

A Decision Support Tool for Planning Neighborhood-Scale Deployment of Low-Speed Shared Automated Shuttles

Lei Zhu, Jinghui Wang, Venu Garikapati, and Stanley Young National Renewable Energy Laboratory (NREL)

99th Annual Meeting of the Transportation Research Board January 14, 2020, Washington D.C.

Background

Connected, automated, and electric vehicles (CAEV) and **Mobility-as-a-Service (MaaS)**

In the short term, many cities are testing low-speed automated electric shuttles as a shared on-demand mobility service in **geo-fenced regions**.

Transportation planners rely on travel demand simulation and models to understand the mobility and energy impacts

Existing models lack the capabilities to model emerging mobility technologies such as on-demand shared mobility



Automated Mobility District (AMD)



AMD simulation toolkit is desired

What is an Automated Mobility District?

An AMD is a campus-sized implementation of Connected and automated vehicle (CAV) technology to realize all the benefits of a fully electric automated mobility service within a confined region or district.



Real-World AMD Demonstrations

Find out when driverless vehicles will be hitting the streets of this North Texas city









DEEP DIVE

How autonomous shuttles are changing city transportation

Current	Upcoming
Denver, CO	New York City, NY
Houston, TX	Rhode Island
Arlington, TX	Austin, TX
Las Vegas, NV	Reston, VA
Jacksonville, FL	Battle Creek, MD
Columbus, OH	Columbus – Linden, OH
Ann Arbor, MI	Sacramento State University, CA
Bishop Ranch, CA	Dublin, CA
Gainesville, FL	Rivium Park, Netherlands
Babcock Ranch, FL	

Automated Mobility Districts

Characteristics

Fully automated and driverless cars

Service constrained to an area with high trip demand

Mix of on-demand and fixedroute services

Multi-modal access within/at the perimeter









Operational Challenges

Customer demand (adoption rate)

Fleet size

Operational configuration:

Fixed route vs. on-demand

Battery capacity

Mobility/energy impacts

Current State of AMD Modeling

Where We Are

Existing tools primarily emphasize:

 The road network, with minimal to no consideration for pedestrian/bike/transit



 Solutions not customized to guide early-stage deployments

Where We Want To Be

Need modeling tools that:

 Capture private as well as shared **economies** in vehicles

 Are built based on data from field deployments of emerging transportation technology

 Can quantify energy as well as mobility benefits

AMD Simulation Toolkit: Model Flow

Travel Demand

- Origin–destination data from regional travel demand model
- Local surveys or counts
- Induced travel demand
- Passenger travel behavior, adoption rates



Mode Choice Modeling

- Initially tagged to be developed based on user surveys from Greenville
- Resorting to a model based on existing literature owing to lack of data from Greenville



SUMO

(Mobility Analysis)

- SUMO Simulator of Urban Mobility
- Carries out the network simulation of vehicles
- SUMO will output travel trajectories



