Analysis of Real-World Lead Vehicle Operation for the Integration of Modal Emissions and Traffic Simulation Models

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ABSTRACT

New models and data are needed in microscopic traffic simulation tools to allow effective use with newer modal tailpipe emissions models. Traffic simulation models offer the ability to simulate large second-by-second vehicle operation datasets as input for emissions models. However, more data is needed to improve simulation of second-by-second vehicle speed. This research analyzes and models the vehicle dynamics of unconstrained drivers in real-world driving situations based on road geometry. Vehicle dynamics data were collected using an instrumented vehicle driven by 22 volunteers, over a 17-mile predetermined test route. The objective of this research was to analyze and model the non-random speed variations in unconstrained lead drivers. The results of this study suggest horizontal and vertical curvatures have a significant impact on the second-by-second operation of an unconstrained lead vehicle. Furthermore, these non-random changes in speed are important considerations since they can produce considerable variations in the level of tailpipe emissions.

INTRODUCTION

Estimating vehicle emissions based on second-by-second vehicle operation creates a significant motivation to link microscopic traffic simulation models to more accurate operating-mode based regional mobile emissions models. Because the collection of a large representative second-by-second vehicle operation dataset for every traffic circumstance is not realistic, the use of microscopic traffic simulation models to replicate the real world second-by-second driver behavior for hundreds of vehicles and traveling patterns is ideal. The simulated vehicle driving cycle data could be integrated into a mobile emissions model such as the new version of EPA's MOVES to allow for improvements in emissions modeling of project-level transportation alternatives or traffic conditions. Unfortunately, very few real world vehicle driving cycle datasets exist, especially for lead vehicles (following vehicles have long been modeled using car following theories which pre-date wide-spread use of computer traffic simulations). Moreover, detailed models to incorporate second-by-second vehicle operating mode data into traffic simulation models are limited. This paper investigates the second-by-second variation of lead vehicle dynamics in a real-world, on-road dataset as a function of road geometry.

RESEARCH MOTIVATION

Two factors motivate this research: the feasibility to collect on-road second-by-second vehicle operations data with readily available technology; and the desire to integrate microscopic computer traffic simulation models for use with modal tailpipe emissions models.

Microscopic simulation models typically use "car following theory" to capture the temporal changes in an individual vehicle's velocity, and thus its location in response to the vehicle it is following: the lead vehicle [1]. Brackstone and McDonald identified five groups of car following models: Gazis-Herman-Rothery, collision-avoidance model, linear models, psychophysical and fuzzy-logic. While these models are used to describe the behavior of the following car, few research efforts have studied and modeled the behavior of the lead vehicle. Default lead vehicle behavior is modeled as a constant speed until it approaches another vehicle. This assigned "desired" speed typically varies between individual simulated vehicles (on a normal distribution) and is often a function of the speed limit or free flow speed of a given link.

Some models, such as PARAMICS, have optional sub routines that alter this vehicle speed, including lead vehicle speed, as a function of roadway characteristics (such as horizontal curvature when it is coded into the network), but these advanced options are rarely used, presumably not only because few network databases have curvature and grade coded, but also because we lack the real-world vehicle operating data to calibrate these functions. Recent work [2,3] has indicated that assumptions regarding car following rules make differences to emissions estimates and also to the overall aggregate traffic conditions predicted by microscopic traffic simulation models. Researchers have alluded to the need to collect lead vehicle data [2], but to date only a few studies have done so [4, 5].

BACKGROUND

Second-by-second Vehicle Speed Variation

Previous studies have investigated the impacts of curvature on vehicle dynamics. The majority of research efforts that focused on the impacts of roadway geometry on driver behavior and speed used observational techniques to collect data for analysis. Most of these studies used RADAR, LIDAR, or pneumatic tubes to record vehicle speeds at finite locations [6, 7]. One limitation with these approaches is that driver behavior may be significantly impacted due to the perception of law enforcement or the presence of observers. Another limitation is the finite locations of speed data collection and a continuous time series of second-by-second speeds cannot be obtained. Past curvature studies have been limited because second-by-second speed and acceleration profiles were not easily attainable.

Existing studies have suggested that roadway geometry has a significant impact on the speed profiles of vehicles [4-7]. Figueroa and Tarko used regression models to determine that there are “transition” sections approaching and exiting horizontal curves where speed changes are suspected to take place. They concluded that 66% of the deceleration events and 72% of the acceleration events in their dataset occurred on the tangent sections approaching and exiting horizontal curves.

However, Figueroa and Tarko did not consider vertical curvature in their analysis. Research conducted by Gabriel et al. is one of the few studies to consider the three dimensional highway alignments in predicting operating speeds. Their research suggests that by including vertical curvature into regression equations there is a 33% increase in model accuracy implying that future operating speed models should include three dimensional alignments. However, the study conducted was limited in the number of curves they studied. Only two types of alignment combinations were studied: sag vertical curve combined with circular horizontal curve and crest vertical curve combined with circular horizontal curve. They conclude that future research was necessary to establish a more robust three dimensional model for operating speed prediction.

This paper extends previous work on curvature impacts on vehicle operation in two ways: 1) by investigating a range of curves, and 2) by using an instrumented vehicle to collect a second-by-second real-world velocity profile. Instrumented vehicles are now in more wide-spread use to capture vehicle operations to consider the impacts of horizontal curvature on driver speed behavior [5]. The study by Nie and Hassan contributes several key findings relevant to this paper: 1) the effects of road geometry on driver speed vary with road type (i.e. two-lane rural highway vs. local connector roads); 2) driver speed selection is highly correlated with the geometric features; 3) drivers were more cautious on continuous curves than on isolated curves with long approach and departure tangents; 4) drivers do not maintain a constant speed; and 5) acceleration and deceleration events take place on curved sections.

Traffic Simulation Models

Previous traffic simulation research has focused on more aggregate calibration and the comparison of different computer models, all having some degree of success. These studies have been conducted with many different simulation programs but recently include the following most often: VISSIM, CORSIM, PARAMICS, and AIMSUM [8-19]. Traffic simulation models offer the potential to generate large amounts of second-by-second data from individual vehicles while keeping the costs of data collection low. Because it is impractical to collect real-world tailpipe data for hundreds of drivers on a full range of facility conditions, traffic simulation model validation and calibration is critical to ensure that the simulation model accurately represents the real-world system. The validation and calibration of these models is not a trivial task, as the non-stationary and auto-correlated nature of traffic flow complicates the process [20-22].

