Optimal Variable Speed Limit Control for Real-time Freeway Congestions

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Abstract

It is well recognized that proper control of traffic speed can contribute to both a reduction in accidents and improved efficiency of freeway operations. Regarding the real-time traffic congestions, a variable speed limit (VSL) control system along freeway is able to improve the capacity of the downstream bottleneck. To respond to this need, this study firstly proposed a VSL control model, based on a macroscopic traffic flow model. Due to the inaccurate prediction of the macroscopic model, an enhanced module is further introduced, adopting the concept of Kalman Filter. Also, considering the fact that drivers may not follow the displayed VSL in real-world applications, the computed optimal VSL value would be adjusted according to the detected compliance rate. Our extensive simulation analysis with a VISSIM simulator has revealed the benefits of the proposed VSL control model, compared with the case without VSL. Also the results indicated that the compliance rate of drivers can served as a important factor which may impact the operational efficiency of the VSL system.

Keywords: Variable Speed Limit, Kalman Filter, Traffic Congestions, Compliance Rate.

1. Introduction

Recurrent congestion which happens on freeway segment around metropolitan area is becoming more severe with the continuous growth of commuting traffic demand. The deteriorating traffic condition always prevents fully utilizing the expensive freeway infrastructure. Building new highway is not always possible due to geometric limitation and actually is not favourable because of limited financial budget. Instead, several traffic control methods have received increasing interest since the emerging of intelligent transportation systems (ITS) in 1980s, such as ramp metering and variable speed limit control.

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VSL is designed to reduce the speed difference (harmonize the traffic flow) on some hazardous highway segments, thus decrease the rear-end collision rate and improve traffic safety (Steel, P, 2005; Ulfarsson, 2005; Anund 2009). Recently, it is discovered that VSL may also have potential to mitigate traffic congestion and improve traffic efficiency in work-zones and freeway bottleneck sections. Through properly displayed and dynamically changed speed limit based on the traffic condition along controlled segment, it is believed that VSL can smooth the transition between upstream and downstream flow and prevent the appearance of shockwave. As a result, the capacity of the downstream bottleneck would not drop and the travel time and throughput may be improved.

Under the work-zone condition, besides the target to enhance safety, Michigan Department of Transportation (MDOT) (Lyles, 2003), Lin et al. (2004), Kang and Chang (2004), and Kwan et al. (2007) also considered to improve efficiency when developing VSL control logic. Except the lack of comprehensive data for solid analysis by Lyles, all other studies reported that VSL control can show a better performance regarding throughput and/or travel speed.

VSL is designed to enhance operational efficiency on recurrently congested roadways but the results may vary because of different implemented location characteristic and control algorithm adopted. The Dutch VSL experiment (1990) showed no improvement in capacity which may be attributed to its advisory purpose. Bertini (2006) analyzed the data obtained from German Autobahn 9 (A9) near Munich, Germany and found strong correlation between the VSL and dynamic of the traffic condition of bottleneck location. Most recently, Chang et al. (2011) reported a successful implementation of integrated VSL and travel time information system on MD 100 near Coca-Cola Drive which improves travel time and throughput by 10-25%.

Along another path, some researchers and engineers either use simulation method or focus on the theoretical perspective to analyze the effectiveness of VSL control. In the United State, a study on the I-495 Capital Beltway (2009) revealed that VSL can postpone the formulation of bottleneck congestion. Abdel-Aty et al. (2006, 2008) developed VSL system for I-4 through Orlando, Florida to reduce both crash risk and travel time and validate the result in micro-simulation. In Europe, Hegyi et al. (2004, 2005) modified the METANET macroscopic traffic flow model to incorporate the VSL effect and adopted the model predictive control (MPC) approach to determine the optimal speed limit. The VSL effectiveness is also proved using METANET simulation. Papageorgiou et al. (2008) and Carlson et al. (2010) analyzed the effect of VSL on aggregated traffic flow behavior from theoretical perspective. In Carlson’s study they proposed an open-loop integrated optimal control framework to coordinate ramp metering and VSL. The simulation result is promising with an approximate 15% decrease in total travel time. Most recently, Hadiuzzaman and Hadiuzzaman (2012) proposed a modified CTM based VSL control and also used the model predictive control (MPC) method to dynamically change the speed limit in real time. The VISSIM simulation result showed a 15% and 7% improvement in travel time and flow rate. Yang et al. (2013) developed two proactive model embedded with two types of objective functions, which indicates the importance of prediction accuracy and control objective.

