Route Level Dynamic Travel Time Estimation on Freeway: A Case Study in Edmonton on Whitemud Drive

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ABSTRACT

Travel time is increasing critical in Advanced Traveler Information System (ATIS) for traffic management. Several years ago, traditional methods for e.g. travel time measurement and average historical methods were often used. However, they are expensive and inflexible. Besides, lots of mathematical models have been built to tackle this problem. The Static Travel Time Estimation (STTE) method and the Dynamic Travel Time Estimation (DTTE) method are two of the major ones. When speeds on the route have little variation, they can provide similar results. However, when speeds vary a lot, results from the STTE are not as accurate as the DTTE. Therefore, to get accurate estimated travel time, the research would be focused on the DTTE method. The DTTE method consists of Piece-wise Linear Speed-based (PLSB) model and imaged trajectory algorithm. PLSB model provides section travel times, and imaged trajectories algorithm help to get route travel times. Besides, to evaluate models' performance, traffic scenarios with and without VSL control are applied. Results in the thesis show that the DTTE method can stably provide more accurate estimations than the STTE method.

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LIST OF ABBREVIATION

TTP	Travel Time Prediction
ATIS	Advanced Traveler Information System
AVI	Automatic Vehicle Identification
ANN	Artificial Neural Network
OD	Origin-Destination
DTT	Dynamic Travel Time
STT	Static Travel Time
VSL	Variable Speed Limit
VIP	Video Image Processor
VDS	Vehicle Detector System
RMSE	Root Mean Square Error
MARE	Mean Absolute Relative Error (%)
FD	Fundamental Diagram
PLSB	Piece-wise Linear Speed-based
WMD	Whitemud Drive
WB	Westbound

CHAPTER 1. INTRODUCTION

This chapter mainly presents the background of peak hour travel time estimation on freeway using loop detector data. Also it indicates research problems, motivation, objectives and the thesis structure.

1.1 Background

With the development of Advanced Traveler Information System (ATIS), route travel time estimation has become increasingly important. As noted in a report from the California Department of Transportation," rapid changes in link travel time represent perhaps the most robust and deterministic indicator of an incident (and) link travel time... is perhaps the most important parameter for ATIS functions such as congestion routing" [1] . This means that evaluating travel time estimation method's performance when slow speeds happen can describe methods' accuracy more suitably.

In ATIS, models usually used in travel time estimation can be divided into three types: historical, current and predictive. Prediction models also can be distinguished as two kinds according to their analysis principles: statistical models and analytical models. [2]

Statistical models can be characterized as methods using a time series of historical and current traffic variables such as travel times, speeds, and volumes as input. Numerous statistical methods have been proposed, such as the ARIMA model, linear model, and neural networks. However, travel time estimation based on statistical models would be influenced by traffic behaviors and chaotic elements heavily. To avoid random factors, analytical models are proposed. These models predict data by using microscopic or macroscopic traffic simulators, such as METANET, NETCELL, and MITSIM. They usually require dynamic Origin-Destination (OD) matrices as input and predicted travel times evolve naturally from the simulation results.

Speed and flow data for research are collected by several loop detectors installed along the research segment for 24 hours. To enhance estimation accuracy, the segment is divided into several sections with considering loop detectors' positions. Two travel time estimation methods are proposed: the Static Travel Time Estimation (STTE) method and the Dynamic Travel Time Estimation (DTTE) method [3].

The STTE method supposes that vehicles maintain speeds without any changing when crossing a section. Sometimes in the calculation, the speed would be the average value of speeds measured from adjacent loop detectors on the same time stamp [5].

The DTTE method assumes that speeds are changed linearly in each section. And to track vehicles' travel time when speeds are changed dynamically, vehicle trajectories are imaged to help estimate travel time along a segment [6].

The thesis will be focused on the method of DTTE, for the reason that in practice, speeds are dynamically changing. If they are assumed to be static, the calculation error should be increased. To verify this assumption, results from two methods are compared. And a field testing from 122 St to 159 St on the Whitemud Drive in Edmonton is proposed.

1.2 Problem statement

Although plenty of models are used for travel time estimation, including regression model, Bayesian model, and historical method and so on, most of them are not accurate under special traffic conditions. These definitely will bring errors of travel time estimation. Thus, in order to achieve accurate estimation, models should be based on real-time data, and its prediction time length should be small.

1.3 Research motivation

The testing road is an important urban freeway in Edmonton. In peak hour, congestion always happens there. The city of Edmonton once used probe vehicles to find real-time travel time. Then it is found that results from probe vehicles can be influenced by experimenter easily, and expense is high for long term monitoring.

In August 2015, Variable Speed Limit (VSL) control testing was implemented on the research route. This is a traffic management measure to control driving conditions by giving flexible suggestion speeds to drivers. To find whether it improved driving environment or not, travel time is a critical indicator.

Thus, if travel time estimation models in the thesis is proved to be accurate. It can satisfy previous demands and be applied in further research.

1.4 Research objectives

The study is focused on proposing a travel time estimation method which can accurately estimate travel time for vehicles in a freeway. Specific objectives are shown as follows:

1. Design field experiments which can exactly satisfy research requirements.

2. Compare results from the STTE and the DTTE methods.

3. Evaluate the VSL control's performance by using the DTTE method.

1.5 Structure of thesis

The thesis includes 5 chapters:

Chapter 1 introduces the background of travel time estimation in peak hour; describes actual problems and presents research motivation and objectives.

Chapter 2 is the literature review chapter. This chapter reviews several travel time measurement methods, static travel time estimation methods and dynamic travel time estimation models, summarizes their weaknesses and compares them with estimation model used in the thesis.

Chapter 3 describes methodology application frameworks including data source, framework and models.

Chapter 4 discusses differences of two methods, evaluates their accuracy compared with reference travel time data and uses the DTTE method to assess the VSL control measure's performance.

Chapter 5 makes a conclusion and provides suggestions for future work.

CHAPTER 2. LITERATURE REVIEW

This chapter provides a systematic review of travel time estimation methods. Techniques and methodologies are conclusively introduced. In addition, their difference with models used in the thesis are also summarized.

2.1 Travel time measurement

Travel time data can be recorded by various techniques and methods. Drivers can determine the travel time by making use of instance license plate recognition, toll- gates, and in-car system [4]. Measurements methods can be divided into three types: (1) Site-based measurement (2) Vehicle-based measurement (3) Sensor-based measurement [7]. Site-based methods match vehicles license plate characters and arrival times at selected routes and fixed points, for example, the registration plate matching techniques [8] and cellular telephone systems. Vehicle -based methods mainly record information of traffic stream [9], including floating car [8] and probe vehicle methods [10]. Sensor-based methods collect raw data from stationary sensor as loop detectors [11], transponders [12] or radio beacons [12] installed on roads.

2.2 Static travel time methods

Static travel time methods usually do not have any model assumption. Naive methods are applied for their less computational effort and easy implementation

[14] . According to data types used, they can be classified into two types: instantaneous travel time methods and historical average methods.

2.2.1 Instantaneous travel time methods

The basic assumption is that the prevailing traffic conditions (speeds, densities, queues etc.) will remain constant. When conditions are stable without too much variation, the estimation of this method can be accurate, especially on freeway. But when speed is dramatically changing, its estimation accuracy will be deteriorated [15] .

2.2.2 Historical average

For long-term travel time estimation, the historical average method can be treated as a valuable approach in many cases. But its application is conditioned on a given time when average time trend has similar linear trend with historical time. In reality, when travel time distribution is scattered, estimators' ability would be poor [14] .To overcome this problem, hybrid models which combined historical and real-time data together are proposed. For example, using GPS probe data with historical data to build a hybrid model framework for estimating travel time [16] . Aude's research shows that this model indeed achieves a 16% improvement compared to simple historical average methods.

2.3 Dynamic travel time estimation models

2.3.1 Classification of model types

Dynamic travel time estimation model implies that when building model, speeds taken into consideration are dynamically changing. A rich body of literatures have been devoted to the development of route level dynamic travel time estimation. They can be divided into three major categories: parametric methods (e.g. linear regression, time series models, dynamic traffic assignment models, kalman filtering techniques), nonparametric statistical methods (e.g. neural network models, simulation models, Bayesian models, Support Vector Regression), and hybrid integration methods [17].

1) Parametric methods

Many previous studies are based on parametric methods. The term 'parametric' indicates that only the parameters of the model need to using data; the structure of the model is predetermined. 'Unseen' cases such as incidents can be modeled. Another advantage of these methods is that usually less data is needed compared to non-parametric models. Some parametric models have shown good performance, in accuracy as well as computational effort. Van Hinsbergen and Van Lint [18] combined linear regression model and locally weighted linear regression model in a Bayesian framework to improve estimation accuracy and reliability. Although their proposed combination methodology exhibits accurate results, their model may produce larger estimation errors when each sub-model in the model layer is biased. Chen and Chien [19] compared link-based and path-based travel time estimation models using Kalman filtering algorithm with simulated synthetic probe data. Chien and Kuchipudi [20] re-evaluated Chen and Chien's model with historical and real-time automatic vehicle identification data. They found estimation accuracy is highly determined by both probe vehicle market penetration rate and network congestion level.

2) Nonparametric statistical methods

Nonparametric statistical methods are also frequently used. The term non-parametric is not meant to imply that these models completely lack parameters but that the number and nature of the parameters are flexible and not fixed in advance. Model structure also need to be determined from data. Therefore, more data is required than for parametric models. But, unseen cases such as incidents pose a problem as the model structure is derived from data. Park and Rilett [21] proposed two clustering-based modular Artificial Neural Network (ANN) models for freeway short-term link travel time forecasting. Considering the fact of link travel time correlation, Rilett and Park [22] applied a spectral-based neural network to the corridor travel time estimation. Park and Lee [23] showed that the Bayesian model and neural network model can provide good estimates for link travel time. Bajwa et al. [24] used a pattern recognition method to search in a database for traffic patterns similar to current conditions. However, abnormal traffic patterns caused by non-recurrent congestions or incidents deteriorate the performance of their model.

3) Hybrid frameworks

Hybrid frameworks integrated two or more models for travel time estimation. Juri et al.[25] reported the use of a two-stage hybrid integration model for online travel time estimation within a roll-horizon framework. In each roll, freeway entry volume is estimated by a time series model and these volumes are fed into a cell transmission-based traffic model to generate desired travel time estimation. Kuchipudi and Chien[26] tested a hybrid model incorporating path-based and link-based models with real-world data, in order to achieve promising estimation results under different traffic conditions.

2.3.2 Model examples review

In order to better illustrate referred models, several of them are introduced in following part.

1) Regression travel time estimation models

Travel-time calculation depends on vehicle speed, traffic flow and occupancy, which are highly sensitive to weather conditions and traffic incidents. So to reach optimal accuracy can be difficult. But, daily, weekly and seasonal patterns can still be observed at a large scale. This is the basic operation principle of regression models.

Regression models for travel time estimation including support vector regression [27], Gaussian process regression[28] and multivariate nonparametric regression [29]. Support vector regression model makes use of support vector machine theory by Vanpnik of the AT&T Bell Laboratories, which is based on the structural risk minimization principle [27]. Gaussian process regression is used mainly for its capability for fitting arbitrary-shaped curves and free from pathological behavior for regions with few data points [30]. The multivariate nonparametric regression model can be described as a k nearest neighbor (k-n n) model. Recent observations are matched with those contained in a data base of historical observations. From all of the matched data, either the k nearest matches or all the matched below a given distance threshold are located. The successive observations from these “best” matches are averaged to obtain the forecasts [29].

2) Bayesian travel time estimation model

The Bayesian dynamic model views the forecast process as a stochastic process and provides estimated travel times along their associated confidence interval to account for traffic dynamics and uncertainly. This is according to the concept of Bayesian inference.

The Bayesian forecasting framework, which is developed from probabilistic inference, provides a linkage between the priori information and the posteriori travel time distribution using the new measurements from the updated information set [32]. The study requires both historical travel times and prevailing traffic information as inputs.

2.4 Literature review summary

Research in the thesis hopes to provide real-time travel times information. Hence travel time estimation here should be dynamic and up-dated. Travel time measurements are inflexible and cannot achieve estimation process. For Static travel time methods, they can estimate travel time under ordinary traffic conditions, but when congestion and special accidents happen, their accuracy will be influenced a lot. Model used here is one of hybrid frameworks. It combines the METANET model and the STTE method together. Compared with models referred before, it not only decreases noise from historical data, but also can handle simulations of special traffic status. And The STTE and DTTE's major differences are shown as below:

Table 1: Major difference between STTE and DTTE

STTE	DTTE
Regard situation changing	Consider situation changing
Not so accurate under special traffic environment	Be accurate used in unseen cases
Be conditioned by historical data	Available for real time estimation

CHAPTER 3. METHODOLOGY AND IMPLEMENTATION

This chapter introduces model framework and methodologies implementation in research. It presents how to estimate travel time based on measured data, including loop detector data and video data. The framework is composed by four steps.

3.1 Data Source types

3.1.1 Loop detector data

Loop detectors are installed to measure speed, volume and density data. They usually are installed under the road surface. When a vehicle appears in the scale of an installed loop detector, the inductance will be induced. And the resulting increase in oscillator frequency is detected by the electronics unit and the controller will quickly interpret this as a vehicle [33].

Real-time traffic information is recorded every 20 seconds. As shown in Fig. 1, along the experiment site, there are 8 main lanes, 4 on-ramp and 5 off-ramp loop detector stations.

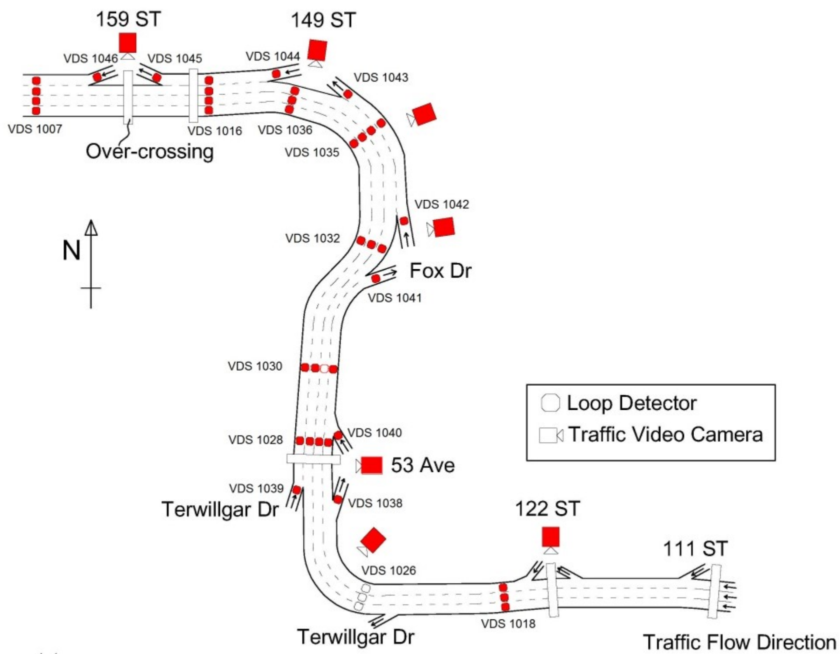


Figure 1. Loop detector station positions in research segment

3.1.2 Video data

For video can transmit images which are easy to interpret, it is widely used in transportation research. A video image processor (VIP) system typically consists of one or more cameras, a microprocessor-based computer for digitizing and analyzing imageries and software for interpreting images [34]. Camera Sensors are often installed higher than road face.

From 122 Street to 159 Street in the Whitemud Drive, the city of Edmonton has installed 8 camera observation points for real-time traffic condition monitoring.

Time stamps and images of vehicles are recorded by video. Vehicles passing through the route with same appearance are regarded as reference vehicles. Meanwhile, their time stamps arriving the route's entrance and exit are recorded.

Time interval between time stamps can be considered as vehicles' travel time during the segment. Measured reference travel time data can be used to evaluate estimation models' accuracy.

3.2 Research implementation

3.2.1 Research framework

Before being applied in practice, travel time estimation models' accuracy should be evaluated. Thus, results from both the DTTE and STTE methods are compared with reference travel time data. In addition, in order to prove the DTTE method's advantages in experiments than the STTE method, several indexes are proposed to doing particular analysis. The framework of research can be divided into 4 steps:

The first step is the prediction step. In this step, the METANET model will be used to predict density and speed data based on real-time measured data.

The second step is travel time estimation step. Data estimated in the first step would be used as the input data for travel time estimation. Travel times are calculated by the DTTE and STTE methods individually.

The third step is the evaluation step. Estimation results are evaluated by reference travel times. If error is small, the estimation process is regarded to be accurate.

The fourth step is the methods comparison step. Mean Absolute Relative Error (MARE) is used to access two methods' accuracy for the whole testing time. Root Mean Square Error (RMSE) value is introduced to weigh which method can steadily perform better.

The whole framework is shown as follows:

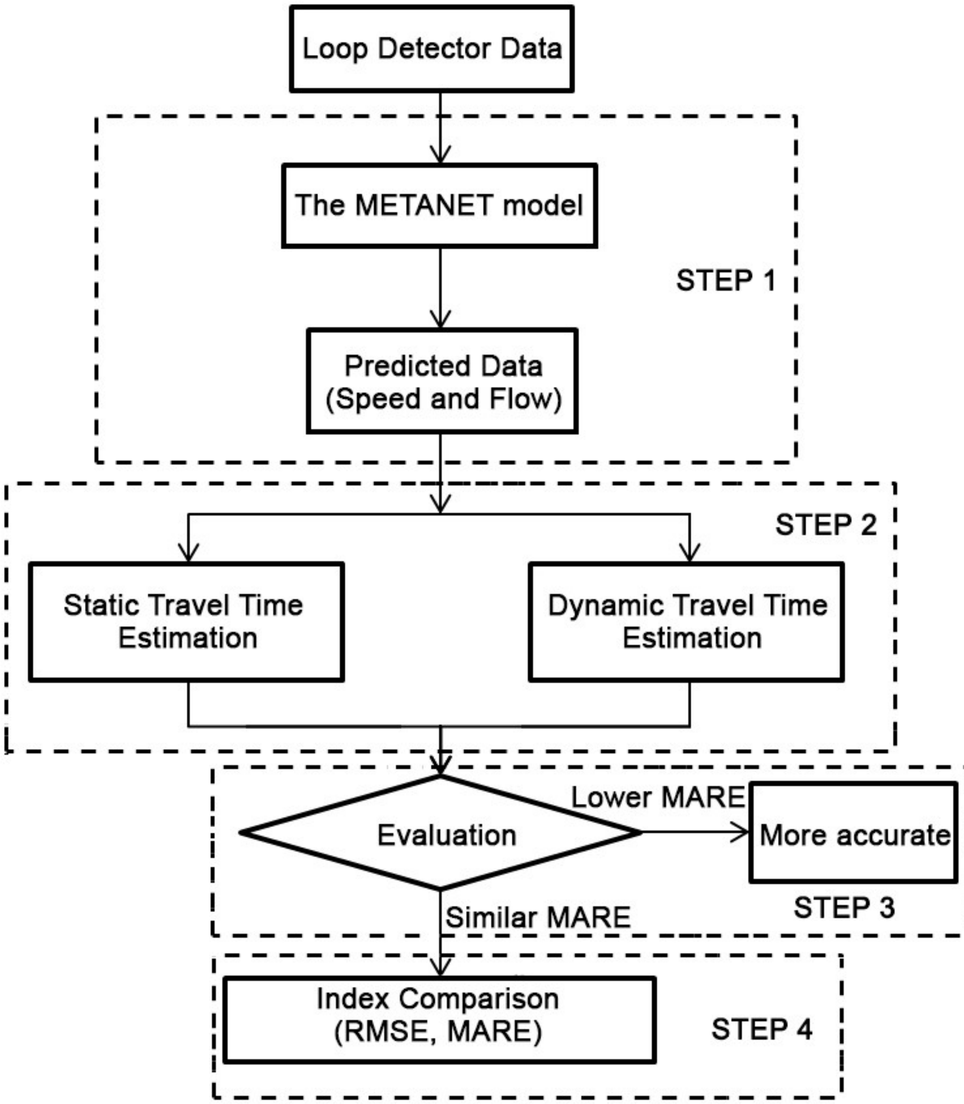


Figure 2. Whole framework of models procession

3.2.2 The METANET prediction model

A METANET-based prediction model [35] is used to simulate traffic status. It is a macroscopic model to predict speed and density data certain time steps later. This means that based on measured data, the METANET model can predict what the speed and density data would be in the same position after certain time interval.

