Title
An Innovative Framework to Evaluate the Performance of Connected Vehicle Applications: From the Perspective of Speed Variation-Based Entropy (SVE)

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An Innovative Framework to Evaluate the Performance of Connected Vehicle Applications: From the Perspective of Speed Variation-Based Entropy (SVE)

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Abstract—Recently, a significant number of Connected Vehicle (CV) applications have emerged to offer solutions to some of the problems caused by increasing traffic demands. To better understand the influence of different CV applications on traffic in a relatively unified manner, a novel measure of effectiveness (MOE) called speed variation-based entropy (SVE) is proposed. An analytical study was carried out on different types of CV applications by relating SVE with other conventional MOEs on safety, mobility, and environmental sustainability. Four applications–High Speed Differential Warning (HSDW), Lane Speed Monitoring (LSM), Eco-Speed Harmonization (ESH), and Eco-Approach and Departure (EAD), representing safety-, mobility- and environment-focused CV applications–were selected for detailed evaluation. Results from the sensitivity analysis on technology penetration rate and congestion level reveal that: 1) SVE can accurately represent the speed variation of individual vehicles and the overall traffic; 2) the proposed SVE distribution can be used as an MOE for CV applications in a more holistic way and at different scales; and 3) the overall SVE has a strong positive correlation with conventional MOEs (i.e., average conflict frequency and average fuel consumption) especially under freeway scenarios. Therefore, conventional MOEs can be estimated and explained by SVE under a variety of scenarios.

I. Introduction

Increasing demand for travel causes problems in terms of traffic accidents, congestion, and greenhouse gas (GHG) emissions. For example, over 30,000 people perish in crashes on U.S. highways in 2016 [1]. Also, the global status report on road safety 2015 indicates that worldwide the total number of road traffic deaths has plateaued at 1.25 million per year [2]. Moreover, the ever-growing travel demand contributes to significant congestion on both highways and major urban corridors during peak hours [3]. The U.S. Federal Highway Administration's Urban Congestion Report estimated that the average duration of daily congestion in 2016 was more than 4 hours in more than 50 American metropolitan areas and the hours of congestion keeps increasing [4]. In addition, according to the U.S. Environmental Protection Agency (EPA)'s annual report [5], the transportation sector is one of the largest contributors to nationwide GHG emissions, which increased by 4.2% in 2015, the third successive year of increases in transport emissions [6]. All of the aforementioned issues become more complex when considering the unpredictability of driver behaviors, such as frequent stop-and-go, overtaking, and cut-in maneuvers.

Over the last decade, Connected Vehicle (CV) technology has emerged, and many CV-based applications have been developed as promising solutions to these problems [7]–[9]. In general, CV applications can be divided into three major categories: safety-focused, mobility-focused, and environment-focused. As summarized in the Connected Vehicle Reference Implementation Architecture (CVRIA) [10], a significant amount of safety-/mobility-/environment-oriented CV applications have been developed. Some of them have already been implemented in real-world situations, including Blind Spot Warning (BSW), Emergency Electronic Brake Light (EEBL), Speed Harmonization, Smart Parking, and Connected Eco-driving. Some CV applications consider road conditions as another influential factor to transportation performance [11]. Besides these fully-developed applications, many extended CV applications are still under development, such as Lane Speed Monitoring (LSM) [12], High Speed Differential Warning (HSDW) [13] and Eco-Speed Harmonization (ESH) [14]. In addition, there are numerous research activities all over the world studying vehicle-to-everything-based connected and automated vehicles [15]. Examples include the safe- and eco-driving control for connected and automated vehicles [16], the collision-free departure optimization of automated vehicles in the highway environment [17], and the coordination of connected and automated vehicles at intersections and highway on-ramps [18].

To evaluate the performance of CV applications, a variety of conventional Measures of Effectiveness (MOEs) have been proposed over the years, mainly covering safety, mobility, and environmental sustainability. For example, with regard to the safety MOE, Jiang et al. used time-to-collision (TTC) as the surrogate measure of collision severity to address vehicle-to-pedestrian (V2P) conflict, with the goal of providing databases for future CV development [19]. Fan et al. evaluated traffic conflicts using the Surrogate Safety Assessment Model (SSAM) [20]–[21], in which the TTC can be predicted according to relative speed and longitudinal offset between two adjacent vehicles. As for mobility MOEs, Ernst et al. proposed the estimated travel time distribution as a measure of effectiveness to conduct a comparative study on vehicle identification methods [22]. Also, the corridor efficiency, i.e., the ratio of vehicle miles traveled (VMT) to vehicle hours traveled (VHT), was used in traffic models to measure highway congestion [23]. In addition to average speed, many other parameters, such as Positive Kinetic Energy (PKE), Total Absolute second-by-second Difference (TAD) and Coefficient of Variation, were investigated to evaluate the variability in velocity. These parameters can reflect, to some extent, the "stop-and-go" pattern in traffic, where acceleration and deceleration play an important role [24]. In terms of environmental MOEs, Barth et al. used outputs from the Comprehensive Modal Emissions Model (CMEM) to compare the fuel consumption and CO2 emissions of eco-driving vehicles versus non-eco-driving vehicles under a variety of conditions [25].

However, few studies have focused on holistically evaluating CV applications in terms of safety, mobility, and environment [26]. Even fewer studies have attempted to examine the speed variation-based MOE and explore its connection with conventional MOEs. In this paper, Speed Variation-based Entropy (SVE) is recommended as a way to evaluate the effectiveness of different CV applications on application-equipped vehicles and unequipped vehicles in terms of the system's degree of order. Four CV applications, i.e., HSDW, LSM, ESH, and EAD, were selected to represent three major categories: safety-, mobility-, and environment-focused, and evaluated in the framework of SVE.

The rest of this paper is organized as follows: Section II presents the research background of three conventional MOEs, modeling tools, and four selected CV applications, followed by the description of a proposed framework for SVE-based evaluation in Section III. Section IV briefly introduces the simulation model and scenarios. In Section V, simulation studies are conducted to evaluate the effectiveness of target applications from the perspective of SVE as well as safety, mobility, and environmental impacts. The last section concludes this paper with further discussion and future work.

II. Research Background

A. Conventional MOEs

Conventionally, three major types of MOEs are used to evaluate the performance of CV applications:

- *Safety MOEs*. Minimum time to collision (TTC) is regarded as a surrogate measure of the likelihood of a conflict occurring [27]. An occurrence when the minimum TTC drops below a predefined threshold may be recognized as a potential conflict. In this study, safety performance is evaluated by the normalized conflict frequency defined below:

$$CF = \frac{\sum_{i=1}^{n} cn_i}{n} \tag{1}$$

  where cn_i is the number of conflicts caused by vehicle i; n is the total number of vehicles. It is noted that in this study each conflict is only associated with the second vehicle (i.e., the one occupying the conflict area at a later instant) which is assumed to be responsible for the potential conflict.

- *Mobility MOEs*. Corridor efficiency or average speed, $\bar{v}$, is used in this study to evaluate mobility performance:

$$\bar{v} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{N_t} VMT_{i,t}}{\sum_{t=1}^{T}\sum_{i=1}^{N_t} VHT_{i,t}} \tag{2}$$

  where $VMT_{i,t}$ and $VHT_{i,t}$ represent vehicle miles traveled and vehicle hours travelled, respectively, for vehicle i in time step t; N_t is the total vehicle number in a range of road network in time step t; T is the certain time duration of interest within the range of road network.

- *Environmental MOEs*. In this study, the fuel consumption of an individual vehicle or fleet is used to measure the environmental performance.

B. Modeling Tools

Three modeling tools are used in this study:

- *PARAMICS*. The PARAllel MICroscopic Simulator is a high-resolution traffic simulation tool capable of modeling large-scale roadway networks and the movement of each individual vehicle [28]. By taking advantage of Application Programming Interfaces (APIs) (coded in C++ language), users can customize individual vehicle behavior, such as longitudinal speed, lane changing, and route choice, and access output data for performance evaluation, including 1) VMT and VHT; 2) vehicle trajectory files; and 3) fuel consumption.
- *SSAM*. The Surrogate Safety Assessment Model (SSAM) is a post-processing model designed for the safety analysis of traffic facilities, roadway designs, and operational strategies. It analyzes the vehicle trajectory data (.trj file) generated from a microscopic simulation model (Paramics in this study) [21], and outputs the number of potential conflicts as described in Section II.A.
- *MOVES*. The MOtor Vehicle Emission Simulator (MOVES) is a state-of-the-art modeling tool developed by the U.S. Environmental Protection Agency (USEPA) for estimating the energy consumption and emissions from mobile sources at different scales (from the macroscopic to mesoscopic and microscopic levels) [29]. More specifically, the following four steps are conducted: 1) extracting second-by-second speed profiles for each individual vehicle; 2) calculating the associated vehicle specific power (VSP); 3) identifying the operating mode (OpMode) distribution based on speed, acceleration, and VSP; and 4) estimating the rates of energy consumption and emissions according to the look-up tables available in the MOVES database for the associated vehicle type.

The interaction among different modeling tools is illustrated in Figure 1.

C. Representative CV Applications

Four selected CV applications have been selected for analysis, representing safety-, mobility-, and environment-focused applications, respectively. These applications include High Speed Differential (HSDW), Lane Speed Monitoring (LSM), Eco-Speed Harmonization (ESH), and Eco-Approach and Departure (EAD).

1) High Speed Differential Warning (HSDW) Application

A vehicle-to-vehicle (V2V) communication-based CV application, named High Speed Differential Warning (HSDW), was recently developed [13]. Information (such as instantaneous speed and location) can be obtained via V2V communication in the form of Basic Safety Messages (BSM) [30]. By exchanging such information within the communication range, this application can identify different scenarios (see Figure 2) where high-speed differentials exist between the host vehicle and remote vehicles on the current lane or adjacent lanes. Then the application will provide the driver with guidance on deceleration or lane-changing operation, aiming to reduce the risk of collision [13].

2) Lane Speed Monitoring (LSM) Application

The Lane Speed Monitoring (LSM) application, proposed by Tian et al. is aimed at providing the driver with downstream lane-level traffic conditions via connectivity and assistance in selecting the lane with the least travel time. The lane-change recommendations provided to the driver rely on the estimate of traffic states, which are the downstream lane-level average speeds calculated within a certain time duration based on the collection of dynamic vehicle information within the communication range [12].

