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U.S. Department of Energy

Smart Charge Management and Vehicle Grid Integration Deep Dive

April 2024

Nithin Manne, Jason D. Harper
ANL EV-Smart Grid Interoperability Center
Advanced Mobility and Grid Integration Technology
April 4, 2024

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Smart Charge Management and Vehicle Grid Integration: FUSE

EVrest Employee Charging Program Pilot

Updates on EVrest pilot with data analysis and insights

U.S. DEPARTMENT OF ENERGY | Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

EVrest: EV Reservation System Deployment

Complete Workplace EV Charge Reservation System (EVrest) ANL Alpha Pilot

EVrest: EV Reservation System

ANL Deployment

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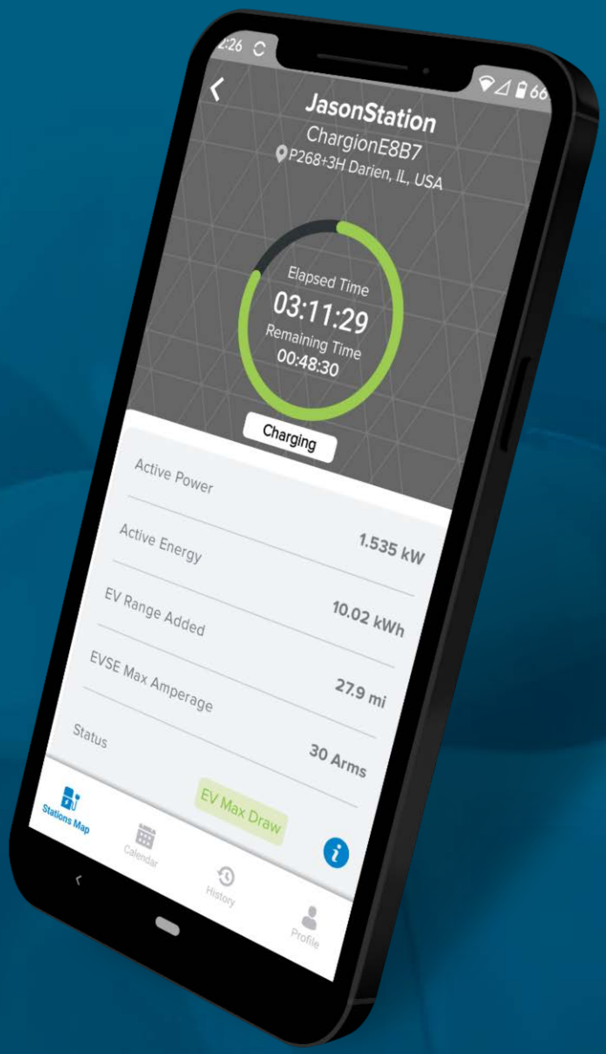
- EV Charge Reservation Mobile App
    - iOS and Android
- Allows EV Drivers the Ability to Reserve a Specific Port/Station for Future Use
- Integrates with ANL's OCPP CSMS Platform to Enable Future Smart Charging Algorithm Development and EV Charging Behavior Research



EVrest
Background

10-09-23
Registration Opened

10-13-23
10 of 12 AC Ports at Bldg. 300 go live

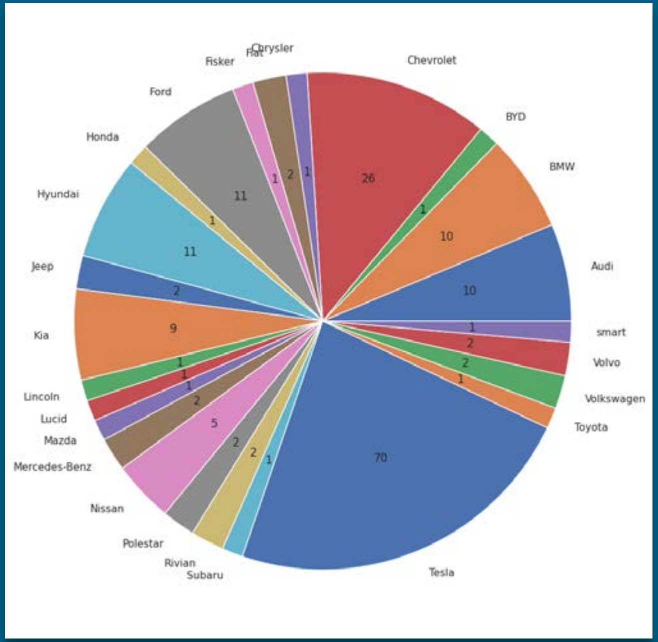
11-22-23
7 of 8 AC Ports at Bldg. 242 go live

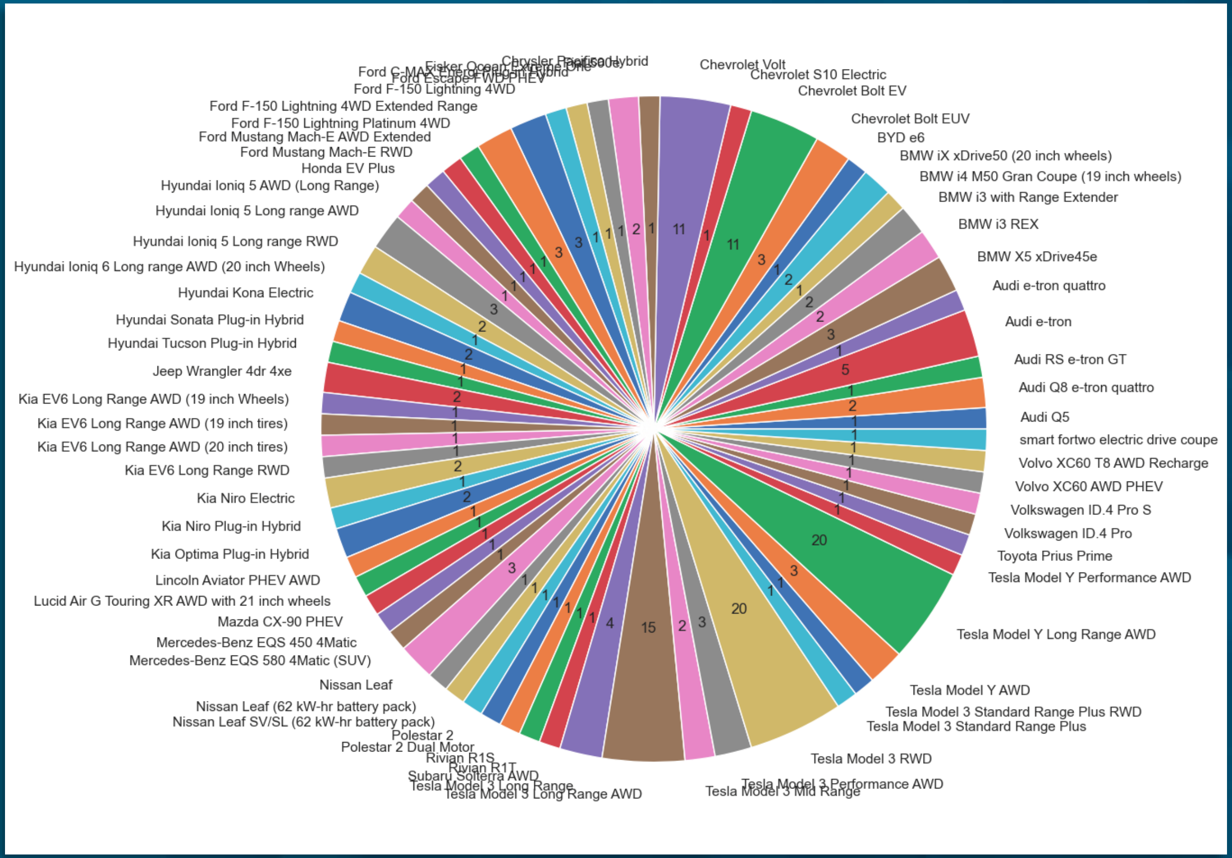
11-29-23
3 of 4 DC Charger at Bldg. 300 go live

