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Suitability of Synthetic Driving Profiles from Traffic Micro-Simulation for Real-World Energy Analysis

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Abstract

A shift towards increased levels of driving automation is generally expected to result in improved safety and traffic congestion outcomes. However, little empirical data exists to estimate the impact that automated driving could have on energy consumption and greenhouse gas emissions. In the absence of empirical data on differences between drive cycles from present day vehicles (primarily operated by humans) and future vehicles (partially or fully operated by computers) one approach is to model both situations over identical traffic conditions. Such an exercise requires traffic micro-simulation to not only accurately model vehicle operation under high levels of automation, but also (and potentially more challenging) vehicle operation under present day human drivers.

This work seeks to quantify the ability of a commercial traffic micro-simulation program to accurately model real-world drive cycles in vehicles operated primarily by humans in terms of driving speed, acceleration, and simulated fuel economy. Synthetic profiles from models of freeway and arterial facilities near Atlanta, Georgia, are compared to empirical data collected from real-world drivers on the same facilities. Empirical and synthetic drive cycles are then simulated in a powertrain efficiency model to enable comparison on the basis of fuel economy. Synthetic profiles from traffic micro-simulation were found to exhibit low levels of transient behavior relative to the empirical data. Even with these differences, the synthetic and empirical data in this study agree well in terms of driving speed and simulated fuel economy.

The differences in transient behavior between simulated and empirical data suggest that larger stochastic contributions in traffic micro-simulation (relative to those present in the traffic micro-simulation tool used in this study) are required to fully capture the arbitrary elements of human driving. Interestingly, the lack of stochastic contributions from models of human drivers in this study did not result in a significant discrepancy between fuel economy simulations based on synthetic and empirical data; a finding with implications on the potential energy efficiency gains of automated vehicle technology.

Keywords: Traffic Micro-Simulation, Real-world Driving Data, Automotive Efficiency

Introduction

Recent advancements in the areas of remote sensing, signal processing, data fusion, and machine learning have sparked growing public interest in the near-term viability of driverless vehicles. Several automotive companies have projected making various degrees of vehicle automation publically available in the next 5 to 10 years. This impending paradigm shift towards increased levels of automation and a marginalized role of human drivers is generally expected to result in improved safety and traffic congestion outcomes. However, less effort has been invested in estimating the impact automated driving could have on automotive energy consumption and greenhouse gas emissions.

Automotive simulation tools for quantifying fuel use and emission outputs are mature and widely used in industry, government, and research sectors. Given the sensitive nature of vehicle efficiency to operating characteristics, it is necessary to input information on the performance envelope over which the vehicle model is being evaluated (often described by a time series of requested speed values known as a drive cycle). Traditionally these drive cycles are selected from a suite of standard regulatory cycles (such as the U.S. Environmental Protection Agency's city and highway tests) or collected from on-road measurements of vehicle speed over specific routes.

Given that commercial-grade automated driving technology is still in its infancy, very little public data are available for understanding how a computer program would operate a vehicle differently than a human under identical traffic conditions. Additionally, the degree to which high penetrations of automated vehicles could impact the driving style of human drivers and traffic in general is unknown. Such controlled experiments are often best addressed via a modeling and simulation approach that enables repeatable tests under representative conditions with variable inputs.

As with automotive simulation tools, traffic simulation programs for quantifying vehicle operation relative to complex relationships between vehicle performance, driver behavior, traffic conditions, roadway geometry, and signalized control are generally mature. Traffic simulation tools are widely used by planning agencies to estimate how facility upgrades (such as additional lanes, extended turning lanes, improved signal control, etc.) will impact transportation efficiency as described by statistics such as travel times, queue lengths, and flow rates.

Before directly linking traffic and energy simulation tools, it is important to understand the ability of traffic micro-simulation to generate synthetic profiles representative of real-world driving. Two traffic models of real-world facilities will be presented: 1) a high-speed controlled access freeway facility, and 2) a low-speed signalized arterial facility. Synthetic drive cycle outputs from both facility models will be compared to global positioning system (GPS) data from real-world drivers on the same facilities to quantify agreement in several dimensions. Additionally, real and synthetic drive cycles will be simulated in a powertrain efficiency model to understand the ability of traffic simulation to generate representative real-world drive cycles.

Agreement between synthetic and empirical drive cycles in terms of driving speed, acceleration, and simulated fuel economy would indicate that existing traffic micro-simulation models of human drivers are sufficient for establishing baseline efficiency values in energy analysis of automated vehicle technology (in which existing driver models would be used as the control and various automated driving models, which have yet to be developed, would be used as the experiment). Disagreement between synthetic and empirical drive cycles would indicate that modification to existing behavior models of human drivers are necessary in order to accurately establish a baseline in analysis of automated vehicle technology.

