Improving Motorway Mobility and Environmental Performance via Vehicle Trajectory Data-Based Control

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\textbf{ABSTRACT} High cost and relatively low reliability of stationary sensors hinder the wide spread of advanced motorway traffic control measures. In this research, we propose a vehicle trajectory data based variable speed limit (VSL) controller to improve mobility and environmental performance of motorways. First, a model based estimator is designed to estimate traffic states using data directly derived from probe vehicle with spacing measurement equipment (PVSMEs). Extended kalman filter (EKF) and METANET model are employed as the data assimilation tool and the process model for the estimator, respectively. Next, we incorporate the estimator with a model predictive control (MPC) to realize optimal VSL control. Finally, a 3.2km stretch in Auckland, New Zealand is selected and simulated to evaluate the proposed VSL under various PVSME penetration rates and traffic scenarios. The simulation results reveal that the PVSME-based VSL controller offers an effective solution to improve mobility and environmental performance of motorways. With an increase in PVSME penetration rates, the mobility and environmental benefits of the PVSME-based VSL increase.

\textbf{INDEX TERMS} Emission reduction, travel time reduction, trajectory data, motorway control.

\textbf{I. INTRODUCTION}

Variable speed limit (VSL) is an emerging ITS measure for motorway traffic management where the speed limit of motorway sections is determined based on real-time traffic conditions with an attempt to improve safety and harmonize the traffic flow by decreasing speed variation among vehicles across lanes, within the same lane and also between upstream and downstream traffic flows. VSL control has also proven to be an effective measure for travel time and emission reduction of motorway systems \cite{1}--\cite{6}. The majority of the existing VSL systems utilize traffic measurements from the stationary sensors to determine the appropriate speed limits. As a foundation, reliable and accurate real-time traffic data ensures the success of a VSL system, which requires a high coverage of stationary sensors and consequently high installation and maintenance costs. Furthermore, the accuracy and precision of stationary sensors may be not reliable \cite{7}. Both high cost and relatively low reliability of stationary sensors hinder their deployment and, therefore, the wide spread of advanced motorway traffic control measures.

Although the original purpose of vehicle trajectory data is for advanced driver assistance systems (ADASs), i.e., autonomous driving and adaptive cruise control \cite{8}, it can be also valuable for macroscopic traffic condition monitoring and macroscopic controls since effective ADAS requires the precisely measured spacing and speed data of the vehicle. Several studies have been conducted to explore the utilization of data collected from ADAS-equipped vehicles which are also referred to as probe vehicle with spacing measurement equipment (PVSME). In \cite{9}--\cite{11}, the traffic state was estimated based on the trajectory data of PVSMEs.

Although mobile data collection has begun to spread in the practical uses, a limited number of studies have investigated how probe vehicles can be used as part of a motorway control system. In Yang and Jin \cite{12}, speed limits were provided to individual vehicles to smooth their trajectories in stop-and-go traffic. Kattan \textit{et al.} \cite{13} proposed a probe-based VSL algorithm using space mean speeds (SMSs) and corresponding space-based densities derived from probe vehicles.

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Khondaker and Kattan [14] presented a VSL control method for reducing the travel time, crash probability and fuel consumption in a connected vehicle environment.

Recent works have exploited the utilization of vehicle automation and communication technologies in mainstream traffic flow control. Grumert et al. [15] used communication between the infrastructure and the vehicles to transmit speed limits to upstream vehicles before the VMS become visible to the drivers. Roncoli et al. [16] investigated the use of vehicle automation and communication systems (VACS) for the coordinated application of ramp metering, VSL, and lane changing control. Müller et al [17] studied the impacts of different Automated Vehicle (AV) penetration rates on VSL performance. Han et al. [18] developed VSL algorithms to improve bottleneck discharge rates and reduce system delays using the Connected Vehicle (CV) technology. Han and Ahn [19] developed a breakdown probability model based on the observed headways. They designed a proactive control method to reduce the breakdown probability considering connected automated vehicles (CAVs). Perraki et al. [20] used the MPC strategy proposed by Roncoli et al. [21] to assess CAVs and conventional control measures for a complex real network in a realistic simulation environment. Grumert and Tapani [22] proposed a CV based VSL system in which CVs are used to estimate traffic state and the current speed limit is communicated directly to the CVs.