161
Registered Users

81
iOS Devices

76
Android Devices





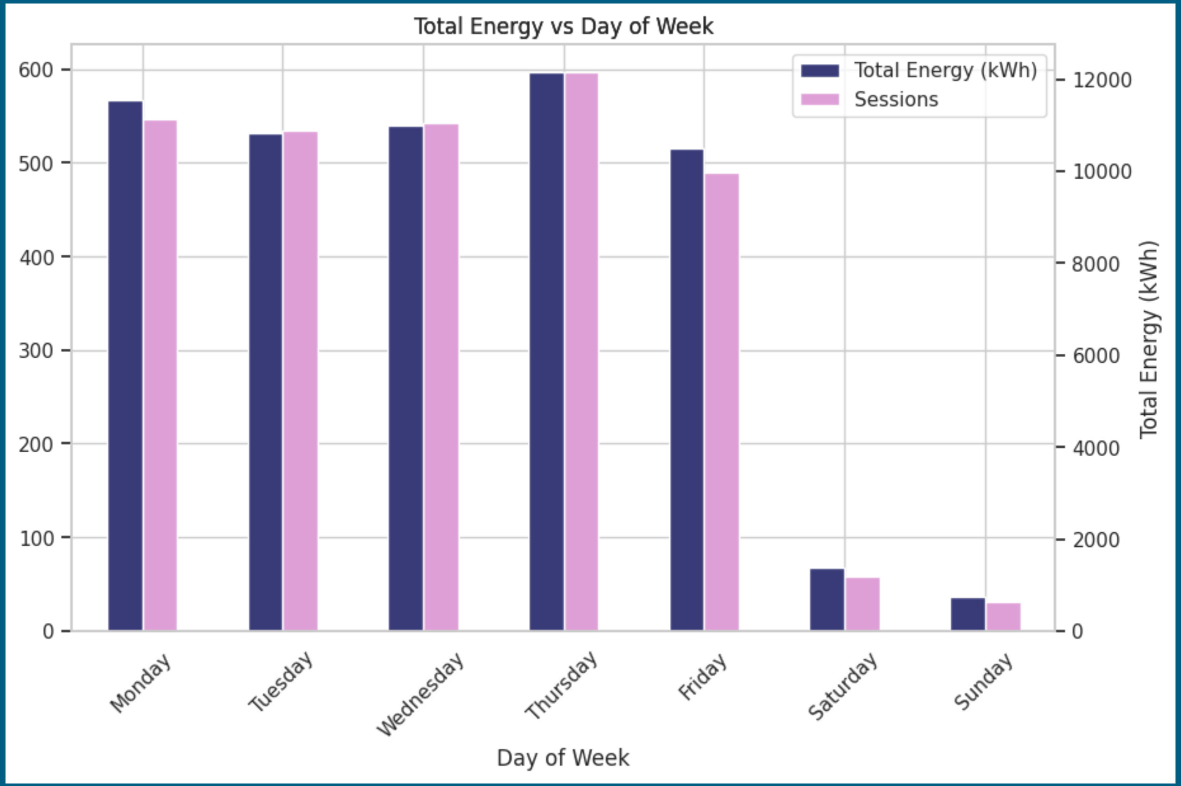
EVrest
Session Data

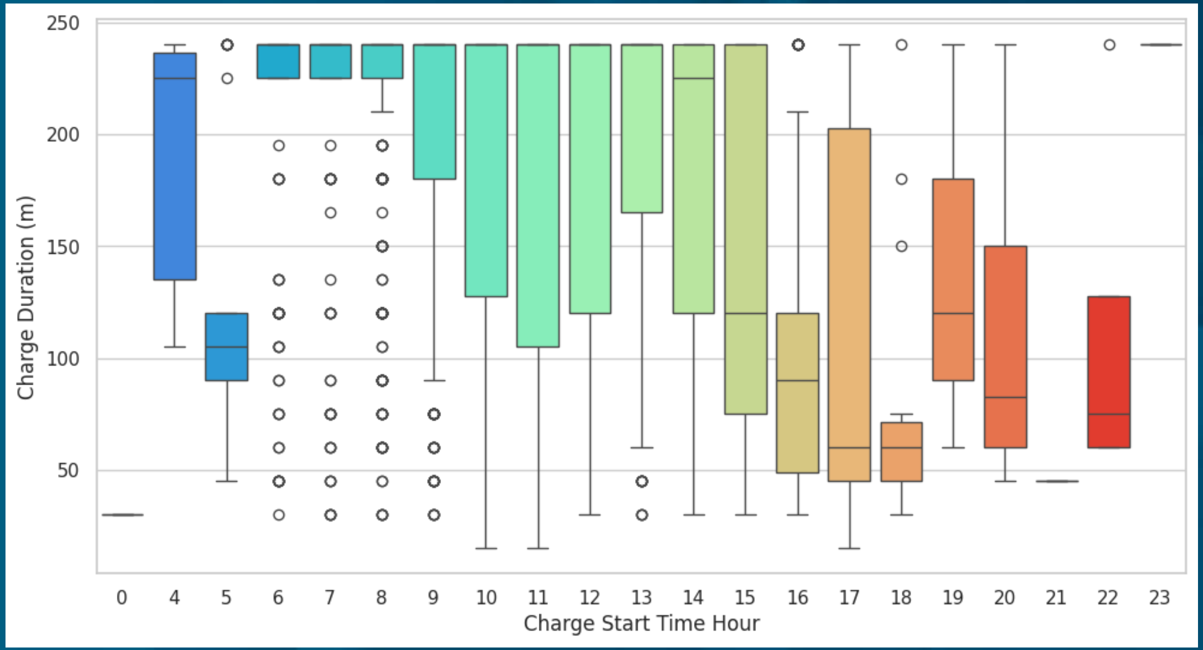
10/10/23 – 4/2/24

2799
AC and DC Charge Sessions

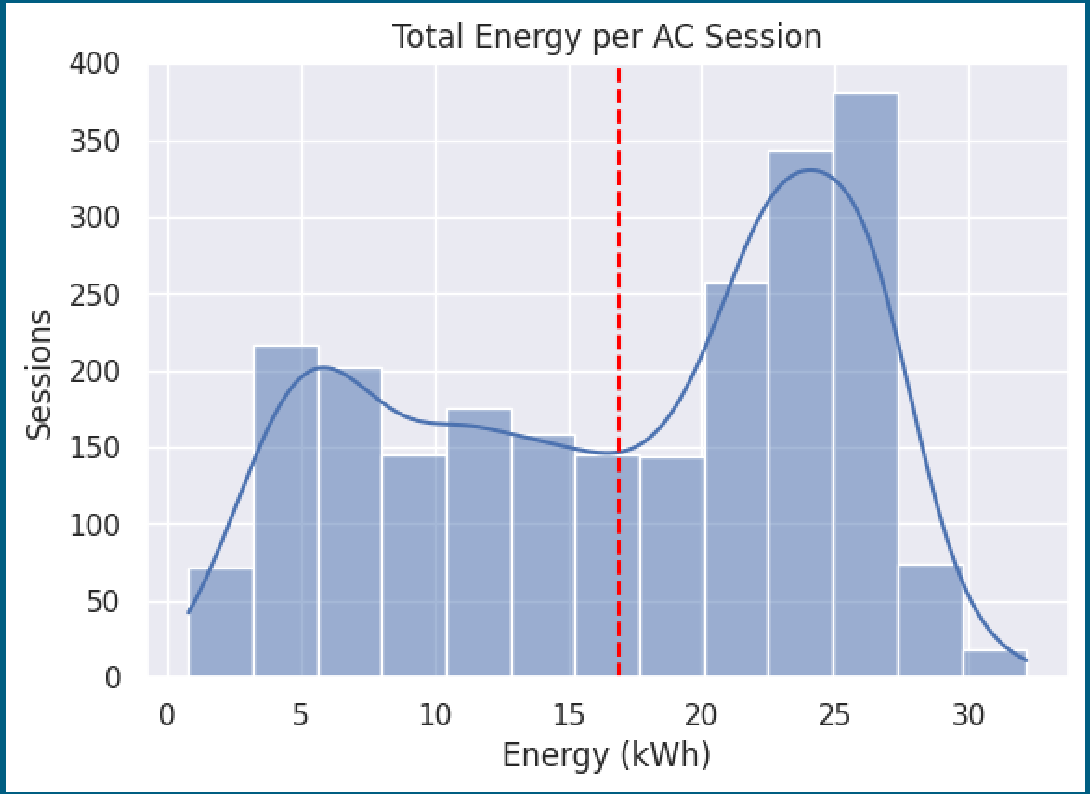
58 MWh
Total Energy Dispensed

127
Registered Users who have completed at least one reservation

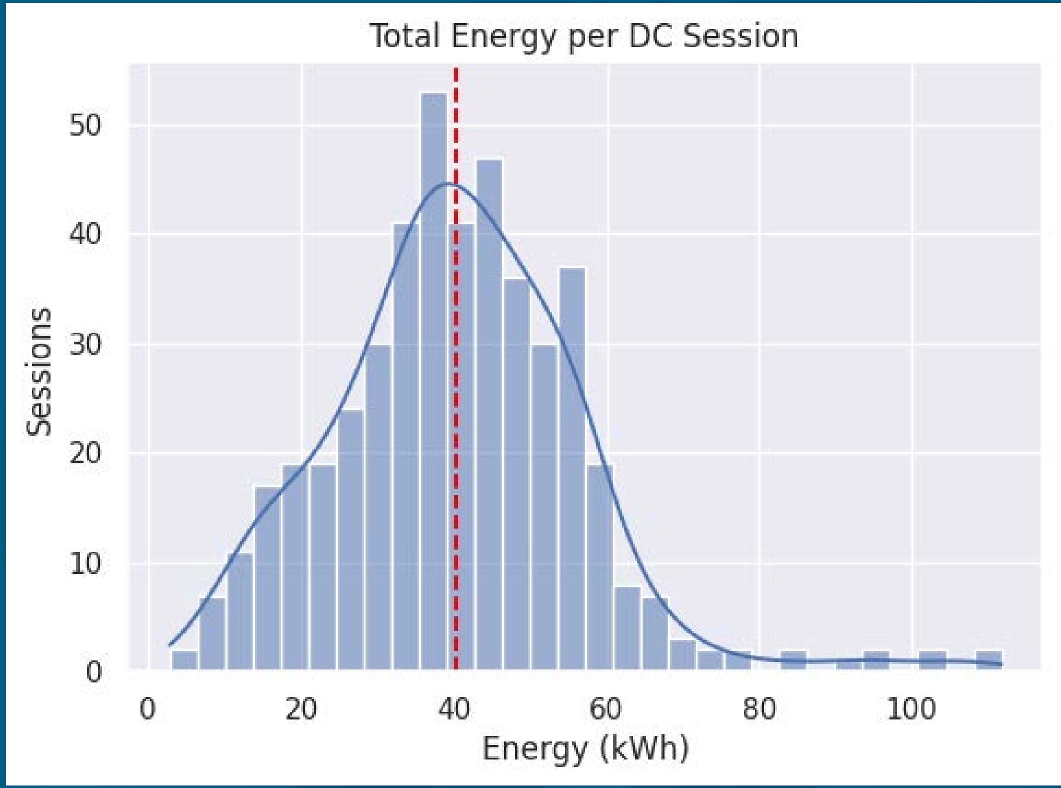




What is the Distribution of Energy per Reservation (AC vs DC)?

