Modeling Impact of Autonomous Vehicles at Network Level

BY

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THESIS

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0. Abstract

This study attempts to quantify the change in emissions resulting from autonomous vehicles (AVs). Three different scopes are defined for AVs and emission quantities are estimated using both established and theoretical methods. AVs show potential to reduce total emissions at all three scopes, with measurements varying from 3.0-14.5% in reduction depending on varying assumptions. Main findings were that this reduction is not negligible, is sensitive to traffic demand, and greatest at full market penetration. It was also found that lower market penetration may generate a greater inventory of total vehicle emissions, contrary to popular thought.

1. Introduction

To best serve a growing population, new transportation technologies and practices are constantly being developed. Among these is the *Autonomous Vehicle* (AV). Levels of automation are defined by the Society of Automotive Engineers (SAE). The *SAE Level* begins at 0 (no automation) and ends at 5 (full automation) [37, 32]. Levels 0 through 2 rely on a person monitoring the traffic environment, while 3 through 5 rely on the AV system. When the term "autonomous vehicle" is used in literature, it is generally referring to a level 4 (high automation) or 5 (full automation). Since AVs are still in a developmental phase, it is not known exactly how they will be implemented. Victoria Transport Policy Institute provides a rough timeline for this.

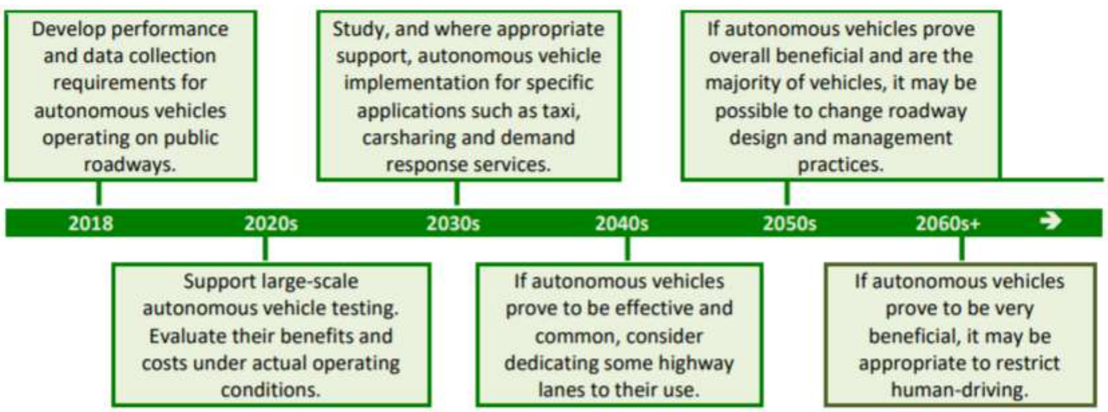

Figure 1: AV Implementation Forecast [32]

It will likely be several years before AVs are introduced to transportation networks at large scale. At the individual level, future AV market penetration is also unclear. What is known is that per capita vehicle ownership is not increasing the same way it has in the past [32, 35]. This may be partly due to an increased portion of people living in an urban environment or changing consumer preferences. Forecasting vehicle ownership is critical for understanding how AVs will affect future transportation systems.

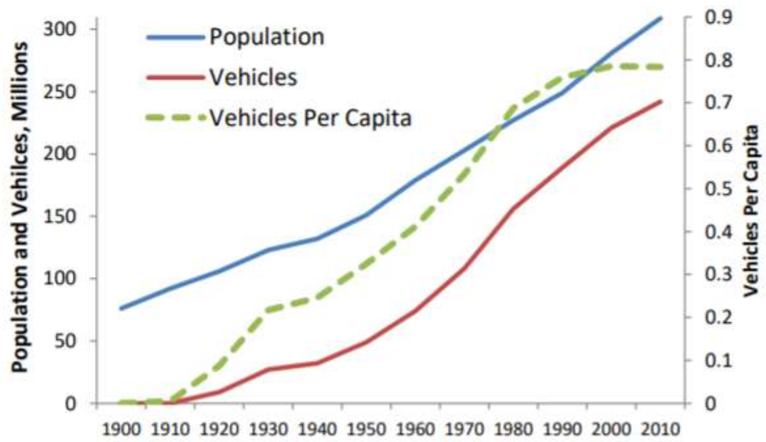

Figure 2: US Vehicle Ownership [32]

A common idea for the future of transportation is the *Shared Autonomous Vehicle* (SAV) network. This study will not specifically consider the "shared" aspect but previous literature regarding SAVs is still relevant. SAV networks are thought to provide service similar to taxis, Uber, or Lyft, but without a driver. These vehicles are not owned by a single person, which challenges the current vehicle ownership climate and decreases the barriers of entry for vehicle ownership. Accessibility to vehicles increases as well. The exact structure (i.e. cost, subscription requirements) is still under debate as well as legal policies.

Safety is arguably the most important factor when considering vehicle technologies. 40% of crash fatalities result from alcohol or drugs, and 90% of crashes result from driver error [6, 33, 34]. These incidents can be reduced or nearly eliminated using AVs.

When AVs are implemented, their impact will come two-fold. Older technologies such as the conventional self-driven vehicle will be phased out and replaced by AVs, and additional traffic will be a result of the newfound convenience that they provide. Even with the increased volume, some critics still believe that at an individual level, AVs provide positive benefits [6,36]. Brownell (2013) provided a framework for a transportation technology to follow if it is to replace the existing self-driven vehicle. In this paper, five *Key Transit Criteria* are established [31]:

1. The system must reduce congestion and decrease commuting times

2. It must be safer than automobiles

3. It must have fewer negative environmental impacts than automobiles

4. It must be economically viable and financially feasible

5. It must offer its passengers comfort and convenience to rival the automobile

All of these criteria should be considered for network scale AV implementation, however, this study only addresses 1 and 3. In fact, the idea is that AVs lower environmental impact from reduced congestion and travel time. Reduction in environmental impact (emissions) is caused by vehicle operation alone. No additional vehicle technologies for AVs are considered, and it is assumed that AVs are equal in size to standard vehicles and use the same fuel. These assumptions may not be accurate when considering all five criteria, but help isolate criteria number 1.

Existing literature primarily focuses on technology adaptation. Little has been focused on driving patterns at network scale. This lack of available information has prompted this to focus specifically on AV performance at network level, with a focus on environmental impact. Autonomous vehicles are thought to offer benefits in terms of convenience, increased capacity [1-3], safety benefit, increased fuel economy, and reduced emissions [4-9]. Their capacity and emission benefits are a result of smoother acceleration and fewer stop-and-go movement [10,11,12]. This study will attempt to quantify these benefits by offering comparison of AVs to conventional vehicles (CV) in a three-scope progression, with increasing complexity. Here they will be briefly introduced, then explained in further detail in the methodology section.

Scope I: Drive Schedule Comparison

First, an individual drive schedule comparison is considered. Comparable drive schedules are constructed for an autonomous vehicle and a standard vehicle. They serve as input for emissions simulation. The output yields emission reduction simply due to operational driving behavior between two different vehicles.

Scope II: Theoretical Macroscopic Network

Second, a theoretical macroscopic network is modeled. The common flow-density assumptions are used to estimate how AVs increase capacity. Average speeds and volumes for calculated for a base case as well as an AV network (100% penetration). These values are ran in an emissions simulator then results are compared.

Scope III: Microsimulation

Third, a microsimulation captures individual drive schedules for all vehicles operating in a network. Five simulations reflecting possible market penetration ratios of AVs are considered. A base case (0% penetration) will be established along with 2%, 5%, 20%, 50% and 100% scenarios. The actual process is described exhaustively in the methodology section.

Three different individual analyses are performed, each of which yield an estimate of emission reduction by autonomous vehicles. The progression of scope is designed to build upon previous levels and offer an increasingly accurate methodology for emission estimation at network scale.

2. Literature Review

Autonomous vehicles are expected to significantly impact our current transportation situation. AVs operate with higher situational awareness than a human driver. This translates to quicker reaction times and lower required headway, increasing traffic capacity [13]. This capacity increase becomes higher as AV penetration reaches 100%.

A critical feature of AVs is their ability to obtain information about surrounding traffic and nearby vehicles. Their communication tools have been shown to reduce fuel consumption by 5-7% [13-16]. Adaptive cruise control systems can be used to further decrease headway requirements and resulting emissions [15-17]. Platooning abilities of AVs have also been shown to provide similar benefits [18-20]. Fagnant (2015) focuses on vehicle-to-vehicle communication and drive schedule smoothing algorithms and found that traffic (congestion) speeds could increase by up to 13% when using AVs [6] . The study also estimated that fuel economy may increase by up to 39%. An increase in fuel economy translates to a decrease in emissions per mile traveled.

Routing algorithms can be designed for a group of AVs to serve rider demand. Fagnant (2015) uses agent-based modeling to generate trips. Here, the goal was to join trips from similar riders, increasing per-vehicle ridership and decreasing cold starts. The model works by first calculating the required SAV fleet size for a given network, then running a 100-day simulation. During the simulation, the SAVs attempt to best serve the required person trips. A base case was constructed along with other scenarios for policy analysis. The overall conclusion made was that each SAV could serve the demand for eleven standard vehicles. Total VMT increases by 10% but overall emissions are thought to decrease. Agent-based modeling allows for dynamic trip making and routing, but does not estimate a drive schedule for the SAV fleet. This study provides insight as to how SAVs may be introduced into a city and how they will suit rider demand. [30]

In existing AV literature, a paradoxical relationship is commonly found for autonomous vehicles. This makes AVs difficult to study or model entirely. AVs are relatively early in their development and implementation, so theoretical models are constructed due to the small amount of existing operational data.

3. Emission Calculation Frameworks

Before the methodologies are explained in further detail, the frameworks for emission estimation must be established. There are two different ways emissions are calculated in this study. The first is EPA's Motor Vehicle Emission Simulator (MOVES). Scope I and Scope II both use this software, however the input data specified varies slightly. Scope III uses what is called the Newton-based GHG Model (NGM). It is entirely theoretical in its application and is not part of a software package. Emission calculations are performed manually (using a Python script) for the NGM model.

3.1. EPA MOVES

EPA's MOVES is the standard software for mobile source emissions in the U.S. Alternative softwares available include EMFAC, designed specifically for California, and VT-Micro, developed at Virginia Tech. Emission simulators attempt to model emissions as a product of a vehicle's operational activity and its corresponding emission rate.

MOVES offers two main types of analyses for estimating emissions. A *drive schedule* analysis lets the user input a vehicle's drive schedule, a second-by-second time series of a vehicle's speed and acceleration. MOVES calculates specified emission inventories for this vehicle. Scope I uses MOVES drive schedule estimation. The second option is a *project level* analysis. A MOVES project level analysis allows the user to input a group of links. Each link has an assigned length, average speed, and hourly volume. MOVES computes an inventory for the entire project area over the time span of an hour. Scope II uses MOVES project level estimation.

Emission rates in MOVES are a result of a vehicle's *Operating Mode* (OpMode). This is a function of a vehicle's speed as well as *Vehicle Specific Power* (VSP). The VSP equation as used in MOVES is

$$VSP\left[\frac{kW}{Mg}\right] = \frac{(Av\ + Bv^2 + Cv^3 + mva)}{m}$$

Since average speed is used, the acceleration term becomes zero, simplifying the equation to

$$VSP\left[\frac{kW}{Mg}\right] = \frac{(Av\ + Bv^2 + Cv^3)}{m}$$

Where velocity *v* is in $\left[\frac{m}{s}\right]$and vehicle weight *m* is in metric tons. A, B, and C represent coefficients for rolling resistance, rotating resistance, and drag.

VSP along with operational speed are used to classify which OpMode a vehicle is in as defined in MOVES.

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Speed Class [mph]</th></tr>
<tr><th>1-25</th><th>25-50</th><th>50+</th></tr>
<tr><th rowspan="12">VSP Class $\left[\frac{\mathbf{kW}}{\mathbf{tonne}}\right]$</th><th>30+</th><td rowspan="7">16</td><td>30</td><td>40</td></tr>
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<tr><th>3-6</th><td>13</td><td>23</td><td rowspan="3">33</td></tr>
<tr><th>0-3</th><td>12</td><td>22</td></tr>
<tr><th><0</th><td>11</td><td>21</td></tr>
</table>

Table 1: MOVES OpModes [21]

Run specifications in MOVES lets the user customize the simulation to best suit their project. Meteorology, vehicle age distributions and fuel types are just a few parameters that can be set in the run specification. No parameters in MOVES run specifications were altered to account for standard vs. AV types. The differences were only due to driving behaviors (drive schedules for Scope I and average speeds for Scope II). Technologies for AVs may result in different emission rates compared to standard vehicles, but for this analysis only the operational differences were considered.

