Assessing Emissions Impacts of Automated Vehicles

A&WMA's 109th Annual Conference & Exhibition
New Orleans, Louisiana
June 20-23, 2016

Paper #1105

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ABSTRACT

With their potential for transforming surface transportation, understanding the impacts and benefits of automated vehicles (AVs) with regards to safety, mobility, energy and the environment is a necessary first step for informing policy to aid the successful introduction of AVs into an already complex transportation system. As part of a larger work to develop a framework for assessing impacts of AVs in several different areas of interest, this paper serves as an early implementation proof-of-concept for a methodology to integrate microsimulation runs with MOVES analysis to calculate emissions and fuel consumption for AVs. Four scenarios for a single-lane, 2-mile-long roadway are modeled in a microsimulation model: at-capacity with only human drivers, at-capacity with only automated vehicles, over capacity with only human drivers, over capacity with only automated vehicles. In this study, automated vehicles are only modeled very simply, by removing oscillation in following distance behind other vehicles. The trajectory data is used to calculate and assign operating modes for the vehicles along the roadway. Using MOVES 2014a, this operating mode distribution is used to calculate fuel consumption and emissions for certain pollutants and results are discussed and compared. It was found that automated vehicles oscillate less around a primary operating mode and also, overall, produce less emissions and consume less fuel than a roadway with only human drivers. This study indicates that a proper assessment of emissions and fuel consumption can be calculated from output from a microsimulation model. Later work will investigate a variety of other scenarios that simulate anticipated automated vehicle behavior and vehicle operations.

INTRODUCTION

Automated vehicles (AVs) have the potential to bring about transformative safety, mobility, energy, and environmental benefits in the surface transportation system. These benefits could include crash avoidance, reduced energy consumption and vehicle emissions, reduced travel times, improved travel time reliability and multimodal connections, improved transportation system efficiency and improved accessibility, particularly for persons with disabilities and the growing aging population [1].

AVs are being introduced into a complex transportation system. Second-order impacts, such as the possibility of increased vehicle-miles traveled (VMT), are of significant concern. Given the complexity of the impacts, a modeling framework is needed to ensure that they are adequately captured. The USDOT Volpe National Transportation Systems Center is developing such a framework for assessing the benefits of automated vehicles. This framework includes estimating the potential safety, mobility, energy and environmental benefits (as well as potential dis-benefits) of technologies associated with automated vehicles as they are introduced into the national transportation system [2].

The framework's scope and complexity are exhibited in the figure below.

