A Probe-Based Variable Speed Limit System

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A Probe-Based Variable Speed Limit System

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Abstract

This paper presents the results of an evaluation of a candidate variable speed limit (VSL) system that takes the space mean speeds (SMSs) from probe vehicles as its main input. The presented algorithm extends the capability of a model predictive control (MPC) VSL model with the input of SMS derived from vehicle probes and their corresponding space-based densities, instead of spot-based densities and detector speeds. The developed probe-based VSL was evaluated on an 8-kilometer stretch of Highway 2, in Calgary, Alberta, using Paramics microsimulation software. The performance of the probe-based VSL algorithm was examined under various traffic conditions and probe vehicle parameters. The findings of the probe-based VSL analysis support previous findings taking input from point detectors and showing that the efficiency of the VSL strategies was efficient only for a limited range of traffic conditions. The results of the analysis show the effectiveness of developing advanced freeway control algorithms that use the main input parameters from vehicle probes. The performance of the probe-based VSL system was also comparable to, and in some cases outperformed, the point-based detector algorithm. However, the algorithm was shown to be effective only for a high frequency of information updates and under a relatively high percentage of vehicles probe penetration percentage.

*Keywords*: variable speed limit; safety, vehicle probes; space mean speed; freeway control; microcimulation
1. Introduction

Variable speed limit (VSL) systems are intelligent transportation system (ITS) tools that enable dynamic changes in the posted speed limit, in response to prevailing traffic and/or weather conditions. The objectives of these systems are the smoothing of traffic flow and improvement in safety by advising/forcing drivers to adjust their speeds to better respond to changing downstream traffic conditions. Examples of prevailing conditions that may necessitate a change in the speed limit are lane closures, reduced visibility, slippery road surfaces and developing queues.

VSL has proven to be effective in improving safety, which is mostly achieved due to the homogenization of speeds on multilane highways. Speed harmonization results from the reduction of speed differences among vehicles in the same lane and of the speed differentiation among adjacent lanes (Lee et al., 2006 and Abdel-Aty et al., 2006). Increasing freeway throughput may also result; however, this was shown to be effective only for a limited range of traffic conditions (Hegyi et al., 2005, Carlson et al., 2010, Papageorgiou et al., 2008 and Heydecker et al., 2011).

Although VSL systems have been implemented in a limited number of jurisdictions throughout the world, the majority of the existing systems utilize traffic speed and volume point detection technology to determine the appropriate speeds at which drivers should be traveling, given prevailing roadway, weather and traffic conditions. In order to have an effective VSL system, a high coverage of vehicular detectors may be required. This corresponds to high costs associated with the installation, maintenance and communication needed for these detectors. In addition, point detectors are also prone to high failure rates [Herrera et al., 2010]. The high infrastructure
cost and relatively low reliability of these detector technologies defers their installation and, thus, the deployment of advanced freeway management tools for highways in numerous places around the world.

There is a need, therefore, for a cost-effective solution for gathering reliable real traffic data that can also be used as input to advanced traffic control systems. Today, any vehicle that carries a Global Positioning System (GPS) enabled device (e.g. smart phone, navigation device and, in the future, connected vehicle) can act as a mobile sensor able to provide cost-effective and reliable traffic data [Leduc, 2008]. For instance, several mobile sensing applications (e.g. Mobile Google Maps, Waze 2012, GeoLife 2012 and CarWeb 2012) are able to obtain a significant penetration rate from the GPS in smart phones or navigation devices to collect users’ real-time traffic information and, in return, provide several location-based services for busy highways and arterials in major European and North American cities. Such GPS-enabled device can act as a probe, providing direct estimates of its positioning at various time stamps and thus its space mean speed (SMS) which are more reliable indicators of congestion. The constant provision of such data from moving probes can provide network-wide traffic information conditions over whole freeway sections. In addition, such data can reflect the occurrence, intensity and location of shockwaves that may result from events such as traffic discharged from the on-ramps and the presence of a lane blockage.

With the promising role that such mobile sensor detection technology can play in the next generation of traffic data collection comes great controversy and debates about the privacy issues surrounding such information extraction. While protecting privacy issues, the Mobile Century
field experiment in California was conceived as a proof of concept for such a traffic monitoring system, showing the feasibility of using GPS-enabled mobile phones as traffic sensors.

There is a large body of literature on extracting data from vehicular probes (Herrera et al., 2010, Hellinga et al., 2008, Yang et al., 2009, Van Zuylen et al., 2010, Vautin et al., 2011 and Hoh et al., 2008). However, most of the research on probe vehicles is still mainly focused on traffic state estimation and prediction, with limited efforts on the further exploitation of this data for traffic control strategies. There is a need to utilize this probe data to develop advanced freeway control algorithms, taking as the main input such passively collected data. Such systems are also expected to decrease the cost associated with deployment of advanced traffic controls. They can also be particularly suitable for jurisdictions with a lack of resources for installation of traffic monitoring infrastructure systems, such as vehicle detectors.

In this study, data generated from a microsimulation model was used to examine how the data derived from probe vehicles as mobile sensors can be used as input to a VSL system. The Model Predictive Control (MPC) based VSL algorithm (Hegyi et al., 2005) was extended to take as input SMS data derived from vehicle probes. The use of probe vehicles was used to effectively monitor and detect the occurrence, location and magnitude of backpropagating shockwaves. Such information was then used as input to freeway control algorithms to trigger VSL activation.

The next section of the paper presents a literature review of previous VSL algorithms. Section 3 presents the probe-based VSL algorithm. The results of the test runs and the sensitivity analysis are reported in section 4, where the VSL algorithm’s performance is evaluated and discussed. Conclusions and recommendations for future research are presented in the final section.
2. Review of the Literature

VSL literature can be divided into two broad categories: reactive rule-based approaches; and, proactive approaches, also known as model predictive control (MPC). Early VSL studies were mainly formulated as simple reactive rule-based logic. In these approaches, real-time VSL decisions were changed depending on preselected thresholds of traffic flow, occupancy or mean speed. The main objectives of these approaches were harmonization of speed differences and stabilization of traffic flow. Examples of such systems are those developed by Zackor (1979), Smulders (1990), Smulders and Helleman (1998), Rama (1999), and Piao and McDonald (2008). These studies were successful in showing the effectiveness of VSL systems in harmonizing traffic and improving safety.

In addition, Lee et al. (2006), Abdel-Aty et al. (2006, 2007) and Allaby et al. (2007) examined the efficiency of VSL as an effective crash prevention tool through the performance of rule-based VSL systems that were integrated with a real-time crash prediction model. The results of these microsimulation studies were not quite consistent. Lee et al. (2006) findings showed that real-time VSL systems could reduce crash potential, but at the expense of higher travel times. On the other hand, Abdel-Aty et al. (2006) indicated that VSL systems provided a significant reduction in crash probability only for non-congested conditions. No substantial safety benefit was associated with VSL application for congested conditions. In addition to improved safety, Park and Yadlapati (2003), Lavansiri (2003), Pei-Wei et al. (2004) and Lyles et al. (2004) also showed the effectiveness of some rule-based VSL systems in improving throughput and reducing travel time for vehicles travelling through work zones. In a more recent study, Soriguera et al.
(2013) showed the effectiveness of VSL in reducing accident risk, emissions and fuel consumption and. However, that was achieved on the expense of higher induced delays.

