14-1481

Application of AIMSUN Micro Simulation Model in Estimating Emissions on Signalized Arterial Corridors

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November 13, 2013

Text words 5,530 plus 2,000 words for 8 Tables/Figures= 7,530 Words

ABSTRACT

Tailpipe emissions from on-road vehicles have negative impacts on the air quality of a region and are influenced by several factors including driver behavior, road characteristics and traffic conditions. Vehicles on arterial roads typically experience frequent stops followed by acceleration events which produce more tailpipe emissions. Microscopic simulation models can generate synthetic vehicle activity which can be used to estimate emissions on a facility. For accurate estimation of the emissions from an arterial facility, it is necessary to ensure that the simulated vehicle activity closely represents field observed vehicle activity. The objective of this paper is to investigate if adjusting a selected set of simulation parameters using field-observed speed trajectories at high temporal resolution can improve the emissions estimated from simulated trajectories on a signalized arterial corridor. In this paper, simulated and field-observed speed trajectories were characterized by Vehicle Specific Power (VSP). Emissions were estimated based on VSP modal emission rates and the time spent by vehicles in each VSP mode. The emissions were compared for routes along an urban arterial and for shorter segments within each route. At both spatial scales, the emissions from parameter-adjusted simulation vehicles having the same average number of stops and travel time distribution as field-observed vehicles were closer to real-world emissions than the simulation vehicles under default model parameters. Adjusting the parameters also allowed the model to be able to capture emissions hotspots along the routes more accurately than when the parameters had default values. Currently, microscopic simulation models are calibrated based on improving traffic performance measures. The findings from this paper present the potential for additional calibration of micro-simulation models based on improving emissions estimates from simulated vehicle activity.

INTRODUCTION

The transportation sector is a significant contributor to air quality problems in the United States *(1)*. The U.S. Environmental Protection Agency (US EPA) established the National Ambient Air Quality Standards (NAAQS) for six criteria pollutants, including carbon monoxide (CO), nitrogen dioxide (NO_2) *(2)*. In 2012, 61% of the nation's total emissions of carbon monoxide and 35% of total emissions of nitrogen oxide were produced by highway vehicles *(3)*. Given the role of mobile sources in local, regional, national and global air quality, it is imperative that the impacts of vehicle tailpipe emissions on the environment be given sufficient consideration when planning, implementing or evaluating transportation facilities.

Vehicle tailpipe emissions during driving or idling after the engine has warmed up are known as running emissions *(4)*. Running emissions are affected by several factors, including size, age, and type of vehicle, driver behavior, road infrastructure and prevailing traffic conditions *(5, 6)*. Modern strategies to reduce vehicle emissions include improving traffic operations, reducing congestion and vehicle miles travelled and encouraging efficient vehicles *(7)*. Microscopic traffic simulation tools produce detailed vehicle trajectories and are suitable for evaluating local or network-wide improvements in traffic control and management. Vehicle trajectories from a calibrated and validated micro-simulation model can be used as input for microscopic emissions models to estimate emissions at various levels of aggregation. Simulated vehicles exhibit choppy speed profiles with sharp accelerations and decelerations and an inclination to maximize the time spent cruising. Traffic on freeways typically experiences fewer stops, higher speeds and lower accelerations/decelerations when cruising, in contrast to arterial traffic. As a result, the emissions estimated from freeway vehicle activity are close to field-based emissions, while the same is not observed for arterial traffic *(8)*.

Existing calibration procedures are highly relevant to modeling traffic well by reducing errors in traffic performance measures in simulation. However, these procedures do not focus on reducing errors in emissions estimates from simulated vehicle activity. A comprehensive methodology driven by field data is required to calibrate and validate microscopic traffic simulation so that simulation can be used to evaluate existing traffic conditions and accurately predict the environmental effectiveness of alternative strategies. As such this paper investigates the following research questions:

1. Can adjusting the internal behavioral parameters within AIMSUN micro-simulation software based on field-observed trajectories improve emissions estimates on a signalized arterial corridor?
2. What metrics from simulation trajectories are most useful for estimating emissions accurately under parameters adjusted using field data
3. At which level of aggregation is vehicle activity and emission estimates from field data and simulation comparable?
    - Route level – directional paths on entire arterial
    - Section level – mid-block to midblock distances, referred to as sections on each route, to capture emissions hotspots; a "hotspot" is defined as a local peak in the emissions rate per unit distance relative to upstream and downstream sections.
    - Second-by-second level – instantaneous vehicle activity on routes

First, the existing literature on the integration of microscopic simulation tools with emissions models is reviewed. A methodology is presented to use field-observed trajectories in identifying suitable values for behavioral model parameters in AIMSUN micro-simulator for

improved emissions estimates on a signalized arterial corridor. Key results from the analysis are discussed, followed by the conclusions and recommendations for future research.

BACKGROUND

Macroscopic and mesoscopic traffic models are used to simulate large traffic networks and the vehicle activity produced is suitable for estimating emissions on a regional scale. The microscopic approach is more suited to operation level analysis and modeling the emissions impacts of individual vehicles, based on instantaneous speed and acceleration levels *(9)*.

Integration of Micro-simulation models with emissions models

Several studies demonstrated the integration of traffic microscopic simulation models with external emissions models and the application to evaluating traffic operations. For example, the Comprehensive Modal Emissions Model (CMEM) is a microscopic modal emissions model that uses second-by-second vehicle activity data to calculate the instantaneous emissions of HC, CO, NO_x and CO_2 based on vehicle operating modes of deceleration, idling, acceleration and cruising (Smit et al., 2010). An interface between the VISSIM micro-simulation model and CMEM was developed by matching vehicle types, to enable quantification and comparison of vehicle emissions for two traffic control and management strategies *(10)*. The VISSIM model was calibrated with road infrastructure data, traffic volumes, signal timing plans and public transport line information. The integrated models were used to show that signal timing optimization improved both traffic operations and emissions. In another study, a VISSIM model was calibrated with extensive field data including turning movement counts, saturation flow rates, and spot speeds, and validated with corridor travel times. The traffic model was integrated with CMEM and VISGAOST, a stochastic signal optimization tool to minimize fuel use and CO_2 emissions on signalized corridors *(11)*. Nam et al. (2003) coupled VISSIM and CMEM to investigate the relationship between emissions and driver aggressiveness. VISSIM and CMEM were also coupled to observe the changes in short-run emissions and long -run emissions due to induced demand in a network from two traffic-flow improvements *(12)*. In both studies VISSIM was calibrated and validated with local data.

INTEGRATION, a microscopic simulation and traffic assignment model and the emissions model VT-Micro, were used to compare an isolated intersection served by a traffic signal, all-way stop and two-way stop controls and a single-lane roundabout (Ahn etal. 2009). The simulation model was calibrated with field data and validated with the length of side street queues. A study combining the PARAMICS micro-simulation model with CMEM demonstrated that the Advanced Driver Alert Systems (ADAS) reduced emissions at hypothetical signalized intersections *(13)*. CMEM and PARAMICS were coupled to investigate the impacts on vehicle emissions from Intelligent Speed Adaptation (ISA) technologies *(14)*, High Occupancy Vehicle (HOV) lanes *(15)*, High Occupancy Toll (HOT) lanes and uphill truck climbing lanes *(16)*. The emissions from varying freeway speed limits in Houston, TX were investigated by combining three different emissions models with micro-scale simulation data from TRANSIMS. The authors found that under congested conditions, the MOBILE suit of models estimate lower emissions than the TRANSIMS emissions module because of being unable to capture sharp accelerations and decelerations using the average speed approach.