From the literature review, one can observe that most reactive control algorithm failed to improve the traffic flow efficiency, while those proactive models can generate better control strategies. Despite the control benefit of the existing proactive models, there are still some additional issues need to be further discussed. For example, how the drivers’ compliance rate and number of VSLs can influence the operational efficiency of a VSL control system. To respond to this need, this study firstly proposes a prediction model based on the modified macroscopic traffic flow model, and enhances the prediction accuracy with the employment of Kalman Filter. Given the traffic flow model, one can easily predict the traffic state in the next few minutes, and an optimization model is proposed according to the prediction. For the safety concern, each speed limit would remain unchanged during pre-defined control horizon. Also, to take the drivers’ compliance rate into account, the obtained optimal speed limit from the optimization model would be adjusted according to the detected speed over the last control horizon.

This paper is organized as follows: The formulation of macroscopic traffic flow model is briefly described in the next section. After that the details of data detection along with Kalman filter model are illustrated in section 3. Based on the traffic flow model, an optimization model is introduced in Section 4. Section 5 details the system
architecture and adjusts the optimal speed limit according to the drivers’ compliance rate to VSL. Design of simulation experiments for evaluating the performance of our proposed algorithm under the real-time control environment is reported in section 6. Conclusions and future research work are summarized in the last section.

2. Macroscopic Traffic Flow Model

To perform an optimal dynamic VSL control, a prediction model is required to predict the traffic state evolution, and an optimization model is needed to determine the proper speed limits, considering the complex interactions between traffic states and all control parameters. A calibrated traffic flow model is used as the basis of prediction and optimization. Due to the concern for on-line applications, the proposed VSL control model uses a linear speed-density relation for its dynamic update process.

As shown in Fig. 1, for convenience of computation, the target freeway segment is subdivided into N subsections with length $\Delta l$, while the time discretization is based on a time interval $\Delta T$. Firstly, it is necessary to use the conservation law to approximate the evolution of dynamic density. For each subsection $i$, the mean density, $d_i(k)$, during control time interval $k$ is determined by the difference between the input and output flows:

$$d_i(k) = d_i(k-1) + \frac{\Delta T}{\Delta l * n_i} [q_{i+1}(k) - q_i(k) + r_i(k) - s_i(k)]$$

where, $n_i$ is the number of lanes in subsection $i$; $q_i(k)$ denotes transition flow rate entering segment $(i-1)$ from segment $i$ during interval $k$; $r_i(k)$ is the on-ramp flow rate entering segment $i$ during interval $k$; and $s_i(k)$ indicates the off-ramp flow rate entering segment $i$ during interval $k$.

In addition, the transition flow between adjacent subsections is taken as a weighted average between two neighboring segments flows, that is:

$$q_i(k) = \alpha_i Q_i(k) + (1 - \alpha_i) Q_{i+1}(k)$$

where, $Q_i(k)$ denotes the average flow rate in segment $i$ during interval $k$; $\alpha_i$ (transition flow weight factor) can be calibrated with field measurements. Wu and Chang (1999) stated that it should be lie within the interval $[0.5,1.0]$. Cremer and Schoof, for example, calibrated it to be 0.95 with field data.

For the average speed, $u_i(k)$, one can also establish its evolution relation with the following properly selected speed-density relation and shock-wave formation equations:

$$u_i(k) = u_i(k-1) + \beta_i [S(d_i(k-1)] - u_i(k-1)] + w_i(k-1)$$

The second component describes an adaptation of the average speed to the speed-density characteristics, as:
This equation is originally formulated by Hadiuzzaman (2012); and the third component of Eq. (3) takes into account the density difference between downstream and upstream segment (Papageorgiou et al., 2008), that is:

\[ w_i(k) = \frac{v \Delta T}{\pi \Delta l} \cdot \frac{d(i - 1, k) - d(i, k)}{d(i, k) + \kappa} \]  

3. Data Detection and Kalman Filter

As shown in Fig. 2, the proposed VSL system consists of detectors, variable speed limit signs and a central processing unit to execute control actions. For the target freeway stretch, an upstream detector is used to capture the free flow arrival rate and a downstream detector can record the bottleneck discharging rate. Also, additional detectors are placed at those on-ramps and off-ramps. Several VSLs along with detectors would be installed between the upstream and downstream detectors. In a field application, those detectors will update their collected data following a specified interval.

