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Energy and emissions impacts of a freeway-based dynamic eco-driving system

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ABSTRACT

Surface transportation consumes a vast quantity of fuel and accounts for about a third of the US CO_2 emissions. In addition to the use of more fuel-efficient vehicles and carbon-neutral alternative fuels, fuel consumption and CO_2 emissions can be lowered through a variety of strategies that reduce congestion, smooth traffic flow, and reduce excessive vehicle speeds. Eco-driving is one such strategy. It typically consists of changing a person's driving behavior by providing general static advice to the driver (e.g. do not accelerate too quickly, reduce speeds, etc.). In this study, we investigate the concept of dynamic eco-driving, where advice is given in real-time to drivers changing traffic conditions in the vehicle's vicinity. This dynamic strategy takes advantage of real-time traffic sensing and telematics, allowing for a traffic management system to monitor traffic speed, density, and flow, and then communicates advice in real-time back to the vehicles. By providing dynamic advice to drivers, approximately 10–20% in fuel savings and lower CO_2 emissions are possible without a significant increase in travel time. Based on simulations, it was found that in general, higher percentage reductions in fuel consumption and CO_2 emission occur during severe compared to less congested scenarios. Real-world experiments have also been carried out, showing similar reductions but to a slightly smaller degree.

1. Introduction

To reduce greenhouse gas (GHG) emissions – particularly carbon dioxide (CO_2) – from the transportation sector, policy makers in the US are pushing for more fuel-efficient vehicles and the use of alternative fuels (California Energy Commission, 2005). In addition, more efficient traffic operational strategies that relieve roadway congestion can have a significant impact on reducing CO_2 from transportation (Barth and Boriboonsomsin, 2008).

Eco-driving can be considered as one such strategy that has recently become an important research theme worldwide due to increasing fuel costs and the general desire to reduce CO_2 emissions (Gense, 2000). Eco-driving primarily consists of a variety of driving techniques that save fuel and lower emissions. Eco-driving programs attempt to change a driver's behavior through general advice, such as: do not drive too fast; do not accelerate too quickly; shift gears sooner to keep engine speed lower; maintain steady speeds; and keep the vehicle in good maintenance (e.g. check for proper tire pressure frequently). Additional rules apply while driving in traffic, such as anticipating traffic flow when accelerating and slowing down smoothly for stopped traffic.

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Several eco-driving programs have been initiated in Europe, yielding fuel economy improvements on the order of 5–20% (Jowit, 2006; CIECA, 2007). In several of these programs, it was found that another benefit of eco-driving is a *safety* improvement, since higher speeds are reduced and there are less perturbations in the traffic stream. Preliminary work in Japan has also shown similar improvements (Shinpo, 2007). To date, substantially less attention has been placed on eco-driving in the US. Nevertheless, positive responses to eco-driving by the public have started to draw attention and actions from vehicle manufacturers[1].

It is important to note that nearly all eco-driving-related research to date has been on providing static advice to drivers and measuring before-and-after differences. However, when coupled with Intelligent transportation system (ITS) technology, there are also different ways of providing dynamic eco-driving advice to drivers based on traffic conditions and other external variables such as weather conditions. This dynamic eco-driving advice can be implemented using real-time traffic sensing and telematics, allowing for a traffic management center to communicate in real-time with equipped vehicles.

2. Background

Speed and acceleration have a large impact on a vehicle's fuel economy and tailpipe emissions; both pollutant and GHG emissions. In turn, speed and acceleration are the primary factors that determine the power requirements necessary for specific driving maneuvers. The power requirements of a vehicle are relatively straightforward to calculate in real-time. In addition to knowing the dynamic variables of speed and acceleration, other static variables play a role such as vehicle weight, aerodynamic drag, rolling resistance, and road grade. Tractive power requirements (in kilowatts) placed on a vehicle (at the wheels) is given in simplest form as:

$$P_{tractive} = \frac{M}{1000} \cdot V \cdot (a + g \cdot \sin\theta) + \left(M \cdot g \cdot C_r + \frac{\rho}{2} \cdot V^2 \cdot A \cdot C_a\right) \cdot \frac{V}{1000} \tag{1}$$

where M is the vehicle mass (kg), V is the vehicle velocity (meters/second), a is the vehicle acceleration (m/s^2), g is the gravitational constant (9.81 m/s^2), θ is the road grade angle, C_r is the rolling resistance coefficient, ρ is the mass density of air (1.225 kg/m^3, depending on temperature and altitude), A is the cross sectional area (m^2), and C_a is the aerodynamic drag coefficient.

To translate this tractive power requirement to demanded engine power requirements, the following simple relationship can be used as a first approximation:

$$P_{engine} = \frac{P_{tractive}}{\eta_{tf}} + P_{accessories} \tag{2}$$

where η_{tf} is the combined efficiency of the transmission and final drive, and $P_{accessories}$ is the engine power demand associated with the operation of accessories, such as air conditioning, power steering and brakes, and electrical loads. In the final model, $P_{accessories}$ can be modeled as a function of engine speed, and η_{tf} can be modeled in terms of engine speed and $P_{tractive}$.

The power requirements on the engine P_{engine} is directly related to fuel consumption:

$$\frac{dF}{dt} \approx \lambda \left(k \cdot N \cdot D + \frac{P_{engine}}{\eta_{engine}}\right) \tag{3}$$

where λ is the fuel/air equivalence ratio, k is the engine friction factor (it represents the fuel energy used at zero power output to overcome engine friction per engine revolution and unit of engine displacement), N is engine speed, D is engine displacement, and η_{engine} is a measure of indicated engine efficiency. This equation is simple but fairly accurate to determine fuel use rate (in kilowatts), typically within 5% of actual fuel use for the majority of driving conditions (Barth et al., 1999).