Below is a brief explanation of the prediction model. To apply the METANET model, the freeway corridor is divided into several sections (i =1, 2...N) of length L_i and lanes λ_i (as shown in Fig.6). The evolution of traffic density $\rho_i(k)$ in vehicles per kilometer per lane (veh/km/ln) and traffic speed $v_i(k)$ in kilometers per hour (km/h) at each time index t (where, $t = kT$, T=the discrete time step, k = the time step presently in the calculation) are calculated by Eq. 1 and 2 [36] :

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{L_i\lambda_i}\left(\lambda_{i-1}q_{i-1}(k) - \lambda_i q_i(k) + r_i(k) - s_i(k)\right) \tag{1}$$

Where,

q: Boundary flow between segments in vehicles per hour (veh/h);

R: On-ramp meter rates;

S: Off-ramp flow.

$$v_i(k+1) = v_i(k) + \frac{T}{\tau}\{V[\rho_i(k)] - v_i(k)\} + \frac{T}{L_i}v_i(k)[v_{i-1}(k) - v_i(k)] - \frac{\eta T[\rho_{i+1}(k) - \rho_i(k)]}{\tau L_i[\rho_i(k) + \kappa]} \tag{2}$$

Where, $V[\rho_i(k)] = v_{f,i} exp\left[-\frac{1}{a_i}\left(\frac{\rho_i(k)}{\rho_{cr,j}}\right)^{\alpha_i}\right]$

τ : Reaction term parameter in hours (h);

υ : Anticipation parameter (km^2 per hour, km^2/h);

κ : Positive constant (veh/km/ln)—these are global parameters that are calibrated from measured data.

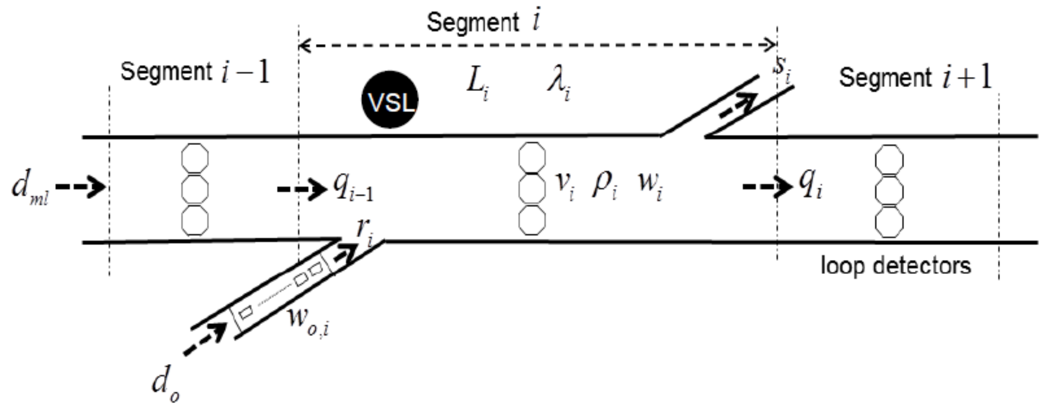


Figure 3. Segmentation of Freeway Links

In order to make the simulated result similar to actual loop detector data after optimization at the greatest extent, fundamental diagram (FD) related parameters $[\nu_f, \rho_{cr}, \alpha]$ of the METANET model were calibrated to be [80, 35, 2.8] based on field traffic data. Similarly, with the given demand inputs for mainline and on-ramps, the global parameters $[\tau, \nu, \kappa]$ in Eq. 2 were optimized by Sequential Quadratic Programming at 0.02, 28.8, and 10, respectively.

But when the VSL control strategy is proposed, the FD (speed-density relation) has been replaced as it appears in the original METANET with the optimal control variable μ [37]:

$$v_i(k+1) = v_i(k) + \frac{T}{\tau}\{\mu_i(k) - v_i(k)\} + \frac{T}{L_i}v_i(k)[v_{i-1}(k) - v_i(k)] - \frac{\eta T[\rho_{i+1}(k) - \rho_i(k)]}{\tau L_i[\rho_i(k) + \kappa]} \tag{3}$$

μ is an optimal control variable, which is defined by the VSL control system. Doing so, the VSL control variable becomes a free control variable.

Thus, under situations without and with VSL control, equations used in METANET models are different in some extent.

3.2.3 The Static Travel Time Estimation (STTE) method

The STTE method assumes that speeds of vehicles passing through a section is the average of speeds measured by adjacent loop detectors in the same time section. So in each half part of a section, speeds of vehicles would be fixed. Eq. 4 can explain this directly [38]:

$$\mathrm{v}(\mathrm{x},\mathrm{t}) = \begin{cases} \mathrm{v}(d_i,\mathrm{t}) & \forall\, x \in \left(x_i, x_i + \frac{s}{2}\right) \ \ and\ t \in [t, t - DI] \\ \mathrm{v}(d_{i+1},\mathrm{t}) & \forall\, x \in \left(x_i + \frac{s}{2}, x_{i+1}\right) \ \ and\ t \in [t, t - DI] \end{cases} \tag{4}$$

Where: x_i and x_{i+1} are the distance positions for the loops d_i and d_{i+1}.

And section travel time can be calculated from Eq. 5:

$$t_i(k) = \frac{1}{2}\left(\frac{L_i}{\bar{v}_{A,k}} + \frac{L_i}{\bar{v}_{B,k}}\right) \tag{5}$$

The segment travel time T is the sum of section travel times:

$$\mathrm{T} = \sum_{\mathrm{i}}^{\mathrm{k}} \mathrm{t}_{\mathrm{i}}(\mathrm{k}) \tag{6}$$

3.2.4 The Dynamic Travel Time Estimation (DTTE) method

The dynamic travel time estimation method is composed of two parts: the piece-wise linear speed-based (PLSB) model and the trajectory assumption model. The PLSB model [39] can calculate section-level travel time. A route consists of several sections. Meanwhile, during vehicles' traveling, speeds are changed in different time interval. Thus, in order to estimate route travel time precisely, the trajectory assumption model is introduced which can image vehicles' trajectories.

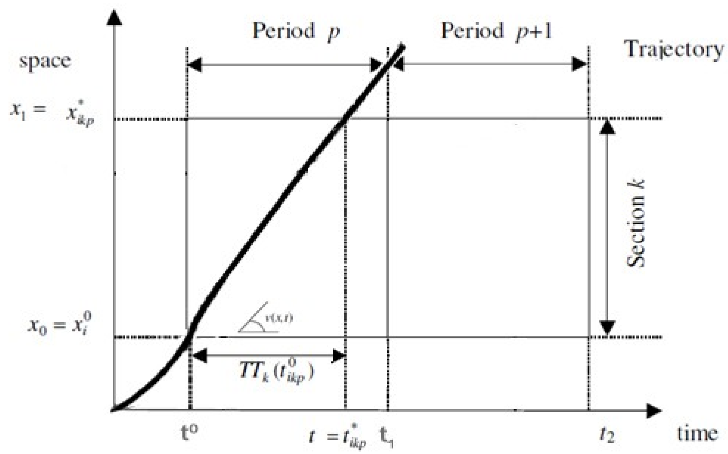
1) Section travel time estimation

The piece-wise linear speed–based (PLSB) model is used to calculate section travel time, t. For PLSB model, the time for a vehicle passing over space $[x_0,x_1]$ is defined as the time needed for a vehicle i passing a particular section k. The speed v(x, t) depicts the steepness of its trajectory. Compared with static travel time estimation method, the PLSB assumes that the steepness is a linear changing line instead of a horizontal line. Periods p and p+1 here are fixed times of 20 seconds. In a period, measured data from loop detectors including speed and density are fixed.

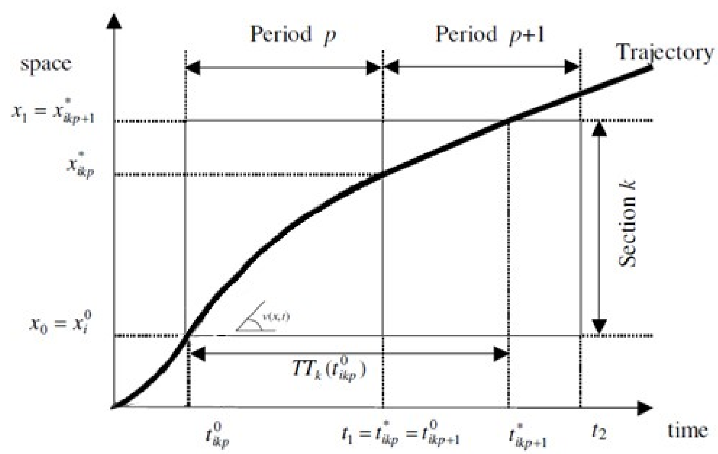
For the whole segment, speed data measured from loop detectors in each section are changed every 20 seconds in testing site, then, speed of section V (k) $=v_{20n}(k)$, n=1, 2, 3……K, $v_{20n}(k)$ is fixed in section k during time period 20n. But if the n is changed, vehicles still do not exit section k. When such a situation happens, speed being used in estimation would be also changed. Considering the speed on section k is a convex combination of the time average speeds at up and downstream detectors, denoted by V (d,p) and V(d+1,p) respectively. To discover when vehicles exiting section k, speed is changed or not, the condition as follow is used [6] :

$$x_i^0 + \left(\frac{V(d,p)}{A} + x_i^0 - x_0\right) * \left(e^{A(t_1 - t_i^0)} - 1\right) > x_1 \tag{7}$$

Figure 4 depicts trajectories of vehicles without and with condition 7 hold. When condition is hold, travel time for vehicles passing through section is less than t_1 as shown in Fig. 4(a). Otherwise, if condition is not hold, after the time period of t_1, vehicles will not exit the position x_1, and at this time, the speed for calculation should be changed.



(a)



(b)

Figure 4. Vehicle trajectory (a) condition is hold; (b) conditions is not hold

Following equations are used to calculate the exit location and time [6]:

$$\{x_i^*, t_i^*\} = \begin{cases} \left\{x_1, t_i^0 + \frac{1}{A} ln\left(\frac{\frac{V(d,p)}{A} + x_1 - x_0}{\frac{V(d,p)}{A} + x_i^0 - x_0}\right)\right\}, & \text{condition holds} \\ \left\{x_i^0 + \left(\frac{V(d,p)}{A} + x_i^0 - x_0\right) * \left(e^{A*\left(t_1 - t_i^0\right)} - 1\right), t_1\right\}, & otherwise \end{cases} \quad (8)$$

$$A = \frac{V(d+1,p) - V(d,p)}{x_{d+1} - x_d}, \text{ and } A \neq 0 \quad (9)$$

Where,

i : A vehicle;

p, P: Measurement period and total number of measurement periods, respectively;

t_0, t_1: Start and end of measurement period p, respectively;

x_0, x_1: Start and end location of section k, respectively;

L_k: Length of section k;

$\{x^0_{ikp}, t^0_{ikp}\}$: Entry location and time of a vehicle in section k, period p;

$\{x^*_{ikp}, t^*_{ikp}\}$: Exit location and time of a vehicle in section k, period p;

$x_i(t)$: Trajectory of vehicle i as a function of time;

$v_i(t)$: Speed of vehicle i as a function of time;

V(k,p): Mean speed on section k during time period p.

Care must be taken if A's value is close to zero. This could lead to numerical problems. In practice this is applied when the upstream and downstream observed speeds are nearly equalled.

2) Route- level travel time estimation (trajectory assumption algorithm)

Using the PLSB model, section level travel time can be estimated. But for the route which is composed of several sections, the trajectory assumption algorithm in Fig. 5 is proposed.

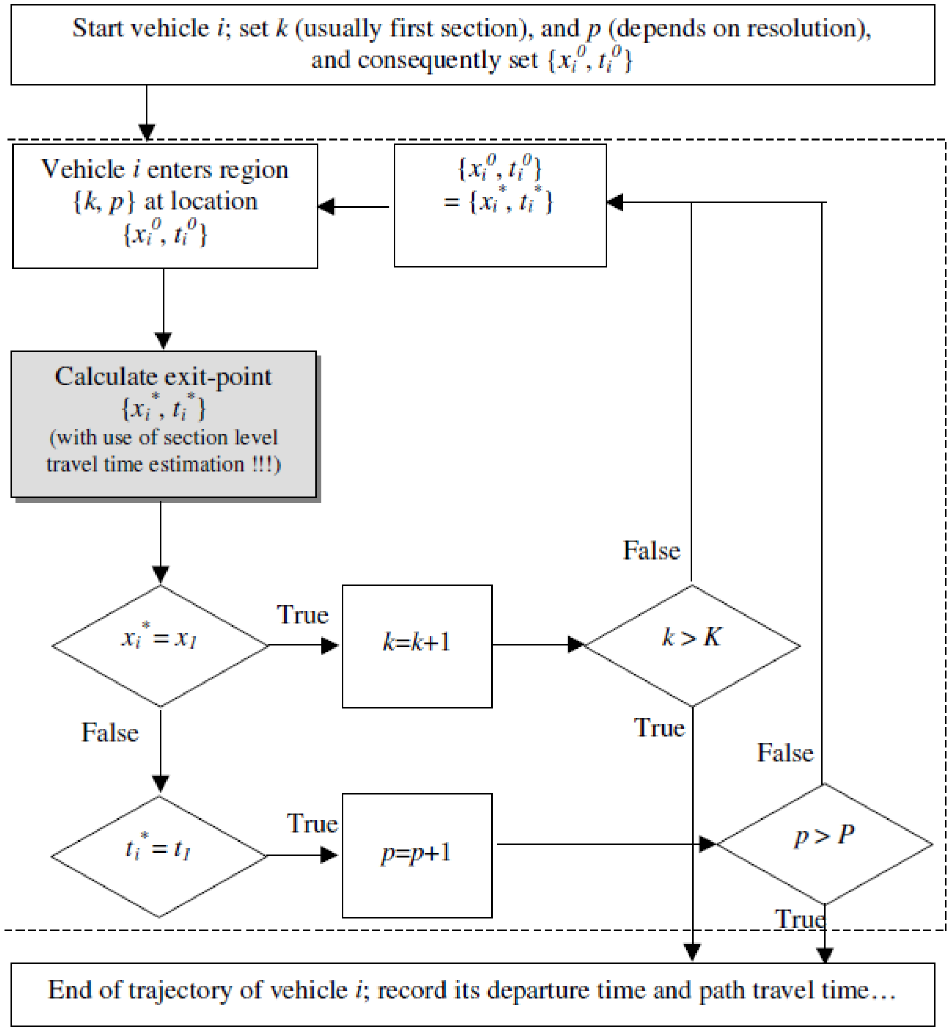


Figure 5. Imaged trajectory algorithm for route-level travel time [6]

The trajectory algorithm for a single vehicle trajectory can be schematically presented, as in Fig.5. It assumes that the time interval P is defined; in the space-time diagram, time stamps would be n*P (0, P, 2*P, 3*P….i*P). When a vehicle enters region (k,p) at location (x0,t0), it exits at (x*, t*). Assuming that the whole travel time during this section is p (0 ≤ p ≤ i*P), if p<P, the vehicle enters next section, and the travel time will be accumulated; this algorithm will be repeated until the sum of time p>P.

Otherwise, when the time p ＞ P， at this time, if the vehicle exits the exit position x0, following calculation will use the speed at position (x1, t1), P＜t1＜2*P, if it does not exit the location x*, vehicle will travel with the speed at the position (x0, t1) until it passes the location x0.

3.3 Summary of case study and method implementation

The estimation process can be divided into three steps: prediction step, travel time estimation step, and evaluation step. If estimation model is proved to be accurate, an application case study would be proposed to verify models' practicability in transportation research.

Meanwhile, in thesis, one macroscopic prediction model, two travel time estimation methods and a trajectory model are introduced. The prediction model is the METANET model, which is used to predict traffic statues. Two travel time estimation methods are the STTE method and the DTTE method. Because travel time calculated from the DTTE method is only section-level time, so, to get route travel time, the trajectory assumption model is used.

CHAPTER 4. CASE STUDY AND RESULTS ANALYSIS

This chapter analyses estimation results without and with VSL control. To evaluate accuracy, results are compared with reference travel time. Besides, indexes as MARE and RMSE are introduced to figure out differences between two methods. Further, a case study example is introduced to prove the DTTE method's practicability and applicability.

4.1 A field testing

4.1.1 Research corridor

The experiment route is a segment on the Whitemud Drive, from the 122 Street to the 159 Street. The total length is 6.8 kilometers.

In the Edmonton's transportation network, the Whitemud Drive is an east-west direction main road with heavy flow. In peak hour, congestion always happens.

The research route has traffic control accessed and sensors infrastructure installed. Sensors, including loop detectors and cameras, can provide real time and historical data for transportation research. The research uses loop detector data for travel time estimation and videos as reference data to evaluate the accuracy of predictions.

4.1.2 Route division

According to the PLSB method, the corridor can be divided into different short sections. In order to guarantee travel time estimation models' feasibility under various conditions, section division should satisfy two major requirements:

1) Loop detectors on sections' entrances and exits should work normally in experiment days.

2) Sections' lengths should be different.