![Fig. 2 Illustration of detector locations along the target freeway segment](image)

Note that the relationship of density and speed is much more complicate in reality. However, due to the need of efficiency for on-line operations, the macroscopic traffic flow model has approximated speed-density with a linear function. Therefore, an enhanced module should be adopted to address these deficiencies. As the fact that the number of traffic variables to be estimated is usually much larger than the number of traffic variables that directly measured, some existing studies utilized the Kalman filter theory for estimation correction. The Kalman filter is an optimal state estimator applied to a dynamic system that involves random noise and includes a limited amount of noisy real-time measurements. In this section, a Kalman Filter based optimization model is t and a comprehensive control strategy.

Consider a traffic detector installed at the boundary of two adjacent segments \( i \) and \( i+1 \), as illustrated in Fig. 1. Denote \( t \) as the time interval index of detector data updating, for the flow measurement, we have:

\[ m_i^q(t) = q_i(t) + \epsilon_i^q(t) \]  

where, \( m_i^q(t) \) denotes the flow measurement during the time period \([ (k-1)T, kT ] \), and the mean speed measurement is \( m_i^u(t) \) given by:

\[ m_i^u(t) = u_i(t) + \epsilon_i^u(t) \]  

Similarly, for the on-ramp and off-ramp flow measurement, we have:
\[ m_i^r(t) = r_i(t) + \varepsilon_i^r(t) \]  
\[ m_i^s(t) = s_i(t) + \varepsilon_i^s(t) \]

All measurement noises are assumed zero-mean Gaussian White, and the standard variance of each measurement noise is assumed known.

For the convenience of discussion, we define vectors: estimated traffic state vector \( \mathbf{y}(k) \) and system input vector \( \mathbf{u}(k) \):

\[ \mathbf{y}(k) = [ q_1(k) \ u_1(k) \ q_2(k) \ u_2(k) \ \cdots \ q_N(k) \ u_N(k) ]^T \]
\[ \mathbf{u}(k) = [ q_0(k) \ v_0(k) \ q_{N+1}(k) \ v_{N+1}(k) \ r_1(k) \ \cdots \ r_N(k) \ s_1(k) \ \cdots \ s_N(k) ]^T \]

Therefore, the dynamic traffic flow model could be represented as:

\[ \mathbf{y}(k) = f(\mathbf{y}(k), \mathbf{u}(k)) + \mathbf{w}(k) \]  
(10)

where, \( \mathbf{w}(k) \) is the process noise of the prediction model and \( \mathbf{w}(k) \sim N(0, \mathbf{Q}) \).

Also define \( \mathbf{z}(k) \) as the vector of measure, then:

\[ \mathbf{z}(k) = \mathbf{H}\mathbf{y}(k) + \mathbf{v}(k) \]  
(11)

where, \( \mathbf{v}(k) \) is the measurement noise and \( \mathbf{v}(k) \sim N(0, \mathbf{R}) \).

Define \( \hat{\mathbf{y}}(k) \) as the priori state estimation at step \( k \), and a priori estimate error covariance matrix is given by:

\[ \mathbf{P}^r(k) = \mathbb{E}\{ [\mathbf{y}(k) - \hat{\mathbf{y}}(k)] [\mathbf{y}(k) - \hat{\mathbf{y}}(k)]^T \} \]  
(12)

Ever iteration, the priori error covariance is updated by:

\[ \mathbf{P}'(k) = \mathbf{A}\mathbf{P}(k)\mathbf{A}^T + \mathbf{Q} \]  
(13)

Then the recursive equation of the KF is as follows:

\[ \mathbf{y}(k) = \hat{\mathbf{y}}(k) + \mathbf{K}(k)(\mathbf{z}(k) - \mathbf{H}\hat{\mathbf{y}}(k)) \]  
(14)