3.2. Newton-based GHG Model

Scope III emission calculation is not handled by MOVES. It would not be computationally efficient to generate individual drive schedules from all vehicles during the microsimulation, then use MOVES for estimation. Instead, a more theoretical model is used. This is called the Newton-based GHG Model (NGM). Since it is not available in a standalone software, it needs to be explained in detail here. The NGM builds off previous work on the formulation of the *Ideal Brake-loss Car* (IBC) [26-27]. In this hypothetical formulation, energy is only required when a vehicle accelerates and produces useful work. All other energy uses are ignored, such as drag, rolling friction, and internal combustion losses.

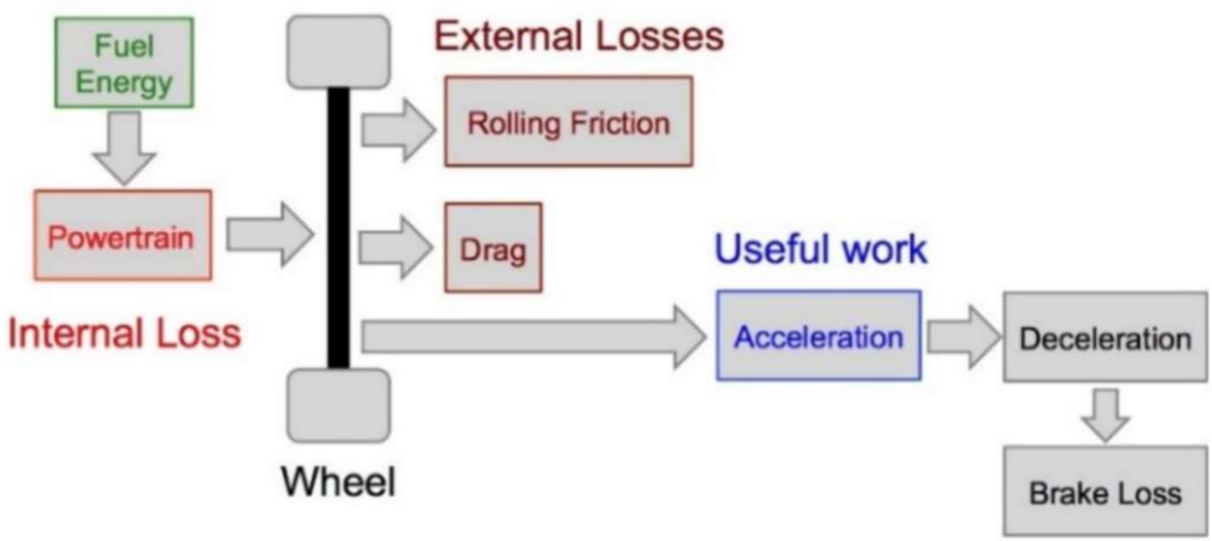

Figure 3: Vehicle Energy Flow [26-27]

Energy required for a vehicle's drive schedule $(a, v)_i$ over time T can be modeled as

$$E = M \int_0^T a_+ v \, dt$$

Where a_+ is positive acceleration. If a is negative, a_+ is zero.

Only accounting for useful work in this ideal scenario is of course unrealistic. It is common to use road load equation to account for other losses. Road load power is defined as:

$$f_{RL} = M(a + g\sin(\theta) + MgC_{rr} + 0.5C_d A\rho v^2$$

It includes coefficients C_{rr} and C_D for rolling resistance and drag, respectively. NGM combines this road load formula with the IBC theory. For a given drive schedule, NGM computes the energy quantity required to produce that work for a vehicle. The quantity of fuel required is known via potential energy in the specified fuel. Applying a conversion factor results in GHG emissions for a vehicle along its drive schedule. For a vehicle to traveling at a given velocity and acceleration, the instantaneous emission rate of a vehicle can be modeled as:

$$\zeta(x,t) = \begin{cases} \dfrac{\Gamma_{idl}}{E_{gas}\eta}(Ma + MgC_{rr} + 0.5C_{dA}\rho v^2), & \text{if } Ma + MgC_{rr} + 0.5C_{dA}\rho v^2 \geq 0 \\ \dfrac{r\Gamma_{idl}}{E_{gas}\eta}(Ma + MgC_{rr} + 0.5C_{dA}\rho v^2), & \text{otherwise} \end{cases}$$

$\zeta(x,t)$ has units of $\left[\frac{\mathrm{g}}{\mathrm{m}}\right]$. To obtain results in terms of $\left[\frac{\mathrm{g}}{\mathrm{s}}\right]$, the equation can simply be multiplied by its velocity $\left(\left[\frac{\mathrm{g}}{\mathrm{m}}\right] \times \left[\frac{\mathrm{m}}{\mathrm{s}}\right] = \left[\frac{\mathrm{g}}{\mathrm{s}}\right]\right)$.

$$\mathrm{E}\left[\frac{\mathrm{g}}{\mathrm{s}}\right] = \zeta * v$$

Where E is instantaneous CO_2 emissions. Assumptions for vehicle parameters are shown below.

Parameter	Definition	Value
Γ_{idl}	CO_2 emissions from gasoline	$8{,}887\ \left[\frac{\text{g CO}_2}{\text{gal}}\right]$
η	Reaction efficiency	1.0
E_{gas}	Energy in gasoline	$33.7\ \left[\frac{\text{kWh}}{\text{gal}}\right]$
r	Regeneration efficiency ratio	0 (no regeneration)
C_{rr}	Rolling resistance	0.015
C_dA	Aerodynamic drag area	0.079
ρ	Air Density	$1.225\ \left[\frac{\text{kg}}{\text{m}^3}\right]$
M	Vehicle mass	1678 kg (3700 lb)
v	Vehicle speed	Result of simulation
a	Vehicle acceleration	Result of simulation

Table 2: NGM Calculation Parameters

The Microsimulation generates motionstates for vehicles at a given time. This is equivalent to the vehicle's acceleration (a) and speed (v) at a given time. By assuming this motionstate is constant is constant over the microsimulation's step length, this rate represents the quantity of emissions generated during this step length. For example, if the instantaneous emission rate, E, is $2\left[\frac{\text{g}}{\text{s}}\right]$ and step length is [1s], the quantity of emissions generated during that entire step is 2[g].

NGM is similar to EPA MOVES, which was used in Scope II analysis. Recall the VSP function,

$$VSP\left[\frac{kW}{Mg}\right] = \frac{(Av\ + Bv^2 + Cv^3 + mva)}{m}$$

Which is used to classify a vehicle's operating mode, and therefore emissions. The primary difference is that MOVES emission rates are results of laboratory testing of different operating modes for a vehicle. The VSP equation serves to classify an operating mode (i.e. which set of testing data is used) for emission estimation purposes. NGM on the other hand is completely theoretical. The instantaneous emission equation can be modified for vehicle-specific parameters but the result is not restricted or fitted by any real-world data. NGM can take any set of continuous data and provide an emission estimate. MOVES takes emission data and assigns that rate to vehicles operating at (roughly) equivalent states.

Some brief outside validation has been performed for NGM. Results from the NGM equation were compared to field measurements of CO_2 [28]

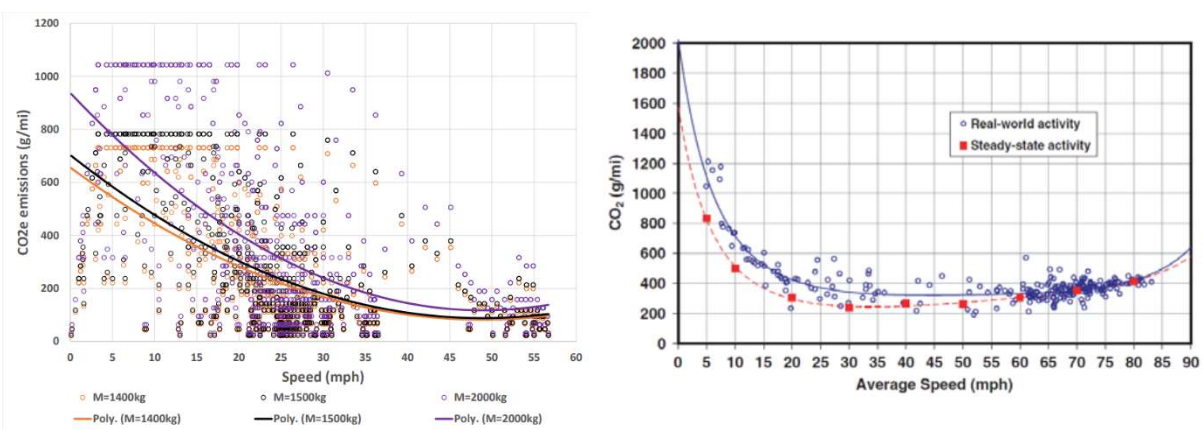

Figure 4: NGM Validation [26-27]

For a theoretical framework to overtake an established input parameters need to be thoroughly studied to quantify results. The continuous nature of NGM allows for a much smaller aggregation period (i.e. seconds or milliseconds versus hours in MOVES). With the increase in computer speeds, continuous emission simulators may be developed in the near future.

In review, the simplified table below categorizes how emissions are calculated at each scope

Scope	Method
Scope I	MOVES drive schedule
Scope II	MOVES project level
Scope III	NGM manual calculation

Table 3: Emission Calculation Method by Scope

4. Methodology

4.1. Scope I – Drive Schedule Comparison

The first scope's strategy starts with developing a drive schedule for an autonomous vehicle. Testing data for the Udacity self-driving car was aggregated into seconds. Corresponding speed values were taken, representing the drive schedule [12].

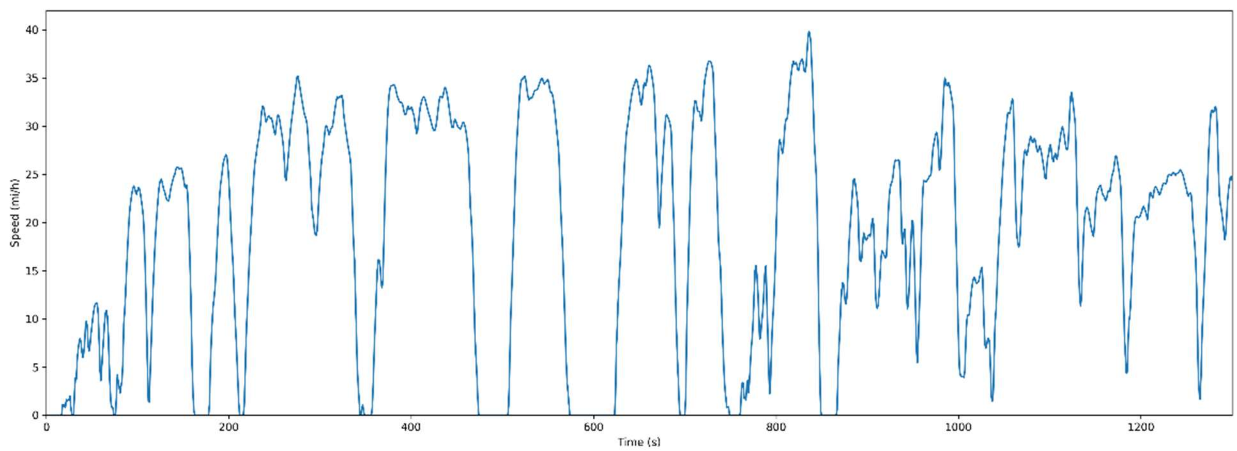

FIGURE 5: Self-driving Car Drive Schedule

A baseline drive schedule is required for direct comparison to the AV drive schedule. The EPA publishes the Urban Dynamometer Drive Schedule (UDDS) [25], which will serve as this baseline. UDDS contains second-by-second speed data, so it is readily available in the same format as the aggregated AV schedule.

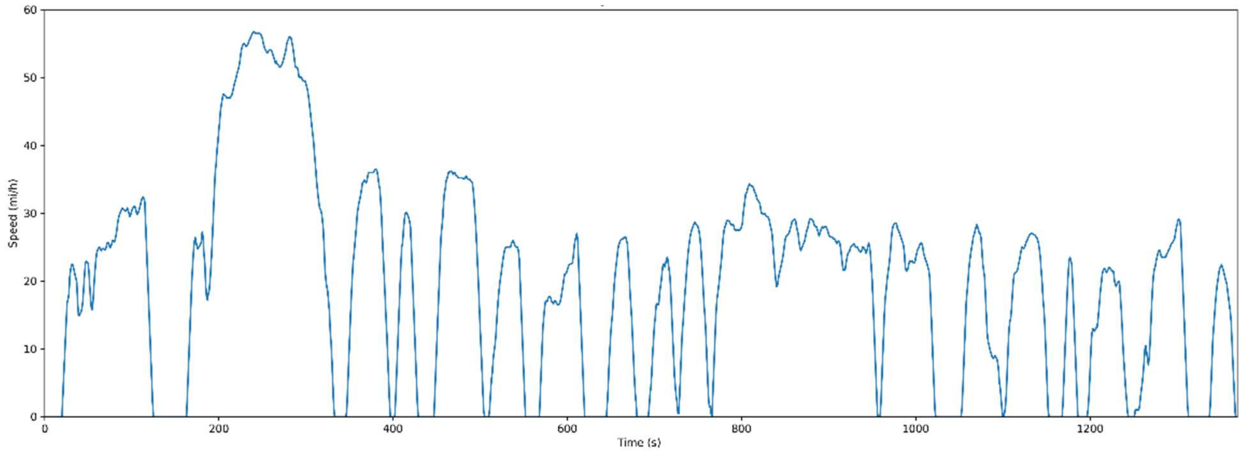

FIGURE 6: EPA UDDS

MOVES can take a time series drive schedule as an input for estimating emissions. Scope I analysis is exactly this – a MOVES simulation for the two drive schedules. Along with the specified drive schedule, the run specification for MOVES includes information about assumptions made in the simulation. For this comparison, the only difference between the run specifications is the drive schedule (i.e. AV vs. UDDS).