The limitations of the above rule-based strategies can be mainly attributed to the reactive rather than proactive nature of the control. Due to the resultant time lag, reacting to real-time traffic measurements as a basis for real-time control is significantly inferior to the use of predictive information. By the time VSL actions are deployed, traffic conditions may have already reached breakdown, and VSL control is able to do little in resolving the situation.

MPC (model predictive control) approaches were developed as a remedy to these issues. In MPC approaches, future traffic is predicted. Thus, bottleneck formations are anticipated before they even occur, and remedial VSL strategies are injected in the system to reduce the inflow to the anticipated jammed area and resolve shockwaves before traffic reaches breakdown. MPC approaches typically consist of monitoring, a state estimation/prediction and a control optimization process. Traffic optimization is repeated after a specified time, with a newly collected data set to update the demand prediction based on the prevailing new traffic state. This closed-loop feedback control approach has the advantage of reducing the discrepancy between demand prediction and real demand.

One of the pioneering MPC-based VSL studies was initiated by Hegyi et al. (2005), who considered VSL systems as a method to eliminate or reduce shockwaves in a metastable state traffic condition, which is defined as a traffic state in which small disturbances dissolve, but large disturbances lead to breakdowns (Kerner and Rehborn, 1996). Such shockwaves occur when the conditions of the vehicle stream suddenly vary when the traffic flow is close to saturation. For instance, one car changes lanes, forcing the driver behind to slow down (or even
stop) to give right of way. A virtual shockwave will send the “slow down” wave to the drivers behind, affecting one car at a time. Similar shockwaves may occur when traffic flow approaches a car accident area (backward shockwave). The main concept that was used in Hegyi’s work was the compensation or decrease of the shockwave that was created by uncontrollable external conditions resulting from an incident or construction by creating an artificial shockwave that would be generated by reducing the speed of the traffic flow approaching the bottleneck, thus delaying the onset of congestion.

Hegyi et al. (2005) applied the MPC scheme using the METANET macroscopic traffic prediction model to control the dynamism of traffic in a proactive fashion. The advantages of this MPC approach have been made clear through its adoption in several subsequent VSL studies (Zhang et al., 2005; Popov et al., 2008; Hegyi et al., 2008; Hegyi and Hoogendoorn, 2010; Ghods et al., 2010; Carlson et al., 2010, 2012).

Recent VSL research has been mainly focused on the integrated control of both ramp metering and VSLs. Abdel-Aty and Dhindsa (2007), Caligaris et al. (2007), Papamichail et al. (2008), Kamel et al. (2009), Carlson et al. (2010), Lu et al. (2011) and Yun (2011) showed that, compared with using each strategy alone, traffic flow efficiency can be substantially improved when VSL control measures are integrated with coordinated ramp metering.

VSL system also has the potential to reduce greenhouse emissions (GHG), since emissions and fuel consumptions are higher during stop-and-go and congested traffic conditions. Zegeye et al. (2010) used MPC approach to assess the impact of the dynamic speed limit control in reducing CO₂ emissions, fuel consumption and travel time. His study concluded that reduction of total time spent (TTS) alone couldn’t meet the requirement of reducing emissions. Grumert et al.
(2013) introduced a cooperative VSL system using connected vehicle to compare its performance with an existing VSL system. The cooperative VSL system showed a more harmonized flow and less varying speed pattern, reduction of high acceleration and deceleration rates which reduced environmental impact. In order to evaluate the effectiveness of VSL system, Castro et al. (2014) developed a single indicator called Positive Accumulated Acceleration (PAA) which was based on accumulated acceleration in a section (or instantaneous speed variations). The results of the study showed slightly increased throughput while penalising travel times and a positive impact on emission.

In the majority of the above-reviewed VSL algorithms, point traffic detectors were used for extracting traffic data. For traffic parameters extracted from point detectors to be representative enough of the whole freeway section, intensive coverage is needed. However, data extracted from point detectors is mainly spot densities, flow and time mean speed (TMS), and this spot data is used to get indirect estimates of section densities and SMS information that are needed as input to the fundamental traffic flow relationship (Kattan and Saidi, 2013). Such point detector information is unable to directly reflect the accurate location and intensity of shockwaves forming behind a fixed or a moving bottleneck, such as near on-ramps, lane blockages or slow moving vehicles.

In addition, Heydecker and Addison (2011) showed that maximum recorded density occurs as the density attained by traffic when the speed is forced to be zero by some blockage; however, a density this high will not necessary cause traffic to stop. The authors found that, even at the highest densities recorded, traffic could be found to still continue to flow. Thus, they suggested that, for VSL controlled freeways, SMS values should be used as the explanatory variables to
determine density and flow. Taking spot density readings as the controlling variable in designing VSL strategies may lead to a suboptimal solution.

The use of vehicle probes as mobile sensors has recently been attracting growing attention from transportation engineers, as they provide a low cost, reliable temporal and spatial coverage of the traffic state on the entire freeway. Hellinga et al. (2008) proposed a method to estimate route travel time between two reported probe locations through the use of virtual trip lines. Probe vehicles were thus able to provide information on vehicle speed and their location at regular time stamps. The corresponding point-to-point travel time could be used to directly estimate SMS of traffic on several sections based on the virtual trip line concept. SMS information is a good indicator of traffic congestion and can be used in the fundamental traffic flow relationship to derive other traffic parameters, such as section density and flow. Herrera et al. (2010) showed that mobile GPS-enabled devices were able to provide reliable traffic information with a penetration rate as low as 2%.

This research has taken a further step and investigated an aspect of traffic control that is of growing relevance: the use of probe vehicle data (and, in the future, data from connected vehicles) as the main inputs of a freeway control algorithm. Thus, speed information derived from probe vehicles was examined as the main input parameter in a VSL algorithm. Assuming that SMSs of vehicles equipped with GPS-enabled cell phones were obtained for each time step interval on each segment of the freeway, estimates of section density were derived from these SMSs, which were input to the VSL, as presented in detail in the next section.
3. Overview of the Methodology

Fig. 1 illustrates a schematic of a freeway section that contains the mainline section with several on- and off-ramps. In this research, the Paramics microsimulator was used to model the study area, monitor the demand and extract traffic data from the simulated probe vehicles. It is important to emphasize that the traffic information for the main stream was obtained through probe vehicles alone. The average speed of probe vehicles over the time step, $t$, on each section, $i$, of the freeway was obtained as an estimate of section SMS. As Fig. 1 shows, one checking traffic detector and one checkout detector were installed on the on-ramps to capture the queue length and the flow entering the freeway.

Fig. 2 illustrates the general MPC framework followed for the developed proactive probe-based VSL approach. The framework consists of four major interrelated components: 1) data input, 2) traffic state estimation and prediction model, 3) an optimization component based on a rolling horizon VSL control, and 4) a control action that implements the first step of the optimization results. As indicated in Fig. 2, traffic conditions on the freeway are affected by: 1) existing traffic demand, 2) possible disturbances resulting from random events (e.g., incidents, shockwaves, slow moving vehicles), and 3) optimal VSL displays that were obtained from the control.