Based on the power requirements and related fuel consumption, tailpipe emissions of carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), and oxides of nitrogen (NO_x) can be estimated. This is the basis of a second-by-second energy/emissions model called Comprehensive Modal Emissions Model (CMEM)[2].

The model can predict second-by-second vehicle emissions and fuel consumption given any vehicle trajectory (i.e. velocity, acceleration, road grade). It is comprehensive in that it covers a variety of vehicle types and emission control technologies; consists of nearly 30 vehicle/technology categories from the smallest light-duty vehicles to Class-8 heavy-duty diesel trucks. With CMEM, it is possible to predict fuel consumption and emissions from individual vehicles or from an entire fleet, operating under a variety of traffic conditions. This type of microscale model is important for developing and evaluating transportation technologies and policies, particularly those related to ITS. In the past, large regional emissions inventory models were applied to these types of microscale evaluations with little success. By modeling at the microscale using CMEM, fuel consumption and CO_2 emissions are generally within 5% of real-world values and pollutant emissions generally within 15%.

One of the important features of CMEM is that it uses a physical, power-demand approach based on a parameterized analytical representation of fuel consumption and emissions production. The entire fuel consumption and emissions process is

[1] For example, Ford now offers an online eco-driving tutorial on one of its websites (http://www.drivingskillsforlife.com). Toyota also plans to make eco-driving indicators standard in all of its vehicles (Toyota, 2008).

[2] The model was originally developed under sponsorship of the US National Cooperative Highway Research Program (NCHRP) and the US Environmental Protection Agency (EPA).

broken down into components that correspond to physical phenomena associated with vehicle operation and emissions production. Each component is modeled as an analytical representation consisting of parameters that are characteristic of the process and vary according to the vehicle type, engine, emission technology, and level of deterioration. One distinct advantage of this approach is that it is possible to adjust many of these physical parameters to predict energy consumption and emissions of future vehicle models and applications of new technology (e.g. aftertreatment devices).[3]

CMEM is designed so that it can interface with a wide variety of transportation models and/or data sets to perform detailed fuel consumption analyses and to produce a localized emissions inventory. CMEM has been developed primarily for microscale transportation models that typically produce second-by-second vehicle trajectories (location, velocity, acceleration). These vehicle trajectories can be applied directly to the model, resulting in both individual and aggregate energy/emissions estimates. CMEM has been successfully integrated with the state-of-the-art traffic simulation model PARAMICS (Quadstone, 2008). PARAMICS consists of a suite of high performance software tools for microscopic traffic simulation. Individual vehicles are modeled in fine detail for the duration of their entire trip, providing good estimates of traffic flow, travel time, and congestion information, as well as enabling the modeling of the interface between drivers and ITS. One of the key features of PARAMICS is that it allows users to easily integrate additional modules through the use of an application-programming interface (API). A separate CMEM API was developed for PARAMICS that can predict emissions and fuel consumption in real-time (Barth et al., 2001).

3. Methodology

Since vehicle speed and acceleration affect fuel consumption and emissions, it is desired to adjust them while still meeting specific driving requirements and trip plans. If we consider speed, it is possible to dynamically provide speed advice at particular locations and time instances based on external conditions (e.g. weather, traffic, etc.). This has been researched in the form of intelligent speed adaptation (ISA) (Carsten and Fowkes, 2000; Almquist et al., 1991). ISA uses time and/or location information to manage vehicle speed, primarily for safety purposes. More specifically, it comprises a process that monitors the speed of a vehicle, compares it to an externally defined set speed, and takes corrective action (e.g. advising the driver and/or governing the maximum speed). Most ISA systems rely on technologies such as global position system receivers, on-board roadway databases, and/or wireless communication. They can be implemented in a variety of ways, depending on how the set speed is determined (Varhelyi and Makinen, 2001). ISA systems intervene with driver behavior in a number of ways, including; advisory, where limits are displayed on a messaging device and the driver changes vehicle speed accordingly; active support, where the control system can change vehicle speed but driver can override; and mandatory, where ISA controls maximum speed and driver cannot override.

Most work on ISA has used macroscopic traffic flow models to examine changes in overall freeway traffic characteristics (e.g. speed, density, and flow) due to the implementation of speed management (Oh and Oh, 2005; Lu et al., 2006). It has provided some initial insight on overall traffic effects, however, the microscopic effects (e.g. individual vehicle trajectories) associated with implementing this type of speed control are not well understood. If the microscopic effects can be determined, then it will be possible to estimate vehicle emissions and energy consumption impacts of various speed and acceleration modification techniques for a variety of roadway conditions.

Here, we develop an eco-driving technique that manages speed and acceleration while driving on roadways to reduce fuel consumption and vehicle emissions. Under congested conditions, traffic instability (i.e. stop-and-go conditions) can often develop. This instability generally takes place when traffic is flowing at or near the roadway capacity, and some type of perturbation occurs (e.g. sudden slowing, lane drop, accident, etc.). Traffic flow instability is characterized by significant speed variations in the individual vehicles due to the random and non-homogenous nature of individual driver behavior.