4.1.1. Scope I Results

A project level inventory for Total Energy Consumption (TEC) and CO_2 was generated in MOVES. These values are representative of a single hour time period.

	TEC (kJ)	CO_2 (g)
EPA UDDS	101,589	7,301
AV	93,473	6,718
% change (from UDDS)	-8.0%	-8.0%

Table 4: Drive Schedule emission comparison

Scope I comparison encapsulated the differences in emissions from conventional and autonomous vehicles due to driving behavior. Both metrics showed a benefit from AVs. Emissions calculated with MOVES certainly show that a vehicle following the AV drive schedule contributes less emissions than a vehicle following the EPA's UDDS schedule. Considering the similarity of the schedules, the reductions in emissions from AVs seems significant. But does this drive schedule comparison truly capture the environmental advantage of AVs? This scope does not truly capture the environmental advantage of AVs entirely, for a few reasons. The first is that no evidence has been provided that these two schedules can properly model the same vehicle, since their locations are not necessarily comparable. This simply asks why an individual dataset (Udacity AV testing in the Bay Area, California) should be directly comparable to the published (UDDS) dataset provided by the EPA. Instead of adapting an AV schedule to be more comparable to that of the EPA, maybe another approach should be taken. The second reason is that an individual drive schedule cannot be used for larger scale analysis, due to congestion and vehicle interaction. It brings up the argument that AVs are advantageous in congested (urban) networks, and that their drive schedule *alone* is not representative of this advantage.

4.2. Scope II – Theoretical Macroscopic Network

Scope II attempts to address the shortcomings found in Scope I. What if network scale traffic demand data was used to model emissions, while considering traffic congestion? Conveniently enough, the Chicago Metropolitan Agency for Planning (CMAP) provides travel demand data for Chicago and its suburban counties, as well as parts of Wisconsin and Indiana. Its network includes data for assigned traffic volumes for each link covered in the area for eight different time periods throughout the day. Let's now define the study area, since the entirety of CMAP data will not be needed. Below is a geographical representation of the selected study area.

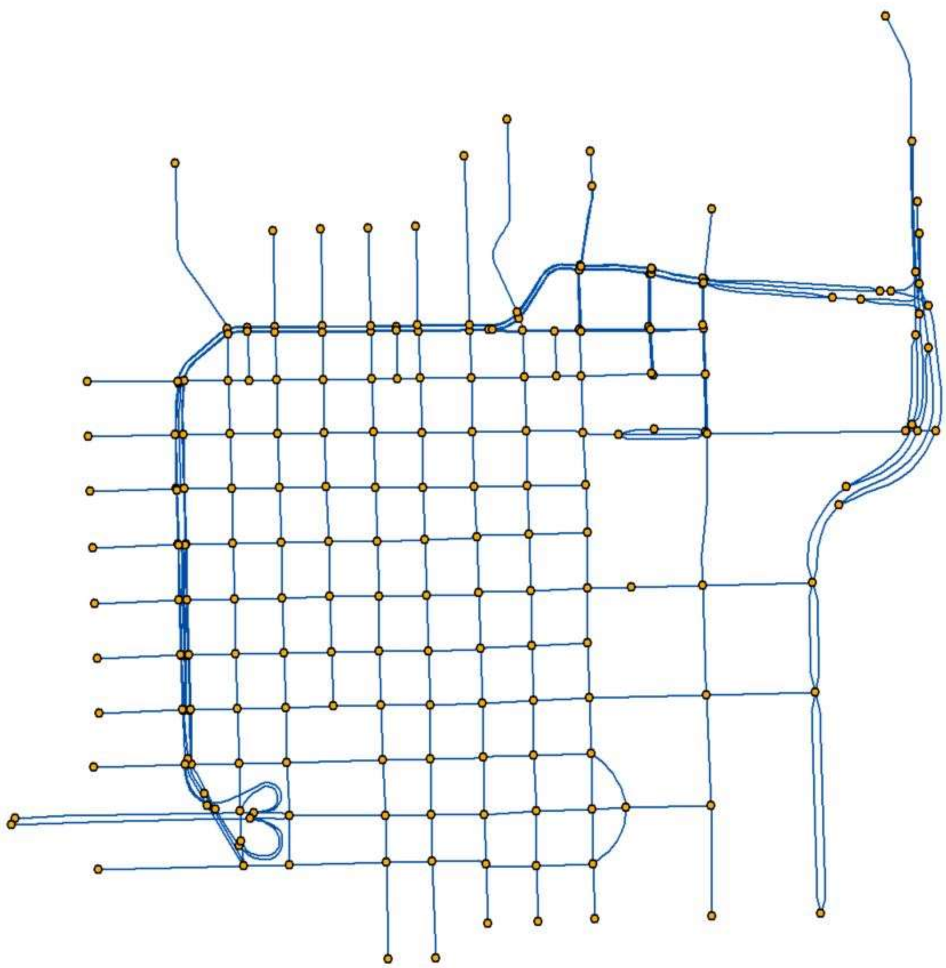

Figure 6: Downtown Chicago Traffic Network

The area chosen represents the central business district of Chicago (known as the *Loop*) as well as immediate road and highway connections. Additional information is available for every link shown in the network, including:

- Number of lanes, n
- Capacity per lane, $q_{cap}[\frac{\text{veh}}{\text{h}}]$
- Posted speed limit, u_{posted}

Overall, 452 links are used. All links are directional (i.e. each direction has its own volume), so for a two-way street they appear as a single segment in the figure.

With this scope now defined, CMAP's demand data can be used for analysis. We assume a linear flow-density (FD) relationship applies for each segment in the network mentioned. Fundamentally, the FD relationship has three main variables: flow (q), density (k), and speed (u). The free-flow speed, u_f, for each link is assigned in relation to a posted (known) speed limit as follows:

$$u_f(u_{posted}) = \begin{cases} u_{posted}, & \text{for signalized street segments} \\ 1.15 \times u_{posted}, & \text{for highway or freeway segments} \end{cases}$$

This accounts for driver tendency to exceed speed limits when traveling on highways [22]. Since capacity flow q_{cap} is also known, the physical jam density of a link can be calculated as:

$$k_{jam} = \frac{4 \times q_{cap}}{u_f}$$

A flow-density curve can be constructed for each link, following the parabolic equation:

$$q = u_f\left[k - \frac{k^2}{k_{jam}}\right]$$

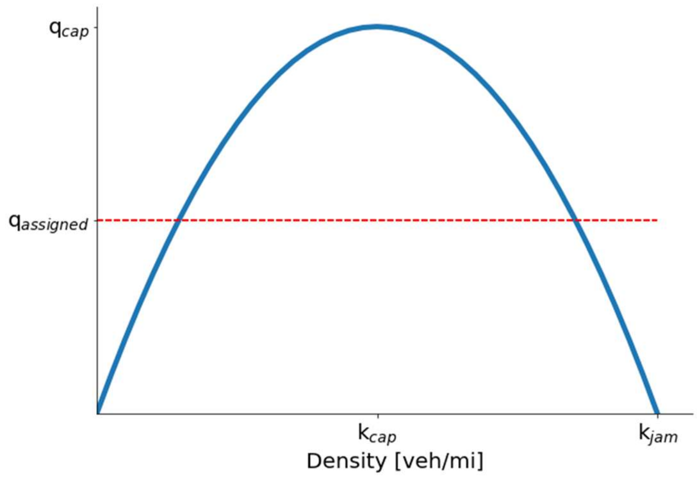

Figure 7: Flow-Density Curve

Since assigned flow is not equal to capacity flow, a theoretical operating point needs to be solved for.

$$q = u_f \left[k - \frac{k^2}{k_{jam}} \right] = q_{assigned}$$

$$u_f \left[k - \frac{k^2}{k_{jam}} \right] - q_{assigned} = 0$$

This equation has two solutions, but the lower density will be taken for this study. The assumption is that the link is operating below its capacity. Once the density k is solved for, the operating speed of the link, u, is

$$u \left[\frac{\text{mi}}{\text{h}} \right] = \frac{q_{assigned} \left[\frac{\text{veh}}{\text{h}} \right]}{k \left[\frac{\text{veh}}{\text{mi}} \right]}$$

The new capacity is a result of a decrease in required headway for AVs. Headway is the amount of time between vehicles and the unit is $\left[\frac{s}{veh} \right]$. Alternatively, it is the inverse of flow.

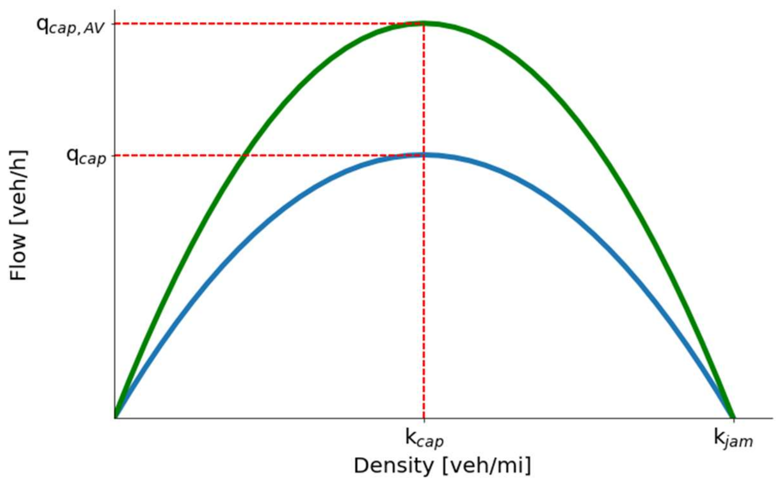

Figure 8: Flow-Density Curve (with shifted capacity)

To create this theoretical network level comparison, this headway gain for AVs needs to be defined. A 2.5 second reaction time is commonly recommended by the American Association of State Highway and Transportation Officials (AASHTO). This will be considered the standard headway for conventional vehicles. For AVs, a 1 second headway will be assumed. The relative gain in flow is the ratio of these two headways:

$$q_{cap,CAV} = \frac{1}{h_{CAV}} = \frac{h_{standard}}{h_{CAV}} \times q_{cap,standard}$$

$$q_{cap,CAV} = 2.5 \times q_{cap,standard}$$

In other words, the capacity flow of AVs can be thought to be 2.5 times the capacity flow of standard vehicles. The headway; however, applies to separate vehicles. When the connective aspect of AVs is considered, this headway only applies to different platoons. A platoon of AVs are a single traveling entity, so the theoretical assigned volume actually decreases by a factor of the number of vehicles in the platoon:

$$q_{assigned,CAV} = \frac{q_{assigned}}{n_{vehicles}}$$

This does not alter the hourly volume when calculating emissions in MOVES since the number of physical vehicles does not change. Jam density and free-flow speeds are road design parameters, therefore other constants for the flow-density curve remain the same. Speeds for CAVs are calculated using the same parabolic method as explained previously, but now the assigned flow is lower.

Interaction within the traveling platoon can also be considered when attempting to estimate the effect of AVs. Platooning reduces air drag experienced upon the vehicles (or at least those following a lead vehicle). Rather than performing calculations for every n^{th} vehicle in an operating platoon, the average drag reduction can be utilized.

