Quantifying the Mobility and Energy Benefits of Automated Mobility Districts Using Microscopic Traffic Simulation

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ABSTRACT

Connected and automated vehicles (CAVs) are increasingly being discussed as the basis for shared mobility and on-demand services to replace privately owned vehicles. The rapid growth of Transportation Networking Companies (TNCs) and their increasing investment in automated vehicle (AV) technologies attests to this. Combining the concepts of TNCs, with AV and on-demand transit services, the term "automated mobility district" (AMD) describes a district-scale implementation of CAV technology to realize the full benefits of a shared, fully automated vehicle service within a confined region. This research effort provides a modeling architecture for AMDs along with a preliminary analysis to quantify the mobility and energy benefits of such districts. A customized open-source microscopic mobility simulation toolkit built on the Simulation of Urban Mobility (SUMO) platform is implemented for AMD performance evaluation. Experimental scenarios are tested with different combinations of operational variables to provide insights on energy and mobility gains that can be realized in AMDs.

INTRODUCTION

Major disruptive technologies that are set to redefine the way in which people view travel include connected and automated vehicles (CAVs), and shared mobility made possible through transportation networking companies (TNCs) enabled by smartphone applications. Automated vehicles (AVs) will change the way in which a driver interacts with a vehicle and increase productivity during travel. Shared mobility, on the other hand, brings economic and system efficiencies. Economic efficiencies may be realized by less vehicle ownership and more vehicle "usership" (where one vehicle is shared by multiple persons/families as and when the need arises). System efficiencies will be manifested through lesser vehicle miles traveled on the road, due to the sharing of a vehicle by multiple passengers for a single trip. To maximize the gains in personal productivity, economic, and system efficiencies, automation and shared mobility should go hand in hand, rather than as separate technological developments. Many companies are already exploring avenues for shared automated mobility as a way of the future (Waymo, 2017; Afshar, 2017). Along these lines, a concept called automated mobility districts (AMDs) has emerged which describes a district-scale implementation of CAV technology to realize the full benefits of an AV-shared-mobility service within a confined geographic region or district. In an AMD, autonomous fleets of shuttles (electric or gasoline) serve the majority of the mobility needs of people in the district. Personal vehicle(s) use within the district may be discouraged through parking availability and pricing, or prohibited by disallowing physical access by private vehicles, such as recreational parks and some university campuses. Recently, Young et al. (Young et al., 2017) outlined a fundamental modeling framework for AMDs along with a comprehensive summary of related work. Figure 1 depicts the basic concept and the modeling structure of an AMD.

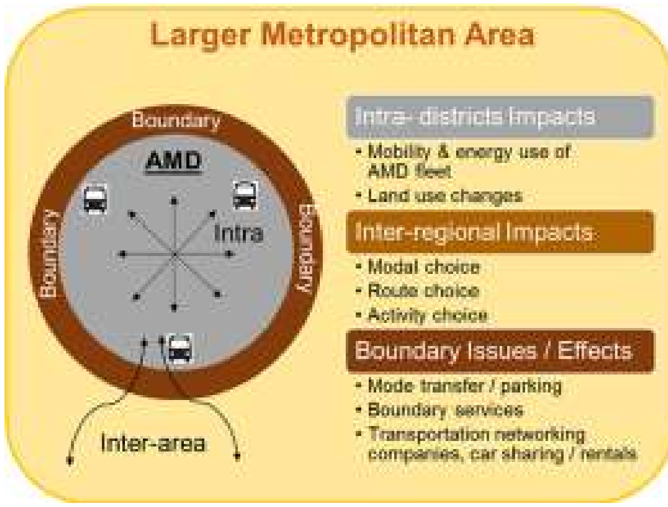


Figure 1. Sketch of an automated mobility district (AMD) (Young et al., 2017).