The VSL control algorithm presented in this paper is an extension of Hegyi et al.’s (2005) MPC based VSL algorithm. However, as opposed to point detector data, the presented VSL system used SMS data directly extracted from vehicle probes as input. Assuming that speed data could be obtained during each time step interval and on each segment of the freeway separately, any
changes in freeway conditions were reflected as changes in the speed of all vehicles, including vehicles acting as probes when traveling on the examined freeway segment. A macroscopic traffic flow model was used to convert this SMS data to density readings, as required for the traffic prediction step. The algorithm constantly checked for shockwave occurrence and location through the SMSs of probe vehicles moving in the network. The VSL was triggered only when a significant backpropagating shockwaves was anticipated. If the occurrence of a backpropagating shockwave was confirmed, the VSL algorithm was activated, and the optimal VSL values were determined.

As mentioned earlier, on-ramp queue information was monitored through the installation of two detectors on each on-ramp. The objective function was based on minimization of the total time spent (TTS) in the network for a prediction horizon of five minutes in a rolling horizon fashion. Thus, only the VSL outputs corresponding to the first estimation steps were considered final and implemented. The control time step was one minute, meaning that the VSL system was able to adjust the value on the variable message signs (VMSs) every minute if required. Thus, the cycle was repeated at 60-second intervals with a new data set of probe data.

The following sections describe the details of the probe-based MPC approach, as related to traffic input parameters, traffic state prediction, system-wide optimization and control input.
3.1. Traffic Input

As shown in Fig. 2, an effective VSL control strategy has to capture the dynamics of the transportation system (i.e., demand fluctuation, occurrence of incidents and weather conditions) and be able to be responsive in real time.

The SMS speed information from probe vehicles is extracted separately for each time step on each segment of the freeway. Any possible changes in freeway conditions are reflected as changes in the speed of vehicles. These speed data are used as input to a traffic estimation/prediction model to estimate the density and the demand over a short-term horizon, $T$ (i.e., 5 minutes).

The on-ramp detectors are used to calculate the vehicle demand on the on-ramps. In other words, the difference between the number of vehicles allowed to enter the freeway during the next time step and the demand arriving at the on-ramp plus a possible residual queue on the ramp from previous time steps (if not yet served) determine the length of the queue on the on-ramps.

3.2. Shockwave Occurrence and Traffic State Estimation/Prediction

After the SMS data are received from the simulation, SMS data from probe vehicles are used to estimate the corresponding densities and flows at each section of the freeway based on a traffic flow model. In this research, Van Aerde’s (1995) traffic flow model was used to convert the SMS to densities and flows for each section. Van Aerde’s model formulations are:
\[
k = \frac{1}{C_1 + \frac{C_2}{U_f - U} + C_3 \times U}
\]

\[
q = \frac{U}{C_1 + \frac{C_2}{U_f - U} + C_3 \times U}
\]

Where: \(U\) - average SMS speed of vehicle probes,

\[C_1\] - Fixed distance headway constant (km),

\[C_2\] - First variable distance headway constant (km²/h),

\[C_3\] - Second variable distance headway constant (h),

\[U_f\] - Free speed (km/h),

\[U_c\] - Speed at capacity (km/h),

\[q_c\] - Flow at capacity (veh/h), and

\[k_j\] - jam density (veh/km).

The above-listed model parameters are based on the posted speed limits of the freeway in the study area and the observed maximum capacity and jam density and speed at capacity estimates.

The model also checks for the occurrence of possible backpropagating shockwaves resulting from sudden increases in flow and density on the freeway, due to traffic discharged from the on-
ramps or lane blockages. Thus, the next step determines whether a shockwave has occurred between any two sections of the road. For this purpose, the system calculates the speed of the shockwave between sections \(i+1\) and \(i\), \(W_{i,i+1}\), starting with the downstream sections and working towards the upstream ones, based on the shockwave theory of Lighthill and Whitham (1955):

\[
W_{i,i+1} = \frac{q_{i+1} - q_i}{k_{i+1} - k_i}
\]  

(3)

If the algorithm identifies the presence of a backpropagating shockwave of high intensity, the VSL is triggered. The threshold of 10 km/h for the shockwave speed was chosen, based on trial-and-error experiments performed prior to the thorough VSL algorithm analysis. The test runs were performed for 0 km/h, 10 km/h and 20 km/h shockwave speed values. The value of 20 km/h showed insignificant improvements in the traffic system, since the VSL algorithm would be initiated too late, resulting in the inability of VSL alone to positively affect the delay. Alternatively, the VSL algorithm activated at a 0 km/h shockwave speed created excessive delays even for low demands by unnecessarily reducing the speed limits on the variable message signs, when even just a small shockwave (i.e. 0.005 km/h) was sensed by the algorithm.

Thus, the system initiates the VSL algorithm based on the following conditions:

- If \(W_{i,i+1} \geq -10\), VSL is not activated. In this case, the displayed speed limits are equal to the current fixed speed limit sign (100 km/h is commonly used for freeways) or the previously implemented VSL sign.
\[ W_{i,i+1} < -10, \text{ VSL is activated; and, the controlled VSL } v_{\text{ctrl},i}(t) \in (60, 70, 80, 90, 100) \text{ – of a system-wide objective function is optimized (as described next) over a future horizon. Note that the VSL is initiated and the algorithm implemented in a rolling horizon fashion until the shockwaves are resolved.} \]

Next, the traffic state is estimated for the future time step. The traffic prediction is conducted based on the principle of traffic conservation, which states that the density of the next time step \((t+1)\) is equal to the density of the current time step, \(t\), plus the inflow minus the outflow:

\[ k_i(t + 1) = k_i(t) + \frac{T}{L} (q_{i-1}(t) - q_i(t)) \]  

(4)

The mean predicted speed for the next time step \((t+1)\) depends on the observed speed at the current time step, \(t\), which is directly extracted from probe vehicles plus relaxation, convection and anticipation terms (Hegyi et al., 2003). It is to be noted that a section’s density and flow used in equation 5 are obtained directly from the observed SMS data and estimated space density using Van Aerde’s model (1995).

Formula 5 represents the dynamic behavior of the vehicles in the network based on a simple 2nd order model introduced by Payne (1971) and modified by Papageorgiou et al. (1990). It is to be noted that this prediction model is capable of reproducing relevant phenomena, such as shockwaves, capacity drops at on-ramps and blockages. The speed in section \(i\) at time step \(t+1\) equals the speed at time step \(t\) plus the following terms:

- **Relaxation** considers the difference between the desired average speed and the actual speed of a vehicle. For instance, after a driver passes a traffic slowdown area, he/she will try to accelerate to the speed of the flow.
• Convection accounts for the speed adjustment of the drivers exiting section \(i-1\) and entering section \(i\).

• Anticipation accounts for the ability of drivers to see traffic conditions ahead and adjust their speed accordingly.