In general, vehicle trajectory data has been shown to be useful for traffic state estimation, which can be used as input to the VSL system. Nevertheless, previous papers leave several issues that could be enhanced. Firstly, the majority of proposed VSL systems completely or partially rely on the information from fixed point sensors. It is interesting to exploit how PVSME can be used as the only data source. Secondly, limited studies considered the influence of PVSME penetration on traffic flow which are important in VSL control.

In this research, we propose a trajectory based VSL controller to improve mobility and environmental performance of motorways. First, a model based estimator is designed to estimate traffic states using data directly derived from PVSMEs. Extended Kalman filter (EKF) and METANET model are employed as the data assimilation tool and the process model for the estimator, respectively. Next, we incorporate the estimator with a model predictive control (MPC) to realize optimal VSL control. Finally, a 3.2km stretch in Auckland, New Zealand is selected and simulated to evaluate the proposed VSL under various PVSME penetration rates and traffic scenarios.

II. MODEL BASED TRAFFIC STATE ESTIMATOR

In this research, we propose a PVSME data based traffic state estimation (TSE) method, as illustrated in Fig. 1. The TSE method consists of: a dynamic traffic flow model (process model), an observation model; and an extended Kalman filter. The first two elements can be cast in a discrete state-space form:

\[ x(t+1) = f(x(t), u(t)) \quad (1) \]
\[ y(t) = h(x(t)) \quad (2) \]

where, \( f(.) \) and \( h(.) \) are process and observation models respectively; \( t \) is TSE time index; \( x(t) \) and \( y(t) \) are state and observation vectors respectively; and \( u(t) \) is a vector of inputs and disturbances.

A. PROCESS MODEL

We select an extended METANET model by Hegyi et al. [23] incorporating the effect of VSL is selected to describe traffic dynamics. The METANET model represents a network as a directed graph with the links (indicated by the index \( m \)) corresponding to motorway stretches. Each link \( m \) is divided into \( N_m \) segments (indicated by the index \( i \)) of length \( L \). Each segment \( i \) of link \( m \) is characterized by the traffic density \( \rho_{m,i}(k) \), the mean speed \( v_{m,i}(k) \) (km/h), and the traffic volume \( q_{m,i}(k) \), where \( k \) indicates the time index. And \( T \) is the time step used for the simulation of the traffic flow (typically \( T = 10 \) s).

The outflow of each segment is equal to the density multiplied by the mean speed and the number of lanes on that segment (denoted by \( \lambda_m \)):

\[ q_{m,i}(k) = v_{m,i}(k)\rho_{m,i}(k) \quad (3) \]

The density of a segment equals the previous density plus the inflow from the upstream segment, minus the outflow of the segment itself:

\[ \rho_{m,i}(k+1) = \rho_{m,i}(k) + \frac{T}{\lambda_m L_m} [q_{m,i-1}(k) - q_{m,i}(k)] \quad (4) \]

The mean speed at time instant \( k+1 \) equals the mean speed at time instant \( k \) plus a relaxation term that expresses that the drivers try to achieve a desired speed, a convolution term that expresses the speed increase (or decrease) caused by the
inflow of vehicles, and an anticipation term that expresses the speed decrease (increase) as drivers experience a density increase (decrease) downstream:

\[ v_{m,i}(k+1) = v_{m,i}(k) + \frac{T}{\tau} [V[q_{m,i}(k)] - v_{m,i}(k)] \]
\[ + \frac{T}{L_m} [v_{m,i-1}(k) - v_{m,i}(k)] v_{m,i}(k) \]
\[ - \frac{\vartheta T}{\tau L_m} \rho_{m,i+1}(k) - \rho_{m,i}(k) \]
\[ = \frac{\vartheta T}{\tau L_m} \rho_{m,i}(k) + \gamma \]  
\[ V[q_{m,i}(k)] = \min[v_{\text{free},i}, \exp[- \frac{1}{\alpha_m} \left( \frac{\rho_{m,i}(k)}{\rho_{\text{crit},m}} \right)^\alpha_m], \]
\[ (1 + a) v_{\text{control},i}(k)] \]  

(5)  

(6)

where, \( \vartheta \) is speed anticipation term parameter (km²/h), \( \tau \) is time constant of the speed relaxation term (h), \( \gamma \) is METANET speed anticipation term parameter (veh/km/lane) and \( \alpha_m \) are model parameters; \( v_{\text{control}}, \rho_{\text{crit}}, v_{\text{free}}, \) and \( a \) is the speed limit, critical density, free flow speed and non-compliance rate respectively.