Considering previous requirements, section division is shown in Fig. 6:

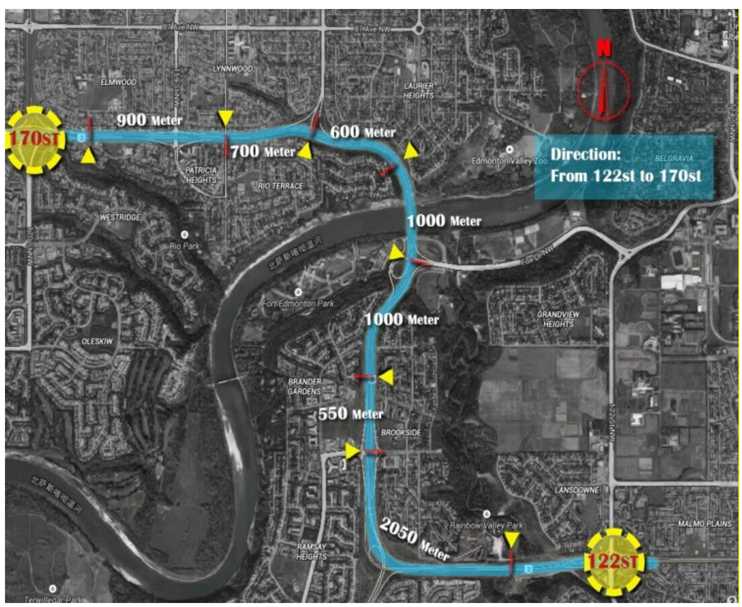


Figure 6. Sections division of the research route

Lengths of divided sections are presented in Tab. 1. Because the Vehicle Detector System (VDS) 1026 does not work, so it is hard to estimate traffic status in this position. Then the section from 122 Street to 53 Avenue on the Whitemud Drive becomes the longest one of 2050 meters,

Table 2. Distance of sections

Section (No.)	Section location (At Whitemud Drive)	Distance (Meters)
1	122 St - 53 Ave	2050
2	53 Ave - 58 Ave	550
3	58 Ave - Fox Dr	1000
4	Fox Dr - 142a St	1000
5	142a St - 149 St	600
6	149 St - 156 St	700
7	156 St - 159 St	900

4.1.3 Prediction time length division

For speed prediction, length of time interval directly has an influence on prediction accuracy. A case study of Aug. 17th is shown in Fig.7:

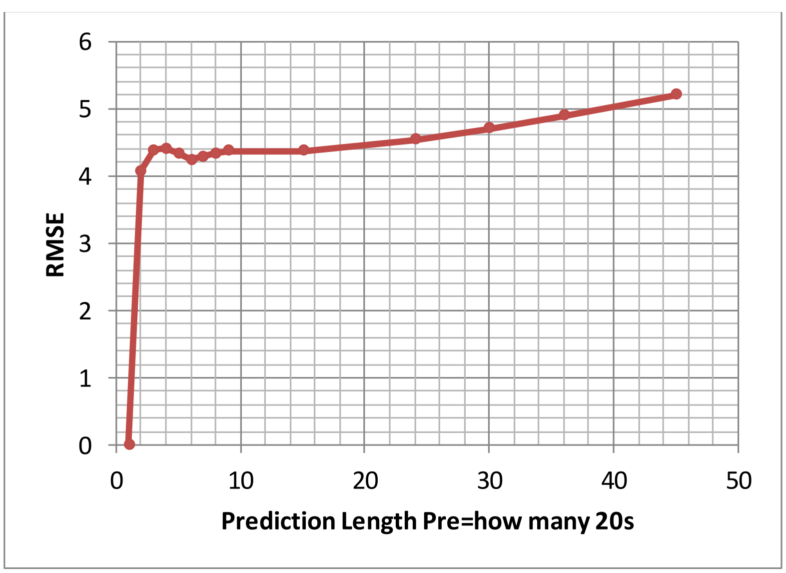


Figure 7. RMSE values profile when prediction time length added (Aug.17th)

Table 3 RMSE values of different prediction time lengths (Aug. 17th)

Prediction Length = (20 sec)	RMSE
1	0
2	4.07
3	4.38
4	4.40
5	4.33
6	4.23
7	4.28
8	4.33
9	4.37
15	4.36
24	4.53
30	4.70
36	4.89
45	5.20

Figure 7 and table 2 show that when prediction length is increasing, validation accuracy will be decreased. Meanwhile, concluding from historical data, travel times in this route from 122 St. to 159 St. are usually less than 15 minutes, to 142a St. is less than 10 minutes, and to 53 Ave. is no more than 5 minutes. Thus, in order to improve prediction accuracy from just using a constant prediction length, the route is divided into zone with three prediction lengths, which can be seen in Fig.8.

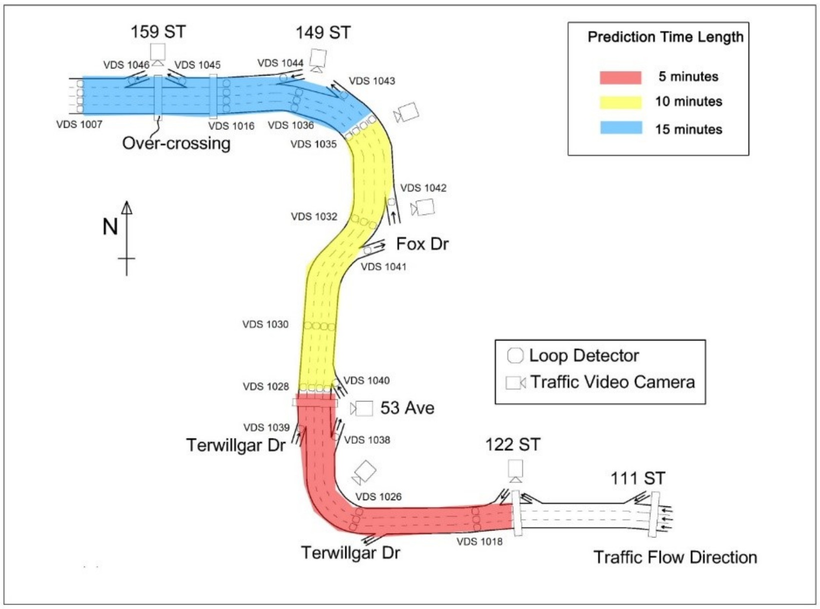


Figure 8 Prediction time length division

4.1.4 Scenario choosing

Concluding from past transportation works, variables contributing to a better estimation of travel times are often as follows [5]:

- Time of day
- Mean speed
- Maximum speed
- Number of vehicles
- Most recent travel time
- Mean speed in bottlenecks
- Mean speed in between congested areas

• Maximum speed in between congested areas

• Length of congested area

Among referred variables, time of days and mean speed are two major factors considered here. First, estimations are processed in PM peak hour, from 4:30 - 6:30 PM. In peak hour, influences from speed variation and driving behaviors on travel time are more apparent than under freeway condition. Thus, if the model under congestion environments performs well, it can also be used in other time periods.

Meanwhile, in August, the city of Edmonton implemented the Variable Speed limit (VSL) control strategy on this route. This is a kind of strategy in traffic management system aiming to decease travel time on route level by giving adaptable suggested speed to drivers.

So, to evaluate estimation methods' accuracy under referred two traffic conditions, four weeks in May and August are chosen individually for following reasons:

1) Edmonton is a city with snowy days happening nearly half of a year. Such weather may influence estimation results. Selecting these two months can avoid data noise from snow weather for there are mostly sunny days in May and August.

2) The route has heavy flow every day, including lots of heavy trucks. Loop detectors are installed under road surface, so traffic events may cause damage on them, which leads to missing data. In these two

months, measured data are complete to provide a favourable environment for research.

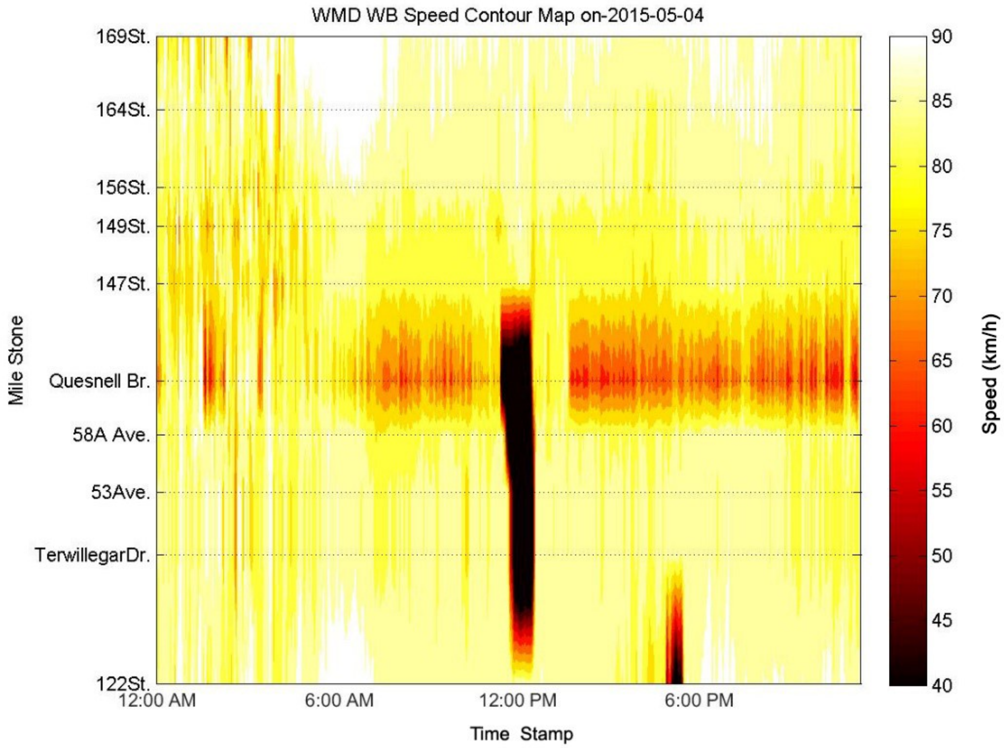
3) VSL control was applied in August, and there had been no specific strategy carried out in May. Thus, choosing these two months with different traffic conditions can evaluate the estimation model's applicability under various situations.

4.2 Results analysis

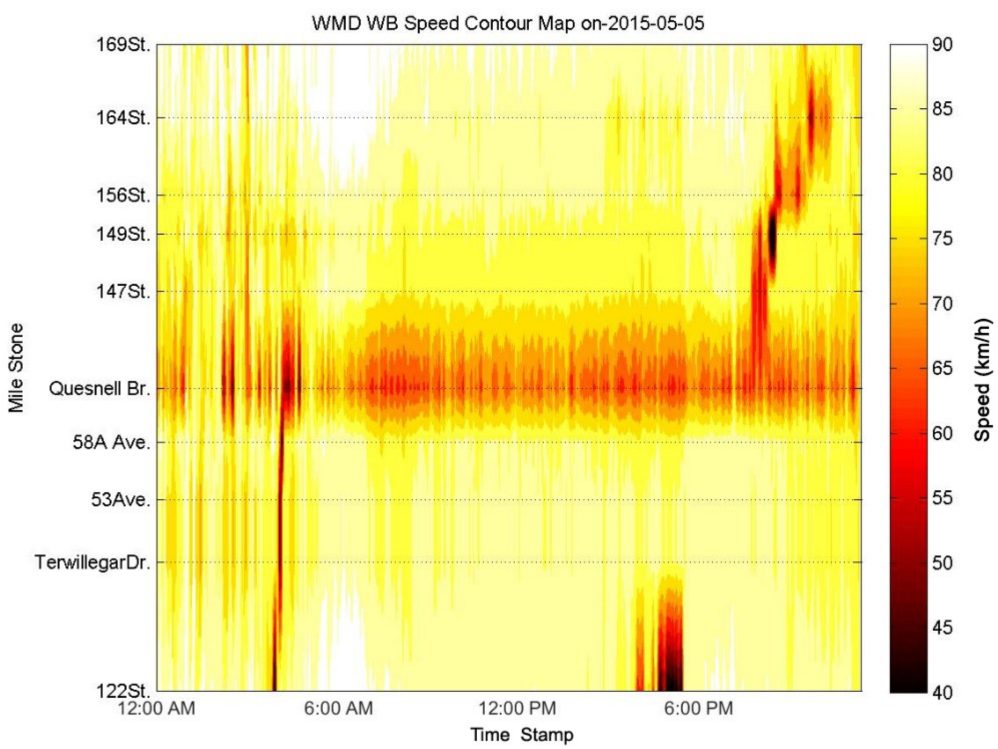
4.2.1 Travel time estimation evaluation (without VSL control)

Measured and predicted speeds are compared in validation part. The RMSE is used to judge whether predictions are accurate or not. If RMSE value is small, predictions are considered to be similar with reference travel times during the whole travelling.

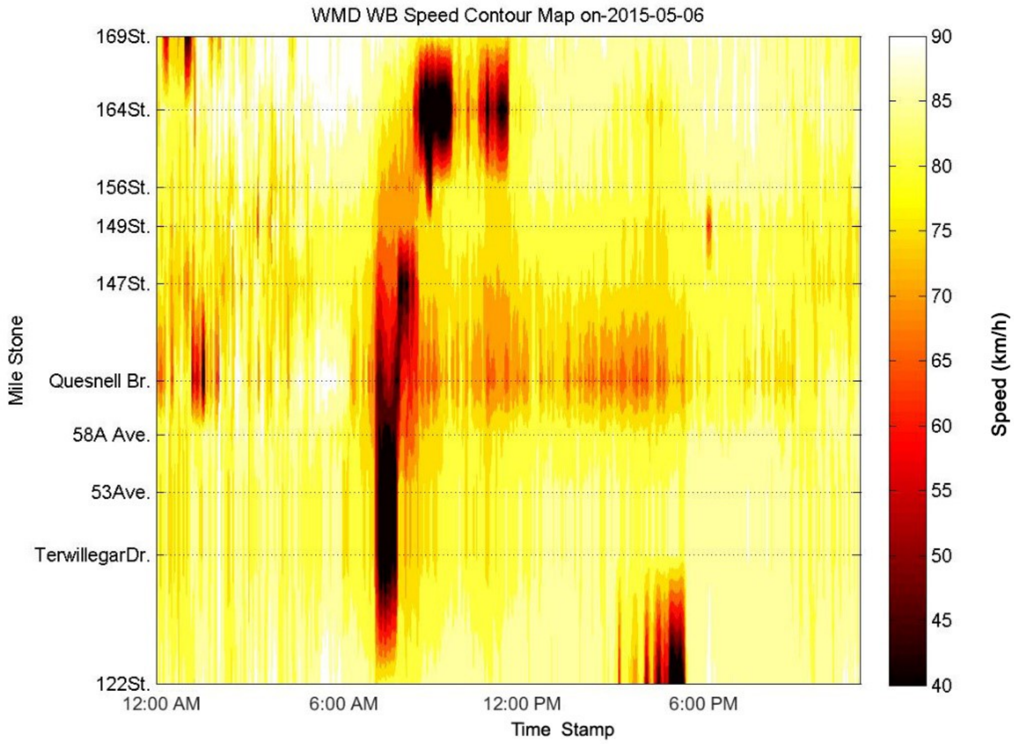
To better illustrate estimations with no VSL control, results from five days in May when apparently congestion happened are chosen and shown in the following part. They are May 4^{th}, 5^{th}, 6^{th}, 14^{th} and 27^{th}.


WMD WB Speed Contour Map on-2015-05-04
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
Mile Stone
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

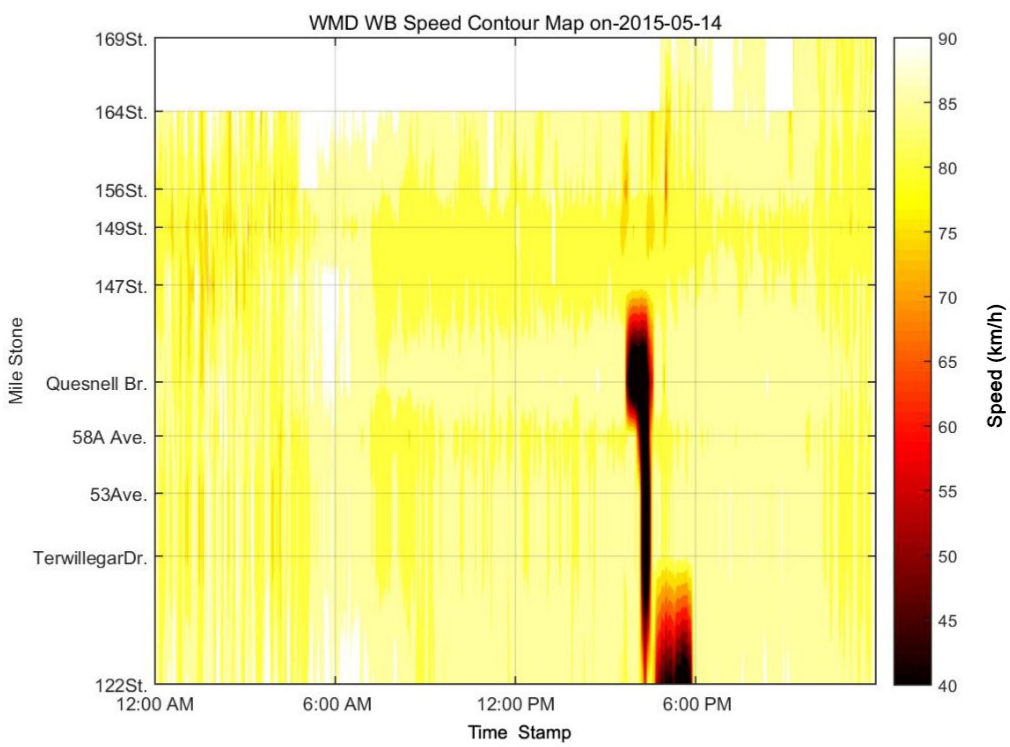
(a)


WMD WB Speed Contour Map on-2015-05-05
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
Mile Stone
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

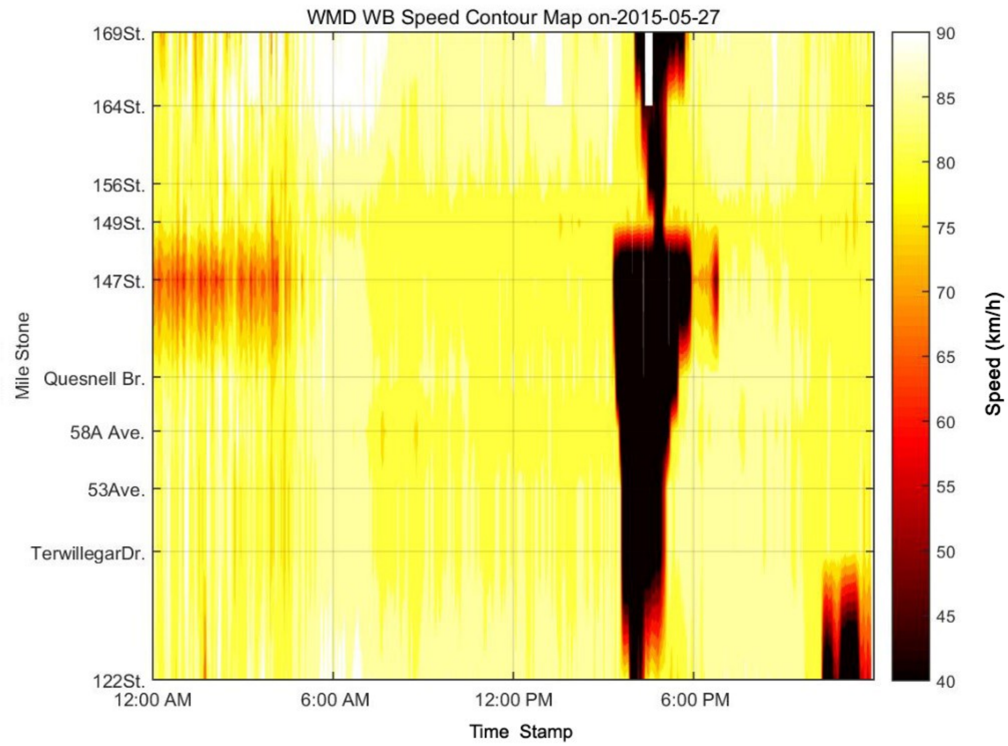
(b)


WMD WB Speed Contour Map on-2015-05-06
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
Mile Stone
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

(c)


WMD WB Speed Contour Map on-2015-05-14
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
Mile Stone
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

(d)



(e)

Figure 9. White Mud Drive (WMD) West Bound (WB) contour map without VSL control (a) May 4th; (b) May 5th; (c) May 6th; (d) May 14th; (e) May 27th;

Figure 9 shows that the most serious congestion appeared on May 27th. It is obvious since speeds of the whole route were decreased to 45 km/h in PM peak hour.