This roadway congestion has been categorized into different ‘‘levels-of-service” or LOS (Transportation Research Board, 1994). For freeways (i.e. non-interrupted flow), LOS can be represented as a ratio of the traffic flow divided by the roadway capacity. There are several different LOS values that range from the letters ‘‘A–F”. For these levels-of-service, a typical vehicle velocity trajectory will have different characteristics – Fig. 1. Under LOS A, vehicles will typically travel near the highway's free flow speed, with little acceleration/deceleration perturbations. As LOS conditions get progressively worse (i.e. LOS B, C, D, E, and F), vehicles will encounter lower average speeds with a greater number of acceleration/deceleration events.

The acceleration/deceleration events that occur under heavy congestion result in higher fuel consumption and vehicle emissions per unit distance. The overall goal of dynamic eco-driving is to smooth the traffic flow (and thereby decreasing fuel consumption) by dynamically advising vehicles to travel at specific speeds. It is also beneficial to actively specify acceleration rates although accelerations are already limited indirectly when advising specific speeds. For example, if the average traffic speed is 48 km/h under LOS E conditions, the maximum speed of the vehicle can be limited so that sharp accelerations that bring velocities well above this limit can be eliminated. These speed advisory techniques can be accomplished without adversely affecting the overall travel times – the net result is a smoother vehicle velocity profile.

[3] For further information on the CMEM effort, see Barth et al. (1996a, 1999, 2004).

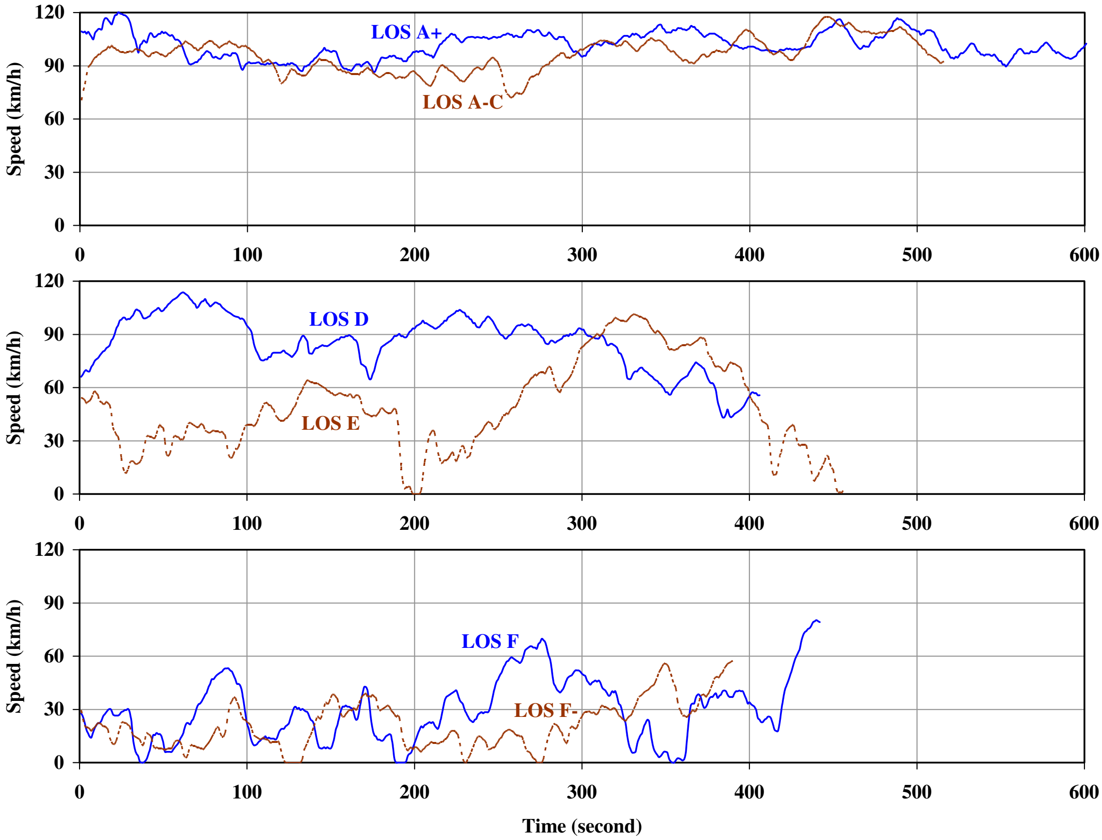

Fig. 1. Example vehicle velocity trajectories for different congestion levels-of-service on a freeway.

3.1. System architecture

This dynamic eco-driving system requires that real-time traffic conditions are readily available, such that a system algorithm can determine optimal speed values on a link-by-link basis in a roadway network – Fig. 2. Several different components interact together. This architecture takes advantage of the existing California Freeway Performance Measurement System (PeMS) (Choe et al., 2002). The system consists of numerous embedded loop detectors on the major freeways in California, each reporting flow and occupancy and thus allowing average traffic speed to be computed. These data are collected through local Traffic Management Centers (TMCs), and then filtered, processed, and made accessible at 30-second intervals on the Internet via the PeMS server. The overall eco-driving strategy occurs primarily on a system server (potentially located at a traffic management center), where the PeMS data (e.g. average traffic speed on a link-by-link basis) are collected and processed. An algorithm determines an optimal "set" speed for an individual vehicle traveling on the network, based on the vehicle's location, direction, and PeMS data in the vicinity. This suggested set speed is communicated to the instrumented vehicle via a wireless communications provider. We utilized instrumented vehicles that can also provide velocity trajectory data back to the system server for analysis.

Again, the overall system is designed for travel on freeways (non-interrupted flow) because that is where traffic performance measurements are currently made. The overall methodology relies on traffic performance data being collected at sufficiently high spatial resolution (i.e. every few kilometers or so) and time resolution (i.e. every few minutes). The information must also be made available quickly with low latency (i.e. less than 30 s).