3) Eco-Speed Harmonization (ESH) Application

In addition to HSDW and LSM, another CV application developed by Wu et al. is Eco-Speed Harmonization (ESH), which is able to advise the driver with the appropriate speed needed to reduce unnecessary stop-and-go maneuvers, and thus,

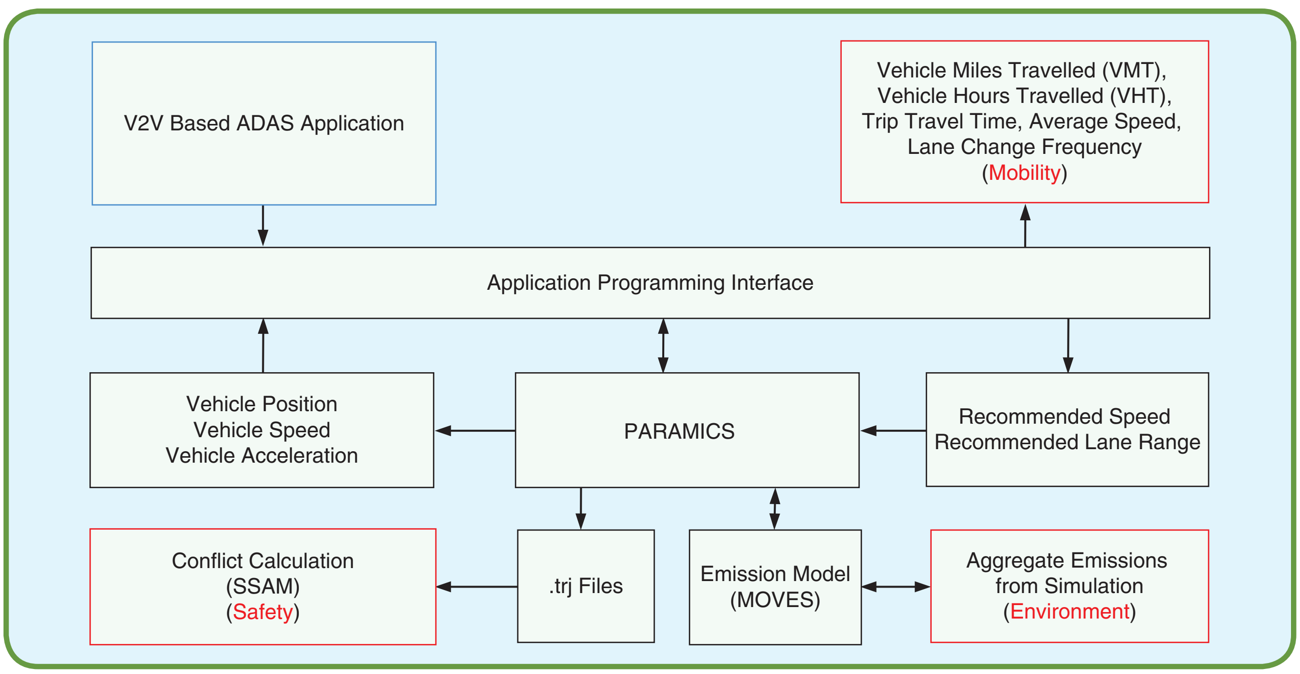

FIG 1 Interaction among different modeling tools.

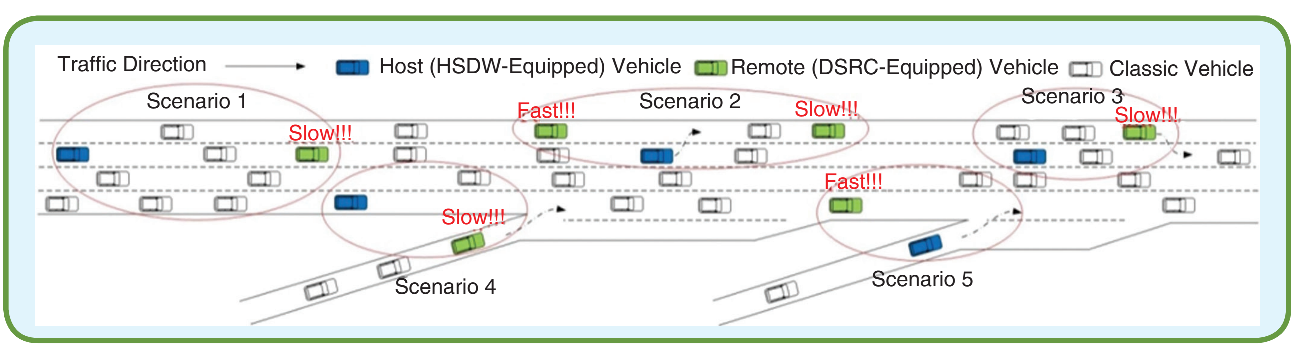

FIG 2 Possible HSDW scenarios [13].

regulate traffic flow based on downstream traffic conditions, especially when approaching bottleneck/congestion areas [10]. Connected vehicles and DSRC-equipped roadside equipment exchange information with each other, and the average speed of road segments can be monitored and transmitted to the associated connected vehicles to encourage smooth driving at energy-efficient speeds for entire traffic flows [14].

4) Eco-Approach and Departure (EAD) Application

In addition to the three CV applications mentioned above, the Eco-Approach Departure (EAD) application [31] is designed to reduce energy consumption for the vehicle traveling along signalized corridors, by communicating with the signal phase and timing (SPaT) information of the upcoming traffic signals. More specifically, the application-equipped vehicle uses this traffic signal data, provides advisory speed profile to the driver and allows the driver to adapt the vehicle's speed to pass the next traffic signal in the most eco-friendly manner.

III. Framework of Speed Variation-Based Entropy (SVE)

A. Entropy

Entropy has been widely used in many branches of science, ranging from classical thermodynamics to statistical mechanics and information theory [32]–[35]. In thermodynamics, entropy has been loosely associated with the amount of order or chaos. It can be understood as a measurement of molecular disorder within a macroscopic system and the maximum entropy will be achieved as an isolated system spontaneously evolves toward thermodynamic equilibrium. In his seminal paper, Shannon put forward the Shannon entropy and used it as a measure of the amount of information that is missing before reception [36]. More specifically, the Shannon entropy of a discrete variable X with a probability mass function (PMF) $p(x) = Pr\{X = x\}, x \in X$, is defined as

$$H(X) = -\sum_{x} p(x) \log_2 p(x) \tag{3}$$

Further, Prigogine and Lewis et al. defined entropy as a measure of ignorance [37], regarding the gain in entropy as loss of information [38]. In transportation-related research, Baslamisli et al. proposed an approach to identify the surface type of road by calculating the entropies of the sprung mass vertical acceleration of a vehicle running over roads with different qualities [39]. Tan et al. used the entropy of driver steering angle to measure discontinuity and to evaluate the effectiveness of drivers' steering controls to distinguish driving skill levels [40]. In addition, Wang et al. proposed an approach for marking intersection areas by analyzing the entropy of vehicles' moving direction [41].

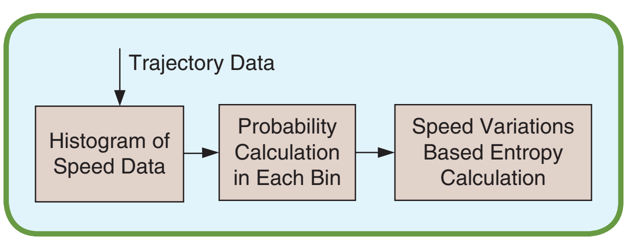

FIG 3 Three-step procedure for SVE calculation.

B. Speed Variation-Based Entropy (SVE)

Fluctuations in vehicle speed have a significant impact on traffic operation. As mentioned previously, a variety of MOEs have been developed to address the variability in velocity. However, most of them rely on conventional statistics, such as mean and standard deviation, which may not be able to capture enough spectrum of the speed distribution. Inspired by the Shannon entropy (as described in Section III.A), the Speed Variation-based Entropy (SVE) is proposed in this study to evaluate the performance of CV applications in terms of smoother maneuvering of equipped vehicles and entire traffic when additional information is introduced via connectivity. A three-step procedure to calculate the SVE from each individual vehicle's trajectory is show in Figure 3.

Based on second-by-second trajectory data, a histogram of the speed data classifies speed data into a certain number of bins, representing the distribution of sample frequency over the speed range. The probability value in each bin can be calculated by dividing the frequency per bin by the total size of the speed data. Equation (3) is applied to calculate the entropy of speed variations. The entropy in this study is in units of bits, since base-2 logarithms are used.

By calculating the SVE-based MOE on speed trajectories, the speed variations information can be grouped from a trip-by-trip perspective. For an individual vehicle, the time-speed diagram is employed to describe its speed characteristics changing with time. The 2-D time-speed information could then be reduced into one single entropy value, which is the SVE defined above. Therefore, for each vehicle trip, there is an associated SVE value to represent speed variations during the whole trip. Then, the SVE distribution based on the SVE values of all trips can be obtained. It is expected that the trip-based SVE distributions can well represent the effects of CV applications on traffic streams and the degree of traffic smoothness/chaos.

As one example, Figure 4 illustrates the speed distribution of two trips of an individual vehicle. The entropy of the high concentration distribution (red dash line) is smaller than that of the more spread-out distribution (black solid line). This result is consistent with the customized entropy "definition": the less concentrated the speed value is, the larger customized entropy would be, leading to more uncertainties for complete knowledge of the event or process, e.g., stop-and-go behaviors and relevant traffic condition. Based on the definition of entropy as aforementioned, the corresponding trip-by-trip-based SVE values are calculated.

Moreover, based on the Fundamental Diagram (FD) [42] such as the Greenshield's one, as the traffic becomes denser, cars driven under constant time headway have lower equilibrium speed. In the meanwhile, the smallest speed variations and the stop-and-go behaviors can be amplified further by human drivers, causing traffic jam. It is expected that relevant performance (e.g., potential conflict risk, average speed and fuel consumption) in such traffic condition would deteriorate due to the increased stop-and-go behaviors. More insights relevant to the traffic jam propagation and the effects of driver behavior can be found in [43]. In addition, the Connected Cruise Control algorithms have been designed to control the longitudinal behavior of connected automated vehicles, in order to reduce speed variations, mitigate traffic waves and improve energy efficiency, which has been verified in field experiments [44]. Driving behavior control features such as the Cooperative Adaptive Cruise Control (CACC) may regulate the traffic flows by implementing the platooning of autonomous vehicles [45] and taking into consideration the stability of the vehicle string [46], to increase the road throughput. The CACC longitudinal control algorithm is robust against speed variations, therefore, the average speed might not reduce as the SVE increases in this case. It is noted that the SVE measures speed variations but not the average speed (i.e., high average speed and low average velocity cases could have the same SVE value), which might lead to a complicated relationship between SVE and the mobility performance (e.g., average speed).

