

Automated Mobility District Toolkit

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Background

On-demand transportation services have seen a dramatic rise in the past decade, thanks to technology.

Connected and automated vehicle (CAV) technology holds potential for a major transformation in the on-demand mobility services landscape.

The timeline for fully automated vehicles (AVs) to reach the critical market share is still uncertain.

In the short term, many cities in the United States and abroad are testing low-speed automated electric shuttles (AES) as a shared on-demand mobility service in geo-fenced regions.

Automated Mobility District (AMD)

What is an Automated Mobility District?

An AMD is a campus-sized implementation of 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

BY BILL HANNA

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Source: https://www.startelegram.com/news/local/community/arlington/article213011 984.html

Self-driving shuttles to start circling Scioto Mile soon



Source:

https://www.bizjournals.com/columbus/news/2018/12/04/selfdriving-shuttles-to-start-circling-scioto.html



DEEP DIVE

How autonomous shuttles are changing city transportation

Source: https://www.smartcitiesdive.com/news/autonomous-shuttles-city-transportation/551489/

	Current	Upcoming
	Denver, CO	New York City, NY
	Houston, TX	Rhode Island
No. of Concession, Name	Arlington, TX	Austin, TX
14 012 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1	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 fixed route services

Multi-modal access within/at the perimeter

Operational Challenges



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
- Privately owned vehicles, but do not model shared economies
- 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 from field deployments of emerging transportation technology
- Can quantify energy and emissions 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

SUMO

(Mobility Analysis)

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



(Energy Analysis)

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

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

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

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 \{\text{Auto, Walk, AES, Fixed Route}\}\$ α is the constant value x_j is j^{th} mode choice attribute β_j is coef. of attribute x_j

- 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

	Value of IVTT (\$/h)	Value o (\$	of OVTT /h)
Car	10	(0
Fixed Route	17	3	34
Walk	10	3	34
AES in Setting 1	10	3	34
AES in Setting 2	17	3	34
Setting 1 51.95%	40% 6	0%	12.34% <mark>1</mark> 80%
Setting 1 51.95% 20% Setting 2 52.27%	40% 6	0% 24.03%	12.34% 1 80% 8.44% 1

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



AMD Simulation Sample



Optimization Framework: Workflow



Optimization Model

Formulation

- The problem is formulated as a constrained mixed integer program
- Decision variables are integers
- Set of constraints are linear in nature
- Combinatorial problem

Challenges

- General solution approaches include branchand-bound and cutting-plane methods
- Smaller networks can be solved using commercial solvers such as IBM CPLEX and Gurobi
- Computational complexity rises with the size of the graph (network) and the number of ondemand requests
- Exact solution methods are not scalable for large networks

Case Study: Greenville, South Carolina

- Location: Greenville, South
 Carolina
- Analysis period: a.m. peak hour (6 a.m.-9 a.m.)
- The time-dependent demand distribution:
 - Known and deterministic
 - Total 378 trips
 - AMD share is about 50%
 - Distributed among eight traffic analysis zones
- $\circ~$ AES configuration:
 - Capacity: 2, 4, and 8 passengers
 - Range: 20, 30, and 50 km



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

Travel Cost and Energy Consumption

- Link travel time data are obtained from the microscopic traffic simulation tool, SUMO, at a resolution of 15 minutes
- We model the a.m. peak hour (6 a.m.–9 a.m.) in the Greenville, South Carolina, network
- We assume dynamic travel time that changes each 15-minute interval. Thus, we have (180/15) or 12 interval horizons
- An average speed and energy look-up table is developed using FASTSim**
- A relationship between average driving speed and energy consumption rate is developed using SUMO



**Brooker, A., Gonder, J., Wang, L., Wood, E., et al., "FASTSim: A Model to Estimate Vehicle Efficiency, Cost, and Performance," SAE Technical Paper 2015-01-0973, 2015, doi:10.4271/2015-01-0973.

Findings: Travel Time (Cost)



 Tabu search performs better compared with commonly used heuristics: RSTM and RSRH

 Tabu search provides lower travel time (cost) in all demand cases and all AES ranges (the overall savings range from 2% to 10%)

RSTM: Real-time solution with trip matching (RSTM) does not use any information regarding future demand for the AMD service. **RSRH:** Real-time solution with rolling horizon (RSRH) routing uses limited information about future requests from the customers. **Demand:** Medium (baseline) \rightarrow 177 requests; Low \rightarrow 134 requests (25% \downarrow baseline); High \rightarrow 194 requests (10% \uparrow baseline)

Findings: Energy Consumption



RSTM: Real-time solution with trip matching (RSTM) does not use any information regarding future demand for the AMD service. **RSRH:** Real-time solution with rolling horizon (RSRH) routing uses limited information about future requests from the customers. **Demand:** Medium (baseline) \rightarrow 177 requests; Low \rightarrow 134 requests (25% \downarrow baseline); High \rightarrow 194 requests (10% \uparrow baseline)

Findings: Minimum Number of Vehicles Required



- The results are intuitive and conform to general expectations
- The minimum number of vehicles required rises with higher demand and shorter AES range
- Higher number of vehicles as the trips are heavily dispersed in space and time

Next Steps

- Integrating more constraints into the optimization module
 - Soft time window for waiting time
 - Trip duration threshold for group rides
- Replicating the AMD modeling process in one location in addition to Greenville
- Incorporation of additional 'mobility on-demand' modes
- Integrating the toolkit into a regional travel demand model
- Inter-AMD travel modeling and simulation

Thank you

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