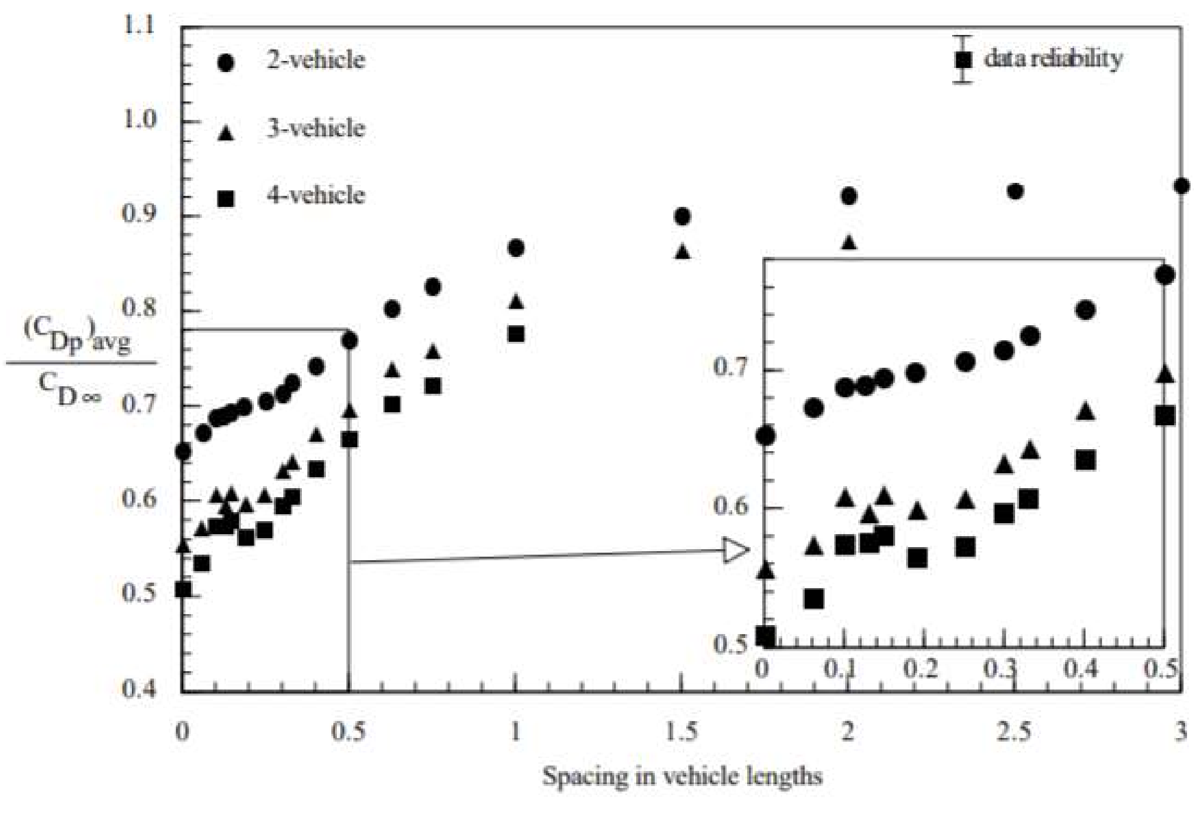

Figure 9: Drag Reduction (Zabat et al) [23]

Assuming a constant 4-vehicle platoon traveling with 0.5 car length spacing, the overall coefficient of drag is reduced to 66% of what a non-platooning vehicle would experience [23].

This assumption allows for real platooning finding to be utilized in the same emission estimation framework. Again, the VSP equation as used in MOVES is

$$VSP\left[\frac{kW}{Mg}\right] = \frac{(Av\ + Bv^2 + Cv^3)}{m}$$

For a light duty vehicle, the A, B, and C coefficients used are 0.19161, 0.00254, and 0.00041, respectively [24]. The drag coefficient can be adjusted to 66% of its original, as per Zabat et. All (1995) [23].

$$C_{new} = C_{old} \times 0.66 = 0.00041 \times 0.66 = 0.00027$$

Assuming a 3,700 pound (1.68 tonne) value for *m*, the VSP equation can be reconstructed. Each link now has a different speed and VSP and can be classified into an operating mode as defined in MOVES. The updated speeds and operating modes were inputted in MOVES for emission estimation.

4.2.1. Scope II Results

MOVES computed project level inventory for Total Energy Consumption (TEC) and CO_2. These values are representative of a single hour time period. Two time periods from the original CMAP data were utilized in Scope II analysis. Assigned flow for 7-9am (peak morning rush hour) and 10am-2pm were used for theoretical calculations. Scope II also attempted to quantify the reduction in emissions due to drag advantage from platooning. Results for CVs and AVs for both time periods are shown below.

Time Period	**Description**	**Emission Inventory**	
		TEC (kJ)	**CO_2 (g)**
Peak (7-9am)	CV	281,003,200	20,194,766
	AV w/o drag reduction	240,335,920 (-14.5%)	17,272,138 (-14.5%)
	AV w/ drag reduction	240,335,920 (-14.5%)	17,272,138 (-14.5%)
Off-Peak (10am-2pm)	CV	166,279,472	11,949,950
	AV w/o drag reduction	157,776,912 (-5.1%)	11,388,898 (-4.7%)
	AV w/ drag reduction	157,776,912 (-5.1%)	11,388,898 (-4.7%)

Table 5: Scope II Emission Comparison

Emission reduction from AVs was larger for the peak traffic time period than for off-peak. This supports the prediction that AV potential for emission reduction is not just from individual driving behavior, but their capability to effectively increase flow for an urban network. The results suggest that the level of reduction is scalable, meaning the effects are greater for urban networks as the traffic flow approaches (or exceeds) capacity.

It was found that there is no additional reduction in emissions when drag reduction is considered. Recall that MOVES emission rates are a result of operating mode. The operating mode can change if an average link speed crosses a threshold of either 25 or 50 miles per hour. It can also change based on VSP, which was altered by the drag coefficient reduction. The bins for VSP are quite large (3 $\left[\frac{\text{kW}}{\text{tonne}}\right]$ differences). 426 out of 452 (94%) of links remained in the same OpMode when CAVs were implemented in the peak time period and 417 out of 452 (92%) remained in the same OpMode during off-peak. These changes did not alter the emission rate enough to cause differing results in MOVES. The emission reduction with air drag considered should be higher, though it is difficult to model using the EPA’s current regulatory model for on road emissions. MOVES may not be the ideal tool for effectively measuring the environmental impact of AV platooning specifically. Scope I and Scope II provide a solid foundation for the construction of Scope III.

4.3. Scope III - Microsimulation

Recall that there are two main sources of emission reduction for autonomous vehicles:

- Smoother driving behavior (at the individual level)
- Increase in traffic capacity (when multiple vehicles are introduced to a network)

Each of these sources are captured in Scope I and Scope II, respectively. Neither scope accounts for both, however. Both were shown to impact emissions, so an accurate model should include both sources.

Scope II network used data from CMAP's link-level analysis [38]. The dataset included hourly volumes for every street segment. The macroscopic assumptions limited the network as a collection of street segments (links) with a vector of traffic variables (e.g. average speed, volume, capacity). All calculations were performed individually, meaning no link influenced variables on another. This is a major shortcoming of Scope II analysis. In an urban network, state of nearby links greatly affects traffic demand and vehicles can re-route.

Instead of assuming traffic links are individual pieces of infrastructure, they can be thought of as interacting features on the same network. A network is simply a group of nodes connected by links. In transportation, a trip has a defined starting and ending point (nodes), but can possibly have multiple routes. Algorithms have been developed by graph theorists to model the route taken for any given trip.

Scope III analysis does not look at traffic demand for individual links, but as groups. The aggregated groups of demand are known as *Traffic Assignment Zones* (*TAZ*). TAZs in this paper are defined as a collection of traffic segments. CMAP's regional conformity analysis defines TAZs for the entire covered region. This region has TAZs in Chicago, surrounding suburban counties, and parts of Wisconsin and Indiana. The CMAP defined TAZ is the aggregate level of traffic demand used in Scope III.

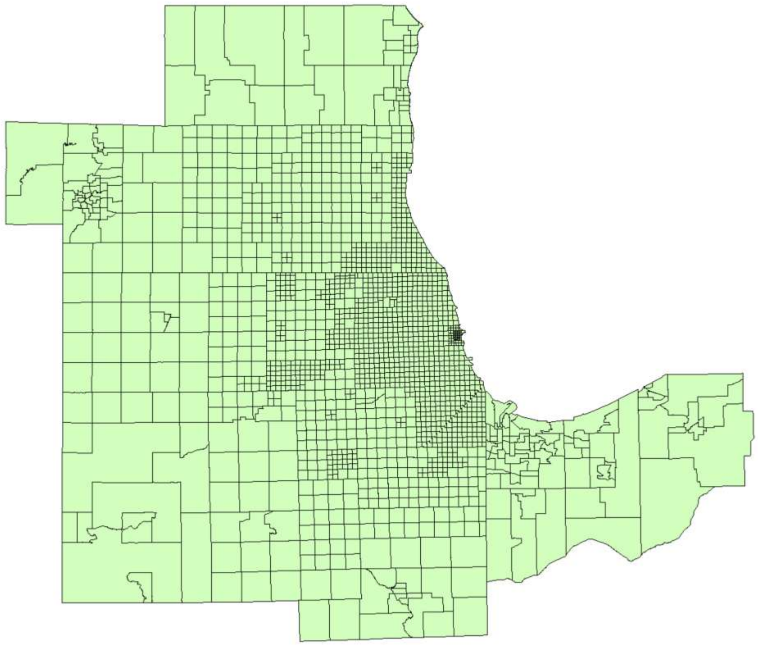

Figure 10: CMAP Conformity Analysis Extent

CMAP's coverage expands much further than the area covered in Scope III. In fact, there are 1944 CMAP defined TAZs and only 31 of them within the Scope III network.

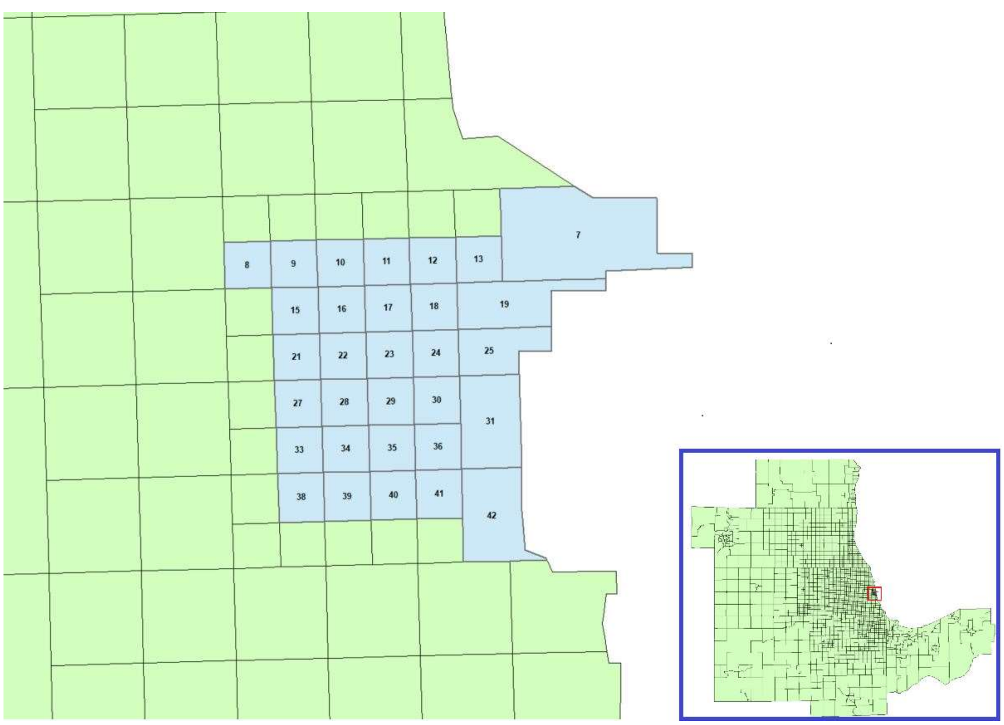

Figure 11: Scope III Network Extent by TAZ

While the Scope III network only covers a small portion of TAZs in the region, the entire extent is still used for demand purposes. Each OD pair of TAZs falls into one of four categories based on location.

Origin	Destination	Required?
In-Network	In-Network	**Yes**
In-Network	Out-of-Network	**Yes**
Out-of-Network	In-Network	**Yes**
Out-of-Network	Out-of-Network	**No**

Table 6: TAZ OD Pair Categories

As long as either the origin or destination TAZ is within the network, there will be traffic within the network. Only when the origin and destination are both out-of-network can the corresponding demand be ignored. This requires the assumption that this out-of-network pair does not travel along any segment within the Scope III network.

All three of these required categories need to be considered as demand for Scope III analysis. For trips originating in-network with in-network destinations, this is simple. Both O and D TAZs are within the network, so the OD demand remains unchanged. But what about trips having either O or D TAZs outside of the network?

The total OD matrix with dimensions 1944 x 1944 needs to be converted to a 31 x 31 matrix, so all demand is contained in the network. Demand originating in-network with a destination out-of-network needs to be modeled as completely in-network. The same applies for demand with an origin out-of-network and destination in-network. The figure below illustrates this adjustment.