3.2. Set speed determination algorithm

One way of determining the suggested set speed of a managed vehicle is to use the average traffic speed, which is directly measured by the traffic performance measurement system. As the overall speed changes, so would the set speed of the managed vehicle. In this way, the overall travel time of the managed vehicle does not differ from what would normally occur, however the stop-and-go events would be reduced, thereby improving fuel economy and reducing emissions.

There are also other ways in which dynamic speed control strategies can be developed. For instance, Oh and Oh (2005) developed a dynamic control strategy based on an analytical derivation of a macroscopic traffic flow model, and proved the

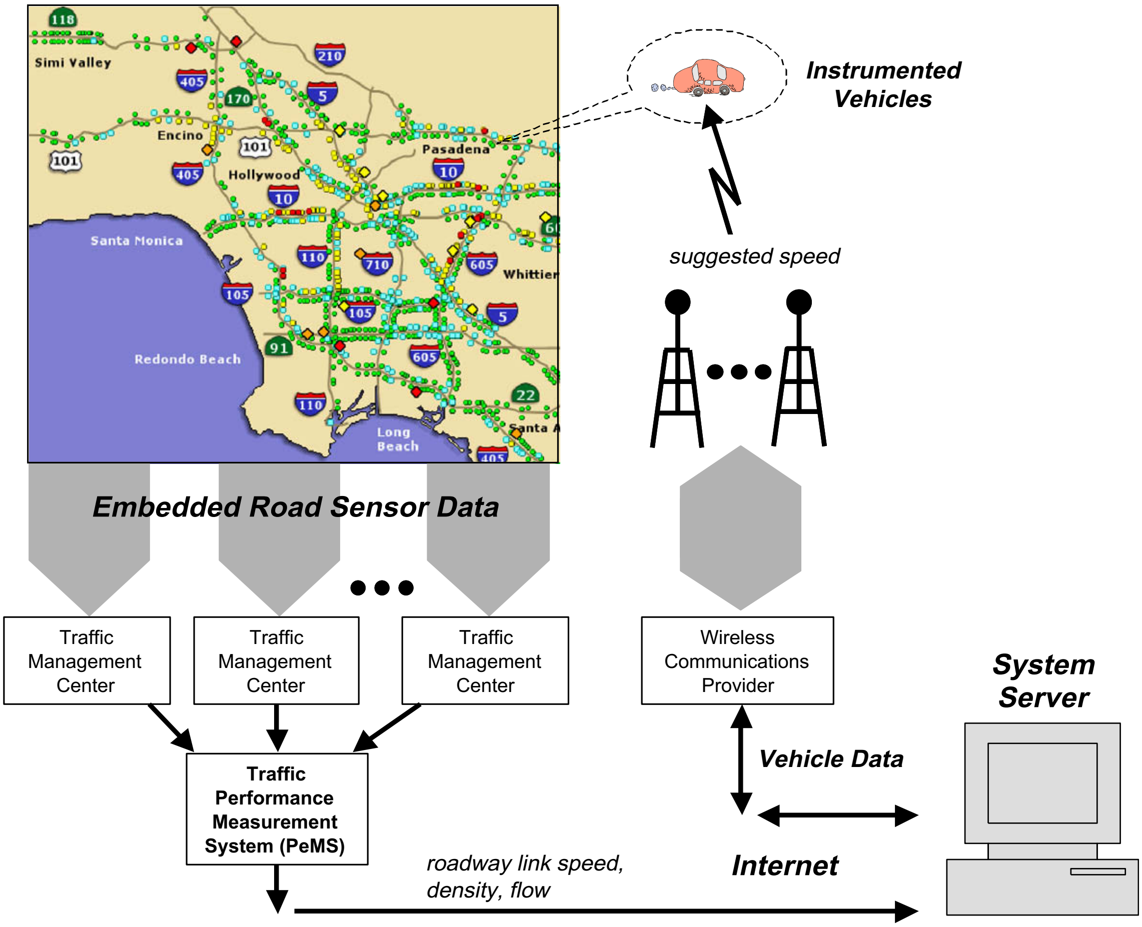

Fig. 2. Overall system architecture for real-world experimentation.

effectiveness of their strategy using a macroscopic simulation tool. Similarly, Lu et al. (2006) applied a model predictive control procedure to a macroscopic model to achieve an optimal coordination of speed limits in a dynamic speed control strategy. In both cases, the derivation of the speed control strategy is based on the traffic flow characteristics of overall traffic stream.

In contrast, we took a microscopic vehicle activity measurement approach. Ideally, the speed management mechanism would eliminate high and low speed peaks so that each managed vehicle travels constantly at the predefined set speed. However, it is impossible for any one vehicle to maintain a set speed during the entire course of the driving because variations will occur occasionally due to random interactions with other vehicles in the traffic. To compensate for the travel time penalty caused by speed drops, the set speed should be set at values greater than the average traffic speed. Deviation from the average traffic speed should vary by the level of congestion with a higher probability of a speed-managed vehicle encountering speed drops in more heavily congested circumstances.

In addition to the average traffic speed, the freeway link LOS value is used as another traffic parameter. Thus for each LOS, the set speed can be calculated as a mean second-by-second traffic speed plus a specific amount of speed adjustment. Given that the amount of adjustment is a function of the standard deviation of traffic speed trajectories, the set speed for traffic under LOS i is:

$$v_i^c = \bar{v}_i + k_i \cdot s_i \tag{4}$$

where v_i^c is a set speed (km/h); $\bar{v}_i$ is the mean of second-by-second speed of all vehicles in traffic (km/h); k_i is a constant; s_i is the standard deviation of second-by-second speed of all vehicles in traffic (km/h): and i = {LOS A, LOS B, LOS C, LOS D, LOS E, LOS F}.