C. Curve Fitting of Discrete SVE Distributions

When examining the empirical SVE distributions (i.e., using histograms), the Weibull distribution was selected in this study for histogram fitting to gain further insight. The Weibull distribution is widely used for weather forecasting [47], reliability engineering, and failure analysis of systems.

The probability density function (PDF) of a Weibull random variable is:

$$f(x;A,B)=\begin{cases}\frac{B}{A}\left(\frac{x}{A}\right)^{B-1}e^{-(x/A)^B} & x\geq 0\\ 0 & x<0\end{cases} \tag{4}$$

where $B>0$ is the shape parameter, and $A>0$ is the scale parameter of the distribution.

In a Weibull distribution, $B>1$ exists for an "aging" system, which by this hypothesis, means as time passes, the traffic system tends to be chaotic due to microscopic (e.g., stop-and-go maneuvers and lane changes) and macroscopic (e.g., demand fluctuations, vehicle mix, and roadway geometry) disturbances. Moreover, the mode and inter-quartile range (IQR) of the fitted Weibull distribution can be regarded as potential surrogate measures that indicate the traffic system degree of chaos. The smaller the mode of SVE distribution is, the smoother the traffic system is, since the majority of vehicles in roadway transportation

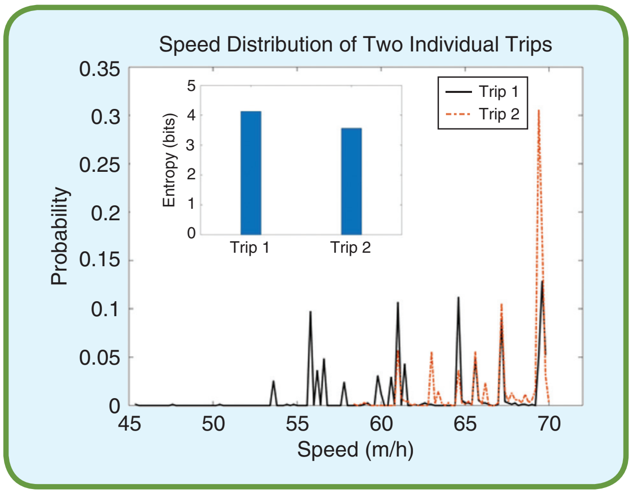

FIG 4 Time-speed diagram for two individual trips.

have small speed variations. The larger the IQR of SVE distribution is, the more unpredictable and chaotic the traffic condition is, due to the larger diversity of SVE values.

For multi-modal distributions, the Weibull mixture [48] probability distribution function is used to better fit the discrete SVE distribution, which is defined as

$$f(x)=\sum_i pf_i(x) \tag{5}$$

where $f_i(x)$ is i-th component, which also follows a Weibull probability distribution; p is the mixture parameter or weight.

IV. Simulation Setup

A. Simulation Model

In this work, a segment of California SR-91E has been coded and used for a simulation study, which consists of a 15-mile corridor between the Orange County Line and Tyler Street in Riverside, California (see Figure 5). The number of lanes ranges from four to six, and there are nine pairs of on-/off-ramps. The traffic conditions usually fall into levels of service (LOS) C to E [49] during peak hours. Traffic demands, origin-destination (O-D) patterns, and driving behaviors have been calibrated to match that of a typical weekday morning in the summer [50]. The segment of California SR-91E is used to test HSDW, LSM, and ESH. In addition, EAD is designed for vehicles when they pass through signalized intersections, therefore, the EAD application has been tested in a three-intersection signalized corridor in Palo Alto, CA, with three lanes in each direction, where the traffic patterns and signal control have been calibrated with field data.

B. Simulation Scenarios

To better understand the effectiveness of applications, comprehensive simulation tests have been conducted over the following system parameters:

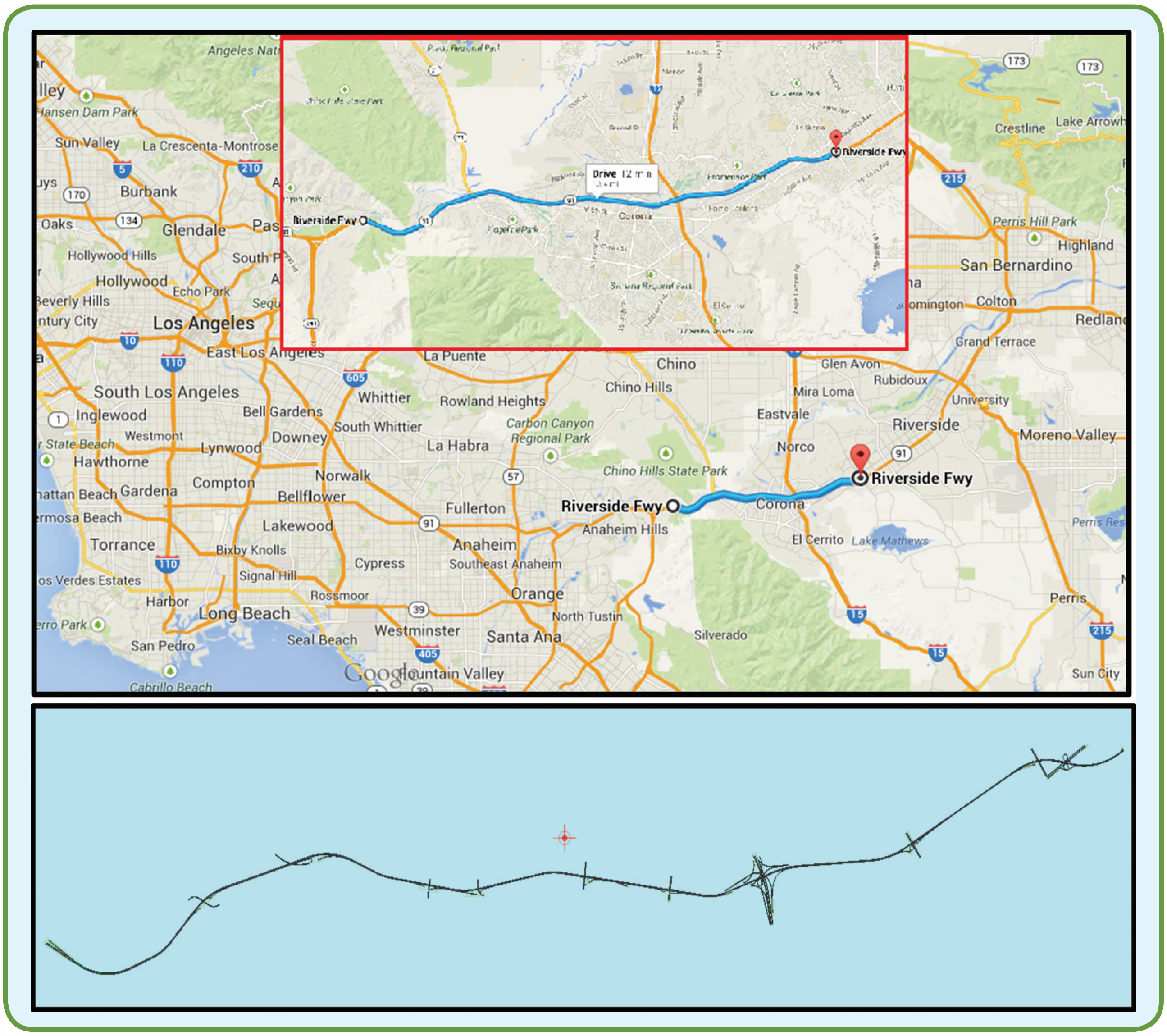

FIG 5 Road network of the California SR-91E in real-world and PARAMICS.

- *Penetration rate of DSRC-equipped vehicles.* In this study, a full range (8 total levels) of penetration rates are examined for conventional MOEs, including 0% (baseline), 10%, 20%, 30%, 40%, 50%, 80% and 100%, under the calibrated traffic demand pattern (LOS D). The application-equipped rate is set the same as the DSRC-equipped rate in this study.
- *Congestion level.* For the highway scenarios, during a three-hour simulation period, two levels of traffic volume are to be evaluated: 25,000 vehicles (calibrated), and 32,000 vehicles per simulation run. It is worth to note that the car following logic was carefully calibrated for the 25,000 veh/run case so that the SVE results are somewhat independent of the logic. Further analysis on the average speed indicates that these two cases represent the traffic conditions of LOS D (transitional flows) and LOS E (unstable flows), respectively, according to the Highway Capacity Manual (HCM) 2010 [49]. For the signalized intersection scenarios, there are two levels of traffic volume: 5000 vehicles/run (v/c = 0.38, referred to as moderate traffic), and 10000 vehicles/run (v/c = 0.76, referred to as relatively heavy traffic).

V. Simulation Results

A. SVE-Based MOE Evaluation for CV Applications

1) CV Applications' Effects on Traffic

The SVE-based MOEs of four selected applications (HSDW, LSM, ESH, and EAD) are first analyzed. All the four applications were first tested under the 20% penetration rate for application-equipped vehicles. For the highway scenarios and signalized intersections, total traffic volume levels are 25,000 vehicles per run and 5000 vehicles per run, respectively (both cases are moderate traffic condition).

Figure 6 shows the SVE distributions of application-unequipped vehicles (before) and application-equipped vehicles (after) of corresponding applications, with the following key observations:

a) It can be observed that minor changes occurred in the SVE distributions between the HSDW-equipped and HSDW-unequipped vehicles, and they have very similar modes and IQRs. A potential explanation is that the HSDW application is not triggered frequently enough in this moderate and relatively stable traffic condition (25,000 vehicles/run).
b) In the LSM application scenario, SVE distribution of LSM-equipped vehicles shifts to the right, compared with that of LSM-unequipped vehicles. A hypothesis is that LSM-equipped vehicles always switch to faster lanes, and those extra lateral disturbances cause higher velocity fluctuations.