Emissions are sensitive to individual vehicle trajectories and the calibration of behavioral parameters that affect the second-by-second vehicle activity within the micro-simulation must be investigated. In a study to benchmark common microscopic traffic flow models, optimal parameter settings were developed using GPS data *(17)*. Optimized model parameters in the literature included maximum velocity, accelerations, decelerations and others that control random braking behavior and time delays in driver reaction. Travel times and link speed are common measures of performance used in the optimization process *(18)*.

On-board Emissions Measurements and VSP Modal Approach

Emission factors are empirical relationships between vehicle activity and resulting emissions *(19)*. CMEM and MODEM estimate emission factors based on data from dynamometer testing in the laboratory. Although this method is considered to be accurate and highly standardized, emission factors from on-board measurement data are more representative of emissions in the field. Portable Emissions Measurement Systems (PEMS) can capture second-by-second micro-scale emissions under real-world operating conditions *(20, 21)*. As part of previous and on-going research, NC State University has developed an extensive database of high-resolution vehicle operation and emissions measurements from PEMS equipped vehicles on pre-defined test routes. Light duty gasoline vehicles with a wide range of manufacturers, engine sizes and model years collected data on the routes, which represent alternative commutes between the same origins and destinations, covering several facility types including freeways, ramps, local and arterial streets and a range of road grades *(22, 23)*.

Second-by-second vehicle activity can be characterized by Vehicle Specific Power (VSP) and modal emission factors developed from instantaneous emissions data. VSP accounts for vehicle kinetic energy, rolling resistance, aerodynamic drag and changes in potential energy associated with road grade. Frey et al. (2002) showed that it is feasible to group instantaneous VSP into 14 discrete "bins" or "modes". Each VSP mode is associated with an average emission rate based on dynamometer testing or field-based measurements *(6)*. For a typical light-duty gasoline vehicle VSP is estimated as *(24)*:

$$\boldsymbol{VSP = v\,(1.1a + 9.81\,(sin(tan^{-1}(r))) + 0.132) + 3.02 * 10^{-4}v^3}$$

$VSP = Vehicle\ Specific\ Power\ (kW/ton)$
$v = velocity\ (m/s)$
$a = acceleration\ (m/s^2)$
$r = road\ grade$

The US EPA's MOVES emissions model uses VSP to determine the fraction of time a vehicle spends in 23 operating mode bins. For a given vehicle type, age and pollutant, MOVES estimates an operating mode bin average emission rate. The fraction of time and average rate for each operating mode bin summed over all bins is used to estimate average rates for a given trajectory. The emissions on one-way and two-way streets in peak and off-peak periods were compared using VISSIM-generated traffic data and MOVES *(25)*. The PARAMICS micro-simulation model was integrated with both CMEM and MOVES to investigate alternative intersection designs. CMEM and MOVES were found to produce similar estimates for NO_x but widely different estimates for CO because MOVES used a more detailed modeling approach. One study integrated VSP-based emissions modeling with micro-scale vehicle activity from VISSIM to show that optimizing signal timing on a coordinated corridor and controlling traffic demand significantly reduces vehicle emissions *(26)*. The VSP modal emissions analysis was

also used to quantify emissions at single-lane roundabouts in Raleigh, NC and Lisbon, Portugal *(27)*.

Use of VSP in estimating emissions was also demonstrated by Swidan (2011) in a study of a regional road network in North Carolina modeled in AIMSUN. That study used the modal emission factors estimated from data collected on the same road network using PEMS with the VSP distributions from AIMSUN-simulated data and found that for freeway segments, the empirical emissions and emissions calculated from the modal model were within ± 10% of each other. Emissions estimates for arterial roads differed more substantially because of greater differences in VSP distributions between simulation and real world data. Swidan (2011) *(28)* recommended that for evaluating emissions on arterial segments using the VSP modal approach, the internal behavioral model parameters in AIMSUN should be calibrated appropriately to generate vehicle activity that is more representative of the real world.

Song et al. (2012) calibrated several behavioral parameters in VISSIM using GPS and Remote Traffic Microwave Sensors (RTMS) data from expressways in Beijing, China, including: (1) Desired Speed distribution, (2) Desired Acceleration Distribution, (3) Maximum Acceleration, (4) Desired Deceleration Distribution, (5) Maximum Deceleration, (6) Maximum Deceleration for Co-operative Braking (7) Safety Distance Reduction Factor and (8) Maximum Look Ahead Distance. They observed that second-by-second empirical vehicle activity and simulated vehicle activity from the calibrated and validated simulation model did not yield the same VSP distributions Emission rates per unit distance were calculated using MOVES. Simulation model overestimated emissions for low speed conditions by up to 248% and underestimated emissions for high speed conditions by up to 16%. It was found that these errors were systematic errors in the traffic simulation models because they remained statistically the same when a sensitivity analysis was performed on 8 parameters by increasing and decreasing their values by 10% *(29)*.

METHODOLOGY

This section presents descriptions of the AIMSUN micro-simulation model, study site and field-collected vehicle activity data and the methodology by which simulation parameters are adjusted using the field data.

AIMSUN Microscopic Simulation Model

AIMSUN is the core simulation module in the software package developed by TSS. The FHWA recommends selecting the fewest possible number of parameters for calibration and running the simulation repeatedly under calibrated values for robust results. AIMSUN has the smaller number of modeling parameters when compared to popular micro-simulation tools such as VISSIM, PARAMICS and MITSIM *(30)*. Several sub-models make up the behavioral core models in AIMSUN, including: (1) car-following, (2) lane-changing, (3) gap acceptance for lane changing, (4) gap acceptance for give-way, (5) overtaking, (6) on-ramp, (7) off-ramp, and (8). look-ahead. A review of the controllable parameters and their roles in AIMSUN's internal behavioral models are summarized in Table 1.

TABLE 1 Controllable Vehicle Attributes, Local and Global Parameters in AIMSUN

	Attribute	Values	Influences	Current/Default Value	Unit
Vehicle Attributes	Name	Character string	No influence	-	-
	Length	Mean, deviation, minimum and maximum	Influences effective vehicle length in car following	4, 0.5, 3.40, 4.60	m
	Width	”	No influence	2, 0, 2, 2	m
	Max. Desired Speed	”	Car-following, lane changing, travel time, queue discharge	110, 10, 80, 150	km/h
				68.4, 6.2, 49.7, 93.2	*mph*
	Max. Acceleration	”	Car following, lane changing, travel time, queue discharge	3, 0.2, 2.60, 3.40	m/s^2
				6.71, 0.45, 5.82, 7.61	*mph/s*
	Normal Deceleration	”	Car following, lane changing, travel time, queue discharge	4, 0.25, 3.50, 4.50	m/s^2
				8.95, 0.56, 7.83, 10.1	*mph/s*
	Maximum Deceleration	”	Lane changing, travel time, queue discharge	6, 0.5, 5, 7	m/s^2
				13.4, 1.12, 11.2, 15.7	*mph/s*
	Speed Acceptance	”	Car following, travel time, queue discharge	1.1, 0.1, 0.9, 1.3	-
	Minimum dist. between stopped vehicles	”	Influences effective vehicle length in car following, capacity, queue length	1, 0.3, 0.5, 1.5	m
	Max. give-way time	”	Lane changing, gap acceptance	10, 2.5, 5, 15	s
	Sensitivity Factor	”	Deceleration component of car following; <1 means follower is more aggressive	1, 0, 1, 1	
	Minimum Headway	”	Car following model v.6	0, 0, 0, 0	s
	Overtaking to stay on fast lane	”	Lane changing, overtaking	0	%
	Undertaking cases	”	Lane changing, overtaking	0	%
	Imprudent lane changing cases	”	Lane changing, overtaking	0	%
	Sensitivity for Imprudent lane change	”	Lane changing, overtaking	1	-