The aggregated traffic spot speed collected by loop sensors can be used to represent the mean of second-by-second vehicle speed trajectory as they correlate well with each other (Barth et al., 1996b). These data can also be obtained in real-time via PeMS. On the other hand, data concerning the standard deviation of second-by-second traffic speed is not readily available in real-time, but can be derived from representative driving trajectory data for each LOS, collected through a traffic activity measurement program.

3.3. Traffic data collection

To estimate the standard deviation of traffic speeds for different LOS values, we collected driving trajectory data using three probe passenger vehicles on freeways in Southern California during September 2005, May 2006, and March 2007. To represent general traffic conditions, the data collection occurred uniformly over the day and collection dates were equally distributed from Monday to Friday. Multiple drivers are used to take into account the fact that different people drive differently even under the same LOS. In general, drivers were instructed to mimic the general traffic flow, i.e. not driving too aggressively (passing many other vehicles), nor driving too passively (being passed by many other vehicles). The drivers were free to drive in different lanes on the roadway as the lane information was simultaneously recorded. In addition to the probe vehicle data, macroscopic traffic data from PeMS were gathered simultaneously. Using information about latitude, longitude, and time stamps, the probe vehicle data were spatially and temporally matched with the PeMS data.

Typically, vehicle detector stations (VDS) in the PeMS network are located around 1.0–1.6 km apart. The spatial coverage of each VDS is from the midpoint between itself and the upstream VDS and to the midpoint between itself and the downstream VDS. The LOS value for loop detectors at each VDS is updated every 30 s; hence every half-minute the second-by-second driving trajectories were spatially mapped with the corresponding VDS. A vehicle running in lane l within the coverage of VDS i at time t is considered to experience the LOS reported by the loop detector in lane l at VDS i during period p. This process started at the beginning of the driving trace is repeated until the end of the driving trace.

Table 1 summarizes the statistics of the second-by-second speed data for each LOS. Fig. 3 plots the mean speed and its variation. It can be seen that the mean speed values correlate well with the definition of each LOS. LOS A, B, and C are in stable flow. Thus, the mean speed values are relatively high and the speed variations are low. The mean speed values for LOS D, E, and F drop significantly from one LOS to the next LOS, as the traffic experiences progressively worse congestion. The speed variation is highest for LOS D and E.

Given the real-time average traffic velocity from the vehicle detector stations along with the derived standard deviations of microscopic velocity, the last step in deriving a dynamic set speed based on Eq. (4) is to determine different values for k (as a function of LOS). The k term is a scaling factor chosen to minimize travel time differences between an eco-driving-enabled vehicle and one that is not. To determine the k values, we have performed in-depth analysis using a microscopic traffic simulator, as described in (Servin et al., 2008). A freeway section was simulated with different travel demand values while limiting capacity to create "stabilized" congestion events for each level of service. With a 20% penetration rate of eco-driving vehicles in the fleet, we compared the travel times of the eco-driving vehicles with the non-eco-driving vehicles for different k values at different LOS. The results are summarized in Table 2.

Table 1
Statistics of measured second-by-second speed values.

LOS	N (s)	Mean (km/h)	Standard deviation (km/h)	Coefficient of variation	95% Upper confidence limit	95% Lower confidence limit
A	1721	121.6	7.1	0.1	122.0	121.3
B	1892	114.1	11.6	0.1	114.6	113.4
C	2414	108.1	10.8	0.1	108.6	107.8
D	1770	89.8	27.5	0.3	91.1	88.5
E	1104	58.6	35.2	0.6	60.7	56.5
F	6195	23.8	17.2	0.7	24.1	23.3

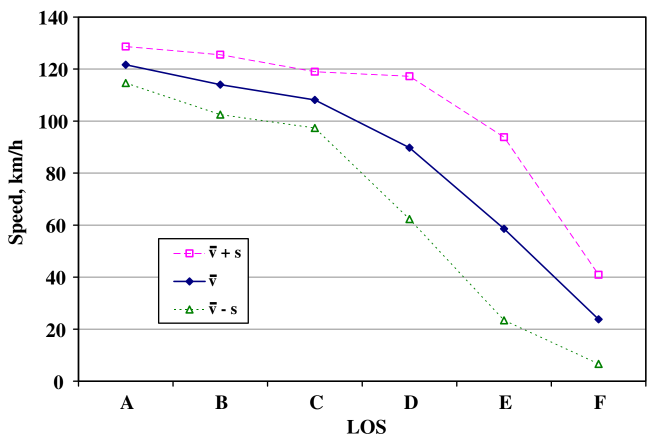

Fig. 3. Variation of speed trajectories under different levels of congestion.

The selected k values appear to progress with lower LOS (from 0.00 to 0.95), except for LOS E; likely so because the standard deviation of speed at LOS E is the highest. Even a small value of k will have a large impact on the set speed for this LOS. Also shown in Table 2 are the computed and final set speeds for the mean traffic speed values from Table 1, using Eq. (4). The values are rounded to the nearest speed with an increment of 5 km/h to obtain the final set speeds, which are regarded as the recommended maximum speeds for eco-driving vehicles under different levels of congestion. The rounding of the final set speeds is aimed at providing easy-to-comprehend information to the drivers.