FASTSim

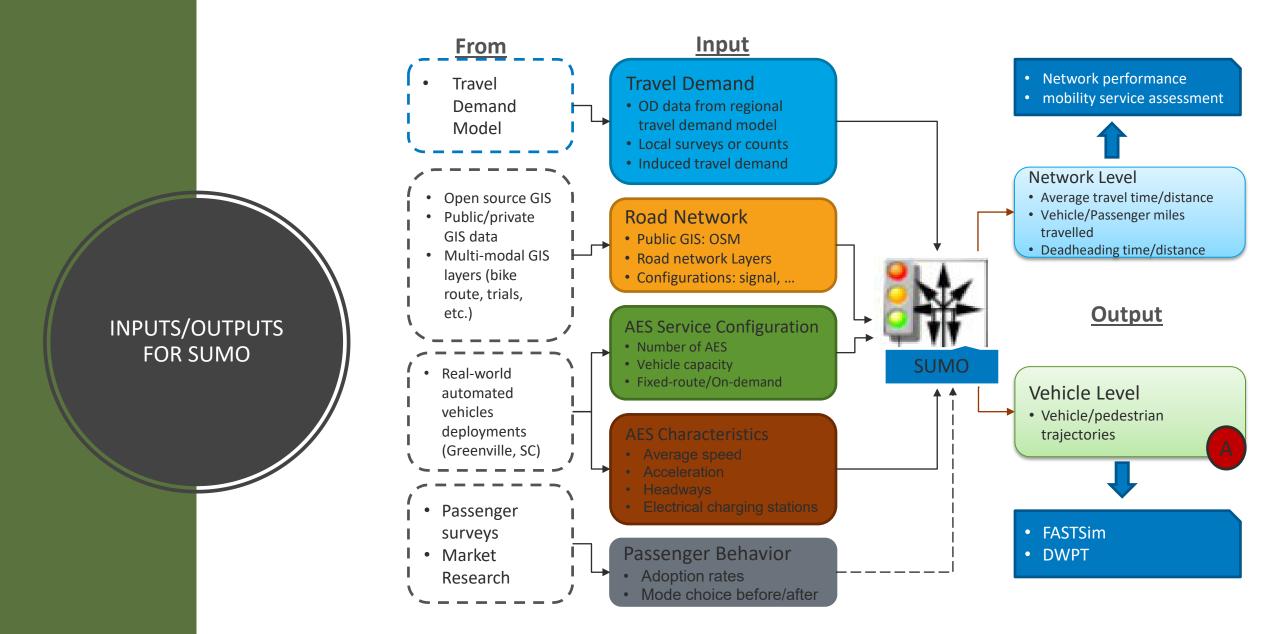
(Energy Analysis)

- FASTSim Future **Automotive Systems Technology Simulator**
- FASTSim will output vehicle energy consumption

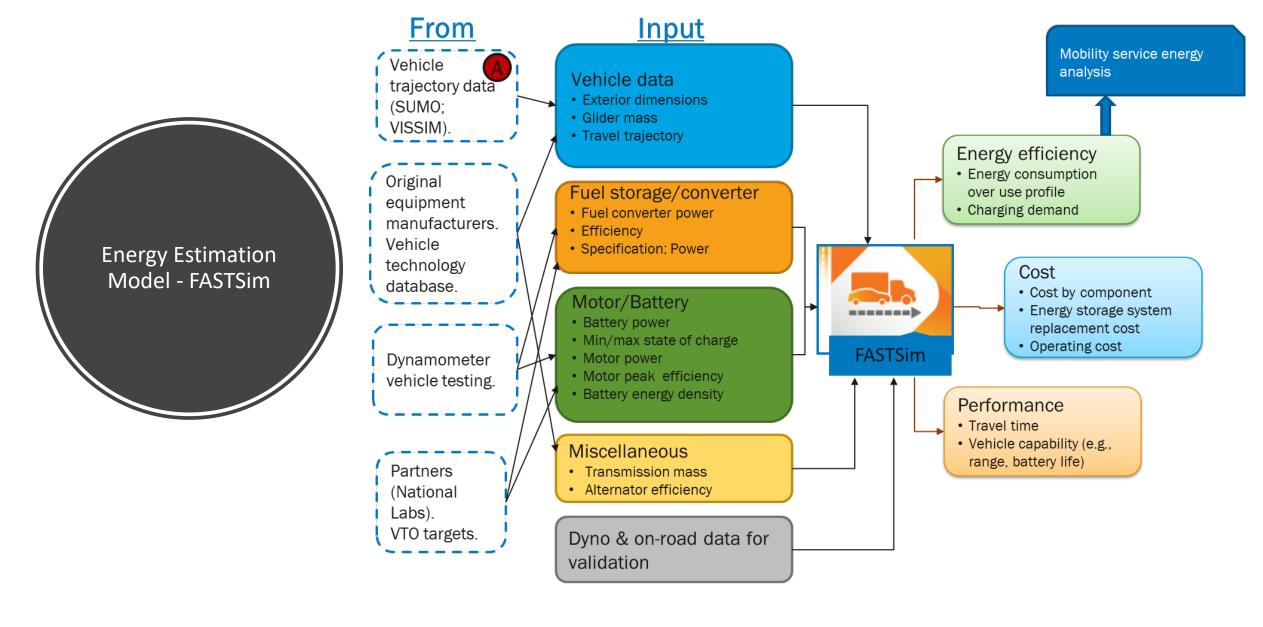


Optimization Module

- Fleet size: How many electric shuttle units will be required?
- Routes: What are the optimal routes that minimize travel time and energy consumption?
- How do we find solutions that meet customers' expected waiting time and overall trip duration?