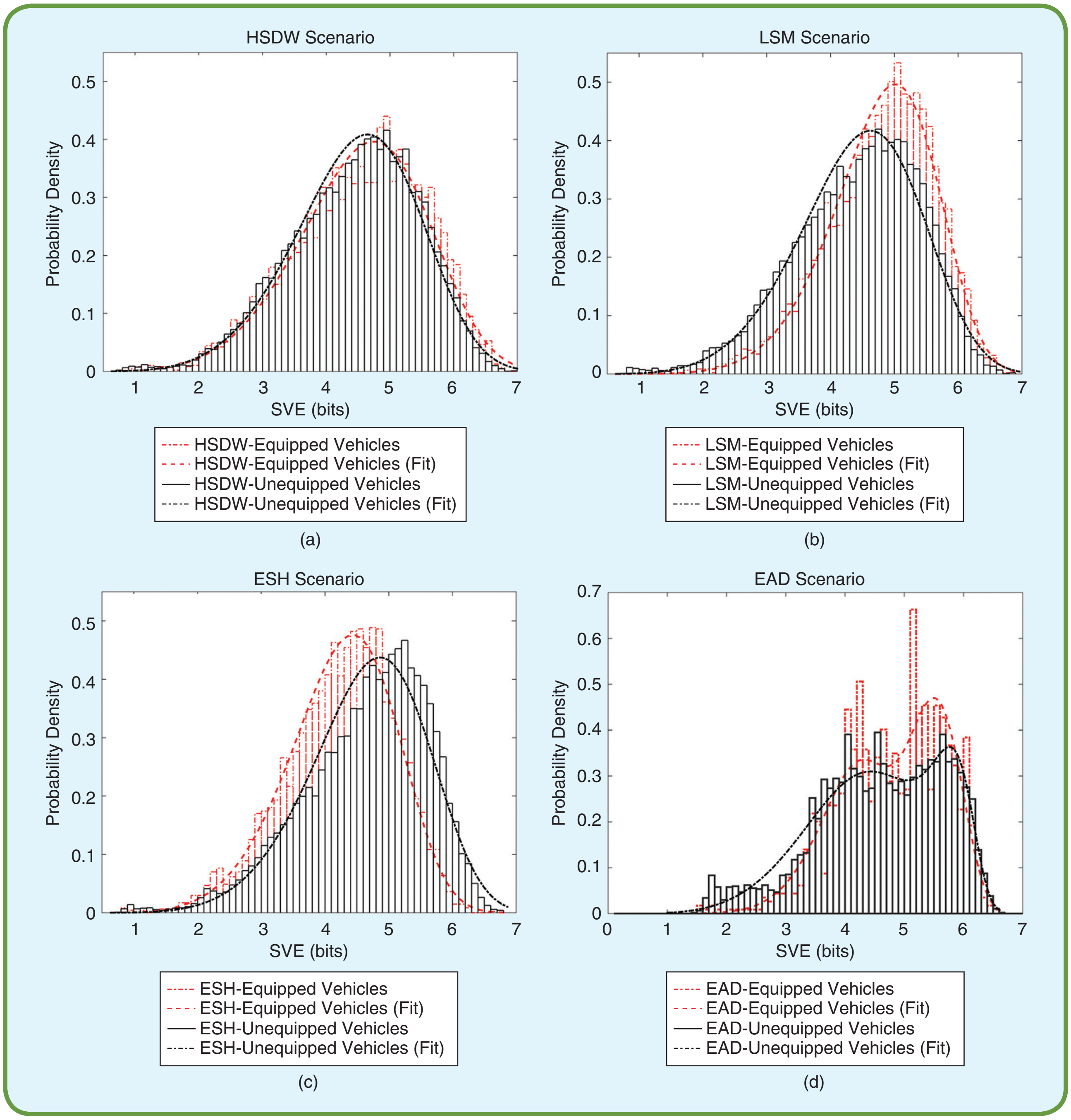

FIG 6 Time SVE distributions of four different CV applications (moderate traffic, 20% penetration rate). (a) HSDW application, (b) LSM application, (c) ESH application, and (d) EAD application.

c) In the ESH scenario, a significant left shift is observed in the SVE distribution of ESH-equipped vehicles compared with that of the ESH-unequipped vehicles. The mode of ESH-equipped vehicles and ESH-unequipped vehicles are 4.4 bits and 4.9 bits, respectively. Smaller modes and IQRs of ESH-equipped vehicles means they do have smaller speed variations as well as travel in a more predictable way than ESH-unequipped vehicles. In this case, ESH-equipped vehicles obtain smoother velocity and then smaller SVE via additional information brought by roadside infrastructure.
d) The SVE distributions in the EAD scenario are multi-mode. The reason could be that there are interruptions from external factors (such as traffic signals). Note that these disturbances affect the speed variations rather than the SVE distribution's performance. In fact, the multiple modes in the SVE distributions show that there exist disturbances in the speed variations (such as many stop-and-wait behaviors caused by signalized intersections and/or highly congested traffic conditions).

2) Sensitivity Analysis

Penetration Rate

The ESH and the EAD applications are taken as examples for penetration rate sensitivity analysis in moderate traffic (25,000 veh/run for ESH and 5000 veh/run for EAD), and three levels of penetration rate of application-equipped vehicles are selected: 10%, 50% and 80%. We can observe from Figure 7 that both the ESH and the EAD are robust to the variation of penetration rate compared to the other applications: the safety capability, mobility performance and fuel consumption have not changed much across different penetration rate levels (see Table I). Therefore we used these applications as examples to verify that the entropy-based MOE (i.e., SVE) can be an indicator, showing how the other MOEs change (or even hardly change), in order to demonstrate the consistency in SVE with other MOEs. The cases showing how SVE varies with other MOEs as the number of application-equipped vehicles increases are presented in the following traffic volume sensitivity analysis (i.e., for the LSM application and the EAD application).

Traffic Volume

First, Figure 8(a) presents a comparison between two baselines (where there is a 0% penetration rate of application-equipped vehicles) of different congestion levels. It shows that a shift to the right of SVE distribution under the 32,000 veh/run baseline case is observed with respect to that of the 25,000 veh/run baseline case, because higher traffic demand may cause higher speed fluctuations/chaos on the road (See Figure 8(a)).

Second, as for the congestion level sensitivity analysis, the penetration rate of application-equipped vehicles is fixed at 20%, and the LSM application and the EAD application are selected as the sensitivity analysis scenarios. a) The LSM scenarios: In comparison of Figure 8(b) and Figure 8(c), significant changes in SVE distributions in the LSM scenario can be observed. The SVE distribution tends to be dual-modal, instead of unimodal, under heavier traffic conditions. Figure 8(c) shows that besides the vehicles that are subject to higher speed variations (the high mode), a certain number of vehicles have smaller speed variations (the low mode). An explanation for the dual-mode phenomena in Figure 8(c) is that the whole traffic flow slows down as vehicle numbers keep increasing on the network in such a congested traffic condition, and additional lane change behaviors induced by the LSM applications as extra disturbances to the traffic lead to much slower speeds with smaller speed variations. b) The EAD scenarios: It can be observed that there already exist multiple modes in the baselines of the SVE distributions under the signalized intersections scenarios, since the traffic light signals cause many stop-and-wait behaviors, leading to the fluctuations in speed variations and the multi-mode SVE distributions (see Figure 8(d)). In addition, by comparing the baselines in Figure 8(d), it can be concluded that the more congested traffic condition causes the right-shift of the SVE distribution' mode. The SVE values of the majority of vehicles will become larger in the relatively heavy traffic condition.

B. Correlations Between SVE and Conventional MOEs

1) Baseline SVE Versus Conventional MOEs

Figure 9 shows the relationship between SVE and the other three conventional MOEs in the case of baseline settings (i.e., 0% application-equipped vehicles, and 25,000 veh/run in the highway scenario):

- *Safety*. The number of conflicts is minor when SVE is small. When higher SVE is observed, vehicles are exposed to a higher conflict number;
- *Mobility*. There is no strong correlation between SVE and the average speed. For example, overall traffic that moves slowly but smoothly may have similar SVE as fast, free-flow traffic;
- *Environment*. When SVE is higher, the fuel consumption increases, floating within a certain bandwidth range, e.g., 300 KJ/mile (this testing scenario focuses on the region with dense data samples).

2) SVE Versus Conventional MOEs for Four Selected CV Applications

It can be expected that the conventional MOEs of different CV applications can be roughly obtained through the corresponding SVE. Table I and Table II list the three conventional MOEs of sensitivity analysis cases in some CV application scenarios (corresponding to the SVE MOE