The concept of having automated mobility in dense activity centers is gaining much attention in the context of smart cities. Bill Gates recently acquired land in Arizona to develop a smart city and one of the facets of this smart city is transportation through AVs (Buono, 2017). In the U.S., the Federal Highway Administration (FHWA) has recently announced funding for the first-ever deployment of automated taxi shuttles in three neighborhoods in Greenville, South Carolina (FHWA, 2017). Many automated shuttle manufacturers are conducting early-stage demos to test the commercial viability of on-demand automated shuttle services to complement as well as augment traditional transit services (Bo-gyung, 2017; Hawkins, 2017).

From a historical perspective, systems such as personal rapid transit (PRT), automated transit networks (ATN), or group rapid transit (GRT) may be synonymous to the mobility service delivery concept of an AMD, it should be noted that AMDs do not require additional infrastructure (such as separate lanes, or elevated guideways, etc.,) for operation. In an AMD, automated fleets of electric shuttles can be deployed on existing roadways to serve the passengers "on-demand." This not only saves capital costs (avoiding guideway construction) but also provides users with a door-to-door service which transit systems such as PRT, ATN, and GRT fail to provide. With low-speed automated electric shuttle demonstrations conducted in several urban environments across the U.S., and policy movements in cities to reduce vehicle speed ("twenty is plenty") to return the urban street to pedestrians, viable deployment paths are emerging for the fledgling AV technology to provide service in attraction-dense districts. AMDs are not unlike areas termed as "*special generators*" in existing transportation demand models (TDMs). Areas such as airports, large university campuses, and central business districts (CBDs) frequently have their own sub-models to reflect their unique characteristics. The AMD modeling effort, termed the AMD toolkit, provides a special generator sub-model to be exercised within existing TDM frameworks.

This study is motivated by the necessity for a flexible and easy-adopt methodology and toolkit to quantify the mobility and energy benefits anticipated from AMDs, which can be considered as shared AVs (SAVs) deployed in a district-scale. While there have been a few research efforts that looked at the mobility benefits of SAVs (Fagnant et al., 2015; Zhang et al., 2015), to the best knowledge of the authors, no research has been done on quantifying the energy benefits of AMDs. To accomplish this, an open source tool was developed utilizing both the Simulation of Urban Mobility (SUMO) and the Future Automotive Systems Technology Simulator (FASTSim). SUMO (Krajzewicz et al., 2012) is a microscopic and continuous road traffic simulation package to quantify the mobility benefits of an AMD. FASTSim (Brooker et al., 2015) is an energy analysis tool to quantify the energy expenditure of vehicles given highly granular (second-by-second) trajectory information combined with vehicle operating parameters. Utilizing this AMD toolkit, this research aims to test various operational configurations of AMDs (fixed route, on-demand, mixed services), and develop performance metrics for AMDs focusing on its mobility and energy benefits at the system level.

While the larger research theme here is to develop an AMD modeling and simulation toolkit informed by real-world AMD deployments, such as the one in the Greenville, SC, this paper presents scenario-based analyses to quantify the energy impacts of an AMD implementation based on a reasonable set of assumptions. Travel demand (trips between different origins and destinations) is expected to be defined external to the toolkit, and the toolkit will simulate the travel for various operational and market penetration scenarios of automated shuttles in a small network in order to quantify the mobility and energy benefits of an AMD. The toolkit is flexible, allowing an analyst to experiment with distinct sets of assumptions. In this paper, only travel within an AMD is modeled to quantify the intra-district impacts of an AMD. Future research efforts will embed the AMD into a region model as a special generator and focus on travel between and AMD and the rest of the region, and on travel between multiple AMDs in a region to evoke to the inter-regional impacts.