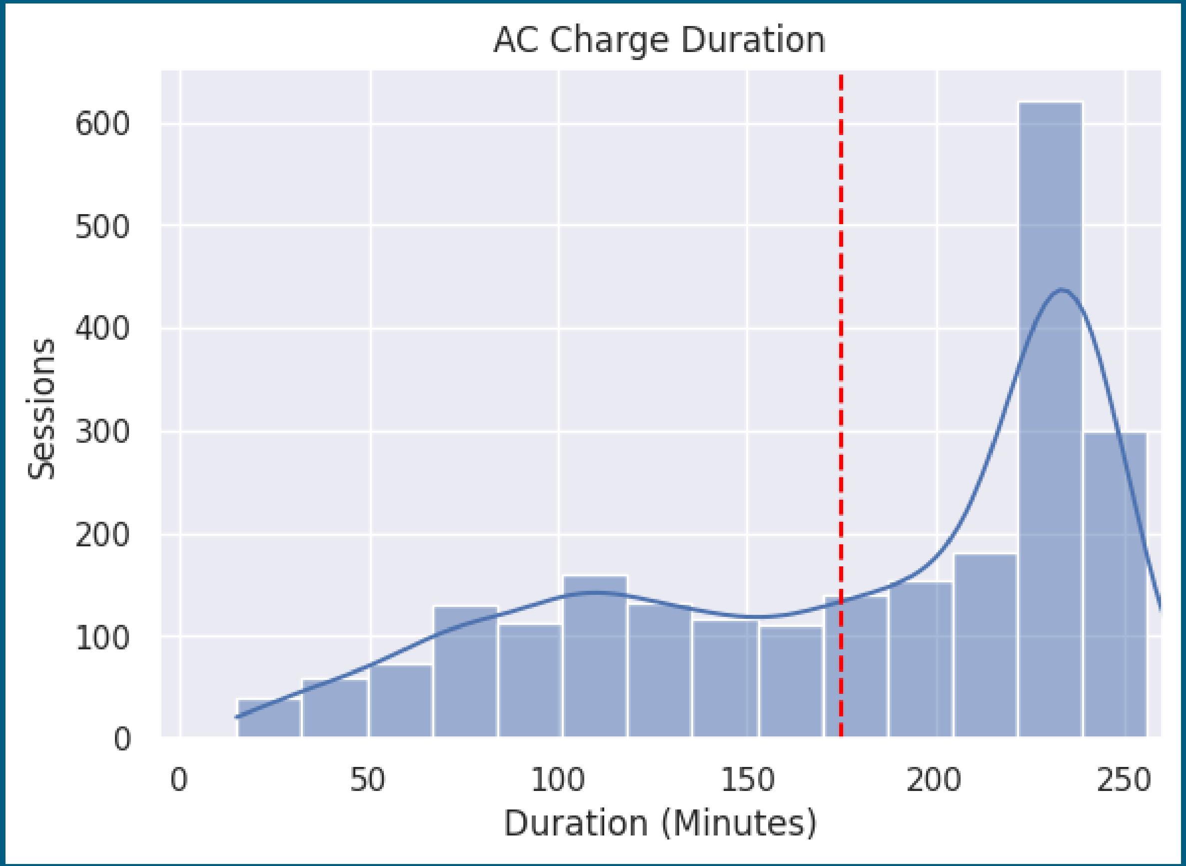


Mean: 16.88 kWh per session

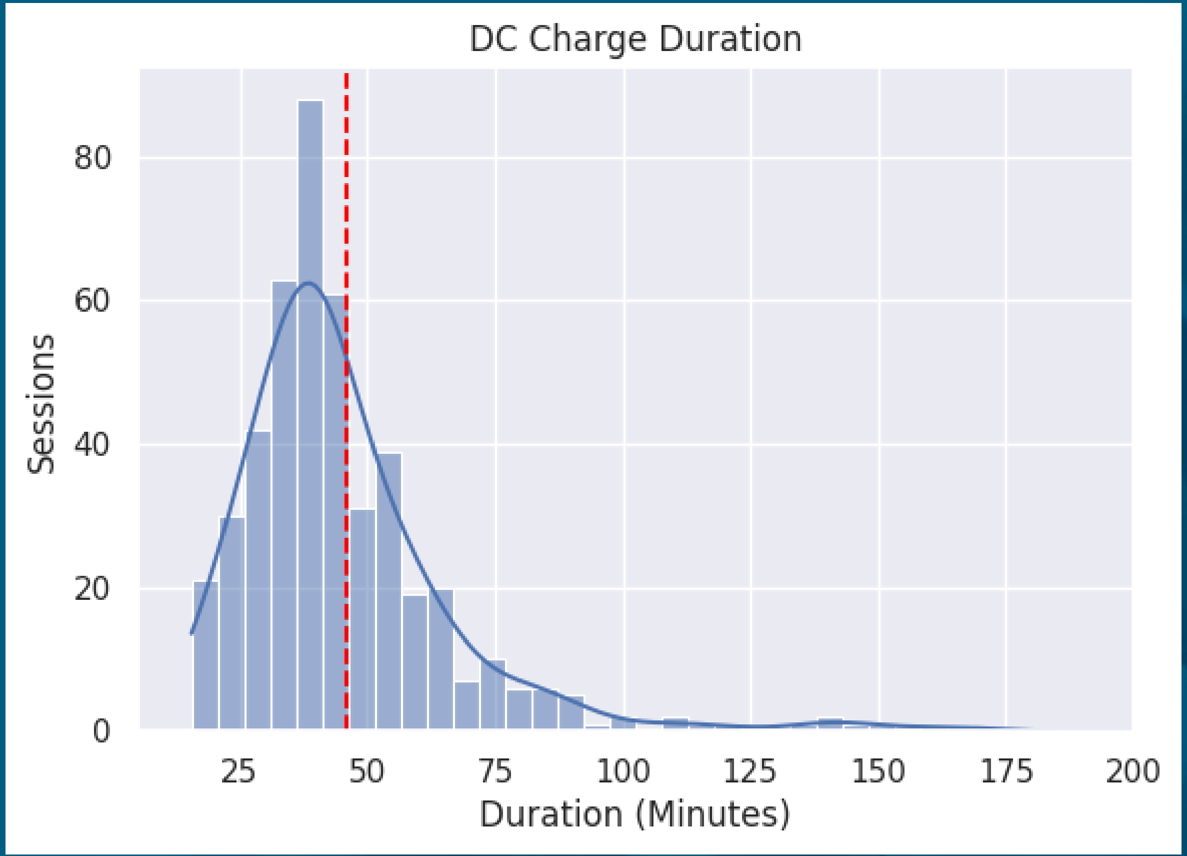


Mean: 40.31 kWh per session

What is the Distribution of Charge Duration per Reservation (AC vs DC)?



Mean: 175.51 minutes (~3 hours)

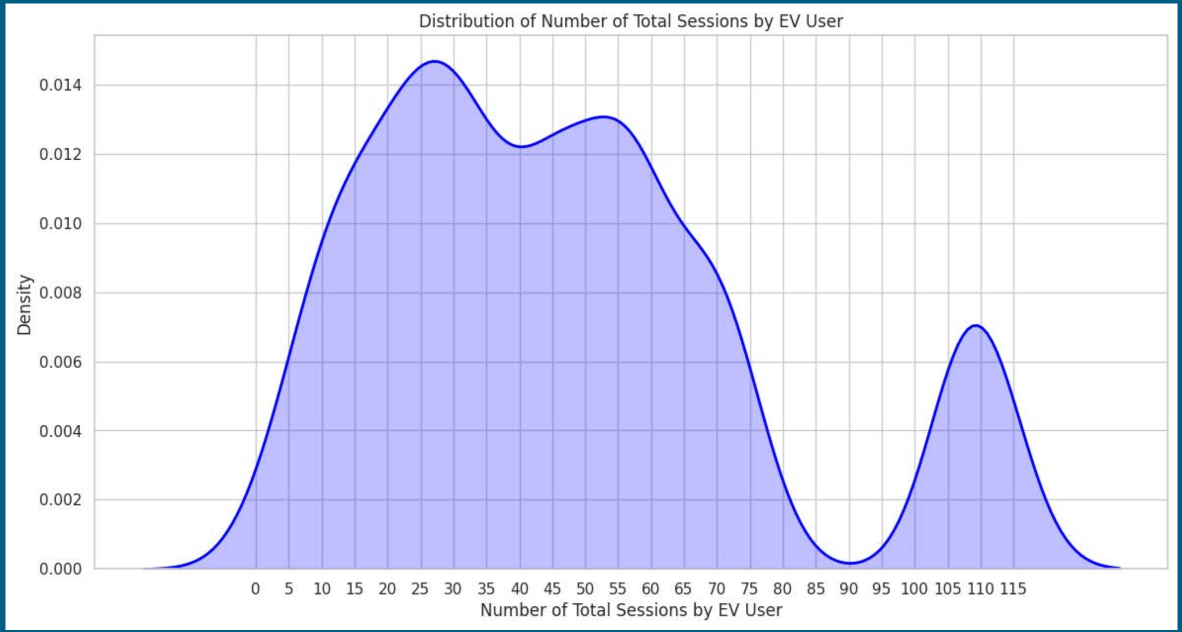


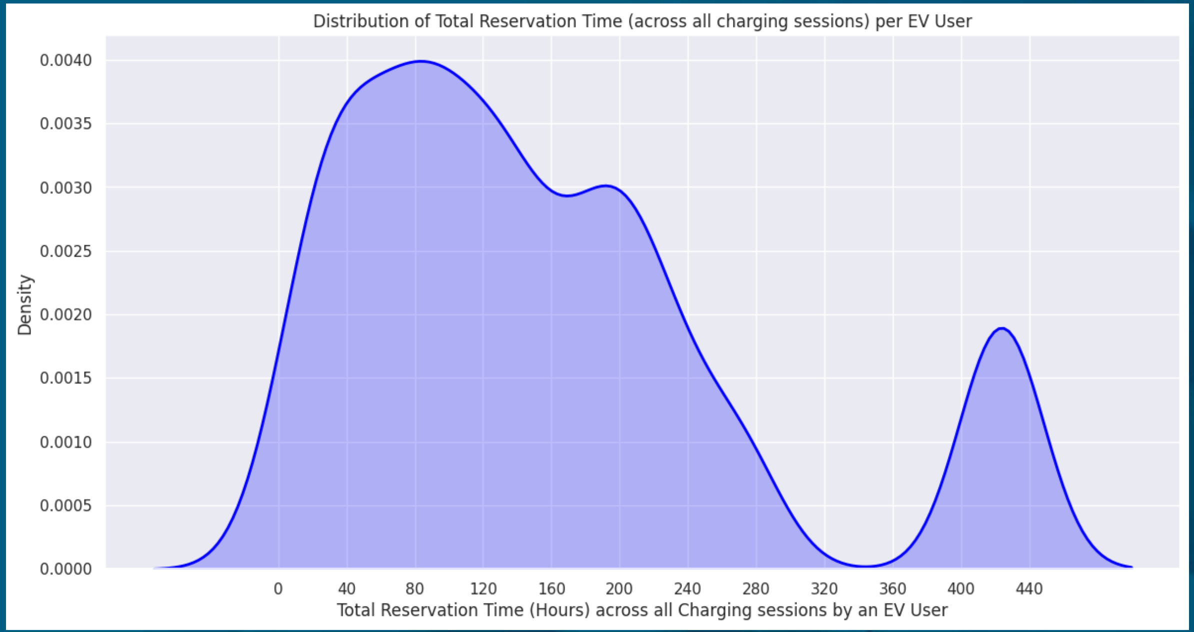
Mean: 46.07 minutes

Note: Employees can reserve up to 4 hours, but we allow up to 4 hours 15 min of charging because we allow charging to begin in the 15 minute window before their actual reservation if the port is available.