These three terms enter the speed prediction equation as (Papageorgiou 1990):

\[
v_i(t + 1) = v_i(t) + \frac{T}{\tau} \left( V(k_i(t)) - v_i(t) \right) +
\]

\[
\frac{T}{L} v_i(t)(v_{i-1}(t) - v_i(t)) - \eta \frac{T}{\tau L} \frac{k_i(t) - k_{i+1}(t)}{k_i(t) + \kappa}
\]

where: \(T\) = simulation time step size used in this work,

\(L\) = segment length,

\(\tau = 0.005\) (h) - constant that indicates the drivers’ swiftness (a larger \(\tau\) indicates a slower reaction),

\(\kappa = 40\) (veh/km/lane) - speed anticipation term parameter, and

\(\eta\) - speed anticipation term parameter \((\text{km}^2/\text{h})\).
To account for the dynamics of drivers’ anticipation, parameter $\eta$ was adopted as follows (Hegyi et al., 2005):

$$\eta_i(t) = \begin{cases} 65, & \text{if } k_{i+1}(t) \geq k_i(t) \\ 30, & \text{else} \end{cases}$$

$U(k_i(t))$ is presented as:

$$U(k_i(t)) = \min \left( (1 + \alpha) v_{ctrl,i}(t), v_{free} \exp \left[ -\frac{1}{\alpha} \left( \frac{k_i(t)}{k_{crit}} \right)^a \right] \right)$$  \hspace{1cm} (6)

where: $v_{ctrl,i}(t)$ - VSL value implemented on segment $i$ at time step $t$,

$v_{free}$ - free-flow speed of traffic,

$k_{crit}$ - critical density,

$a$ - parameter of the fundamental diagram, taken to be 1.867 (Hegyi et al., 2005), and

$(1+\alpha)$ - noncompliance factor, where $\alpha$ is taken to be 0.05.

In formula 6, a noncompliance factor is introduced to reflect the drivers’ target speed (Hegyi et al., 2005):

- If $(1+\alpha) < 1$, the target speed is lower than the control speed; therefore, drivers are compliant

with the VSL.
• If \((1+\alpha) >1\), the target speed is higher than the control speed; therefore, drivers exceed the VSL.

For network sections that include on-ramps, the length of the queue for the next time step \(w_r(t+1)\) is obtained as the current queue, \(w_r(t)\), plus the demand, \(d_r(t)\), minus the outflow, \(o_r(t)\):

\[
w_r(t + 1) = w_r(t) + \tau(d_r(t) - o_r(t))
\]  

(7)

As mentioned previously, demand \(d_r(t)\) and outflow \(o_r(t)\) can be extracted from the simulation model by placing two detectors on each on-ramp. It is important to note that \(w_r(t)\) is indirectly a function of the control value of VSL at time step \(t\) as the number of vehicles that are discharged from the on-ramps to the freeway depends on the capacity of the freeway at time \(t\), which in turn is dependent on the posted speed limit at time \(t\).

3.3. System-Wide Optimization

The objective function used in this paper is based on Total Time Spent (TTS) which is the most widely used form adopted by many studies. However, slight modifications were introduced in the use of TTS as objective function. In this research, VSL was only triggered if the backpropagating shockwave exceeded the value of 10 km/h. In addition, the usual spot density estimates were replaced with section density estimated from SMS of probes. For convenience, the objective function, \(TTS(t)\), adopted in this research is as follows:
\[
TTS(t) = T \sum_{t=1}^{Np} \left\{ \sum_{i=1}^{\text{Number of sections}} k_i(t) L \lambda + T \sum_{r=1}^{\text{Number of on-ramps}} \omega_r(t) \right\} + \alpha_{\text{speed}} \sum_{t=1}^{Nc} \sum_{i=1}^{\text{Number of activated VSL}} \left( \frac{v_{\text{ctrl},i}(t) - v_{\text{ctrl},i}(t-1)}{v_{\text{free}}} \right)
\]

subject to: 
\[
|v_{\text{ctrl},i}(t+1) - v_{\text{ctrl},i}(t)| \leq 10,
\]
\[
|v_{\text{ctrl},i}(t) - v_{\text{ctrl},i+1}(t)| \leq 10.
\]

where: \(k_i(t)\) - section density on segment \(i\) at time \(t\) transformed from SMS, which are estimated from probes,

\(L\) - length of the segment,

\(\lambda\) - number of lanes on the highway,

\(\omega_r(t)\) - queue on ramp \(r\),

\(v_{\text{ctrl},i}(t)\) - control variable to be determined related to the VMS value indicating the speed limit on section \(i\) at time \(t\),

\(v_{\text{free}}\) - free flow speed of traffic, taken to be 100 km/h, and
\[ \alpha_{\text{speed}} = 2 \] - a non-negative parameter, expressing the importance of each term (Hegyi et al., 2005).

In summary, the optimization function attempts to compute the VSL control parameters that would minimize the system delays over the short-term horizon, \( N_p \), of 5 minutes in a rolling horizon fashion. This function attempts to minimize two objective functions:

- The total time spent in the network (including on-ramp queue delays), and
- The variation of VSL signs for each segment where VSL is implemented, to ensure a smooth transition between one displayed VSL and the previous one.

The algorithm computes the total predictive delay over a prediction horizon, \( N_p \), of 5 minutes and chooses the values that would optimize the objective function over a time of 5 minutes long. To minimize the computational complexity, the control horizon, \( N_c \), was chosen to be 3 minutes.

### 3.4. Implemented Control Action

In the step of control action, only VSL displays corresponding to the earlier time step of \( t+1 \) are considered final and implemented. The remaining steps are re-estimated in the succeeding estimation steps in a rolling horizon fashion. Thus, at each new time instant, \( t' \), a new optimization is performed over the prediction horizon, \( t', \ldots, t'+ N_p \).

It is to be noted that, in the presented approach, satellite orbit errors, atmospheric delays, satellite and receiver clock biases and drifts can cause stochastic errors in GPS data collection (Yi, 2007). The system may experience short-term losses of signals due to the signal blockage, interference or jamming. This problem of presence of noisy measurements might be alleviated...
through the use of a filtering algorithm to remove outliers. In order to account for such errors, complex mathematical models can be used for error estimation. To keep the complexity of the algorithm presented in this research at a moderate level, the error of a GPS technology was not taken into account; however, it is a logical extension of this work. More work need to be conducted to examine how the performance of the developed algorithm will be affected with the presence of noisy measurement.

The next section examines the implementation of an application programming interface (API) in the Paramics microsimulation model. The API was developed in Paramics to extend the functionality of the package in extracting the probe data to be used as input to the VSL algorithm.

4. Study Area and Scenario Examined

The analysis was conducted in Paramics on a real simulated test network that represented an 8-km southbound section of Deerfoot Trail (Highway 2) in Calgary, Alberta, Canada. As shown in Fig. 3, the study area extended from McKnight Boulevard to Memorial Drive and included four on-ramps/off ramps. The Paramics model was coded and calibrated for the morning (AM) peak with the help of City of Calgary personnel. Updated AM peak origin/destination data were provided by the City of Calgary and calibrated based on recent traffic counts using the Paramics estimator. Paramics’ specific parameters, such as minimum gap, mean target headway, mean driver reaction time, traffic assignment feedback period and feedback smoothing factor, were
manually calibrated in the simulation model to reflect recent traffic counts obtained from Alberta Transportation (2010).