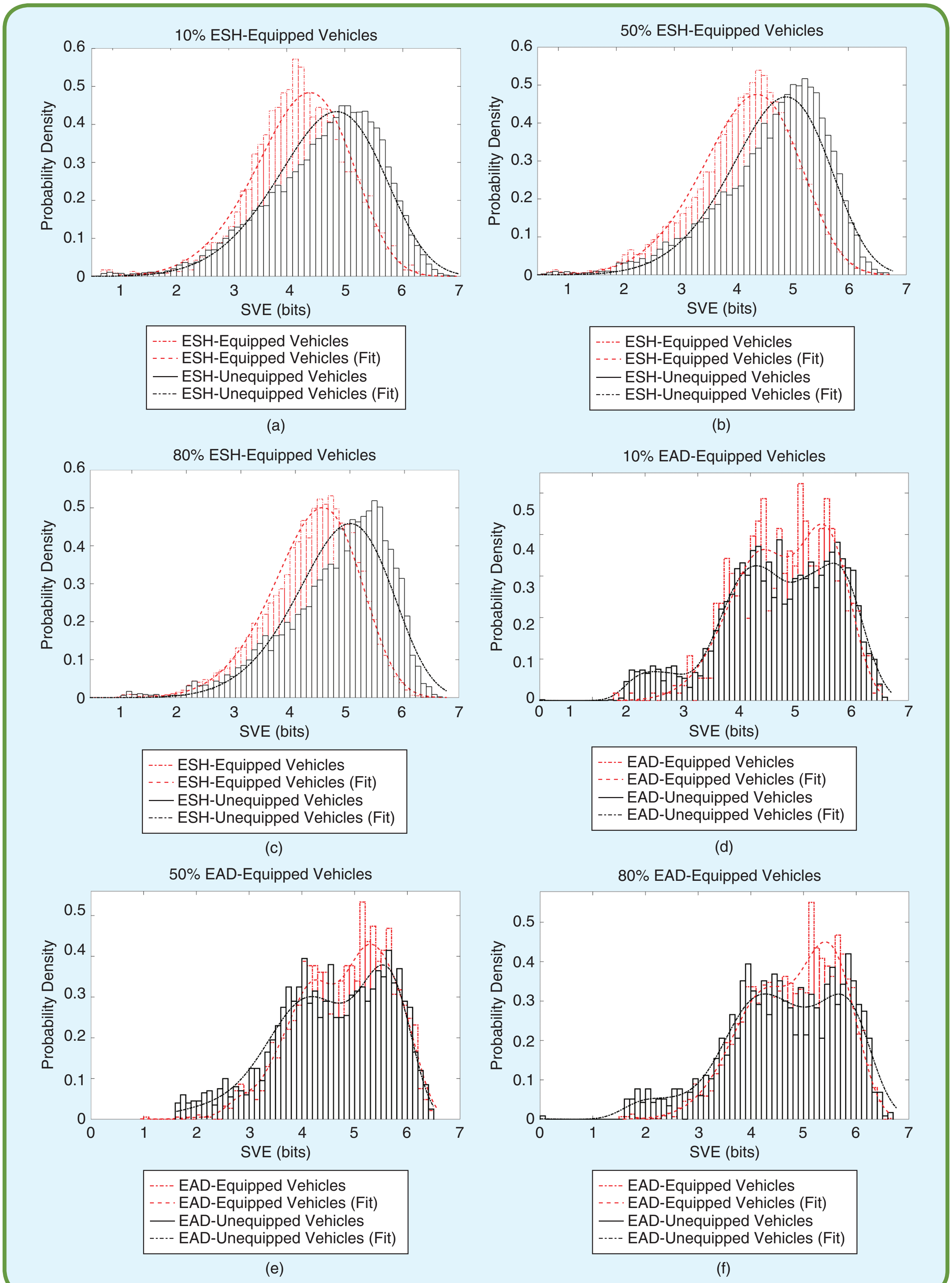

FIG 7 SVE distributions of different penetration rates (moderate traffic). (a) 10% ESH penetration rate, (b) 50% ESH penetration rate, (c) 80% ESH penetration rate, (d) 10% EAD penetration rate, (e) 50% EAD penetration rate, and (f) 80% EAD penetration rate.

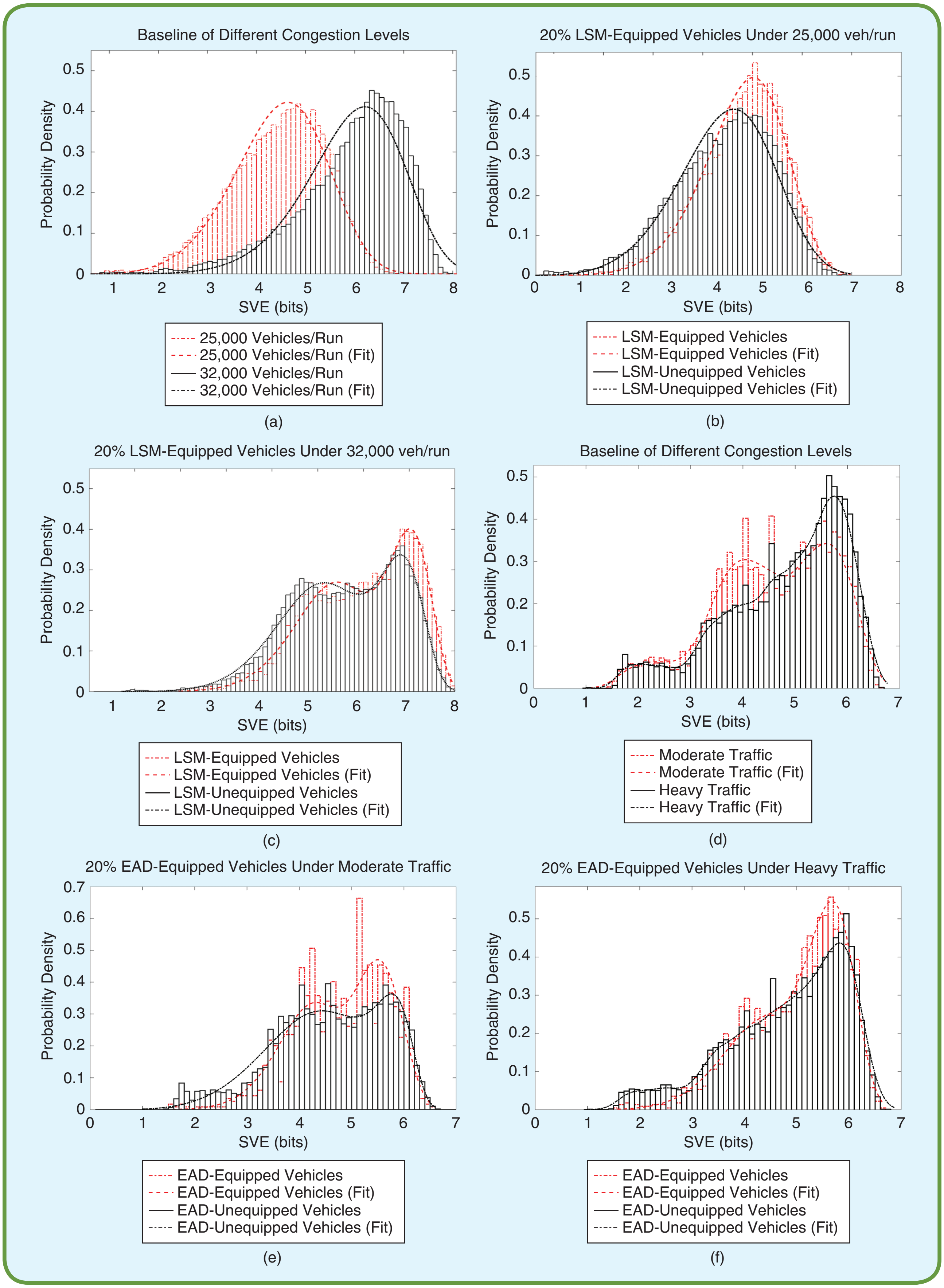

FIG 8 SVE distributions of different traffic volumes in LSM scenario and EAD scenario (Baseline cases and 20% penetration rate). (a) no LSM-equipped vehicles, (b) 25,000 veh/run for LSM, (c) 32,000 veh/run for LSM, (d) no EAD-equipped vehicles, (e) Moderate traffic for EAD, and (f) Heavy traffic for EAD.

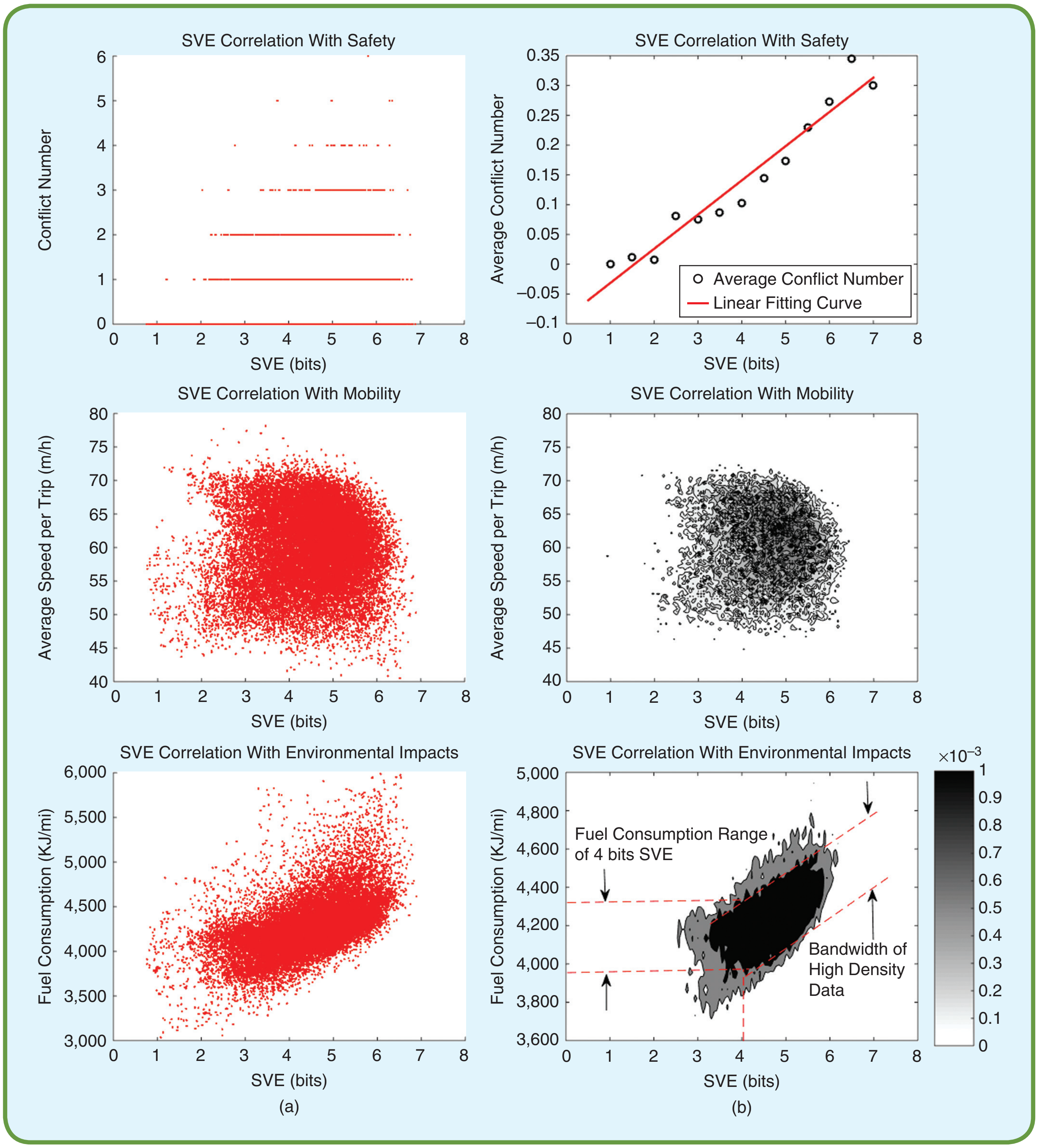

FIG 9 Baseline SVE correlations with three conventional MOEs (0% penetration rate, 25,000 veh/run). (a) Scatter plot and (b) post-processing data (averaging, fitting and density plot).

sensitivity analysis in Section V.A.2) to explore the correlations between SVE and conventional MOEs.

a) Penetration rate

Based on the general correlations between SVE and conventional MOEs in Figure 9, the corresponding estimated conflict frequencies of ESH-equipped and unequipped vehicles are 0.1638 and 0.1925, with estimated fuel consumption ranges from 4000-4,300 KJ/mile and 4,200-4,500 KJ/mile, which are consistent with the numerical results in Table I. The conflict frequency difference between estimation and actual results is less than 0.02.