At each METANET model time index \( k \), the traffic states (mean speed, density and volume) are aggregated. The relationship between the METANET model time index \( k \) and data-assimilation time index \( t \) is given by

\[ k = t \times C \]  

(7)

where, \( C \) is an integer.

The state vector \( x(t) \) and input vector \( u(t) \) is defined as follows:

\[ x(t) = \begin{bmatrix} \rho_{1,1}(t) \cdots \rho_{m,i}(t) \cdots \rho_{M,N_M}(t) \\ v_{1,1}(t) \cdots v_{m,i}(t) \cdots v_{M,N_M}(t) \end{bmatrix} \]  

(8)

\[ u(t) = \begin{bmatrix} q_0(t) \\ r_{on,1,1}(t) \cdots r_{on,m,i}(t) \cdots r_{on,M,N_M}(t) \\ r_{off,1,1}(t) \cdots r_{off,m,i}(t) \cdots r_{off,M,N_M}(t) \\ v_{\text{control},1,1}(t) \cdots v_{\text{control},m,i}(t) \cdots v_{\text{control},M,N_M}(t) \end{bmatrix} \]  

(9)

where \( q_0, r_{on} \) and \( r_{off} \) are mainline inflow, on-ramp inflow and off-ramp outflow respectively.

**B. OBSERVATION MODEL**

The observation vector \( y(t) \) is defined to have the same property with the state vector \( x(t) \) as

\[ y(t) = \begin{bmatrix} \rho'_{1,1}(t) \cdots \rho'_{m,i}(t) \cdots \rho'_{M,N_M}(t) \\ v'_{1,1}(t) \cdots v'_{m,i}(t) \cdots v'_{M,N_M}(t) \end{bmatrix} \]  

(10)

where, \( \rho'(t) \) and \( v'(t) \) can be estimated using collected PVSME data.

We modified a simplified TSE method by Seo et al. [10] to estimate traffic states (density and speed) using PVSME data. Fig. 2 illustrates the concept of the method via a time-space diagram, where \( s_n \) are time-space regions between the

![FIGURE 2. Time-space region A with probe vehicle data.](image-url)
TABLE 1. EKF estimation procedure.

- Set $t = 0$, initialize $x_0$, $P_0$, and other model variables.
for $t=1:N_t$ (for each time step)
- Prediction step
  Calculate:
  a prior state estimate $\hat{x}^- (t)$
  a prior error covariance $P^- (t)$
- Correction step
  Calculate:
  Kalman gain $K(t)$
  a posterior state estimate $\hat{x} (t)$
  a posterior error covariance $P(t)$

By replacing $N(A)$ in (17)-(19) with $PV(A)$ which is the set of all PVSMEs in $A$, $\rho(t), v(t)$ in (10) and $r_{on}, r_{off}, q_0$ in (8) can be computed via

$$q' (A) = \sum_{n\in PV(A)} D_n(A)$$
$$\rho' (A) = \sum_{n\in PV(A)} T_{nn}(A)$$
$$v' (A) = \sum_{n\in PV(A)} D_n(A)$$

C. DATA-ASSIMILATION

The EKF applies the Kalman filter procedure to the non-linear traffic systems via linearizing the state-space traffic system models. The EKF estimation procedure is outlined in Table 1. The general procedure of EKF can be described as follows: In prediction step, the system equation is used to compute the predicted state $\hat{x}^- (t|t-1)$ that serves as a prior state estimate

$$\hat{x} (t|t-1) = f[\hat{x} (t-1|t-1), u (t-1)]$$

A prior for the error covariance $P(t|t-1)$ is given by

$$P(t|t-1) = F(t)P(t|t-1)F^T(t) + E_o(t)$$

where $F(t)$ is the Jacobian matrix associated with $f(.)$; and $E_o(t)$ is the covariance matrix associated with $e_o(t)$.