EVrest Reservation Usage

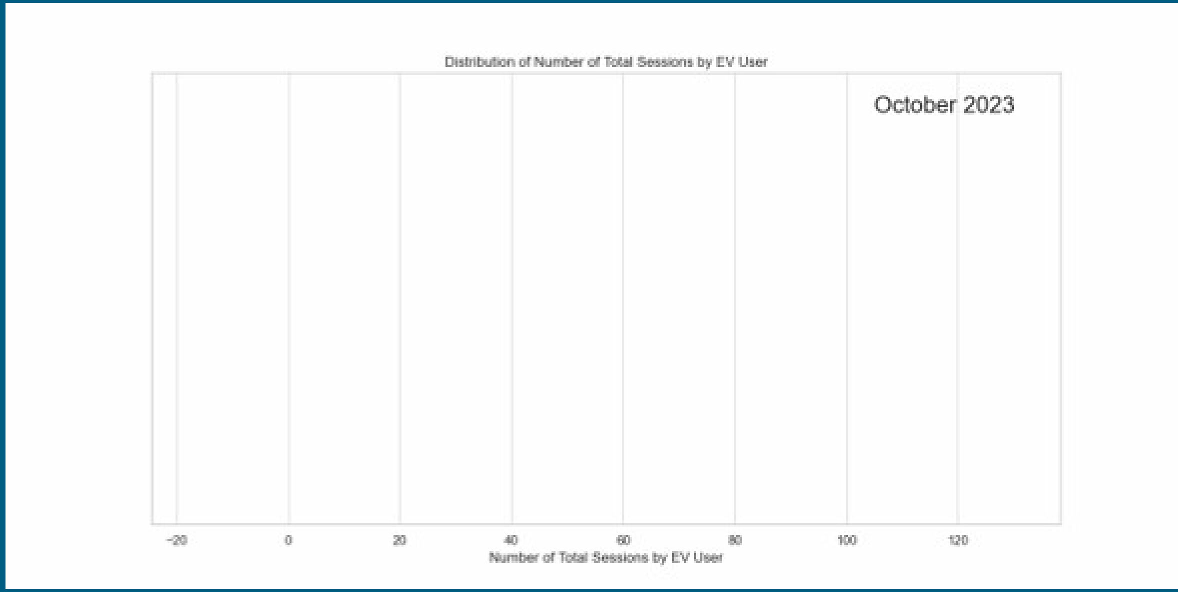
Distribution Plots

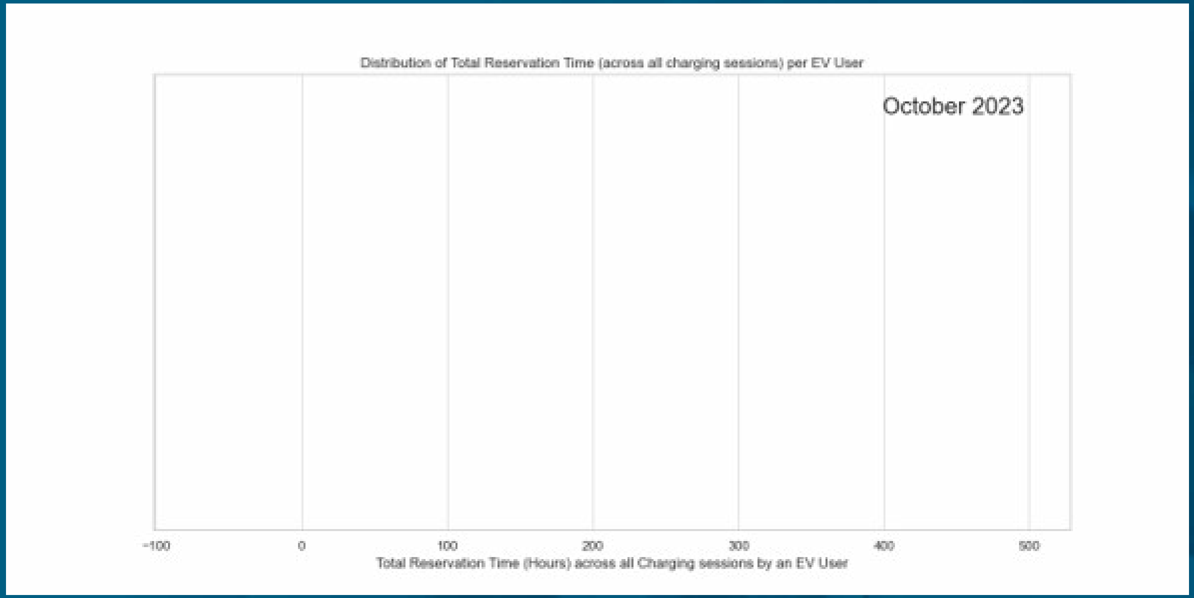




- 3 distinct peaks corresponding to groups of users
- Possible explanations:
  - Different launch dates at different locations around ANL
  - User Behavior

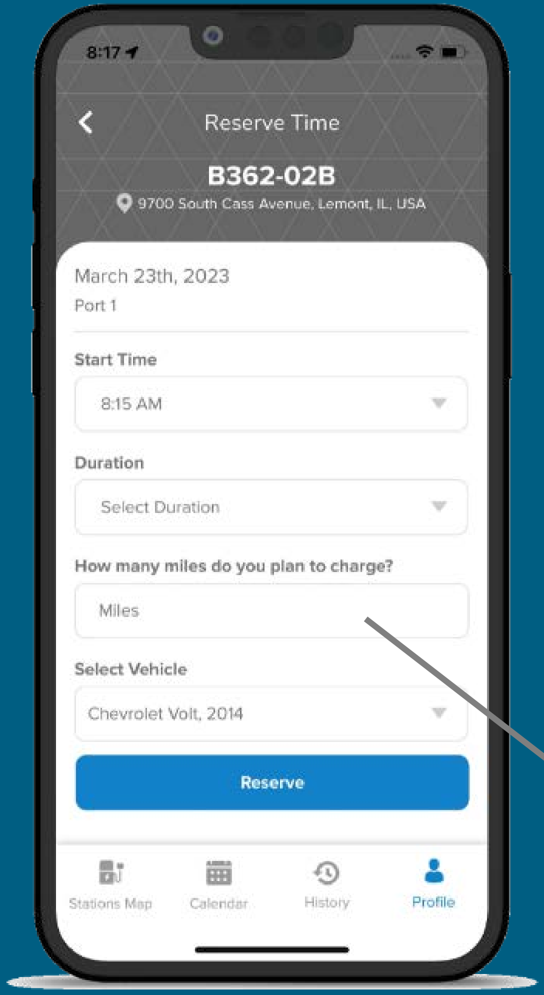
EVrest Reservation Usage
Distribution Plots





- 3 distinct peaks corresponding to groups of users
- Possible explanations:
  - Different launch dates at different locations around ANL
  - User Behavior

Flexibility



$$\text{Pre-Flexibility} = 1 - \left(\frac{\text{Requested Energy (kWh)}}{\text{Duration (h)}} \times \frac{1}{\text{EVmaxPower (kW)}}\right)$$

$$\text{Post-Flexibility} = 1 - \left(\frac{\text{Dispensed Energy (kWh)}}{\text{Duration (h)}} \times \frac{1}{\text{EVmaxPower (kW)}}\right)$$

Pre-Flexibility: Calculated based on driver inputs and used in SCM algorithms

Post-Flexibility: Actual flexibility calculated after charge session has occurred, dispensed energy is <u>minimum of actual energy dispensed or requested energy</u>.

This requested miles is limited based on

- *Max Power available to the EVSE (new)*
- *Max Power drawn by the vehicle (new)*
- *Range of the Vehicle*

Flexibility > 0: SCM could be applied
Flexibility <= 0: SCM can not be applied

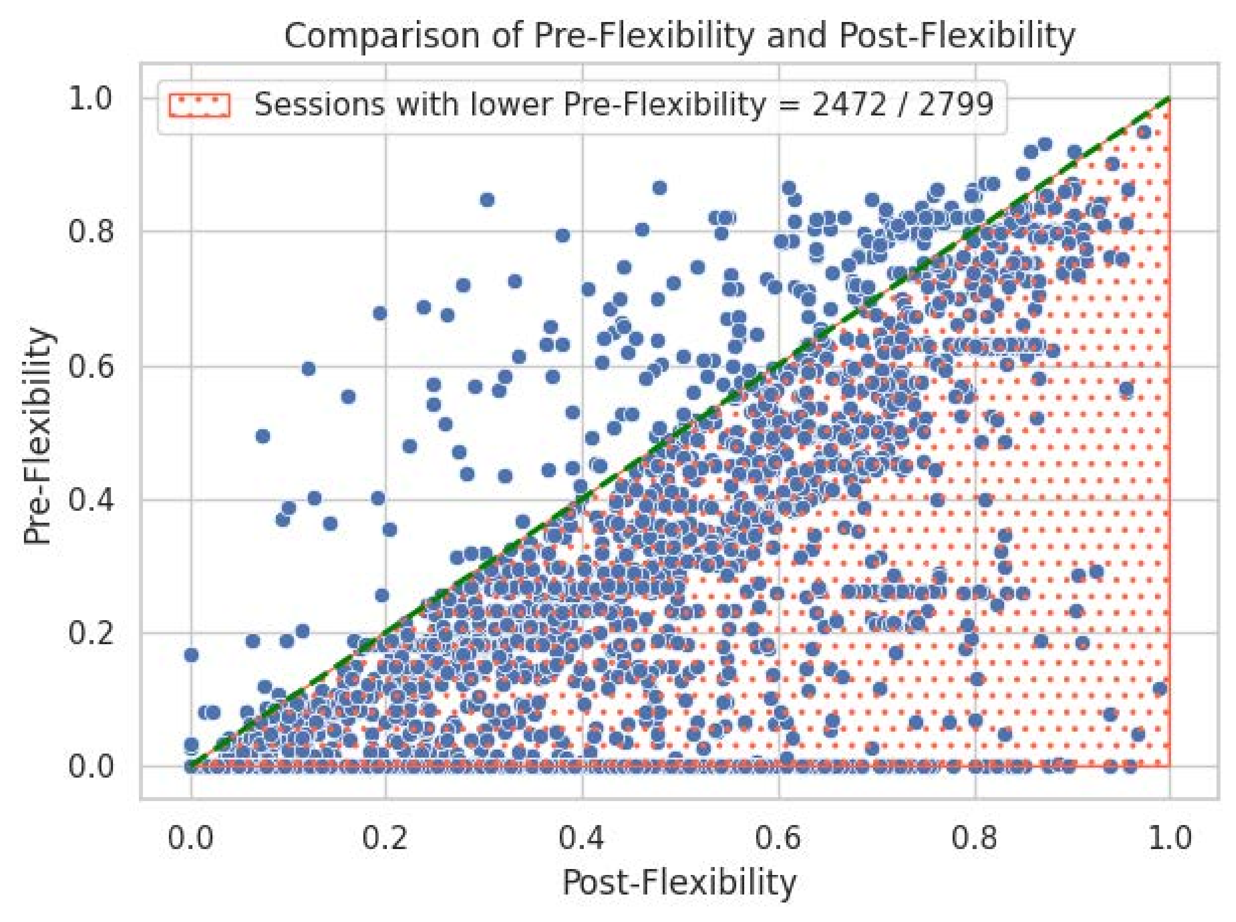
Q: How can someone charge less than requested (green) but still have flexibility?
A: Driver or EV ends charging session before reaching driver's target energy.