Table I. Conventional MOEs of penetration rate sensitivity analysis.

		Penetration Rate Sensitivity Analysis					
		ESH (25,000 veh/run)			EAD (Moderate Traffic)		
Penetration Rate		S[a]	M[b]	E[c]	S[a]	M[b]	E[c]
10%	Equipped	0.1504	58.3	4158.9	0.0973	22.1	4043.3
	Unequipped	0.1861	59.9	4295.3	0.0973	22.2	4332.5
50%	Equipped	0.1646	58.6	4168.4	0.0767	21.7	4139.0
	Unequipped	0.1812	59.3	4276.0	0.0801	22.3	4273.5
80%	Equipped	0.1711	59.0	4195.2	0.0616	21.7	4178.0
	Unequipped	0.2129	59.5	4291.5	0.1028	22.2	4317.4

[a]Safety MOE: Conflict frequency.
[b]Mobility MOE: Average speed (mph).
[c]Environmental impacts MOE: Fuel consumption (KJ/mile).

Table II. Conventional MOEs of traffic volume sensitivity analysis.

		Traffic Volume Sensitivity Analysis					
		LSM (20% Penetration Rate)			EAD (20% Penetration Rate)		
Traffic Volume		S[a]	M[b]	E[c]	S[a]	M[b]	E[c]
Moderate traffic	Equipped	0.3922	65.5	4502.1	0.0497	21.6	4120.3
	Unequipped	0.2189	61.1	4315.6	0.1006	22.3	4338.6
Heavy traffic	Equipped	2.1334	21.3	6005.0	0.1742	20.9	4203.9
	Unequipped	1.4382	21.4	5733.0	0.2144	21.6	4305.3

[a]Safety MOE: Conflict frequency.
[b]Mobility MOE: Average speed (mph).
[c]Environmental impacts MOE: Fuel consumption (KJ/mile).

Moreover, the correlation between SVE and average speed, fuel consumption, and conflict frequency are plotted and calculated, respectively (see Figure 10 and Table III). To be clear, in this case there are seven penetration rate levels for seven SVE samples, i.e., 10%, 20%, 30%, 40%, 50%, 80%, and 100%. Every entropy value is available for each penetration rate level under the moderate traffic (25,000 vehicles/run for the highway scenario and 5000 vehicles/run for the downtown scenario), where each entropy value is calculated based on the overall vehicle speed data in the entire network during the full simulation time. The corresponding conventional MOEs are average values of overall vehicles under the same scenarios.

In Figure 10, it can be concluded that SVE has a strong negative correlation with average speed, and an obvious positive correlation with fuel consumption and conflict frequency in the HSDW and LSM scenarios. This result meets the expectation that high entropy values reflect more chaotic traffic in terms of high conflict frequency, low average speed, and high fuel consumption. However, the ESH scenario is a special case where SVE versus safety and SVE versus mobility do not show such a trend in correlation coefficients. Several potential reasons are: a) for the safety aspect, since the traffic system is subject to less fluctuation across different penetration rates in the ESH scenario (as mentioned in penetration rate sensitivity analysis in terms of SVE MOE in Section V.A.2), the fluctuation in conventional MOEs (e.g., conflict frequency) is very small (note that to be observed distinctly, the y-axis limit for safety in the ESH scenario is relatively small in Figure 10) across different penetration rates, which leads to the 0.3916 correlation coefficient (see Table III); and b) on the other hand, for the mobility aspect, it can be concluded that the ESH system sacrifices the mobility to some extent in order to smooth overall traffic flow and keep the speed within a certain range for energy saving, as the penetration rate increases. The EAD application is designed to smooth the longitudinal trajectories of the application-equipped vehicles and reduce the fuel consumption. However, the impacts of such application on other unequipped vehicles/the overall traffic could be amplified due to the signalized intersections. In Figure 10, we observe that the overall SVE increases as the penetration rate of the EAD application increases, while the EAD is robust against the surrounding variations (the three MOEs in the EAD scenario are relatively stable). Please note that to be observed distinctly, the y-axis limits for the three MOEs in the EAD scenario are relatively small. In this case, SVE versus conflict risk/fuel consumption is not positively correlated any more (see Table III). By combining the conventional MOEs and the SVEs, we can understand how the application affects the overall traffic (smoothing or causing chaos in speed variations) and whether the application is robust against surrounding variations.

Table III. Correlation coefficients between SVE and conventional MOEs (moderate traffic, varied penetration rate).

Application	HSDW			LSM			ESH			EAD		
MOE	SVE vs S[a]	SVE vs M[b]	SVE vs E[c]	SVE vs S	SVE vs M	SVE vs E	SVE vs S	SVE vs M	SVE vs E	SVE vs S	SVE vs M	SVE vs E
Correlation coefficient	0.9811	–0.8950	0.9490	0.7942	–0.7576	0.8717	0.3916	0.9681	0.9941	–0.9499	–0.6765	–0.9131

[a]Safety MOE: Conflict frequency.
[b]Mobility MOE: Average speed (mph).
[c]Environmental impacts MOE: Fuel consumption (KJ/mi).

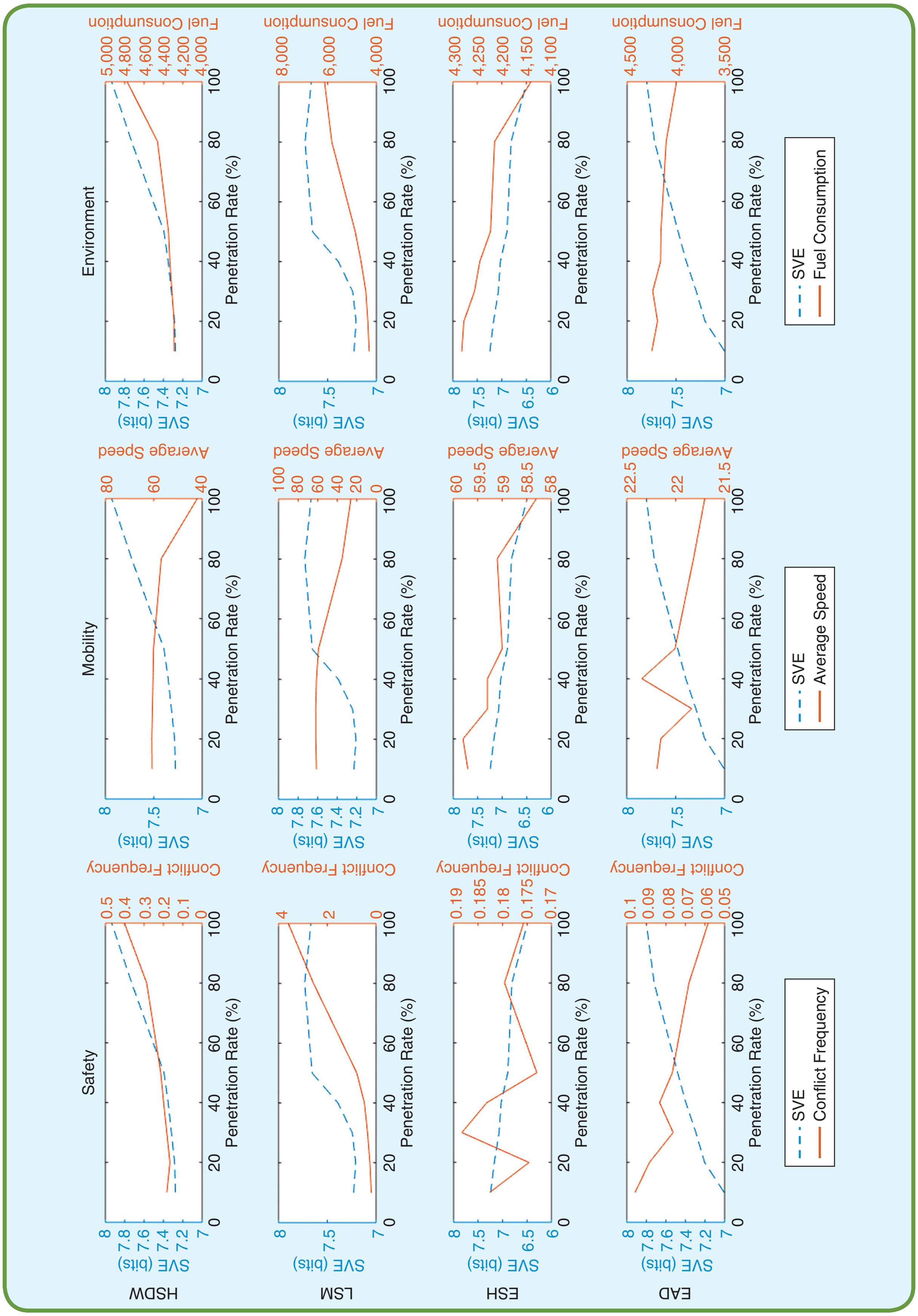

FIG 10 SVE versus three conventional MOEs across different penetration rate levels for four different CV applications (moderate traffic).

b) Traffic volume

Regarding the LSM, for the 25,000 veh/run case, the estimated average conflict frequency is 0.1983 based on the mode of LSM-equipped vehicles (i.e., 5 bits, see Figure 8(b)), and the estimated fuel consumption is 4,200-4,500 KJ/mile (both results are based on correlations in Figure 9). The actual conflict frequency is 0.3922 (see Table II) due to induced lane changes by LSM-equipped vehicles. In combination with Figure 8(c), it can be concluded that average traffic speeds drop dramatically from 47 mph (baseline) to 21 mph, and significant increases of fuel consumption and conflict frequency are witnessed in the congested LSM scenario (see Table II). Regarding the EAD, the SVE value increases as the traffic volume increases, and the safety, mobility, and sustainability impacts performance deteriorate due to the higher speed variations in the heavy traffic condition (see Table II).