For tailpipe emissions modeling, the microscopic traffic simulation models offer great potential because simulated one-second vehicle operation data could be used as input for operating mode based emissions models. However, in order to be useful for future mode-based emissions models, traffic simulation models will need to produce results that are much more detailed than average speed. For example, the EPA's MOVES model is incorporating Vehicle Specific Power (VSP) into the model to predict emissions estimates. However, MOVES and current traffic simulation models do not incorporate true road grade. Therefore, an accurate calculation of VSP for a realistic range of real world conditions is impossible given the current modeling structure. Furthermore, the vehicle dynamics generated by these simulation packages need to be evaluated to ensure the second-by-second model output is realistic.

This research proposes using second-by-second real-world data, collected from multiple drivers, to study unconstrained lead vehicle operation. This research is important because it contributes to improving the interface between traffic simulation models and the next generation of modal emissions models: measuring real-world one-second vehicle dynamics and comparison to corresponding simulated conditions.

DATA COLLECTION

The overall objective of this data collection effort was to obtain on-board, on-road, real-world vehicle operations as well as tailpipe emissions data on a 17-mile predefined test route in northeast Connecticut. The data used in this analysis were collected between October 11th and October 27th, 2006 using an instrumented light-duty minivan driven by twenty-two different volunteer drivers. The drivers that participated in the study were recruited from the University of Connecticut community via email and personal communication. All drivers were asked to drive the route at least twice in a row. These drivers included undergraduates, graduate students, and faculty members with between 1 and 40 years of driving experience.

Test Route

The route chosen for this research was selected to contain multiple road types (freeways, rural two-lane highways and local stop-controlled roads) and varying degrees of both vertical and horizontal curvature. The Connecticut Department of Transportation (ConnDOT) collected and provided the route geometric data using an ARAN photologging van. The ARAN van is equipped with a set of gyroscopes to collect detailed road geometry such as curvature and grade. Grade and curvature data were collected continuously and recorded every 10 meters along the entire length of the test route. According to the manufacturer, the ARAN system is capable of providing grade and curvature data at "rod and level" accuracy and meets the Federal Highway Administrations (FHWA) regulations for curve classification [23].

Vehicle Instrumentation

The 1999 Toyota Sienna minivan was instrumented to collect spatial location, vehicle/engine operating parameters, and tailpipe emissions data simultaneously. Spatial location data were collected using GPS receivers. The Garmin 16 HVS antenna [24] was used to synchronize all instruments to GPS time. The Garmin GPS unit has a published positional accuracy rate of less than 49 feet, velocity accuracy at steady-state speed of 0.12 mph and a reacquisition time of less than 2 seconds.

An AutoEnginuity ST01 ScanTool collected vehicle velocity, engine load and engine RPM from the vehicle's on-board computer. Vehicle acceleration data were collected using a Crossbow CXLO2LF3 accelerometer mounted on the roof. This accelerometer is a three-axis accelerometer with a measurable range of –2g to +2g and a 50 Hz response rate. The accelerometer selected for this research has a low noise density and a reported accuracy of ± 0.01 volts (0.2 mph/s). The GPS receiver and ScanTool were powered by the vehicle, while the accelerometer was powered through the data collection port of the desktop computer. Real-world on-board gas and particulate tailpipe emissions data were also collected simultaneously but are not used in this analysis. The van was also equipped with a forward facing video camera to record driving conditions experienced by the driver.

Data Preparation

Data from each of the instruments were merged into one master database. The GPS data from the ARAN van, and the GPS data from the instrumented minivan allowed the grade and vehicle operations datasets to be joined based on spatial location in ArcGIS. Therefore, every record in the vehicle operations dataset was assigned a grade (in percent) and horizontal curvature (radius in meters) based on the ARAN data point that was closest to it in proximity.

Other research studies have identified surrogate variables that can be calculated to describe how a vehicle is operating. One such variable is VSP. VSP is a measure of engine power demand that is calculated from the measured velocity, acceleration and road grade[26]. The joining of road grade to the emissions dataset allows the calculation of VSP when investigating causal factors in vehicle emissions. VSP is highly correlated to increased concentrations of gas phase vehicle emissions [25-28]. VSP for each second of data was calculated using Equation 1 [26]:

$$\mathbf{VSP = 1.1(v * a) + 9.81(grade * v) + 0.213(v) + 0.000305(v^3)} \qquad \textbf{[Equation 1]}$$

v = velocity (m/s);
a = acceleration (m/s^2);
grade = rise/run (i.e. arctan(slope in degrees))

However, the calculation of a variable from three different sources propagates errors. Specifically, when calculating VSP, potential sources of measurement error (velocity (at ± 1 mph), acceleration (at ± 0.2 mph/s) and grade (no reported error)) are multiplied, added and cubed. While the propagation of error has been limited by instrumentation selection, it cannot be eliminated.

In order to analyze the true unconstrained or "free flow" driving of an individual, constrained vs. unconstrained driving was noted in the data. The data from the forward facing video camera were used to determine if the test vehicle was constrained by a vehicle, traffic control device or obstacle. The time (HH:MM:SS) at which the driver became constrained (Tc_s) and the second the driver became unconstrained (Tc_e) were recorded. The time displayed on the camera was adjusted to match the time recorded by the GPS to ensure the camera was synchronized with the other instruments. For this paper, data where the vehicle was considered unconstrained were extracted and used in the analysis of the real-world lead vehicle operations. A driver was classified as constrained at time Tc_s to time Tc_e if one of the four following criteria were met:

1) If the driver was following another vehicle with less than 5-second headway or if a vehicle ahead of the instrumented vehicle applied their brakes. Actual headways were not recorded using instruments, but estimated using landmarks along the roadway to determine the time interval between the lead vehicle and the test vehicle.
2) If an intersection with a red or amber signal was visible at any point during the approach to an intersection. The instant a red or amber traffic signal was visible in the frame of the camera the vehicle was classified as constrained.

3) If there were roadside obstructions that were not part of the typical road geometry. For instance, if there were construction signs warning of roadwork ahead the data would be considered constrained.
4) If there were any abnormal conditions encountered by a driver that had a noticeable impact on the operation of the test vehicle. For example, if an instrumented van was approaching the intersection with a driveway and it was obvious that the test vehicle reacted to the possibility someone would pull out in front of them, then the vehicle would be classified as constrained.