And the Kalman factor \( \mathbf{K}(k) \) and post error covariance matrix is updated by:

\[ \mathbf{K}(k) = \mathbf{P}^r(k)\mathbf{H}^T(\mathbf{H}\mathbf{P}^r(k)\mathbf{H}^T + \mathbf{R})^{-1} \]  
(15)
\[ \mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k)\mathbf{H})\mathbf{P}'(k) \]  
(16)

Note that the detector data update interval \( T_d \) is larger than the unit time interval \( \Delta T \) of the traffic flow prediction model. Therefore, for every \( T_d \) seconds, the KF adjustment of prediction model is given by:

\[ \mathbf{y}(t) = \hat{\mathbf{y}}(t) + \mathbf{K}(t)(\mathbf{z}(t) - \mathbf{H}\hat{\mathbf{y}}(t)) \]  
(17)

For the start of a new control horizon, the new prediction and optimization models are based on the adjusted traffic state.

4. Optimization Model

To improve the traffic efficiency, the total travel time is a major measurement of effectness to evaluate the VSL system. Consequently, an optimization model aims to minimize the total travel time over the control horizon is given by:

\[ \max \sum_{k}^{T_C} \sum_{i}^{N} n_i d_i(k) \Delta T \]  
(18)

Assuming driver’s perception distance to be \( \Delta l \), the VSL controlled area is started from one segment ahead of the VSL location.
The mean speed is limited by:

\[
\begin{align*}
\begin{cases}
    u_j \leq u_i(k) \leq u_f & \text{segment i without VSL control} \\
    u_j \leq u_i(k) \leq u_f v_i(k) & \text{segment i with VSL control}
\end{cases}
\end{align*}
\]  

(19)

And,

\[
0 < v_i(k) \leq 1
\]  

(20)

The density boundary is given by:

\[
0 \leq d_i(k) \leq d_f
\]  

(21)

The Transition flow rate is determined by the mean speed, density, the capacity of target segment, and the remaining capacity of the downstream segment:

\[
q_i(k) = \min\{d_i(k)u_i(k)n_i, q_{\max}n_i, (d_f - d_{i-1}(k))n_i \gamma\}
\]  

(22)

Also, to prevent of confusing drivers, the VSL system doesn’t allow a significant speed changing,

\[
-\delta \leq u_i^f v_i(k) - u_i^f v_i(k-1) \leq \delta
\]  

(23)

where, \(\delta\) is the maximum speed difference.

The optimization model would be summarized as follows:

\[
\max \sum_{k} \sum_{i} n_i d_i(k) \Delta T
\]

Subject to:

\[
\begin{align*}
\begin{cases}
    u_j \leq u_i(k) \leq u_f & \text{segment i without VSL control} \\
    u_j \leq u_i(k) \leq u_f v_i(k) & \text{segment i with VSL control}
\end{cases}
\end{align*}
\]

\[
0 < v_i(k) \leq 1
\]

\[
0 \leq d_i(k) \leq d_f
\]

\[
q_i(k) = \min\{d_i(k)u_i(k)n_i, q_{\max}n_i, (d_f - d_{i-1}(k))n_i \gamma\}
\]

\[
-\delta \leq u_i^f v_i(k) - u_i^f v_i(k-1) \leq \delta
\]

Due to the limited number of feasible solutions, the optimization model could be solved efficiently by a simple decision tree.

5. System Architecture

Depending on the approaching volumes, driver compliance rate, and the resulting congestion condition of the target freeway stretch, the central processing unit will compute the time-varying optimal speed limit dynamically. However, for the consideration of safety and also to avoid of confusing drivers, the displayed speed limit is not allowed to revising frequently. In this study, we assume a \(T_C\)-length control horizon in which the speed limit remains constant.

Note that the optimization model and Kalman Filter model would be activated when the new detector data is available. However, the detector data update interval \(T_d\) is usually smaller than the control horizon length \(T_C\) in reality, which means multiple optimal speed limits could be obtained before the following control horizon. In this study, the last obtained speed limit will be used as the next displayed speed limit as long as the variance among those speed limits is smaller than the pre-determined threshold. Otherwise the median value would be used.