TABLE 1 Continued from previous page

Local Parameters (arterial sections)	Section speed limit	Single value	Car following, lane-changing	57	km/h
				35	mph
	Lane speed limit	”	Car following, travel times	-	km/h
	Turning speed	”	Car following, Influences turning capacity, travel times	-	km/h
	Visibility distance at Junctions	”	Give way	25	m
	Yellow Box Speed	”	Speed of a vehicle approaching a yellow box junction will depend on whether leader vehicle is below this speed; junction capacity	10	km/h
				6.2	mph
	Distance Zone 1 (distance to zone where overtaking can occur)	”	Lane Changing model, turning proportions, blocking situations	388.89	m
	Distance Zone 2 (distance to zone where vehicles look for a gap to closer to the correct side of the road from which the turning movement can be completed.)	”		58.33	m
	Time Distance On-ramp	”	On-ramp model, on-ramp capacity	97.22	m
	Section slope	”	Acceleration in car-following model	0	
	Maximum Give Way Time Variability	”	Gap acceptance/give way	0	s
	Reaction Time Variation	Absolute integer	Local variation of reaction times	0	s

TABLE 1 Continued from previous page

Global Parameters	No. of vehicles	Single value	2-lane car following model	4	veh
	Maximum Distance ahead	”	2-lane car following model	100	m
	Maximum Speed Difference	”	2-lane car following model	50	km/h
	Maximum Speed Difference On-ramp	”	2-lane car following model	70	km/h
	Percent overtake	”	lane-changing model	90	%
	Distance zone variability	”	lane-changing model	40	%
	Percent recover	”	lane-changing model	95	%
	Road side of vehicle movement	”	lane-changing model	left	
	Simulation step	Single value between 0.1 and 1.5 seconds	Updating of unconditional events scheduling list (e.g. signal phases)	1.00	s
	Reaction Time	Single value (can be "fixed" if equal to simulation time step or "variable" for a vehicle type using a discrete probability model)	All internal models, section and on-ramp capacities	1.00	s
	Reaction Time at Stop	Single value - fixed or variable	Affects all internal models, stop and go capacity, queue measures	1.35	s
	Reaction time for front vehicle at traffic light	”	Affects all internal models	1.35	s
	Queue up speed	Single value	Queue measures	1.00	m/s
	Queue leaving speed	”	Queue measures	4.00	m/s

According to Table 1, many of the controllable parameters affect the car following and lane changing models in AIMSUN. The position and speed of every vehicle in AIMSUN is updated after checking for lane-changing decisions and applying the Gipps car-following model *(31)*. The Gipps car-following model places limits on the driver's braking ability to maintain a safe distance from the preceding vehicle *(32)*. The model has two components. The first controls the acceleration of the follower vehicle when it is not affected by the leader, such as under free-flow conditions. The follower accelerates, but as it approaches the maximum desired speed, its acceleration decreases to zero *(30)*. The second component of the Gipps model sets constraints on the speed of a vehicle in the next time step by considering the effect of its leader, which becomes important in congested situations. Since the VSP-based emissions model is highly dependent on the instantaneous speed and acceleration of vehicles, the following parameters which appear in the car following model were selected for investigation:

1. Maximum desired speed
2. Maximum desired acceleration
3. Normal deceleration

The maximum desired speed and acceleration are the highest speed and acceleration a vehicle can travel at any point and time in the network. The normal deceleration is the highest deceleration rate that a vehicle can achieve under normal circumstances *(31)*. It is different from maximum deceleration, which occurs during severe braking.

As shown in Table 1, the selected parameters influence the AIMSUN car following and lane changing models as well as the travel time and queue discharge behavior in the network. Although other parameters such as the "Speed Acceptance", which affect the car following algorithms, could also be adjusted, the data required is beyond the scope of this research. Therefore, these parameters are left with AIMSUN default values.

Study Site

The study site is a 2 mile-long stretch of arterial corridor on Hillsborough Street, in Raleigh, NC. Hillsborough Street runs in east- and westbound directions between downtown and Interstate-40, serving 15,000 vehicles per day *(33)*. The selected corridor begins in the area adjacent to NC State University's main campus and continues to the west to the I-440 entry/exit ramps. While Hillsborough Street carries commuter traffic to and from downtown and the interstate, it also serves local traffic generated by the university, supporting commercial establishments and residential neighborhoods. There are 14 coordinated signalized intersections. Several intersections are concentrated in the eastern end of the corridor with inter-signal distances between 270 and 1,825 feet.

Two routes were defined in the study site: (1) Hillsborough Westbound and (2) Hillsborough Eastbound. Hillsborough Westbound begins just before the intersection with Enterprise Street and continues to the on-ramp to I440 East. Hillsborough Eastbound begins after the off-ramp from I-440 and ends just past the intersection with Enterprise Street. Through traffic on Hillsborough Street is served by single lanes towards the eastern end of the corridor, and by dual lanes in the western end. A schematic of this corridor, modeled in AIMSUN, is shown in Figure 1**.**

