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ABSTRACT

This paper describes research undertaken to establish plausible fuel-speed curves (FSC) for hypothetical advanced powertrain vehicles. These FSC are needed to account for the effects of congestion in long-term transportation scenario analysis considering fuel consumption and emissions. We use the PERE fuel consumption model with real-world driving schedules and a range of vehicle characteristics to estimate fuel economy (FE) in varying traffic conditions for light-duty internal combustion engine (ICE) vehicles, hybrid gas-electric vehicles (HEV), fully electric vehicles (EV), and fuel cell vehicles (FCV). FSC are fit to model results for each of 145 hypothetical vehicles. Analysis of the FSC shows that advanced powertrain vehicles are expected to perform proportionally better in congestion than ICE vehicles (when compared to their performance in free-flow conditions). HEV are less sensitive to average speed than ICE vehicles, and tend to maintain their free-flow FE down to 20 mph. FE increases for EV and FCV from free-flow conditions down to about 20-30 mph. Beyond powertrain type differences, relative FE in congestion is expected to improve for vehicles with less weight, smaller engines, higher hybrid thresholds, and lower accessory loads (such as air conditioning usage). Relative FE in congestion also improves for vehicle characteristics that disproportionately reduce efficiency at higher speeds, such as higher aerodynamic drag and rolling resistance. In order to implement these FSC for scenario analysis, we propose a bounded approach based on a qualitative characterization of the future vehicle fleet. The results presented in this paper will assist analysis of the roles that vehicle technology and congestion mitigation can play in reducing fuel consumption and emissions from roadway travel.

1 Introduction

Traffic congestion has been steadily increasing in the U.S. for decades [1]. Increasing levels of congestion lead to longer travel times, lower average speeds, and increased vehicle speed variability. These affect engine/motor operating loads and operating duration, which in turn affect fuel efficiency. At the same time, the U.S. vehicle fleet continues to evolve, with new powertrain types such as Hybrid Electric Vehicles (HEV), Fuel Cell Vehicles (FCV), and fully Electric Vehicles (EV) [2]. This paper addresses how these new vehicle technologies will respond to congestion, in terms of fuel efficiency. The Oregon Department of Transportation (ODOT) has developed a model to forecast transportation-related greenhouse gas emissions, called the Greenhouse gas Statewide Transportation Emissions Planning model or GreenSTEP [3]. GreenSTEP is a modeling tool that can be used to assess the impact of a range of policies and other factors on transportation-related greenhouse gas emissions. It is designed to operate within the context of the large uncertainties of long-term transportation planning. One of the improvements needed in the model is the ability to account for the impact of future technological changes on vehicle fuel efficiency in congestion.

Vehicle fuel efficiency can be expressed as Fuel Economy (FE), in travel distance per unit volume of fuel – in the U.S. as miles per gallon (mpg). Fuel-Speed Curves (FSC) summarize the relationship between vehicle fuel economy and congestion level (indicated by travel speed) for average, aggregate conditions. Thus FSC can serve to estimate fuel consumption in congestion for macroscopic traffic and transportation models.

In the GreenSTEP model, normalized FSC are used to adjust average fuel efficiencies for varying levels of metropolitan congestion. While FSC for conventional, Internal Combustion Engine (ICE) vehicles have been previously studied (and adopted in GreenSTEP), FSC for advanced powertrain vehicles have received less attention. In order to enable incorporation of the impacts of congestion on advanced vehicles in GreenSTEP, this research develops FSC for HEV, FCV, and EV. Fuel economy at varying average travel speeds is estimated using an advanced-vehicle fuel consumption model with archetypal speed profiles. Then, representative FSC are estimated for each vehicle type, based on a range of vehicle characteristics. The next section describes relevant background information and literature, and is followed by a presentation of the modeling methodology. Then, results for FSC calculation are show, followed by a section discussing of the application of these FSC for transportation scenario analysis.

2 Background and Literature

2.1 Congestion and Fuel Economy

Traffic congestion affects vehicle fuel economy through lower average travel speed and increased vehicle speed variability (accelerations and decelerations). These influence engine/motor operating loads and operating duration, which in turn impact fuel consumption per mile of travel [4]. FSC show these aggregate relationships as the expected average FE at a given average travel speed, including typical acceleration and deceleration activity (often for specific vehicle and roadway types). In this way the speed variable in FSC is a proxy for congestion level, indicative of both average speed and speed variability for archetypal conditions.

FSC are the fuel equivalent of Emissions-Speed Curves (ESC), which are used to estimate the aggregate impact of congestion on vehicle pollution emissions rates [5–7]. The ESC approach has been shown to adequately represent congestion effects (related to both average speed and speed variability) if the curves are based on representative, real-world driving patterns [8], [9]. The EPA has created a set of realistic driving schedules (driving patterns) for inclusion in their MOVES 2010 mobile-source emissions model [10], [11]. Existing research on FSC for ICE vehicles indicates that increasing levels of congestion – with lower average speeds – generally lead to increased fuel consumption rates [6]. At very high speeds, however, fuel consumption rates increase as well, and there is an optimal average speed for fuel economy which depends on the vehicle fleet – typically between 45 and 65 mph [12].

2.2 Fuel Economy of Advanced Vehicles

Given concerns about energy consumption and climate impacts of the U.S. vehicle fleet, there has been considerable attention paid to the potential fuel economy of advanced powertrain vehicles [2], [4], [13], [14]. Fuel economy estimates for advanced vehicles are challenging because few, if any, dynamometer test data are available. Thus, vehicle fuel consumption modeling is often undertaken to estimate or predict the performance of these vehicles. Various studies have demonstrated or predicted substantial fuel consumption or greenhouse gas emissions savings from the substitution of advanced powertrain vehicles for conventional Internal Combustion Engine (ICE) vehicles in the fleet [2], [15–17].

Fuel consumption modeling for advanced vehicles has focused on average overall fuel economy. But speed-based or congestion-based FE estimates are needed to predict the effects of varying congestion levels on the performance of these vehicles. Delorme, Karbowski, & Sharer [18] modeled the speed-dependent fuel consumption rates of select medium and heavy-duty vehicles, including several hybrid versions. They point out the importance of using realistic driving patterns and the challenge of a lack of a standard set of vehicle technical specifications for advanced vehicle modeling. Fontaras, Pistikopoulos, and Samaras [19] modeled two hybrid passenger cars and found lower optimal speeds with respect to fuel consumption for the hybrid cars than for conventional cars (and lower overall fuel consumption rates). While modeling such as this suggests different FSC for advanced vehicles than for ICE vehicles, these studies do not provide the array of FSC needed for scenario testing of a variety of potential advanced vehicles in congestion.

Beyond the unique mechanical performance of advanced vehicles, some studies have suggested that advanced vehicles are driven differently. An empirical study by the EPA in Kansas City showed less aggressive driving for HEV than for ICE vehicles [11]. The report acknowledges, however, that there are several other possible explanations besides driver behavior change in response to HEV/ICE vehicle differences. Other possibilities include less power available in the test hybrid vehicles and self-selection of fuel-conscious drivers for hybrid ownership. Alessandrini & Orecchini [20] studied EV operating in Rome and also found less aggressive driving – presumably owing to the limited power of the vehicles.