While the ARAN van provides point-based curvature there are other curvature characteristics that were hypothesized to impact driver behavior. Using the calculated radius from the ARAN data, more descriptive statistics were generated to describe each curve along the test route. The first calculated variable was length of curve (LC). Knowing where the tangent sections start and end allowed the identification of the starting and ending station of each curve, then by simple subtraction the LC was calculated.

Knowing the LC, the deflection angle (DA) for each curve could be calculated using the given radius (R) and substituting into Equation 2 [29] and making unit conversions. The curve deflection angle represents the degree at which the tangent section of the roadway deviates into the turn. The deflection angle is important because the larger the deflection angle, the more severe the turn and presumably the more significant a curve's impact on unconstrained velocity.

$$DA = \left[\left[\frac{R}{LC} \right] * 57.3 \right] \div 2 \qquad \textbf{[Equation 2]}$$

The lengths of tangent sections approaching and departing a curve are also hypothesized to have an impact on the variation in unconstrained velocity. The tangent sections of the horizontal alignment provide motorists with a clear view of the road ahead (given small grades) and the ability to travel at higher speeds between curves. It is hypothesized that longer tangent sections allow drivers to accelerate to a "comfortable" cruising speed before needing to decelerate to a perceived safe speed to negotiate an upcoming curve. Therefore, the length of the tangent approaching (LT_A) and the length of the tangent departing (LT_D) a curve were added to the dataset by simply subtracting the stations of the beginning of tangent from the end of tangent.

Finally, the data were reduced further into two subsets based on their location on subsections of the test route. The first criteria were defined based on a uniform posted speed limit along the entire section of the section. The second main criteria were that major intersections were not included which may alter the behavior of a driver. Keeping these criteria in mind two portions of the test route were selected for further analysis. The "Curves Section" (Figure 1) of the test route contains multiple horizontal curves of varying radii, and limited grades. Radii ranged from 153 meters up to 2000 meters while grades in this section were limited to -5% to 5%. Analysis of this section of the test route (State Route 32), focuses on the effects of horizontal curvature on unconstrained second-by-second velocities since grades are relatively small. According to the American Association of State Highway and Transportation Officials [29];

> "It is generally accepted that nearly all passenger cars can readily negotiate grades as steep as 4 to 5 percent without an appreciable loss in speed below that normally maintained on level roads"

AASHTO goes on to say that once grades go above +3 % (upgrades) there begins to be a slight impact on speeds and the impact progresses with an increase in grade.

Recognizing there are grade impacts on speed, the "Grade Section" (Figure 1) of the test route (Route 195) was selected as a second study section due to the large degree of vertical curvature (grades range from -8% to 11%) and limited variation in horizontal alignment (only 2 horizontal curves in this section, both with radii greater than 1000 meters). This section of the test route will focus on investigating the effects of grade on unconstrained vehicle velocity. Figure 1 identifies these sections along the test route.

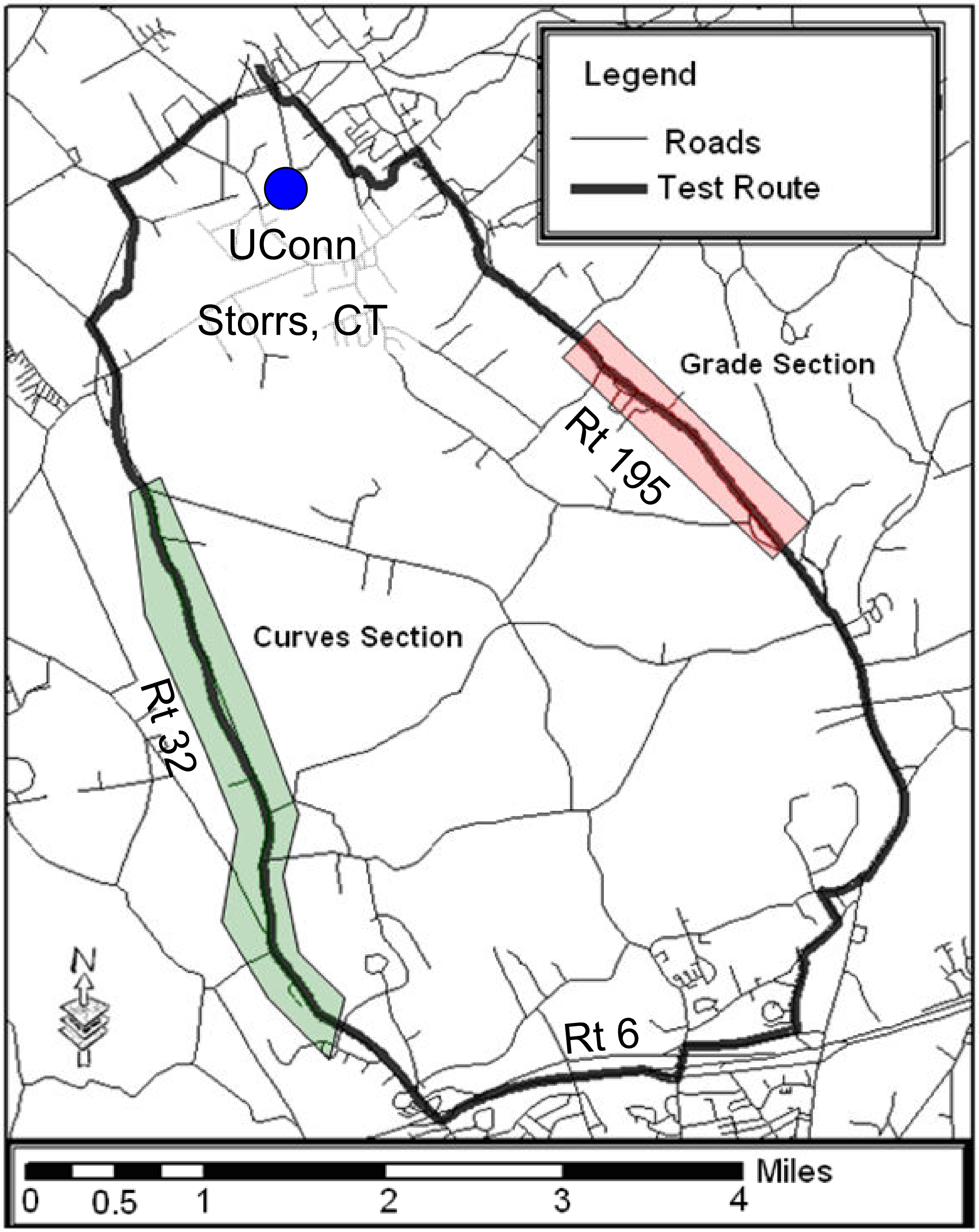


Figure 1: Test Route Subsections

DATA ANALYSIS

Analysis of the video data indicated that 45.4% of the data were classified as constrained while 54.5% of the data were classified as unconstrained (or a lead vehicle).