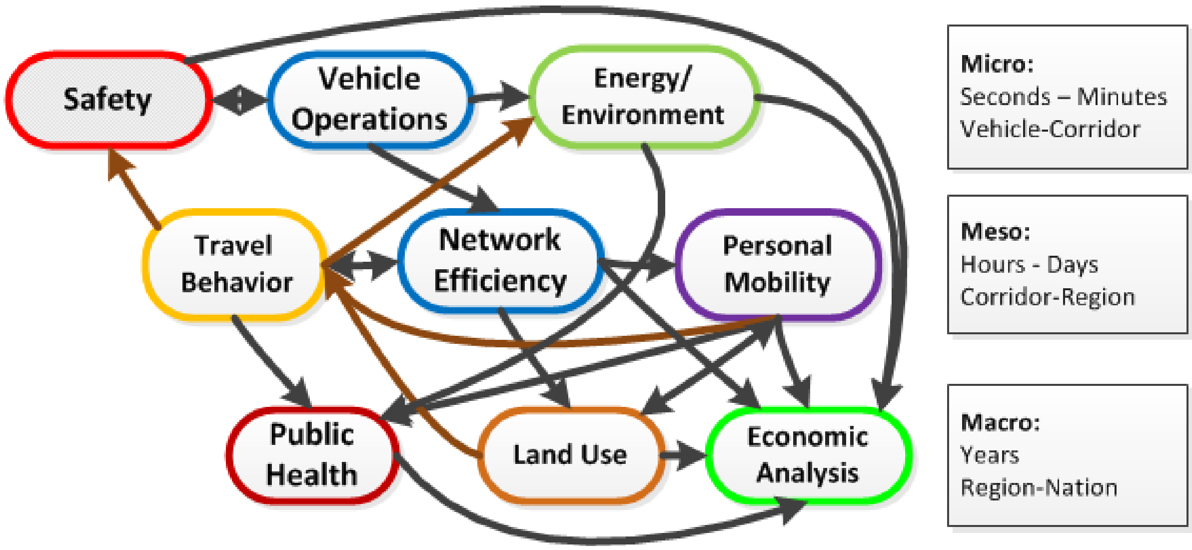

Figure 1: Automated Vehicle Impacts Framework

Environmental impacts are highly dependent on other factors within the framework. Changes in vehicle speeds, vehicle miles traveled, reduced idling times from congestion, as well as changes in car following distances and improved aerodynamic characteristics will alter fuel consumption and emissions. As a result, it is critical to understand and implement an appropriate methodology for determining environmental impacts given anticipated automated vehicle impacts that are assessed in other parts of the framework. This paper stands as a proof-of-concept for early implementation of a methodology in which automated vehicle operations are modeled in a microsimulation model and appropriate MOVES runs set-up and analyzed to calculate appropriate emissions and fuel consumption impacts.

BACKGROUND

A number of studies have linked microsimulation modeling to microscopic fuel consumption and emissions models in order to estimate environmental impacts analysis [2], [3], [4], [5], [6] [7] [8], [9] and Chamberlain (2012)[1]. We are using a similar methodology, utilizing a second-by-second drive schedule output characterizing driving behavior from the microsimulation model as a key input into MOVES2014a to obtain fuel consumption and emissions. MOVES2014a was chosen because of its availability as a regulatory tool as well as its robust, yet simple to learn methodology.

MOVES2014a operates by calculating emission rates based on a variety of inputs, including vehicle type, age, fuel, speed, acceleration, vehicle miles traveled, idling times, number of cold starts, soak times as well as meteorological data and road-link characteristics. For running emissions, rates are estimated through assignment into operating modes. For light-duty vehicles, a key indicator of operating mode assignment is through the calculation of the vehicle specific power (VSP), or tractive power exerted by the vehicle normalized by the vehicle's weight. Given a second-by-second drive schedule, VSP can be calculated using the following equation;

$$VSP_t = \frac{Av_t + Bv_t^2 + Cv_t^3 + mv_t a_t}{m}$$

In which,
A = tire rolling resistance term (KW sec/m)
B = rotational resistance term (KW sec/m^2)
C = aerodynamic drag term (KW sec/m^3)
v_t = velocity at time, t (m/s)
a_t = acceleration at time, t (m/s^2)
m = mass (kg)

Once the VSP_t is calculated, an operating mode can be assigned. These are defined bins for operating speed and acceleration. Operating modes are shown in the Table 1:

[1] Chamberlain, Choices to Make When Conducting a Hot-Spot Analysis Using MOVES, Transportation Research Board ADC20 Workshop for Hotspot Analysis 2/11/2012.