AES: automated electric shuttle; GIS: geographic information system



- 2016 Toyota Camry is selected to represent gasoline shared and automated vehicles (SAV) and all regular cars
- 2getthere's GRT (group rapid transit) vehicles for shared and automated electric shuttles

AMD SUMO Simulation

Vehicle Ridesharing Service



1. System Status Check

Gathering information on current location and travel data of passengers as well as SAVs

2. Ride Matching

Matching passengers to available SAVs

3. Vehicle Routing

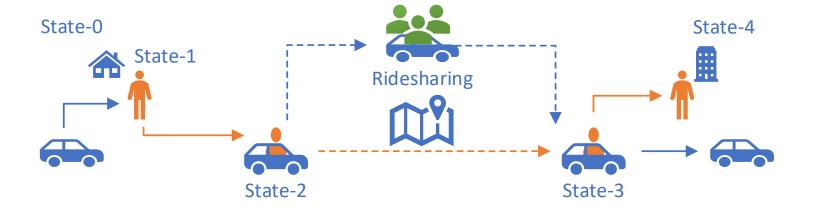
Calculating an SAV routing strategy

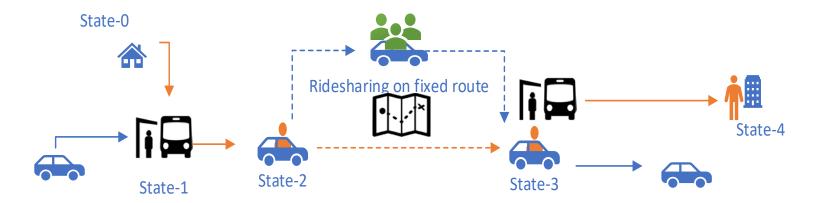
4. Redistribution Strategy

Relocating SAVs for incoming trip requests

AMD SUMO Simulation

Passenger Behavior States





States of passengers

- 0 Initialization
- 1 Arrive at pickup location and wait
- 2 Get onboard
- 3 Arrive at drop-off location and alight
- 4 Arrive at destination and stop

Case Study: Greenville, South Carolina

- Location: Greenville, South Carolina
- Analysis period: morning peak hours (6 a.m. – 9 a.m.)
- The time-dependent demand distribution: Total 308 trips
- Four modes:
 - CAR: regular car
 - WAK: pedestrian
 - DTD: on-demand door-to-door ridesharing
 - FXR: on-demand fixed-route ridesharing
- AES configuration:
 - SAV Capacity: four passengers
 - Total 10 SAVs: six for FXR mode and four for DTD