In the correction step, the predictions of mean and covariance are corrected based on the observations. The Kalman gain $K(t)$ is calculated to determine the optimal weight put on both the predicted state and observation input

$$K(t) = \frac{P(t|t-1)H(t)}{H(t)P(t|t-1)H^T(t) + E_o(t)}$$

where $H(t)$ is the Jacobian matrix associated with $h$; and $E_o(t)$ is the covariance matrix associated with $e_o(t)$. Then, The state estimate $\hat{x} (t|t)$ and error covariance $P(t|t)$ are updated as follows:

$$\hat{x} (t|t) = \hat{x} (t|t-1) + K(t)[y(t) - h(\hat{x} (t|t-1))]$$
$$P(t|t) = [I - K(t)H(t)]P(t|t-1)$$

where $I$ denotes the identity matrix. At each time step, EKF performs prediction and correction. This recursive assimilation technique converges, as the error covariance $P$ tends to get smaller and smaller over time.

III. MODEL PREDICTIVE CONTROL

We apply the MPC to solve the optimal PVSME-based VSL control problem. The objective of MPC is to obtain a sequence of control actions yielding an optimal traffic behavior. The METANET model is again employed as the prediction model for MPC scheme, in which dynamic evolution of traffic states is described by

$$x(t + 1) = f[x'(t), u_{control}(t), u_{uncontrol}(t)]$$
$$x'(t) = [\hat{\rho}_1, \hat{\rho}_2, \ldots, \hat{\rho}_{M,N_M}(t)]$$
$$u_{control}(t) = [v_{control,1,1}(t), v_{control,1,2}(t), \ldots, v_{control,M,N_M}(t)]$$
$$u_{uncontrol}(t) = [r_{on,1,1}(t), r_{on,1,2}(t), \ldots, r_{on,1,M,N_M}(t)]$$

where, $x'(t)$ is the last estimated state vector at time step $t$; $\hat{\rho}_{m,i}(t)$ and $\hat{v}_{m,i}(t)$ are estimated based on the collected PVSME data using the proposed TSE method.

In this study, the MPC controller finds the optimal control actions $v_{control,m,i}$ along the control horizon $N_a$ by minimizing the following objective function:

$$J(t) = T \sum_{t=1}^{N_p} \left[ \sum_{m,i \in I_{on}} w_{m,i}(t + l) + \sum_{m,i} \rho_{m,i}(t + l) \right] + a_{vsl} \sum_{l=0}^{N_a - 1} \sum_{m,i \in I_{on}} [v_{control,m,i}(t + l) - v_{control,m,i}(t + l - 1)]^2$$

subject to

$$v_{control,m,i}(t + l) - v_{control,m,i}(t + l - 1) \leq Limit_1$$
$$v_{control,m,i}(t + l) - v_{control,m,i-1}(t + l) \leq Limit_2$$

where, $N_p$ is the prediction horizon ($N_p \geq N_a$); $a_{vsl}$ is a non-negative weight parameter; $w_{m,i}$ is the on-ramp queue length; and $I_{on}$ and $I_{on}$ are the sets of pairs of indexes ($m$, $i$) of the links and segments with VSL controllers and on-ramps respectively. The objective function contains one term for the Total Travel Time (TTT) and one term penalizing abrupt variations in VSL. Spatial and temporal difference between the VSL values are constrained via (33) and (34) so as to ensure driver safety and comfort. Fig. 3 illustrates the structure of the MPC based VSL controller.

IV. DESCRIPTION OF THE TEST BED

A real motorway section was chosen to evaluate the PVSEM-based VSL. The considered section is part of the Auckland Motorway State Highway 1 (SH1) in New Zealand.
FIGURE 3. Structure of MPC based VSL controller.

FIGURE 4. Layout of the test bed.

(see Fig. 4) which contains two pairs of on-off ramps and 9 detection locations (black box). The 3.2 km stretch was simulated using SUMO micro-simulator [24]. New Zealand Transport Agency provided the real traffic data collected from fixed detectors. The simulation model was calibrated and validated based on the GEH value [25].