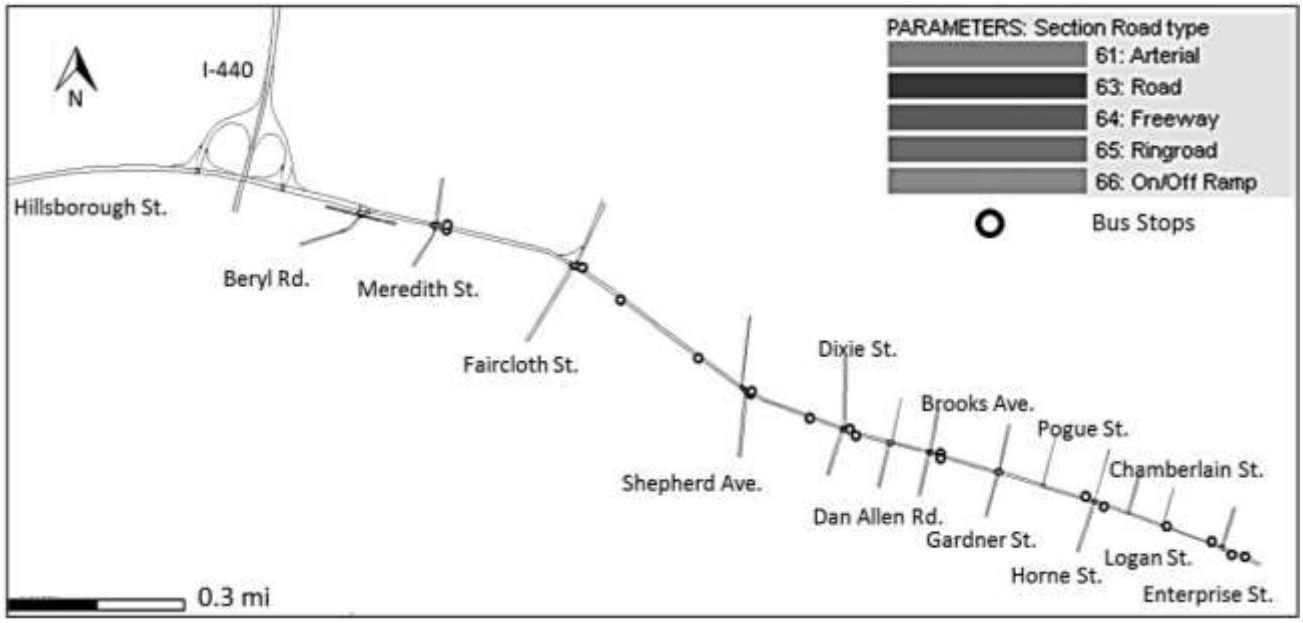


FIGURE 1 Schematic of the Hillsborough Street arterial corridor in AIMSUN

Field Data

Second-by-second vehicle activity and location data of 53 PEMS-equipped vehicles were extracted from the NCSU vehicle emissions database. All vehicles were either passenger cars or passenger trucks, tested between 2010 and 2012 and driven by different drivers. The ages of the vehicles ranged from 0 to 14 years at the time of testing. The engine displacements were between 1.4L and 5.4L. The gross weight of the vehicles ranged from 1,720 lbs to 7,400 lbs. The mileage accumulated by the vehicles was between 615 miles and 282,206 miles.

Due to the nature of the traffic near the NC State University campus, the afternoon peak hour was defined as 4.30 to 6.00pm and the off peak periods were defined between 1.00 to 4.30pm and 6.00 to– 8.30pm. Although all 53 vehicles completed the two routes on Hillsborough Street, trajectories that did not occur in the afternoon (peak/off-peak), or had missing data points were not selected for the analysis. A total of 86 complete field trajectories from both routes were extracted by matching the OBD data with location data from the GPS units. The field trajectories in the Hillsborough Westbound direction in the afternoon off- peak hour are plotted in Figure 2 to observe speed changes on the corridor under uncongested conditions.

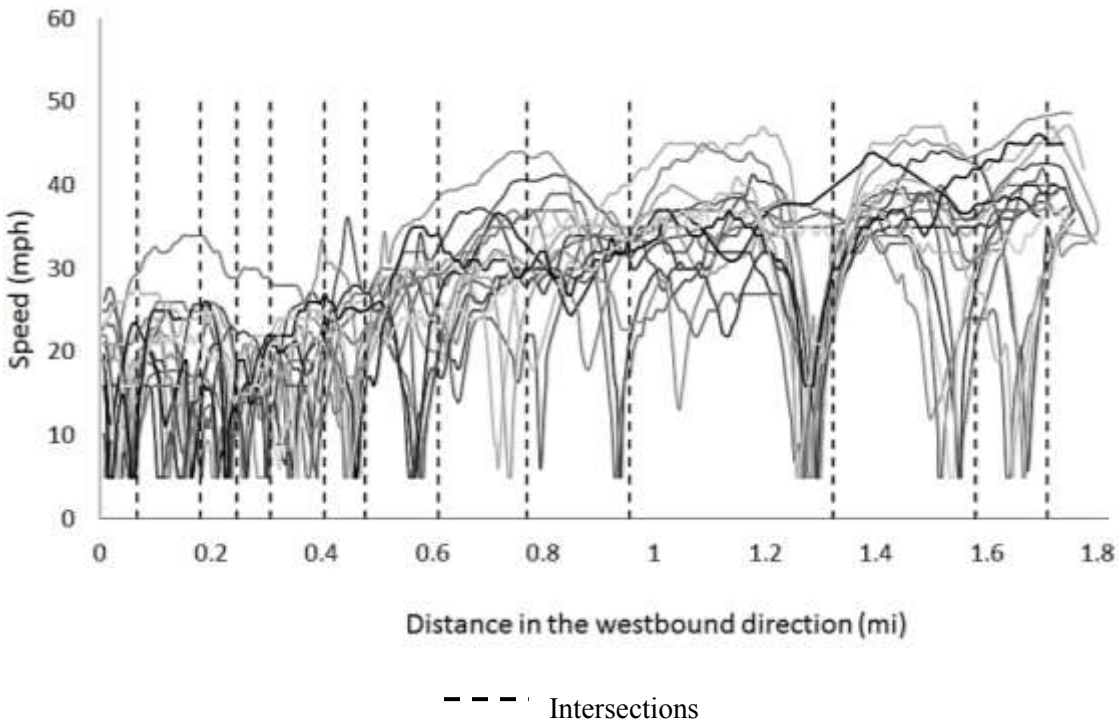


FIGURE 2 Twenty field observed vehicle trajectories in the Hillsborough Westbound route during the afternoon off-peak period

Vehicle travel on the selected corridor is characterized by frequent stops associated with signalized intersections. For the portion of the corridor immediately adjacent to the NCSU campus from 0.0 to 0.6 miles distance, most have only one through lane in each travel direction and is divided by a median. With a few exceptions the peak travel speed for this portion is typically 30mph over the first 0.4 miles, increasing to 35mph up to 0.6 miles. After clearing an intersection at 0.8 miles the peak speeds increase to approximately 45mph. On the latter portion of the route, there are two through lanes in each direction and no median. Although the posted speed limit for the latter portion of the corridor is mostly 35mph, the desired speed is clearly higher. Therefore in AIMSUN the arterial speed limit was set at 45mph rather than the city-wide 35mph limit.

Adjustment of Simulation Parameters

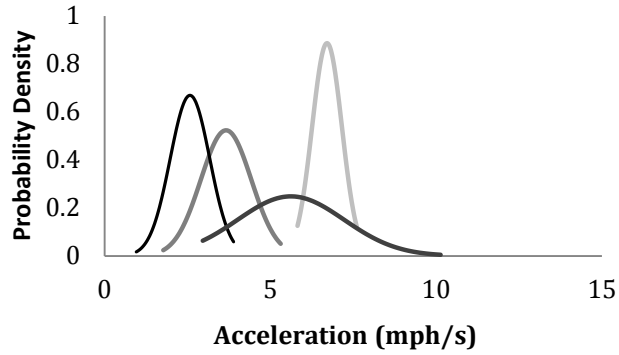
Measurements from the selected field trajectories were used to adjust the values of the relevant parameters in AIMSUN. The selected AIMSUN parameters are specified in terms of truncated normal distributions *(31)*. The values for each parameter are sampled from the distribution for each vehicle that enters the network. Three sets of parameter values were defined to check which set allowed emissions estimates from simulation trajectories to be closest to field trajectories. The following sets of values of each parameter were obtained:

1. Maximum values – the maximum instantaneous (based on 1Hz data) speeds, accelerations and decelerations from each directional vehicle trajectory
2. 95th percentile values – the 95th percentile instantaneous accelerations and decelerations from each directional vehicle trajectory

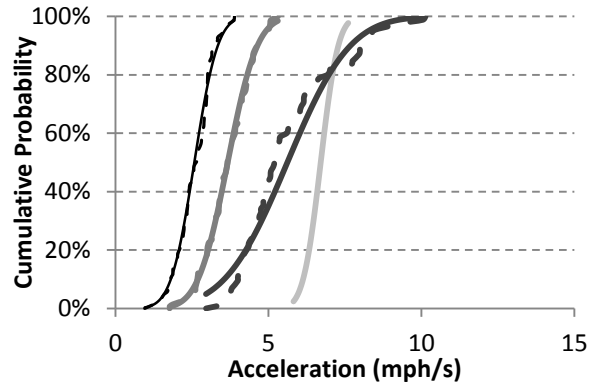
3. 85th percentile values – the 85th percentile accelerations and decelerations from individual directional trajectories in the study area.