Lastly, the correlation between SVE and the three conventional MOEs of the four selected CV applications across two congestion levels is shown in Figure 11. Each entropy value is calculated based on the overall vehicle speed data on the entire network during the full simulation time. A 20% penetration rate of application-equipped vehicles is fixed herein. The results show that higher SVE is associated with higher conflict frequency, lower average speed, and higher energy consumption for both HSDW and ESH. Again, as mentioned in Section III.B, as the traffic becomes denser, human drivers can amplify the smallest speed variations into a full-on stop-and-go jam. This could well explain the negative correlation results between the SVE and traffic mobility performance for HSDW, ESH, and EAD in Figure 11. In addition, since the relation between the SVE and the average speed itself is relatively complicated (see analysis in Section III.B), the SVE is smaller in denser traffic and the SVE distributions are used at the same time to evaluate the LSM scenario. The SVE distributions of the LSM scenario are associated with a more unpredictable and chaotic traffic condition (the chaos can be determined from the dual-mode SVE distributions with large variance) (see Figure 8(c)), indicating higher conflict risk, lower traffic speed, and high fuel consumption (see Figure 11).

3) Discussions

To draw a more general conclusion on the correlation between SVE and vehicle performance, the conflict frequency, average speed and fuel consumption have been estimated for each individual vehicle (application-equipped) during its whole trip. The correlation coefficients between SVE values of individual vehicles and their safety, mobility and environmental sustainability performance measures for all the four CV applications are shown in Table IV. Comparing Table III with Table IV, the correlation coefficients between the SVE and the conflict frequency/fuel consumption are still positive. But the correlation of the SVE and the vehicle's performance measures from the individual vehicle perspective is not as strong as the correlation of the SVE distribution or the entropy of overall vehicles and the overall performance measures (e.g., average conflict number and average fuel consumption) (please also refer to Figure 9, as compared to all the individual samples, the SVE shows stronger positive correlation with the average conflict frequency).

VI. Discussion and Future Work

This paper proposed a Speed Variation-based Entropy (SVE) as a new Measure of Effectiveness (MOE) for CV applications, at both the individual vehicle and the traffic levels. The SVE distribution (based on each individual trip) can be used as an alternative MOE for traffic systems. Four representative applications were selected, and the SVE distributions were analyzed in comparison to MOEs related to safety, mobility, and environmental impacts.

The proposed SVE (and SVE distribution) method, as a pointer, is capable of providing the clue or verification for researchers about the network-wide safety and environmental sustainability performance. The SVE has a strong correlation with conventional MOEs for CV applications especially under freeway scenarios. For example, results from this study show that the average conflict frequency and the average fuel consumption have a strong positive correlation with the SVE distributions and overall SVEs. Modelers can calculate the SVE and then use the SVE to estimate the conventional MOEs under a variety of scenarios. However, the relation between the SVE and the average speed itself is relatively complicated (either positive or negative correlation), depending on the design of CV applications (as discussed in the last paragraph of Section III.B and the last paragraph of Section V.B.2). Therefore the SVE might be not a proper indicator to evaluate the mobility performance (e.g., average speed) for the type of applications with string stability (e.g., cooperative adaptive cruise control). Please note that even the proposed SVE is not closely associated with the speed values, but the noise in speed measurement could still affect the performance of the proposed SVE measure since the inaccurate speed measurement could cause errored calculation of speed variations.

The SVE and its distribution can be used as an alternative MOE for CV applications evaluation in a more holistic way from the perspective of the entire traffic system status observation, which otherwise needs to be jointly reflected and evaluated by several (usually more than one) conventional MOEs. We can observe the entire traffic status through the SVE distributions (mode and IQR): A system with a larger mode and a broader inter-quartile range (IQR) of the SVE distribution is more chaotic and less predictable (usually with deteriorated conventional MOEs simultaneously).

Furthermore, entropy calculation from different perspectives (e.g., space-based and time-based SVE calculation) and its relationship with other fundamental traffic system parameters (e.g., capacity, density, and flow) remain as future work. In addition to the speed variation based entropy,

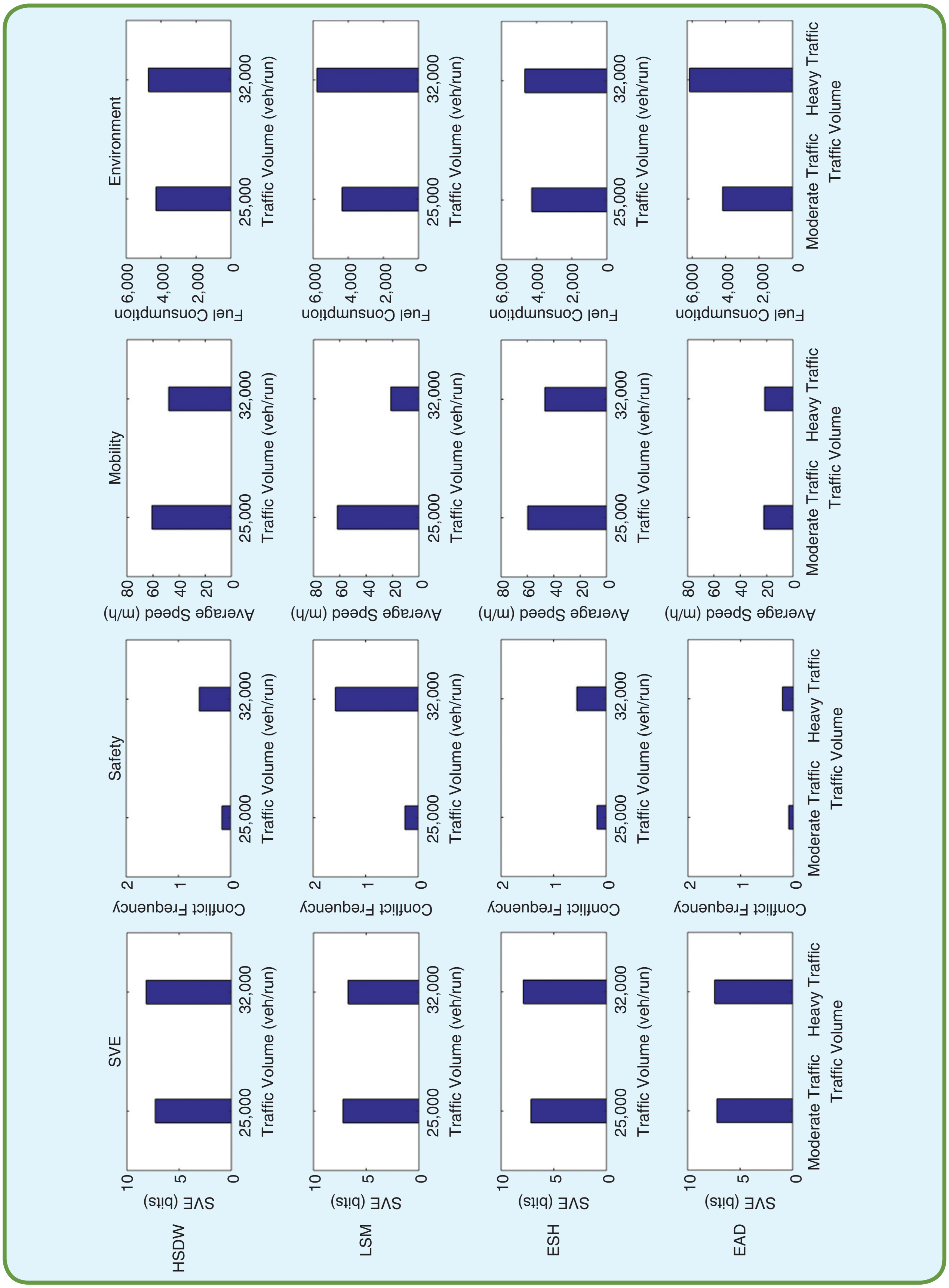

FIG 11 SVE versus three conventional MOEs across two different congestion levels for three different CV applications (20% penetration rate of application-equipped vehicles).

Table IV. Correlation coefficients between SVE and conventional MOEs (heavy traffic, 20% penetration rate).

Application	HSDW			LSM			ESH			EAD		
MOE	SVE vs S[a]	SVE vs M[b]	SVE vs E[c]	SVE vs S	SVE vs M	SVE vs E	SVE vs S	SVE vs M	SVE vs E	SVE vs S	SVE vs M	SVE vs E
Correlation coefficient	0.1040	–0.4092	0.1989	0.0613	0.0809	–0.0837	0.0812	–0.4362	0.1881	0.1589	0.0346	0.1435

[a]Safety MOE: Conflict frequency.
[b]Mobility MOE: Average speed (mph).
[c]Environmental impacts MOE: Fuel consumption (KJ/mi).

such an entropy-based framework (and relevant entropy distribution analysis) proposed in this paper can be used in other traffic evaluations as well, such as vehicles' headway, travel time, and steering angel, in order to better understand traffic condition of interest. For example, entropy of vehicles' moving direction can be analyzed to mark intersection areas. In addition, headway entropy or travel time entropy can be used to determine the degree of traffic chaos and traffic system reliability. Entropy based criteria enable the accurate identification of traffic conditions, and therefore would play an indispensable role in the development of CV applications.