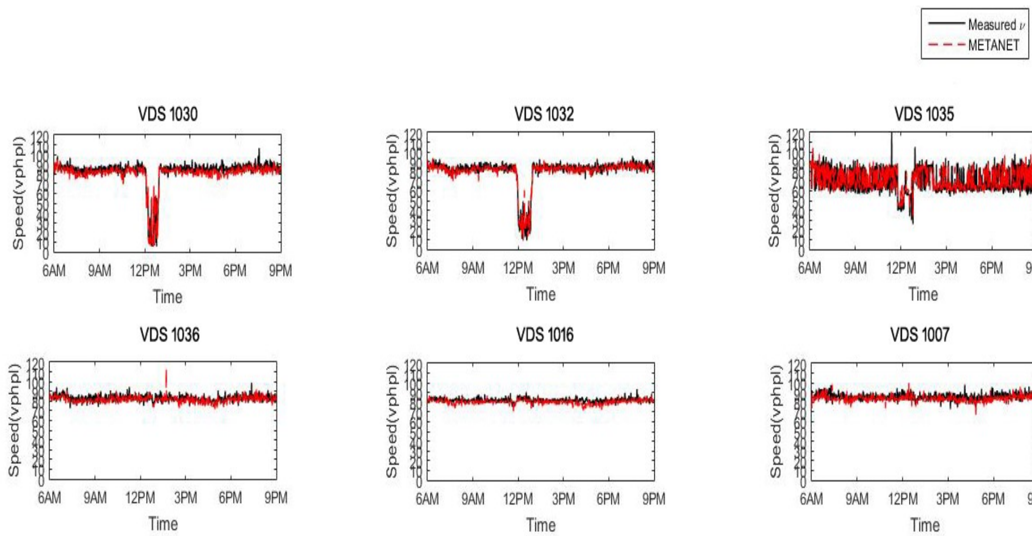
On May 14th, vehicles' speeds travelling from 122 St to the 147 St are lower than 60 km/h. After passing this corridor, there was no congestion, and average speeds are increased to 80km/h.

On remaining days, speeds from the 122 Street to the Terwillegar Dr. are near 60 km/h, usually slower than other sections, where speeds are about 80 km/h.

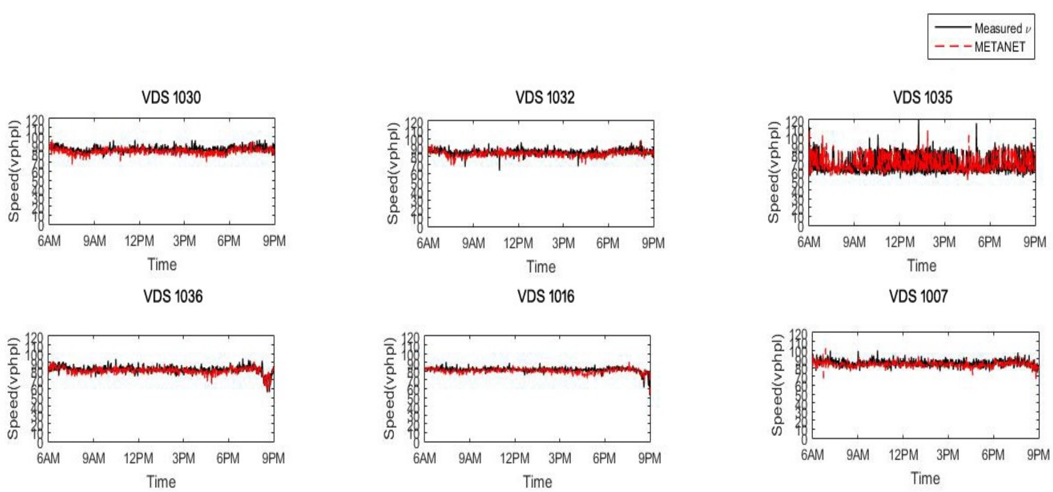
1) Speed prediction analysis

Figure 10 depicts speed validation of sample days. Red lines describe predicted speeds, and black lines represent measured speeds.

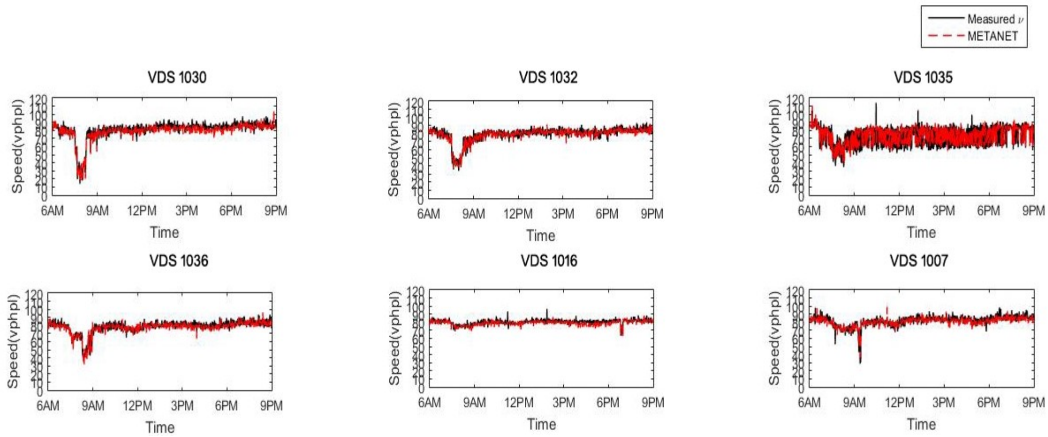
In May, machine's breakdown led to data missing on VDS 1026, so speed prediction of this link cannot be completed. Thus, speed validation is only finished for 6 links.



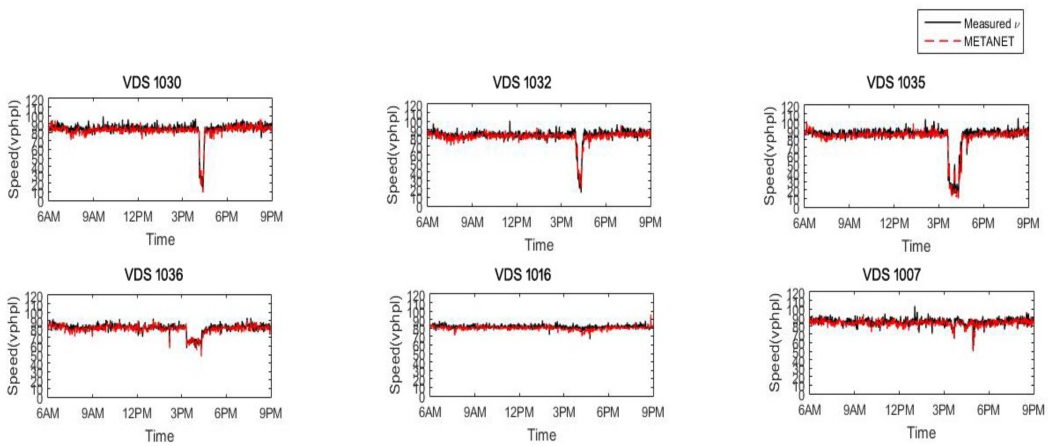
(a)



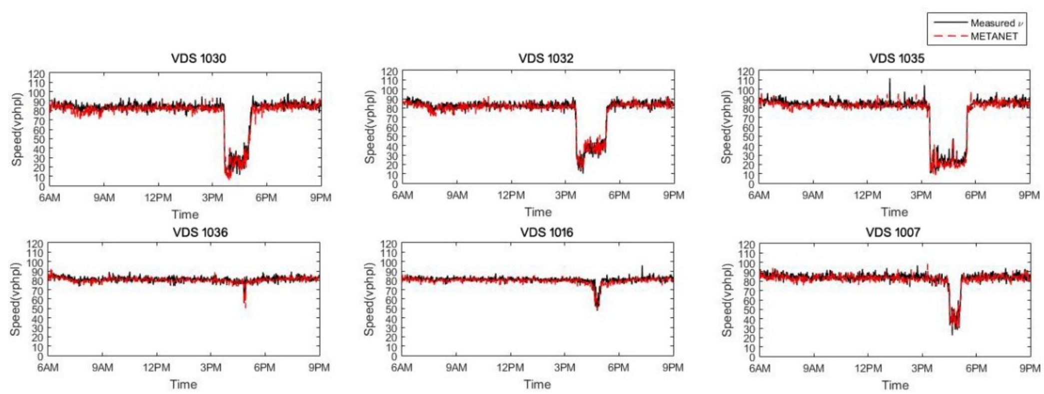
(b)



(c)



(d)



(e)

Figure 10. Speed prediction validation without VSL control (a) May 4th; (b) May 5th; (c) May 6th; (d) May 14th; (e) May 27th;

Overall, the METANET model presents satisfactory performance in May. Even on May 27th, the whole route was congested in Peak hour, its RMSE values are still under 5.

On May 4th, 5th and 6th, speeds faced continuous variation, which indeed influenced model performance to some extent. Thus, RMSE values of these three days are 6.63, 6.52, and 6.31 individually. But, compared with measured speeds, validation errors near 6 are still considered to be acceptable. So, the METANET model can be applied in the scenario without VSL control.

Table 4. Index of travel speed validation without VSL control

Data (M/D)	RMSE Value
05/04	6.63
05/05	6.52
05/06	6.31
05/14	4.06
05/27	3.85

When the accuracy of the METANET model is demonstrated, its predicted speeds can be used as input data of travel time estimation. Travel time calculated from STTE method and DTTE method are compared with reference times. To analyse methods' performances, several indexes are introduced, i.e. the Mean Absolute Relative Time Error (MARE) (%) value [40], the Root Mean Squared Error (RMSE).

$$\mathrm{MARE} = \sum_{\mathrm{P}} \left| \frac{\hat{t}(\mathrm{P}) - \bar{t}(P)}{\hat{t}(\mathrm{P})} \right| \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{P}} \sum_{\mathrm{P}=1}^{\mathrm{P}} (\hat{t}(\mathrm{p}) - \bar{t}(\mathrm{P}))^2} \tag{11}$$

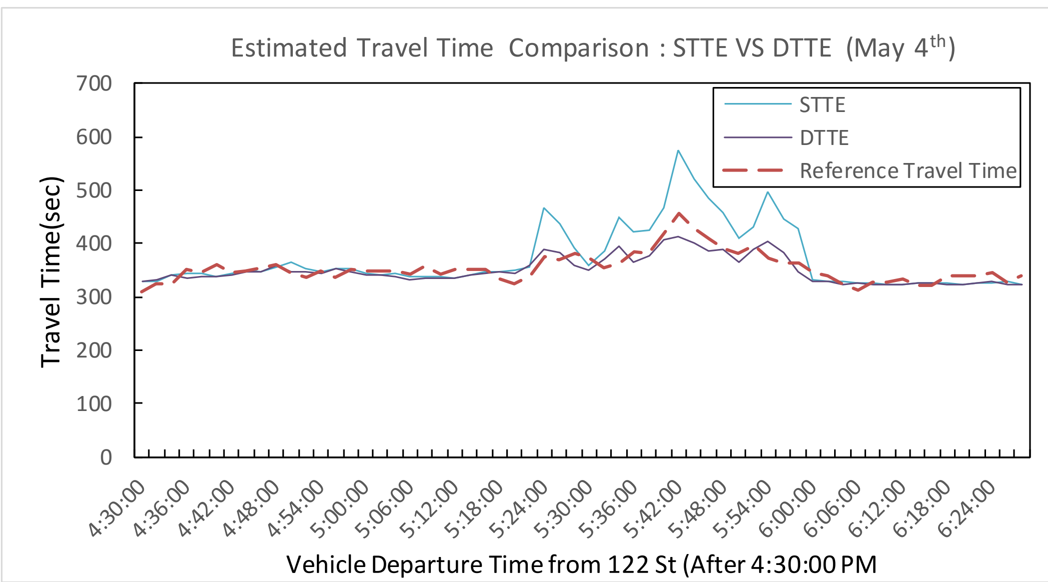
Where:

P: The number of time periods with travel time estimated.

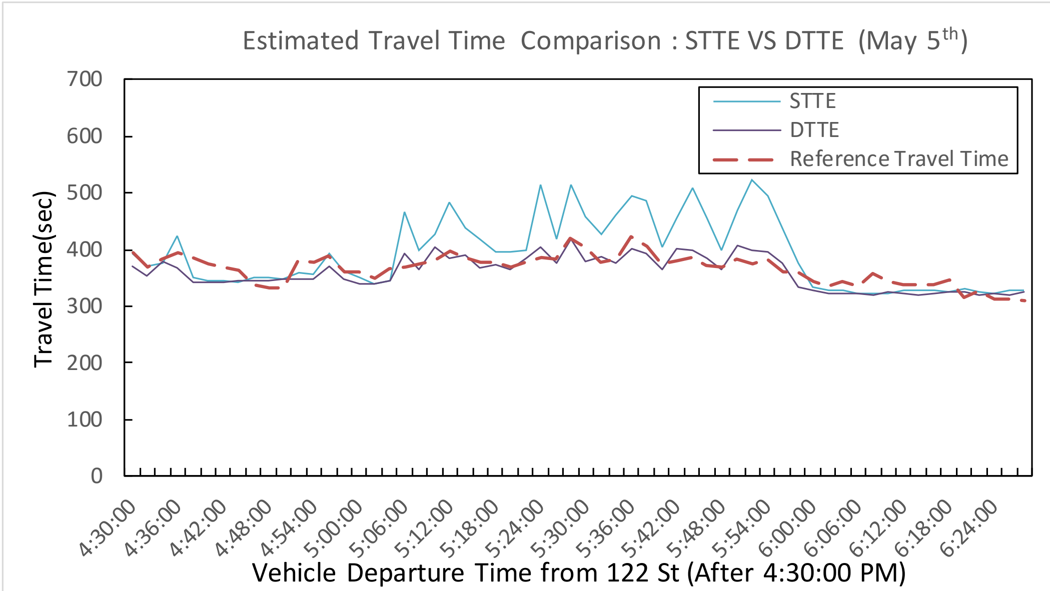
$\hat{t}(\mathrm{P})$: Estimated travel time in the time period p.

$\bar{t}(\mathrm{P})$: The average reference travel time in the time period p.

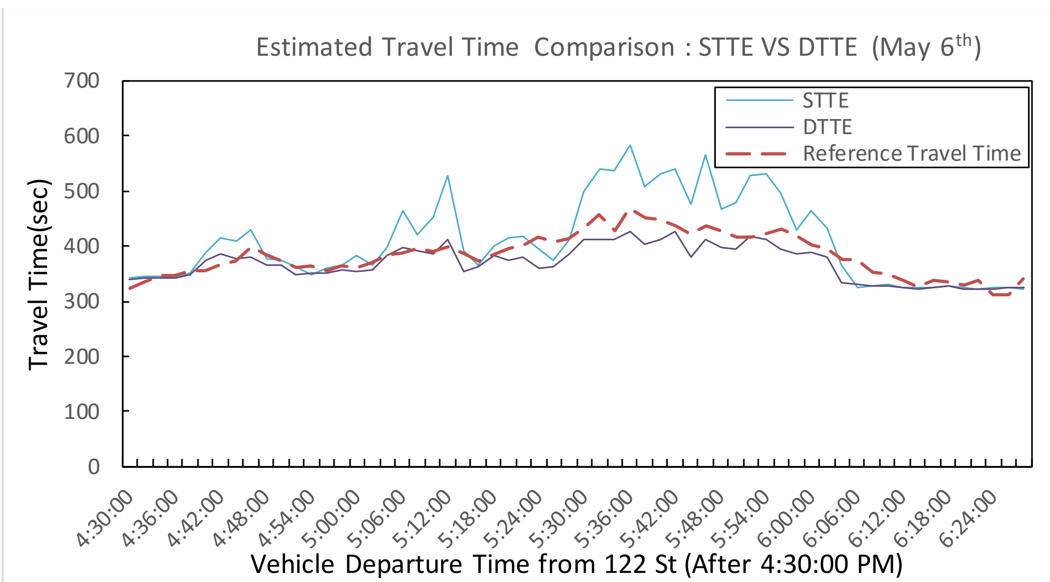
For each day, estimated travel times from the STTE method and the DTTE method are compared. Following graphs present results.



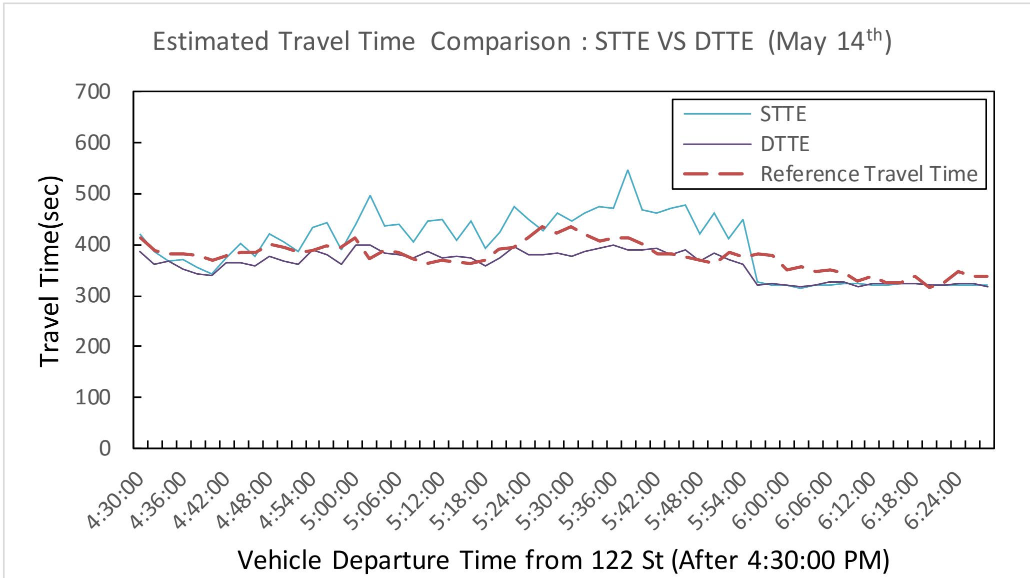
(a)


Estimated Travel Time Comparison : STTE VS DTTE (May 5th)
STTE
DTTE
Reference Travel Time
Travel Time(sec)
0
100
200
300
400
500
600
700
4:30:00
4:36:00
4:42:00
4:48:00
4:54:00
5:00:00
5:06:00
5:12:00
5:18:00
5:24:00
5:30:00
5:36:00
5:42:00
5:48:00
5:54:00
6:00:00
6:06:00
6:12:00
6:18:00
6:24:00
Vehicle Departure Time from 122 St (After 4:30:00 PM)

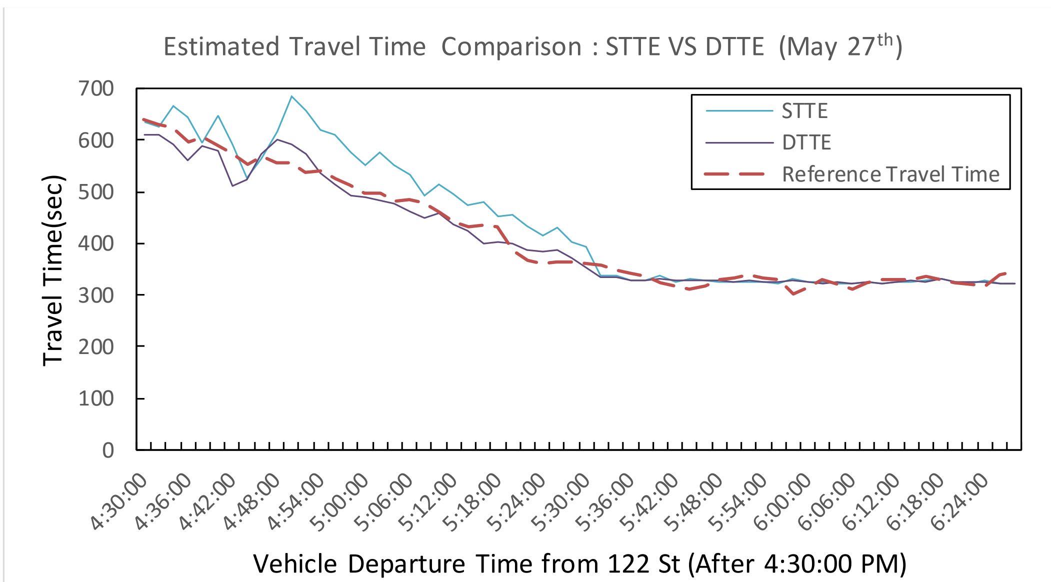
(b)


Estimated Travel Time Comparison : STTE VS DTTE (May 6th)
STTE
DTTE
Reference Travel Time
Travel Time(sec)
0
100
200
300
400
500
600
700
4:30:00
4:36:00
4:42:00
4:48:00
4:54:00
5:00:00
5:06:00
5:12:00
5:18:00
5:24:00
5:30:00
5:36:00
5:42:00
5:48:00
5:54:00
6:00:00
6:06:00
6:12:00
6:18:00
6:24:00
Vehicle Departure Time from 122 St (After 4:30:00 PM)

(c)



(d)



(e)

Figure 11. Comparison of the STTE and DTTE estimation results (a) May 4th; (b) May 5th; (c) May 6th; (d) May 14th; (e) May 27th;

On May 4th, estimated travel time is 371 seconds for the STTE method, and 350 seconds for the DTTE method. Compared with the reference travel time 359 seconds, the DTTE's performance is better than the STTE method's. During the two hours period, the DTTE's MARE value is 2.70% and RMSE is 9.71. They are both lower than results outputted from the STTE method (3.18% for MARE and 35.06 for RMSE).