It was assumed that the maximum speeds from empirical data sufficiently represent the maximum speeds desired by drivers on the arterial under normal circumstances, while maximum accelerations or decelerations may include events under non-normal circumstances. Therefore, no distributions of 95th and 85th percentile maximum desired speeds were defined. The distributions were truncated at the maximum and minimum values observed in the field for each parameter. The mean and standard deviations are associated with the normal distribution of parameters prior to truncation.

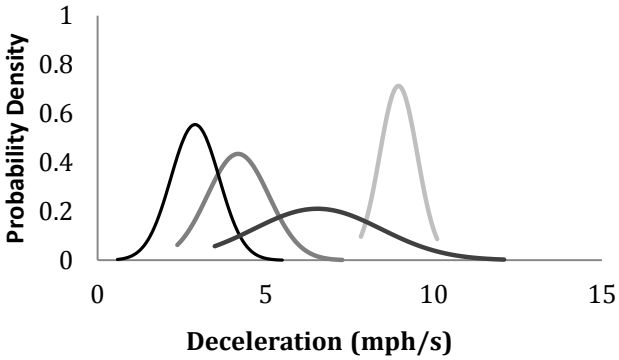
The observations were categorized into peak or off-peak periods in which the respective trajectories occurred. Kolmogorov-Smirnov (KS) tests showed no statistically significant differences between the parameter distributions in the two time periods (peak/off-peak). Therefore all 86 trajectories were combined to generate distributions of each parameter value. The truncated normal distributions of the parameters are shown in Figure 3 in comparison to the AIMSUN default distributions. Figure 3 also shows cumulative distribution functions confirming that overall the truncated normal parameter distributions represent the distributions of the actual field observations reasonably well.



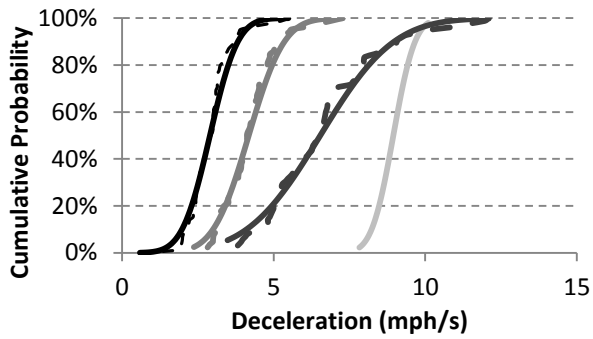
(a) Maximum desired acceleration distributions



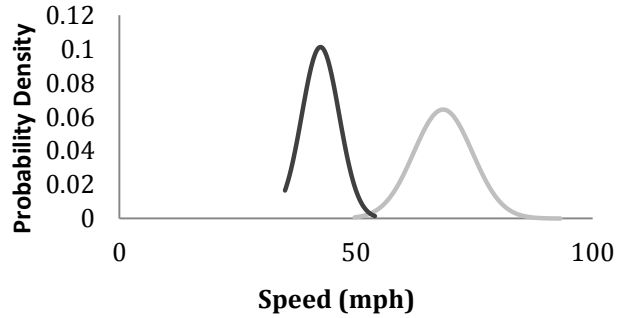
(b) Cumulative probabilities for maximum desired accelerations (truncated normal distribution vs. empirical)



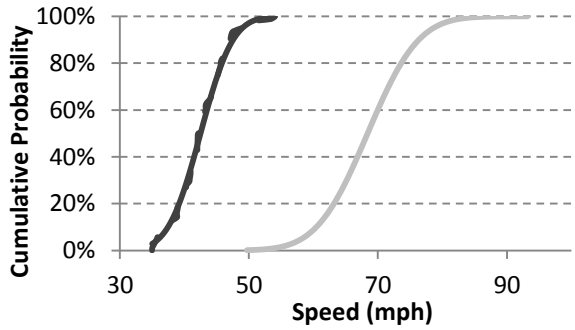
(c) Normal deceleration distribution



(d) Cumulative probabilities for normal deceleration (truncated normal distribution vs. empirical)



(e) Maximum desired speed distribution



(b) Cumulative probabilities for maximum desired speed (truncated normal distribution vs. empirical)

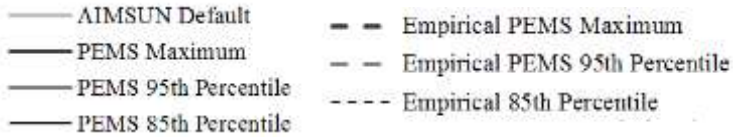


FIGURE 3 Truncated Normal Distributions and Cumulative Distribution Functions of AIMSUN Default, PEMS Maximum, PEMS 95th Percentile and PEMS 85th Percentile Parameters Values

Matching Field and Simulated Trajectories

As an initial assessment of parameter distributions, the AIMSUN simulation was adjusted with the PEMS maximum, 95th and 85th percentile accelerations and decelerations. The speed distribution was kept at PEMS maximum values across all simulation runs. The network was loaded with traffic in the afternoon peak hour and simulated for one hour. Second-by-second vehicle trajectories can be extracted from AIMSUN using Application Programming Interface (API) tool. Trajectories with space mean speeds within a range of 10 km/h can be grouped together *(34)*. For initial assessment of the calibration parameters, emissions estimates from simulated and empirical trajectories which are within a ± 2.5 mph of average space mean speed were compared. Four simulated trajectories and four empirical trajectories in the westbound direction were extracted to cover a range of travel times. Each empirical and simulated trajectory is characterized by the instantaneous speeds and accelerations of a real or simulated vehicle as it traverses the corridor.