With more than half of the data classified as unconstrained, these data suggest, second-by-second lead vehicle operation accounts for a significant portion of the overall travel on this rural test section. However, it should be noted that data were collected from 9AM to 2PM on multiple days thus missing the morning and afternoon peak travel periods. This may have biased the percent time unconstrained due to the lower number of vehicles on the road during off peak travel times. Therefore, the percent time unconstrained cannot be applied to all time periods without further study.

Curve Section Analysis

To ensure that the variation seen in vehicle velocity is not specific to one vehicle, time series plots were overlaid for the Curves Section (Figure 2). The X-axis is the distance along the test route (chainage in miles) and Y-axis is the individual vehicle's velocity along the subsection of the test route. The drivers plotted in Figure 2 were unconstrained for the entire length of the curve subsection. The majority of drivers increase their velocity from chainage (in miles) 3.4 to 3.6 then a gradual decrease from 3.6 to 3.9 miles.

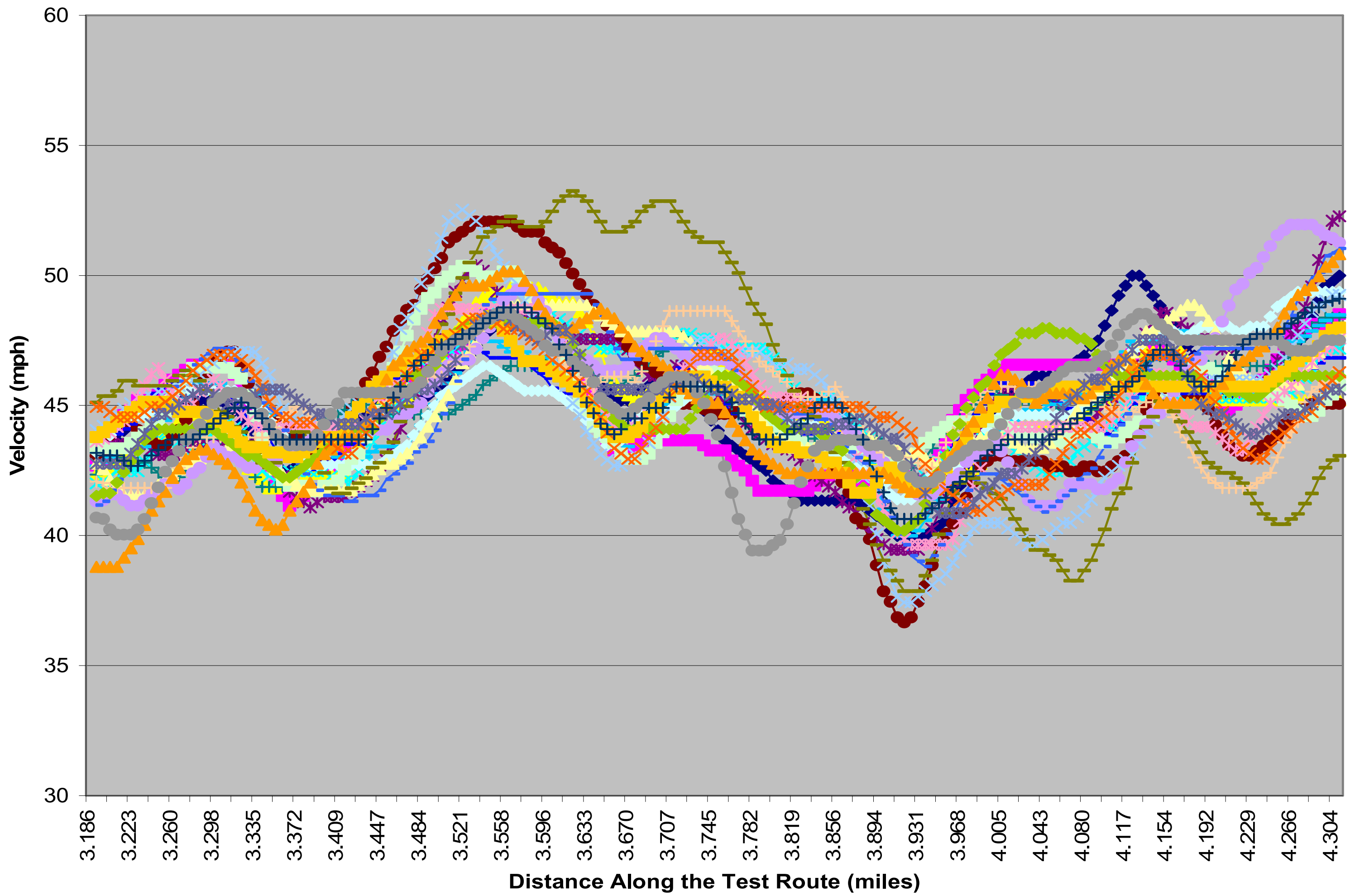


Figure 2: Time-Series Plots for Multiple Test Runs

To test statistically if the test runs had similar patterns in velocity profiles, a correlation analysis was conducted between drivers. The mean speed was approximately 45 mph, with a standard deviation of 2.4 mph. Note that the speed limit on this section of road is 40 mph and 24 of the 25 series have a mean speed above 40 mph.