Methodology

A commercial traffic micro-simulator was used to generate synthetic drive cycles for a given mix of vehicles (light-duty passenger and heavy-duty commercial vehicles) traveling on a specific facility. Traffic models were built by constructing road networks based on satellite imagery and calibrating with raw traffic data (i.e., link speed, traffic volume) from public databases. Once calibrated, synthetic drive cycles from the model were compared to real-world cycles from GPS instrumented vehicles traversing the same facility. Comparisons are performed in terms of drive cycle speed/acceleration statistics and simulated fuel economy from a powertrain efficiency model.

Raw traffic data used in this work was sourced from public databases. Specifically, vehicle drive cycle data were obtained from the National Renewable Energy Laboratory's Transportation Secure Data Center (TSDC) [1], and traffic count data were sourced from the Information Center of the Georgia Department of Transportation (GDOT) [2].

Vissim

In order to evaluate powertrain efficiency, it is necessary to model the individual dynamics of each vehicle under consideration. Only microscopic traffic simulation tools can provide such level of modeling detail. In microscopic traffic simulators, each simulated vehicle is controlled by car-following and lane-changing models which can be adjusted to accommodate specific traffic scenarios. PTV Group's commercial traffic micro-simulator, Vissim 7.0 [3] was selected for this study.

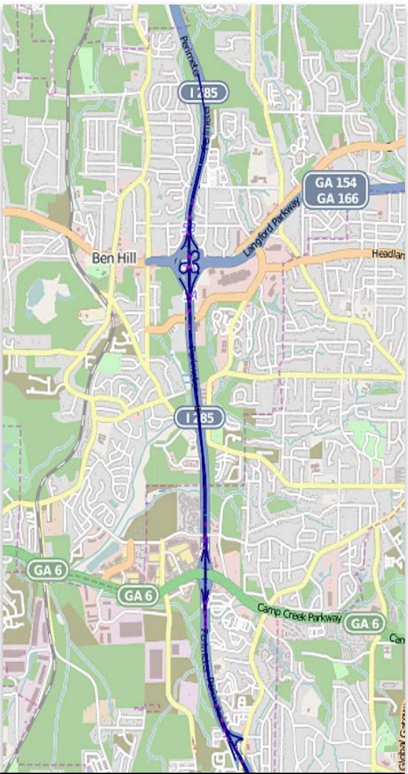


Figure 1 - Atlanta freeway model.

Two traffic models of real-world facilities were developed: 1) a high-speed controlled access freeway facility, and 2) a low-speed signalized arterial facility. The details of the modeling and calibration efforts are described in the following sections.

Freeway Model

A 5-mile freeway section of I-285 through Atlanta, Georgia, was selected for this study (Figure 1). Model calibration was based on empirical traffic data from weekday evening rush hours (4 p.m. – 6 p.m.) during August 2011. The choice of this particular time frame was based on the availability of raw traffic data from both the TSDC and GDOT. Evening rush hour on this facility resulted in the largest number of GPS vehicle traces and the most accurate vehicle count in the region of interest.

TSDC GPS vehicle speeds and travel times were used in parallel with GDOT vehicle counts to calibrate traffic volume and vehicle composition for the freeway model. Vissim calibration involved three aspects: 1) speed distribution, 2) routing and traffic volume, and 3) driving behavior. Distributions of desired vehicle speeds were informed by instantaneous vehicle speed statistics from the TSDC. Table 1 shows the speed of TSDC passenger vehicles collected on I-285 and from the Vissim model (the speed was compared at two locations). For heavy-duty vehicles, we used Vissim’s default speed distribution with an average of 55 mph. This choice was based on the speed limits in the field and also suggested values from U.S. Federal Highway Administration’s guidelines [4].

Table 1 - Comparison on link speed.