The proposed VSL strategy employs METANET model to describe traffic dynamics in which several parameters need to be calibrated so as to have a realistic model. The calibration is performed by using genetic algorithm whose purpose is to minimize the difference between the data coming from the extended METANET model and the “real” data coming from the developed SUMO model. The objective function is defined as

\[
J'(k) = \sum_{k=1}^{K} \sum_{m=1}^{M} \left( \frac{q_{\text{metanet}} - q_{\text{sumo}}}{q_{\text{average}}} \right)^2 \\
+ \sum_{k=1}^{K} \sum_{m=1}^{M} \left( \frac{\rho_{\text{metanet}} - \rho_{\text{sumo}}}{\rho_{\text{average}}} \right)^2 \\
+ \sum_{k=1}^{K} \sum_{m=1}^{M} \left( \frac{v_{\text{metanet}} - v_{\text{sumo}}}{v_{\text{average}}} \right)^2
\]  

(35)

where metanet and sumo indicate the data from METANET model and SUMO model respectively. We use the average to have compatible measures to add.

The utilized numerical algorithm to solve the MPC optimization problem is the MATLAB implementation of the SQP algorithm (fmincon) that is efficient in MPC optimization. This optimization method has the advantage that the constraints can be formulated explicitly, without the use of a penalty term in the objective function.

Two emission models are available in SUMO, one that is based on the German HBEFA (the older one), and one that is based on PHEM from the TU Graz and is named PHEMlight in SUMO. The idea is the same, based on interpolation they assign to the acceleration and speed in each time-step the emission values. The difference is in the tables behind these two: the HBEFA tables are a kind of average over many different vehicles and different traffic scenarios, while the PHEM data-base is much cleaner. A good description can be found in [26]. The simulation results shown here are based on the HBEFA approach. It should be noted that we have tested both models in a few examples, the PHEMlight produced slightly higher, but not totally different results.

Total travel time (TTT) is commonly used to reflect overall performance of the network. A lower TTT represents lower delay and a higher outflow and therefore better traffic conditions. TTT can be expressed as follows in vehicles times hours (veh*h):

\[
\text{TTT} = T \sum_{k=1}^{K} \sum_{i=1}^{N} \rho_i(k) \Delta I\text{ (36)}
\]

where, \( \rho_i \) is density of a segment \( i \), \( T \) is measurement duration, \( \Delta I \) is the distance between two measured stations \( i-1 \) and \( i \), \( N \) is a number of measurement stations, and \( K \) is a time horizon.

Two levels of traffic conditions were tested, namely, heavily congested traffic (mean volume > 0.95 * capacity, 6:30am-8:30 am) and lightly congested traffic (mean volume ≈ 0.95 * capacity, 9:00am-11:00 am). Three different control scenarios were tested including:

- no control scenario in which no control action is applied;
- detector-based VSL control scenario in which speed limits are determined based on the data from loop detectors; and
- probe-based VSL control scenario in which the proposed VSL controller is applied.

V. ANALYSIS RESULTS

A. HEAVILY CONGESTED TRAFFIC

In this study, total travel time (TTT) was used to measure the mobility gains of VSL. Fig. 5 presents the TTT values computed for different control scenarios under heavily congested traffic conditions. It was observed that with the increase of PVSME shares, the effectiveness of the proposed probe-VSL controller increased. At the initial stage of PVSME deployment (1% penetration rate), the mobility gain due to the probe-based VSL was negligible; while, the probe-based VSL with 5% PVSMEs recorded an 8% improvement in TTT compared to the no-control case. The improvement further increased to 16% and 22% at 10% and
20% PVSME penetration rates, respectively. When more than 30% PVSMEs were present on motorways, the proposed VSL controller witnessed around 30% reduction in TTT compared with the no-control scenario, which approached the TTT reduction produced by the stationary detector-based VSL controller.

To investigate the influence of the probe-based VSL on environmental performance of motorway systems, we calculated the emissions and fuel consumption under heavily congested traffic, which are shown in Table 2. It can be clearly observed that emissions and fuel consumption were dramatically reduced via applying VSL. Even the probe based VSL with relatively low PVSME shares (e.g., 5% or 10% shares) could yield noticeable environmental benefits. The lowest emissions and fuel consumption were recorded when 50% PVSMEs were deployed among all the tested probe-based VSL cases.