For both empirical and simulated trajectories, the second-by-second vehicle activities were characterized in terms of VSP distributions. A set of fleet average modal emission factors was developed from same PEMS database maintained by NC State University *(21)* and can be found elsewhere in literature (Anya et al., 2013). The fleet average modal emission factors were used to compute route-level emissions for each trajectory. The maximum desired speed, maximum desired acceleration and normal deceleration in simulation were adjusted with four sets of parameter values – (1) AIMSUN default values, (2) maximum values from PEMS trajectories (3) 95th percentile values from PEMS trajectories and (4). 85th percentile values from PEMS trajectories. The initial route-level emissions analysis of trajectories selected under each of these four sets of parameter values produced different emissions per unit distance. The set of parameter values under which a simulated trajectory produced emissions estimates closest to field-based emissions estimates was investigated further. To assess the context in which emissions estimates can be accurately estimated from simulated vehicle activity, the VSP modal analysis was performed at the route level and at the section level for 13 sections (mid-block to mid-block lengths) within the Hillsborough Westbound route. Under the simplified assumption that VSP is most sensitive to the product of speed and acceleration, a detailed look was taken at the second-by-second speed-acceleration pairs from vehicle activity. The effect of road grade was not relevant since the study site is on relatively flat terrain. The second-by-second level analysis was used to investigate the differences in the distribution of accelerations (positive/negative) between the empirical and simulated data under adjusted parameters in 10mph speed bins. The 10mph speed bins allowed for differences in accelerations to be observed across low speeds and high speeds separately.

For the detailed analysis of the impact of matching simulated and real-world travel times and number of stops on the emissions from samples of 30 simulated trajectories, three samples were selected based on matching (1) travel time distribution, (2) average number of stops and (3) both travel time distribution and average number of stops from sample of field-observed trajectories. It was assumed that 30 trajectories provided a large enough sample size to detect The travel time distributions of selected simulated vehicles and all empirical trajectories on a route were matched using the concept of Latin Hypercube Sampling which ensures that a range of values of a selected variable is represented in the sampled set *(35)*.

According to Rakha & Ding (2003), the aggressiveness of a vehicle stop in terms acceleration or deceleration, has significant impact on tailpipe emissions, especially for

pollutants such as HC and CO. Accelerations associated with several stops can increase emissions on the route. A complete stop was defined as a cycle of decelerating to below 5 mph followed by accelerating above 15 mph. The average number of stops was counted from the field trajectories and a sample of 30 simulated trajectories was selected to match the field-observed average number of stops. The third sample from AIMSUN simulation was selected to reflect both the field-observed travel time distribution and average number of stops.

Results and Discussion

This section presents results from the initial assessment of adjusting simulation parameters followed by detailed analysis of emissions from vehicle activity simulated under the most suitable set of parameter distributions.

Initial Assessment of Parameter Distributions

Table 2 shows results of the initial assessment of parameter values. AIMSUN default and PEMS maximum parameter values produced higher absolute percentage differences from the route-level empirical emission rates of CO_2 per unit distance across the travel times. Similar trends are found but not reported for the emission rates of NO, HC and CO. The simulated vehicles with 85th percentile parameter distributions produced estimates with lowest errors rates.

TABLE 2 Selected Route-level CO_2 Emission Rates per unit Distance from Empirical Data and Simulation Based on Different Parameter Distributions

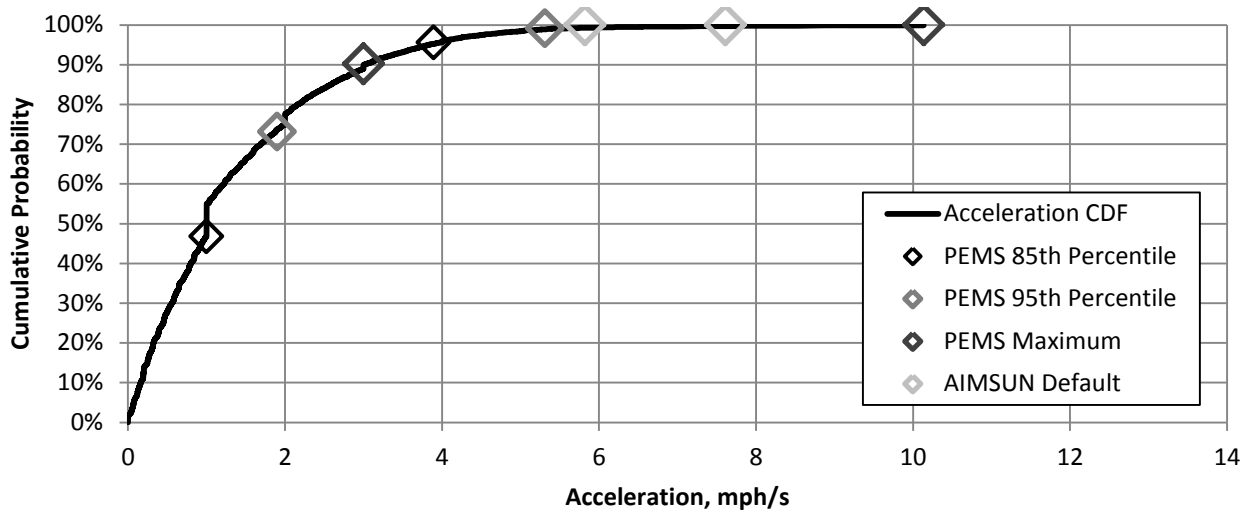
Travel time (min)		Empirical (g/mi)	% Difference (Simulated vs. Empirical) AIMSUN Default	PEMS Max.	PEMS 95th %ile	PEMS 85th %ile
Low (Empirical: 4.67; AIMSUN Default: 4.68; PEMS Max.: 4.83; PEMS 95th %ile:4.77; PEMS 85th %ile:4.98)	Rate	304	394	406	368	362
	% Δ*		*29%*	*33%*	*21%*	*19%*
Intermediate (Empirical: 5.42; AIMSUN Default: 5.43; PEMS Max.: 5.57; PEMS 95th %ile:5.23; PEMS 85th %ile: 5.28)	Rate	379	410	437	387	405
	% Δ*		*8%*	*15%*	*2%*	*7%*
Intermediate (Empirical: 5.75; AIMSUN Default: 5.68; PEMS Max.: 5.77; PEMS 95th %ile:5.75; PEMS 85th %ile: 5.75)	Rate	384	436	450	431	416
	% Δ*		*13%*	*17%*	*12%*	*8%*
High (Empirical: 7.80; AIMSUN Default: 7.13; PEMS Max.: 7.15; PEMS 95th %ile:7.15; PEMS 85th %ile: 7.47)	Rate	431	527	512	473	457
	% Δ*		*22%*	*19%*	*10%*	*6%*

**Percent difference between empirical and simulated emissions calculated as:* $\frac{simulated-empirical}{empirical} * 100\%$

