Methods for Modeling Shared, Automated, Electric Vehicles in Ridesharing and First/Last Mile Applications

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Introduction

• Ridesharing operations are likely to induce **imbalances in the spatial & temporal vehicle distribution.**

• The management of such operations becomes complicated due to:
  – demand characteristics
  – imbalance issues
  – operational constraints
  – the need to maximize the use of ridesharing systems
Introduction

- The use of **electric vehicles** (EVs) can further increase complexity when **charging stations** considerations are included.

- This presentation outlines the design and implementation of a model to simulate **shared autonomous electric vehicles** (SAEVs) for ridesharing operations & last mile connection service.
Simulation Design

Discrete-time SAEV Simulator

Travel Request with Time Windows

Move SAEVs and Update Position

Vehicle Relocation

Demand Clustering Using Similarity Evaluation

Rideshare Matching Optimization

Phase – I: Determine Number of Charging Stations

Generate Charging Stations & SAEVs

Phase – II: Determine Number of SAEVs

SAEV Simulation Framework
Simulation Design

- An important design decision is to determine the "initial state" of the system.
  - Number of vehicles
  - Number of charging stations and ports
  - Spatial distribution of vehicles and charging stations
A number of approaches can be adopted to **initialize the system**:

- **Fleet Size**
  - Setting the fleet size equal to the peak total demand.
  - Initialize the system with zero vehicles and create them only as needed.
Simulation Design

• Charging Infrastructure
  – initialize the system without charging infrastructure
  – create charging stations only as needed.

• Vehicle Repositioning
  – If the relocation costs compensate the additional earnings, a relocation strategy should be applied.
  – the goal is to minimize the total number of empty vehicle miles travelled.
  – All relocation models involve modeling trip demand in the system.
Simulation Design

• In the existing literature, the majority of RELOCATION models involve minimizing a generalized cost function calculated as a function of passenger wait times and empty VMT (Song and Earl, 2008; Douglas, 2015).

• Dynamic ridesharing adds significant complexity to the theoretical models.

• Instead of using a system optimal approach, vehicles can broadly relocate from areas of lower expected demand to higher expected demand.

• There is a direct tradeoff between size of relocation zone (computational precision) and computational time.
Simulation Design

Vehicle Assignment Strategies

• For a given fleet of vehicles, the objective is to minimize the system-wide total vehicle miles traveled (VMT).

• Various strategies can be adopted to identify assignment opportunities:
  – Closest Available: traveler is assigned the closest vehicle within some predefined service radius.
Simulation Design

- Minimize the number of vehicle miles required to accommodate the trip.
- Iterate through a queue of waiting passengers and assign on FIFO basis.

• Alternatively, formulate optimization problem such that it maximizes occupancy and minimizes total distance to pick-up.
  - Formulation is NP-hard, thus making it inviable for simulation.
  - The objective function does not consider preferences of passengers in tow.

• Passenger Time Minimization minimizes the total trip time at the cost of forfeiting ridesharing opportunities.
Simulation Design

Capacitated Vehicle Routing Problem with Time Windows

• The problem of determining optimal routes to pickup and drop-off multiple travelers within a given time interval using vehicles with fixed capacities is formulated as CVRPTW.

• Jaw et al. (1986) formulated multiple-vehicle dial-a-ride problem (DARP) with pickup and dropoff time windows.


• Jung et al. (2013) developed a constrained optimization scheme based on capacitated vehicle routing problem with time windows for shared-taxi systems.
Simulation Design

- Complexity associated with solving NP-hard CVRP requires ridesharing problem to be decomposed into sub-problems.
- The search space is divided into a number of subspaces.
- At each time step, similarity matrices are established representing origins and destinations of travelers sharing ride.
Simulation Design

- Cluster size is limited to accommodate vehicle capacity
- Alternatively, clusters can be formulated without any specific size if travelers in each cluster can be served by more than one vehicle.
- For each such cluster, a vehicle routing problem is solved to determine an optimal route to serve all travelers in that cluster.
Simulation Design

The arrival time for vehicle

\[ b_j = b_i + \sum_{m=1}^{n} d_{im} + t_{ij} \]

The waiting time for vehicle \( v \) at node \( j \) is computed as follows,

\[ W_j = \max \left\{ 0, e_j - b_i + \sum_{m=1}^{n} d_{im} + t_{ij} \right\} \]

The total travel time \( T \) and distance \( S \) for route \( R_v \) can be defined as follows,

\[ T(R_v) = t_{0i} + \sum_{j=2}^{k} (t_{j-1j}) + \sum_{j=1}^{k} W_j + \sum_{j=1}^{k} \sum_{m=1}^{n} d_{jm} \]

\[ D(R_v) = s_{0i} + \sum_{j=2}^{k} (s_{j-1j}) \]

For each vertex \( n \) visited by vehicle \( v \)

\[ s_{0i} + \sum_{j=2}^{k} (s_{j-1j}) \leq L_v \]

\[ \sum_{i=1}^{k} q_i \leq Q_v \]

\[ e_i \leq b_i \leq l_i \]

\[ \min TD(S) = \sum_{i=1}^{l} (D(R_i)) \]

where \( TD \) denotes total distance covered in miles.