The beacon tool in the Paramics microsimulation model is an object that delivers information to the drivers and was used to simulate VMSs. Based on the VSL optimization evaluation results, the API changed the variable speed message sign value if needed. To avoid long queues forming on the on-ramps, the signs were placed well in advance of each on-ramp (400 to 700 meters) as a reasonable approximation.

To collect information on on-ramp queues, two detectors were placed at the entrance and exit of each on-ramp. To represent probe vehicles, a special vehicle category was created in Paramics modeler with the desired percentage. Thus the real-time individual probe vehicle speeds were collected at regular time stamps and then converted to SMSs. The speeds for individual probe vehicles were taken at every simulated second, and the average SMS of each section was computed at the end of the time step. This high sampling frequency of 1 second is feasible for current GPS-enabled cell phones, due to the high bandwidth of the new cellular networks (i.e., 4G and LTE networks) and to the rapid improvements in servers’ capabilities. The percentage of probe data can be easily changed in the Paramics API through vehicle type.

Several scenarios were examined to examine the performance of the probe-based VSL under various traffic- and probe-related parameters. This analysis compared the simulation results for “no control” and “VSL algorithm control” scenarios. The performance of the algorithm was examined as affected by several factors:
• Traffic demand under these levels of traffic conditions (i.e., loading scenarios of 80%, 100% and, 120%);

• Performance of the algorithm under non-recurrent traffic conditions corresponding to one lane blockage;

• Probe penetration rates (number and composition of probe vehicles in the network) of 2.8%, 6% 10%, 20% and, 40%);

• Probe data collection frequencies of 1, 5 and 10 seconds; and

• Performance of the probe-based VSL compared to the detector-based VSL.

The following measures of effectiveness (MOE) were generated from the Paramics analyzer:

• Freeway link delay (sec/veh),

• Freeway link speed variance (km/h),

• Freeway flow (veh/h), and

• Freeway average speed (km/h).

All simulation runs were conducted for 1 hour and 15 minutes (AM peak for southbound traffic). The first fifteen minutes was a warm-up period and was disregarded from the MOE. Thus, the actual data were collected during the remaining full one-hour peak period. All reported runs correspond to the average of 10 Paramics runs with different random seeds. These random numbers are utilized by Paramics to calculate different traffic assignment parameters, such as car following, lane changing, route choice and release of demand. Thus, Paramics creates a dynamic traffic model for each seed number and varying traffic demand on the freeway section. The same set of random seeds was used for the simulation of the different examined different scenarios. It
is important to note that, in all runs except in the sensitivity analyses of vehicle composition, the probe readings were assumed to be extracted from passenger cars only.

5. Results and Discussions

5.1. Sensitivity to Various Traffic Loading Levels

Simulation runs examined the performance of the presented VSL algorithm for two types of congestion: recurrent congestion, and non-recurrent congestion resulting in lane closure. All scenarios were compared for two cases: a probe-based VSL control scenario; and, the corresponding uncontrolled case. In each case, the following loading scenarios were examined:

- Close to AM peak traffic condition (80% loading scenario with Level of Service (LOS) of D close to E),
- Prevailing AM peak congested traffic (100% loading scenario with LOS of E),
- Higher than the regular peak (120% loading scenario with traffic close to breakdown).

It is to be noted that the VSL scenarios examined in this section corresponded to a probe vehicle penetration rate of 20%; in other words, only 20% of the vehicles in the network were able to provide the system with the speed data. In addition, the probe readings were assumed to be extracted every second and from passenger cars only.
5.1.1 Recurrent Congestion

Table 1 reports the results for the 10 Paramics runs for the various examined congestion levels. At 80% loading, the VSL control case resulted in no statistically significant reductions in speed variance compared to the uncontrolled case. Only speed reduction was shown to be statistically significant at a 5% level of confidence. Furthermore, a slight decrease in traffic throughput resulted. These findings support earlier studies (Allaby et al., 2007) indicating that, when the freeway conditions are not close to critical, the role of VSL is mainly confined to reducing the speeds, which is a sign of improved safety conditions; however, this may occur at the expense of increased travel time and, thus, reduced throughput.

In the other two examined levels of loading (100 and 120%), the application of VSL resulted in decreases in traffic delays (5.4 and 2.2%, respectively), reductions in average speeds (2.7 and 4.5%, respectively) and a slight increase in throughput (0.1 and 0.5%, respectively) compared to the uncontrolled cases. These results were statistically significant at a 5% confidence level. These results indicate that the probe-based VSL was efficient at improving traffic flow for nearly saturated and unsaturated traffic conditions. When the algorithm sensed the occurrence of a significant backpropagating shockwave that may have resulted in a traffic breakdown, the probe-based VSL induced small reductions in speed limit values to limit the flow temporarily and resolve the backpropagating shockwave without creating large disturbances.

In summary, the simulation runs for recurrent congestion confirm the earlier findings in showing the effectiveness of probe-based VSL systems for only a limited range of traffic
conditions. In the stable state (i.e., 80% loading), there was not much to control other than attempting to reduce and harmonize the speed. However, for higher congestion levels, the probe-based VSL was shown to be effective at the same range of traffic conditions (i.e., metastable state condition) as other VSL approaches taking input from traffic detectors (Hegyi et al., 2005; Papageorgiou et al., 2008). A more detailed comparison of the performances of the detector-based and probe-based VSL approaches is presented in section 5.4.

5.1.2 Non-Recurrent Congestion

This section evaluates the performance of the probe-based VSL algorithm in cases of non-recurrent congestion causing a lane blockage, such as car collisions or road construction. To model such traffic situations, a lane on the main freeway in the section of the Memorial Drive off-ramp was blocked through the Paramics simulation model interface.

Table 2 summarizes the results for several simulation runs with various loadings and 20% probe vehicle penetration rates. Overall, the results show the efficiency of the VSL system receiving probe data in controlling non-recurrent congestion resulting in lane closure. This effectiveness was consistent for all examined traffic loading levels. The developed system managed to decrease the average speed limit and speed variance of traffic, resulting in significant improvements in traffic throughput (reaching up to 8.05%). The decreases in the mainline delay were also significant (ranging from 7.97% to 28.7%), and the average traffic speed was slightly decreased. The variance of speed was also reduced, indicating the likely safety benefits
associated with VSL implementation. These improvements were all statistically significant for 80% and 100% loading.

Fig. 4 shows the traffic throughput in various sections of the study area with the implementation of VSL compared to the uncontrolled case, with 80% loading and a 10% probe penetration rate. The figure shows that the probe-based VSL substantially suppressed the variation of the traffic flow value. The bottleneck causing the lane closure is clearly reflected as a drop in traffic flow close to Memorial Drive in the figure. The VSL system was able to stabilize and smooth the traffic flow on the whole freeway. It allowed a significantly larger number of vehicles to pass through the vicinity of the bottleneck area than did the uncontrolled case scenario.