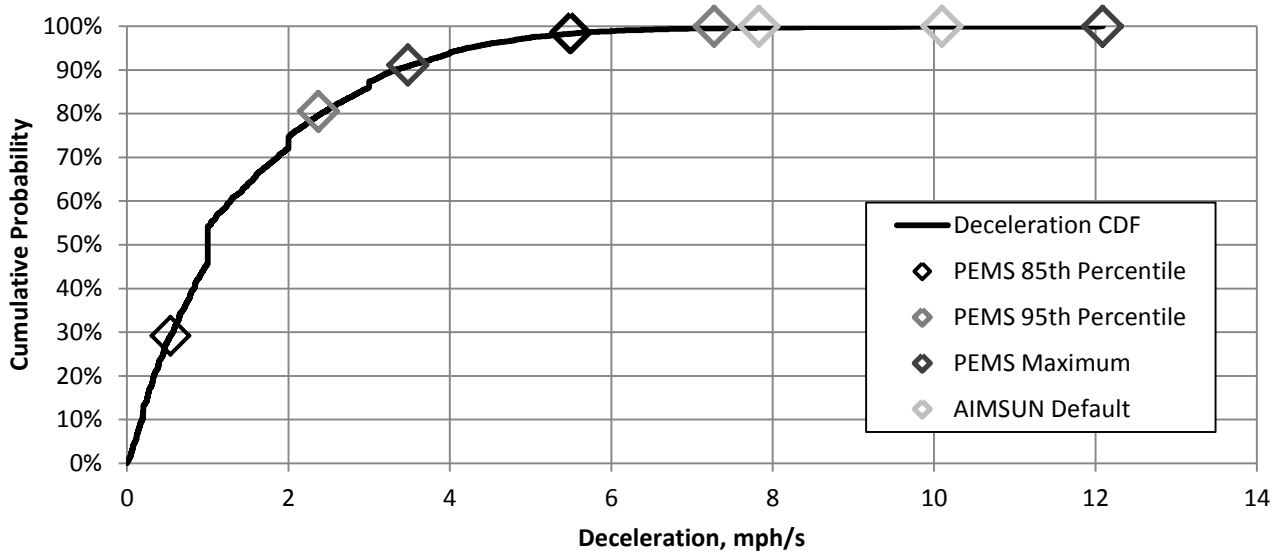
The 85th percentile parameters yield the closest emission rates to field-based rates. To investigate if this is a result of more realistic vehicle activity, the range of the distributions of PEMS maximum, 95th and 85th percentile and AIMSUN default values and their relative positions are superimposed on the cumulative distributions of all instantaneous accelerations and decelerations from 86 empirical trajectories in Figure 4. There is a clear indication that 85th percentile parameters do not account for 5% of the high accelerations observed in field data. While the 85th percentile distribution is more representative of accelerations and decelerations observed in the field, sampling from it may limit the maximum accelerations or decelerations achievable in simulation. For example, 85% of the accelerations observed in field data are below 2.5 mph/s (which is the mean value of the 85th percentile accelerations); if a vehicle entering the simulated network has a maximum achievable acceleration of 2.5 mph/s it cannot exhibit any instantaneous accelerations greater than 2.5 mph/s when travelling unconstrained below the speed limit. This is not a realistic scenario.

Conversely, both AIMSUN default accelerations and decelerations would be observed in less than the highest 1% of empirical accelerations and decelerations. The range of the PEMS maximum parameters is the largest among the distributions considered. However, most of the PEMS maximum observations appear in 10-15% of the empirical data. These observations suggest that using the PEMS maximum accelerations may not allow simulated vehicle activity to follow empirical vehicle activity closely. Therefore the 95th percentile values of

acceleration/decelerations and PEMS maximum speeds were selected for the set of adjusted parameters.



(a) Cumulative Distribution function of empirical instantaneous accelerations in mph/s



(b) Cumulative Distribution function of empirical instantaneous decelerations in mph/s

FIGURE 4 Relative positions of the range and mean values of empirical maximum, 95th percentile, 85th percentile and AIMSUN default parameter distributions

Route-level Analysis with 95th Percentile Parameter Distributions

Table 3 shows that when the simulated sample under of trajectories was chosen based on having both the same travel time distribution and average number of stops as field trajectories, the emissions estimates was closer to the field-based estimates across all pollutants, than when only the travel time distribution was controlled. The differences in emissions of CO_2 and HC per unit distance were below 5%, while difference in estimates of NO and CO were at or below 15%. Only the estimation errors for NO_x were statistically significant. The average number of stop controlled trajectories produced lower emissions estimates than the field-based sample. The average travel time of the stop-controlled sample was much lower than the average field-based travel time. Comparisons of the average travel times and average number of stops between randomly selected simulation samples of 30 trajectories indicated a positive correlation between the average number of stops and average travel time. Field-collected sample of trajectories has high average travel time, but low average number of stops. Therefore, to match the average driving cycle in simulation with the average driving cycle in the field, it is necessary to control for both the travel time and the average number of stops in the simulated sample.

TABLE 3 Summary route-level emissions on Hillsborough Westbound route from calibration of AIMSUN model and sample selection

Sample		**NO (mg/mi)** (Std. Error)	**HC (mg/mi)** (Std. Error)	**CO (mg/mi)** (Std. Error)	**CO_2 (g/mi)** (Std. Error)
Field Data (30 trajectories)	Rate	153 (*9*)	111 (*5*)	894 (*59*)	420 (*18*)
AIMSUN Default (30 trajectories)	Rate	221 (*4*)	128 (*3*)	1285 (*25*)	485 (*11*)
	% Diff.	**45%**	15%	**44%**	**16%**
Calibrated (Travel time distribution controlled) (30 trajectories)	Rate	183 (*3*)	118 (*2*)	1031 (*20*)	448 (*9*)
	% Diff.	**20%**	**6%**	**15%**	7%
Calibrated (Avg. no of stops controlled) (30 trajectories)	Rate	145 (*7*)	91 (*5*)	793 (*37*)	346 (*19*)
	% Diff.	-5%	**-18%**	-11%	**-17%**
Calibrated (Travel time distribution and avg. no of stops controlled) (30 trajectories)	Rate	176 (*3*)	115 (*2*)	990 (*19*)	436 (*6*)
	% Diff.	**15%**	3%	11%	4%

*Bolded figures indicate differences that are statistically significant at the 5% significance level