The reference time on May 5th is 377 seconds, estimated travel time for the STTE method is 392 seconds and that for the DTTE method is 359 seconds. Even though the two methods' MAREs are nearly the same, but when considering RMSE value, for the DTTE is 17.56, apparently better-behaved than the STTE method's 40.37.

Sudden outpouring of snow increased travel time on May 6th. So the reference travel time is 383 seconds, when estimated travel time based on STTE method is 410 seconds, and 369 seconds for the DTTE method. The two methods' MARE values are all less than 10%. But DTTE's MARE value is 3.90% and RMSE is 14.94, while STTE's MARE value is 7.01% and its RMSE is 51.08. So the DTTE's performance is better-behaved than the STTE method for this day.

On May 14th, the reference travel time is 377 seconds, estimated travel time based on the STTE method is 399 seconds and 361 seconds for the DTTE method. The MARE value for STTE is 6.03%, when the DTTE's MARE value is only 4.26%. And the STTE's RMSE bias is 50.20, almost triple the DTTE's 16.05.

Most severe congestion happened on May 27th, which made speeds along the whole route to be under 45 km/h in the peak hour. The average reference travel time is 426 seconds. The STTE method's time is 440 seconds, and for the DTTE method is 412 seconds. Their MAREs are all near 3.5%. The STTE's RMSE is

34.46, and DTTE's is 14.67. The DTTE method can be more reliable to do accurate estimation.

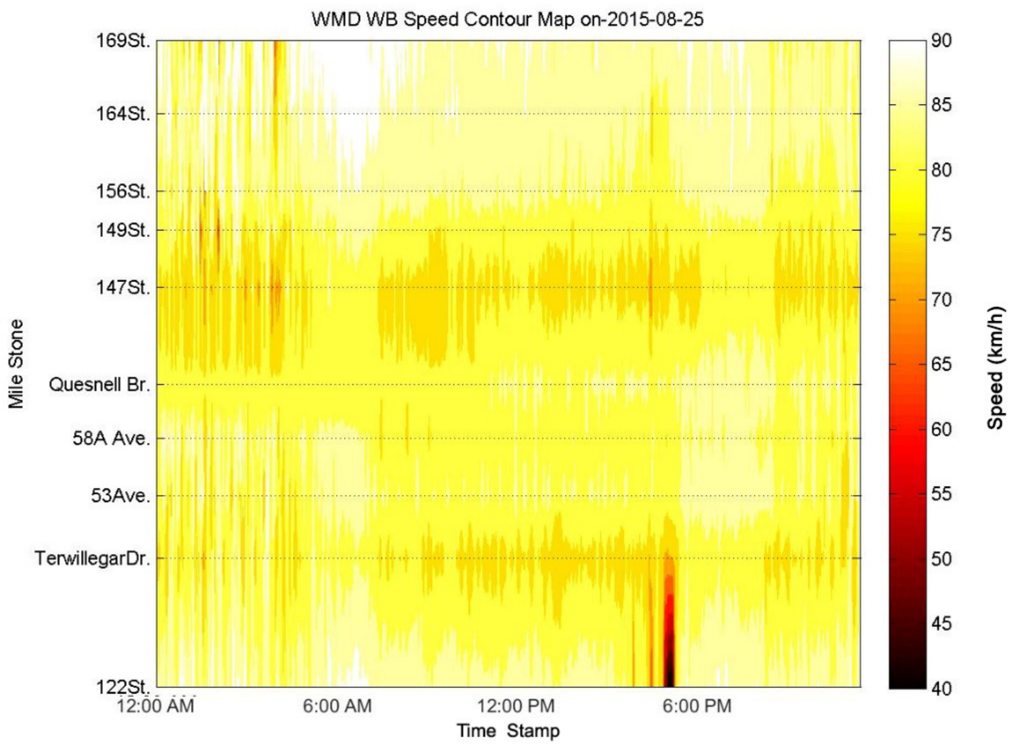
Table 5. Evaluation of the DTTE and STTE method's performance without VSL control

Date	Method Type	Index		
		Travel Time	MARE	RMSE
05/04	STTE	371	3.18%	35.06
	DTTE	350	-2.70%	9.71
	Reference travel time	359		
05/05	STTE	392	4.14%	40.38
	DTTE	359	-4.58%	17.22
	Reference travel time	376		
05/06	STTE	410	7.01%	51.08
	DTTE	369	-3.90%	14.94
	Reference travel time	383		
05/14	STTE	399	6.03%	50.20
	DTTE	361	-4.26%	16.05
	Reference travel time	377		
05/27	STTE	440	3.23%	34.46
	DTTE	412	-3.44%	14.67
	Reference travel time	427		

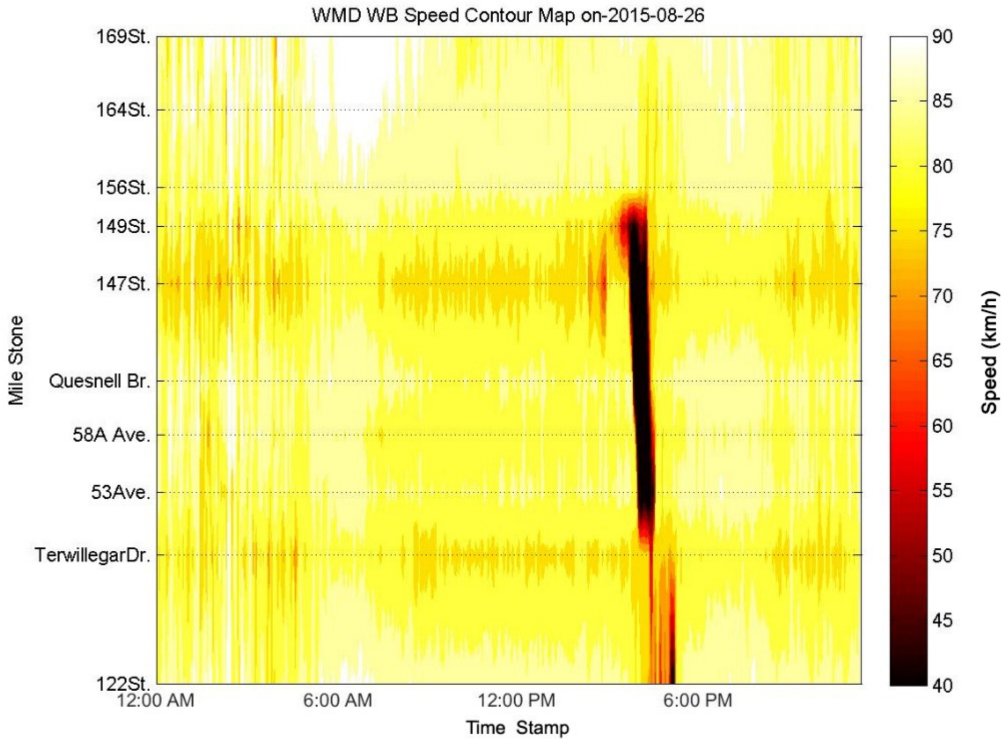
In PM peak hours, when speeds vary a lot, estimation accuracy decreased. Meanwhile, their MARE and RMSE values are increased. Then, on May 6th, MARE values of both the DTTE and STTE are almost higher compared to other days.

Over all, in sample days, MARE and RMSE values of the DTTE method are less than the STTE method's. Thus it achieves better travel time estimations than the STTE method when there was no VSL control applied. During the whole peak hour, the DTTE method's results are more reliable to produce similar results with reference times.

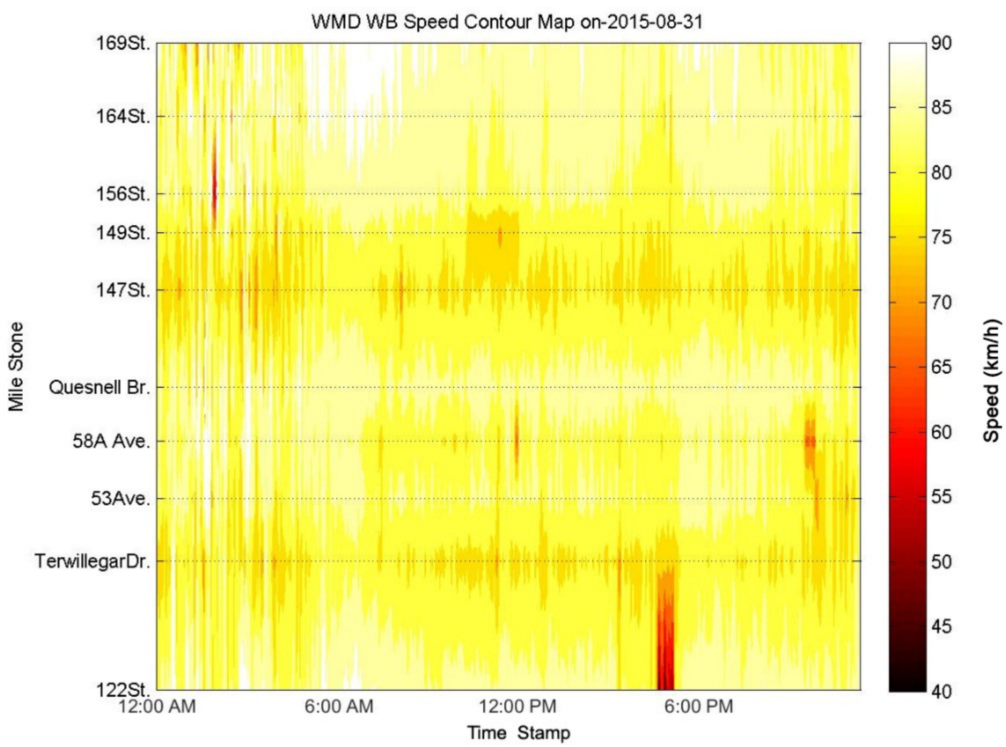
4.2.2 Travel time estimation evaluation (with VSL control)



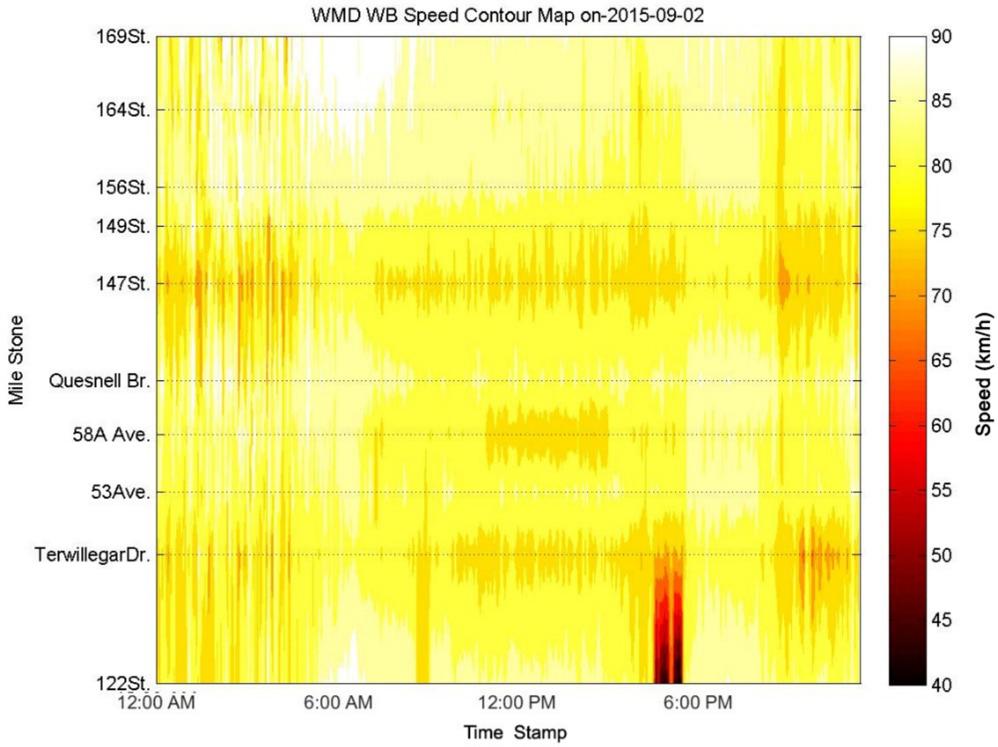
(a)


WMD WB Speed Contour Map on-2015-08-26
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
Mile Stone
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

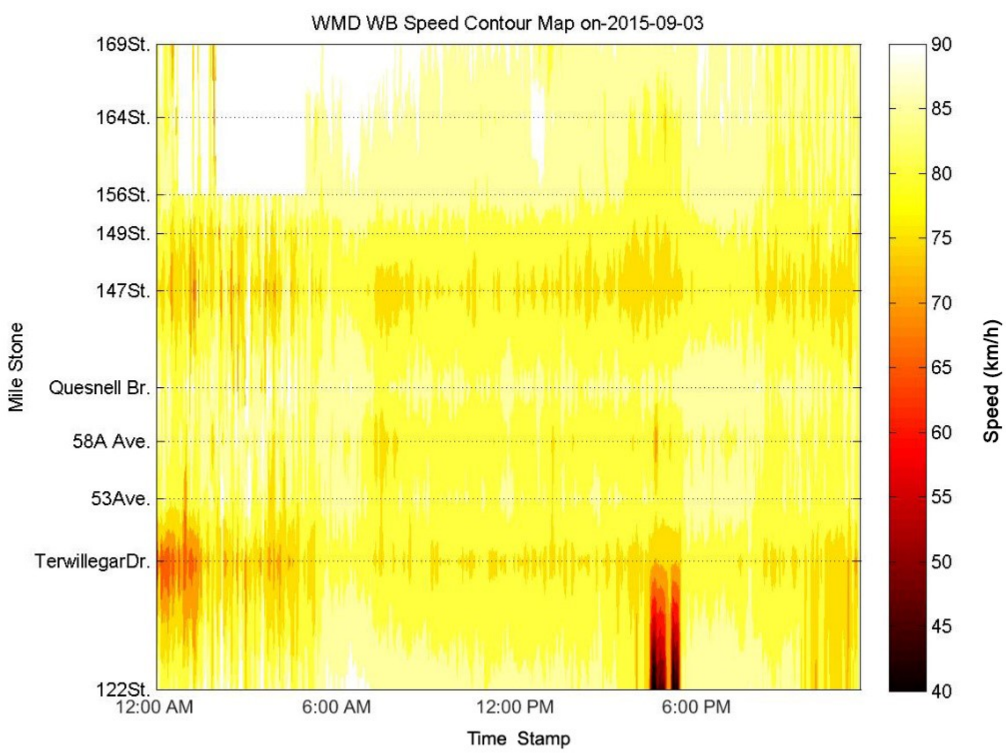
(b)


WMD WB Speed Contour Map on-2015-08-31
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
Mile Stone
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

（c）


WMD WB Speed Contour Map on-2015-09-02
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
Mile Stone
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

(d)


WMD WB Speed Contour Map on-2015-09-03
169St.
164St.
156St.
149St.
147St.
Quesnell Br.
58A Ave.
53Ave.
TerwillegarDr.
122St.
Mile Stone
12:00 AM
6:00 AM
12:00 PM
6:00 PM
Time Stamp
90
85
80
75
70
65
60
55
50
45
40
Speed (km/h)

(e)

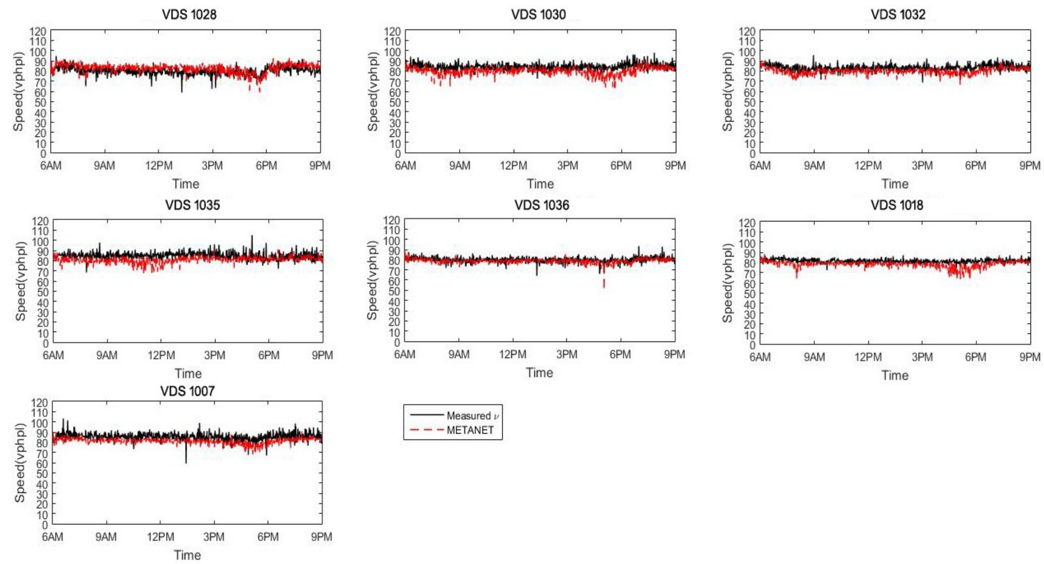
Figure 12. White Mud Drive (WMD) West Bound (WB) contour map with VSL control (a) Aug. 25^{th}; (b) Aug. 26^{th}; (c) Aug. 31^{st}; (d) Sept. 2^{nd}; (e) Sept.3^{rd};

After the VSL control strategy was applied, speeds were increased, and congestion was efficiently relieved during peak hour compared with situations in May. But traffic jam still occurred from 122 St to Terwillegar Drive during some times. To explain estimation models' function under VSL control environment, five days are also selected. They are Aug.25^{th}, Aug. 26^{th}, Aug. 31^{st}, Sept. 2^{nd} and Sept. 3^{rd}.