In severe congestion (120% loading), the results also showed a decrease in traffic delays on the freeway, but it was not statistically significant (with a 5% confidence level). The main explanation can be attributed to the fact that, once a breakdown condition occurred, the VSL control was able to do little in resolving the situation. However, the VSL system was still shown to lead to an increase in speed harmonization over the whole freeway, which is an indicator of effective shockwave suppression; accordingly, a likely improvement in safety would result in preventing the occurrence of secondary collisions. In addition, the resulting increase in throughput was high and statistically significant, again confirming the field observations of Papageorgiou et al. (2008) and Heydecker and Addison (2011), showing the capability of VSL in enabling higher flows at overcritical traffic conditions.
In summary, it can be concluded that, in the case of lane closures, the improvements due to VSL seemed to decrease with increased congestion level. These findings were expected, since VSL alone cannot lead to substantial improvements at severe congestion levels resulting from both high congestion and lane closure. At such critical congestion levels, additional freeway traffic management tools, such as ramp metering and advanced traveler information systems (ATIS) should be used in coordination with VSL to alleviate severe congestion.

5.2. Sensitivity to Vehicle Probe Composition and Probe Penetration Rate for Recurrent Congestion

In this section, the penetration rate of the probe vehicles that provide their speed information was changed through Paramics. Several levels of penetration rates were thus examined. Only loadings of 100 and 120% were examined in this section, since the VSL was not shown to be very effective at the 80% loading level.

Most commercial vehicles are already equipped with GPS devices; thus, some municipalities may already be collecting data from these vehicle types (McCormack, 2011). Thus, it is interesting to examine if the presented probe-based VSL algorithm can be applied when probe information is extracted from commercial vehicles. However, the characteristics of driver behaviors, such as acceleration, deceleration, lane changing maneuvers, and gap acceptance, are different for drivers of commercial vehicles and drivers of passenger vehicles. This can be explained with the increased driving experience of drivers of commercial vehicles and the drivability of the heavy commercial vehicles. These driving behaviors are definitely reflected in
different speeds and vehicular trajectory profiles. Thus, it is important to examine the performance of the probe-based VSL algorithm with different compositions of commercial and passenger vehicles acting as probes. It is to be noted that this problem is not present with point detectors, since the data is collected from all types of vehicle passing over the detectors.

Based on the traffic counts provided by Alberta Transportation (2010), the total percentage of such vehicles is 2.8% of the total traffic flow during the AM period. Thus, we first assumed that all probe information was derived from all heavy vehicles traveling on the freeway (2.8% probe vehicle penetration); and, we also used a penetration rate of 6%, assuming that 2.8% of the probes were heavy vehicles and the rest were passenger cars. The runs of 10, 20 and 40% assumed that all probe vehicles were passenger vehicles.

The results of these simulation runs, which are presented in Table 3, show that, for cases where data or part of the data were extracted from commercial vehicles, the probe-based VSL system was not able to effectively manage traffic and, in fact, induced higher delays, and reduced the throughput. This was true at both examined loadings (100 and 120%). An explanation can be based on the fact that, if only one or two segments of the freeway contain a slow moving probe truck that is providing speed data, the average speed for the section will be a value lower than its mean, as trucks tend to maintain lower speed limits in comparison to smaller vehicles, even at low congestion scenarios. This phenomenon may cause the VSL algorithm to sense a false shockwave and lower the VSL, increasing delays.

The runs of 10, 20 and 40% assumed that all probe data were derived only from passenger vehicles. The results reported in Table 3 indicate that, at loadings of 100 and 120%, the average
speed and speed variance were reduced for all examined probe penetration rates, as compared to the uncontrolled scenario (statistically significant reduction at 5% level of confidence).

Only the VSL system with a penetration rate of 20% showed reductions in average delay and improvements in throughput. This was true for both examined traffic-loading levels. However, the VSL system receiving information with penetration rates of 10 and 40% at 100% loading resulted in increased delays and decreased traffic flow, in comparison to uncontrolled case, but this was not statistical significant at a 5% confidence level.

On the other hand, at 120% loading, the results showed a slight reduction in traffic delays for probe penetration rates of 10, 20 and 40%. It is to be noted that the difference among these improvements were not shown to be statistically significant at a 5% level of confidence. Again, the 20% penetration rate was shown to result in the best performance. More work needs to be conducted in the future to understand why the results at the 40% penetration rates were always less effective than those at 20% for both the 100 and 120% loadings.

In summary, these simulation runs indicate a high sensitivity of the algorithm to the penetration rate. In addition, the findings related to vehicle composition played an important role in the presented probe-based VSL system. The performance of the algorithm was shown to be quite sensitive to the composition of the vehicle probes. The findings from this section highlight the fact that not every type of vehicle with GPS equipment is effective in acting as a probe to provide input to the presented VSL algorithm.
5.3. Sensitivity Analysis of Frequency of Disseminating Speed Information

In all the previous experiments, the probe vehicles were assumed to transmit their positioning and speed information at a frequency of one second. In this section, three different frequencies for information dissemination were examined: 1, 5 and 10 seconds. It is to be noted that according to the Society of Automotive Engineers (SAE) J2735 standards, a frequency of information update of 4 sec is needed for vehicles travelling at low speed (i.e. below 32 km/h), 20 s frequency of information update is needed for vehicles travelling at higher speeds (i.e. above 95 km/h), and a linear interpolation for vehicles in between. Since vehicular speeds obtained in the examined scenarios was on average around 60 km/h, a maximum frequency of information update of 10 sec is adopted in the sensitivity analysis.

The simulation runs were again conducted for traffic-loading levels of 100 and 120% and at a probe penetration rate of 20%. Table 4 reports the results.

Table 4 shows that the VSL with more frequent speed information updates (i.e., one second) was more effective in reducing and harmonizing the speeds over the freeway section. Improvements in throughputs were also obtained and were statistically significant at a 5% level of confidence. However, the effects on delays and throughput did not change in a consistent fashion and depended on the loading level.

Less frequent information updates (i.e., 5 and 10 seconds) seemed to deteriorate the situation for both examined loadings. Instead of improving the traffic flow, the VSL system created more congestion on the freeway, which was reflected in significantly increased delays and drastic...
reductions in throughput and speed. There was even a significant increase in speed variance, contradicting the main objectives of VSL. This effect was even more pronounced at the higher congestion level. At a loading level of 120%, both update frequencies of 5 and 10 seconds led the system in becoming unstable, resulting in breakdown condition with an average density much higher than the critical density. This can be attributed to the fact that, at saturated traffic conditions, the traffic speed may have high variance. A slight temporal disturbance that may be resolved by the system could be wrongly reported as a significant shockwave formation, unnecessarily triggering VSL initiation. Thus, it is important to get frequent updates of vehicle probes’ speeds to be able to properly monitor traffic.

In summary, these simulation runs indicate the high sensitivity of the algorithm to the frequency of information dissemination. The probe-based VSL was shown to be effective only at a high information update frequency. It is important to note that the probe-based VSL with a frequency of 1 second for information updates was shown to result in overall improvements compared to the no VSL case. On the other hand, lower frequencies for information updates were shown to result in the deterioration of traffic conditions and, in some cases, to drive the system to total breakdown.