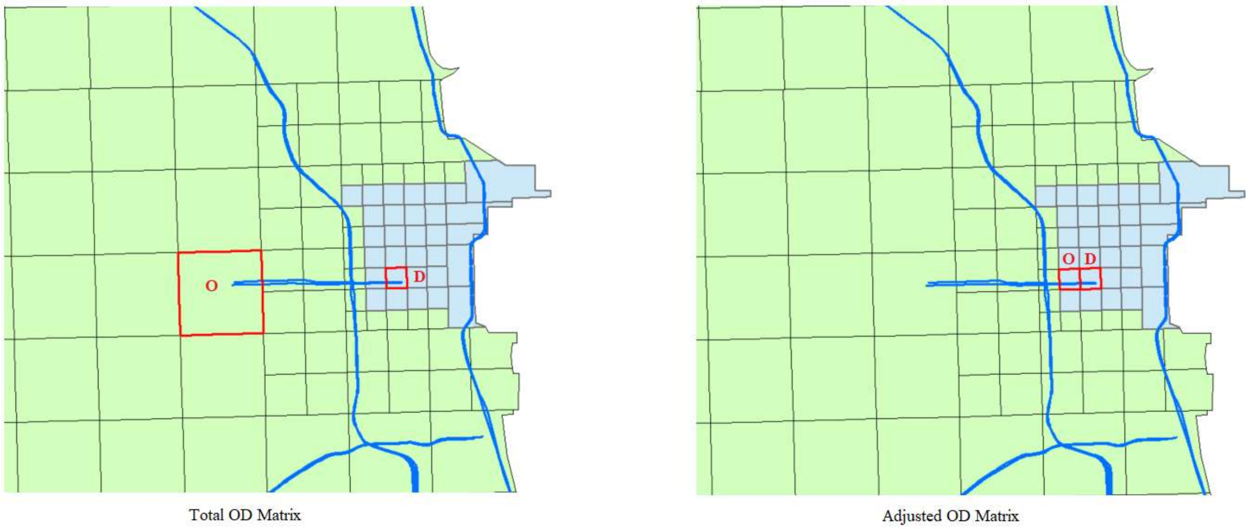

Figure 12: OD Adjustment for an out-of-network Origin

In-network TAZ are shown as blue, and out-of-network TAZ as green. The blue lines are major highways, which connect surrounding areas to the downtown area. In this case, it is assumed that the vehicle with this OD pair will travel along this highway to the destination. Only a portion of this path (shown in the adjusted matrix illustration) is within the Scope III network. When running the microsimulation, the vehicle will be introduced in the adjusted origin, keeping the same destination. Likewise, for the opposite pair (i.e. origin in-network with destination out-of-network), the same concept applies.

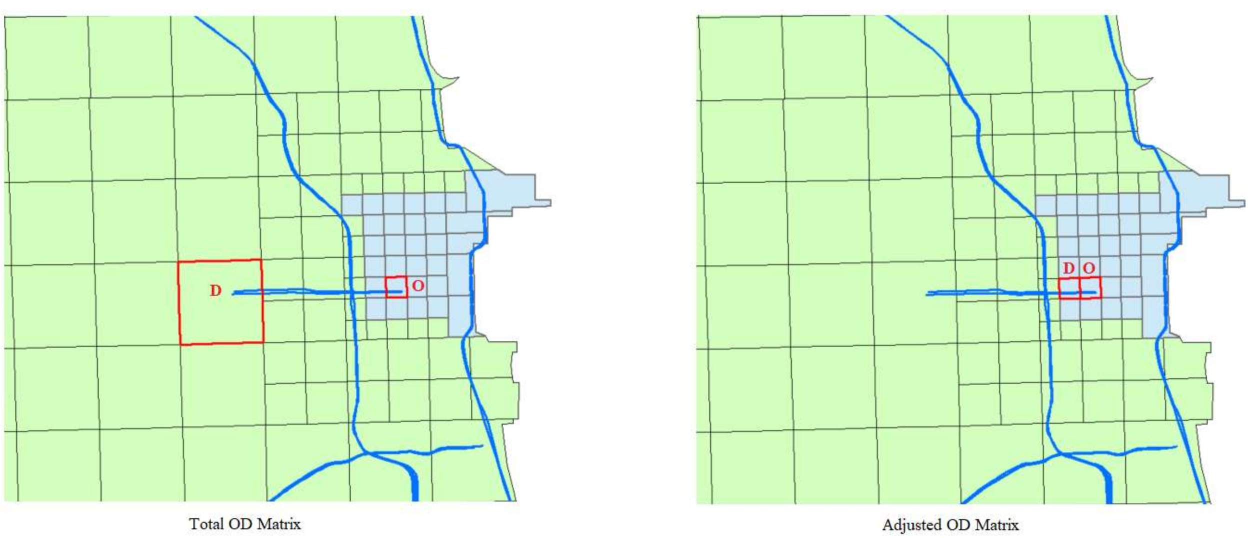

Figure 13: OD Adjustment for an out-of-network Destination

The resulting adjusted TAZ will be referred to as a *bridge*. They connect in-network to out-of-network. This term highlights that as well as not conflating with direction (i.e. the “out-to-in” bridge is the same as the “in-to-out” bridge).

The adjusted OD matrix is created when this concept is applied to all required OD pairs. For this to be done, out-of-network TAZ need to be mapped to an in-network equivalent. This needs to be done for all 1944 TAZ, since there can be network demand starting at or originating from anywhere in the region. The process of taking the total OD matrix and producing an in-network matrix is called *Regional Assignment*.

Regional Assignment starts by assigning a region to each TAZ. A TAZ’s region can either be Network, or one of five directional regions: North, Northwest, South, Southwest or West. North and South regions are relatively small and represent areas close to Lake Shore Drive. Norhwest, West, and Southwest are suburban regions sprawling away from Chicago. They are grouped by which highways would allow for travel from the region to or from downtown Chicago. A traveler originating from the Northwest region may consider taking I-90, one from the West region may take I-290, and one from the Southwest region may take I-55. This is taken into account when assig

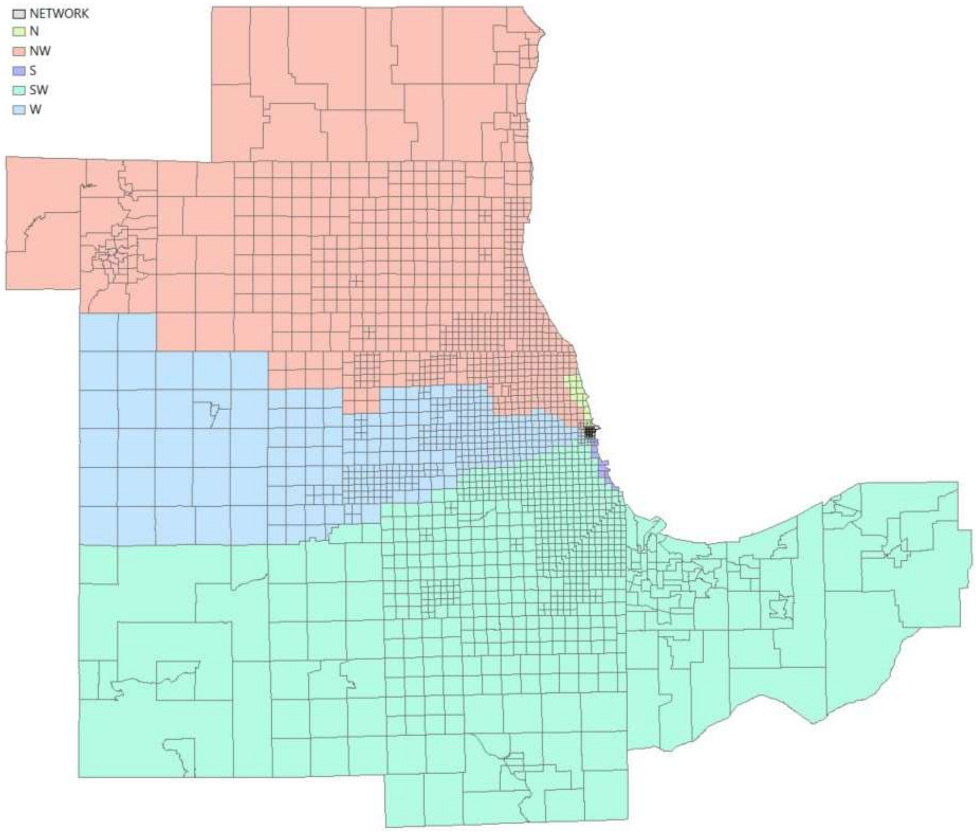

Figure 14: TAZ by Region

Each directional region contains a list of possible network bridges for each network *goal* TAZ. The *goal* TAZ is a network bridge that the out-of-network TAZ will be assigned as in the *adjusted* network. The *adjusted* TAZ is chosen randomly based on weight factors of the contained roads. Selecting the *adjusted* TAZ is performed by a simple two-step process. In fact, this method is used again in the paper so it should be defined for clarity. Whenever a TAZ or link is randomly generated, it goes through the following process to obtain a random *choice*. The choice method can be used to get a random TAZ from a selection of TAZs, or an individual link within a TAZ. This process has two steps

1. Weights of all possible bridges are calculated based on a weight variable for all links within each TAZ
2. A choice is selected randomly, conditional all weights.

Weights are defined by a weight variable calculated the same for every network edge based on CMAP data. This formula is

$$Weight = LaneCapacity \times Lanes \times Adjustment$$

Where $$Adjustment = \begin{cases} 1.5 \text{ for highway links} \\ 1.0 \text{ otherwise} \end{cases}$$

For example, if out-of-network origin needs to be mapped to an in-network equivalent, a *choice* can be made from an array of potential in-network insertion TAZs. From there, a *choice* can be made again to select a specific link within that selected TAZ. Regional Assignment is a choice selected from a TAZ array based on what region the out-of-network TAZ lies in.

The original demand data originates from CMAP conformity analysis data. Three files are used, including home-based work trips, home-based other trips, and non home-based trips. Two of these files are given in Production-Attraction (PA) format, which need to be converted to OD format. These PA volumes are converted to OD form with the following equation:

$$[\mathrm{OD}] = \frac{1}{2} * ([\mathrm{PA}] + [\mathrm{PA}]^{\mathrm{T}})$$

The Total OD Matrix . OD_{Total}, contains demand for OD pairs over the course of a day. It is the sum of home-based work trips, home-based other trips, and non-home based trips. For the hour-long analysis, we need to introduce a *k-factor* that represents the proportion of traffic over a specific hour. This can be represented as:

$$OD_{hour} = OD_{total} \times k_{hour}$$

The k_{hour} for morning peak traffic (7-9am) is 0.091. In other words, it is estimated that 9.1% of all trips occur between 7am – 8am, and another 9.1% between 8am – 9am. This number is simply an average of k-factors from the network of links from CMAP, used in Scope II analysis. Since the networks in Scope II and Scope III are similar, the same k-factor was taken.

Now that the hour demand volume for each OD pair is known, regional assignment can be performed iteratively for each individual trip for every required OD pair. Note that hourly volumes need to be rounded to the nearest integer since they represent a trip.

After regional assignment is applied, OD_{hour} is adjusted to a 31 x 31 matrix containing only in-network trips. The same total demand remains unchanged. These trips, however, are defined only by their origin and destination TAZs. Recall that TAZs are simply a collection of links within an area. For each trip, the origin and destination *links* are chosen randomly considering the same weight variable used in OD adjustment. The same choice method as explained before is used here. This time, the options are an array of links that fall within the given TAZ. Trips are now defined not only with OD TAZs, but also with OD links. All links within the network are shown in red overlaying network TAZs below.

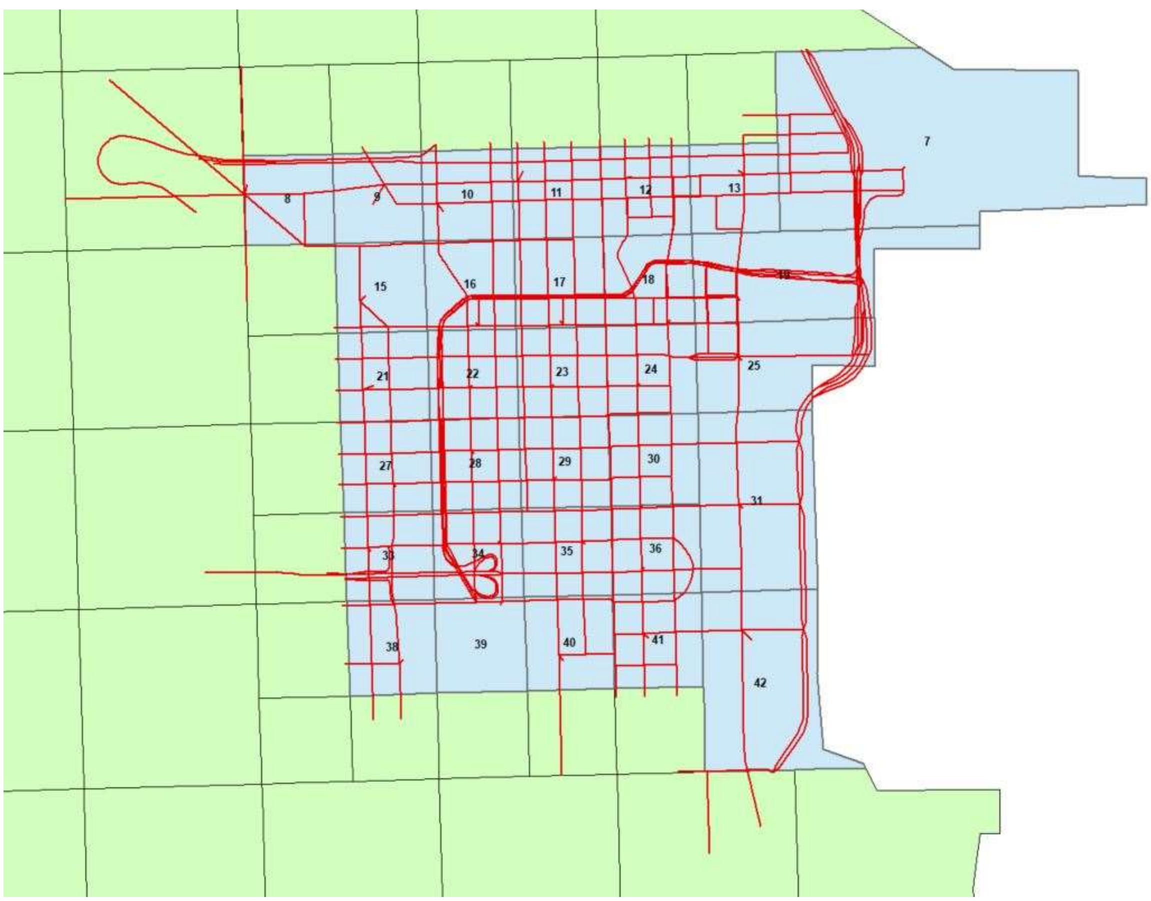

Figure 15: In-Network Links

Some links extend outside of their assigned TAZ. Trips originally from out-of-network are inserted (or have trips ending) along one of these edges. These link-defined trips are the starting point of a traffic microsimulation. The basic idea of a microsimulation is to introduce vehicles in a network and allow them to travel along their route. As more vehicles are introduced, congestion will naturally occur. If a possible route is more congested or has a longer travel time, a vehicle may decide to re-route. This is all captured within a microsimulation. When the simulation finishes, drive schedules for every vehicle within will be available. The acceleration and speed for every time step are evaluated with the previously defined NGM equation to calculate emissions.