	Real-world (location 1)	**Synthetic** (location 1)	**Real-world** (location 2)	**Synthetic** (location 2)
Mean, mph	**65.0**	**66.5**	**65.3**	**64.7**
Median, mph	**66.6**	**67.0**	**67.0**	**64.5**
Standard Deviation, mph	**6.1**	**5.6**	**10.0**	**5.7**
Minimum, mph	**48.6**	**46.8**	**17.7**	**41.6**
Maximum, mph	**72.5**	**78.6**	**76.5**	**78.6**
Trip Count	**44**	**4,451**	**39**	**4,849**

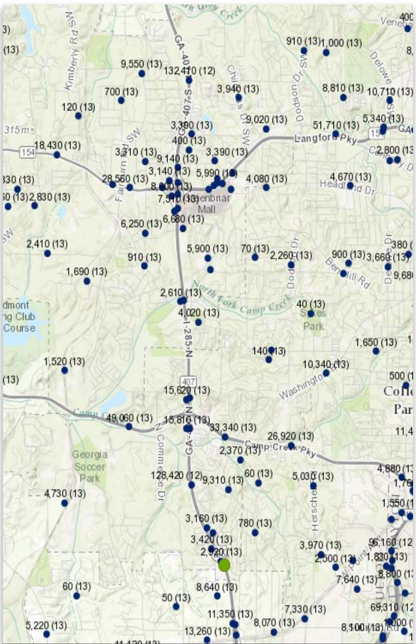


Figure 2 - Traffic counting stations.

Routing and traffic volume were calibrated with vehicle count data from GDOT. Figure 2 shows a map of counting stations in the region with permanent stations in green and temporary stations in blue. Temporary stations were in place on this facility during the August 29–31, 2011, timeframe. Coincidently, several TSDC GPS traces were also collected during this timeframe. GDOT traffic count data were translated into vehicle volume and then programmed in Vissim. Composition between light-duty passenger and heavy-duty commercial vehicles was approximated using the “annual average daily truck traffic count” from the permanent counting station.

Driving behavior was controlled using the Wiedemann 99 [5] and Free Lane Selection models for car-following and lane-changing maneuvers, respectively. These two models are dedicated to Vissim; in fact, it is generally the driving behavior model that distinguishes microscopic traffics simulators from one to another. Parameter settings embedded in the selected Vissim driver model are discussed at greater length in the results section of this paper.

In addition to the comparison on link speed, the model was also validated in terms of vehicle travel time. From TSDC GPS data, 23 unique vehicle records were found to traverse the I-285 facility of interest during weekday rush hours in August 2011. A total of 35 trips were extracted from these 23 vehicle records, with each trip corresponding to a vehicle trace that traversed the entire 5-mile corridor. The results of the travel time analysis are shown in Table 2.

Table 2 - Comparison on travel time.

	Real-world	Synthetic
Mean, sec	272.4	280.6
Median, sec	260	277.3
Standard Deviation, sec	41.2	19.7
Minimum, sec	234	236.1
Maximum, sec	420	360.9
Trip Count	35	4,166

Arterial Model

An arterial network in suburban Atlanta is also considered. A 2-mile corridor on Georgia State Highway 34 containing five signalized intersections was replicated, as shown in Figure 3. Traffic conditions were calibrated to the same weekday evening hours as in the freeway model.

Figure 3 - Atlanta arterial model.

Calibration of the arterial model was based on a macroscopic traffic model provided by contacts at the Atlanta Regional Commission. Information on signal timing, traffic flow dynamics, and travel demand were ported from the macroscopic model into Vissim. To better model traffic during the period of interest, TSDC and GDOT databases were used to adjust traffic volume and vehicle speed distributions. The TSDC contained 40 unique vehicle records from this facility, and GDOT traffic counts were available from temporary counting stations.

FASTSim

Fuel economy simulations in this analysis were performed using NREL's Future Automotive Systems Technology Simulator (FASTSim). FASTSim is a research-oriented, vehicle simulation tool developed to evaluate the impact of various technologies on vehicle performance, cost, and utility in conventional and advanced technology powertrains. Please refer to [6] for a detailed explanation of the FASTSim program.

Light-duty speed profiles generated using Vissim were simulated in FASTSim assuming a mid-size sedan chassis powered by a conventional gasoline spark-ignited engine with parameters similar to the 2012 Ford Fusion. Relevant parameters of this powertrain model can be found in Table 3.

Table 3 – Select parameters for FASTSim model of a conventional gasoline sedan.

Frontal Area	2.12 m^2
Coefficient of Drag	0.33
Coefficient of Rolling Resistance	0.007
Simulated Mass	1,644 kg
Accessory Load	700 W
Rated Engine Power	131 kW
Simulated Composite EPA Fuel Economy	8.7 L/100 km (27 mpg)

A time series plot of results from a FASTSim simulation with the sedan model run over the U.S. Environmental Protection Agency's (EPA's) highway drive cycle (Highway Fuel Economy Test drive cycle, or HWFET) is shown in Figure 4. Achieved vehicle speed is overlaid with target speed alongside friction braking power, engine power, and engine efficiency results.