5.4. Comparison of Probe-Based and Detector-Based VSL Control Systems

The performance of the VSL with input data from loop detectors was compared to that of the probe-based VSL system. Paramics allows users to extract traffic flow information directly from point detectors. A total of twelve point detectors were placed along the study area. Several
detectors were placed on longer stretches of the highway (i.e. there were four point detectors implemented in section 4 of the freeway), and the readings were averaged.

According to the fundamental flow relationship, SMS rather than TMS should be used. Wardrop (1952) proposed a formula to determine TMS based on SMS measurement and SMS variance (Wardrop, 1952). However, unlike probe data collection, where the speed provided was SMS, detectors transfer time mean speed (TMS) information and traffic flow information. Thus, variance of SMS is unknown which makes it difficult to derive SMS from Wardrop formula. Rakha and Zhang (2005) presented another formulation to link TMS and SMS based on the knowledge of variance of TMS. However, speed variance is often not available from typical point detectors (Rakha and Zhang, 2005). Thus, in this paper, TMS readings were directly extracted from these detectors, and converted to SMS, according to the following simple formula (HCM, 2010):

\[ S_R = 1.026 \times S_T - 3.042 \]  

(10)

where \( S_R \) - space mean speed (km/h), and

\( S_T \) - time mean speed (km/h).

Density was then estimated from the detectors traffic flow readings and the above SMS, simply using the fundamental traffic-flow relationship (equation 7).

It is to be noted that, as the traffic flow information and density were obtained differently than in the probe-based data case, Van Aerde’s model (1995) was no longer needed for all scenarios extracting information form loop detectors. The estimated values of SMS in equation 10 and the density and flow parameters were then plugged into the same optimization process that was used for the probe-based algorithm.
Table 5 reports the results of the analysis for the loadings of 100 and 120% in two cases: recurrent congestion, and non-recurrent congestion of minor incident with one lane closure. For comparison purposes, the performances of the probe-based VSL for the previous runs for the probe penetration rates of 10, 20 and 40% are also shown in the table.

The case of 100% loading at recurrent conditions showed that the results derived for the probe-based VSL system outperformed the detector-based VSL at the penetration rate of 20%. This was true for all examined MOEs. The detector-based VSL showed better performance at the penetration rates of 10 and the 40%. However, this difference was not shown to be statistically significant in comparison to probe-based VSL at penetration rates of 10, 20 and 40%, for the exception of speed limit reduction. Therefore, it can be concluded that the tested data collection methods result in similar impacts on the traffic system with 100% demand and normal conditions.

For a non-recurrent minor incident scenario at a loading of 100%, the probe-based VSL system showed higher performances than the detector-based VSL for all MOEs. This was consistent for all examined probe penetration rates. Furthermore, the average throughput parameter was significantly increased by 6.1, 4.6 and 1.9% for the penetration rates of 10, 20 and 40%, respectively, of the probe-based VSL, in comparison to detector-based VSL (statistically significant with a 5% level of confidence). As Table 5 indicates, the probe-based VSL system demonstrated the ability to slightly improve traffic conditions, in terms of average delay, compared to detector-based VSL. However, that was not shown to be statistically significant (with a 5% level of confidence).
Table 5 also reports the results of the probe-based VSL algorithm compared to a detector-based VSL algorithm for 120% loading. In recurrent congestion, the probe-based VSL system demonstrated the ability to improve traffic conditions, in terms of average delay, compared to the detector-based VSL. In fact, the traffic delays were reduced by 0.8, 1.8 and 0.8% for probe penetration rates of 10, 20 and 40%, respectively. However, the results for the probe-based VSL did not show significance (with a 5% level of confidence) in comparison to the detector-based VSL.

In the scenarios of a minor accident and traffic loading of 120%, the detector-based VSL showed higher levels of improvement at 9.5, 5.3 and 4.3% in the average delay, compared to results of the probe-based VSL with penetration rates of 10, 20 and 40%, respectively. However, the VSL with the 40% probe penetration rate managed to significantly outperform the detector-based VSL, by increasing the throughput. With respect to improvements in speed and throughput, no statistical significance was shown in the cases of probe-based VSL with penetration rates of 20 and 40%, in comparison to the detector-based VSL.

Overall, the performances of the VSL algorithm with data extracted from probes were shown to be comparable to and, in some cases, outperform the results with data coming from point detectors. Furthermore, the implementation of the developed probe-based VSL significantly improved the average throughput, in comparison to detector-based VSL, for the majority of the examined runs and most of the considered probe penetration rates.

It is important to also note that twelve loop detectors were needed for 8-km stretch of the highway. Thus, in addition to similar performances, consideration should be given to the high installation and maintenance costs for detector-based technology, as the equipment needs to be
physically installed on the pavement. Probe vehicles, on the other hand, can give reliable network-wide travel time information at a relatively low cost (Cayford et al., 2006). Thus, reductions in the deployment cost of such advanced freeway control are also expected.

6. Conclusions and Future Work

In this research, a probe-based VSL algorithm was tested on an 8-km stretch of the Deerfoot Trail located in Calgary, Alberta. The presented algorithm extends the capability of the VSL model of Hegyi et al. (2005) when taking as the input data SMS information derived from vehicle probes constantly moving in the network. In addition, the VSL was only triggered if significant backpropagating shockwaves were detected. The location and occurrence of these potential shockwaves were monitored through the probe vehicles constantly moving in the network. If the occurrence of a significant backpropagating shockwave was anticipated, the VSL algorithm was activated. The optimal VSL values were aimed at minimizing the total time spent (TTS) in the network for a horizon of 5 minutes. However, only the VSL outputs corresponding to the first estimation steps were considered final and implemented. The cycle was repeated for each 60-second interval with a new set of collected probe data.

To evaluate its performance under various conditions, the algorithm was tested for several traffic levels and for a lane blockage case. The algorithm was also tested for different cases of vehicle probe distribution and information update frequency. Finally, the probe-based algorithm was compared to a conventional VSL algorithm that takes detectors data as the input. It is to be
noted that the examined probe-based and detector-based algorithms followed the same control logic with the only difference being the type of input data.

Overall, the findings from this paper indicate the efficiency of probe-based VSL in harmonizing speed for the examined range of traffic conditions, which is also a sign of improved safety conditions. However, the improvement in delays and throughput were shown to be limited to some traffic conditions. In some cases, increased travel times and delays may result, which is similar to the findings reported by Allaby et al. (2007).

The sensitivity analysis related to the probe penetration rate and information update frequency shows the sensitivity of the algorithm to these parameters. A high information update frequency of 1 second was shown to be necessary for VSL control to function properly. Otherwise, even a slight temporal disturbance that may be resolved on its own by the system may be wrongly reported as a significant shockwave formation and trigger unnecessary VSL initiation, even driving the system to breakdown.

In addition, the probe-based VSL was shown to always result in significant and consistent improvement at a 20% probe penetration rate, compared to the uncontrolled case. However, at close to critical traffic conditions resulting from either recurrent or non-recurrent traffic congestion, even a probe penetration rate of 10% was efficient. The case examining the possibility of relying on commercial vehicles to report traffic state seemed to send erroneous messages regarding shockwave propagation, due to the relatively lower speed of heavy vehicles, resulting in the VSL being triggered unnecessarily and deteriorating the traffic conditions.