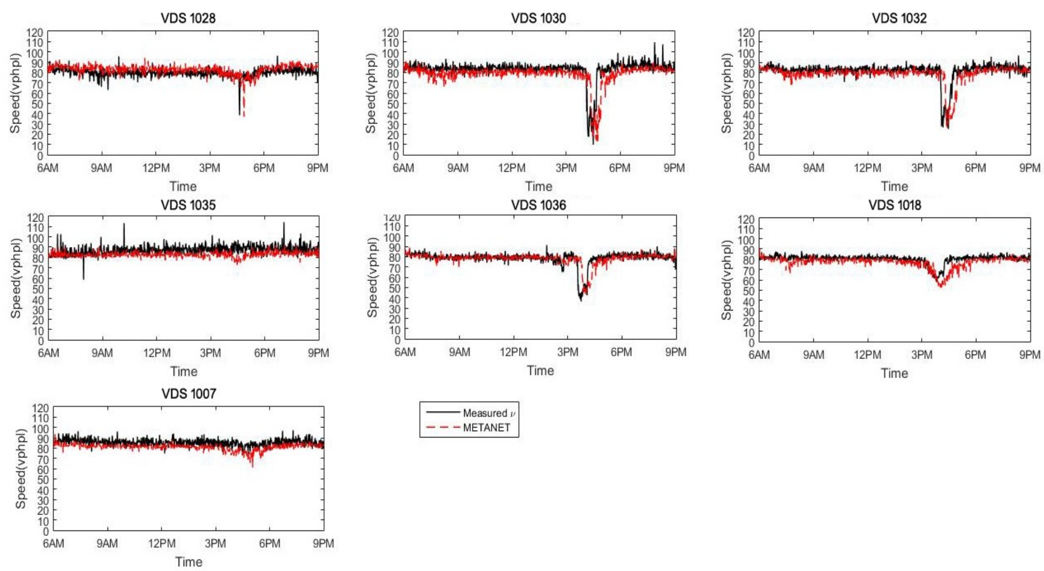
On the whole, in these five days, speeds were around 75 km/h, this is a speed near limit speed (80km/h) for the Whitemud Drive. But, slow speeds around 60km/h still appeared from 122 St to Terwillegar Dr in several days. And on Aug.26^{th}, low speeds even happened along the whole testing segment, this though was caused by special traffic accidents.

2) Speed prediction analysis

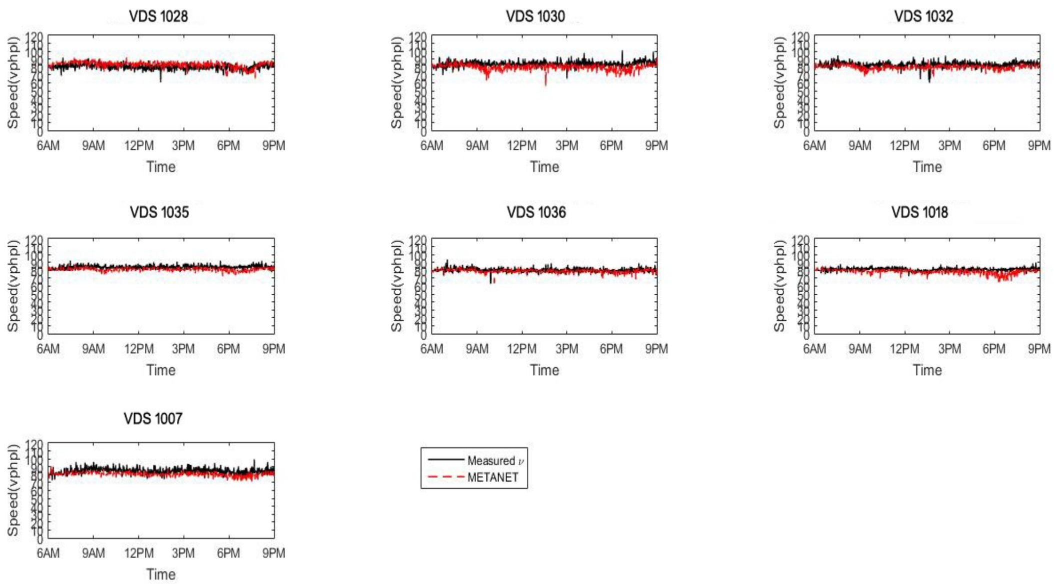
After Aug. 11^{st}, VDS 1026 was repaired, and it could work normally. The number of loop detector stations in main lanes whose measured data can be predicted is 7. They are VDS 1028, VDS 1030, VDS 1032, VDS 1035, VDS 1036, VDS 1016 and VDS 1007.


VDS 1028
VDS 1030
VDS 1032
VDS 1035
VDS 1036
VDS 1018
VDS 1007
Speed(vphpl)
Time
6AM 9AM 12PM 3PM 6PM 9PM
Measured ν
METANET

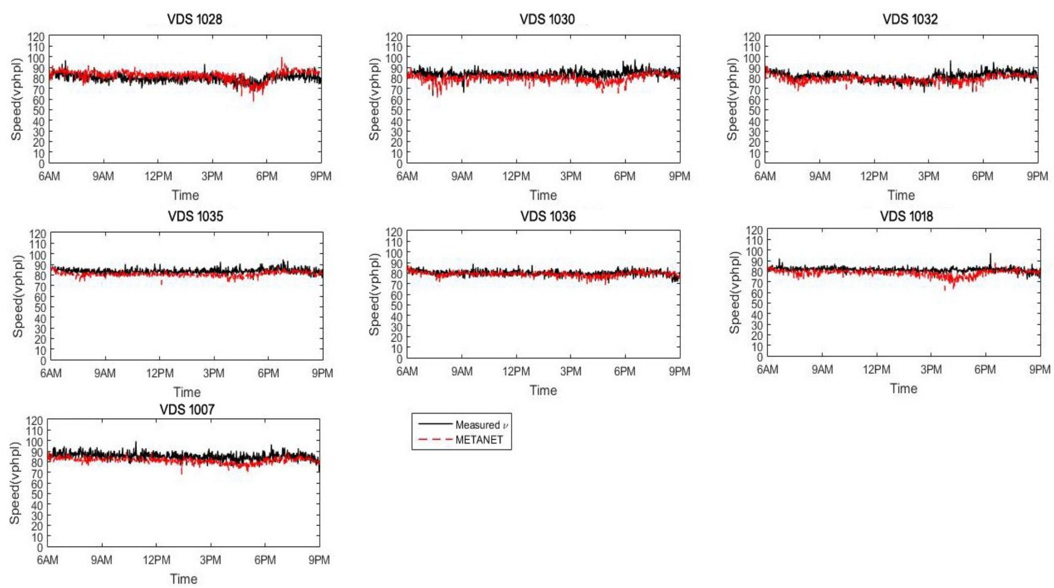
(a)


VDS 1028
VDS 1030
VDS 1032
VDS 1035
VDS 1036
VDS 1018
VDS 1007
Speed(vphpl)
Time
6AM 9AM 12PM 3PM 6PM 9PM
Measured ν
METANET

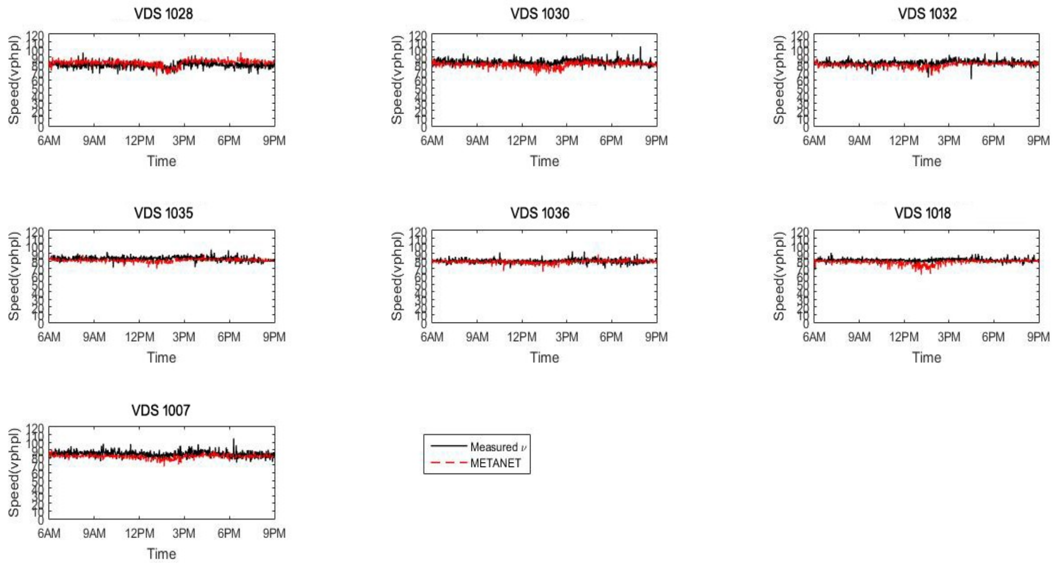
(b)


VDS 1028
VDS 1030
VDS 1032
VDS 1035
VDS 1036
VDS 1018
VDS 1007
Speed(vphpl)
Time
6AM
9AM
12PM
3PM
6PM
9PM
Measured v
METANET

(c)


VDS 1028
VDS 1030
VDS 1032
VDS 1035
VDS 1036
VDS 1018
VDS 1007
Speed(vphpl)
Time
6AM
9AM
12PM
3PM
6PM
9PM
Measured v
METANET

(d)



(e)

Figure 13. Speed prediction validation with VSL control (a) Aug. 25th; (b) Aug.26th; （c）Aug.31st; (d) Sept 2nd; (e) Sept. 3rd;

Compared with predictions in May, even links are added, RMSE values are still small. Thus, the METANET model under VSL control condition can perform well.

And in several days, RMSE values are even less than days in May. This is caused due to the reason that after control strategy is applied, traffic condition improved, and this is beneficial to speed validation.

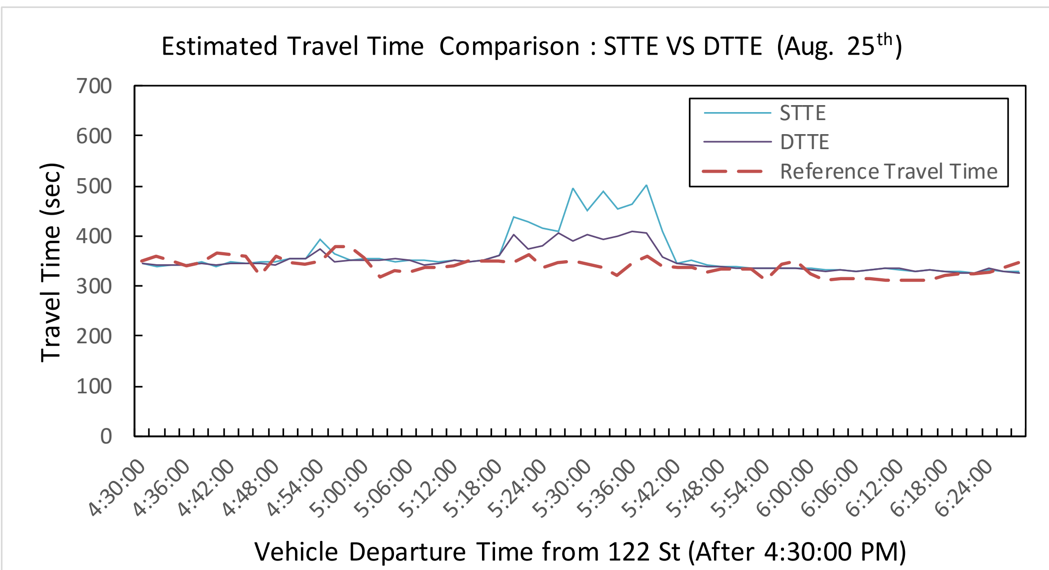
Peak hour speeds in August did not sharply change for most days. Obvious variation only happened on Aug. 26th. And its RMSE value is the highest one with 7.02. For other days, their RMSE are all around 5.

Table 6. Index (RMSE value) of travel speed validation with VSL control

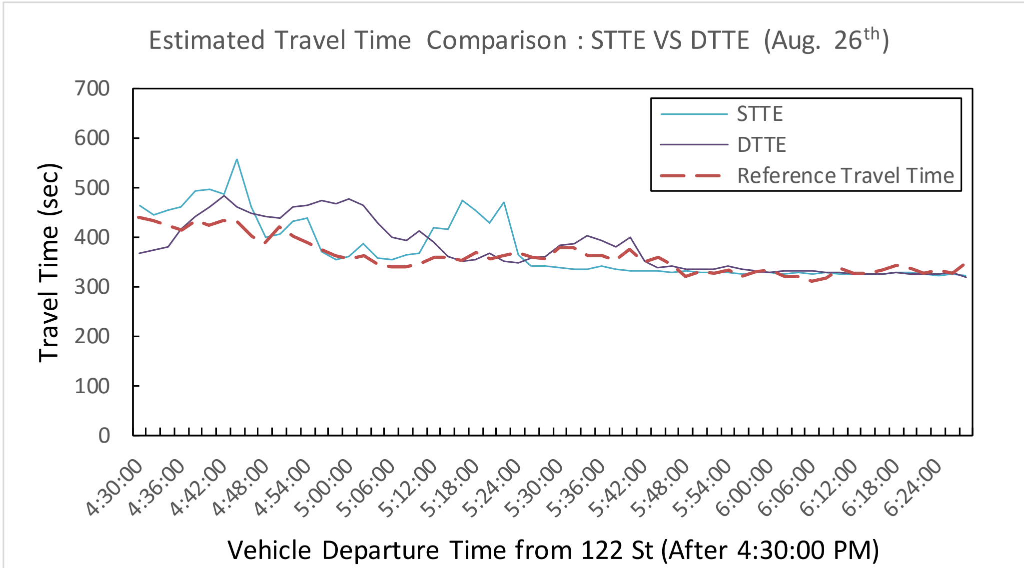
Data (M/D)	RMSE

08/25	5.27
08/26	7.02
08/31	4.93
09/02	4.91
09/03	4.68

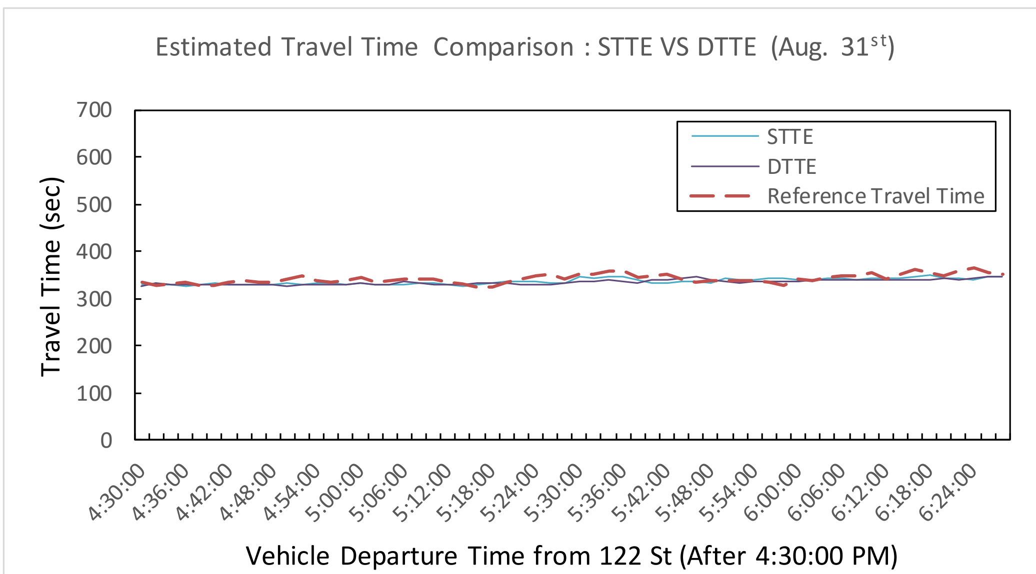
VSL control's implementation influences density, speed and travel time in this segment. To verify whether the model is still under the VSL control, five representative days would also be analysed in Fig.14.