Table 1: Description of assignment of operating mode for MOVES analysis

Operating Mode	Operation Mode Description	Vehicle-Specific Power (VSP_t, kW/metric ton)	Vehicle Speed (v_t, mph)	Vehicle Acceleration (a_t, mph/sec)
0	Deceleration/Braking			$a_t \leq -2.0$ OR ($a_t < -1.0$ AND $a_{t-1} < -1.0$ AND $a_{t-2} < -1.0$)
1	Idle		$-1.0 \leq v_t < 1.0$	
11	Coast	$VSP_t < 0$	$1 \leq v_t < 25$	
12	Cruise/Acceleration	$0 \leq VSP_t < 3$	$1 \leq v_t < 25$	
13	Cruise/Acceleration	$3 \leq VSP_t < 6$	$1 \leq v_t < 25$	
14	Cruise/Acceleration	$6 \leq VSP_t < 9$	$1 \leq v_t < 25$	
15	Cruise/Acceleration	$9 \leq VSP_t < 12$	$1 \leq v_t < 25$	
16	Cruise/Acceleration	$12 \leq VSP_t$	$1 \leq v_t < 25$	
21	Coast	$VSP_t < 0$	$25 \leq v_t < 50$	
22	Cruise/Acceleration	$0 \leq VSP_t < 3$	$25 \leq v_t < 50$	
23	Cruise/Acceleration	$3 \leq VSP_t < 6$	$25 \leq v_t < 50$	
24	Cruise/Acceleration	$6 \leq VSP_t < 9$	$25 \leq v_t < 50$	
25	Cruise/Acceleration	$9 \leq VSP_t < 12$	$25 \leq v_t < 50$	
27	Cruise/Acceleration	$12 \leq VSP_t < 18$	$25 \leq v_t < 50$	
28	Cruise/Acceleration	$18 \leq VSP_t < 24$	$25 \leq v_t < 50$	
29	Cruise/Acceleration	$24 \leq VSP_t < 30$	$25 \leq v_t < 50$	
30	Cruise/Acceleration	$30 \leq VSP_t$	$25 \leq v_t < 50$	
33	Cruise/Acceleration	$VSP_t < 6$	$50 \leq v_t$	
35	Cruise/Acceleration	$6 \leq VSP_t < 12$	$50 \leq v_t$	
37	Cruise/Acceleration	$12 \leq VSP_t < 18$	$50 \leq v_t$	
38	Cruise/Acceleration	$18 \leq VSP_t < 24$	$50 \leq v_t$	
39	Cruise/Acceleration	$24 \leq VSP_t < 30$	$50 \leq v_t$	
40	Cruise/Acceleration	$30 \leq VSP_t$	$50 \leq v_t$	

In order to run MOVES, vehicle type, meteorology, fuel specifications, and road network data which consists of link length, link grade, traffic volume and composition and link speed, must be input (Alam, Ghafghazi, & Hatzopoulou, 2014). Link speed can be supplied through three methods: average speed distribution, second-by-second link drive schedules or operating mode distributions. In this study, we are utilizing operating mode distributions input by externally calculating VSP and assigning op mode using Matlab. Studies have shown that when users input either operating mode distribution or second-by-second driving schedules, MOVES gives better estimates of emissions [2], [10], [4]. Emission rates are estimated given the vehicle characteristics as well as road and meteorological conditions.

DESCRIPTION OF THE APPROACH

To assess the environmental impacts of automated vehicle operations, automated and non-automated vehicles are modeled using the VISSIM microsimulation model. For this study, the work has focused on 0% automated vehicle penetration and 100% automated vehicle penetration on a single-lane roadway link. Automated vehicle driving behavior differs from non-automated ("human") driving behavior in that the Weidman 99 oscillation parameters (CC2, CC4, CC5, CC6, and CC7) have been set to zero, with all other car following parameters and vehicle inputs held equal (desired headway, desired speed, etc.). This alteration indicates that automated vehicles will follow other vehicles with a constant following distance without the oscillations commonly found in human driving. (Note: this one alteration is not intended to represent all vehicle operations and driving behavior of AVs but rather to stand as a first examination of their anticipated behavior.) In the VISSIM model runs, a one-lane roadway link, two miles long, is run through a 4,500-second simulation run, performing calculations and collecting data at a 10 Hz rate. To allow the traffic to reach equilibrium, data is only collected from 900-4,500 second (one hour). Four scenarios are modeled: 1,500 vehicles/hr and 3,000 vehicles/hr each for 100% human drivers and 100% automated driving. The relatively low and high volumes were chosen to depict the roadway operating near capacity and also over capacity. For each scenario, fifteen simulation runs are performed, reporting throughput and average speed for each run. The run with the median average speed of the fifteen simulations is chosen for environmental MOVES analysis.

The four scenarios, with resulting throughput and average speed, are shown in the table below:

Table 2: Scenarios Modeled in VISSIM Microsimulation Runs

Scenario	Drivers	Hourly Volume (vehicles/hour)	Average Speed (miles/hour)
At-capacity	HUMANS	1500	61.7
	AUTOMATED VEHICLES	1500	61.94
Over-capacity	HUMANS	2468	56.16
	AUTOMATED VEHICLES	2599	56.2

The following data are output from the VISSIM model into an output traffic trajectory parameters .fzp file: time, vehicle number, position, velocity, acceleration, time in network, and vehicle type.. These files are then imported and a program is run in MATLAB to average the microsimulation 10 Hz output over each second (for ease of use in MOVES which performs emissions calculations on the 1 Hz scale). Next, the data are analyzed to assign operating modes for each vehicle each second in the network to obtain an overall operating mode distribution for each vehicle type. MOVES runs are set up at the project level to obtain emissions and fuel consumption for the modeled network.