4. Simulation setup and results

To determine the effectiveness of this dynamic eco-driving system, a variety of simulation and real-world experiments are conducted. The simulations are based on a unique integration of the microscopic traffic simulation tool PARAMICS with CMEM. Using this modeling tool, a variety of freeway traffic scenarios are analyzed. As a starting point, a straightforward roadway section is considered; Fig. 4. Different levels of congestion are induced for the segment by varying its travel demand. We focus on "stabilized" congestion levels, where congestion is consistent both spatially and temporally, after any shock waves have passed through the traffic stream. For different congestion levels (specified by different volume-to-capacity ratios), emissions and fuel consumption are compared between non-eco-driving and eco-driving vehicles, for scenario with a 20% penetration rate of eco-driving vehicles. The simulated vehicle fleet is calibrated to a typical vehicle population for Southern California.

An example of an eco-driving vehicle's velocity profile compared to a non-eco-driving vehicle velocity profile is shown in Fig. 5. Stabilized congestion is induced where the average traffic speed is about 40 km/h. These two trajectories have approximately the same travel time, however the eco-driving vehicle has a much smoother velocity trajectory, resulting in lower fuel consumption and emissions. Table 3 provides statistics of the example vehicle trajectories, along with the fuel consumption, CO_2 emissions, and travel time. It can be seen that significant fuel savings and emissions reductions are possible with very little difference in the overall travel time.

Table 2
Selected k values and corresponding control speeds.

LOS	Selected k	$\bar{v}$ (km/h)	s (km/h)	Computed v^f (km/h)	Final v^f (km/h)
A	0.00	121.6	7.1	121.6	120
B	0.30	114.1	11.6	117.6	120
C	0.35	108.1	10.8	111.8	110
D	0.55	89.8	27.5	104.9	105
E	0.10	58.6	35.2	62.1	60
F	0.95	23.8	17.2	40.2	40

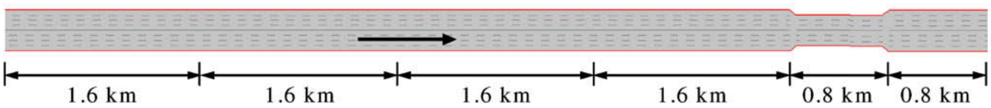

Fig. 4. Basic freeway segment used for simulation.

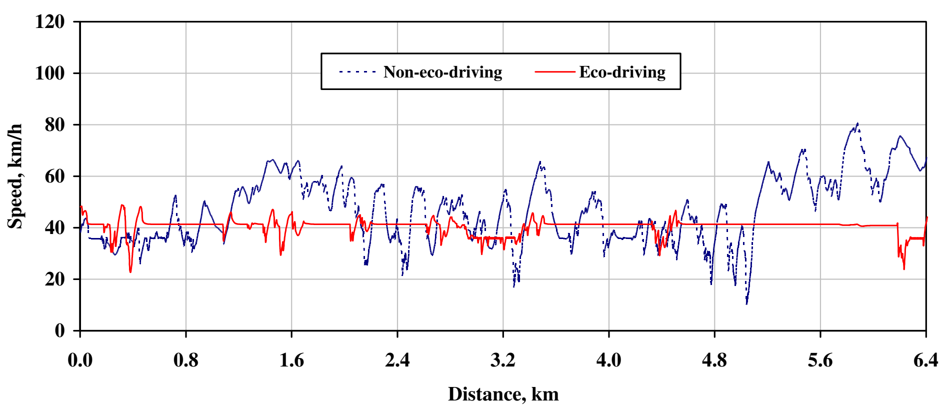

Fig. 5. Velocity trajectories for non-eco-driving vehicle (dash) and an eco-driving vehicle (solid) under stabilized congestion conditions.

Table 3
Fuel consumption, emissions, and travel times for the example vehicle trajectories for a typical passenger vehicle.

Velocity trajectory	Non-eco-driving	Eco-driving	Difference
Max (km/h)	80.5	48.9	−31.7
Min (km/h)	10.3	22.7	+12.4
Average (km/h)	43.3	40.2	−3.05
Std. dev. (km/h)	12.7	3.2	−9.5
Skewness (km/h)	0.64	−2.9	−3.5
CO_2 (g)	1605.13	1044.81	−34.9%
Fuel consumption (g)	531.23	333.29	−37.3%
Travel time (min)	8.9	9.6	+7.7%

To determine the effectiveness of the dynamic eco-driving strategy across different congestion levels, further simulations are needed. It is expected that the dynamic eco-driving technique will have little effect at LOS A when the traffic density is low; the greatest gains should occur during more congested conditions. Using the simulation modeling tools, LOS A–F conditions are simulated using the speed strategy that has the lowest impact on overall travel time – Fig. 6. These fuel savings/emission reductions are calculated for a 20% penetration rate of eco-driving vehicles. The corresponding travel time differences between the two scenarios are also plotted.

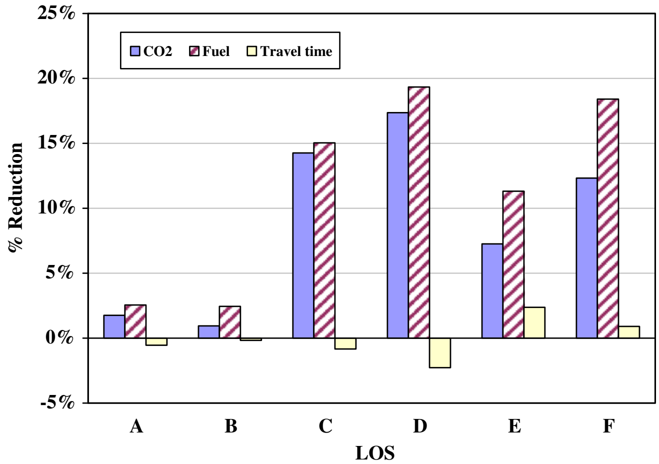

Fig. 6. Percentage savings comparing typical eco-driving vehicle versus typical non-eco-driving vehicle for different congestion conditions (note travel time differences for LOS A–D are close to zero).