LITERATURE REVIEW

To date, a few studies evaluated the benefits of using the autonomous vehicle (AV) for on-demand services based on simulation tools. Fagnant and Kockelman (Fagnant and Kockelman, 2015, 2016) assessed the mobility and environmental benefits of shared autonomous vehicles (SAVs) by modeling the movement of travelers in a grid-based urban area using an agent-based simulation model. The International Transport Forum (International Transport Forum, 2015) explored potential impacts resulting from the deployment of a shared and fully AV fleet by simulating the interaction of travelers, fleet, and dispatchers in the city of Lisbon, Portugal. Zhang et al. (Zhang et al., 2015) included a ridesharing component in an agent-based model to investigate the performance and potential benefits of a SAV system. Boesch et al. (Boesch et al., 2016) researched on the relationship between AV fleet size and travel demand in Zurich, Switzerland. Dia and Farid (Dia and Farid, 2017) designed and applied an agent-based simulation model on a small road network in Melbourne, Australia to understand the travel demand under different scenarios of autonomous on-demand shared mobility. Chen et al. (Chen et al., 2016) developed an agent-based simulation environment to examine the operation of shared autonomous electric vehicles (SAEVs) under scenarios with different vehicle ranges and charging infrastructures. The focus of the majority of the studies in SAV literature so far has been on quantifying the mobility impacts of advanced vehicle technologies. There is limited literature, if any on quantifying the energy impacts of SAVs, much less in the context of district-scale deployments, such as building blocks that impact regional travel.

There are mainly two types of methods that can be used to conduct an energy analysis of vehicle systems. Statistical modeling is one approach, which tries to establish quantitative relationships between different parameters (such as vehicle attributes, average speed) and vehicle energy consumption (Chen et al., 2017; Rakha et al., 2012). For this approach, the predicting parameters are usually at the aggregate level, such as trip average speed, % of time in idling, etc. Another widely adopted approach is that of a physical movement-based powertrain simulation model. This type of model takes vehicular movements as input (at the granularity of a second) and tries to estimate energy demand for time-dependent vehicle movements based on physical theories and transmission efficiency assumptions. There are several energy estimation models that use the second approach for energy analysis (FASTSim, Autonomie, etc.). These models usually take second-by-second vehicle speed profiles and estimate the fuel consumption at the vehicular level. A vehicle-specific, power-based approach along with modal characteristics is more common, such as VT-Micro (Rakha et al., 2004), Comprehensive modal emission model (CMEM) (Scora and Barth, 2006), and the Environmental Protection Agency's (EPA's) MOtor Vehcile Emission Simulator (MOVES) (EPA, 2017). It is often the choice of the analyst, based on the level of resolution needed of the energy impact that is required, that determines the choice of the emissions/energy estimate tool. This study adopts the powertrain simulation model approach as the traffic microsimulation model is able to provide second-by-second vehicle speed profiles.

MODEL DESCRIPTION

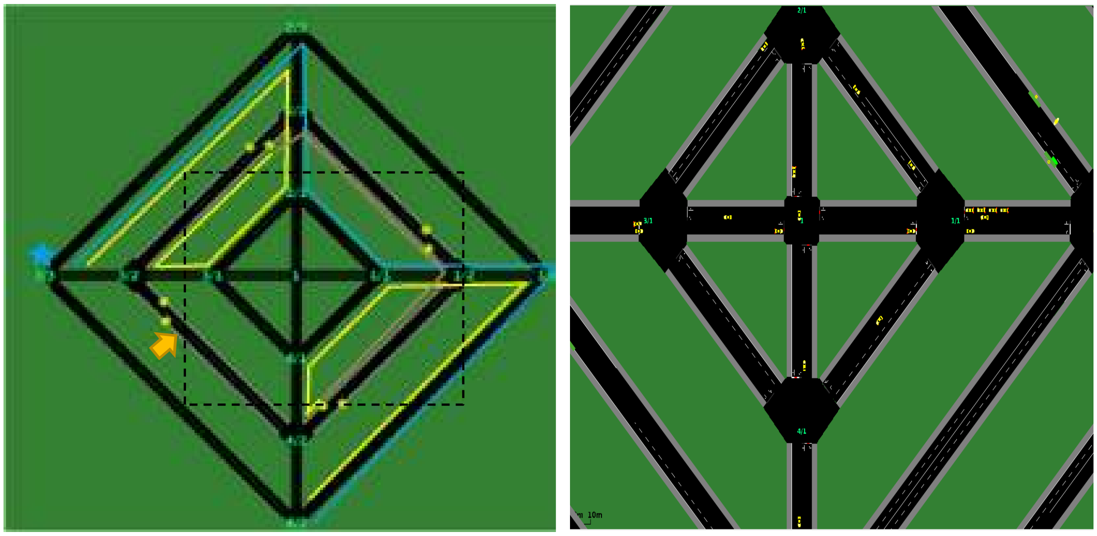
The proposed automated mobility district (AMD) modeling and simulation toolkit builds on the Simulation of Urban Mobility (SUMO)—a microscopic traffic simulation suite, and integrates the Future Automotive Systems Technology Simulator FASTSim, a powertrain energy economy simulation tool. In tandem, the toolkit is able to provide the AMD's fuel/energy and mobility benefits analysis for designated impacts of AMDs under various travel demand scenarios.