MOVES 2014a SET-UP

The following table shows the inputs used to set up the runs in MOVES 2014a to calculate emissions and fuel consumption.

Table 3: MOVES 2014a Input

Category	Variable	Input
Description	---	<blank>
Scale	Model	Onroad
	Domain/Scale	Project
	Calculation Type	Inventory
	Years	2020
	Months	January
	Days	Weekdays
	Hours	00:00 – 00:59
Geographic Bounds	Region	Custom Domain
	StateID	99
	County ID	1
	GPA Fraction	0.0
	Bar. Pressure	28.94
	Vapor Adjust	0.0
	Spill Adjust	0.0
Vehicles/Equipment	Fuels	Diesel, Electricity, Ethanol (E-85), Gasoline
	Source Use Type	Passenger Car
Road Type	Selected Road Type	Rural Restricted Access
Pollutants and Processes (selected)	Total Gaseous Hydrocarbons	Running Exhaust and Crankcase Running Exhaust
	Non-methane Hydrocarbons	
	Volatile Organic Compounds	
	Carbon Monoxide (CO)	
	Oxides of Nitrogen (NOx)	
	Primary Exhaust PM2.5 – Total	
	Primary PM2.5 – Brakewear Particulate	Brakewear
	Primary PM2.5 – Tirewear Particulate	Tirewear
Manage Input Data Series	---	<blank>
Strategies	Rate of Progress	<blank>
General Output	Units	Mass: grams, Energy: Million BTU, Distance: miles
	Activity	Distance Traveled, Source Hours
Output Emission Detail	On and Off Road	<None selected>
	For all Vehicle/Equipment Categories	Fuel Type
Advanced Performance Features	---	<blank>

Project Data Manager

Within the project data manager, data input for the project-level was as described below. Many of the data used in the project-level run were obtained by running a national-scale inventory run for national rates and values.

Table 4: Project Data Sources

Data	Source
Age Distribution	MOVES2014a Default Age Distribution Tool for 2020
AVFT	National-scale inventory run
Fuel Formulation	National-scale inventory run
Fuel Supply	National-scale inventory run
Fuel Usage Fraction	National-scale inventory run
Generic	---
Hotelling	---
I/M Programs	No I/M programs
Links	VISSIM microsimulation model setup and output
Link Source Type	Source type: 21, Source type hour fraction: 1
Meteorological Data	National-scale inventory run
Off-Network	---
Operating Mode Distribution	MATLAB output from VISSIM output
Retrofit Data	---
Tools	---
Zone	all allocation factors set to: 1
Zone Road Type	Road Type: 2, Source hours factor set to: 1

RESULTS AND DISCUSSION

The operating mode distributions calculated from the VISSIM simulation output are shown in Figure 2 and 3 below. These figures show a few things of interest in the differences in vehicle operations between human and automated drivers as modeled.

- First, the primary operating mode for all of the scenarios is operating mode 33, which indicates that the vehicle is cruising or accelerating slightly at a speed greater than 50 mph.
- The human drivers oscillate between op modes 33 and 35, indicating some stronger acceleration than the automated vehicles.
- More operating modes are observed for the over-capacity roadway (Figure 3) than the roadway operating at-capacity (Figure 2). This indicates, as one would expect, that the presence of more vehicles disrupts steady traffic flow, requiring more acceleration and deceleration to avoid colliding with other vehicles. Also,

there is an observed increase in idling in over-capacity conditions compared to the at-capacity conditions.

From these operating mode figures, it can be expected that the emissions from operating mode 33 will dominate total emissions, especially in the automated vehicle case, and that the presence of lower operating modes in the over-capacity case will increase emissions produced, particularly the emissions from idling.