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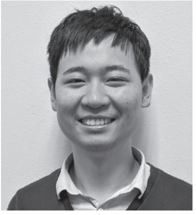

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References

[1] National Highway Traffic Safety Administration (NHTSA), "Traffic safety facts," 2016. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812491

[2] World Health Organization, 2015. [Online]. Available: http://www.who.int/violence_injury_prevention/road_safety_status/2015/en/

[3] D. Schrank, B. Eisele, T. Lomax, and J. Bak, "2015 Urban mobility scorecard," Texas A&M Transp. Inst. and INRIX, TX, USA, 2015. [Online]. Available: http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-scorecard-2015.pdf

[4] Federal Highway Administration (FHWA), "2016 Urban congestion trends," [Online]. Available: https://ops.fhwa.dot.gov/publications/fhwahop17010/fhwahop17010.pdf

[5] Environmental Protection Agency (EPA), "Annual report and accounts," 2016. [Online]. Available: http://www.epa.ie/pubs/reports/other/corporate/EPA_AnnualReport_2016_English_Final_Web.pdf

[6] Environmental Protection Agency (EPA), "Ireland's provisional greenhouse gas emissions in 2015," [Online]. Available: http://www.epa.ie/pubs/reports/air/airemissions/ghgemissions/GHG%201990-2015%20Provisional%20November%202016.pdf

[7] US Department of Transportation (USDOT), "Connected vehicle safety pilot," [Online]. Available: http://www.its.dot.gov/safety_pilot/index.htm

[8] USDOT, "Applications for the Environment: Real-time Information Synthesis (AERIS)," [Online]. Available: http://www.its.dot.gov/aeris/index.htm

[9] USDOT, "Dynamic Mobility Applications (DMA)," [Online]. Available: http://www.its.dot.gov/dma/index.htm

[10] Iteris, "Connected vehicle reference implementation architecture," [Online]. Available: http://www.iteris.com/cvria/html/applications/applications.html

[11] USDOT, "Road weather connected vehicle applications," [Online]. Available: http://www.its.dot.gov/road_weather/index.htm

[12] D. Tian et al., "Evaluating the effectiveness of V2V-based lane speed monitoring application: A simulation study," in *Proc. 19th IEEE Intelligent Transportation Systems*, Rio, Brazil, 2016, pp. 1592–1597.

[13 W. Li et al., "Development and evaluation of high speed differential warning application using vehicle-to-vehicle communication," in *Proc. 96th Annu. Meeting Transportation Research Board*, Washington, DC, USA, 2017, pp.1–17.

[14] G. Wu, D. Kari, X. Qi, K. Boriboonsomsin, and M. J. Barth, "Developing and evaluation an eco-speed harmonization strategy for connected vehicles," in *Proc. 4th Int. Conf. Connected Vehicles and Expo*, Shenzhen, China, 2015, pp. 373–378.

[15] D. Tian, G. Wu, K. Boriboonsomsin, and M. J. Barth, "Performance measurement evaluation framework and co-benefit/tradeoff analysis for connected and automated vehicles (CAV) applications: A survey," *IEEE Intell. Transp. Syst. Mag.*, vol. 10, no. 3, pp. 110–122, June 2018.

[16] J. Han, A. Sciarretta, L. L. Ojeda, G. De Nunzio, and L. Thibault, "Safe- and eco-driving control for connected and automated electric vehicles using analytical state-constrained optimal solution," *IEEE Trans. Intell. Veh.*, vol. 3, no. 2, pp. 163–172, June 2018.

[17] E. Meissner, T. Chantem, and K. Heaslip, "Optimizing departures of automated vehicles from highways while maintaining mainline capacity," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 12, pp. 3498–3511, Dec. 2016.

[18] J. Rios-Torres and A. A. Malikopoulos, "A survey on the coordination of connected and automated vehicles at intersections and merging at highway on-ramps," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 5, pp. 1066–1077, May 2017.

[19] X. Jiang, W. Wang, and K. Bengler, "Intercultural analyses of time-to-collision in vehicle-pedestrian conflict on an urban midblock crosswalk," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 2, pp. 1048–1053, Apr. 2015.

[20] R. Fan, H. Yu, P. Liu, and W. Wang, "Using VISSIM simulation model and Surrogate Safety Assessment Model for estimating field measured traffic conflicts at freeway merge areas," *IET Intell. Transp. Syst.*, vol. 7, no. 1, pp. 68–77, May 2013.

[21] FHWA, "Surrogate Safety Assessment Model (SSAM)," [Online]. Available: http://www.fhwa.dot.gov/publications/research/safety/08049/

[22] J. M. Ernst, J. V. Krogmeier, and D. M. Bullock, "Kullback-Leibler comparison framework for the evaluation of travel time distribution estimates," in *Proc. 15th Int. IEEE Conf. Intelligent Transportation Systems*, Alaska, USA, 2012, pp. 564–569.

[23] C. Chen, Z. Jia, and P. Varaiya, "Causes and cures of highway congestion," *IEEE Control Syst.*, vol. 21, no. 6, pp. 26–32, Dec. 2001.

[24 M. J. Barth, W. Zhu, K. Boriboonsomsin, and L. Ordonez, "Final report: Analysis of GPS-based data for light duty vehicles," *Center for Environmental Research and Technology*, CA, USA, 2006.

[25] M. J. Barth and K. Boriboonsomsin, "Energy and emissions impacts of a freeway-based dynamic eco-driving system," *Transp. Res. D, Transport Environ.*, vol. 14, no. 6, pp. 400–410, Aug. 2009.

[26] W. Li, G. Wu, M. J. Barth, and Y. Zhang, "Safety, mobility and environmental sustainability of eco-approach and departure application at signalized intersections: A simulation study," in *Proc. Int. IEEE Conf. Intelligent Vehicle Symposium*, Gothenburg, Sweden, 2016, pp. 1109–1114.

[27] S.-B. Choi and J. K. Hedrick, "Vehicle longitudinal control using an adaptive observer for automated highway systems," in *Proc. IEEE American Control Conf.*, Seattle, WA, USA, 1995, pp. 3106–3110.

[28] Paramics. [Online]. Available: http://www.paramics-online.com/

[29] U.S. Environmental Protection Agency, "Motor Vehicle Emission Simulator (MOVES)," [Online]. Available: http://www.epa.gov/otaq/models/moves/

[30] J. B. Kenney, "Dedicated Short-Range Communications (DSRC) standards in the United States," *Proc. IEEE J.*, vol. 99, no. 7, pp. 1162–1182, June 2011.

[31] P. Hao, G. Wu, K. Boriboonsomsin, and M. J. Barth, "Eco-approach and departure (EAD) application for actuated signals in real-world traffic," *IEEE Trans. Intell. Transp. Syst.*, pp. 1–11, 2018.

[32] C. G. Chakrabarti and I. Chakrabarty, "Shannon entropy: Axiomatic characterization and application," *Int. J. Math. Math. Sci.*, vol. 2005, no. 17, pp. 2847–2854, Feb. 2005.

[33] E. T. Jaynes, "Information theory and statistical mechanics," *Phys. Rev.*, vol. 106, no. 4, pp. 620–630, 1957.

[34] K. A. Shahkooh, M. Fasanghari, and A. Sharifi, "Prioritization of SMEs strategies in IT fields of developing countries using entropy Shannon," in *Proc. 3rd Int. Conf. Convergence and Hybrid Information Technology*, Busan, Korea, 2008, pp. 261–266.

[35] M. Bhowmik, A. Sarkar, and R. Das, "Shannon entropy based fuzzy distance norm for pixel classification in remote sensing imager," in *Proc. 3rd Int. Conf. Computer, Communication, Control and Information Technology*, India, 2015, pp.1–6.
[36] C. E. Shannon, "A mathematical theory of communication," *Bell Syst. Tech. J.*, vol. 27, no. 4, pp. 623–656, 1948.
[37] I. Prigogine, *The End of Certainty.* New York: Simon & Schuster, Inc.
[38] A. Ben-Naim, *A Farewell to Entropy: Statistical Thermodynamics Based on Information.* Singapore: World Scientific Publishing Co. Pte. Ltd.
[39] S. C. Baslamisli and S. Onel, "Entropy based classification of road-profiles," in *Proc. 10th Biennial Conf. Engineering Systems Design and Analysis*, Istanbul, Turkey, 2010, pp. 1–8.
[40] H.-S. Tan, F. Bu, J. Huang, and Y.-K. Chin, "Charactering driving skills based on entropy analysis of steering frequency response," in *Proc. American Society of Mechanical Engineers 2010 Dynamic Systems and Control Conf.*, Cambridge, MA, USA, 2010, pp. 887–894.
[41] C. Wang, P. Hao, G. Wu, X. Qi, T. Lyu, and M. Barth, "Intersection and stop bar positon extraction from crowdsourced GPS trajectories," in *Proc. 96th Annu. Meeting Transportation Research Board*, Washington, DC, USA, 2017, pp.1–18.
[42] University of Kentucky, "Traffic flow fundamentals," [Online]. Available: https://web.engr.uky.edu/~rsouley/CE%20331/Part%20III%20F13/Traffic-4-TrafficFlowFundamentals.ppt
[43] G. Orosz, R. E. Wilson, and G. Stepan, "Traffic jams: Dynamics and control," *Philoso. Trans. Roy. Soc. A*, vol. 368, no. 1928, pp. 4455–4479, Sept. 2010.
[44] J. I. Ge, S. S. Avedisov, C. R. He, W. B. Qin, M. Sadeghpour, and G. Orosz, "Experimental validation of connected automated vehicle design among human-driven vehicles," *Transp. Res. C*, vol. 91, pp. 335–352, June 2018.
[45] J. Ploeg, N. van de Wouw, and H. Nijmeijer, "Lp string stability of cascaded systems: Application to vehicle platooning," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 2, pp. 786–793, Mar. 2014.
[46] S. E. Li, X. Qin, Y. Zhang, J. Wang, K. Li, and H. Zhang, "Distributed platoon control under topologies with complex eigenvalues: Stability analysis and controller synthesis," *IEEE Trans. Control Syst. Technol.*, early access, pp. 1–15, 2018.
[47] R. Ihaddadene, N. Ihaddadene, and M. Mostefaoui, "Evaluation of three methods for estimating annual and seasonal wind speed distributions," in *Proc. 2nd Int. Renewable and Sustainable Energy Conf.*, Morocco, 2014, pp. 311–316.
[48] A. Maqsood and A. Mohammad, "A comparative study to estimate the parameters of mixed-Weibull distribution," *Pakistan J. Statist. Oper. Res.*, vol. 4, no. 1, pp. 1–8, Jan. 2008.
[49] Transportation Research Board, "Highway capacity manual 2010," [Online]. Available: http://onlinepubs.trb.org/onlinepubs/trnews/trnews273HCM2010.pdf
[50] K. Boriboonsomsin and M. J. Barth, "Final report: Modeling the effectiveness of High Occupancy Vehicle (HOV) lanes at improving air quality," in *Center for Environmental Research and Technology*, CA, USA, 2006.

ITS

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Index Terms—CV applications, performance measures, speed variation, entropy

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