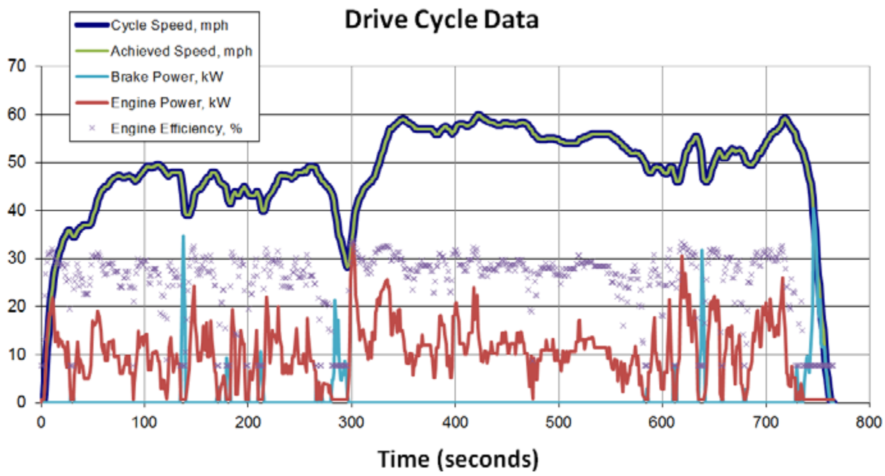


Figure 4 - FASTSim plot of mid-size sedan simulated over EPA HWFET.

Results

Traffic micro-simulation results are presented and compared with real-world GPS trajectories collected from corresponding regions. The results are based on drive cycles that contain second-by-second values of vehicle speed. First, drive cycle characteristics are compared alongside a discussion of the driving behavior settings in Vissim. Second, the estimated fuel economy is compared by applying the powertrain model of a mid-size sedan in FASTSim.

Drive Cycle Characteristics

With an overarching focus on powertrain efficiency, drive cycle metrics derived from the energy equation of vehicle motion are employed to evaluate agreement between synthetic and empirical drive cycles. Two metrics to quantify the similarity between vehicle drive cycles are considered: characteristic acceleration and aerodynamic speed. Characteristic acceleration measures the acceleration and grade intensity of a drive cycle as the positive part of inertial work to accelerate and/or raise the vehicle per unit mass and per unit distance over a drive cycle. Aerodynamic speed measures the average cubic speed to the average speed of a drive cycle, reflecting the impact of aerodynamics on vehicle fuel usage. These metrics are employed in this analysis as surrogates for vehicle efficiency sensitivity to drive cycle characteristics. Please refer to [7] for a detailed derivation of these metrics.

Freeway Model

Figure 5 shows characteristics of the real and simulated drive cycles from the I-285 freeway facility of interest. Real drive cycles collected via GPS are shown in Figure 5a with the drive cycles collected in the evening rush hour colored in red; these were the cycles used to calibrate the Vissim model. In order to better compare the result, we expanded the sample size by relaxing time and space constraints and included additional drive cycles in Figure 5a as blue markers. Relaxed constraints for the real drive cycles included allowing TSDC data from any time of the day on the same 5-mile corridor of I-285 and expanding the corridor to include the northeast side of I-285 in Atlanta. The samples with relaxed constraints include a total of 544 GPS drive cycles retrieved from the TSDC. Figure 5b shows the result of 2,000 simulated drive cycles, with the samples color-coded based on frequency of a two-dimensional histogram.