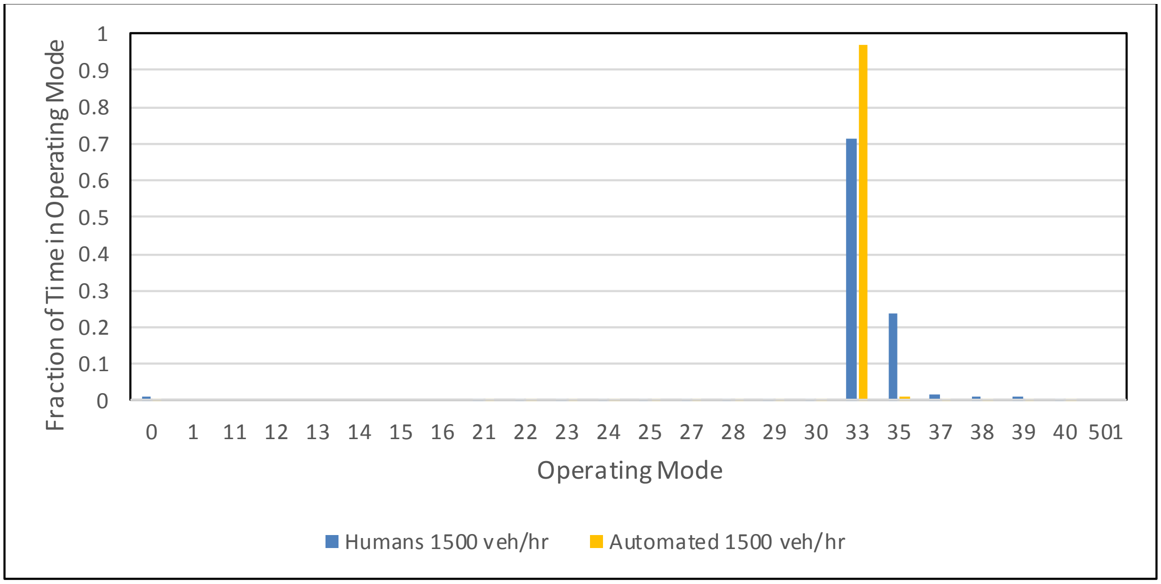

Figure 2: Operating Mode Distribution for At-Capacity Roadway (1500 vehicles/hour)

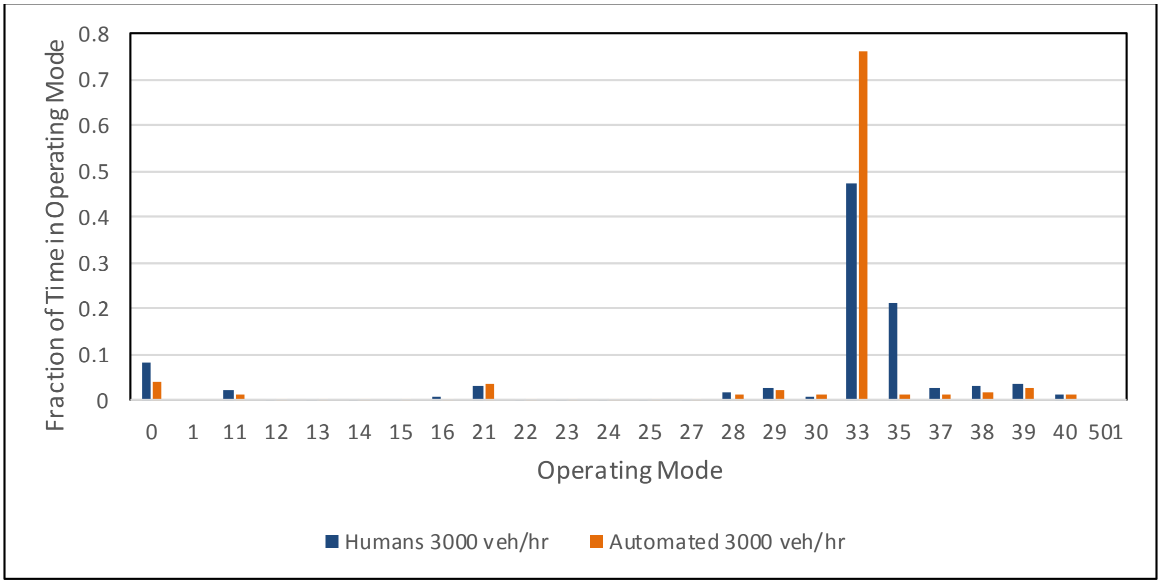

Figure 3: Operating Mode Distribution for Over Capacity Roadway (3000 vehicles/hour)