Shuttle stop

Shuttle stop

Phase 0

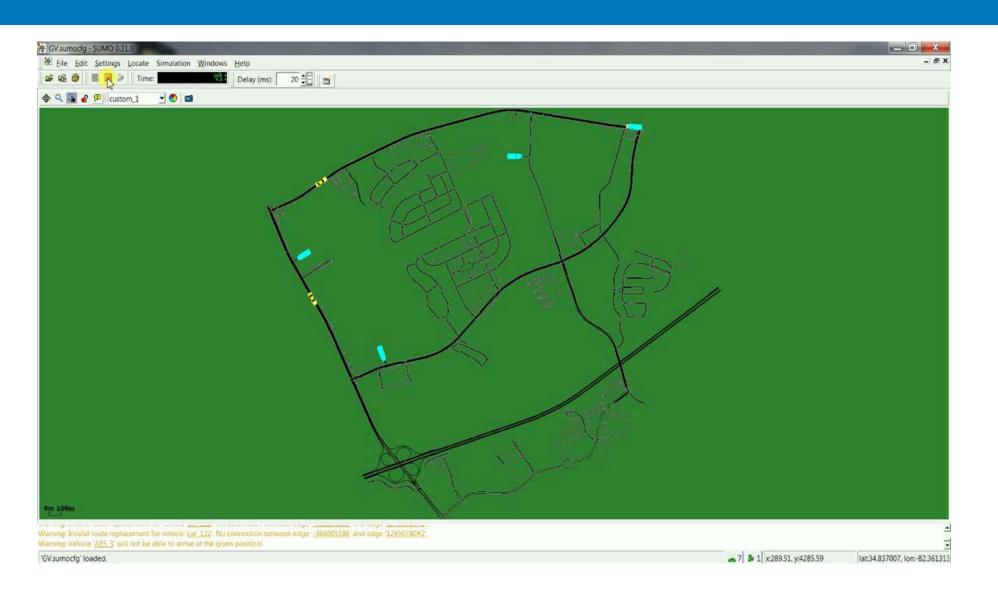
Route

Greenville, South Carolina, network has 554 nodes and 1,340 edges

Network in SUMO and two fixed routes

- In 2017, Greenville, SC won a **Federal Highway Administration grant award** to deploy automated taxis (A-Taxis) in three neighborhoods in the Greenville county.
- In **phase 0**, SAVs were envisioned to be deployed at the Clemson University International Center for Automotive Research (CU-ICAR) facility. In **phase 1**, SAV deployment was planned in the nearby Verdae District, which is a mixed-use urban development

AMD Simulation Sample



Scenario Study and Analysis

Baseline

Scenario 0: with CAR and WAK modes only

DTD mode only

• Scenarios 1 – 3: 10% increments shifting from CAR mode

FXR mode only

• Scenarios 4 – 6: 10% increments shifting from CAR mode

DTD and FXR modes

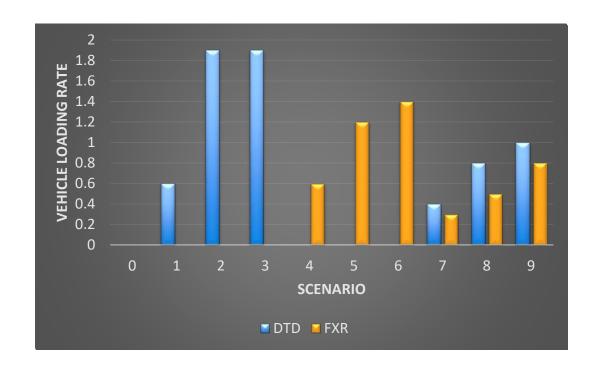
• Scenarios 7 – 9: 10% increments (5% of DTD, 5% of FXR)

	Mode Share Ratio			
Scenario ID	CAR	WAK	DTD	FXR
0	0.8	0.2	0	0
1	0.7	0.2	0.1	0
2	0.6	0.2	0.2	0
3	0.5	0.2	0.3	0
4	0.7	0.2	0	0.1
5	0.6	0.2	0	0.2
6	0.5	0.2	0	0.3
7	0.7	0.2	0.05	0.05
8	0.6	0.2	0.1	0.1
9	0.5	0.2	0.15	0.15

Service Performance Metrics

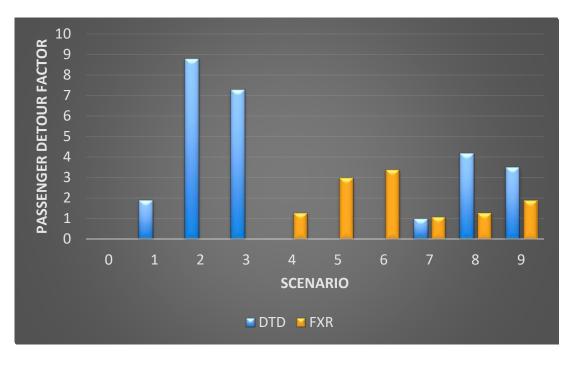
Metric	Unit	Description
VMT	miles	Vehicle miles traveled
VDH	miles	Vehicle deadheading miles traveled (distance traveled with no passenger on
		board)
VTT	seconds	Vehicle travel time
VLR	# of passengers per mile	Vehicle loading rate: distance weighted number of passengers onboard
		divided by the vehicle distance traveled for all SAVs
VEC	gallons or kilowatt-hours	Vehicle energy consumption in fuel (gallons) or electricity (kilowatt-hours)
PDF	-	Passenger detour factor: trip distance of ridesharing modes divided by trip
		distance of regular car mode (time-dependent shortest path)
PWT	seconds	Passenger waiting time