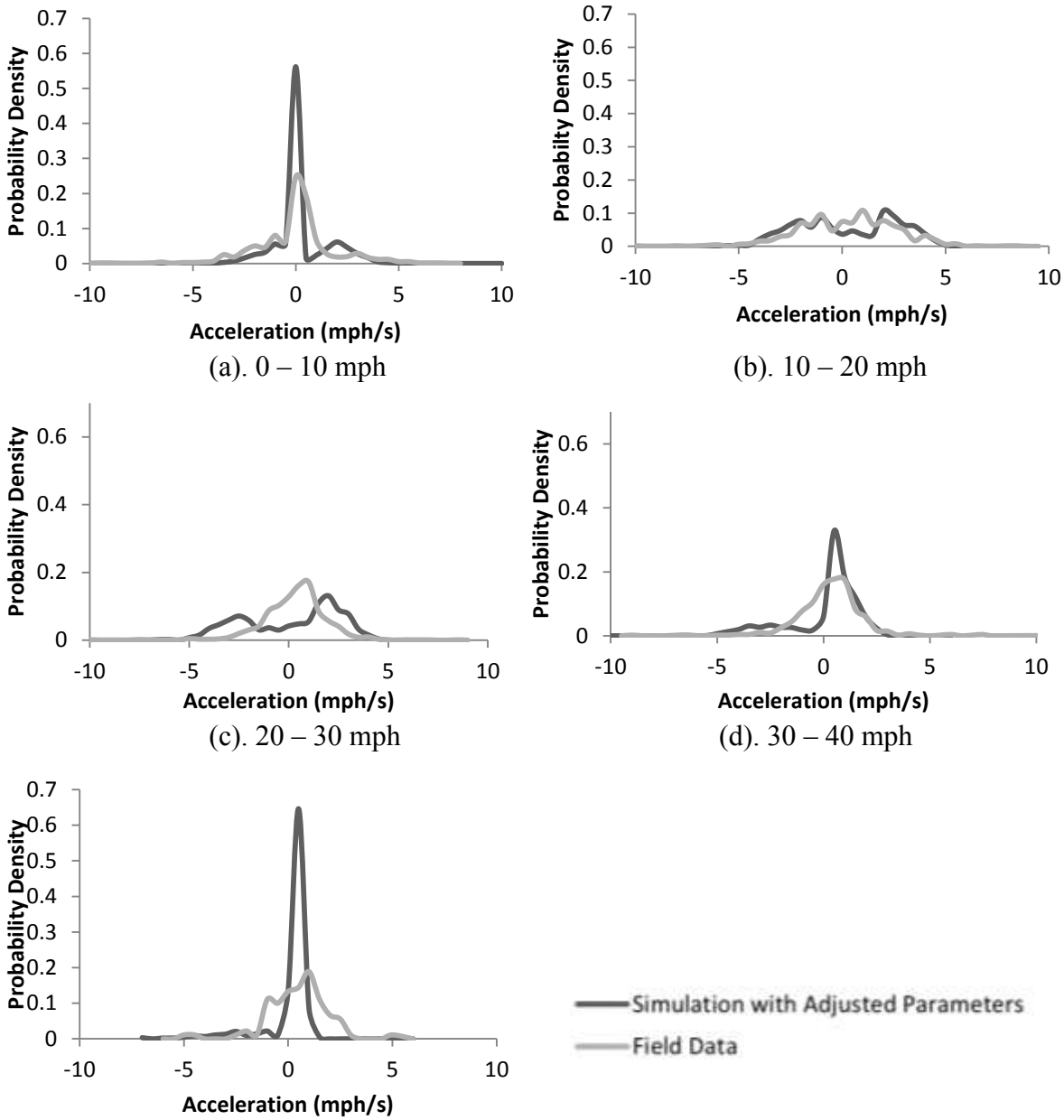
Section-level Analysis

The results from the section-level VSP modal emissions analysis are consistent with the route-level results. Under default parameter values, several of the section-level estimates are farther from the field-based estimates than the two samples with adjusted parameters. The emissions of NO, HC, CO and CO_2 per unit distance from the simulated sample with the same travel time

distribution and average number stops as field-tested vehicles, are lower at 2 of the 13 sections, than the travel time distribution controlled sample. The same emissions hotspots are captured or missed by both the samples from simulated data. Where the intersections are closely spaced, both simulation samples with adjusted parameters are unable to detect the locations of the emissions hotspots.

Second-by-second Level Analysis

The distributions of accelerations (positive/negative) in 10 mph speed bins for the travel-time controlled simulated sample and field data are shown in Figure 5. KS-tests confirm that the distributions of accelerations within each speed bin from field and simulated data are different. Between 0 to 10mph, 30 to 50mph, a higher proportion of accelerations of simulated vehicles is low and has less variability than vehicles in the field. For the speed bins 10 to 20mph and 20 to 30mph, the distributions of positive and negative simulated accelerations are bi-modal in nature. The speed bin 10 to 20 mph reflects stop and go motion. The simulated deceleration behavior in this speed bin appears to be very close to what is observed in the field. The field data shows a higher proportion of observations with lower acceleration values than the simulated data. Between 20 to 30 mph, the field data is uni-modal, centered around low accelerations/decelerations, but with some spread in the data. The simulated data shows that most of the accelerations and decelerations are at the boundary values of the 95th percentile parameter distributions set for the simulation.



(a). 0 – 10 mph

(b). 10 – 20 mph

(c). 20 – 30 mph

(d). 30 – 40 mph

(e). 40 – 50 mph

FIGURE 5 Distribution of empirical and simulated accelerations in 10mph speed bins

CONCLUSIONS

Under the default parameters within the AIMSUN software package, simulated vehicle activity from a signalized arterial corridor at the micro-scale is not representative of real-world vehicle activity. This research showed that adjusting the parameters of the car following model using field data generates more realistic vehicle activity on arterial segments and improves emissions estimates. The truncated normal distributions of three simulation parameters – maximum desired speed and acceleration and normal deceleration – were defined using 95th percentile values from each vehicle trajectory along the routes followed in the field. The resulting vehicle behavior was more realistic because the accelerations and speeds are constrained to the range of values observed in the field.

Route-level emissions estimates are sensitive to both average number of stops and travel time distribution along a route. Matching these factors simultaneously with field-observed trajectories yielded better estimates of emissions from simulation. When a sample of 30 trajectories from the default AIMSUN model had the same travel time distribution as field observed trajectories in on the Hillsborough Westbound route, the emissions of NO_x, HC, CO and CO_2 differed by 45%, 15%, 44% and 16% from the respective field based estimates. Under calibrated parameters, a sample of 30 trajectories lowered the errors in estimates to 20%, 6%, 15% and 7% for emissions per unit distance of NO, HC, CO and CO_2. For a sample based on matching average number of stops observed in field trajectories, the emissions estimates were lower than field-based estimates by up to 18% for HC and 17% for CO_2. A sample of 30 simulated trajectories with the same travel time distribution and average number of stops as field trajectories resulted in emission rates of NO_x, HC, CO and CO_2 having differences of 15%, 3%, 11% and 4% with the field-based estimates respectively. These errors are lower than the other two samples and are statistically insignificant for all pollutants except NO_x.

Section level analysis showed that the emissions hotspots along the route were not effectively captured by the parameter-adjusted model on the Hillsborough Westbound route. However, it produced estimates that were closer to the empirical emission rates at the section level, than the default model. This indicates that although parameter adjustment improves the emissions estimates at the route level, at smaller spatial scales the estimates may not be accurate.

An investigation of the second-by-second speed and accelerations from simulated and field data showed systematic differences in the distribution of positive and negative accelerations between simulated and field data. In low speed bins of 0–10mph or 10– 20mph, the differences in the distribution of simulated and field-based accelerations are less pronounced than in the speed bin of 20–30mph. In the 20–30mph bin, the simulated accelerations and decelerations are higher, implying that vehicles travelling at speeds within the bin are accelerating to higher speeds at or close to their maximum desired rate. Conversely, the field vehicles do not accelerate or decelerate at high rates while travelling between 20–30 mph. Adjusting of car following model parameters reduces the magnitude of the accelerations or decelerations observed in simulated data, but the trajectories still exhibit sharp acceleration and decelerations compared to smoother field trajectories; this is a limitation of AIMSUN. More realistic values of acceleration, deceleration and speeds on the arterials lead to better estimates of emissions at the route level.

A key recommendation is that further investigation be done to ensure that trajectory travel times and average number of stops observed in the field are reflected in all simulated trajectories under adjusted parameters. The parameters associated with the other sub-models in AIMSUN such as the gap-acceptance model, may be adjusted to continue the efforts to match

simulated vehicle activity with real-world activity. Following the presented parameter adjustment and emission estimations, simulated trajectories from AIMSUN can be used effectively to test the impacts on local air quality of traffic management strategies at the route level on signalized arterial corridors.

ACKNOWLEDGMENT

Although the research described here has been funded wholly or in part by the U.S. 2 Environmental Protection Agency's STAR program through EPA Assistance ID No. RD-3 83455001, it has not been subjected to any EPA review and therefore does not necessarily reflect the views of the Agency, and no official endorsement should be inferred.

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