Q: How can someone charge more than requested (red) but still have flexibility?
A: Charge session is not stopped once the EV meets its requested mileage. Driver reserved the port longer than what was required to meet their mileage needs.

Q: How do we combat inaccurate requests and physically impossible mileage requests?
A: Apply a check on the reservation screen

Pre-Flexibility vs. Post-Flexibility

Comparison



- Points on the green line indicate that these sessions have accurate information.
- Points below this line, indicates that the request is larger than what was required, not allowing algorithms to take advantage of their actual flexibility
- Points above this line indicate an error in our estimation of the max power the vehicle can charge at (we base our estimation on historical data)

Correlation of EV Driver’s Charging Attributes

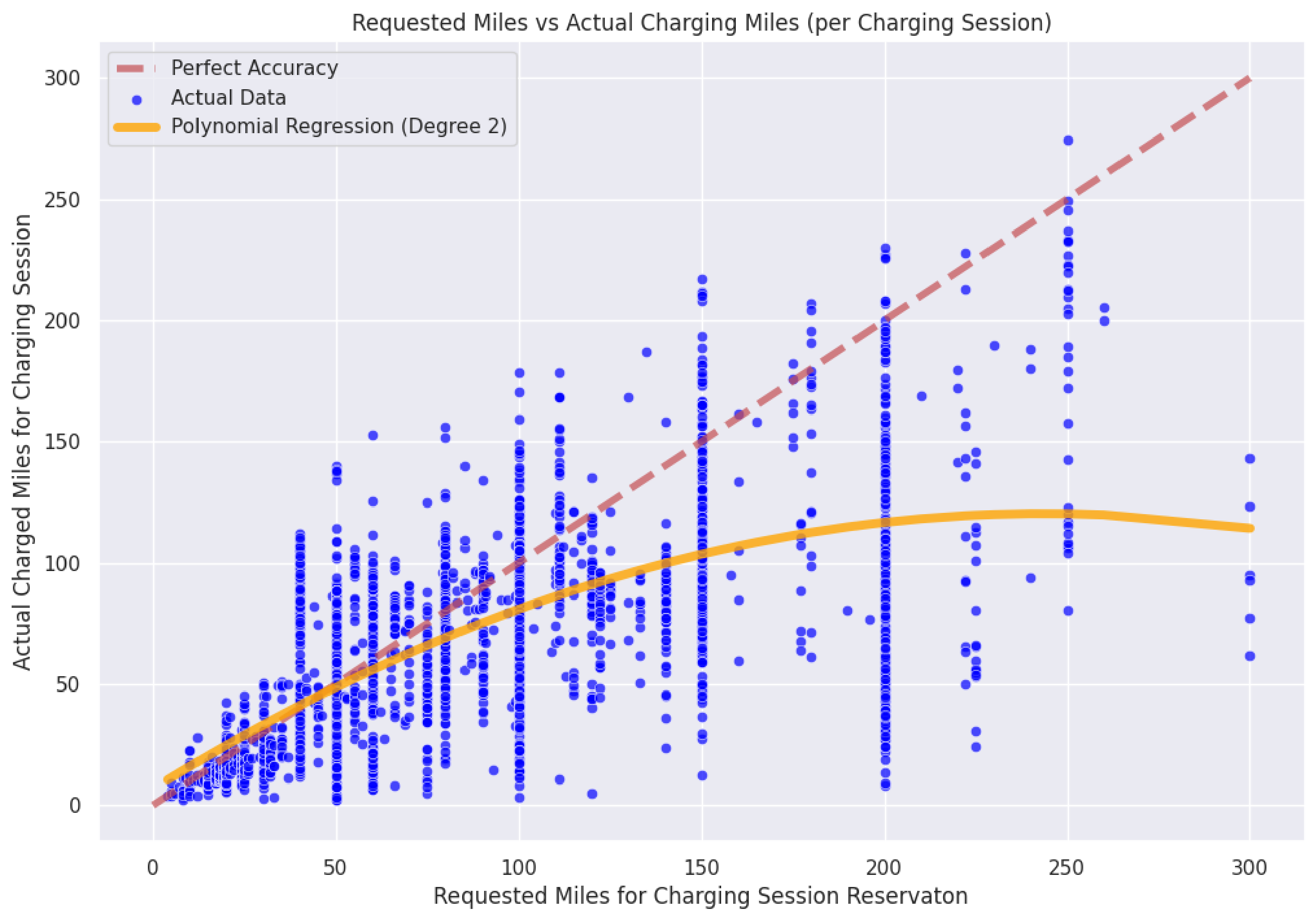
Some interesting correlations:

- ***Average Requested Miles*** & ***Average Actual Miles Charged***
- ***Average Reservation / Session Duration*** & ***Pre / Post-Flexibility***
- ***Average Accuracy*** & ***Average Actual Miles Charged per Session***
- ***Total Number of Sessions by EV Driver*** & ***Post-Flexibility***

	Number of Sessions	Average Requested Miles	Average Accuracy for Requested Miles	Average Actual Miles Charged	Pre-Flexibility	Post-Flexibility	Total Energy Across Sessions	Average Power Draw	Peak Power Draw	Average Reservation Duration	Average of Session Duration
Number of Sessions	1.00	-0.08	-0.04	-0.05	-0.02	-0.08	0.85	-0.22	-0.09	0.34	0.28
Average Requested Miles	-0.08	1.00	-0.06	0.77	0.02	0.05	0.19	0.54	0.36	-0.24	-0.19
Average Accuracy for Requested Miles	-0.04	-0.06	1.00	0.40	0.20	-0.23	0.05	0.25	0.12	-0.08	0.04
Average Actual Miles Charged	-0.05	0.77	0.40	1.00	0.38	0.11	0.29	0.73	0.46	-0.34	-0.21
Pre-Flexibility	-0.02	0.02	0.20	0.38	1.00	0.80	0.11	0.61	0.38	-0.50	-0.59
Post-Flexibility	-0.08	0.05	-0.23	0.11	0.80	1.00	-0.02	0.49	0.34	-0.55	-0.76
Total Energy Across Sessions	0.85	0.19	0.05	0.29	0.11	-0.02	1.00	0.08	0.15	0.16	0.17
Average Power Draw	-0.22	0.54	0.25	0.73	0.61	0.49	0.08	1.00	0.59	-0.76	-0.70
Peak Power Draw	-0.09	0.36	0.12	0.46	0.38	0.34	0.15	0.59	1.00	-0.41	-0.40
Average Reservation Duration	0.34	-0.24	-0.08	-0.34	-0.50	-0.55	0.16	-0.76	-0.41	1.00	0.91
Average of Session Duration	0.28	-0.19	0.04	-0.21	-0.59	-0.76	0.17	-0.70	-0.40	0.91	1.00

How Accurate are Driver Mileage Requests?