Service Performance Metrics

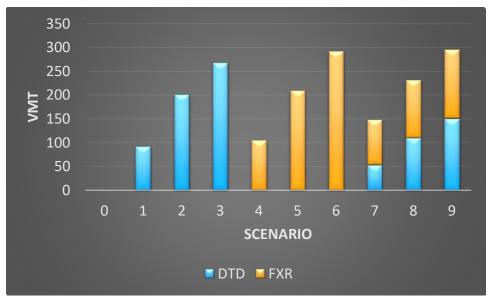


Vehicle loading rate: distance weighted number of passengers on board divided by the vehicle distance traveled for all SAVs; DTD outperforms FXR.

Passenger detour factor: trip distance of ridesharing modes divided by trip distance of regular car mode (time-dependent shortest path).



Service Performance Metrics



Vehicle miles traveled (VMT): VMT increases as number of SAVs increases.

• When both modes are deployed, there are more SAVs operating in the system, leading to higher system-level VMT.



Vehicle energy consumption (VEC): In fuel (gallons) or electricity (kilowatt-hours); similar pattern as VMT

- Scenario 0 has VEC of 17.4 gallons for CAR mode only
- If all SAVs are electric vehicles, the fuel saving ranges from 11% to 38%.

Simulation Results

• The intent of this simulation tool is to help test a variety of deployment scenarios to see what works and what doesn't before actual field deployment for SAVs.

Network-level VMT, VTT, and VEC keep increasing as the SAV share goes up

DTD outperforms FXR mode with lower VDH and higher VLR

DTD mode falls inferior to FXR mode in passenger detour factor (PDF) and passenger wait time (PWT)

Under same mode adoption ratios, deployment of both FXR and DTD modes leads to higher VMT, VTT, and VEC compared to deploying only one mode.

Next Steps

- Incorporation of additional "mobility on-demand" modes and mode choice model
 - Shared bikes, e-scooters, SAVs for first/last mile connections
- Integrating the toolkit into a regional travel demand model
- Utilizing the toolkit in the context of real-world AMD deployment
 - Collecting travel behavior and vehicle dynamics data from these deployments
- More sophisticated routing algorithms and an endogenous mode choice model

Thank you

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NREL/PR-5400-75739

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Vehicle Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.



Mode Choice Modeling

- Modes considered in Greenville AMD simulation
 - 1) Auto, 2) Walk, 3) AES, 4) Fixed Route
- General form of mode choice model

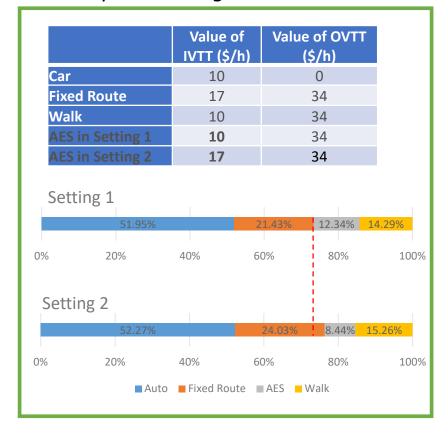
$$V_i = \alpha + \sum_{j=1}^J \beta_j x_j$$

Where

 $i \in \{Auto, Walk, AES, Fixed Route\}$ α is the constant value x_i is j^{th} mode choice attribute θ_i is coeff. of attribute x_i

- Potential attributes of mode choice model
 - *In-vehicle travel time (IVTT)*
 - *Out-of-vehicle travel time (OVTT)*
 - Value of travel distance
 - Fixed cost (fare)
 - Other costs, e.g., parking cost

Example including IVTT and OVTT



- Mode shift observed when value of IVTT changed
- More tests on other attributes in progress

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