SUMO (Krajzewicz et al., 2012) is an open-source, microscopic and multimodal traffic simulation suite. SUMO can be customized with specialty modules to control the network simulation of vehicles. SUMO has been used in several projects worldwide to answer research questions, such as evaluating the performance of traffic lights, vehicle route choice, traffic forecasts, and vehicular communication. Bjärkvik et al. (Bjärkvik et al., 2017) used SUMO to simulate the Drive Me test road traffic condition in Gothenburg, Sweden. Tran Ngoc Nha (Tran Ngoc Nha et al., 2012) adopted SUMO to conduct a comparative study of vehicle routing algorithms for route planning in smart cities. The SUMO simulation platform implicitly provides microscopic and multimodal traffic simulation for vehicles, pedestrians and public transport, and can be extended to additional modes. The multimodal microscopic traffic simulation and simulation interaction capability of SUMO are suitable for implementing the advanced travel models and traffic behaviors for shared mobility, on-demand AV service, which are the pivotal characteristics of AMDs. The detailed second-by-second vehicle traces (speed profiles or driving cycles) provided by SUMO feed the FASTSim to evaluate and compute the vehicle energy and environmental metrics.

Network setup in SUMO

A hypothetical network in SUMO with 13 nodes and 48 links is shown in Figure 2 (a). The network is generated using the *netgenerate* module from SUMO software. The nodes represent the junctions of the road network, and the links represent the roadways between the junctions. In SUMO, a link is referred to as an edge. Each edge in the network is directional and has two lanes.

Automated electric shuttles (AESs) operate on the middle loop (shown with an arrow in Figure 2 [a]) on the network. Each edge in the circuit has a sidewalk lane (shown using grey lanes in Figure 2 [b]) for pedestrians and has an AES stop (denoted as little yellow dots on the middle loop of the network). The number at each junction stands for the junction ID. In Figure 2 (a), lines with different colors are shown to depict how a trip from the same origin (junction "3/3") to same destination (junction "4/3") can be undertaken using different modes. The blue line indicates the car mode, pedestrian paths are depicted using yellow lines, while AES mode is represented by the orange lines. While the car mode from 3/3 to 4/3 involves no transfers (indicated by the blue line), the AES trip (as it is currently modeled) involves three steps: i) walking to a stop (from junction 3/3) to board the AES, ii) travel in the AES, alight in the destination AES stop (orange line in the network) and iii) then walk to the final destination (junction 4/3). In the first iteration of the SUMO simulation, the AES mode is coded as operating on a fixed route. Efforts are underway to relax this assumption, allowing the AES to pick up and drop off passengers anywhere in the network.



(a) (b)

Figure 2. A hypothetic SUMO network (a) and signals (b).

Three traffic signals are assigned at intersections “1,” “4/1,” and “1/1” in the network as shown in Figure 2 (b) (an inset of Figure 2 [a]) and their timing configurations are set to defaults provided by SUMO.

Four AES vehicles are running “on-demand” inside the circuit. This means an AES will be dispatched to pick up a passenger when a trip request is made by the passenger (analogous to most elevator controls). Once an AES is dispatched, it will pick up and drop off the passenger at the designated AES stop nearest the traveler’s destination. The AES will then wait at that destination stop until another request is made for pickup by another traveler. Two AESs operate in the clockwise direction of the loop, while the other two serve the demand in the counter-clockwise direction. In this study, the AES seat capacity is one, which means each AES can only take one passenger at a time.