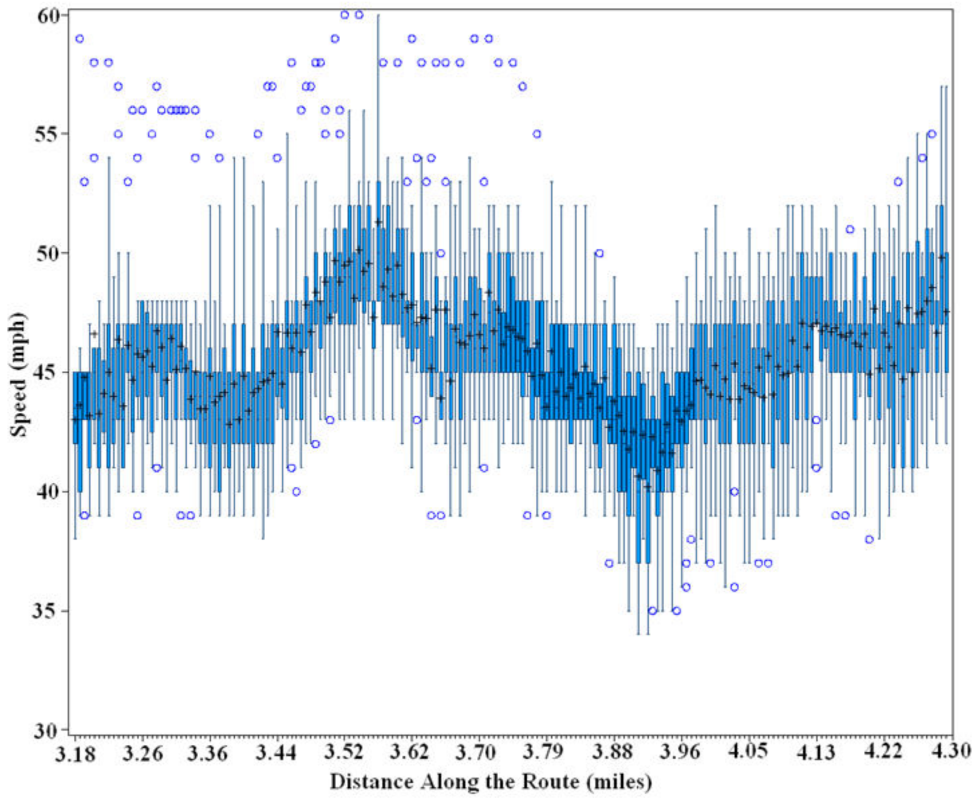
Speed Normalization to Account for Driving Style

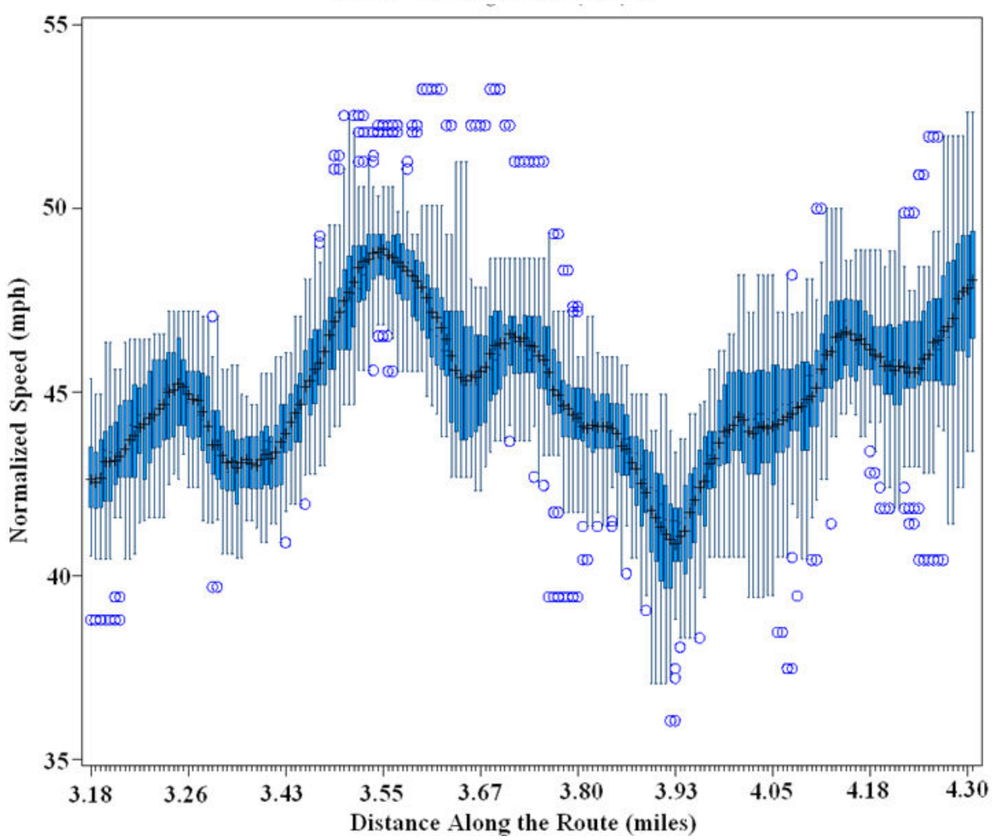
To account for the differences in mean driving speed among the individual test runs, the second-by-second speed data for each series was divided by the mean speed for that individual series. The data were normalized to aid in reducing the impacts of an individual's driving style on the data. This produces a ratio of actual speed over the mean and preserves the temporal and spatial patterns in the speed data. To aid in analysis and produce a vertical axis that is easy to interpret, the speed ratio was multiplied by the mean speed of the all drivers on that section of the test route (44.7 mph).

The correlation analysis was then repeated for the normalized data. This analysis resulted in a mean overall Pearson correlation coefficient 0.78 to 0.89. Overall, this analysis suggests that the patterns in vehicle velocity with respect to location are present and consistent between test runs and drivers. This variation in the second-by-second velocities is not random and should be accounted for in traffic simulation models.

Curve Section Analysis

Using the subset of 25 unconstrained test runs, box plots (Figure 3) were generated for raw speeds and normalized speeds for every tenth of a mile in the curve section. The box plots allowed for a graphical analysis to determine if sections of the test route had speeds that were statistically different from other sections on the test route. From these plots there are sections on the test route that are significantly different then the others (i.e. boxes at locations do not overlap with other sections). Specifically speeds at chainage 3.55 and 3.93 miles are statistically different from each other even though the speed limit stays the same.





<u>Figure 3: Raw and Normalized Speed Box Plot: Curves Section</u>

Grade Section Analysis

A similar analysis was conducted for the Grade Section. A subset of runs were used in this analysis because only 11 of the test runs had continuous unconstrained driving on the Grade Section. Figure 4 shows the box plot of normalized speeds aligned with road grade for the Grade Section to graphically illustrate grade affects vehicle speed. The blue sections of the graph represent a downgrade; the red areas represent an upgrade. Visually one can observe that, in general, as uphill grade increases there was a reduction in vehicle velocity, while segments with a steep downgrade (blue) show an increase in normalized vehicle speed. In Figure 4 the peak speeds are seen at chainage 13.0 (mile) this station corresponds to a section of the route with a negative grade. As the drivers proceed beyond this point on the route the grade becomes a steep upgrade and there is a resulting decrease in speed (stations 13.15 mi to 13.3 mi). Similar to the results for the Curves Section, Figure 4 also shows that there are sections of the route where variations in velocity were consistent with location on the route.