2.3 Modeling Congestion in GreenSTEP

In order to motivate the study methodology, we here describe the role of FSC within GreenSTEP. Average fleet fuel economy by vehicle type and model year is input to each model run. GreenSTEP accounts for congestion effects by adjusting the fleet-average fuel economy (for ICE vehicles only). For each metropolitan area, the Daily Vehicle Miles Traveled (DVMT) are distributed by average speed (average speed ranges are 25-60 mph on freeways and 21-30 mph on arterials). Then, normalized FSC are used to scale the average fleet fuel economy based on the estimated speed distribution of DVMT. Details can be found in the GreenSTEP documentation [3]. The next section describes the modeling methodology of this study, which attempts to develop realistic FE adjustment curves at the GreenSTEP scope of modeling.

3 Methodology

In order to estimate the impacts of congestion on advanced technology vehicles, this research develops FSC for light-duty ICE vehicles, HEV, FCV, and EV. An overview of the modeling procedure is illustrated in Figure 1. First, a large set of real-world driving schedules (a) and a test set of 145 hypothetical vehicles with a variety of characteristics (b) are used as inputs to the PERE model (c) to estimate fuel consumption rates by Vehicle Specific Power (VSP) bin (e) for each vehicle. Next, the same set of driving schedules (a) and vehicle characteristics (b) are used to calculate (d) VSP bin distributions of operating time for each driving schedule, for each vehicle (f). The driving schedules represent a variety of congestion levels on freeway and arterial facilities. Combining (e) and (f) generates estimates of average FE for each driving schedule, for each vehicle (g). We fit these FE estimates to a curve as a function of the average speed for each driving schedule, producing a FSC for each vehicle on each facility type (h). Finally, the freeway and arterial FSC for each vehicle are normalized to the average speeds implied by EPA test driving schedules (i). Section 5 describes a proposed method for implementation of these normalized FSC in a long-range scenario analysis tool. We next describe components of the modeling methodology in more detail.

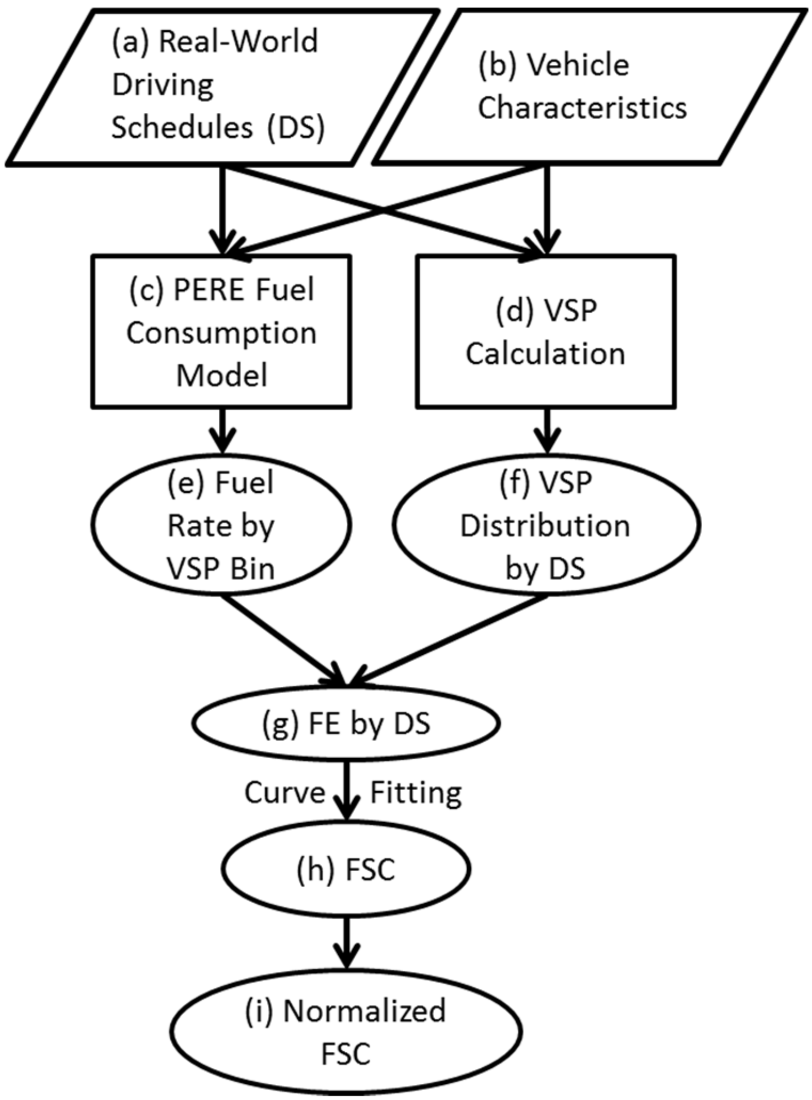

Figure 1. Overview of Modeling Methodology to Generate Normalized FSC

3.1 Fuel Consumption Model

Based on an investigation of potential fuel consumption models, the Physical Emissions Rate Estimator (PERE) is selected as the most appropriate model for this research [4]. PERE is a physical vehicle fuel consumption model developed by the EPA to supplement the MOVES mobile-source emissions model for untested vehicles. PERE adopts a physical approach (similar to the well-known Comprehensive Modal Emissions Model [21]) that is ideal for advanced vehicle technologies without vehicle test data. It also utilizes parameters that are aligned with the scope of vehicle-class modeling performed here. PERE models vehicles in less detail than individual vehicle models such as ADVISOR [13] – which is a limitation in some contexts but appropriate for macroscopic scenario analysis where vehicle characteristics are uncertain.

The primary vehicle input parameters for PERE (in general order of importance as indicated in the PERE documentation) are:

1. Vehicle type
2. Engine indicated (thermal) efficiency
3. Vehicle model year
4. Road load power (method and coefficients)
5. Vehicle weight
6. Engine size (displacement)
7. Motor peak power (HEV/EV only)
8. Fuel cell power rating (FCV only)
9. Hybrid threshold (HEV only)
10. Powertrain type (ICE, HEV, EV, FCV)
11. Fuel type (gas or diesel for ICE – representing spark-ignition or compression-ignition engines)
12. Transmission type (automatic or manual)

The details and model sensitivity for these parameters are discussed in the PERE documentation [4]. In addition to the vehicle parameters, PERE modeling requires an input driving schedule. The driving schedule is a time series of second-by-second vehicle speeds. Vehicle acceleration is differentiated from the speeds, and VSP is calculated using a Road Load Power method, described in the documentation. VSP is a proxy for engine loading, widely used in vehicle emissions and fuel consumption modeling [22], [23].

There are two primary caveats of the PERE modeling approach: 1) PERE only models parallel-configuration HEV, not series-configuration, and 2) the application of PERE for EV has not yet been validated. The first is not major concern, since not all possible advanced-vehicle powertrain configurations can be included at this scale of analysis. The second is more of a concern, but a reasonable limitation given the lack of available validation data at the time of development. There are still few data available on the real-world fuel consumption performance of EV, and PERE is considered the best available tool for this study. It lends confidence to the modeling of EV in PERE that EV are modeled as modified HEV (with the ICE removed), and the HEV model in PERE has been well validated [4].

3.2 Strategy for Implementing PERE

The PERE documentation describes a method for using PERE to derive advanced vehicle fuel consumption rates for MOVES modeling [4]. By this method, the vehicles of interest are modeled over a combination of transient driving schedules, and the average fuel consumption rates binned by the 17 VSP bins used in MOVES [11]. With fuel rates tabulated by VSP bin for each vehicle, total fuel consumption can be quickly computed from the VSP-distribution of second-by-second vehicle activity.