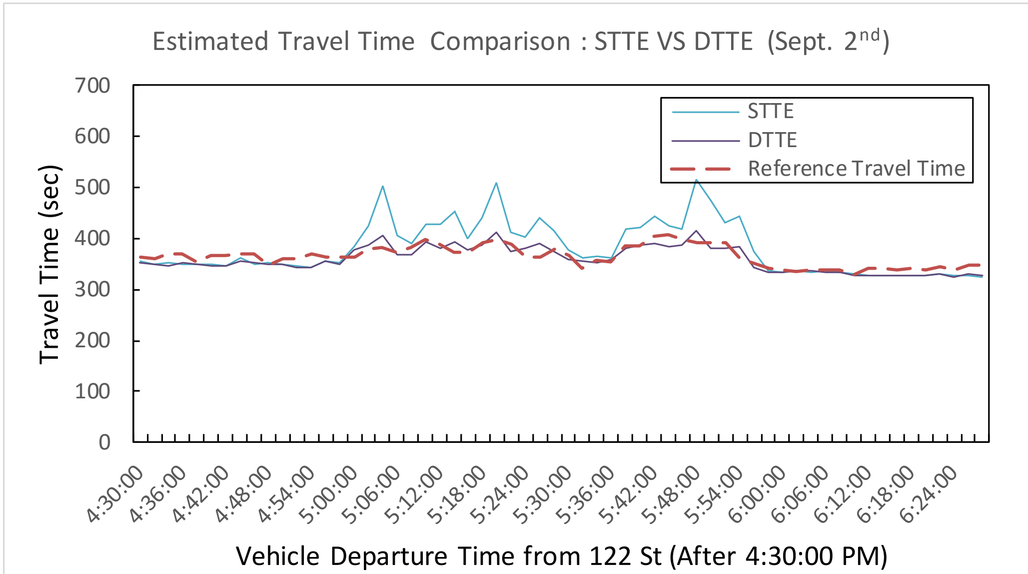
(a)


Estimated Travel Time Comparison : STTE VS DTTE (Aug. 26th)
STTE
DTTE
Reference Travel Time
Travel Time (sec)
700
600
500
400
300
200
100
0
4:30:00
4:36:00
4:42:00
4:48:00
4:54:00
5:00:00
5:06:00
5:12:00
5:18:00
5:24:00
5:30:00
5:36:00
5:42:00
5:48:00
5:54:00
6:00:00
6:06:00
6:12:00
6:18:00
6:24:00
Vehicle Departure Time from 122 St (After 4:30:00 PM)

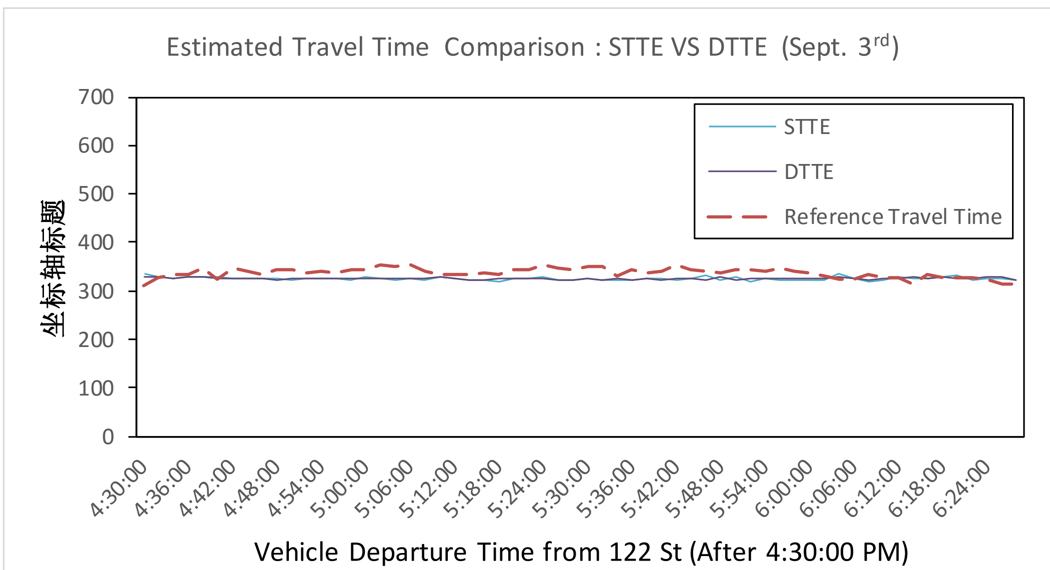
（b）


Estimated Travel Time Comparison : STTE VS DTTE (Aug. 31st)
STTE
DTTE
Reference Travel Time
Travel Time (sec)
700
600
500
400
300
200
100
0
4:30:00
4:36:00
4:42:00
4:48:00
4:54:00
5:00:00
5:06:00
5:12:00
5:18:00
5:24:00
5:30:00
5:36:00
5:42:00
5:48:00
5:54:00
6:00:00
6:06:00
6:12:00
6:18:00
6:24:00
Vehicle Departure Time from 122 St (After 4:30:00 PM)

(c)



(d)



(e)

Figure 14. Comparison of the STTE and DTTE estimation result (a) Aug. 25th; (b) Aug 26th; (c) Aug. 31st; (d) Sept. 2nd; (e) Sept.3rd;

On Aug.25th, the reference travel time is 338 seconds. Estimated travel time is 362 seconds for the STTE method and 351 seconds for the DTTE method. The MARE of DTTE is 2.53%, higher than the STTE's 0.77%. But the DTTE's RMSE is 16.84, lower than the STTE's 24.96. So, both the methods can achieve favorable results.

The day with the lowest average speed in peak hour is Aug.26th. It's estimated time based on the STTE method is 376 seconds and 379 seconds for the DTTE method. Their MARE values are similar and under 5%. But the STTE's RMSE is 40.30, much higher than the DTTE's 16.85.

On Aug. 31st, improved traffic condition decreased the average reference time to 342 seconds. The DTTE estimated travel time is 335 seconds. It's MARE and RMSE values are 2.08% and 7.14. The STTE method's estimation is 326 seconds, MARE is 1.71%, and RMSE is 8.99. On this day, results from the two methods are similar. Therefore, as can be seen, if speeds do not have a drastic variation, the two methods can gain satisfactory and similar estimation.

Reference travel time is 365 seconds on Sept. 2nd. The STTE method's estimated time is 381 seconds, and the MARE is 4.29%. Corresponding, the DTTE's estimation s 359 seconds, its MARE is 1.52%, better than the STTE's.

On Sept. 3rd, the STTE's estimated travel time is 326 seconds, the DTTE's is 326 seconds, and the reference travel time is 338 seconds. On this day, both methods MARE and RMSE values have little difference.

Table 7. Evaluation of the DTTE and STTE method's performance with VSL control

Date (M/D)	Method Type	Index		
		Travel Time	MARE	RMSE
08/25	STTE	363	0.77%	24.96
	DTTE	351	2.53%	16.74
	Reference travel time	338		
08/26	STTE	376	3.70%	40.30

	DTTE	379	4.65%	16.85
	Reference travel time	362		
	STTE	337	1.71%	8.99
08/31	DTTE	335	2.08%	7.14
	Reference travel time	343		
	STTE	381	4.29%	39.22
09/02	DTTE	359	1.52%	13.81
	Reference travel time	365		
	STTE	326	3.55%	16.23
09/03	DTTE	326	3.47%	15.67
	Reference travel time	338		

The results after VSL control was carried out show that, average vehicles speeds and estimation accuracy are increased. The DTTE method's estimation errors are under 5% for all sample days. RMSE value is less than 50. Results show models perform better when the VSL control strategy is applied. This means vehicles' speeds experienced less variation and travelling conditions are improved. Meanwhile, travel time estimation could be more preferable. Thus, models can be used in VSL control environment.

4.2.3 Comparison of two methods with and without VSL control

In the research, five days with and without VSL control are separately selected to be analysed in detail. Evaluation is focused on two aspects, speed validation and travel time estimation. And indexes as RMSE and MARE are proposed to help complete it.

With no VSL control, reference travel times in sample days are all longer than 350 seconds. On May 27th, it is even more than 400 seconds. Under this situation, MAREs of the DTTE method are all less than 5%. In contrast, the DTTE's

MAREs are all more than 5%, except it On May 4th (4.74%). Besides, considering the index of RMSE, the STTE method's RMSE values are all much higher than the DTTE's. Compared with the STTE method, the DTTE method's performance is considered to be more favorable.

When the VSL control was applied, it helped vehicles change speeds more smoothly by giving suggested speeds. Results show that reference travel times are near 350 seconds in sample days. Even the highest one on Sept. 2nd, is only 366 seconds, does not exceed 400 seconds. Improved traffic conditions decreased speeds variation. Thus, in days when congestion is not apparent as Sept. 3rd and Aug. 31st, MAREs and RMSEs of two methods are very similar. But, in other days, the DTTE method's performance is better the STTE's. In conclusion, with VSL control, the DTTE method is still more favorable.

4.3 Application example

Travel time is important in Transportation Management System (TMS). Thus, if estimation models here are confirmed to be accurate and practical, they can be widely used in transportation research.

Meanwhile, VSL control system is used for alleviating recurrent congestion on commuting routes. It is effective when the spatial distribution of the traffic speed on the highway segment exhibits a dramatic reduction from free-flow speed to a congested or stop-and-go level due to volume surge over a short distance. This control system can smooth the transition between free-flow speed and stop-and-go congested conditions, increases average speed, reduce route travel time under congested environment. And, to evaluate the VSL control system, travel time is a crucial criterion [41].

As mentioned, the city of Edmonton had carried out the VSL strategy on the research route. When the DTTE model's accuracy is affirmed, it can be used to analyse the VSL control system's influence, using travel time as a crucial index.

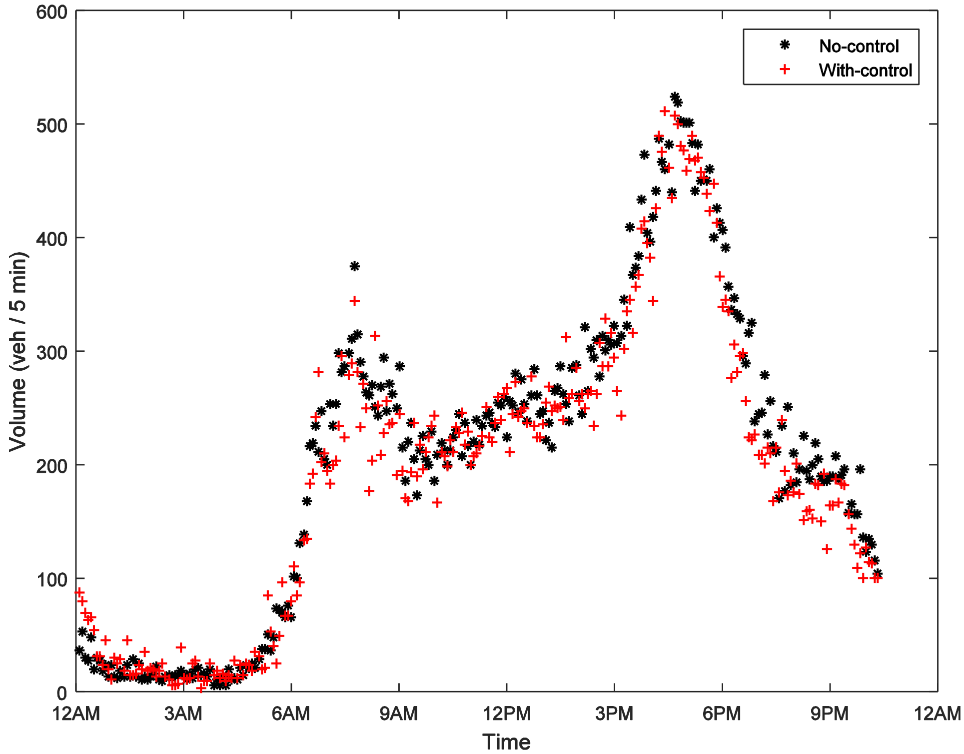
4.3.1 Comparison group

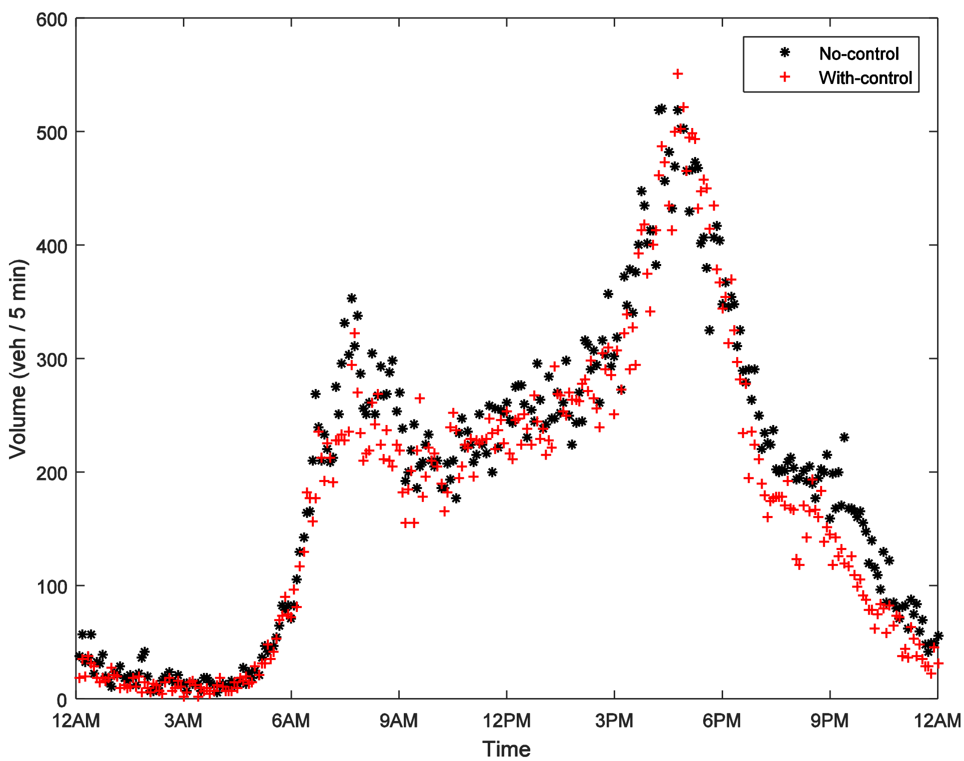
Days before and after the VSL control with similar traffic demand profile during peak hours are chosen to be comparison groups to analyse the VSL control's influence on travel time changing. 16 comparison groups are matched. Here, five of them are presented.

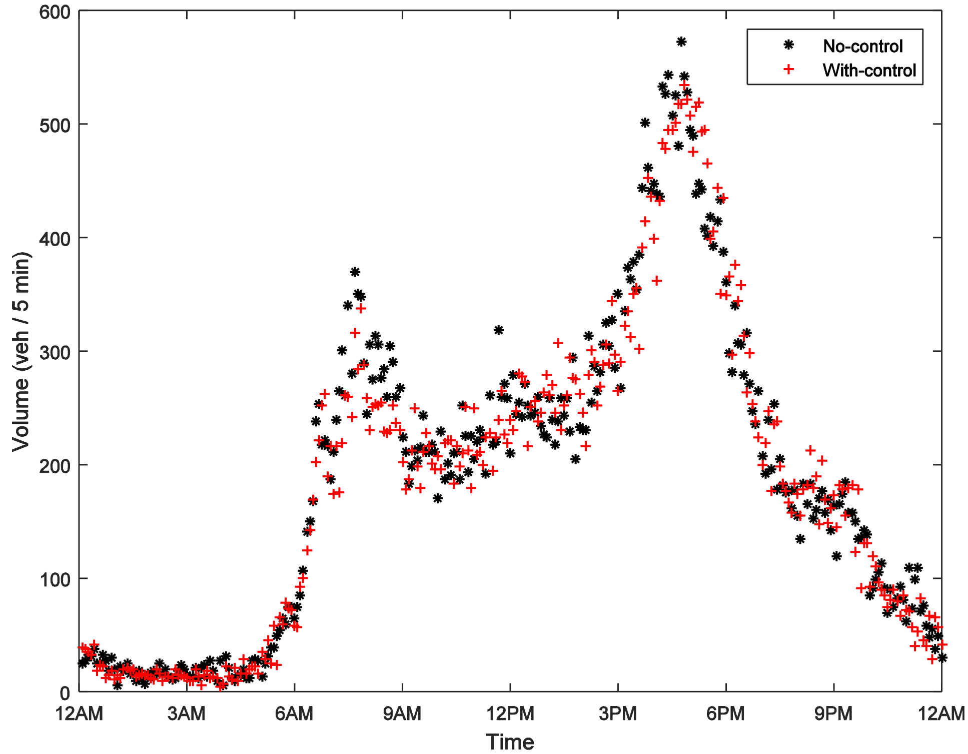
Table 8. Comparison groups of VSL control and Non-VSL control case

VSL control case	Non-VSL control case
Aug.13rd	May 21st
Aug.17th	May 5th
Aug.18th	May 5th
Aug.28th	May 14th
Sept.4th	May 28th

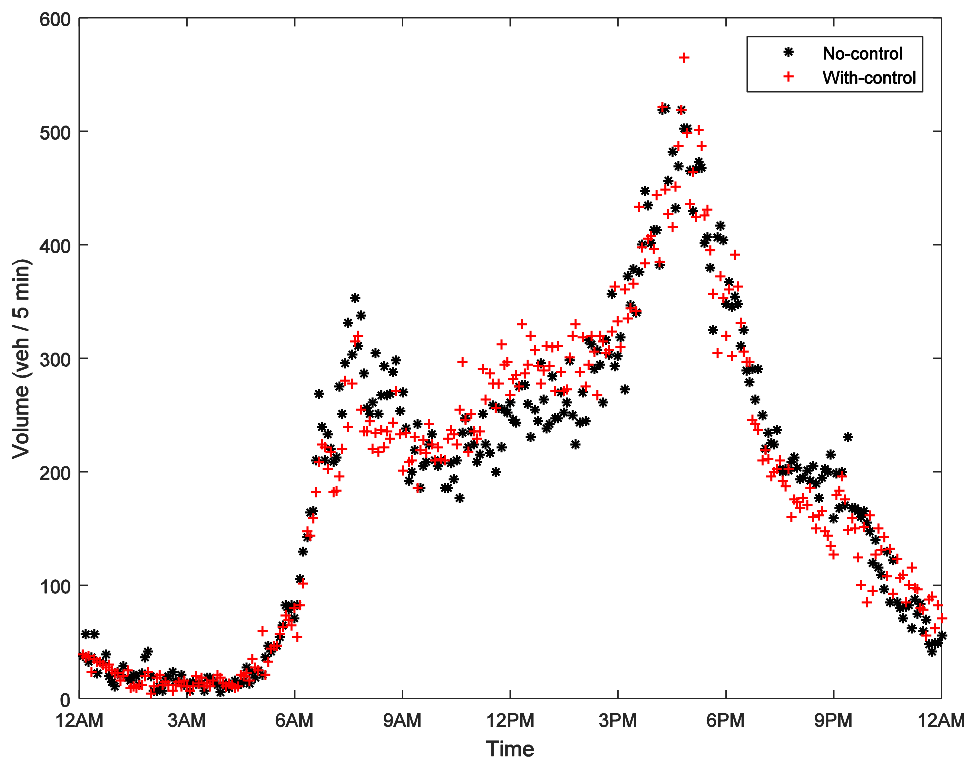
Matching comparison groups, traffic demand is a critical criterion. Traffic demand is mainly reflected by vehicle density. If days have similar density distribution, they can be matched.