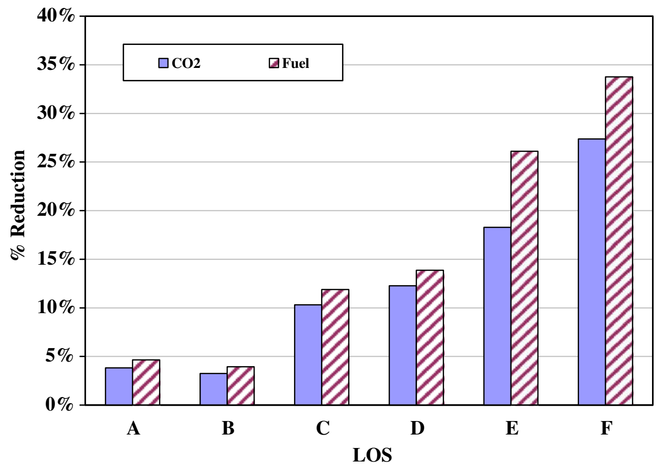

Fig. 7. Percentage savings for the entire traffic stream with a 20% penetration rate of eco-driving vehicles for different congestion conditions, compared to a baseline traffic scenario of 0% eco-driving vehicles.

It is anticipated that the overall traffic flow will be smoother if all vehicles use the dynamic eco-driving technique (i.e. 100% penetration rate), although it is unlikely that this will be so. But even when a few of the vehicles in traffic follow these

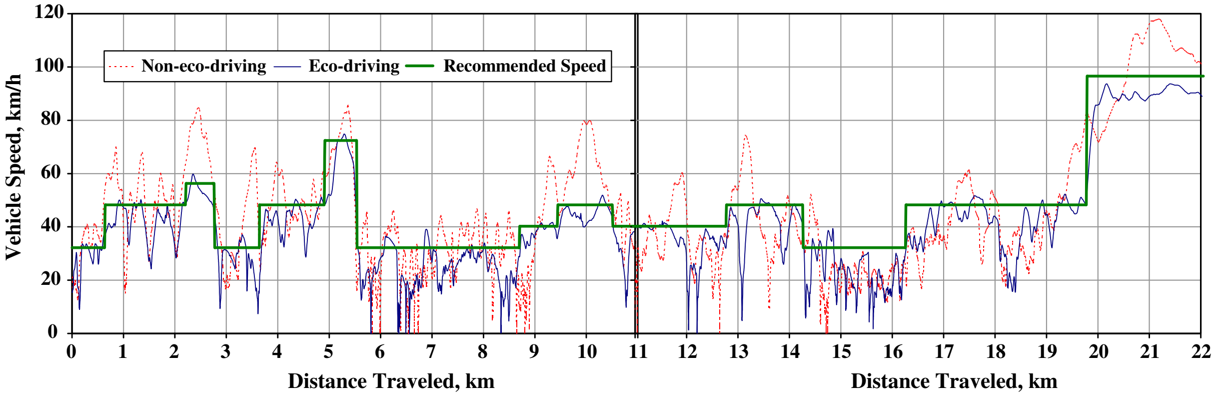

Fig. 8. Velocity versus distance for both the eco-driving vehicle, non-eco-driving vehicle, and recommended speed profile.