Vehicle activity distribution by VSP can be computed from speed profiles – such as embodied in driving schedules [24]. Using coastdown coefficients A, B, and C (also known as Road Load Coefficients - RLC) from the dynamometer load equation, VSP is calculated as

$$VSP = \mathrm{A}\frac{v}{m} + \mathrm{B}\frac{v^2}{m} + \mathrm{C}\frac{v^3}{m} + 1.1v(a + g * \mathrm{grade}) \qquad (1)$$

from [4], where VSP is in kW/Mg, v is speed in m/s, a is acceleration in m/s^2, g is the acceleration due to gravity in m/s^2, and m is vehicle mass in Mg. The three RLC correspond to rolling, rotating, and aerodynamic resistive factors, respectively [4].

The RLC, if not provided as a vehicle parameter, can be estimated from the vehicle mass or the Track Road Load HorsePower (TRLHP) [4], [25]. This approach of using many driving schedules to estimate fuel rates by VSP bin then distributing activity by VSP bin provides more fuel consumption data in each VSP bin and more vehicle activity flexibility than simply using a single driving schedule to model fuel rate at an average speed.

The adopted strategy for advanced vehicle modeling in this research mirrors the PERE-MOVES approach. The additional benefit of this approach is that vehicle activity distributions by VSP bin can be adjusted based on projected changes in roadway operations, vehicle performance, or driver behavior. In this way fuel-speed curves can be sensitive to changing traffic operations and driving behaviors without repeating the engine/fuel modeling process.

3.3 Driving Schedules

The EPA has generated facility-specific driving schedules (included in the MOVES model) for different levels of congestion based on real-world measurements. The MOVES driving schedules are designed to reflect actual on-road vehicle activity (in contrast to the standardized dynamometer test schedules), and so represent actual congestion effects [9], [10]. The MOVES database includes 18 relevant Light-Duty (LD) driving schedules on freeways and arterials with average speeds from 3 to 76 mph. Concatenating the relevant MOVES driving schedules for modeling in PERE leads to a long (3.7 hour) composite driving schedule for binned fuel rate estimates. As discussed above, it is possible that new engine/powertrain technologies could influence driving patterns for certain speed-facility combinations. Given the uncertainty that this is a real effect – and if it is real, what exactly the effect would be – we use the same driving schedules for all vehicles modeled.

In addition to the MOVES driving schedules, we apply real-world vehicle speed data collected on an urban freeway in Portland, Oregon. Vehicle speed data were gathered on OR-217 in the summer and fall of 2010 using second-by-second Global Positioning System (GPS) data in a probe vehicle (passenger car). This freeway had average daily traffic of about 100,000 vehicles in 2009 [26], with regular peak-period congestion in both directions. In total, 59 probe vehicle runs of 6.4 miles each were collected before, during, and after the PM peak period. This produced over ten hours of data, with average speeds on each run from 18 to 54 mph. Lastly, fuel economy is also estimated for the set of EPA test driving schedules used for fuel economy labeling [11].

3.4 Vehicle Characteristics

FSC are generated for the following light-duty vehicle types: conventional ICE (spark-ignition and compression-ignition), HEV, EV, and FCV. Vehicle parameter assumptions as required by PERE are based on a variety of sources. Many representative characteristics are included as defaults within the PERE model (transmission shift points, mechanical efficiency, etc.). Other vehicle characteristics are based on the literature – vehicle projection studies and similar research on future vehicle performance [2], [4], [11], [12], [14], [18], [27], [28]. Some vehicle characteristics (such as RLC) are based on EPA inventory data and modeling guidance for the U.S. vehicle fleet [27].

Additionally, some vehicles' characteristics are based on manufacturers' specifications. We include in the vehicle test matrix vehicles of known attributes (for the 2010 model year), including:

- HEV: Toyota Prius, Toyota Camry Hybrid, Toyota Highlander Hybrid, Honda Civic Hybrid, Honda CR-Z Sport Hybrid, Honda Insight, Ford Escape Hybrid, and Ford Fusion Hybrid
- EV: Nissan Leaf, Tesla Roadster, Coda, and Mitsubishi MiEV
- FCV: Toyota FCHV, Ford Focus, GM HydroGen3, and Honda FCX

Because of the intended use of FSC for long-range scenario analysis with uncertain fleets, the vehicle generation strategy is not to constrain the modeling to existing or even prototype vehicles. The selected vehicle attributes thus include not only the probable but also the possible range of characteristics. In other words, we set the bounds wide enough to capture an uncertain future fleet. Note that in some cases, that means widening the original range of attributes tested in the PERE model (such as for hybrid thresholds).

The key parameters varied over vehicles for FSC shape sensitivity testing are:

1. Vehicle weight
2. Combustion engine size (displacement)
3. Engine indicated efficiency (the thermodynamic efficiency limit of the engine)
4. Electric motor peak power
5. Fuel cell power rating
6. Hybrid threshold (the power demand at which the engine or fuel cell is required in addition to the motor in an HEV or FCV)

7. Transmission type (automatic or manual)
8. Fuel type (gasoline or diesel – also indicates spark-ignition or compression-ignition)
9. Power accessory load (such as air conditioning)
10. Road Load Coefficients (also used in VSP calculation)
11. Model year (which impacts engine and torque parameters through assumed trends)

Other parameters included in the PERE model are not varied due to low model sensitivity [4] or no published information on expected changes to the value. Some combustion engine characteristics are adjusted within PERE based on the vehicle model year (engine friction, enrichment threshold, peak torque, and peak power). The RLC coefficients for VSP calculation (see Equation 1) are based on EPA documentation [27] or estimated from the vehicle weight as described in the PERE documentation [4]. For fuel types other than gasoline or diesel (such as electricity), PERE converts consumed energy to gasoline equivalent units using an assumed energy density for gasoline of 32.7 MJ/L.

The ranges of tested values of vehicle parameters are:

- Model year: 2005 to 2040
- Fuel type: gasoline, diesel
- Transmission type: manual, automatic
- Powertrain type: conventional ICE, hybrid, electric, fuel cell
- Engine size: 1.0 to 4.5 liters
- Vehicle curb weight: 2,000 to 5,000 lbs
- Road load method: weight-based and RLC
- Hybrid threshold: 1 to 6 kW
- Motor peak power: 10 to 215 kW
- Fuel cell power rating: 60 to 155 kW
- Accessory load: 0.75 to 4 kW
- Engine indicated efficiency: 0.4 to 0.6 gasoline, 0.45 to 0.6 diesel

The range of vehicle characteristics is tested over a set of 145 vehicles (not every possible combination of characteristics is modeled). The vehicles represent a range from very small neighborhood electric vehicles to large pickup trucks and Sports Utility Vehicles. Note that these parameters are modeled over their range of values, not simply at the extremes. While the ranges are wide compared to probable vehicle attributes, they also include the set of expected vehicles. Space constraints prevent inclusion of the full table of modeled vehicle attributes. However, vehicles of key interest are included below in Table 1.

