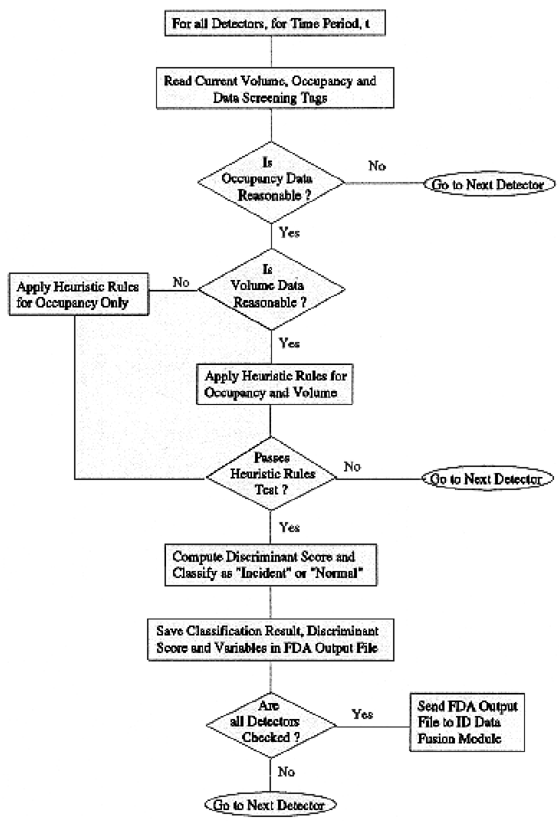

Figure 2-5 Incident Detection Tree by Frank and Shih

Nikhil Bhandari, Frank S. Koppelman, Joseph L. Schofer and Vaneet Sethi [18](1995) integrated data from multiple sources to detect the incident on arterial streets. Three types of data are obtained in their research: loop detectors, probe vehicles and anecdotal sources. Specialized incident detection algorithms are used to determine

[18] Nikhil Bhandari, Frank S. Koppelman, Joseph L. Schofer and Vaneet Sethi,' Arterial Incident Detection Integrating Data from Multiple Sources' Publication for Transportation Research Broad , Washington D.C. January 1995

the incident based on each source of data. The outputs of different algorithms are integrated by a data fusion process to determine the overall likelihood of an incident. Figure 2-6 shows the structure of the algorithm.