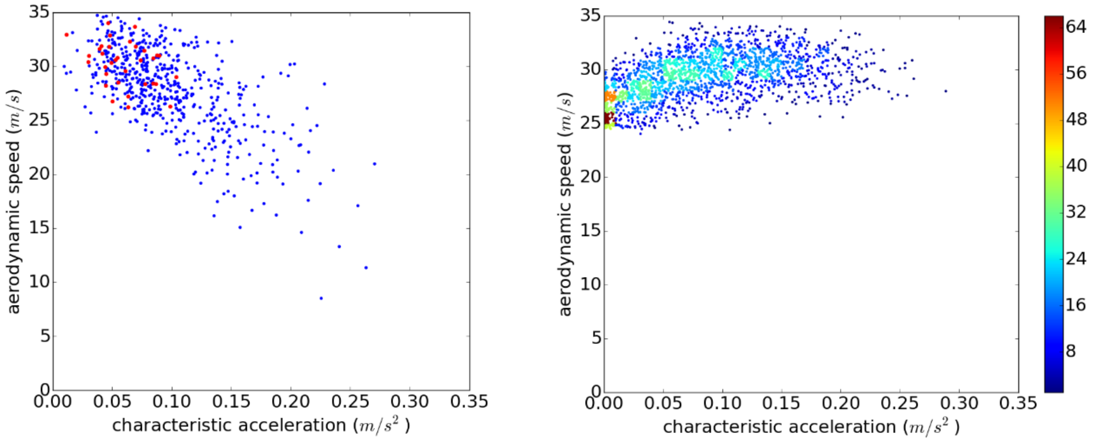


Figure 5a (left) - Speed vs. acceleration metrics for real-world freeway GPS drive cycles. Figure 5b (right) - Speed vs. acceleration metrics for synthetic freeway drive cycles.

Comparing the real-world drive cycles during rush hours (only the red samples in Figure 5a) with their simulated counterparts, we found that there is generally good agreement in terms of aerodynamic speed; however, the characteristic acceleration of simulated cycles scatters in a wider range. In Figure 6, the histograms on aerodynamic speed shows that both the real-world and synthetic drive cycles followed a similar normal distribution. However, there was a significant difference in the frequency distribution of characteristic acceleration.

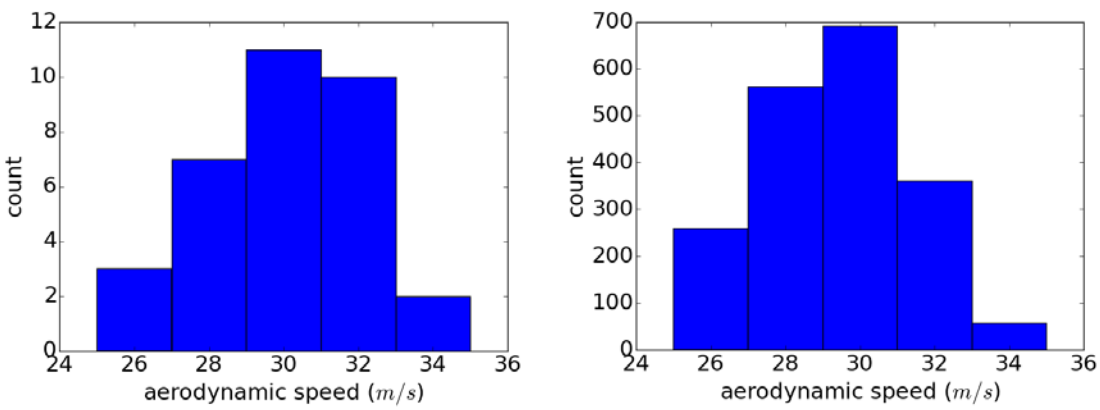


Figure 6a (left) - Histogram of aerodynamic speed for real-world freeway drive cycles. Figure 6b (right) - Histogram of aerodynamic speed for synthetic freeway drive cycles.

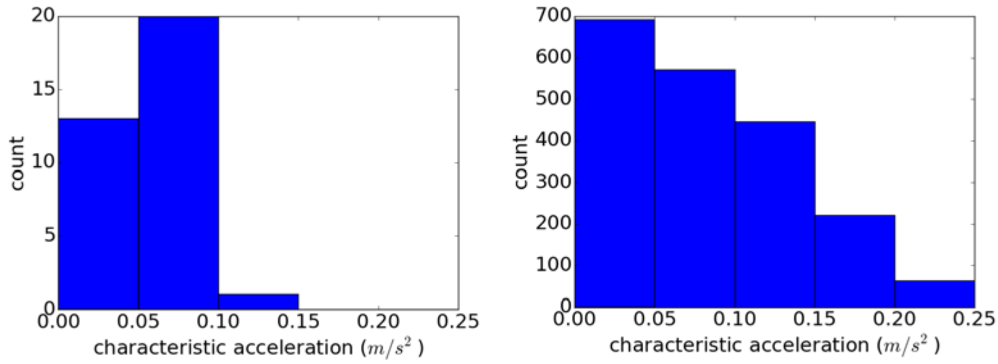


Figure 6c (left) - Histogram of characteristic acceleration for real-world freeway cycles.
Figure 6d (right) - Histogram of characteristic acceleration for synthetic freeway cycles.

Although the number of samples from the TSDC is limited, the results in Figures 6c and 6d point toward a discrepancy in the driving model in Vissim. Traffic simulation tools usually focus on evaluating traffic flow (i.e., link speed, traffic volume, etc.) and consequently may lack the necessary resolution to simulate acceleration rates at the level of detail explored in this study. Further examination of this dimension of the driver model is warranted.