3.5 Fuel-Speed Curve Calculation

The fuel speed curves are calculated from the model output as follows. Let f_b be the PERE-modeled fuel consumption rate (in kg/second) in VSP bin b, where $b \in B$ and B is the set of 17 VSP bins. This is (e) in Figure 1. For EV and FCV, note that f_b is presented in gasoline-equivalent units. Let t_b be the amount of driving time (in seconds) spent in VSP bin b for a given driving schedule – (f) in Figure 1. Then the modeled fuel consumption (in kg) for that driving schedule is calculated

$$f = \sum_{b \in B} (t_b \cdot f_b) \ . \tag{2}$$

For a given fuel density of d_f in kg/gallon and a driving schedule distance of D in miles, the fuel economy FE (in gasoline-equivalent miles per gallon – mpg) for that driving schedule is then calculated

$$FE = \frac{D \cdot d_f}{f} \ . \tag{3}$$

This is (g) in Figure 1. We use $d_f = 0.744 \text{ kg/L}$ for gasoline and $d_f = 0.811 \text{ kg/L}$ for diesel from the PERE model, which converts to $d_f = 2.82 \text{ kg/gallon}$ and $d_f = 3.07 \text{ kg/gallon}$, respectively. The average speed for the driving schedule, v, is simply $v = \frac{3600 \cdot D}{\sum_{b \in B} t_b}$. Note that the driving schedule is indicative of both average speed and speed variability at varying levels of congestion for typical conditions (see Section 2.1).

This fuel modeling approach creates discrete FE–speed data points, so a curve fit is applied to establish a full FSC – (h) in Figure 1. We fit the FSC to an exponentiated 4th-order polynomial functional form, following previous emissions modeling research [5], [7], [29]. The functional form is

$$FE = \exp\left(\sum_{i=0}^{4} \alpha_i v^i\right) , \tag{4}$$

where v is the average travel speed in mph and α_i are fitted parameters. The FSC are fit to this functional form using an iteratively reweighted least squares method. Separate fits are made for freeway and arterial driving schedules. Freeway driving schedules include MOVES and OR-217 sources. Arterial driving schedules are sourced from MOVES only.

Since average fuel economy is an input to the GreenSTEP model, the FSC are only used to adjust fuel economy for varying congestion levels (see Section 2.3). Therefore, we need not calculate absolute fuel economy, but simply how the fuel economy varies with average speed. To do this, we scale the freeway FSC to the modeled FE at the average speed of the "highway" EPA test driving schedule (HFET) – 48.2 mph [11]. For arterials we take a similar approach, using a reference speed 24.4 mph. For FSC normalization to a reference speed v_{ref}, the normalized fuel economy, FE_{norm}, is calculated

$$FE_{norm} = \exp\left(\sum_{i=1}^{4} \alpha_i \left(v^i - {v_{ref}}^i\right)\right) . \tag{5}$$

4 Results

4.1 Fuel Economy and Average Speed

Figure 2 shows the FE-speed data points for all vehicles using all driving schedules. The figure is segmented by powertrain type, with different symbols to represent the different driving schedule sources and FE in gasoline-equivalent units. From Figure 2, we see that EV have the highest fuel economy and ICE the lowest. EV also have the widest range of fuel economies for the modeled vehicles (particularly at lower speeds). For each powertrain type the fuel economy values are fairly steady across the range of average speeds, with the exception of EV.

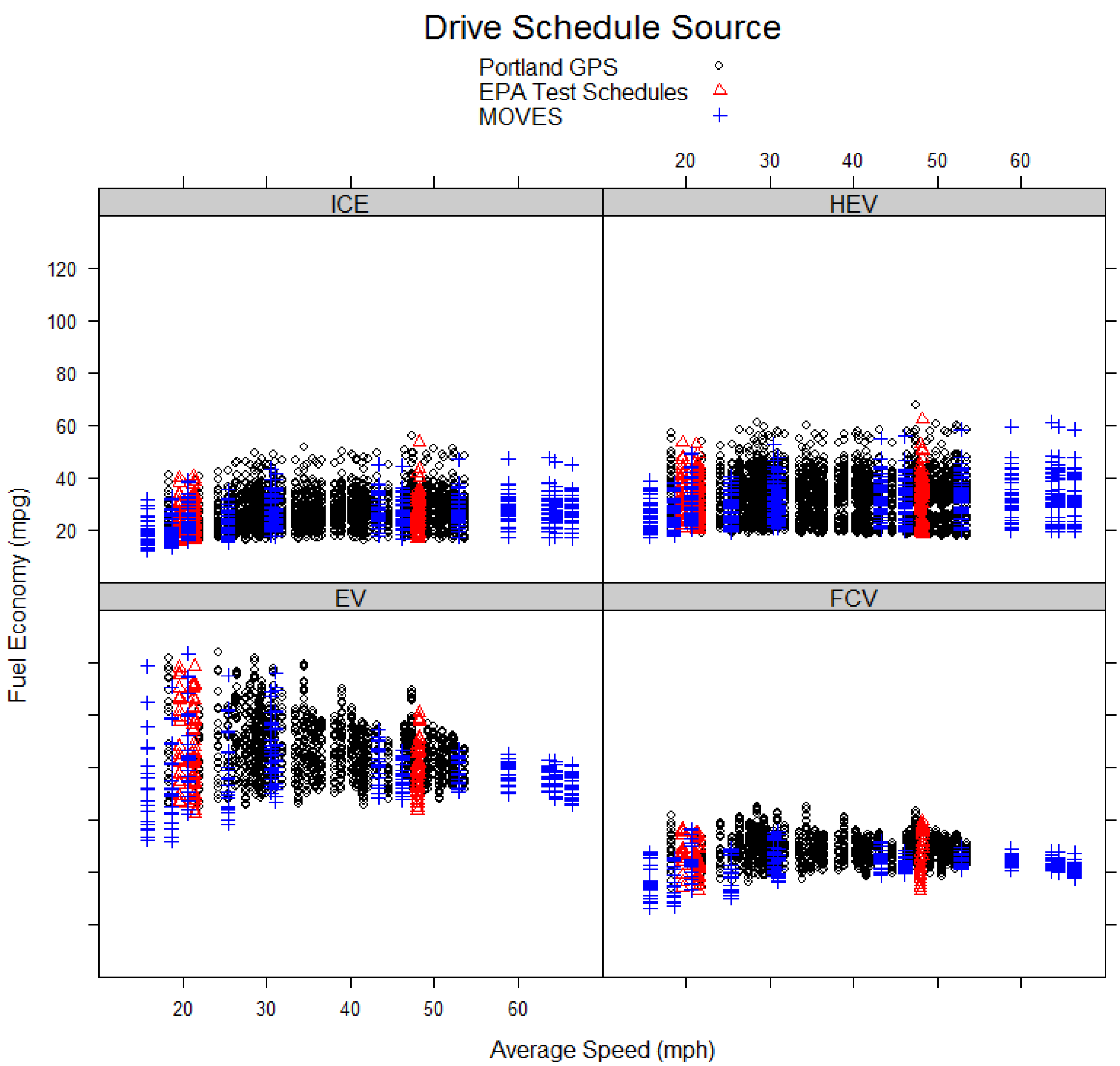

Figure 2. Fuel Economy vs. Average Speed by Powertrain Type for All Driving Schedules

Figure 3 presents the same data, but normalized to the freeway reference speed and excluding MOVES arterial driving schedules. Higher values of normalized FE indicate improved efficiency with respect to the reference speed conditions. These results are similar to Figure 2, but with some of the inter-vehicle overall fuel economy differences removed – thus illuminating the impacts of average speed. ICE vehicle FE is generally flat from free-flow speed down to around 35 mph, at which point FE begins to decrease. For HEV the FE is nearly flat for all except the lowest-speed MOVES driving schedule. EV fuel economy *increases* with decreasing speed from free-flow conditions, down to around 20-30 mph. FCV fuel economy also increases somewhat as speed decreases.