The MOVES 2014a results for criteria pollutants carbon monoxide (CO), nitrogen oxides (NOx), volatile organic compounds (VOCs), and particulate matter less than 2.5 µm ($PM_{2.5}$) for all four scenarios are shown in Figure 4. NOx, VOCs and $PM_{2.5}$ are also shown in the inset graph to give a better depiction of the emissions produced.

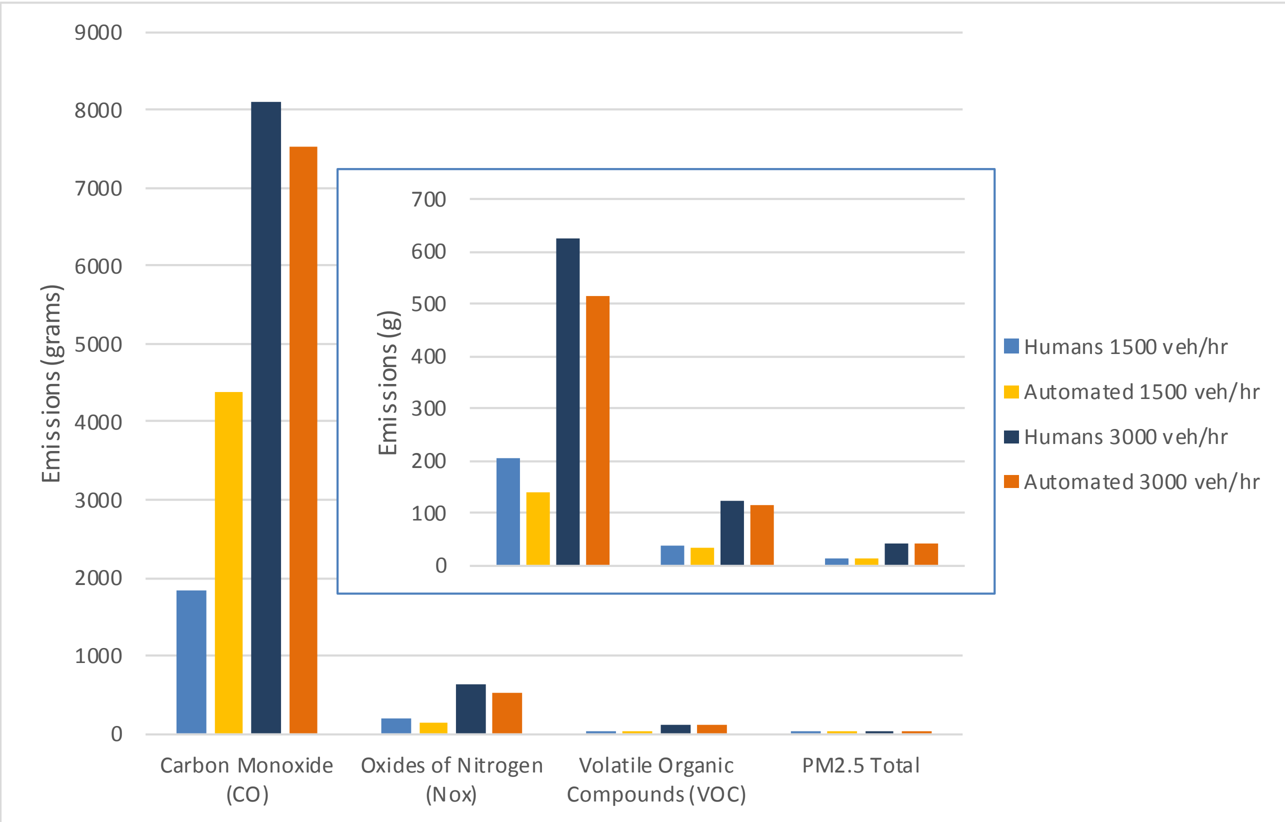

Figure 4: Emissions for four simulations scenarios

For NOx, VOCs, and total PM2.5, automated vehicles perform the same or better (produce less emissions) than human drivers. The greatest benefit of automated vehicles is in NOx, with a 32% and a 17% improvement over the human driver simulation for the at-capacity and over-capacity conditions, respectively.