600
500
400
300
200
100
0
Volume (veh / 5 min)
12AM
3AM
6AM
9AM
12PM
3PM
6PM
9PM
12AM
Time
No-control
With-control
(a)

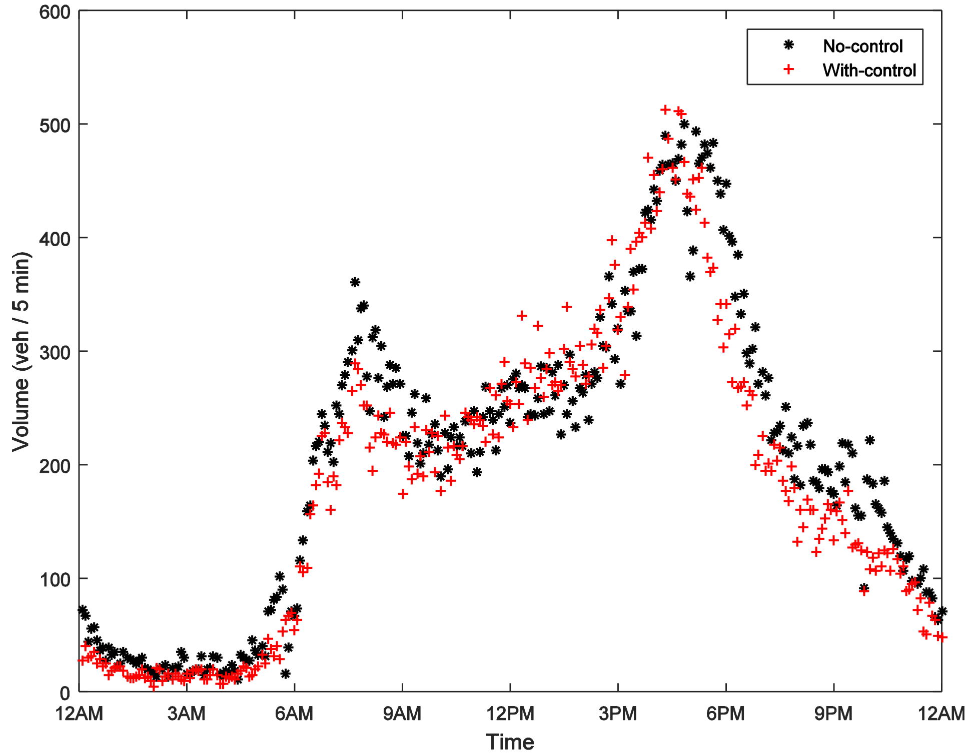

600
500
400
300
200
100
0
Volume (veh / 5 min)
12AM
3AM
6AM
9AM
12PM
3PM
6PM
9PM
12AM
Time
No-control
With-control
(b)


600
500
400
300
200
100
0
Volume (veh / 5 min)
12AM
3AM
6AM
9AM
12PM
3PM
6PM
9PM
12AM
Time
No-control
With-control

(c)


600
500
400
300
200
100
0
Volume (veh / 5 min)
12AM
3AM
6AM
9AM
12PM
3PM
6PM
9PM
12AM
Time
No-control
With-control

(d)



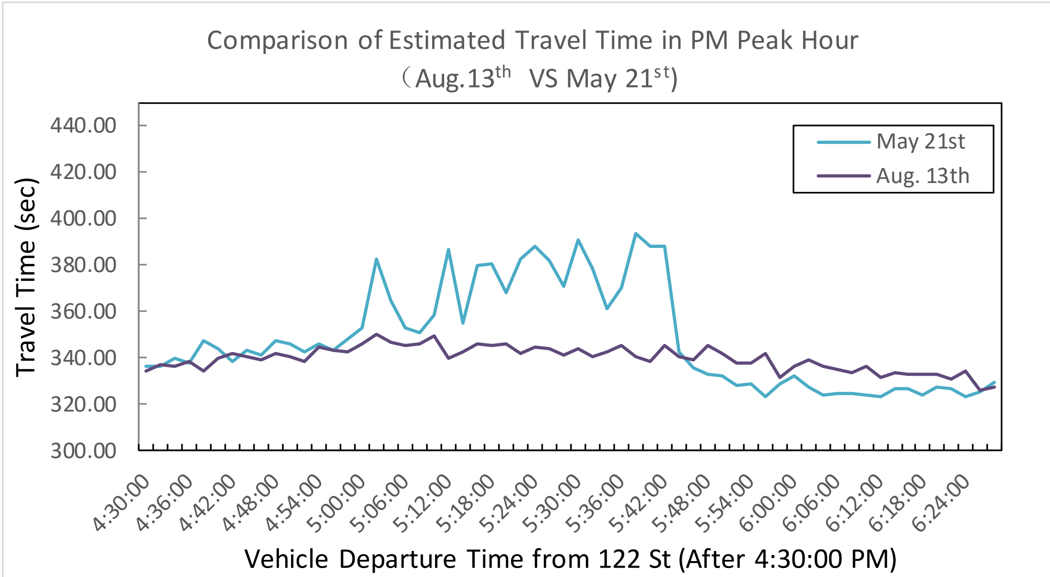
(e)

Figure 15. Comparison time groups with similar density. (a) Aug.13rd VS May 14th; (b) Aug.17th VS May 4th; (c) Aug.18th VS May 5th; (d) Aug.28th VS May 14th; (e) Sept. 4th VS May 28th;

Figure 15 depicts that these five groups have density distribution spots which are nearly the same. So, their travel demands are similar. Travel time estimated in these days can be used to judge the VSL control's influence.

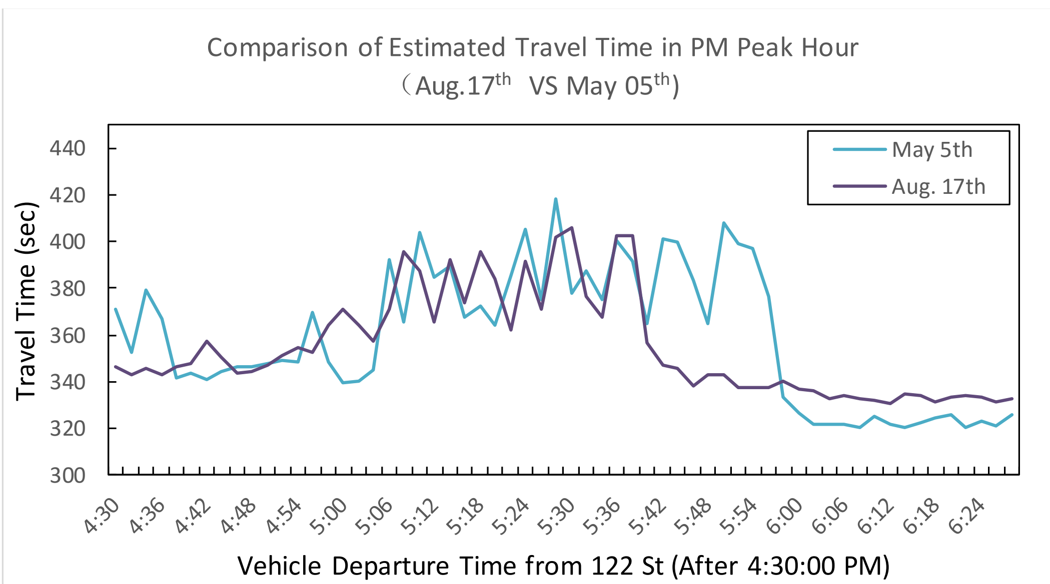
4.3.2 VSL control performance evaluation

Following figures and tables present travel time changing in peak hour before and after the VSL control applied in the research route.



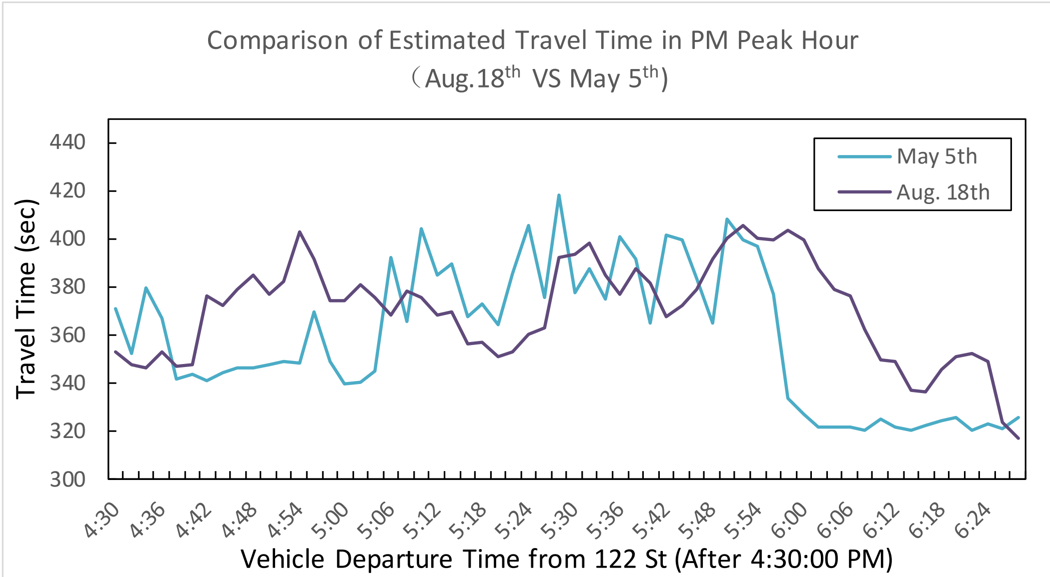
Index type	May 21st	Aug. 13th
Average travel time (sec)	349	340
Saved Travel Time (sec)	-	9
Saved Travel Time Rate (%)	-	2.51%

(a)



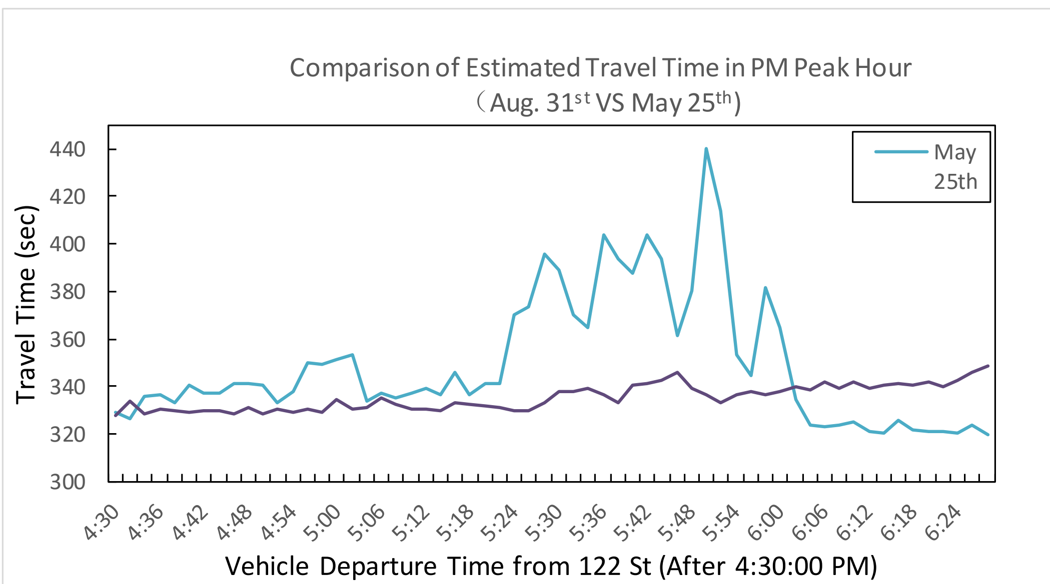
Index type	May 5th	Aug. 17th
Average travel time (sec)	360	355
Saved Travel Time (sec)	-	4
Saved Travel Time Rate (%)	-	1.14%

(b)



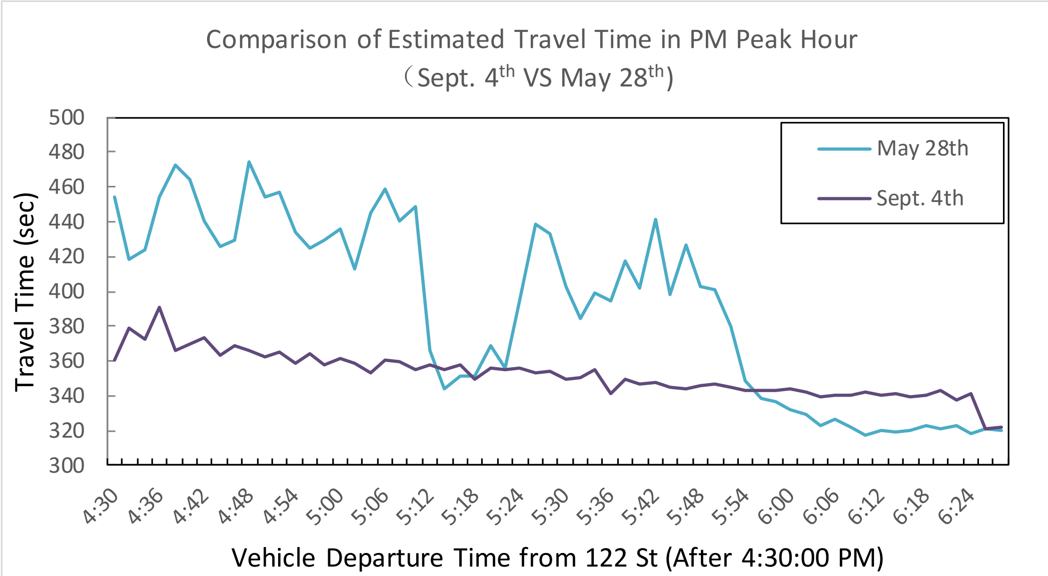
Index type	May 5^{th}	Aug. 18^{th}
Average travel time (sec)	359	370
Saved Travel Time (sec)	-	-11
Saved Travel Time Rate (%)	-	-3.09%

(c)



Index type	May 25^{th}	Aug. 31^{st}
Average travel time (sec)	350	335
Saved Travel Time (sec)	-	14
Saved Travel Time Rate (%)	-	4.06%

(d)



Index type	May 28th	Sept. 4th
Average travel time (sec)	390	352
Saved Travel Time (sec)	-	38
Saved Travel Time Rate (%)	-	9.74%

(e)

Figure 16. VSL control performance evaluation based on travel time changing of comparison groups (a) Aug.13rd VS May 21st; (b) Aug.17th VS May 5th; (c) Aug.18th VS May 5th; (d) Aug.31st VS May 25th ; (e) Sept.4th VS May 28th;

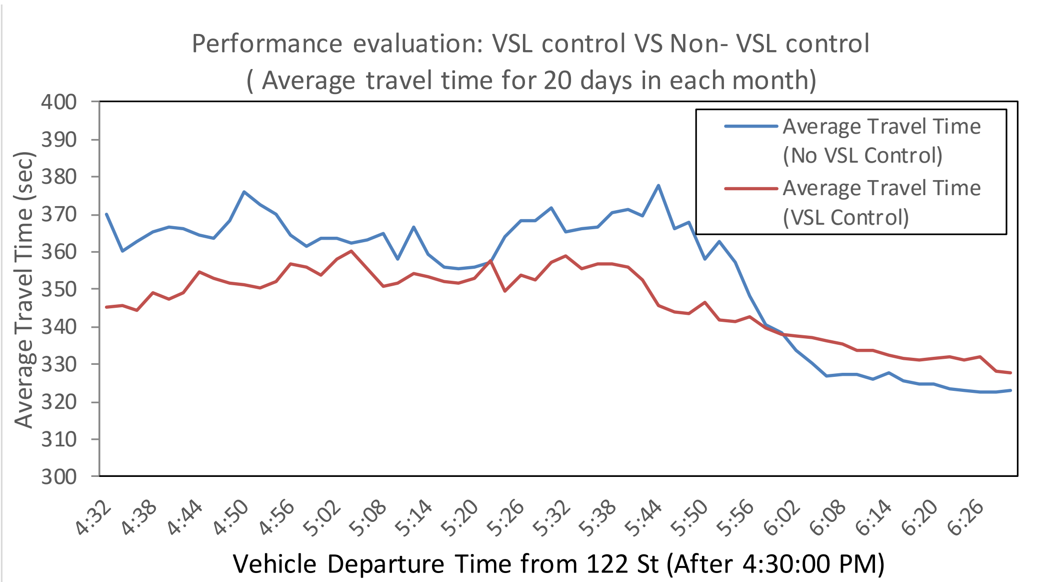
Travel time of the comparison group, May 21st and Aug. 13th are 327seconds and 344 seconds, respectively. 17 seconds is saved after the VSL control's application. Saving rate is 5.02%.

Travel time on Aug.17th is 355 seconds and 359 seconds on May 5th. Saved time is 4 seconds, saving rate is 1.14%.

For May 5th and Aug. 17th, because on Aug.18th, special accidents happened, it caused flow accumulation and increased travel time. Thus average travel time is 370 seconds in this day, 11 seconds higher than May 5th.

Travel time is 350 seconds on May 25th. When the traffic conditions is improved by the VSL control, 14 seconds is decreased.

The highest saving rate of 9.74% is produced by the group of May 28th and Sept.4th. Average travel time before the VSL control is 390 seconds, and 38 seconds is saved.



Index type	Non-control	VSL control
Average travel time (sec)	354	346
Saved Travel Time (sec)	-	8
Saved Travel Time Rate (%)	-	2.19%

Figure 17. VSL control performance evaluation based on average travel time changing

Averaging the travel time for 20 days in each month; it is 354 seconds without VSL control, and 346seconds with VSL control. 8 seconds is saved, and it is about 3.74% comparing with travel time without VSL control. Thus, the VSL control improves traffic conditions on this road, and relieves traffic pressure in the peak hour.

This case shows that travel time estimation models in the thesis can effectively evaluate the VSL control's influence and be applied in related transportation research.

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

This chapter summarizes research work and discusses limitations in research. Also, it provides some suggestions for future work and following research.

5.1 Research summary and limitations

The research consists of two major steps. The first step is data prediction. METANET is used to forecast traffic status certain time interval later, based on measured traffic data. Another step is the travel time estimation step, the Dynamic Travel Time Estimation method is mainly used. Loop detectors measure speed and density data every 20 seconds. Meanwhile, at different time stamps a car arriving at the same position; its speeds should be different. Considering the speed dynamically changing in estimation, the trajectory assumption algorithm is introduced. It simulates vehicles' trajectories, and from this, time stamps of assumed vehicles reaching section exit positions can be confirmed. Then, whole route's travel time can be figured out by adding section travel times together.

In transportation research, there are a multitude of methods and models on travel time estimation. Besides the DTTE method, static travel time estimation (STTE) method is also widely used. It assumes that vehicles travel through segments without any speeds variation and does not consider influences brought out by dynamic speeds. To find strengths of the DTTE method, the STTE estimations method is also introduced here for comparison.

To evaluate models' accuracy, field experiments were carried out on the Whitemud Drive, from 122 Street to 159 Street. The VSL control strategy's application would affects drivers' personal behaviour, and control variable parameters are added in a models building. Thus, travel times are estimated under conditions with and without VSL control.

Speeds in May are lower than in August, and significant congestion almost daily happened in PM peak hour. Summarizing the experiment results, for speed predictions, RMSE in two months are all under 10. Even in most congested days, when speeds are around 40 km/h, RMSE values are still under 8.

In May, comparing with reference travel times, MAREs of the STTE method vary from 3.18% to 7.01%. In contrast, the DTTE's MARE values are all under 5%. Even on May 5th with the highest MARE, it is still only 4.58%. Further, the DTTE's RMSEs of five days are less than 20. But the STTE's are all higher than 30, even jumping to 51.08 on May 27th. RMSE values of two methods in May show that estimation travel times based on the DTTE method are closer to reference travel times.

PM peak hour congestion is improved after the VSL control is applied, speeds varied more smoothly. So, speeds variation is much more stable than it was in May. This caused the STTE's MARE to be a little bit lower than the DTTE's on Aug. 25th, Aug.26th and Aug.31st. But the STTE's RMSEs are still much higher than the DTTE's. So, the DTTE method still provides better results.

In conclusion, the METANET model can achieve accurate predictions in research. Both the travel time estimation methods can be accurate when speeds' are not changing sharply. But, in peak hour with apparent speeds variation, the DTTE method shows better performance than the STTE method in most days. Meanwhile, the DTTE's RMSEs are smaller than the STTE's in all sample days. This means that the DTTE method can estimate travel time accurately all the time, but the STTE method cannot be guaranteed for that.

However, there are still some limitations in the research. Loop detector data are measured every 20 seconds, and they cannot provide traffic information for specified vehicles. If vehicles' information can be tracked, travel time estimation accuracy would be enhanced.

5.2 Future work

Even though the DTTE method can make accurate estimations as shown in the thesis, there is still some room to improve accuracy and study its practicality in different cases. Some potential future works are listed:

1) Improve quality of reference travel time such as using probe vehicles to collect information.

2) The research segment's length is 7.5 km. May be in next step, this route can be extended to test whether models can also be suitable for a longer route.

3) Evaluate the DTTE's accuracy on road with flow interrupted.

Further, the application case in this thesis shows that the DTTE method can be also used to evaluate the VSL control's performance. Thus, once models' accurate estimation ability is verified, it can be widely used in Transportation Management System.

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