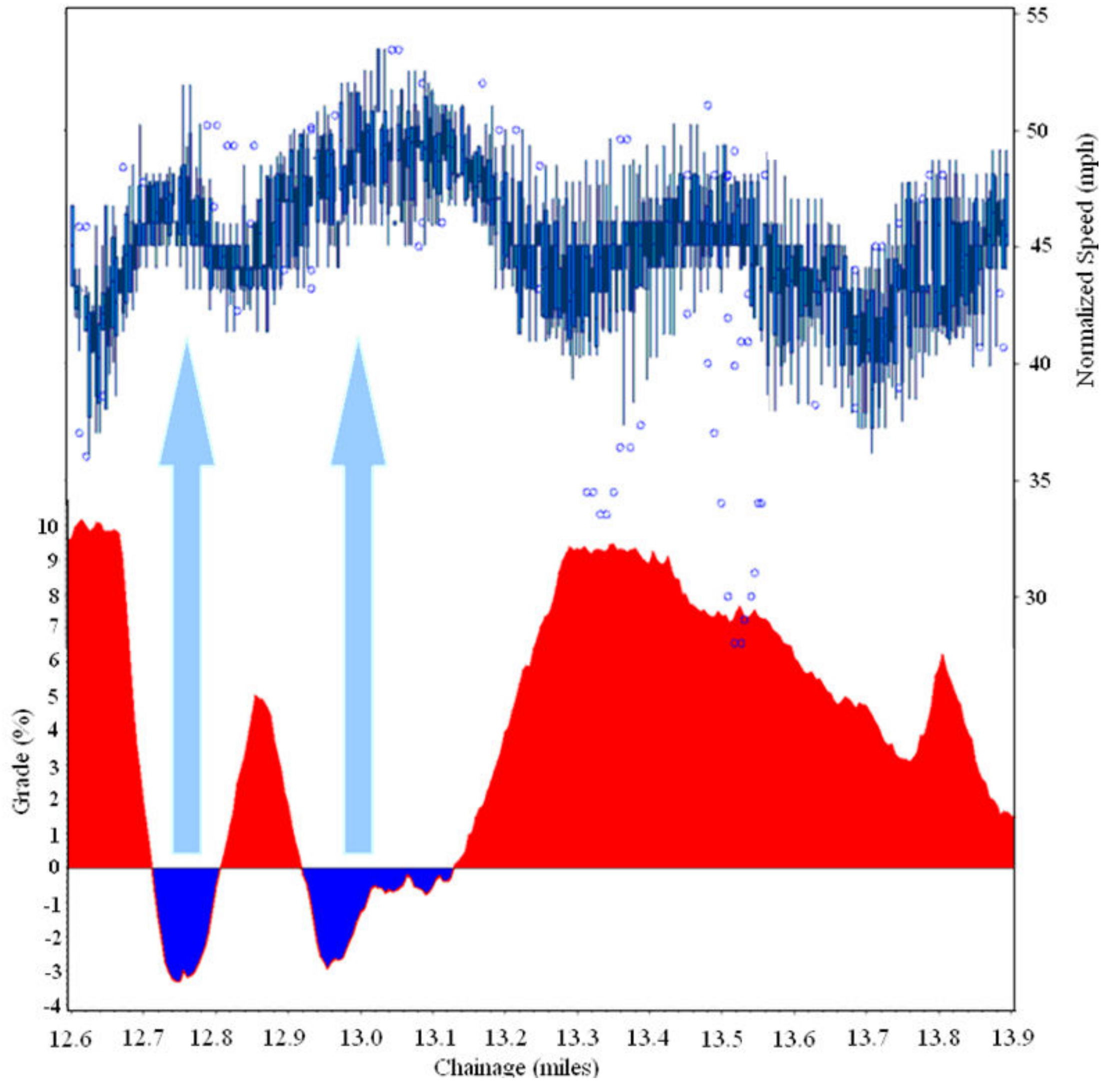


Figure 4: Normalized Speeds Box Plot: Grade Section

The Impact of Vehicle Second-by-Second Operations on Accurately Modeling Emissions

The previous sections described the variation in unconstrained vehicle velocity and identified the second-by-second variations. This section will evaluate the impact of incorporating accurate variations in lead vehicle operations for traffic simulation-based emissions analysis. Research into the correlation of vehicle emission rates and the operating mode of a vehicle has prompted several researchers to develop a system of binning operational data based on the velocity and acceleration of the vehicle at a given time, often 1 second. Most simply, the classes of operating modes have been divided into 4 "bins": idle, acceleration, cruise, and deceleration. Models or estimates of vehicle emissions are "looked up" or grouped by operating bin. The definitions for each bin as outlined by [30] were applied to each second of valid data in this analysis to see if vehicles on horizontal and vertical curves would be coded in different bins thus resulting in different emissions estimates in an emissions model. However, the 4 bin system is now rarely used. The more sophisticated vehicle operating binning system currently used in the new EPA MOVES model was also applied [31]. This new binning method (using VSP and speed) has increased the need for more accurate second-by-second vehicle operation data (i.e. VSP).

The binning analysis of unconstrained driving suggested that when using the traditional 4-bin system, the variation in real-world lead vehicle 1-second speeds on the horizontal and vertical curve sections in this study are not large enough to produce significant differences in the percent time spent in each operating mode. In this case, the lead vehicles would be classified as cruising 95% of the time where the traffic simulation data would predict 100% of time was cruise. This suggests that for unconstrained driving, on rural arterial segments, away from intersections, the speed profiles generated by traffic simulation may be adequate for modal binning if using the traditional 4-bin system.

Table 1 outlines the VSP, speed-based binning definitions used in MOVES2009 that were applied to the data collected for this research [31].