However, for the largest-producing pollutant, carbon monoxide, the human driver simulation at-capacity outperforms the automated vehicles significantly (only producing 1.8 kg of CO compared to 4.4 kg for the automated vehicles). This can be expected because the modeled human-driven vehicles operate at higher operating modes than the automated vehicles, and carbon monoxide emissions have an inverted relationship to speed.

Because carbon monoxide contributes the most to overall emissions, for the at-capacity scenario, human drivers produce only half as much total emissions as automated vehicles. (For the over-capacity scenario automated vehicles produce about 7% fewer emissions overall than the human drivers.) These results show that automated vehicles can produce a dis-benefit under certain conditions, thus validating the importance of developing a robust framework that can fully assess benefits and dis-benefits.

Total fuel consumption for the four modeled scenarios is given below:

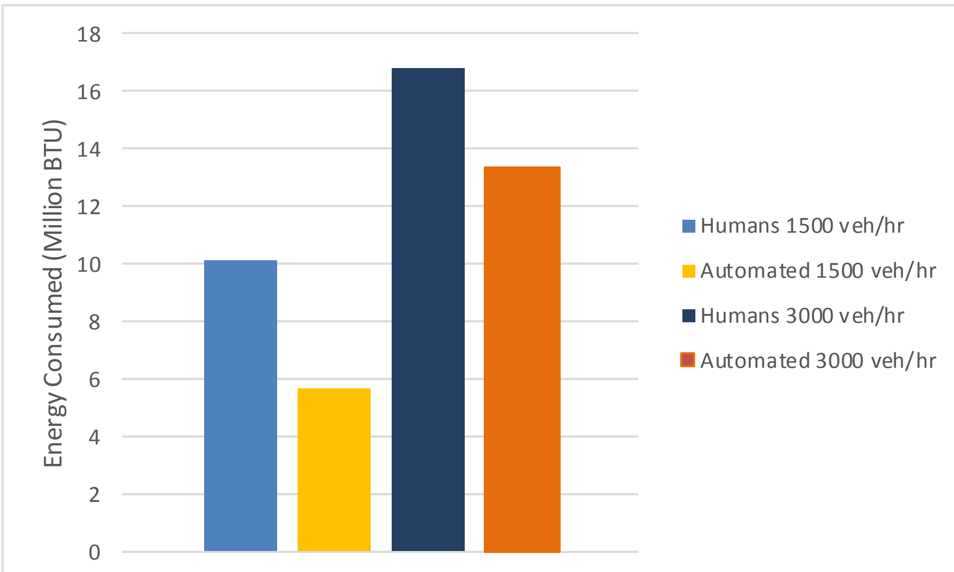

Figure 5: Total fuel consumption for four scenarios

For both roadway conditions, the automated vehicles consume less energy than the human drivers, with 43% and 20% less fuel consumed in the at-capacity and over-capacity conditions, respectively. Combined with the emissions data, this indicates that there can be a trade-off in assessing benefits from automated vehicles since the scenario with the largest decrease in fuel consumption showed the largest dis-benefit in emissions.

SUMMARY

Overall, these results show that emissions and fuel consumption can be calculated and assessed from traffic micro-simulation model output. This study does not pretend to properly assess the benefits or dis-benefits of automated vehicles but rather to prove that such an analysis can be conducted. This study further indicates the necessity of creating a proper framework and methodology for assessing the impacts of automated vehicles arising from the complexity of the changes in vehicle operations and driving behavior that AVs introduce into an already complex transportation system. Later work will investigate a variety of other scenarios that simulate anticipated automated vehicle behavior and vehicle operations.

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KEYWORDS

Automated vehicles, MOVES, microsimulation