For the hypothetical network, the initial simulation is for demand for 300 trips distributed across the 13 origin-destination (OD) pairs. Within this district simulation, all ODs are within feasible walkable distances, and the walk mode is for door-to-door trip completion. The choice of travel modes set encompasses 1) passenger car, 2) AES, 3) walking. Traffic demand is distributed according to a bimodal distribution reflecting a morning and afternoon peak hour during a typical day.

Fixed-route on-demand AES service logic

The fixed-route on-demand AES service logic is comprised of three elements: 1) passenger, 2) AES, and 3) system controller. The service workflow is illustrated in Figure 3. The passengers are the pedestrians who need AES service. Each passenger has their trip plans (origin, destination, departure time). As previously described, there are four AES vehicles serving the fixed-route, on-demand service, two in each direction (clockwise and counter-clockwise). When there is no ride request, AES parks in an AES pickup zone, referred to as a stop, and waits for the ride request. The system controller monitors and controls the whole AES service system, serving as a “brain” to dispatch the appropriate AES and compute its route.

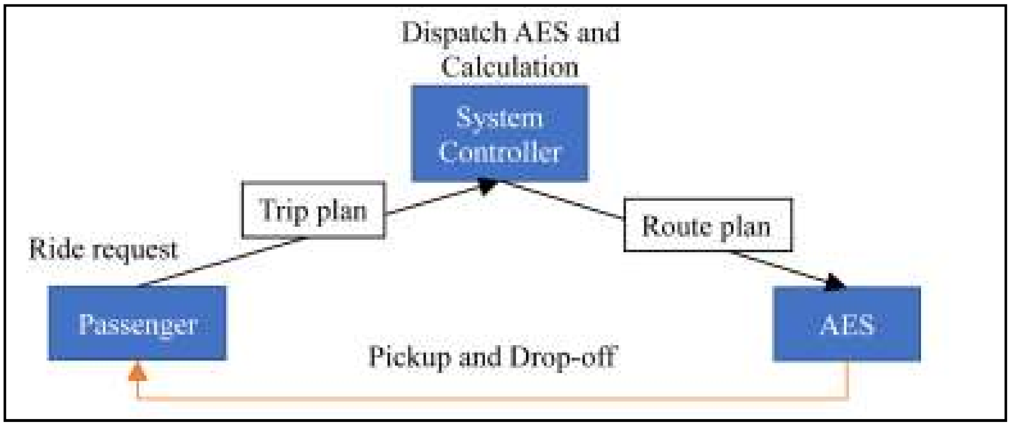


Figure 3. Fixed-route, on-demand AES service workflow.

In any trip involving an AES, the passenger must first walk to the closest departure AES stop. When a passenger arrives at the stop, he/she makes a ride request (such as with the press of a button at the stop, or by using a smartphone to request a ride). Ensuing the ride request, the passengers’ trip plan (origin, destination, etc.) information is sent to the system controller for AES dispatch and route plan calculation. The system controller then dispatches the assigned AES with the route plan for the passenger. When the AES reaches the departure stop where the passenger is located, the passenger alights, the AES then travels to the destination stop closest to the passenger’s final destination, where the passenger disembarks from the AES. The passenger then continues walking to the final destination while the AES waits at the AES stop for the next ride request.

FASTSim for Energy Analysis

FASTSim is used in this study for energy analysis based on the trajectory information delivered by SUMO. FASTSim is a publicly available advanced vehicle powertrain system analysis model that enables rapid and accurate comparison of powertrains and estimates the impact of different technologies and cost improvements for light- and heavy-duty vehicles. More information about FASTSim is available at (https://www.nrel.gov/transportation/fastsim.html).

FASTSim inputs include operational details of the AES drivetrain as well as vehicle design parameters, such as aerodynamic drag, frontal area, mass, and rolling resistance. FASTSim computational results encompass vehicle efficiency, performance time to accelerate from 0–60 mph —cost, and battery life (if applicable). FASTSim can model various vehicle types, including internal combustion engine (ICE) vehicles, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), compressed natural gas (CNG) vehicles, and fuel cell electric vehicles (FCEV). Preloaded vehicle models are included in FASTSim, and the inputs can be modified to represent changes in specific vehicle or component attributes. Zhu et al. (Zhu et al., 2017) have applied FASTSim to build a link-based fuel estimation model for conventional gasoline vehicles and HEVs.