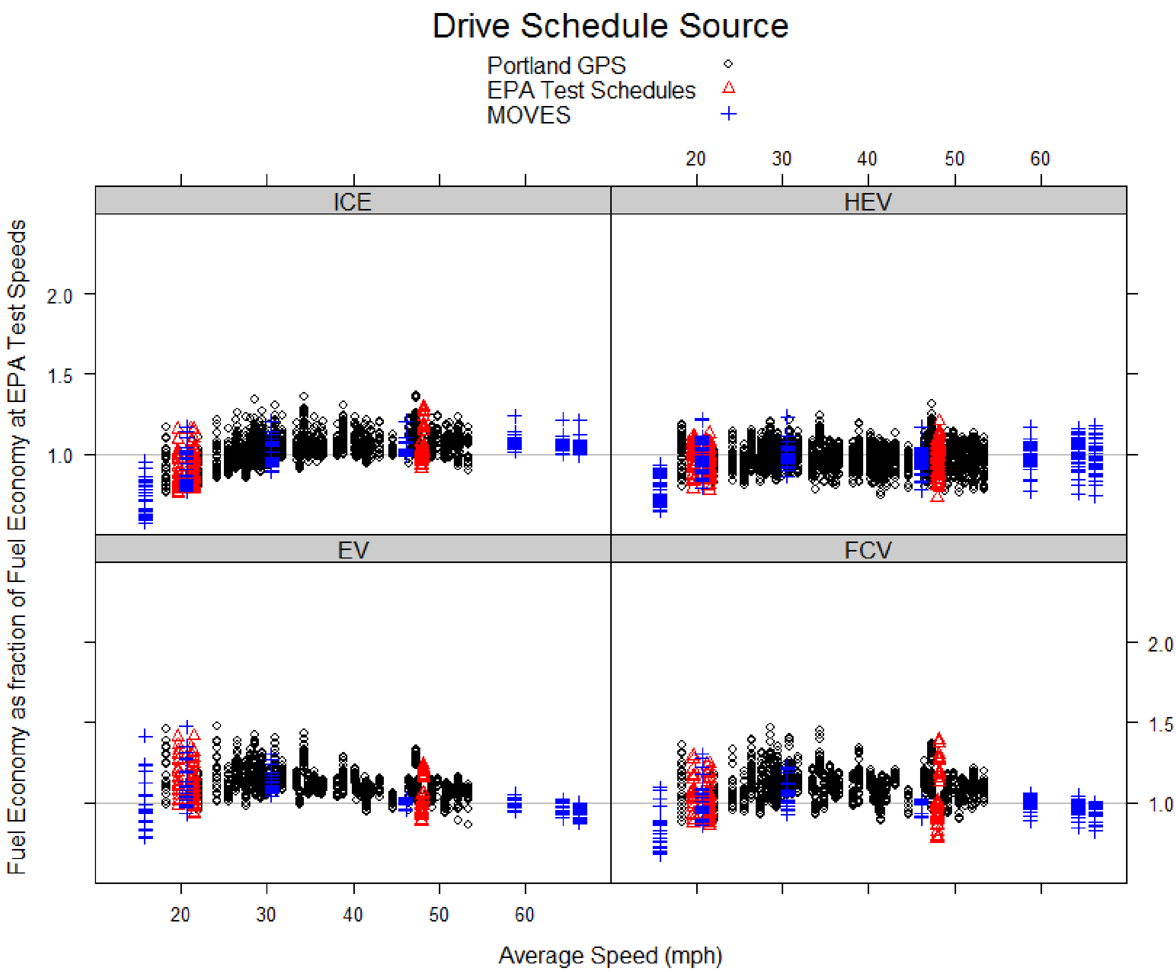

Figure 3. Fuel Economy (Normalized to Reference Speed) vs. Average Speed by Powertrain Type for Freeways

4.2 Fuel-Speed Curves

This section presents the fitted FSC from Equation 4. Two example fits for freeway FSC are shown in Figure 4. Here, two fitted FSC are shown along with the base data (using the MOVES and OR-217 driving schedules). The example low-congestion-efficiency ICE vehicle is a heavy, high-powered gasoline-fueled passenger car. The fit has an approximate R-squared value of 0.96 (calculated as Nagelkerke's generalized R-squared). The example high-congestion-efficiency ICE vehicle is a diesel-fueled passenger truck with moderate power and weight. This fit has a generalized R-squared value of 0.86.

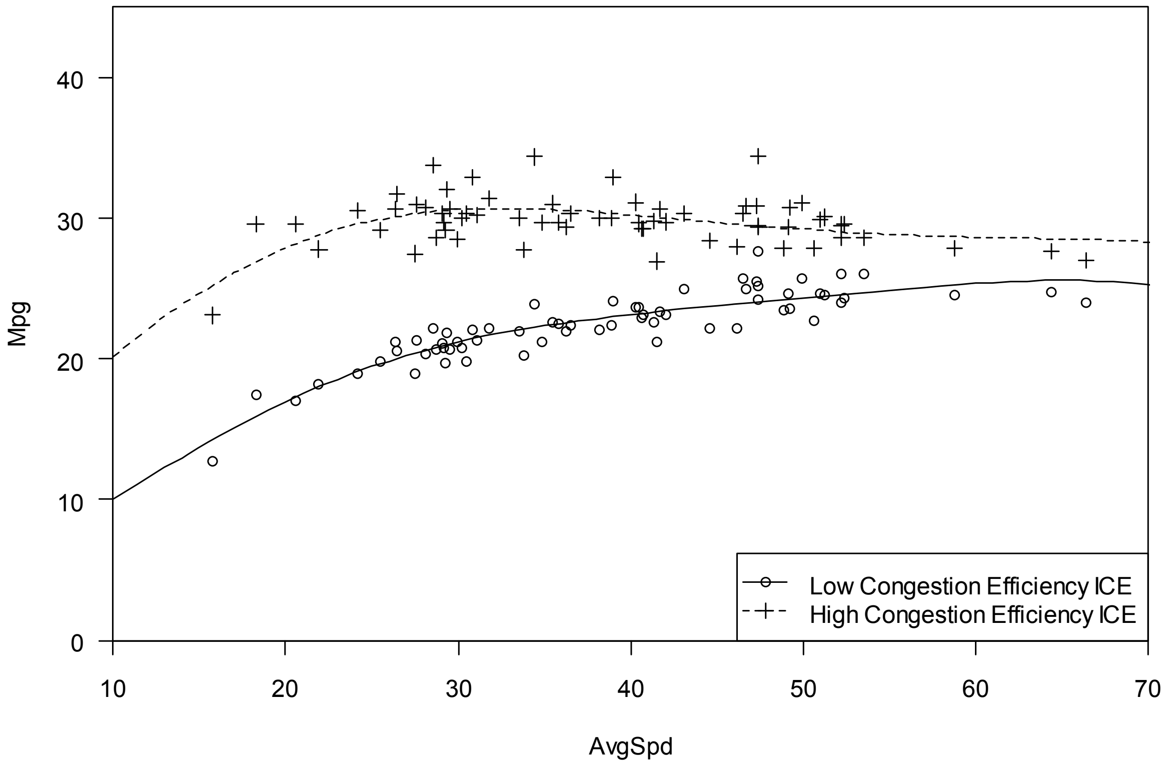

Figure 4. Example Freeway FSC Fits

Figure 5 shows fitted freeway FSC for all modeled vehicles, segmented by powertrain type (again in gasoline-equivalent mpg). There is a wide variety of FE values and FSC shapes, as expected from Figure 2 (note the different vertical scales). Generally, ICE vehicles have varying relationships with speed (positive or negative) for speeds above 30 mph, and decreasing FE at lower speeds below 30 mph. HEV are less sensitive to congestion, with some vehicles' FE not decreasing until below 20 mph. Some HEV have about the same FE performance as ICE vehicles – particularly those with low hybrid thresholds. EV and FCV both show increasing FE with decreasing speed in Figure 5, down to a speed in the range of 20-40 mph.