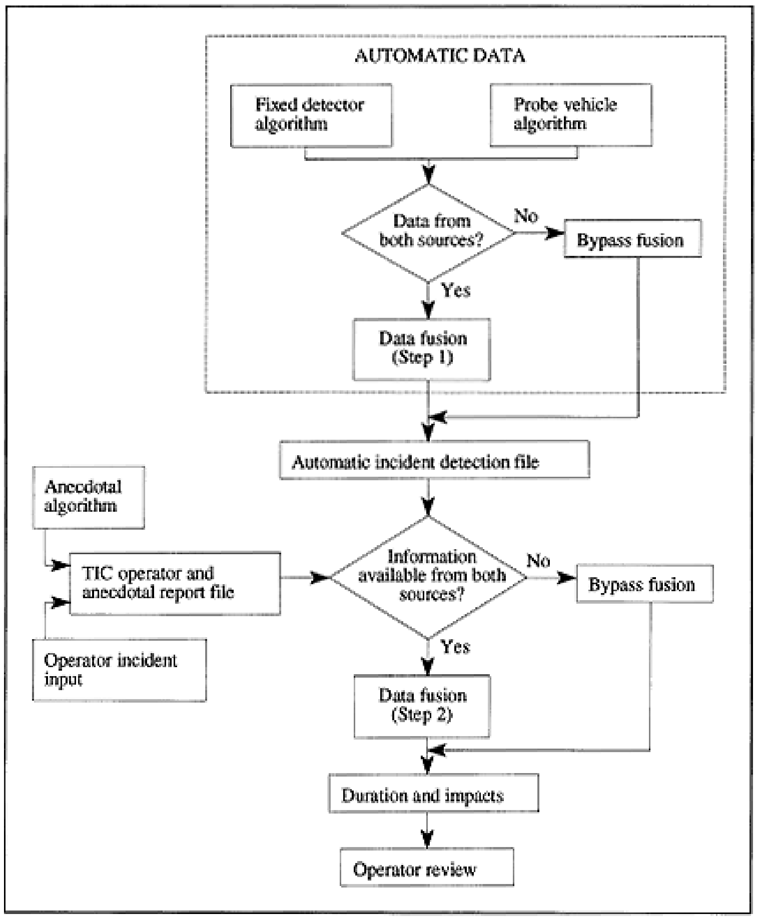

Figure 2-6: The *ADVANCE* Incident Detection System

Sheu and Ritchie[19] developed a methodology for real-time detection and characterization of incidents on arterial streets. The structural of their approach consists of three procedures which are symptom identification for presuming incident occurrences, signal processing for predicting incident effects on traffic behavior and pattern recognition for incident detection. The flow chart of their approach is shown

[19] Jiuh-Biing Sheu and Stephen G. Ritchie,' A new methodology for incident detection and characterization on surface streets' Transportation Research Part C 6 (1998) 315-335. Source www.elsevier.com/locate/trc

in Figure 2-7.

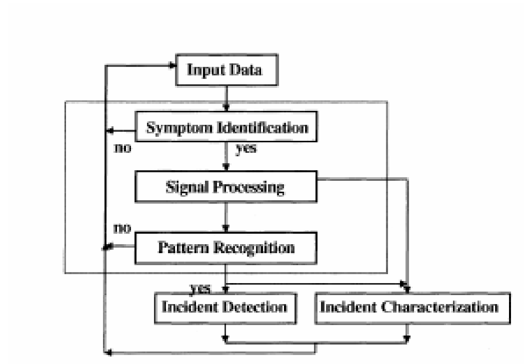

Figure 2-7 Flow Chart

2.6-Incident Response and Clearance Time

Incident response time on urban commute routes are analyzed by WSDOT[20]. Traffic data and incident characteristics are obtained from the loop detectors embedded in roadway and from field review. In their findings, the clearance times are high and vary greatly under fatal collisions, but are low and remain close to one another for non fatal collisions and for non-collision type of incidents. The clearance times for injury collisions are approximately as twice as those for non-injury collisions. It takes about 20 minutes to clear a blocking disabled vehicle and 15 minutes for a non-blocking disabled vehicle. The time to remove debris from travel lanes is approximately 10 to 13 minutes.

2.7- Capacity Reduction Factor under Incident Conditions

The capacity for open lanes will reduce due to the incident. Ling Qin and Brian L.Smith[21] estimated the accident capacity reduction based on the extensive incident data and traffic flow data from Smart Travel Laboratory. In their research, the mean

[20] Measuring Delay and Congestion: Annual Update 2004. by WSDOT
[21] Ling Qin and Brain L.Smith, 'Incident Capacity Estimation', Final report for ITS Center project, Smart Travel Lab Report No. STL-2001-02, 2001.

capacity reduction is 63% for one lane out of three lanes blocked and 77% for two lanes out of three lanes blocked. They found that a random variable should b e utilized to estimate accident capacity reduction.

2.8- Summary of Literature Review

In the past decades, researchers have been actively investigating how to estimate and predict travel time using numerous technologies and algorithms. Many algorithms performed with good accuracy in estimating travel time on freeways under incident and non-incident situations. However, the research of travel time estimation on arterial streets with signal intersections needs further work. Since vehicles may experience belays caused by intersection control, queue build up problems at intersection, lane drop at intersection, and bottleneck on the downstream link, it is more complicated to estimate the real time travel time on arterial streets than on freeway.

Recently, many urban transportation departments are planning to place the detector in the middle of the arterial links in order to monitor traffic and provide travel time information. This deployment provides a good opportunity to utilize the detected traffic data to estimate the real time travel time on the arterial network in one or two minutes update. HCM2000 has been the recommended method to estimate the intersection control delay. However, it has a shortcoming in estimating the initial delay in a relatively short-time interval update as discussed earlier. This thesis plans to modify the algorithms in HCM2000 to develop new algorithms for travel time estimation on arterial streets in real time under non-incident and incident situations.