AMD Simulation Assumptions

The following assumptions were made for the prelimiary AMD analysis:

Network: A hypothetical trapezoidal network (shown in Figure 2) is generated in SUMO. When the AMD toolkit is applied to a real-world deployment, the network will reflect actual roadway geometry of the district served. Such networks can be imported into SUMO from existing Geographic Information System (GIS) shapefiles.

Travel Demand: The travel demand in the network is exogenous to the model (calculated or determined outside the simulation toolkit). For the preliminary analysis, hypothetical traffic demand is generated and distributed across the 13 origin-destination (O-D) pairs in the network. In future iterations, where real-world data will inform the model, travel demand can be obtained from the output of the regional travel demand model (TDM) where an AMD is deployed.

Mode Share: This initial study intends to understand the mobility and energy impacts of an AMD, so the mode shares are "assumed" for various scenarios. For a real-world AMD deployment, the mode shares would reflect observed data once the shuttles run for a few months in the field. For planning purposes, mode shares may be generated through behavior-based modeling approaches common in regional TDMs.

AES Fleet: A total of four automated electric shuttles serve the designated demand in the AMD. This is not a limiting factor, and the number and the seating capacity of shuttles can be increased to cater to additional demand as required. Scenarios that utilize different fleet sizes can examine wait time, responsiveness, deadheading, and optimal re-distribution of vehicles. This remains a future effort.

Vehicle Characteristics: The characteristics of the privately driven cars (vehicle make, model, body type, acceleration/deceleration profiles) in the simulation reflect that of a standard midsize sedan Toyota Camry. This is the most popular sedan by sales volume in the United States in the year 2016[1], and thus representative of an average car. This vehicle has a curb weight of 3,240 lbs., a drag coefficient of 0.28, a length of 190 inches, and an EPA-rated fuel economy of 25 MPG[2]. The vehicle attributes will influence vehicle movements in SUMO simulation and energy consumption in FASTSim simulation. For AES fleets, there are two optional powertrains, i.e., gasoline or electric vehicle. The 2016 Camry is still selected for a gasoline AES fleet. For electric AES fleets, the 2016 Nissan Leaf is chosen, which is one of the major midsize electric sedans in the market. The vehicle models and attributes can be easily customized to specific vehicles in the future. Future work will incorporate

[1] https://www.caranddriver.com/flipbook/sales-tale-these-are-the-25-best-selling-vehicles-of-2016#23
[2] 2016 Camry Product Information. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwivvLGhvOXXAhXGQd8KHSlED-wQFggpMAA&url=https%3A%2F%2Fpressroom.toyota.com%2Freleases%2F2016%2Btoyota%2Bcamry%2Bproduct%2Bspecs.download&usg=AOvVaw2XOALtV9m2cO-3epl0D3yZ

characteristics of existing automated shuttle vehicles as input into SUMO and FASTSim.

SCENARIO DEVELOPMENT

Using the assumptions stated above, the following three scenarios presented in Table 1 were run using SUMO and FASTSim models to quantify the energy and mobility impacts of different travel demand configurations in an AMD.

Table 1. Travel Mode Share of All Scenarios

Scenarios	Car mode	Walk mode	AES mode
Baseline	70%	30%	0%
Transitional	60%	20%	20%
Optimistic	50%	10%	40%

In the baseline scenario, there is no AES service, and the mode splits for car and walk are assumed as 70% and 30%, respectively. In the transitional scenario, AES is assumed to have a mode share of 20% taken evenly from car and walk mode. This scenario reflects early adopters for the AES technology, where there is some interest to utilize this new mode, but not a major mode shift. In the optimistic scenario, AES is expected to gain a significant market share of 40% of total trips.