B. LIGHTLY CONGESTED TRAFFIC

Fig. 6 presents the TTT values for different scenarios under lightly congested traffic. The trend of TTT changes under lightly congested traffic was similar to that under heavily congested traffic. Nevertheless, reduction in TTT was found to be less remarkable in magnitude in lightly congested cases when compared against their counterparts under heavily congested traffic. This might be due to the fact that the motorway stretch was less congested under such condition, thus the impact of VSL on traffic flow decreased. More specifically, at relatively low PVSME penetration rates (1%-5%), the TTT reduction due to VSL was not that significant (less than 3%). When 20% or more PVSMEs were running on motorways,

![Graph showing Total travel time for different scenarios under heavily congested traffic.](image)

**FIGURE 5.** Total travel time for different scenarios under heavily congested traffic.

![Graph showing Total travel time for different scenarios under heavily congested traffic.](image)

**FIGURE 6.** Total travel time for different scenarios under heavily congested traffic.

**TABLE 2.** Emissions under heavily congested traffic.

|         | Baseline | Change* |
|---------|----------|---------|
|         | no-control | 1% | 5% | 10% | 20% | 30% | 50% | Detector |
| CO (mg) | 9.7 x 10^3 | 3% | 14% | 22% | 40% | 56% | 61% | 62%       |
| CO₂ (mg) | 6.5 x 10^4 | 2% | 10% | 16% | 31% | 41% | 46% | 48%       |
| HC (mg)  | 7.2 x 10^5 | 2% | 14% | 20% | 36% | 47% | 56% | 57%       |
| PM₁₀ (mg) | 1.2 x 10^6 | 2% | 12% | 18% | 31% | 46% | 52% | 53%       |
| NOₓ (mg) | 2.4 x 10^6 | 2% | 12% | 18% | 32% | 46% | 53% | 55%       |
| Fuel (ml) | 2.8 x 10^9 | 2% | 13% | 17% | 29% | 38% | 45% | 47%       |

*compared to no-control scenario
about 20% improvement in TTT (compared against the no control case) was achieved by the probe-based VSL, which was comparable to that of the detector-based VSL.

**TABLE 3. Emissions under lightly congested traffic.**

| Behind PVSME penetration rates and traffic scenarios. The estimates were compared with ground-truth data using compared Root Mean Square Error (RMSE). It was observed that the probe-based VSL exerted the positive impact on environmental performance of motorway systems. The environmental benefits of the motorway increased with the increase of PVSME shares. This amelioration was mainly contributed by the improved traffic conditions.

**TABLE 4. State estimation results.**

| PVSME rate | RMSE |
|------------|------|
| Lightly Congested |      |
| Speed (km/h) | 24 20 14 12 5 3 |
| Density (veh/km) | 28 21 15 14 7 3 |
| Heavily Congested |      |
| Speed (km/h) | 27 18 16 15 8 4 |
| Density (veh/km) | 31 21 17 15 10 5 |

*C* compared to no-control scenario

Table 3 shows the environmental measures calculated using lightly congested traffic. It was observed that the probe-based VSL exerted the positive impact on environmental performance of motorway systems. The environmental benefits of the motorway increased with the increase of PVSME shares. This amelioration was mainly contributed by the improved traffic conditions.

**C. TRAFFIC STATE ESTIMATION**

Table 4 shows the state estimation results for different PVSME penetration rates and traffic scenarios. The estimates are compared with ground-truth data using compared Root Mean Square Error (RMSE). It was observed that the PVSME penetration rate plays a vital role in estimation performance. Higher PVSME rate resulted in better estimation performance. It was also shown that lightly congested scenario produced lower RMSE values when compared with heavily congested scenario.

**VI. CONCLUDING REMARKS**

Due to their high cost and relatively low reliability, stationary sensors hinder the wide spread of advanced motorway traffic control measures. However, few studies have explored the utilization of trajectory data in VSL systems. In this research, we developed an enhanced VSL controller on the basis of PVSME data. The proposed controller equipped with various PVSME penetrate rates (ranging between 1% and 50%) was compared with its detector based counterpart under two traffic conditions, namely, heavily congested traffic (>0.95 * capacity) and lightly congested traffic (≈0.7 * capacity). TTT and emissions were adopted to measure the impact of the PVSME based VSL on mobility and environmental performance of motorway systems, respectively. The simulation results showed that the proposed VSL controller that is solely based on trajectory data offered an effective solution to improve mobility and environmental performance of motorway systems. With an increase in PVSME penetration rates, the benefits of the probe-based VSL increased. When 30% or more PVSME were present on motorways, the overall performance of the PVSME-based VSL approached that of the detector-based VSL.

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