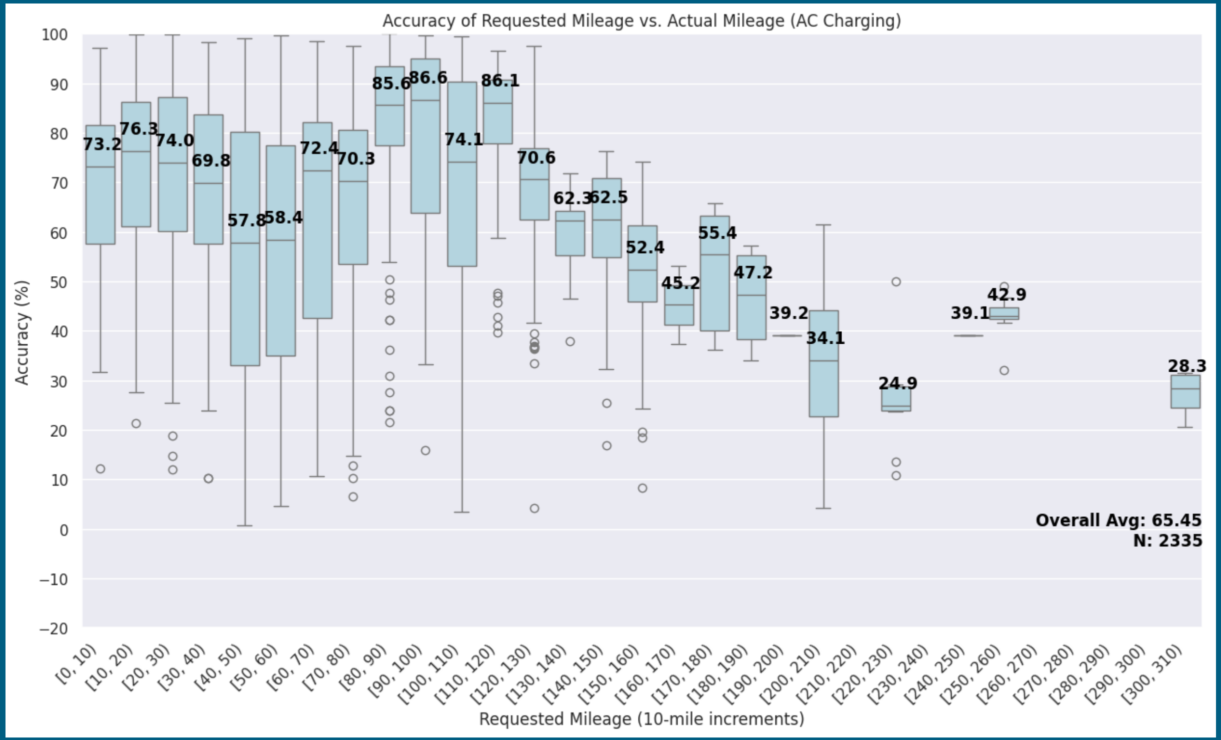
AC & DC sessions combined

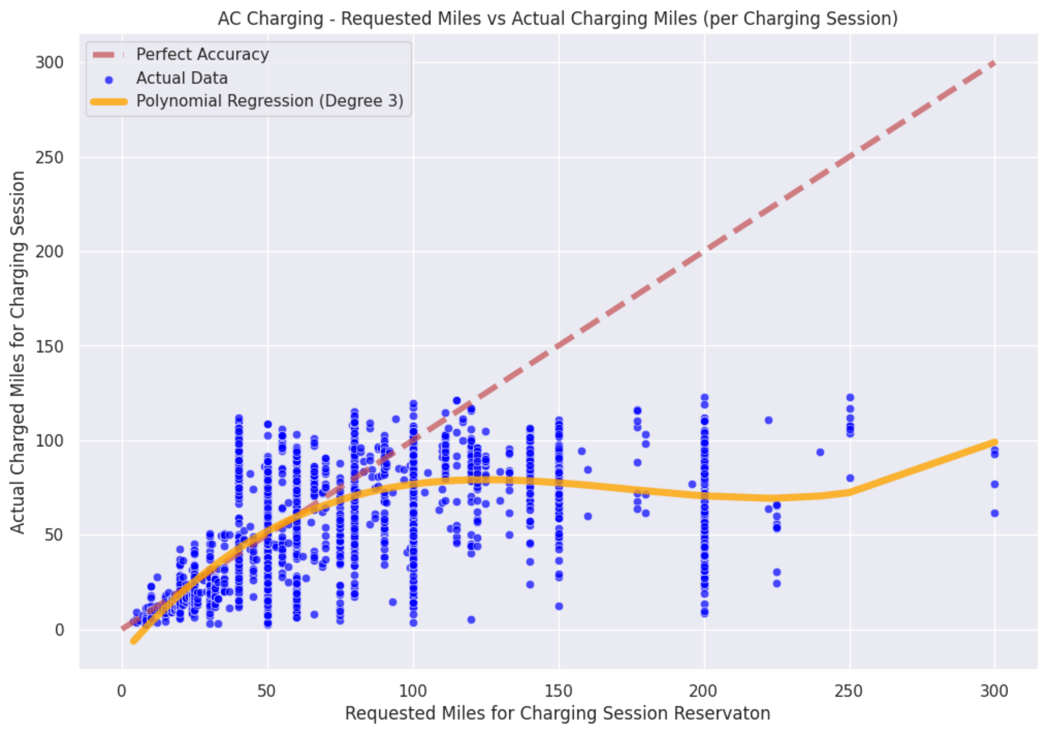


- Variation in accuracy of requested miles across charging sessions
- Polynomial regression explains the varying trend:
    - Lower values of requested miles **(< 100 miles) shows greater accuracy**
    - Higher miles **(> 150) shows significantly lower accuracy**, possibly due to EV users choosing arbitrarily large mileage values during reservation

How Accurate are EV Mileage Requests for AC Charging?

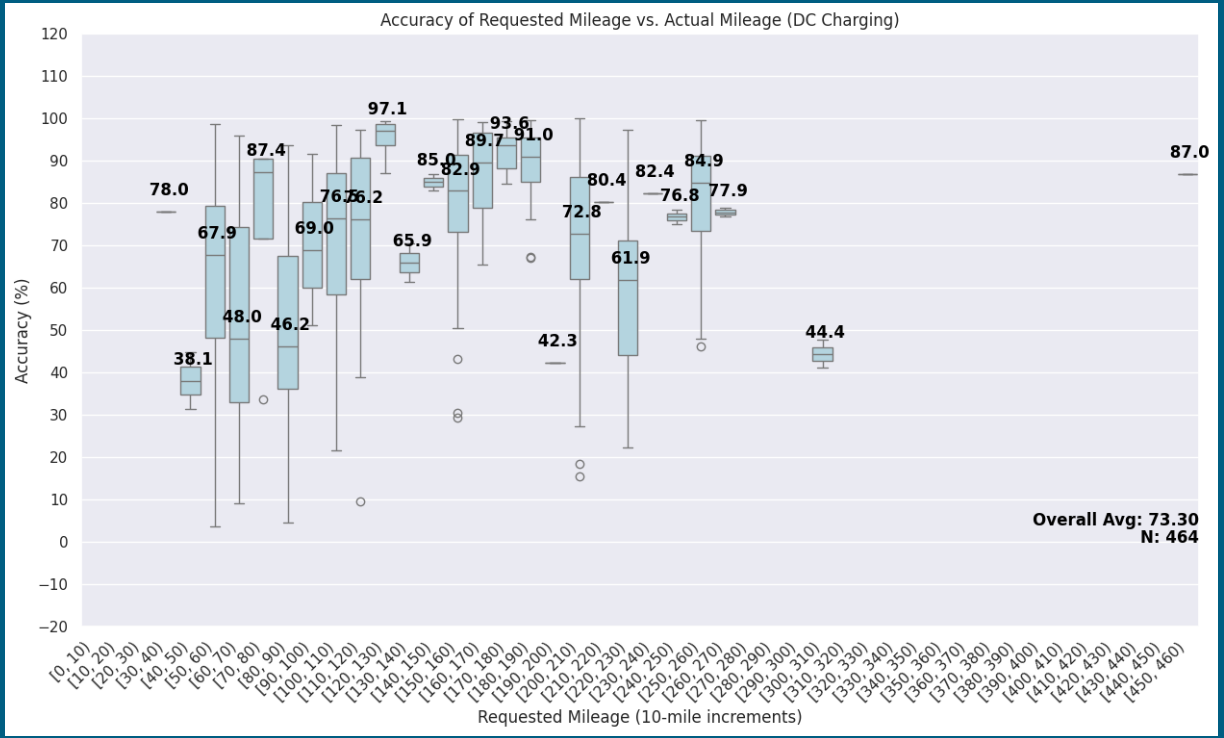
$$\text{Mileage Request Accuracy} = 100 - \left| \frac{\text{Actual Mileage} - \text{Requested Mileage}}{\text{Requested Mileage}} \times 100 \right|$$

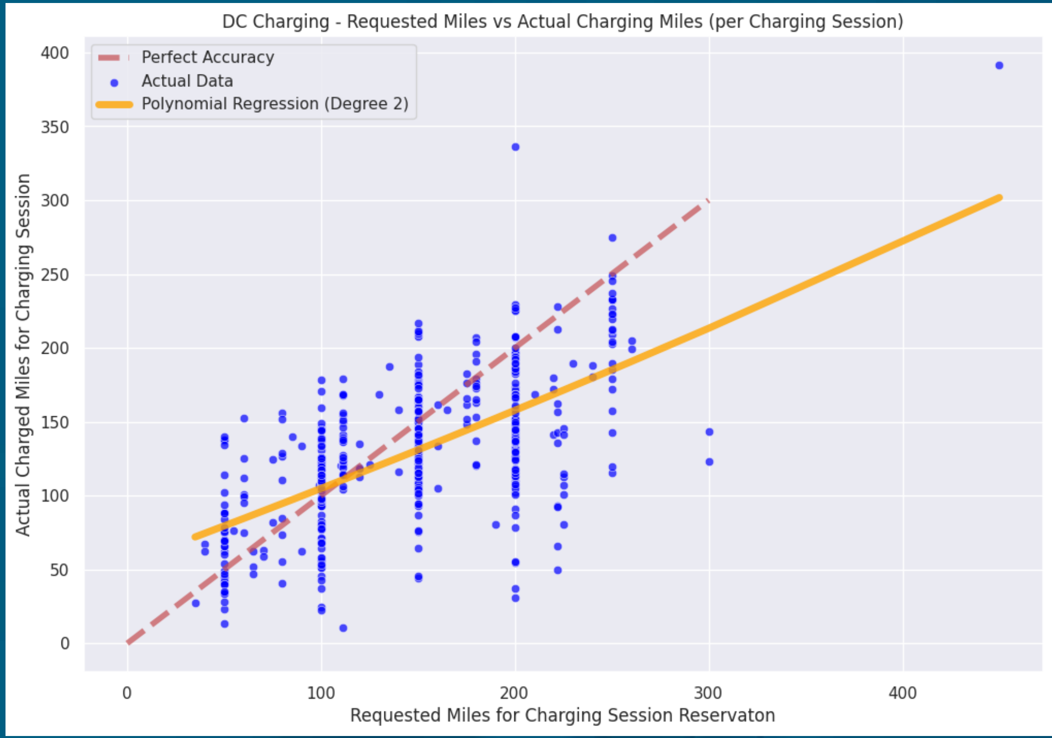




Accuracy diverges above 100 miles due to power rating of EVSE and ~4 hour time limit