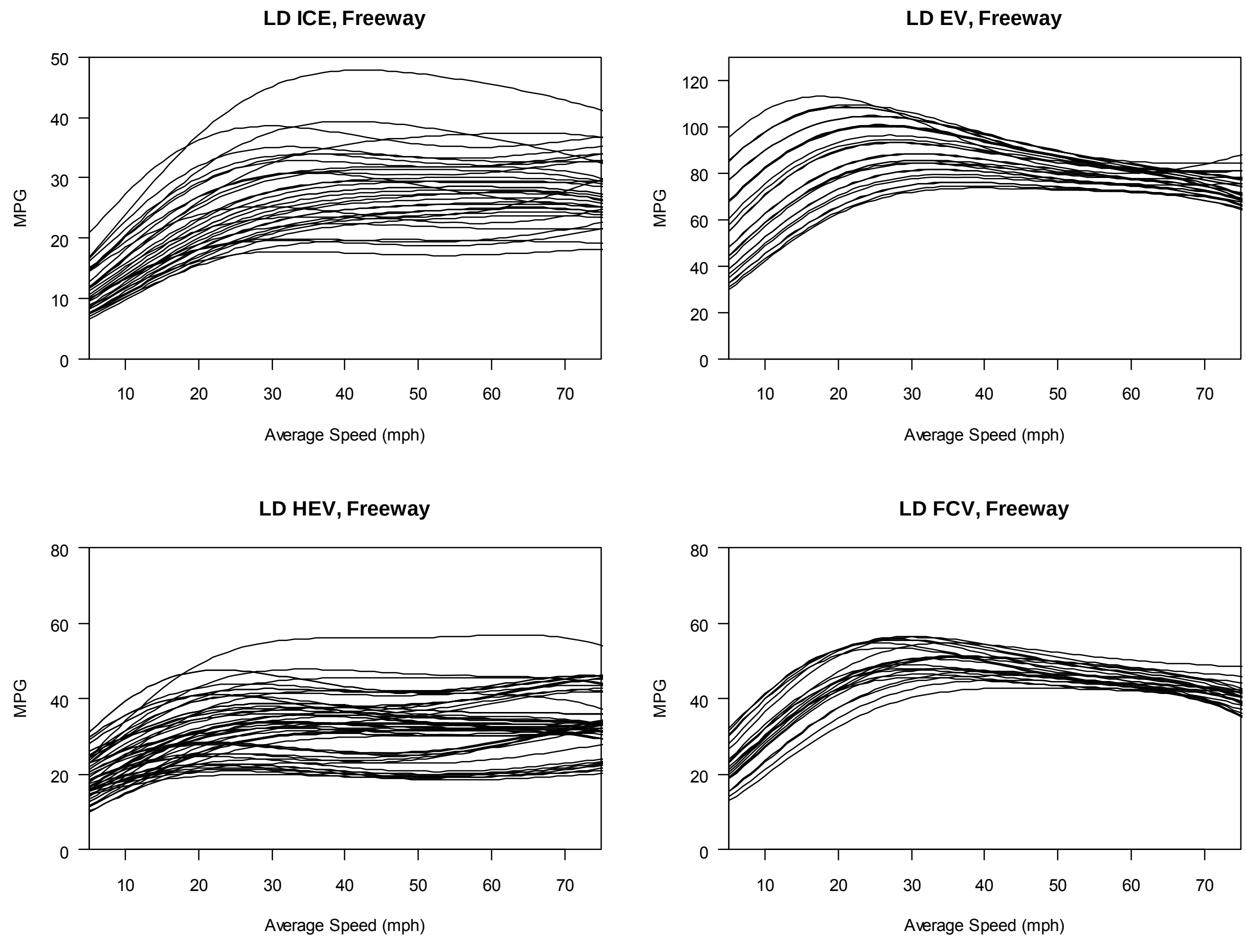

Figure 5. Modeled Individual Freeway FSC by Powertrain Type

4.3 Sensitivity of Fuel Economy in Congestion to Vehicle Characteristics

Fuel economy can vary widely among vehicles for any one driving schedule, as illustrated in Figure 2. This is due to variability in both fuel rates and VSP distributions of operating time. In this section we examine how vehicle characteristics influence the Fuel-Speed data points. Of particular interest is which vehicle characteristics impact the shape of the FSC – i.e., which characteristics most affect relative vehicle performance in congestion. This is different from which vehicle characteristics impact overall fuel economy, and sometimes shows opposite effects. For example, vehicle parameters that mostly improve FE at higher speeds (decreased drag coefficients, for example) will result in poorer *relative* FE in congestion.

Sensitivity analyses show that vehicle weight, engine displacement/fuel cell power, RLC, hybrid threshold, and accessory load are the vehicle characteristics that have the most impact on the fuel economy effects of congestion. Higher vehicle weight, engine size, and accessory load all decrease relative performance in congestion for ICE vehicles, while higher RLC increase relative performance. Compared to cars, passenger trucks and SUV's tend to have more weight and engine power (which both reduce performance in congestion), but also higher RLC (which improves *relative* performance in congestion by disproportionately decreasing efficiency at high speeds). Higher motor peak power slightly increases relative congestion performance for EV, but higher fuel cell power rating decreases relative congestion performance for FCV.

HEV performance in congestion increases with hybrid threshold (since more low-power driving is powered by recovered energy). For HEV the motor and battery characteristics combined with the driving patterns will determine the true hybrid threshold. Assuming HEV improve over time to allow higher hybrid thresholds, the relative HEV performance in congestion will improve as well. Unlike ICE vehicles, HEV can improve their relative FE in congestion with larger engine sizes, because they can utilize the larger ICE nearer optimum efficiency for high power loads but turn off the combustion engine during low-power driving events in congestion. In this study, motor peak power was not a limiting factor in relative efficiency for HEV. High accessory power loads notably degrade the relative efficiency in congestion for fuel efficient vehicles, since a greater portion of total energy demand in congestion is from the static accessory load. Since much of the expected accessory load is from air conditioning usage, improvements over time such as advanced window glazings and cabin ventilation [28] can increase the relative FE in congestion for advanced vehicles.