Scope III uses *Simulation of Urban Mobility* (SUMO) for microsimulation. SUMO is developed by the German Aerospace Center (DLR). It is free, open-sourced, and offers a variety of applications useful for transportation modeling. The minimum input requirements to run a SUMO microsimulation are a *route* file as well as a *network* file. From the link-defined trips, the route file can be constructed. If re-routing is enabled in SUMO, there is no need to actively define the actual route as a list of links, and the origin and destination links are sufficient. The route file is generated through regional assignment. This process is performed outside of SUMO with a few Python libraries specifically developed for this study.

The other requirement is the *network* file. In this simulation the GIS shapefile of streets covering the entire CMAP region was clipped (as shown in Figure 15). This clipped network was passed through the SUMO application called NETCONVERT to obtain the initial SUMO-compatible network. The resulting network is not "perfect" in the sense that some manual editing was required. NETEDIT is a CAD-like interface for editing SUMO network files. It was used for tasks not able to be completed by NETCONVERT. Some of these tasks include:

- Adding traffic signals
- Adjusting junction connections
- Removing extraneous segments

Once these tasks are completed, the network is ready for operation. The desired route file can be specified along with the network file in the configuration file and ran in the SUMO environment.

Figure 16: SUMO Network

Within the *route* file, vehicle types (*vType*) are defined. There are two vTypes in Scope III: *Standard* for the conventional vehicles as well as *AV* for autonomous vehicles. By setting different values for parameters in the vType definitions, the operational behaviors of these are set.

Recall from Scope II analysis, it was assumed that required headway for standard vehicles was 2.5 times higher than headway for an autonomous vehicle. This assumption was held consistent in Scope III analysis through the vType parameter *minGap*. A vehicle's minGap is the smallest distance it must keep from the vehicle in front of them. This is the only parameter that differs between the two vTypes, and will serve as the underlying trait defining an AV for Scope III's simulation.

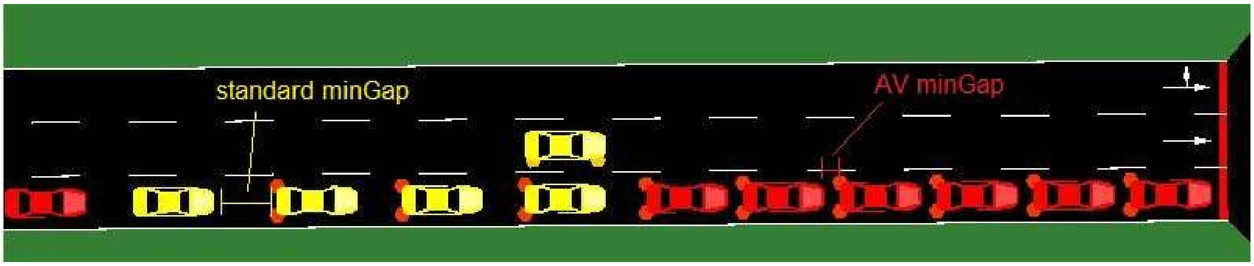

Figure 17: CV and AV minGaps

It is apparent parameter affects link capacity when visualized in SUMO. The AVs (red) towards the right take up less link space than standard vehicles (yellow) due to their lower headway (minGap) requirement.

A key difference in macroscopic and microscopic models is how vehicles are introduced to a network. In macroscopic models, a flow is assigned to a link. In microscopic models, a vehicle has a route with a start and ending link. For a vehicle in SUMO to successfully be inserted into the network, criteria need to be met:

- minGap requirements must be met. A vehicle needs *minGap + length* space at the end of its insertion edge to enter the network.
- A safe time distance must be kept from the next vehicle.

When both distance and time criteria are met, a vehicle can be inserted. If a vehicle is unable to be inserted (i.e. some criteria is not met), it is *backlogged*. SUMO attempts to insert backlogged vehicles during future simulation steps. Since all vehicles are inserted as described in the route file according to their attempted insertion time, the network initially has no volume. This is of course unrealistic when modeling a congested urban network. The Scope III simulation begins with a pre-period of rapid insertion. During this 10-minute pre-period (6:50am – 7:00am) a specified percent of the network demand is inserted as quickly as possible. When the simulation begins at 7:00am, the network has initial volume and is therefore congested. For these reasons, the simulation needs to finish completely to compare emission inventories. Ending prematurely means that not all vehicles finish their routes and the resulting emission calculation will be lower than anticipated.

A vehicle's route ends at its destination link. While vehicles are inserted at the base of a link, their route is finishes at a random location along the length of the sink link. When the vehicle reaches this position, it disappears from the network entirely.

How the vehicle selects its route between origin and destination links is performed by *automatic routing* within SUMO. Every vehicle attempts to minimize its travel time to destination. Routing travel times for individual links are known based on data from other vehicles that have previously traveled along the links. The link travel speed is an averaged weight of the previous 180 seconds. This moving average allows routing to consider the entire traffic light cycle. If vehicles were re-routed constantly without a moving average, a link's travel time may be artificially high if it is calculated during a stopped traffic signal state (i.e. vehicles are stopped at a red light). This also prevents an artificially low travel time that would result from a calculation when all vehicles along a link are traveling at maximum speed (i.e. vehicles traveling during a green light state).

4.3.1. Scope III Results

Recall that the Scope III simulation does not directly calculate emissions. When finished, drive schedule variables (speed and acceleration) are used in the NGM equation to calculate GHG emissions. AV penetration ratios tested in Scope III were 0%, 2%, 5%, 20%, 50%, and 100%. The table below shows total emissions inventories for each penetration ratio as well as the difference from the base (0%) scenario.

AV Penetration Ratio	Total CO_2 Emissions (g)	Difference from 0% scenario
0%	59844774	0%
2%	60226951	0.64%
5%	60485214	1.07%
20%	60157203	0.52%
50%	58877013	-1.62%
100%	57813852	-3.39%

Table 7: NGM Calculated CO_2 Emissions

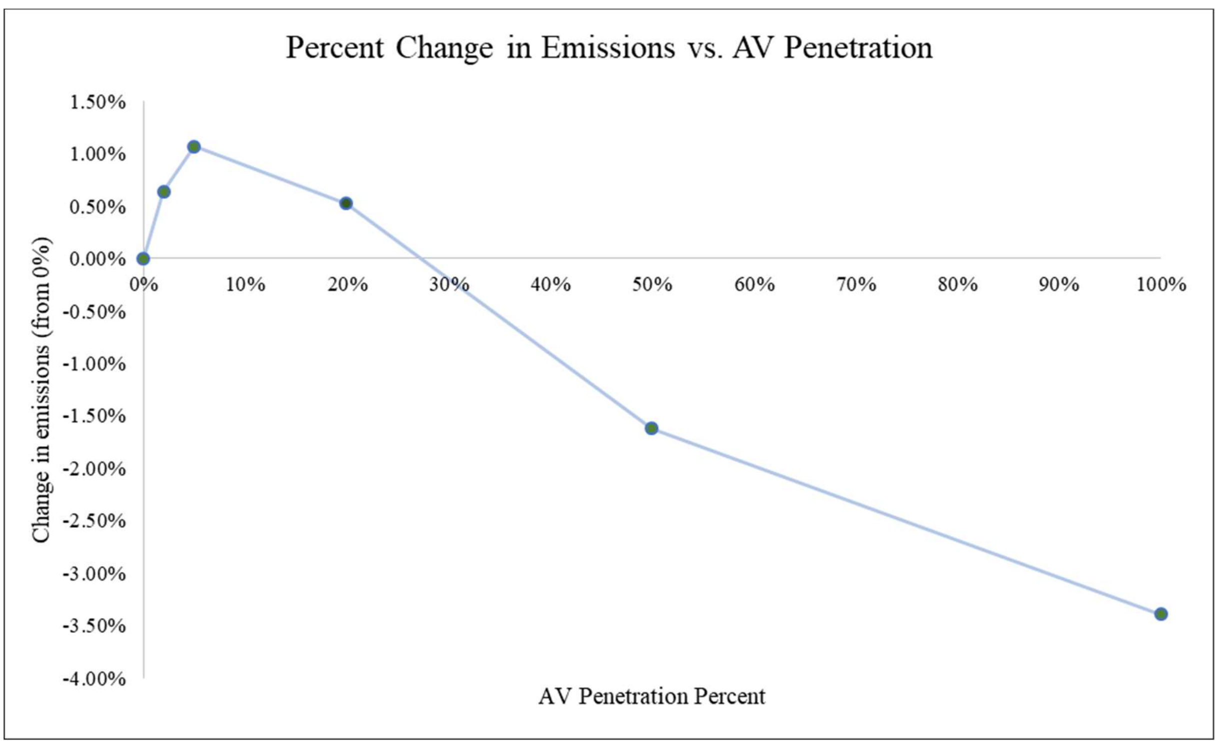

Figure 18: Emission Changes by AV Penetration

4.3.2. Microsimulation Performance

A few simulation performance metrics were tracked during runtime. These include the number of running vehicles, backlogged vehicles, and completed trips in the simulation. Time series plots are provided to analyze overall network performance.

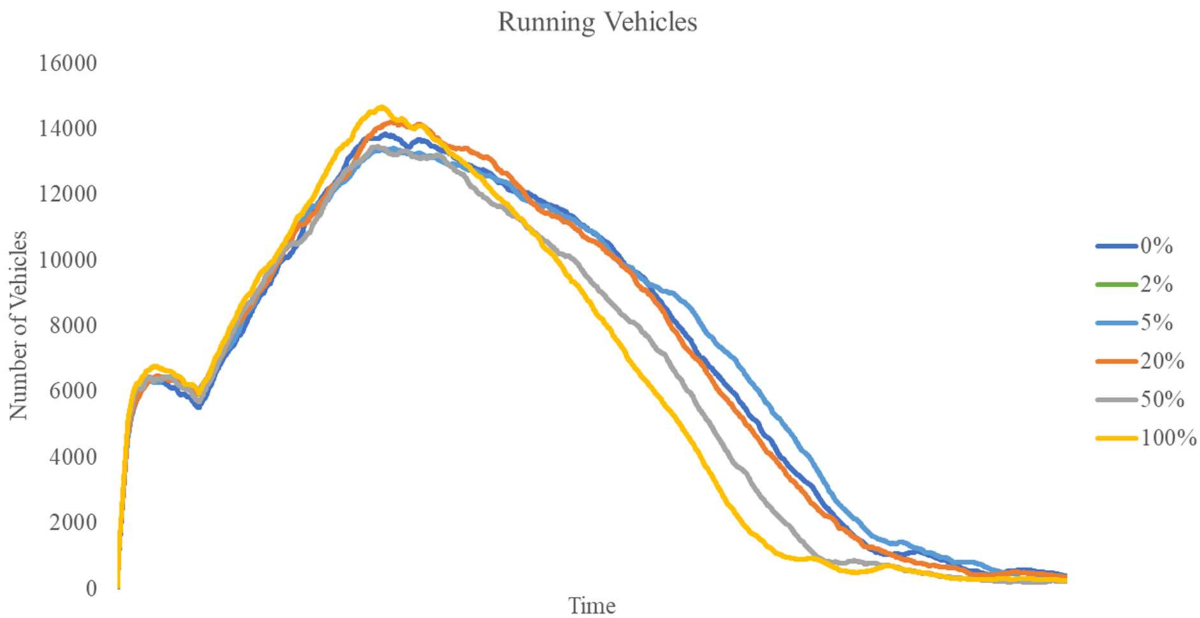

Figure 19: Running Vehicles Time Series

Simulation begins by attempting to insert a large quantity of vehicles in little time. The first peak in vehicles appears during this time period. At 7:00, the rate of insertion is adjusted to a constant rate that accommodates the rest of the vehicles. This change is clearly shown at the first minima on the time series plot. The difference in peaks by AV percentage can be interpreted in how much demand the same network can handle. Note that 100% AV simulation held the highest number of running vehicles. At 50% AV, running vehicle peak is less than all other scenarios. Both 50% and 100% scenarios have shown reduction in total emissions but appear to have different operational characteristics.