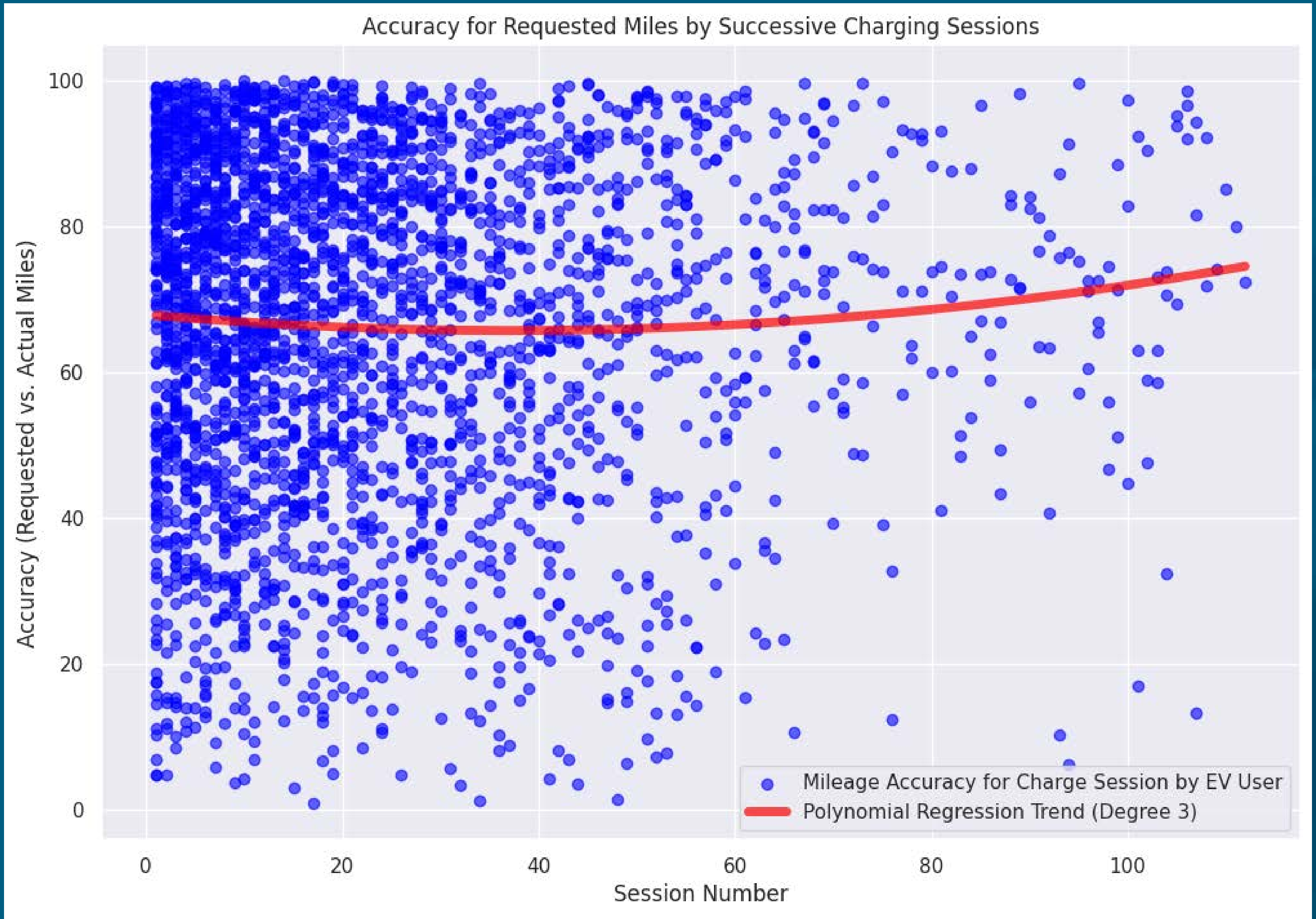
How Accurate are EV Mileage Requests for DC Charging?





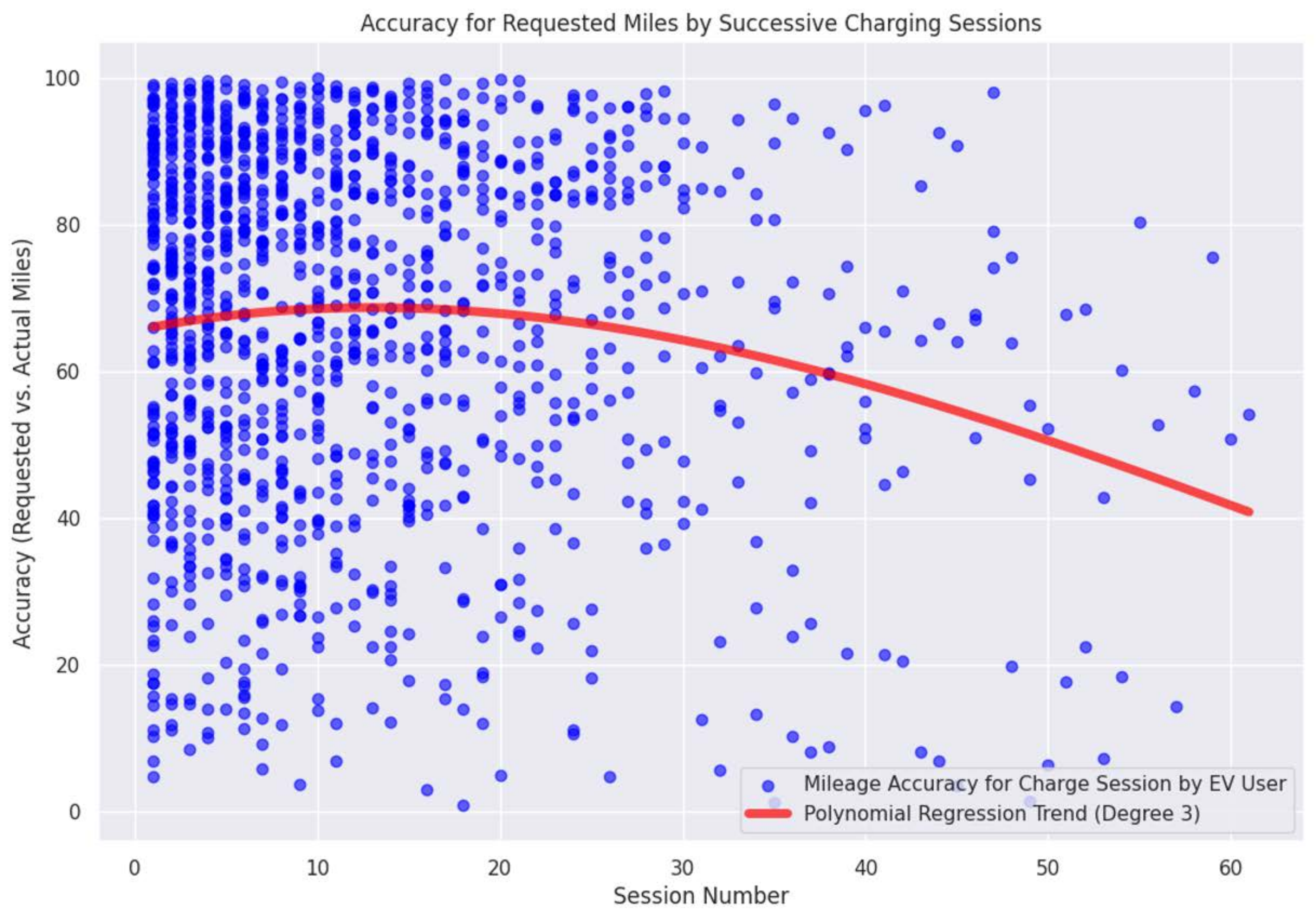
$$\text{Mileage Request Accuracy} = 100 - \left| \frac{\text{Actual Mileage} - \text{Requested Mileage}}{\text{Requested Mileage}} \times 100 \right|$$

How accurate are the requested miles as drivers use EVrest more?



- An increasing trend in accuracy of requested miles (vs. actual miles charged during charging sessions) is visible with increasing usage of EVrest

How accurate are the requested miles as drivers use EVrest more?



- January 2024
- A decreasing trend in accuracy of requested miles (vs. actual miles charged during charging sessions) is visible with increasing usage of EVrest

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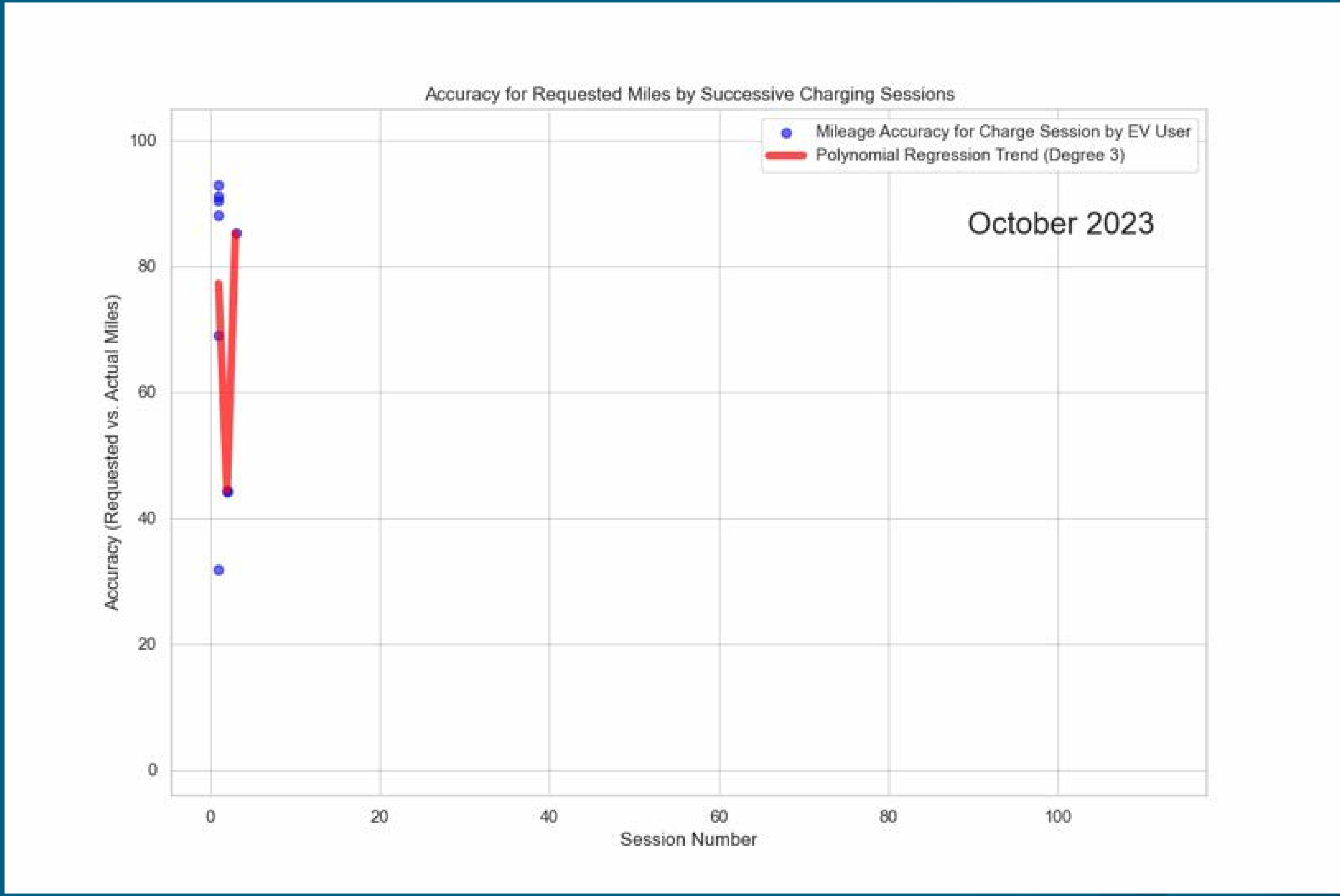
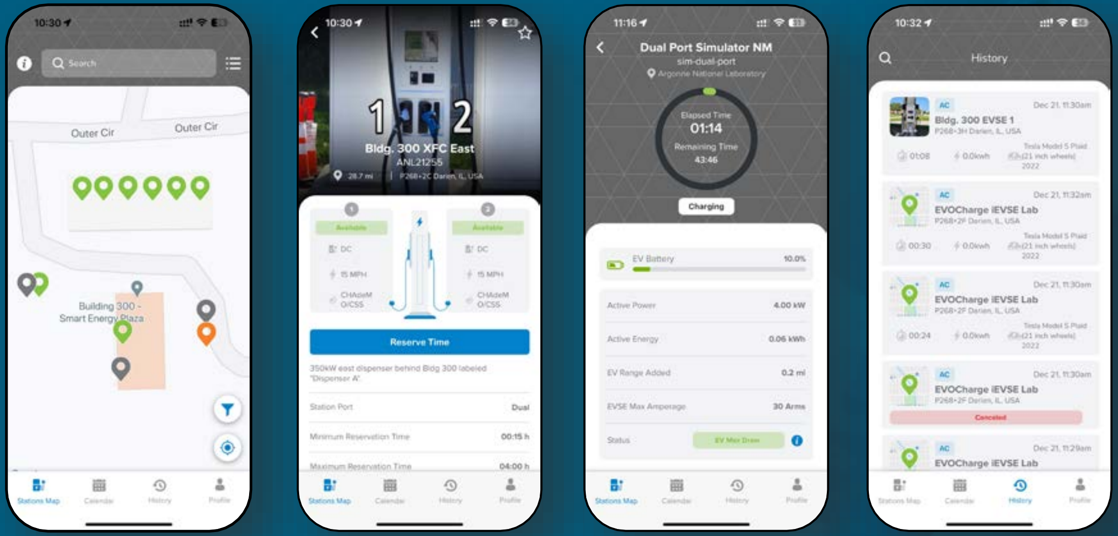