Finally, probe-based data collection proved to be a strong alternative to that of the classic point detector. Although the probe-based VSL did not always outperform the detector-based VSL, it
showed similar results to the detector-based VSL and, therefore, was shown to be a great alternative with an associated decrease in the deployment cost when using probe data collection. Considering the high installation and maintenance costs of loop detectors, probe-based data can be connected at no cost, as there is no special equipment needed for its implementation. For municipalities that already have an intensive detector system on their freeways, a probe-based VSL can be used as a backup alternative in case of detector failure.

In this research, SMS from probes were used as the main input parameter to the VSL system. However, since several municipalities have already intensive coverage of point detectors, it is important to examine the performance of a VSL algorithm that is capable of fusing data from both detector and probe sources. A system that fuses both static (loop detectors) and mobile sensors (GPS-enabled mobile phones) is expected to provide significant advantages over single-source data. In addition to the economic advantage resulting from the need for fewer vehicular detectors, the use of multiple types of sensors and multiple sources of data is expected to increase the accuracy and reliability of traffic information and result in extended spatial and temporal coverage. In turn, this is expected to result in more robust traffic control algorithms.

The possible latency of information and errors that may be due to the inaccuracy of GPS device estimation were not accounted in this paper. Future research can examine the impact of such factors as part of a sensitivity analysis. Finally, in this research, the VSL algorithm was used as the only tool to improve traffic conditions. In the future, a combination of the VSL algorithm and, for example, ramp metering can be evaluated.
Acknowledgements

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References


Fig. 1. Example schematic of a freeway section

Fig. 2. Probe-based VSL Framework
Fig. 3. The study area (source: Google Maps)
Fig. 4. Traffic flow distribution under “no control” (left) and "VSL conditions" (right) at 80% demand

Table 1. Results at various congestion levels

<table>
<thead>
<tr>
<th>Scenario Description</th>
<th>Mainline Delay (sec/veh)</th>
<th>Traffic Flow (veh/h)</th>
<th>Average Speed (km/h)</th>
<th>Variance of Speed (km/h)</th>
</tr>
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<tr>
<td><strong>80% loading</strong></td>
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<tr>
<td>Uncontrolled Case</td>
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<td>98</td>
<td>9.59</td>
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<td>VSL Case</td>
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<td>3975</td>
<td>93</td>
<td>9.56</td>
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<tr>
<td><strong>Change (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-</td>
<td></td>
<td>-0.6%</td>
<td>-5.1%</td>
<td>-0.3%</td>
</tr>
<tr>
<td><strong>100% loading</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uncontrolled Case</td>
<td>335</td>
<td>4315</td>
<td>75</td>
<td>24.2</td>
</tr>
<tr>
<td>VSL Case</td>
<td>317</td>
<td>4320</td>
<td>73</td>
<td>23.9</td>
</tr>
<tr>
<td><strong>Change (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-5.4%</td>
<td>0.1%</td>
<td>-2.7%</td>
<td>-1.24%</td>
<td></td>
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<tr>
<td><strong>120% loading</strong></td>
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<td>VSL Case</td>
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<td>4245</td>
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<td>30.6</td>
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<tr>
<td><strong>Change (%)</strong></td>
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<td>-4.5%</td>
<td>2.7%</td>
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Table 2. Results for the case of one lane closure at various loadings and probe penetration rates (with 20% probes)

<table>
<thead>
<tr>
<th>Scenario Description</th>
<th>Mainline Delay (sec/veh)</th>
<th>Traffic Flow (veh/h)</th>
<th>Average Speed (km/h)</th>
<th>Variance of Speed (km/hr)</th>
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<tr>
<td><strong>Uncontrolled Case</strong></td>
<td>689</td>
<td>3241</td>
<td>68</td>
<td>29.8</td>
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<td>80% loading VSL</td>
<td>491</td>
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<td>68</td>
<td>27.2</td>
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<tr>
<td>% change</td>
<td>-28.74%</td>
<td>8.05%</td>
<td>0.00%</td>
<td>-8.72%</td>
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<tr>
<td><strong>Uncontrolled Case</strong></td>
<td>929</td>
<td>3123</td>
<td>57</td>
<td>35.6</td>
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<tr>
<td>100 % loading VSL</td>
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<td>53</td>
<td>33.6</td>
</tr>
<tr>
<td>% change</td>
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<td>6.28%</td>
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<tr>
<td>% change</td>
<td>-8.09%</td>
<td>5.76%</td>
<td>-8.77%</td>
<td>-3.88%</td>
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Table 3. Results for the probe penetration rate sensitivity analysis

<table>
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<tr>
<th>Scenario Description</th>
<th>Mainline Delay (sec/veh)</th>
<th>Traffic Flow (veh/h)</th>
<th>Average Speed (km/h)</th>
<th>Variance of Speed (km/h)</th>
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</thead>
<tbody>
<tr>
<td>Uncontrolled case</td>
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<td>4315</td>
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<td>24.2</td>
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<td>100% VSL 2.8% probes</td>
<td>517</td>
<td>3815</td>
<td>67</td>
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<td>6% probes</td>
<td>455</td>
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<td>10% probes</td>
<td>349</td>
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<td>73</td>
<td>23.9</td>
</tr>
<tr>
<td>20% probes</td>
<td>317</td>
<td>4320</td>
<td>73</td>
<td>23.9</td>
</tr>
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<td>40% probes</td>
<td>349</td>
<td>4299</td>
<td>73</td>
<td>23.7</td>
</tr>
<tr>
<td>Uncontrolled case</td>
<td>503</td>
<td>4223</td>
<td>67</td>
<td>29.8</td>
</tr>
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<td>120% VSL 2.8% probes</td>
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<td>29.2</td>
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<td>4245</td>
<td>63</td>
<td>30.6</td>
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<td>4212</td>
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<td>28.5</td>
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Table 4. Results for the probe data extraction frequency rate analysis

<table>
<thead>
<tr>
<th>Scenario Description</th>
<th>Mainline Delay (sec/veh)</th>
<th>Traffic Flow (veh/h)</th>
<th>Average Speed (km/h)</th>
<th>Variance of Speed (km/hr)</th>
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</thead>
<tbody>
<tr>
<td>Uncontrolled Case</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>100% loading</td>
<td>335</td>
<td>4315</td>
<td>75</td>
<td>24.2</td>
</tr>
<tr>
<td>VSL</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>1 sec frequency</td>
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<td>4320</td>
<td>73</td>
<td>23.9</td>
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<td>5 sec frequency</td>
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<td>VSL</td>
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<td>1 sec frequency</td>
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Table 5. Comparison of probe-based and detector-based VSL systems for various loadings

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<th>Scenario Description</th>
<th>Mainline Delay (sec/veh)</th>
<th>Traffic Flow (veh/h)</th>
<th>Average Speed (km/h)</th>
<th>Variance of Speed (km/h)</th>
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<tr>
<td>Probe-based VSL</td>
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</tr>
<tr>
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<td>4288</td>
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<td>20% Probes</td>
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<td>73</td>
<td>23.9</td>
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<tr>
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<td>4299</td>
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<td>23.7</td>
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