To explore the potential tendency in real-world drive cycles, we compared the expanded results (samples in blue from Figure 5a) with the synthetic results, and came away with two observations: 1) real-world drivers tended to have higher rates of acceleration at lower speeds, and 2) the large percentage of vehicles with little to no acceleration in the simulation was not observed in real-world drive cycles. These observations suggest that acceleration behavior in the simulated driving environment do not yet reflect the real-world vehicle operation. For example, in a free-flow traffic scenario, real-world drivers seem to make small accelerations as vehicle speed oscillates around some target; however, the simulated driving environment seems to make an over-simplification of neglecting these accelerations.

Discussion on Driving Behavior Settings

Vissim provides two modified versions of Wiedemann's car-following model (Wiedemann 74 and 99). The Wiedemann model mimics both physical and psychological driving behavior; it defines the driver perception thresholds and the regimes formed by these thresholds. We used the Wiedemann 99 car-following model, in which more thresholds are adjustable by the user.

A few researchers have reported general methods for calibrating freeway models [8, 9]. We calibrated our model according to the Vissim manual [10] and the Highway Capacity Manual [11]. Given the complexity of traffic situations, users are asked to use their engineering judgment to calibrate parameters. Existing works usually focus on calibrating vehicle speed and link capacity with little attention paid to driver acceleration and deceleration behavior. A reference for systematically calibrating driver acceleration and deceleration behavior in the Wiedemann models could not be located. In lieu of a procedural approach, driver parameters in this study were calibrated in an iterative fashion.

Two steps were taken to calibrate the model in this study. First, threshold values were determined based on link speed and traffic volume observed in the field. Second, each threshold was adjusted in the car-following and lane-changing model with impacts on characteristic acceleration statistics observed and recorded. Thresholds were initially set to the default values provided by Vissim and then iteratively adjusted to match empirical data on characteristic acceleration. In the Wiedemann 99 car-following model, standstill distance, headway time, and following variation dominate link capacity. No independent threshold was found to have a significant effect (i.e., either condense or expand the range of the scatter graph) on the distribution of the characteristic acceleration. However, changing the parameters of the Wiedemann model and vehicle acceleration capability was only tested independently; it is possible that the combination of a few parameters could yield a more fruitful result.

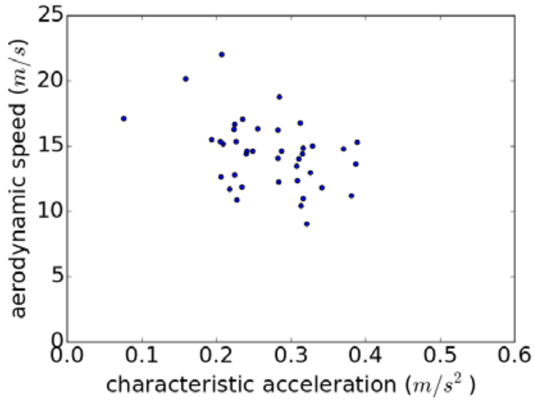
Lane-changing behavior in Vissim was based on Sparmann's model [12]. There are two types of lane changes: necessary and free lane change. The necessary lane change refers to lane changes that are required to reach the next road segment (e.g., making a left turn from the right-most lane). The free lane change is applied when vehicles are trying to reach a higher speed or longer headway. In both of these scenarios, the trailing vehicle will always slow down to let the other vehicle merge to its lane.

In the lane changing model, no individual parameter was found to have an impact on characteristic acceleration. Because Vissim uses a "slow down, let pass" model to simulate merging and lane changing behavior, it only gives control to deceleration. Low end deceleration was selected with the intent of reducing the speed difference between each lane change to mimic the submissive driving behavior in freeway driving.

Arterial Model

Construction of the arterial model was hindered by an inability to identify a significant number of real-world drive cycles that traversed the entire length of the facility. Although GPS traces were available from 40 different vehicles during a two-week period, only three drive cycles were found to consecutively travel through all five modeled intersections. To generalize the driving behavior of vehicles in this region, drivers were assumed to behave similarly in the arterial road during the rush hours. With this assumption, results were aggregated for each vehicle as follows: first, for each drive cycle retrieved from the TSDC, as long as it traveled through one intersection, sub-cycles were truncated within the region of interest and characteristics of the sub-cycle were calculated. Second, vehicle characteristics were aggregated by taking an average of the sub-cycles.