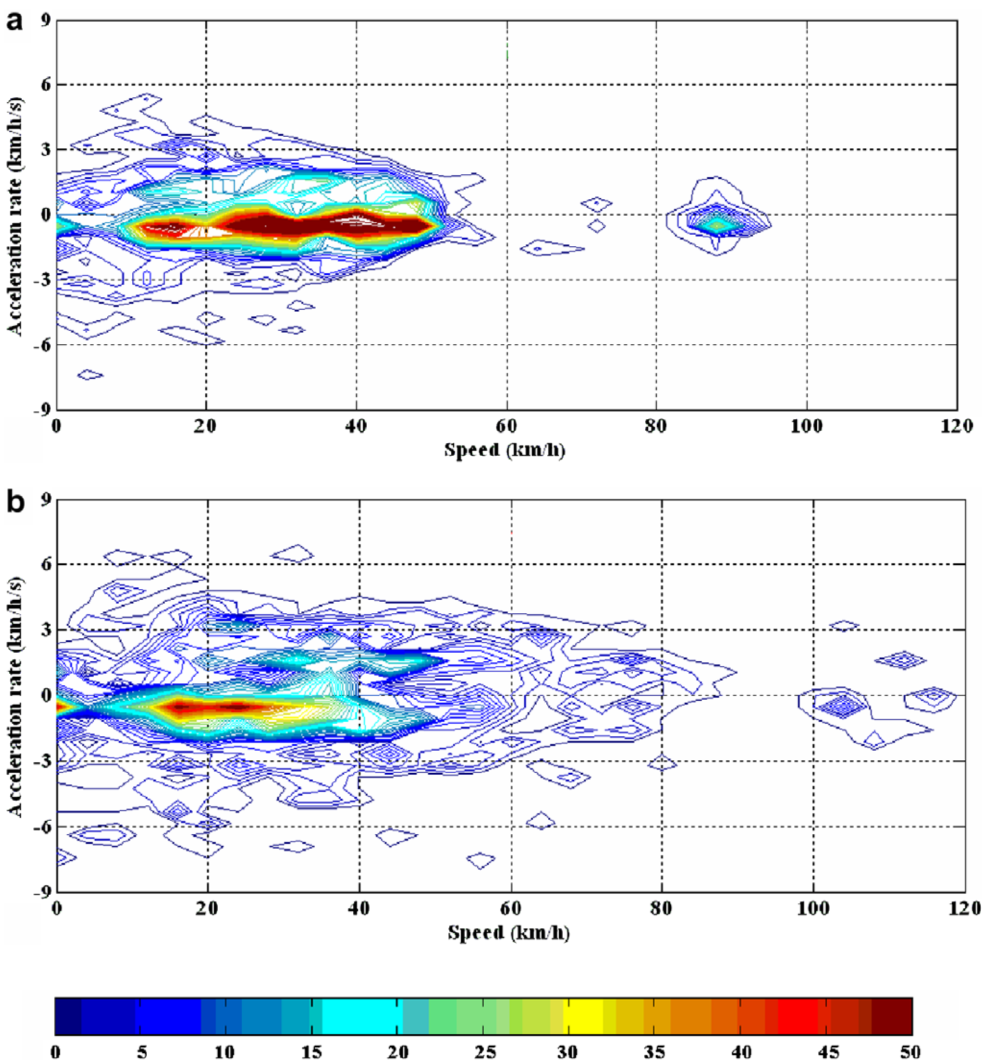

Fig. 9. Speed-acceleration histograms for both (a) eco-driving and (b) non-eco-driving vehicles.

Table 4
Trajectory and energy/emission statistics of experimental runs.

Velocity trajectory	Non-eco-driving	Eco-driving	Difference
Max (km/h)	117.9	93.6	−24.3
Min (km/h)	0.0	0.0	0.0
Average (km/h)	33.9	32.1	−1.9
Std. dev. (km/h)	21.2	17.5	−4.0
Skewness (km/h)	1.7	1.6	−.16
CO_2 (g)	5439	4781	−12%
Fuel (g)	1766	1534	−13%
Travel time (min)	38.9	41.2	+6%

eco-driving techniques, there is still an effect on the overall traffic stream since the eco-driving vehicles will have influence on non-eco-driving vehicles' maneuverability. A non-eco-driving vehicle's velocity is often indirectly limited to that of an eco-driving vehicle in front. This phenomenon occurs until the non-eco-driving vehicle finds a sufficiently large gap in the adjacent lanes to overtake the eco-driving vehicle. Fig. 7 illustrates the percentage fuel/emission reductions for the entire traffic stream, again with a 20% penetration rate of dynamic eco-driving vehicles, compared to a 0% penetration rate. This illustrates that even with 20% of the fleet following these eco-driving rules, overall traffic is smoother and fuel consumption and CO_2 emissions are significantly lower when compared to baseline traffic.

5. Real-world experimentation

In addition to the simulation analysis, some initial real-world experimentation is conducted. The overall system architecture illustrated in Fig. 2 is used. Real-time freeway traffic data (speed, density, flow) were acquired from the California PeMS system and used to compute a dynamic recommended speed for an eco-driving vehicle in traffic. Using telematics feedback to the vehicle, the driver is advised, via a dashboard display, of the recommended speed, and the driver attempts to limit the vehicle speed to that recommended by the system server. The recommended speed was updated dynamically according to the overall traffic data at the vehicle's location.

To serve as a "control" in the experimentation, a second vehicle operated along the same route in the same traffic, however without any recommended speed information. The overall goal was to compare the recorded vehicle trajectories of both the eco-driving vehicle and the non-eco-driving vehicle. The vehicles were sent into traffic under various congestion conditions. A number of experimental runs were accomplished. As an example, high levels of congestion were present on the California SR-91 freeway during the PM peak period. For this example, the velocity profiles for both vehicles are shown in Fig. 8. The figure also shows that the recommended maximum speed was rarely exceeded during the experimentation.

Fig. 9 shows the speed-acceleration histograms of the two vehicles for this example run. It is apparent that the velocity of the eco-driving vehicle was often limited below 56 km/h with fewer and milder acceleration/deceleration events when compared to the histogram of the non-eco-driving vehicle.

Statistics from these experimental runs are provided in Table 4 and show that significant energy and emissions reductions do occur without much penalty to travel time, even for this simple experimental run. Greater energy/emission reductions are likely if greater penetration rates are present as the overall traffic would flow more smoothly because of the influence eco-driving vehicles have on other non-eco-driving vehicles.

6. Conclusions

To date, eco-driving has primarily taken the form of static advice to drivers. In an attempt to reduce fuel consumption and CO_2 emissions further, real-time dynamic advice to drivers can be used. For driving on congested freeways, the proposed methodology provides recommended speeds to drivers. Here, an algorithm for deriving the recommended set speed for these vehicles is described, based on real-time measurements from a traffic performance measurement system. To determine the effectiveness of the overall strategy, the microscopic effects in terms of individual vehicle trajectories are examined, using both simulation modeling tools and limited real-world vehicle experimentation. It was found that fuel consumption and CO_2 emissions can be reduced by an order of 10–20% without drastically affecting overall travel time. The percentage savings depend on the congestion level: under freeflow conditions there is little benefit. However for severe congestion, the savings are considerable.

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