Power demands vary due to external vehicle forces only (mass and RLC inputs), while fuel rates are influenced by all vehicle attributes. From Equation 1, the RLC and vehicle mass have larger impacts at higher speeds (the impact of RLC "*C*" increases with the cube of speed). The impact of acceleration, however, is independent of mass or RLC. Thus, the VSP distribution of high-speed freeway driving schedules (with higher speeds and fewer accelerations) is more impacted by vehicle characteristics (mass and RLC) than the VSP distribution of arterial driving schedules (with more accelerations and lower speeds). More generally, the VSP distribution of vehicle activity in uncongested driving conditions is more impacted by vehicle characteristics than in congested driving conditions. The same holds for arterial versus freeway driving, with freeway driving more impacted by vehicle characteristics.

As demonstrated in Figure 5, there is a range of potential FSC shapes for each vehicle type, depending on the specific vehicle characteristics. Projecting this array of characteristics for future vehicle fleets in scenario analysis is impractical. The next section describes a suggested approach for incorporating these FSC into scenario analysis.

5 Applying Fuel-Speed Curves for Scenario Analysis

This section describes a recommended method for applying advanced-vehicle FSC for scenario analysis, considering the range of plausible curve shapes shown in Section 4. The recommended approach is to use minimum/maximum sensitivity normalized FSC as the bounds of congestion effects. Interpolating between these extreme curves provides speed-based FE adjustment factors to calculate congestion effects on overall fuel economy.

The interpolation distance between the bound FSC is based on a new model input, "Congestion Efficiency", which describes the projected performance of each vehicle type in congestion, with respect to "extreme case" vehicles. Congestion Efficiency ranges from 0 for poorest performance to 1 for maximum relative efficiency performance. Using Congestion Efficiency CE and upper and lower bound *normalized* FSC with curve fit parameters $\alpha_{U,i}$ and $\alpha_{L,i}$, respectively, the interpolated normalized FSC curve is calculated

$$FE = CE \cdot \exp\left(\sum_{i=0}^{4} \alpha_{U,i} v^i\right) + (1 - CE)\exp\left(\sum_{i=0}^{4} \alpha_{L,i} v^i\right) \;. \tag{6}$$

The determination of CE in scenario analysis is based on the sensitivities described in Section 4.3. This approach avoids introducing numerous new vehicle parameters to the scenario analysis, while still allowing some assumptions about the future vehicle fleet to inform the congestion adjustment values.

We selected extreme-case vehicles for FSC bounds based on comparison of the FSC shapes and vehicle attributes. Those vehicles selected are the modeled vehicles of each vehicle type with the highest and lowest relative FE in heavy congestion as compared to FE at free-flow speed (for each facility type). The vehicle characteristics and FSC fit parameters for the selected vehicles are shown in Table 1. The corresponding upper-bound and lower-bound FSC are shown in Figure 6. The selected bounding vehicles in Table 1 are not the most extreme combinations of attributes possible. Rather, they are modeled mixes of vehicle attributes considered possible (if not probable) based on the literature.

Table 1. Extreme-Case Vehicles: Characteristics and FSC Fit Parameters

	Freeways							
	ICE*		HEV*		EV**		FCV**	
Congestion Efficiency	Low	High	Low	High	Low	High	Low	High
Passenger Car/Truck	Car	Truck	Car	Car	Car	Car	Car	Car
Curb Weight (lbs)	5,000	2,500	2,504	2,000	3,800	2,000	3,000	2,000
Engine Displ. (L)	4.5	2.0	1.1	2.0	NA	NA	NA	NA
RLC: A	156.46	235.01	156.46	156.46	156.46	156.46	156.46	156.46
RLC: B	2.002	3.039	2.002	2.002	2.002	2.002	2.002	2.002
RLC: C	0.493	0.748	0.493	0.493	0.493	0.493	0.493	0.493
Motor Peak Power/ Fuel Cell Rating (kW)	NA	NA	68	10	80	100	140	40
Hybrid Threshold (kW)	NA	NA	2	4	NA	NA	NA	NA
Accessory Power (kW)	0.75	0.75	4	0.75	4	0.75	4	0.75
Total Peak Power (kW)	220	98	123	108	80	100	140	40
Specific Power (W/kg)	97	86	108	119	46	110	103	44
α_0	1.514	2.331	1.892	3.122	2.911	4.236	1.984	3.048
α_1	0.1112	0.0809	0.1321	0.0667	0.1132	0.0511	0.1324	0.0955
α_2	-0.0029	-0.0025	-0.0041	-0.0025	-0.0034	-0.0019	-0.0037	-0.0032
α_3	3.63E-5	2.94E-5	5.78E-5	3.44E-5	4.55E-5	2.41E-5	4.60E-5	4.27E-5
α_4	-1.73E-7	-1.15E-7	-2.90E-7	-1.63E-7	-2.27E-7	-1.04E-7	-2.18E-7	-2.00E-7
	Arterial							
	ICE*		HEV*		EV**		FCV**	
Congestion Efficiency	Low	High	Low	High	Low	High	Low	High
Passenger Car/Truck	Car	Truck	Car	Car	Car	Car	Car	Car
Curb Weight (lbs)	3,750	2,500	3,000	3,020	3,800	2,000	3,000	2,000
Engine Displ. (L)	4.5	2.0	1.8	1.3	NA	NA	NA	NA
RLC: A	156.46	235.01	156.46	154.69	156.46	156.46	156.46	156.46
RLC: B	2.002	3.039	2.002	1.977	2.002	2.002	2.002	2.002
RLC: C	0.493	0.748	0.493	0.487	0.493	0.493	0.493	0.493
Motor Peak Power/ Fuel Cell Rating (kW)	NA	NA	60	10	80	100	140	40
Hybrid Threshold (kW)	NA	NA	2	2	NA	NA	NA	NA
Accessory Power (kW)	4	0.75	4	0.75	4	0.75	4	0.75
Total Peak Power (kW)	220	98	148	76	80	100	140	40
Specific Power (W/kg)	129	86	109	55	46	110	103	44
α_0	1.392	2.331	1.803	2.71	2.911	4.236	1.984	3.048
α_1	0.1145	0.0809	0.1204	0.0765	0.1132	0.0511	0.1324	0.0955
α_2	-0.0029	-0.0025	-0.0034	-0.0031	-0.0034	-0.0019	-0.0037	-0.0032
α_3	3.45E-5	2.94E-5	4.36E-5	4.77E-5	4.55E-5	2.41E-5	4.60E-5	4.27E-5
α_4	-1.55E-7	-1.15E-7	-2.06E-7	-2.42E-7	-2.27E-7	-1.04E-7	-2.18E-7	-2.00E-7

* Gasoline-fueled, automatic transmission, engine indicated efficiency of 0.4, model year 2010