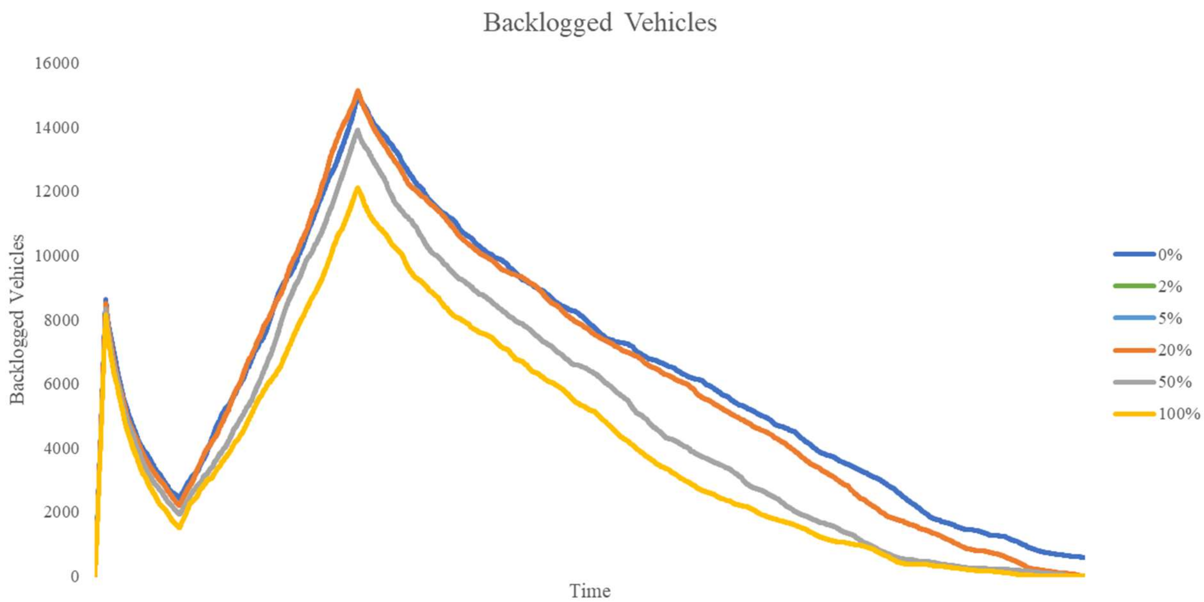

Figure 20: Backlogged Vehicles Time Series

Backlogged vehicles follow a similar trend as the number of running vehicles. The first peak is from the initial fast-as-possible insertion period. Vehicles are inserted at a much higher rate than the network physically allows, so backlog peaks. Backlogged vehicles then decrease until the simulation start time is reached. The simulation begins already congested and with a low number of backlogged vehicles. Backlogged vehicles keep the network congested well after the insertion period is completed. Scenarios with emission reduction have less backlogged vehicles than scenarios with increased emissions. Note that this metric has no direct real-world equivalent. It can loosely be interpreted as the number of vehicles *just* outside of network bounds attempting to enter the network, but held back in traffic. The *difference* in backlogged vehicles is also the number of vehicles operating in the network that could not be inserted at lower penetration scenarios (due to headway requirements).

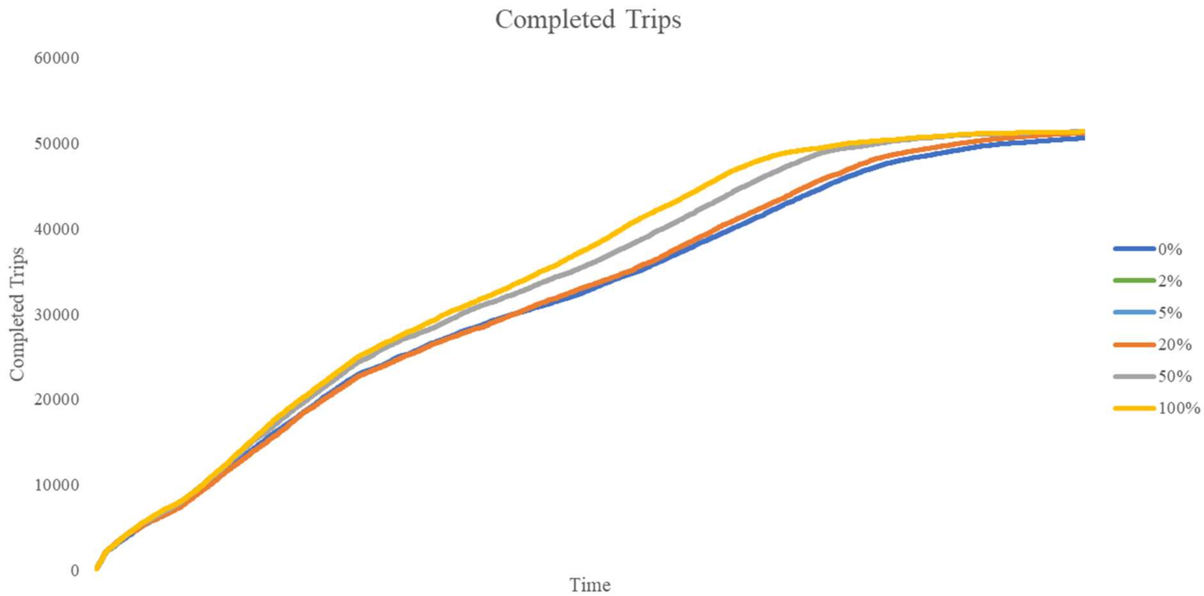

Figure 21: Completed Trips Time Series

All AV penetration scenarios have equal network demand (i.e. number of total trips). When a vehicle reaches its destination edge, its trip is completed. The same general trend is followed for all scenarios, but the higher penetration ratios (50%, 100%) consistently have a larger number of completed trips compared to other scenarios. Combining this with Figure 19 explains that as AV penetration reaches 100%, the network capacity (number of vehicles) increases while simultaneously completing trips at a faster rate. This is essentially the assumption made in Scope II, providing some level of validity.

SUMO produced aggregated link-level measurements for average speed, accumulated wait time, and link occupancy. Macroscopic results use millions of data points from the microsimulation and present them in a way easier to comprehend.

Shown below are the changes in speed with respect to the 0% AV base scenario.

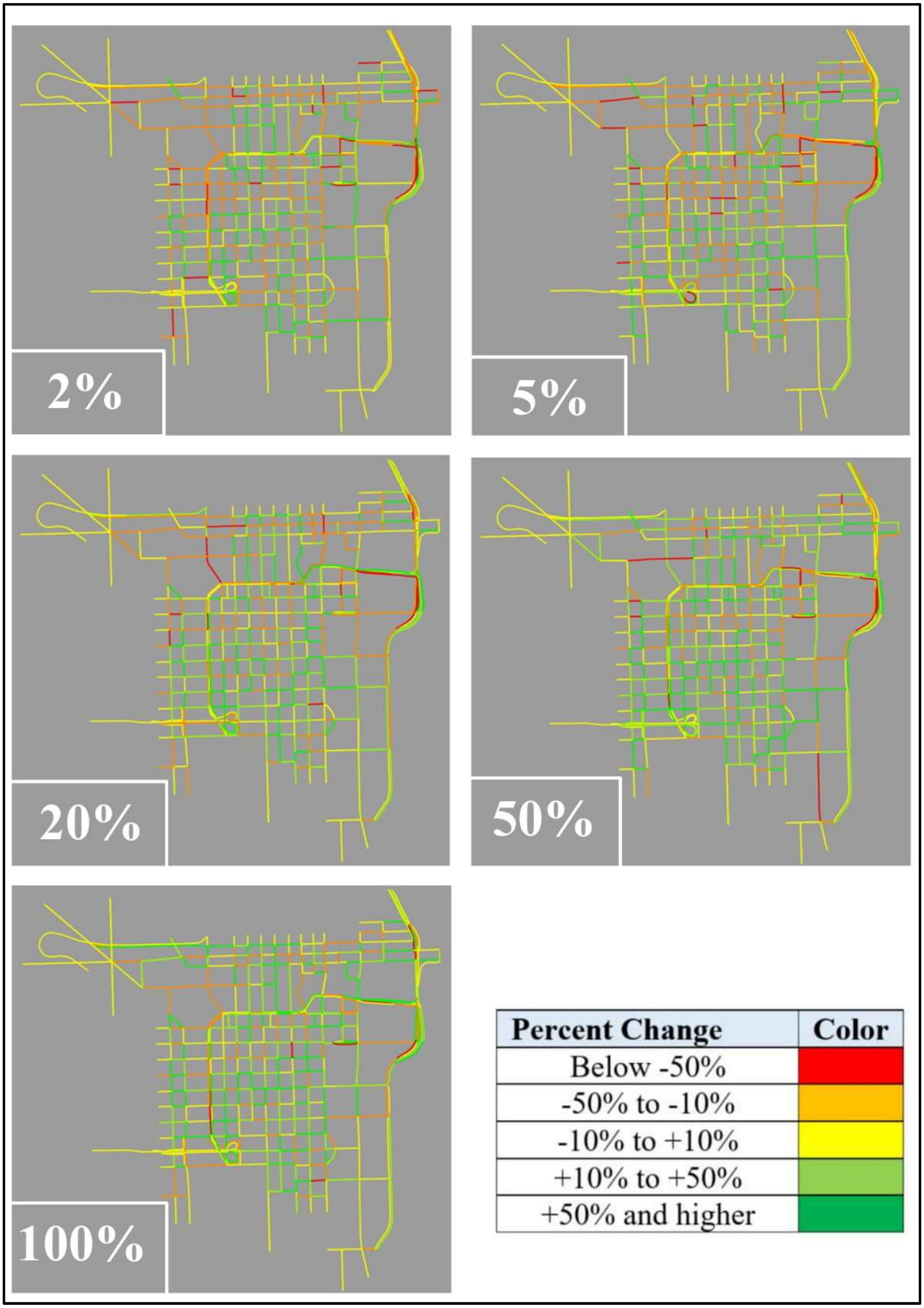

Figure 22: Link-level Speed Changes by AV

When comparing link-level average speeds, it becomes apparent that individual links do not follow the exact trends as others. At full AV penetration, there are some links that have average speeds more than 50% *below* what was measured in the base scenario. This suggests that AV benefit may vary for different infrastructure. Let's examine a few specific links.

The table shown below represents an arterial street in the Chicago network. Its relative location is highlighted below followed by average measurements for speed, wait time, occupancy.

AV Penetration	**Speed**		**Total Wait Time**		**Link Occupancy**		**Location**
	value	**change**	**value**	**change**	**value**	**change**	
0%	1.69	0%	5434.40	0%	5.70	0%	
2%	1.83	8%	8835.20	63%	9.57	68%	
5%	1.52	-10%	8294.80	53%	8.18	44%	
20%	0.83	-51%	11340.90	109%	9.71	70%	
50%	2.95	75%	3596.00	-34%	4.82	-15%	
100%	3.47	105%	2103.60	-61%	3.03	-47%	

Table 8: Arterial Street (1) Simulation Results

This arterial street's speed pattern follows the generalized results. That is, the speed is lowest at the 20% scenario then greatly improves at 50% and 100% penetration. The same applies for total (accumulated) wait time on the link. Link occupancy is defined as the portion of the link is covered by a vehicle and its required headway. Even though more vehicles can physically fit on a link as the AV penetration ratio approaches 100%, the link shows lower occupancy with increasing penetration.