Table 1: EPA MOVES2009 Activity Binning Definitions [31]

Braking (Bin 0)			
Idle (Bin 1)			
VSP/ Instantaneous Speed	0-25 mph	15-50	>50
<0 kW/Tonne	Bin 11	Bin 21	-
0 to 3	Bin 12	Bin 22	-
3 to 6	Bin 13	Bin 23	-
6 to 9	Bin 14	Bin 24	-
9 to 12	Bin 15	Bin 25	-
>= 12	Bin 16	Bin 26	Bin 36
6 to 12	-	-	Bin 35
<6	-	-	Bin 33

When data with a constant velocity in unconstrained conditions (representative of lead vehicle velocity generated by typical traffic simulation models) are binned using the EPA definitions in Table 1, 100% of the data would be assigned to bin number 22. However, when applying the EPA's VSP-speed binning system to the on-road, onboard data along sections A and B for time periods where vehicles were classified as lead vehicles, data would be assigned to seven different bins: 42% of the data were assigned to bin 22, 40% were assigned bin 0 and 17% were assigned to bin 33. The remaining 1% of the data would be distributed over bins 11, 12, 21 and 23. This illustrates how more realistic lead vehicle operations in a traffic simulation model will predict more, higher emitting VSP bins in microscopic emissions estimates. This suggests the current models would underestimate emissions.

To illustrate the real-world impacts of horizontal and vertical curvature on ultrafine PN emissions, two 30 second time periods for a single driver were selected from this dataset. For the first 30 second period, during a curve section of the test route, the driver maintained a constant speed of 43 mph (+- 1mph). The first five seconds of data were removed after a constant speed was reported by the ScanTool to reduce the history effects of acceleration and deceleration on the sample. The ultrafine PN emission rate measured during this experiment [32] for this time period were summarized and the results can be found in Table 2, where first data row "constant speed" displays data for the section mentioned above. The next row (variable speed) displays a summary based on a following 30 seconds of data as the same vehicle and driver approaches a curve. For this section the speed decreases to 37 mph then increases to 47 mph. Table 2 demonstrates that the variation in speed seen in unconstrained driving can have an impact on the range and scale of ultrafine particles emitted. The constant speed section has a mean that is a factor of ten smaller than the variable speed section. And the constant speed section has a much smaller standard deviation than the variable speed section.

Table 2: Comparison of Real-world PN Emissions by Speed Variation

	Mean (#/s)	Max (#/s)	Min (#/s)	Standard Deviation (#/s)
Constant Speed	**7,900,000**	**19,000,000**	**2,000,000**	**5,200,000**
Variable Speed	**75,000,000**	**350,000,000**	**960,000**	**110,000,000**

Table 2 suggests that if a lead vehicle is assigned a constant speed in a traffic simulation model, the emissions impact from that inaccurate assumption could result in an underestimation of the true emissions rate. Furthermore, based on car following theories and equations used in traffic simulation, slight variations in lead vehicle behavior will influence operation of vehicles following the lead vehicle. Overall this suggests variations in second-by-second lead vehicle operation will increase second-by-second PN emissions for the lead vehicles as well as all other vehicles in the traffic simulation.

MODELING LEAD VEHICLE DYNAMICS

Preliminary models were developed to describe the variation in second-by-second velocity of a vehicle for the Curves Section and for the Grade Section independently.

Ordinary linear regression analysis assumes that the error variance is the same for all observations. For this dataset, the error variance is not constant (*heteroscedastic*) and the ordinary least-squares estimates are inefficient. To address these issues of autocorrelation in the time series dataset the use of an autoregressive error model was necessary. The form of this model is represented in Equations 3 and 4.

$$\Delta V_t = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u_t \qquad \textbf{[Equation 3]}$$

$$u_t = \phi_1 u_{t-1} + \phi_2 u_{t-2} + \varepsilon_t \qquad \textbf{[Equation 4]}$$

Where:
ΔV_t= Second-by-second deviation from the mean speed (V_t- Mean Speed)
α=constant (set to zero)
β_k=parameter estimate
$X_{1,k}$= Inverse radius, Length of Curve, Distance from curve, Distance to curve
μ=error estimate
Φ=parameter estimates for the first and second order error estimates
ε= normally distributed error term with mean of zero and standard deviation of σ^2
IN(0,σ^2)

Using the speed deviation as the dependent variable allowed for the development of an autoregressive model. The autoregressive model was further enhanced by specifying a second order (NLAG=2) autoregressive error term. Since the dependent variable has a mean of zero, the model was fit without an intercept (i.e. intercept =0). Multiple iterations of the modeling procedure were performed to remove parameters that were not statistically significant to the model (α=0.05). A correlation analysis determined that none of the predictors used in model development were highly correlated. The maximum correlation coefficient of 0.61 was found between length of curve (Lc) and change in curvature (DA).

Modeling Results: Grade Section

Recall the Grade Section of the route has very few horizontal curves but significant grades (up to 12%). The objective of this first model was to investigate the impacts of grade on speed. The generated model has a total R^2 of 0.90 and a root mean square error of 0.834 mph. Since there were only two horizontal curves on this section, none of the parameters relating to horizontal geometry were found to be significant to the prediction of second-by-second speeds. Grade was determined to be the only independent variable for this section of the test route that was statistically significant. Equations 5 and 6 represent the final model which indicates that, with every 1% increase in grade there will be a 0.33 mph decrease in vehicle velocity. For example on a 5% up-grade one could expect a 1.6 mph decrease in mean speed. Conversely, on a 6% downgrade one could expect an increase in speed of 1.9 mph above the mean travel speed. This analysis indicates that grade can impact the second-by-second speed of a vehicle.