** EV and FCV are the same vehicles for arterials and freeways, model year 2010

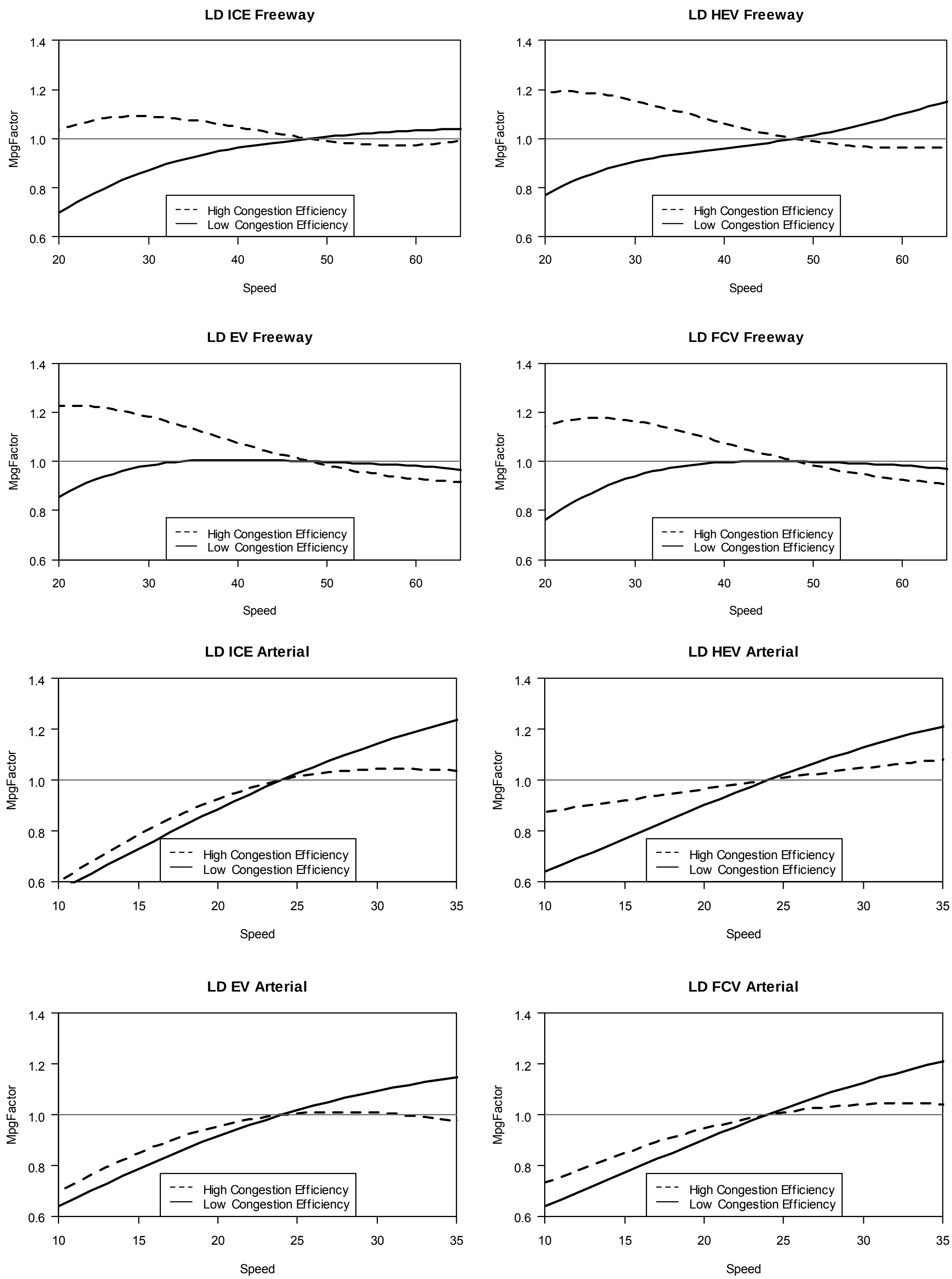

Figure 6. Upper and Lower Bound Normalized FSC

Table 2 lists the vehicle characteristics that are expected to impact the relative efficiency in congestion (CE) for each vehicle powertrain type. This table is based on sensitivity analysis of the modeled vehicle attributes and FSC. Qualitative projection of these attributes can be used to set the new model input, Congestion Efficiency, between 0 and 1. The median Congestion Efficiency value is 0.5, which puts the FE adjustment curve midway between the extreme curves shown in Figure 6. If we expect, for example, average HEV to get lighter over time, we can set the Congestion Efficiency to trend upward for future model years. Note again that CE is increased both by attributes that improve FE in congestion and by attributes that disproportionately decrease FE at higher speeds.

Table 2. Vehicle Characterisitcs Influencing Relative Congestion Efficiency

Powertrain type	Low Relative Congestion Efficiency	High Relative Congestion Efficiency
ICE	heavier weight, larger engine, lower RLC, gasoline fuel, higher accessory loads, earlier model year	lighter weight, smaller engine, higher RLC, diesel fuel, lower accessory loads, later model year
HEV	heavier weight, smaller ICE, lower RLC, lower hybrid threshold, gasoline fuel, higher accessory loads, earlier model year	lighter weight, larger ICE, higher RLC, higher hybrid threshold, diesel fuel, lower accessory loads, later model year
EV	heavier weight, lower RLC, higher accessory loads	lighter weight, higher RLC, lower accessory loads
FCV	heavier weight, higher fuel cell power rating, lower RLC, higher accessory loads	lighter weight, lower fuel cell power rating, higher RLC, lower accessory loads

As a final consideration, we examine the potential impacts of these FSC on overall FE. Using a Congestion Efficiency of 0.5, at 25 mph the freeway ICE FE adjustment factor is 0.94 and all three advanced powertrain vehicle types have FE adjustments over 1 (i.e. efficiency benefits). On arterials, the minimum adjustment factor at 20 mph (for ICE) is 0.92. Thus, the potential adjustments to FE for typical congestion are small. With evolving vehicle fleets containing more advanced vehicles, it is unlikely that the net effect of congestion on FE will be substantially detrimental – and the net effect could be beneficial.

6 Conclusions

This paper describes research undertaken to establish plausible fuel-speed curves (FSC) for advanced vehicles, to be used in long-term transportation scenario analysis. We use the PERE fuel consumption model with real-world driving schedules and a range of advanced vehicle characteristics to estimate vehicle fuel economy in varying traffic conditions. The fuel-speed data points are then used to generate normalized fuel economy versus average speed curves for each of 145 modeled vehicles.

Analysis of the FSC shows that advanced powertrain vehicles are expected to perform better in congestion than ICE vehicles (with respect to FE at free-flow speeds). Many ICE vehicles do not lose fuel efficiency until traffic slows to about 30 mph. HEV are less sensitive to average speed changes than ICE vehicles, and tend to maintain their fuel efficiency down to 20 mph, due to recaptured braking energy. Fuel efficiency *increases* for EV down to about 20-30 mph, below which it degrades. FCV have similar FE effects to EV, though with less sensitivity to speed.

Besides powertrain type, congestion effects vary with other vehicle characteristics as well. Relative fuel efficiency at lower speeds improves for vehicles with lighter weight, smaller engines, higher hybrid thresholds, and lower accessory loads (such as air conditioning). *Relative* performance in congestion can also improve with attributes that disproportionately decrease FE at higher speeds, such as higher aerodynamic drag and rolling resistance factors.

Considering the normalized FSC sensitivity to multiple attributes, we propose a bounded approach for applying the modeled FSC in scenario analysis. In the proposed method, FE adjustments are an interpolation between extreme-case FSC, based on projection of relative congestion efficiency. This allows adjustment for vehicle trends over time without requiring specificity in the vehicle fleet characteristics.

In conclusion, the modeled FSC show that advanced powertrain vehicles can reduce or reverse the fuel efficiency losses associated with typical roadway congestion. On the other hand, advanced vehicles with certain characteristics (heavy and with high accessory power loads, for example) can still have poor relative performance in congestion. The results of this research can assist with broader analysis of the role these differences will play in total fuel consumption and emissions from roadway travel.

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