AV Penetration	**Speed**		**Total Wait Time**		**Link Occupancy**		**Location**
	value	**change**	**value**	**change**	**value**	**change**	
0%	1.52	0%	12801.90	0%	20.83	0%	
2%	1.31	-14%	13014.70	2%	21.38	3%	
5%	3.18	109%	5336.60	-58%	12.48	-40%	
20%	2.21	45%	6727.60	-47%	12.10	-42%	
50%	1.27	-16%	15422.40	20%	24.05	15%	
100%	0.90	-41%	18443.00	44%	24.70	19%	

Table 9: Arterial Street (2) Simulation Results

Results for this selected arterial link are not consistent with the previous one. In fact, speed, wait time, and occupancy increased for the 50% and 100% simulations. Arterial streets in the Chicago network are grid-like and almost identical in length. This allows for a vehicle to have multiple options when navigating the network towards its destination. Recall that routing is performed by individual vehicles minimizing travel time and that no equilibrium is equated. Vehicles are drawn to links that have a lower speed in comparison to alternatives. With the assumption that all vehicles have a re-routing device, the links with shorter travel times induce additional traffic, effectively decreasing future travel time. A cycle of peaks and troughs in link travel time is natural for the arterial grid in Chicago's network. This may be dissipated by applying a noise to link travel times (an option available in SUMO) but was not considered in this study. Alternatively, automatic routing could be disabled. This would imply that all vehicles know their route and are not willing to change it, an assumption not applicable when modeling a real network.

Lake Shore Drive is a highway running north and south in close proximity to Chicago's Loop. This table describes a northbound portion of Lake Shore Drive.

AV Penetration	**Speed**		**Total wait time**		**Link Occupancy**		**Location**
	value	**change**	**value**	**change**	**value**	**change**	
0%	3.91	0%	62662.60	0%	14.62	0%	
2%	3.99	2%	67604.60	8%	14.75	1%	
5%	3.78	-3%	65076.00	4%	14.89	2%	
20%	3.16	-19%	76328.00	22%	19.87	36%	
50%	5.06	29%	55368.50	-12%	13.96	-5%	
100%	4.83	24%	33325.10	-47%	11.18	-24%	

Table 10: Lake Shore Drive (Northbound) Simulation Results

Speed is increased, wait time is decreased, and link occupancy is decreased at high AV penetration. In comparison, results from a southbound Lake Shore Drive link, are shown below.

AV Penetration	Speed		Total Wait Time		Link Occupancy		Location
	value	change	value	change	value	change	
0%	11.29	0%	3096.90	0%	3.22	0%	
2%	9.36	-17%	5895.00	90%	3.29	2%	
5%	7.35	-35%	17752.90	473%	4.83	50%	
20%	8.32	-26%	7401.30	139%	4.43	38%	
50%	11.21	-1%	6268.70	102%	3.24	1%	
100%	18.50	64%	507.00	-84%	1.97	-39%	

Table 11: Lake Shore Drive (Southbound) Simulation Results

Performance for this link peaks at 100%, but bottoms at 5% when considering speed and wait time. From this link-specific dataset, we can only conclude that the penetration ratio effects these performance metrics. The peak (or worst) performance may occur at different penetrations depending on link type (i.e. arterial or highway). Any conclusion drawn from a select sample of possible ratios should be taken cautiously. To fully understand the effect of penetration ratio, *many* more data points would be required.

5. Conclusions

Results by Scope are shown altogether below.

	TEC (kJ)	CO_2 (g)
EPA UDDS	101,589	7,301
AV	93,473	6,718
% change (from UDDS)	-8.0%	-8.0%

Table 4: Drive Schedule emission comparison

Time Period	Description	Emission Inventory	
		TEC (kJ)	CO_2 (g)
Peak (7-9am)	CV	281,003,200	20,194,766
	AV w/o drag reduction	240,335,920 (-14.5%)	17,272,138 (-14.5%)
	AV w/ drag reduction	240,335,920 (-14.5%)	17,272,138 (-14.5%)
Off-Peak (10am-2pm)	CV	166,279,472	11,949,950
	AV w/o drag reduction	157,776,912 (-5.1%)	11,388,898 (-4.7%)
	AV w/ drag reduction	157,776,912 (-5.1%)	11,388,898 (-4.7%)

Table 5: Scope II emission comparison

AV Penetration Ratio	Total CO_2 Emissions (g)	Difference from 0% scenario
0%	59844774	0%
2%	60226951	0.64%
5%	60485214	1.07%
20%	60157203	0.52%
50%	58877013	-1.62%
100%	57813852	-3.39%

Table 7: NGM Calculated CO_2 Emissions

Let's first examine the two extreme cases: a scenario with 0% AV and another with 100% AV. According to all three scopes in this study, we can expect an emission reduction. Scopes I, II, and III quantify this emission reduction as 8%, 5-15% (depending on time of day), and 3.4%. This is not far off from the 5-7% reduction estimate from Kesting et al (2008), which specifically examined adaptive cruise control. It would compare best with Scope I, an individual drive schedule comparison. The AV drive schedule may be assumed to have features that aided in smoothing, whereas the UDDS did not.

In a macroscopic traffic flow model (Scope II), it became apparent that the benefit of AVs varies by time of day due to differences in demand. In future studies, it may be beneficial to aggregate both AV penetration ratios and time-of-day periods to create a matrix of emission reduction provided by AVs. Scope II also found that MOVES sensitivity is not fine enough to capture AV platooning effects, and other methods of measurement would be required for such an analysis.

Scope III yielded the most interesting results. The 100% AV reduction was 3.4%, aligning with results in Scopes I and II. This analysis was the first to introduce a varying level of AV penetration (2%, 5%, 20%, and 50% scenarios). One would expect emissions reductions to show a greater benefit as this penetration increases. The results at lower penetrations are counterintuitive to this assumption. Results from 2 – 20% actually show an *increase* in total emissions. It appears that emission reduction does not begin to occur until between 20-50% AV penetration. The trend that this range follows is not clear until more data points (i.e. additional AV percentage scenarios) are available for statistical analysis. Scope III provides a new perspective on how the benefits of AVs scale with their market penetration. This also sparks the need to understand the phenomenon occurring here. Why do total emissions increase with a low number of autonomous vehicles?

When combining results from all scopes in this study, a few general conclusions can be drawn.

- AV technology allows for emission reduction through driving behavior

- Emission reduction from AVs is greater when traffic demand is higher

- Penetration ratio is a critical factor to consider. Emission reduction is highest approaching a completely autonomous network, and a low penetration percentage may result in higher overall emissions.

These generalized findings are arguably more important than obtaining a quantity to define autonomous vehicle emission reduction. Any estimate *is* an estimate. With AVs still in their infancy, any attempt to model their behavior will result in error. This error can come from input parameter assumptions, aggregated emission assignment (as performed in MOVES), or even a simple programming error. By normalizing the base (0%) scenario and measuring all results with respect to it, different scopes can have the same unit-less metric. It is important to understand that there are several perspectives to take when evaluating autonomous vehicle potential. Congestion-based environmental impact is only one perspective, and it largely ignores others such as safety, legal, or economic issues surrounding AVs. An interdisciplinary approach will be required to fully evaluate autonomous vehicle benefit.

6. References

1. Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). *Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions*. Transportation Research Part A: Policy and Practice.

2. Zachariah, J., Gao, J., Kornhauser, A., & Mufti, T. (2014). *Uncongested Mobility for All: A Proposal for an Area Wide Autonomous Taxi System in New Jersey*. In Transportation Research Board 93rd Annual Meeting.

3. Zhang, R., Spieser, K., Frazzoli, E., & Pavone, M. (2015, July). *Models, algorithms, and evaluation for autonomous mobility-on-demand systems*. American Control Conference (ACC), 2015. IEEE.

4. Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). *User preferences regarding autonomous vehicles*. Transportation Research Part C: Emerging Technologies.

5. Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). *Autonomous vehicles: The next jump in accessibilities?.* Research in Transportation Economics.

6. Fagnant, D. J., & Kockelman, K. (2015). *Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations*. Transportation Research Part A: Policy and Practice.

7. Kockelman, K., Loftus-Otway, L., Stewart, D., Nichols, A., Wagner, W., Li, J., & Liu, J. (2016). *Best practices guidebook for preparing Texas for connected and automated vehicles*. (No. 0-6849-P1).

8. Brown, A., Gonder, J., & Repac, B. (2014). *An analysis of possible energy impacts of automated vehicle. In Road vehicle automation*. Springer International Publishing.

9. Wadud, Z., MacKenzie, D., & Leiby, P. (2016). *Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles*. Transportation Research Part A: Policy and Practice.

10. Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). *Autonomous vehicle technology: A guide for policymakers. Rand Corporation*.

11. Tsugawa, S. (2014). *Results and issues of an automated truck platoon within the energy ITS project*. In Intelligent Vehicles Symposium Proceedings, 2014 IEEE. IEEE

12. Medium. (2017). *We're Building an Open Source Self-Driving Car*. Udacity Inc.

13. Bhavsar, P., He, Y., Chowdhury, M., Fries, R., & Shealy, A. (2014*). Energy consumption reduction strategies for plug-in hybrid electric vehicles with connected vehicle technology in urban areas*. Transportation Research Record: Journal of the

Transportation Research Board.

14. Wu, G., Boriboonsomsin, K., Xia, H., & Barth, M. (2014). *Supplementary benefits from partial vehicle automation in an ecoapproach and departure application at signalized intersections*. Transportation Research Record: Journal of the Transportation Research Board.

15. Rajamani, R., & Shladover, S. E. (2001). *An experimental comparative study of autonomous and co-operative vehicle-follower control systems*. Transportation Research Part C: Emerging Technologies, 9(1).

16. Kesting, A., Treiber, M., Schönhof, M., & Helbing, D. (2008). *Adaptive cruise control design for active congestion avoidance*. Transportation Research Part C: Emerging Technologies, 16(6).

17. Grumert, E., Ma, X., & Tapani, A. (2015). *Analysis of a cooperative variable speed limit system using microscopic traffic simulation*. Transportation research part C: emerging technologies.

18. Nowakowski, C., Shladover, S. E., Lu, X. Y., Thompson, D., & Kailas, A. (2015). *Cooperative adaptive cruise control (CACC) for truck platooning: Operational concept alternatives*.

19. Deng, Q. (2016). *Heavy-Duty Vehicle Platooning: Modeling and Analysis* (Doctoral dissertation, KTH Royal Institute of Technology).

20. Al Alam, A., Gattami, A., & Johansson, K. H. (2010, September). *An experimental study on the fuel reduction potential of heavy duty vehicle platooning*. In Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference. IEEE.

21. Warila, J., Nam, E., Landman, L., Kahan, A. (2011). *Light-Duty Exhaust Emission Rates in MOVES 2010*. US EPA.

22. CMAP. (2014). *Travel Model Documentation*.

23. Zabat, M., Stabile, N., Farascaroli, S., & Browand, F. (1995). *The aerodynamic performance of platoons: A final report. California Partners for Advanced Transit and Highways.* PATH.

24. Ahlawat, R., Bredenbeck, J., Ichige, T. *Estimation of Road Load Parameters via On-road Vehicle Testing*, Tire Technology Expo, 2013, Cologne

25. Environmental Protection Agency. (2015). *Urban Dynamometer Drive Schedule*. https://www.epa.gov/sites/production/files/2015-10/uddscol.txt

26. Patankar, N.A., Lin, J., Patankar, T.N. (2017). *Mileage Efficiency-based Approach to Quantify Energy Consumption and Carbon Emissions of Automotive Vehicles*, 96th Transportation Research Board Annual Meeting, Washington D.C., January 8-12, 2017.

27. Patankar, N.A., Lin, J., Patankar, T.N., (under review). *Mileage Efficiency-based Approach to Quantify Energy Consumption and Carbon Emissions of Automotive Vehicles*, Transportation Research Part D: Transportation and Environment.

28. Barth, M., Boriboonsomsin, K. (2010). *Real-world Carbon Dioxide Impacts of Traffic Congestion*. University of California Transportation Center report no. UCTC-FR-2010-11.

29. Bagloee, S.A. Tavana, M., Asadi, M., Oliver, T. *Autonomous vehicles: challenges, opportunities, and future implications for transportation policies*.

30. Fagnant, D. J., & Kockelman, K. (2014). *The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios*. Transportation Research Part C: Emerging Technologies.

31. Brownell, C.K. (2013). *Shared Autonomous Taxi Networks: An Analysis of Transportation Demand in NJ and a 21st Century Solution for Congestion*. Princeton University.

32. Litman, T. (2018). *Autonomous Vehicle Implementation Predictions, Implications for Transport Planning*. Victoria Transport Policy Institute.

33. National Highway Traffic Safety Administration. (2008). *National Motor Vehicle Crash Causation Survey*. U.S. Department of Transportation, Report DOT HS 811 059.

34. National Highway Traffic Safety Administration. (2012). *Fatal Analysis Reporting System. U.S. Department of Transportation*.

35. Federal Highway Administration. (2016). *Effects of Next-Generation Vehicles on Travel Demand & Highway Capacity*. Fehr and Peers.

36. Smith, B.W. (2013). *Managing autonomous transportation demand*. Santa Clara Law Rev. 52, 1413.ith 2013)

37. Society of Automotive Engineers. (2014). *Levels of Driving Automation Are Defined In New SAE International Standard J3016*, Society of Automotive Engineers.

38. Chicago Metropolitan Agency for Planning. (2017). *Air Quality Conformity Analysis*.

39. German Aerospace Center. (2012). *Recent Development and Applications of SUMO – Simulation of Urban Mobility*.