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\( s_{ij} \): distance associated with edge \((i, j)\).
\( t_{ij} \): time associated with edge \((i, j)\).
\( b_i \): vehicle arrival time at vertex \( i \).
\( d_{im} \): service time for traveler \( m \) at vertex \( i \).
\( q_i \): number of travelers at vertex \( i \).
\( e_i \): earliest arrival time at vertex \( i \).
\( l_i \): latest arrival time at vertex \( i \).
\( L_v \): remaining range of given an electric vehicle \( v \).
\( Q_v \): capacity of vehicle \( v \).
\( R_v \): route for vehicle \( v \).
Simulation Implementation

• Consideration involved in the implementation process:
  – Update time interval: Smaller interval leads to higher precision but slow runtime speed.
  – Map Network: a pixelated network or a street-level map network can be used.
Simulation Implementation

- Mapping rides to nodes: each origin and destination position needs to be mapped to the nearest node on the graph.

- Runtime issues: the sheer scale of the problem can render developed algorithm greatly inefficient.
Simulation Implementation

- Major Differences

Pixelated Network
- Discretized Network into Square or Hexagon Pixels
- Restricts vehicle movement
- A vehicle is located in one of the pixels, and allows simulator to track exact positions
- At each time step, vehicle moves to adjacent pixel
- Simulator updates trajectories over time
- Transitioning from t to t+1 involves search through each pixel
- Ignores traffic patterns
- Heuristic approach for modeling ridesharing

Street-level Map
- Map data to construct nodes and links
- Latitude and Longitude are transformed to Cartesian coordinates
- Origin and destination positions are mapped to the nearest node using nearest-neighbor search (NNS)
- Travelers walk from their true origin to the nearest node for pick-up and vice versa
- Search space for each node is defined by identifying nodes that can be reached in maximum wait time.
- Shortest path between a source and a target is established using search space
Simulation Implementation

Advantages: Pixelated Network

- Pixelation is crude but an easy to adapt approach.
- Pixel size can be reduced to offer higher precision in urban areas, and increased to model suburban areas.
- Similarly, this approach could be regarded as computationally less intensive.

Advantages: Street-level Network

- The street-level network offers higher detail and provides realistic simulation.
- It needs to be individually adapted for each planning area, and is computational intensive.
Use of Grid Based Approach to Evaluate Ridesharing Operations
Evaluate Ridesharing Operations

- Discretize Planning Area
- Generate Trips (O/D)
- Determine Charging Stations and Fleet Size
- Clustering Using Similarity Evaluation
- Rideshare Matching Optimization

[Map showing various regions labeled as Exurban, Downtown, Urban, and Suburban with cell size of 0.25mi x 0.25mi and distances marked as d=30mi, d=15mi, and d=5mi]
Ridesharing for SAEV Fleet

Simulation Runs in 5-min Increments for 24 hours
Illustrative Example

• A 100-mile by 100-mile spatially discretized metropolitan area is generated that is modeled after the population density pattern of Austin, Texas.

• An average trip generation rate and trip length distribution is derived from 2009 National Household Travel Survey.

• Four scenarios are simulated to determine the performance of ridesharing operations given varying SAEV capacity.
Illustrative Example

• As the number of pickup and drop-off locations increase in an itinerary of each vehicle, travelers begin to **experience longer wait times**.
• The number of **vehicles and charging stations significantly reduce** as a result of increasing vehicle occupancy rate.
Conclusions

• Model results demonstrate that ridesharing for SAEVs improves service rate as well as system-wide cost savings ranging from $1.34M to $1.52M due to reduced VMT.

• The model predicts average percentage of travelers that participated in ridesharing at 34.68, and the minimum and maximum wait time per trip incurred by a traveler is computed at 10.88 and 19.87 minutes, respectively.

• The private vehicle replacement rate increases from 3.73 to 7.52 when dynamic ridesharing is introduced (as compared to SAEVs without ridesharing).

• Operators also save: The fleet size reduces from 57,279 to 25,368 when dynamic ridesharing is introduced.
Use of Street-level Network for First Mile Connection
SAEV for First Mile Connection

• SAEVs can help decrease the demand for scarce parking spots, and reduce the need for travelers to drive and park downtown.

Park and Ride Facility replaced by Charging Station
Ridesharing for SAEV Fleet

Seattle Street Level Map from OpenStreetMap (OSM)

- Initialize SAEVs
- Assign Destination (Assumed Park and Ride Facility or feeder service stop)
- Simulate Transit Demand
- Closest Available SAEV using Dijkstra Algorithm
SAEV for First Mile Connection

Planning Area - Seattle
Summary

• This presentation covered various aspects involved in simulation design including:
  – Determining initial state of system
  – State of autonomous agents
  – Parameters associated with charging infrastructure and vehicular fleet
  – Need for vehicle relocation and strategies
  – Vehicle assignment strategies and limitations
  – Decision to employ any particular map network and resulting implications.

• An integrated multi-objective optimization and discrete event simulation framework was proposed to simulate shared autonomous electric vehicles.

• A routing optimization model was proposed and solved using meta-heuristic algorithm.
Thank you for your time!

Questions & Suggestions?

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