Figure 7 shows the resultant drive cycle characteristics of the arterial model. The simulated results were calculated from cycles that traversed the entire section. Although the real-world results scattered in a larger area, both the aerodynamic speed and characteristic accelerations were generally comparable. It might be counter-intuitive that the arterial model achieved a better match than the freeway model, as one might expect the driving behavior on the freeway to be easier to model than those in the arterial scenarios. However, both the freeway and arterial model had a good match in terms of the aerodynamic speed; the main difference was on the characteristic acceleration. In the freeway model, most of the accelerations were caused by lane changes whereas in the arterial model, most of the accelerations were related to the traffic lights. In the freeway scenario, there was more involvement of the driving behavior model, which led to a larger mismatch in terms of characteristic acceleration. Further analytical study is required to confirm this hypothesis.



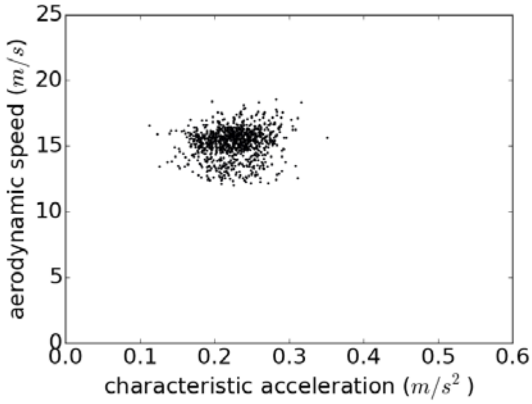


Figure 7a - Speed vs. acceleration metrics for real-world arterial cycles.
Figure 7b - Speed vs. acceleration metrics for synthetic arterial drive cycles.

Fuel Economy Simulations

After studying the drive cycle characteristics, real-world and simulated drive cycles were compared in terms of simulated fuel economy. FASTSim was used in this study. Drive cycles were input to FASTSim, and fuel economy was calculated according to the powertrain model. For simplicity, the same mid-size sedan powertrain model (similar to the 2012 Ford Fusion) was applied to all drive cycles. Table 4 shows the simulation results from both sets of drive cycles relative to freeway driving.

Table 4 - Comparison on fuel economy of the freeway model.

	Real-World Cycles	Synthetic Cycles
Mean, mpg	34.5	34.7
Median, mpg	34.3	34.5
Standard Deviation, mpg	3.4	3.8
Minimum, mpg	28.9	24.6
Maximum, mpg	43.8	42.9
Vehicle Count	34	2,000

The descriptive statistics show a good match on fuel economy. In terms of simulated miles per gallon of gasoline, the difference of mean, median, and standard deviation between real-world and synthetic drive cycles were in the decimal digit. We observed that the mismatch on acceleration behavior did not create a significant deviation in fuel economy between the two sets. This might be mainly caused by the small number of accelerations in the free-flow traffic (i.e., the absolute value of characteristic accelerations were relatively small) and by the fact that tire rolling resistance and aerodynamic drag tend to dominate vehicle power requirements at highway speeds.

Figure 8 shows the graphical distribution of the simulated fuel economy results. This plot confirms the observation that simulated fuel economy from the freeway facility drive cycles was generally comparable. Given a small real-world data set, we achieved a good match between the real-world and synthetic results.

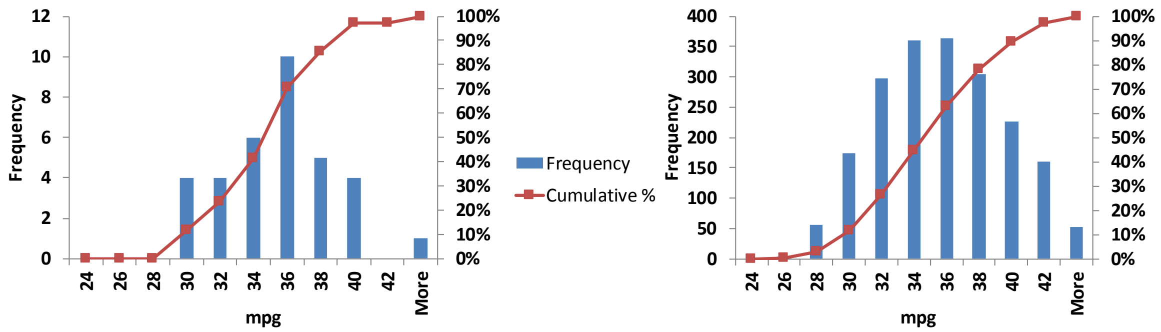


Figure 8a - Simulated fuel economy in the freeway model from real-world drive cycles.
Figure 8b - Simulated fuel economy in the freeway model from synthetic drive cycles.