The assumption that AES will induce a uniform mode share from car and walk was made purely from an operational convenience standpoint. Future efforts will focus on testing a wide array of scenarios that reflect alternate adoption scenarios for the AES mode, as informed from early demonstrations and deployments of AES service.

RESULTS AND DISCUSSION

The automated mobility district (AMD) simulation results for the three scenarios are illustrated in Table 2. The reported performance metrics for the AMD include:

- Vehicle Miles Traveled (VMT)—this is the total of all private vehicles and automated electric shuttle (AES) mileage for the scenario
- Vehicle Average Travel Time (VATT)—the average time of travel in vehicle, (does not include walking), averaged across private vehicles and AES trips
- Vehicle Average Travel Distance (VATD)—the average travel distance (excluding any pedestrian links), averaged across private vehicle and AES trips.
- Fuel Consumption (FC) in gallons of gasoline across the entire system.

The fuel consumption is separated into two sub-scenarios: “gasoline” AES and “electric” AES as previously described. For the electric powered AES sub-scenarios, the AES is assumed not to contribute to gasoline consumption.

Table 2. The Simulation Results for AMD Network Performance.

Scenario	VMT (miles)	VATT (seconds)	VATD (miles)	FC (gasoline/EV)
Baseline	128.8	86.5	0.6	5.9
Transitional	153.8	124.3	0.8	7.0/5.3
Optimistic	175.7	168.5	1.1	8.0/4.5

Compared to the baseline scenario, the transitional and optimistic scenarios exhibit an increase in VMT, VATT, and VATD. VMT of transitional and optimistic scenarios increase by about 19% and 36% respectively compared to baseline, which can primarily be attributed to AES vehicles traveling to the departure stop to pick up a passenger (referred to as overheading). Deadheading (or empty vehicle travel) does not contribute to VMT in this analysis as the AES vehicles park at an AES stop after dropping off a passenger. VATT and VATD also see an increase in transitional and optimistic scenarios, again due to overheading. As AES mode share increases, it is expected that the decrease in fuel consumption using personal vehicles will more than compensate for the increase in VMT due to overheading. If all AES vehicles are gasoline-powered, an increase of fuel consumption is observed. However, if all AES vehicles are electrified, transitional and optimistic scenarios see a decrease of 10% and 26% decrease in fuel consumption respectively.

It should be noted that the initial model is simplistic and does not take into account the source of electricity (coal, natural gas, renewables), or end-times associated with accessing and parking a private vehicle. The intent of this effort was to develop a basic model, and then add complexity to better reflect real-world conditions.

CONCLUSIONS AND FUTURE WORK

As we move into the era of connected and automated vehicles (CAVs), vehicle electrification, and shared mobility in transportation, it is critical to identify and explore the optimal confluence of these technologies that maximize mobility while minimizing energy consumption. One such idea is that of automated mobility districts (AMDs) which is a district-scale implementation of CAVs technology to realize the full benefits of an on-demand shared automated mobility service within a confined geographic region.

This research develops an AMD modeling and simulation toolkit and reports on the preliminary analysis results for hypothetical AMD deployment, exercising the toolkit with three scenarios. The AMD toolkit is capable of simulating detailed vehicle movements for various operational configurations of automated electric shuttle (AES) services including fixed route, on-demand, and mixed services to quantify the mobility and energy benefits of AMDs. The simulation results in terms of mobility and energy impacts show intuitive trends, which provide a validation check for the tool. Transitional and optimistic scenarios see vehicle miles traveled (VMT) increase when compared to the baseline scenario (no AES), which can be mainly attributed to the overhead miles traveled by the AES vehicles to pick up passengers. The study is a first step in the development of a toolkit that can quantify the energy and mobility impacts of real-world AMD deployments. Future research will focus on enhancing the toolkit to integrate and implement different operational configurations of AMDs and define and quantify various performance metrics for AMDs, as well as for the traditional modes in the simulation (vehicles, pedestrians, as well as buses and other traditional mass transit). Examples of such metrics include calculating the overheading time/distance, service rate, passenger waiting time, etc. The model will also be extended to account for parking-related issues (availability and access times).

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