$$\Delta V_t = -0.33(grade) + u_t \quad \textbf{[Equation 5]}$$

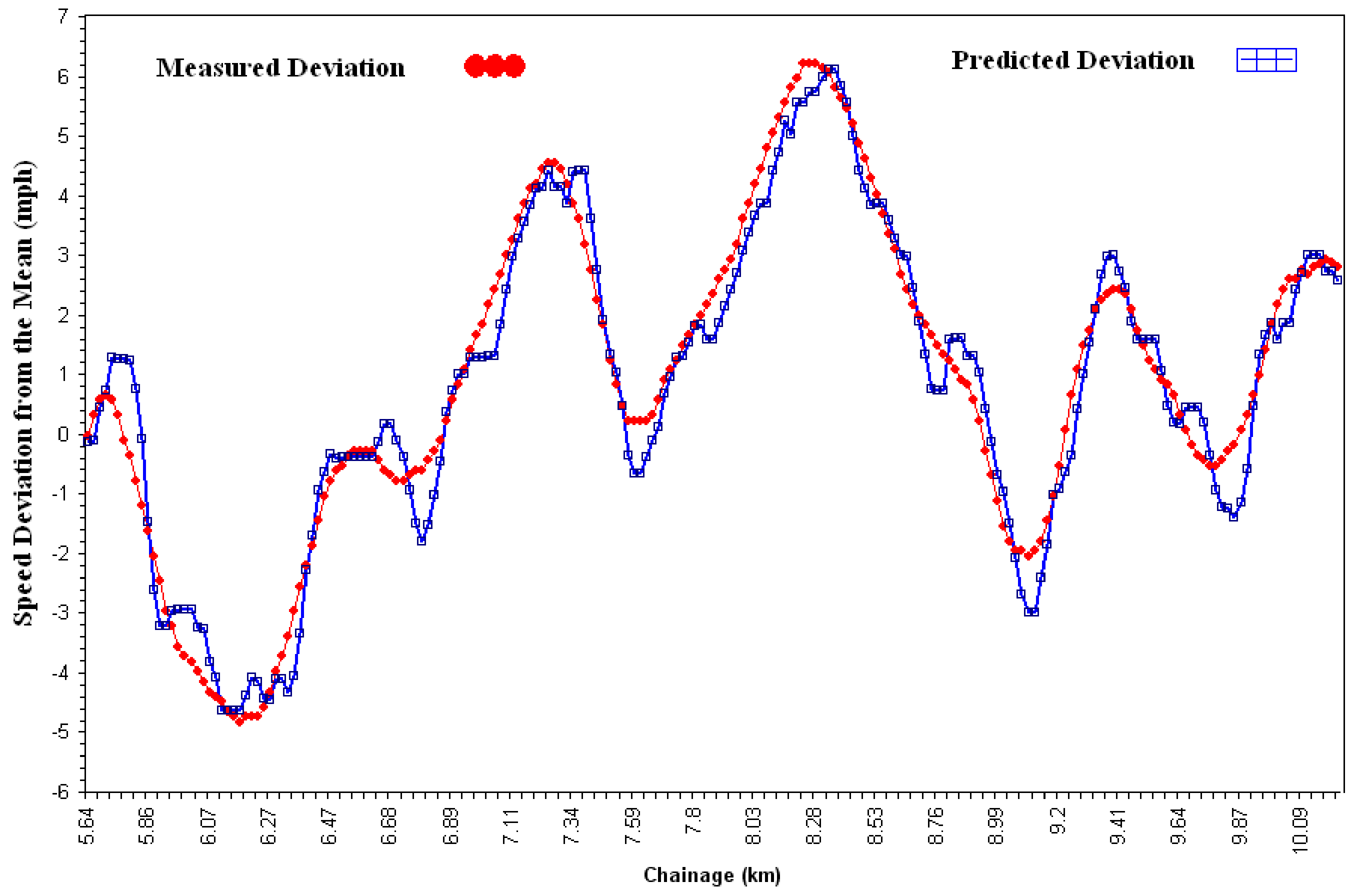
$$u_t = -0.97u_{t-1} + 0.046u_{t-2} + \varepsilon_t \quad \textbf{[Equation 6]}$$

Modeling Results: Curves Section

Using the same modeling techniques, a second order autoregressive error model with an intercept set to zero was developed for the Curve Section Data. The resulting model had a total R^2 of 0.86. Table 3 contains the statistically significant predictors and their estimated coefficients. Figure 5 contains a time series plot of single unconstrained driver's data with the actual and predicted speeds plotted.

Table 3: Full Model Independent Variables For Curve Section

Variables (in KM)	DF	Estimate	Standard Error	t Value	Approx pr>|t|
Inverse radius	1	-0.700	0.015	-4.70	<0.0001
Length of Curve	1	2.815	0.522	5.39	<0.0001
Distance from curve	1	0.322	0.033	9.84	<0.0001
Distance to curve	1	0.833	0.221	3.77	0.0002



<u>Figure 5: Actual and Predicted Speeds for a Single Run</u>

For the curve section of the test route, grade was determined to not be significant when considering the second-by-second speed deviation. Unlike on the Grade Section of the test route the grades on the Curves Section are mild (range from -5% to 4%). This could account for grade not being significant in the Curves Section model. This conclusion fits with the observations made in [29] that grades up to 4% or 5% do not cause an "appreciable" loss in speed. The Curve Section model also indicates that the metrics of a curve and distance from the curve can be used to model the mean change in velocity.

SUMMARY AND CONCLUSIONS

The objective of this research was to quantify and model the second-by-second variation of lead vehicle operations in a real-world, on-road dataset as a function of horizontal and vertical curvature. The initial analysis of vehicle operation on the route demonstrated that there are significant variations in speed along the test route and these variations are systematic with location along the route. Because following vehicles are reacting to the second-by-second operation of the lead vehicle, it is very important that simulated lead vehicle dynamics are accurate. Therefore, there is a need to develop a method to describe this variation so future simulation models would be able to incorporate realistic lead vehicle behavior.

Analysis of the Grade Section shows that grade has a significant impact on vehicle operation. Steep grades can impact lead vehicle behavior and should be incorporated into current traffic simulation models to aid in the modeling real-world vehicle velocity. However grades under 5% do not appear to have a significant impact on speeds. The findings suggest that for grade sections every 1% change in grade there will be a 0.33 mph change in vehicle velocity. For example a grade of +7% would result in a reduction in mean travel speed of 2.3 mph. The curve analysis indicates that the degree of curvature and distance to and from a curve have a significant impact on mean vehicle speed.

The focus on velocity was to demonstrate there are nonrandom variations in vehicle speeds that can be associated with road geometry. This paper has demonstrated that horizontal and vertical curvatures contribute to dynamic operation for lead vehicles. The second-by-second operations of these lead vehicles in turn have a significant impact on the second-by-second patterns of the following vehicles based on accepted car following theories. Therefore, if vehicle dynamics data from traffic simulation output are going to be used for mobile source emissions modeling it is critical that lead vehicle operations be modeled accurately.

The current trend in mobile emissions modeling suggests future models (including the current EPA MOVES model) will utilize second-by-second vehicle operation data for all vehicles in the fleet to create an accurate estimate of emissions for the transportation network. However, current microscopic traffic simulation models were not designed to provide data of the required accuracy. Of particular importance is the exclusion of vertical curvature (or grade) in both traffic simulation or emissions modeling which prevents the accurate calculation of VSP, which much recent research has identified as a key predictor of second-by-second vehicle emissions. We therefore recommend that next steps in both the collection of data for calibration and estimation of new vehicle dynamics models be focused on grade.

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