Given the small number of real-world drive cycles that consecutively traveled the entire arterial facility, the real-world results in Table 5 and Figure 9 were averaged by vehicle on cycles collected in this region. Descriptive statistics in Table 5 for the arterial model also show a good match in terms of fuel economy. Although the difference of simulated fuel economy results between the real-world and synthetic drive cycles are small, in the histograms shown in Figure 9 reveal a larger variance in the real-world results.

Table 5 - Comparison on fuel economy of the arterial model.

	Real-World Cycles	Synthetic Cycles
Mean, mpg	28.3	28.7
Median, mpg	28.0	28.4
Standard Deviation, mpg	4.2	2.5
Minimum, mpg	21.6	21.3
Maximum, mpg	43.7	36.4
Vehicle Count	40	1,000

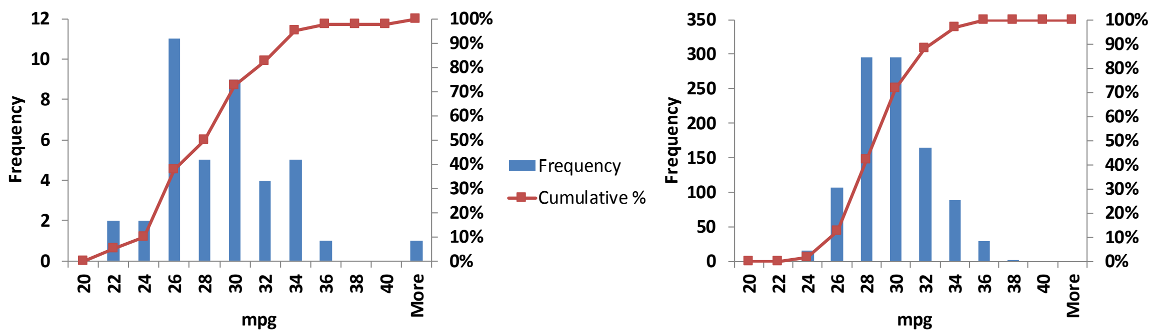


Figure 9a - Simulated fuel economy in the arterial model from real-world drive cycles.
Figure 9b - Simulated fuel economy in the arterial model from synthetic drive cycles.

Summary

Methods for generating synthetic drive cycles for freeway and arterial facilities have been demonstrated through application of traffic micro-simulation. The ability of these methods to generate drive cycles with metrics comparable to real-world data has been quantified relative to empirical vehicle speed profiles in terms of travel time, aerodynamic speed, and characteristic acceleration. Traffic models discussed in this paper were found to produce synthetic drive cycles with lower levels of vehicle speed and acceleration variability than observed in equivalent empirical data. However, when applying synthetic and real-world cycles to a vehicle powertrain efficiency model, drive cycle differences become less evident in terms of simulated fuel economy.

The fact that the absence of stochastic contributions in the model of human driving behavior did not significantly impact agreement between synthetic and empirical drive cycles in terms of simulated fuel economy has implications on the potential energy efficiency gains of automated vehicle technology. For instance, the lack of transient operation on the freeway facility in the synthetic drive cycles likely did not create disagreement with the empirical data in terms of simulated fuel economy due to the fact that aerodynamic and tire rolling resistance loads generally dominate powertrain efficiency at high speeds. For the arterial facility, frequency of start/stop events (which are dictated primarily by signalized control and not driver behavior) was likely the most important attribute in terms of simulated fuel economy; consequently, a lack of stochastic behavior in the synthetic drive cycles did not create significant discrepancies.

Based on these findings, it may seem reasonable to conclude that highly accurate traffic micro-simulation models of human and automated driving behavior could reveal negligible energy efficiency differences. While acknowledging the physical realities this analysis has highlighted regarding potential for drive cycle smoothing on freeway and arterial facilities, it must be reiterated that this was not a dedicated study of automated driving energy efficiency potential. As such, this analysis did not consider a number of avenues by which automated driving technology could enable energy efficiency gains, including: reduced inertial loads associated with decreased take-off acceleration rates, decreased aerodynamic drag resulting from platooning, and improved traffic flow related to decreases in following distances enabled by vehicle-to-vehicle communication (such as cooperative adaptive cruise control).

Future work in this area could include refining traffic models to better reflect real-world vehicle operation (including addition of stochastic elements in driver models of human behavior) and implementing models for connected and autonomous vehicle technology to estimate energy/emission impacts.

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