In real-world application applications, it can be imagined that not all the drivers would exactly follow the displayed speed limit. Therefore, the selected speed limit would be adjusted based on the detected compliance rate. Using the detected travel speed over the previous control horizon, the optimal speed limit would be adjust based on the detected speed:
\[ V_{\text{vsl}}(t+1) = V_{\text{opt}}(t+1) \cdot \frac{\bar{V}_d(t)}{V_{\text{vsl}}(t)} , \quad \text{if } \bar{V}_d(t) > V_{\text{vsl}}(t) \] (24)

where, \( V_{\text{vsl}}(t) \) is the displayed speed limit for control horizon \( t \); \( V_{\text{opt}}(t) \) denotes the selected speed values from the optimization model; \( \bar{V}_d(t) \) is the average detected speed during control horizon \( t \).

The architecture of the entire control system is shown in Fig. 3:

6. Numerical Example

To illustrate the applicability and efficiency of the proposed system, this study has employed VISSIM as an unbiased tool to evaluate the model performance. Using VISSIM-COM interface, this study developed a program to simulate bus operation and signal control logic by VB.NET. During the simulation, the program detects and records the real-time vehicle speeds and volumes, automatically activate the prediction and optimization models, and adjusts the optimal vehicle speeds according to the actual drivers’ compliance rates.
The layout the tested case is shown in Fig. 4. Based on the geometric feature, the whole freeway sketch is divided into nine segments, each of which has a length of 500 m. There are two on-ramps for flow entry which located at segment 0 and 5 respectively. Therefore, the merging area between segment 2 and 3 may cause a potential bottleneck when the upstream traffic volume is high. Also, the short distance between on-ramp (segment 1) and off-ramp (segment 0) may lead to a significant weaving effect and consequently forms another bottleneck. Based on the preliminary analysis, two VSL along with seven detectors are installed along the target freeway. It should be noted that the speed reduction point is located one segment ahead of the VSL sign since drivers’ perception distance is assumed to be one segment in this study.

The tested period is about two hours (6:00AM-8:00AM), which can correspond to a peak hour period. The demand pattern is represented in Fig. 5. Around 55% traffic flows are coming from the upstream segment and the rest are from the on-ramps. Also, about 15% approaching flows take the route via the downstream off-ramp, while the rest 85% flows enter the downstream freeway.

For model comparison, scenarios in terms of different compliance rates are tested and compared with the no-VSL control strategy. Also, to indicate the importance of considering compliance rates in a VSL system, the basic VSL model without speed adjustment (see Eq. 24) is employed for comparison. The tested scenarios are summarized as follows:

Scenario 1: No-VSL control;
Scenario 2: The proposed VSL control with 75% compliance rate;
Scenario 3: The basic VSL control with 75% compliance rate;
Scenario 4: The proposed VSL control with 50% compliance rate;
Scenario 5: The basic VSL control with 50% compliance rate.

Some model parameters are set as follows:
- The transition flow weight factor $\alpha_i$ is 0.95;
- The Speed density adjustment factor $\beta_i$ is 0.8;
- The congestion wave speed $\gamma$ is 25 km/h;
- The Jam traffic density is 100 veh/lane/km;
- The Critical traffic density is 35 km/h;
- The free flow speed is 100 km/h;
- The allowed speed limit variance $\delta$ between two adjacent interval is 10 km/h;
- Parameter $\nu$, $\tau$, $\kappa$ are calibrated by Papageorgiou et al. (2008), given by 20s, 35 km/h and 13 veh/lane/km.

In the Kalman Filter model, the deviation of measurement errors for the flow rate and speed are:

$$D(e^f_i(k)) = 50 \text{ veh/h}, \quad D(r^f_i(k)) = 50 \text{ veh/h}, \quad D(s^f_i(k)) = 50 \text{ veh/h};$$

$$D(e^s_i(k)) = 5 \text{ km/h};$$

The deviation of prediction errors for the flow rate and speed are:

$$D(e^f_i(k)) = 250 \text{ veh/h}, \quad D(e^s_i(k)) = 10 \text{ veh/h}$$

As a major MOE to evaluate traffic efficiency, the time-dependent travel time can clearly reflect the effectiveness of each control strategy. Figure 6-(a) presents the resulting travel time from these two models with 75% compliance rate and the No-VSL scenario. Notably, the travel time starts to increase when the freeway is becoming congested (after 7:00AM). Compared with the No-control scenario, the average travel time is reduced significantly in scenario 2 and 3, demonstrating the benefits under the VSL control. Specifically, the implementation of VSL can help to release traffic congestion more quickly, indicated by the smaller travel time in scenario 2 and 3 after 7:45AM. Also, according to the comparison between scenario 2 and 3, it is easily to observe that the proposed model considering the compliance rate can outperform the basic model. Hence, it can be concluded that taking drivers’ compliance rate into account is essential in a VSL system, even though the compliance rate is high.

Figure (a) Time-dependent travel time among scenario 1, 2 and 3 (75% compliance rate)
A further comparison between different scenarios is shown in Figure 6-(b). Note that during the congested time period (7:15-7:45 AM), the basic VSL model in scenario 5 failed to provide an efficient traffic control, but the travel time is reduced before the start of congestion. The proposed VSL model may not reduce the travel time during the most congested period (7:15-7:45 AM), however, it can still release the traffic congestion much earlier and consequently reduce the average delay. Based on these observations, it is obviously that the proposed model can outperform the basic model and it is more compatible to the decrease of compliance rate.

Table 1 summarizes the MOEs for all scenarios. To prevent the randomness of results, the data have been averaged over 10 simulation replications. Notably, all these VSL controlled scenarios can yield reduction in both average delay and vehicle stops. Among those four, Scenario-2 is the best one which yielded a reduction of 16.08 percent on the vehicle stops and 16.38 percent on the average travel time during the two-hour period. Also, under the lower compliance rate condition, the basic model in scenario 5 cannot offer a significant reduction on both average number of stops and average delay.

Table 1 Performance comparison between different scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>6:00-8:00 Ave. # of Stops</th>
<th>Improvement</th>
<th>6:00-8:00 Ave. Travel Time</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario-1</td>
<td>5.978</td>
<td>/</td>
<td>147.7</td>
<td>/</td>
</tr>
<tr>
<td>Scenario-2</td>
<td>5.017</td>
<td>-16.08%</td>
<td>123.5</td>
<td>-16.38%</td>
</tr>
<tr>
<td>Scenario-3</td>
<td>5.411</td>
<td>-9.48%</td>
<td>129.4</td>
<td>-12.39%</td>
</tr>
<tr>
<td>Scenario-4</td>
<td>5.479</td>
<td>-8.35%</td>
<td>134.8</td>
<td>-8.73%</td>
</tr>
<tr>
<td>Scenario-5</td>
<td>5.81</td>
<td>-2.81%</td>
<td>142.9</td>
<td>-3.25%</td>
</tr>
</tbody>
</table>

According to the simulation results, one can tentatively reach several preliminary conclusions from above analysis. First of all, a proper VSL system can effectively reduce the number of stops and travel time. However, without considering drivers’ compliance rate, the VSL system may not provide accurate prediction and yield an efficient traffic control. Under the low compliance rate condition, the current proposed model still required improvement since the reduction of average delay is not significant. One major reason is the simple adjustment strategy of speed limit, which can limit the control efficiency.

7. Numerical Example

In summary, this study has proposed a proactive VSL control model on recurrently congested freeway segments. The proactive model used embedded traffic flow relations to predict the evolution of congestion pattern and computed the optimal speed limit. To contend with the different drivers’ compliance rate, this study also proposed an adjustment strategy according to the detected actual speed during the past time horizon. The model has been investigated with different compliance rate condition and compared with the no-VSL scenario.
The extensive simulation analysis with VISSIM has revealed that the proposed VSL control models can significantly reduce the travel time and number of vehicle stops over the recurrent bottleneck locations. However, revealing the deficiency of the current adjustment strategy, one of our major further works is to develop a more in-depth model to capture the change of drivers’ compliance rate. Other on-going research tasks associated with VSL implementation include: the potential of using multiple control objectives, the identification of optimal detector locations for updating traffic conditions, and the number of VMS speed displays for smoothing speed transition between free-flow and the bottleneck traffic conditions.

References