- An increasing trend in accuracy of requested miles (vs. actual miles charged during charging sessions) is visible with increasing usage of Evrest

EVrest

Next Steps

- Continue operating EVrest at Argonne
- Look to harden platform, fix bugs, & add new features
- Implement Charge Scheduling on EVrest Platform (FY24 Q4 Deliverable)
- Explore ML predictive Analytics opportunities
- Explore other potential deployments outside the lab (Workplace or MUD)



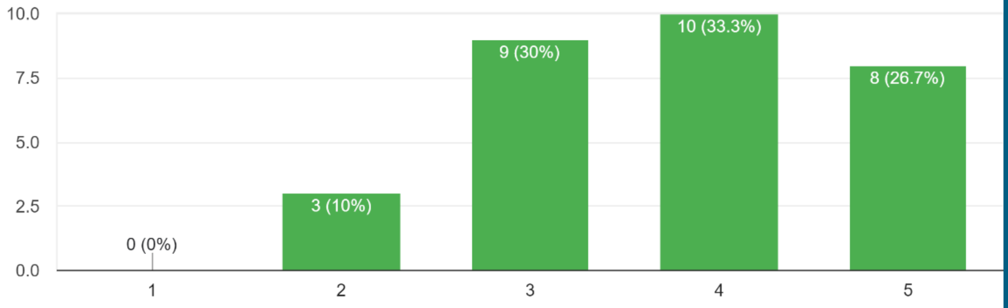
EVrest Employee Survey

Feedback

30 Employees participated in Survey

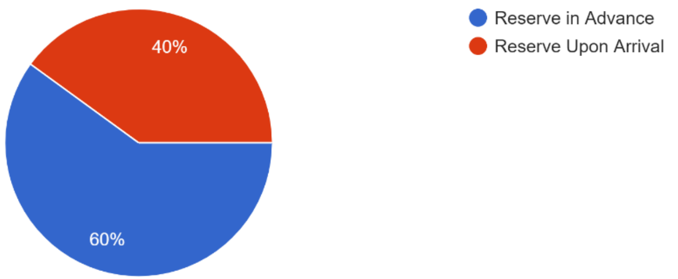
On a scale of 1 to 5, how would you rate the overall user-friendliness of the EVrest app?

30 responses



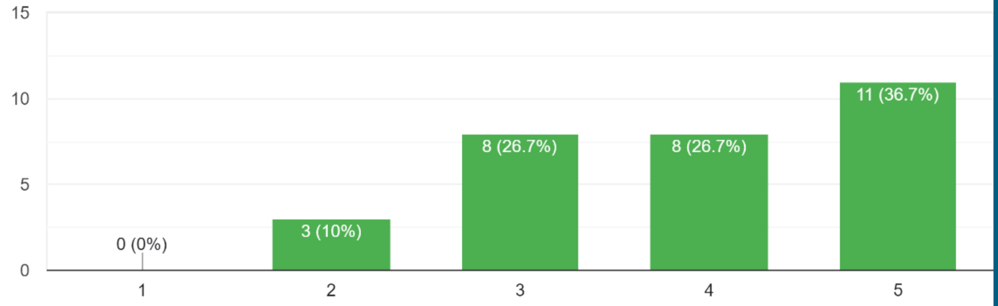
Do you make reservations in advance of pulling up to the station (i.e. hours, days, weeks in advance) or do you make a reservation once you arrive?

30 responses



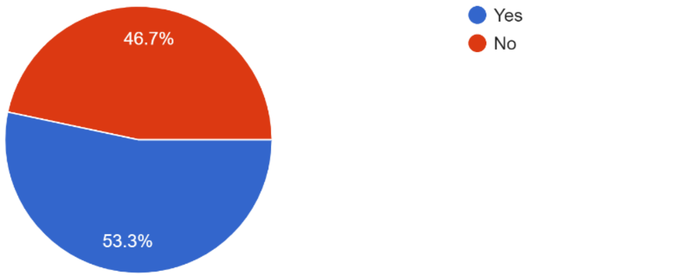
How satisfied are you with the overall ease of making a reservation using the EVrest app?

30 responses



Are you satisfied with the conduct score system as a means to encourage adherence to reservation rules?

30 responses

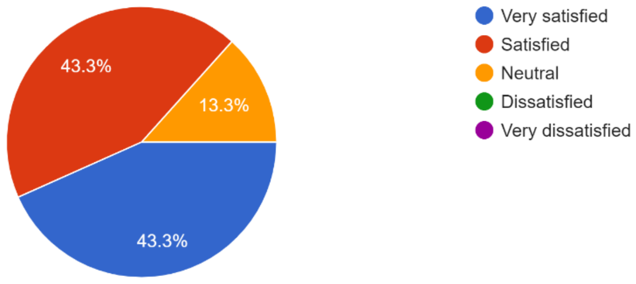


EVrest Employee Survey

Feedback

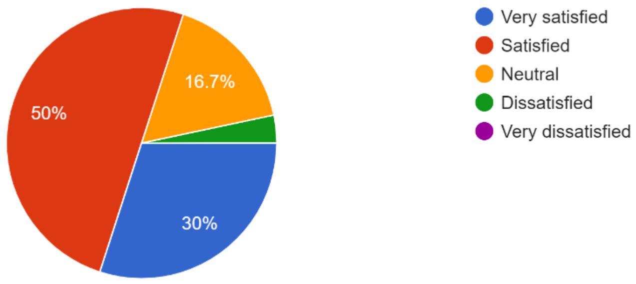
How satisfied are you with the real-time charging status updates provided by the EVrest app?

30 responses



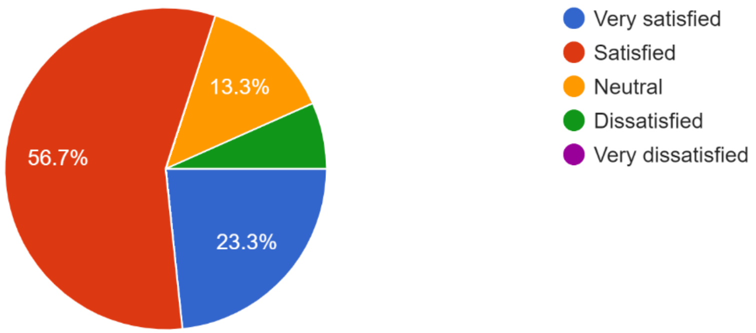
How satisfied are you with the push notifications provided by the EVrest app?

30 responses



Overall how satisfied are you with the EVrest app?

30 responses



User Feedback

Great work! thank you for developing the app and it makes charging much more convenient!

The app has been great I think in cutting down a lot of frustrations that users have had(people parking in your spot randomly even though you booked in advance is a big one).

I like that it will cancel a reservation if not activated within 15 minutes of start time. This allows for others to take a spot if someone reserved it but didn't show up for the appointment time.

Map is easy to deal with, good feedback from User interface

I like that I know the charging station will be free if I've reserved it, and I like that the app lets me know when my car is finished charging.

It's a great system (so much better than Vector)

Improvement Suggestions

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Are there any specific improvements you would suggest for the user interface?

Can you add a payment feature to only charge for the kW used? I have a hybrid and typically only charge 2.5 hrs at 3x/week.

Allow user to start the session, say, up to 15 mins before the reservation starting time without the need to delete the session then rebook the reservation if the user arrives slightly early. The 4 hour window can be kept the same.

A copy and paste option. Or something similar. I have a set schedule at work so I charge at the same time everyday. I counted 15 taps just to make a single reservation. Also entering in the miles seems useless.

Not much value in the “miles you plan to charge” from a user perspective.

It always asks what mileage I want to charge for a session. I don’t know the exact number, but I just want to charge it using the maximum power.

Thank You

Nithin Manne
nmanne@anl.gov

Salman Yousaf
yousaf@anl.gov

Jason D. Harper
jharper@anl.gov

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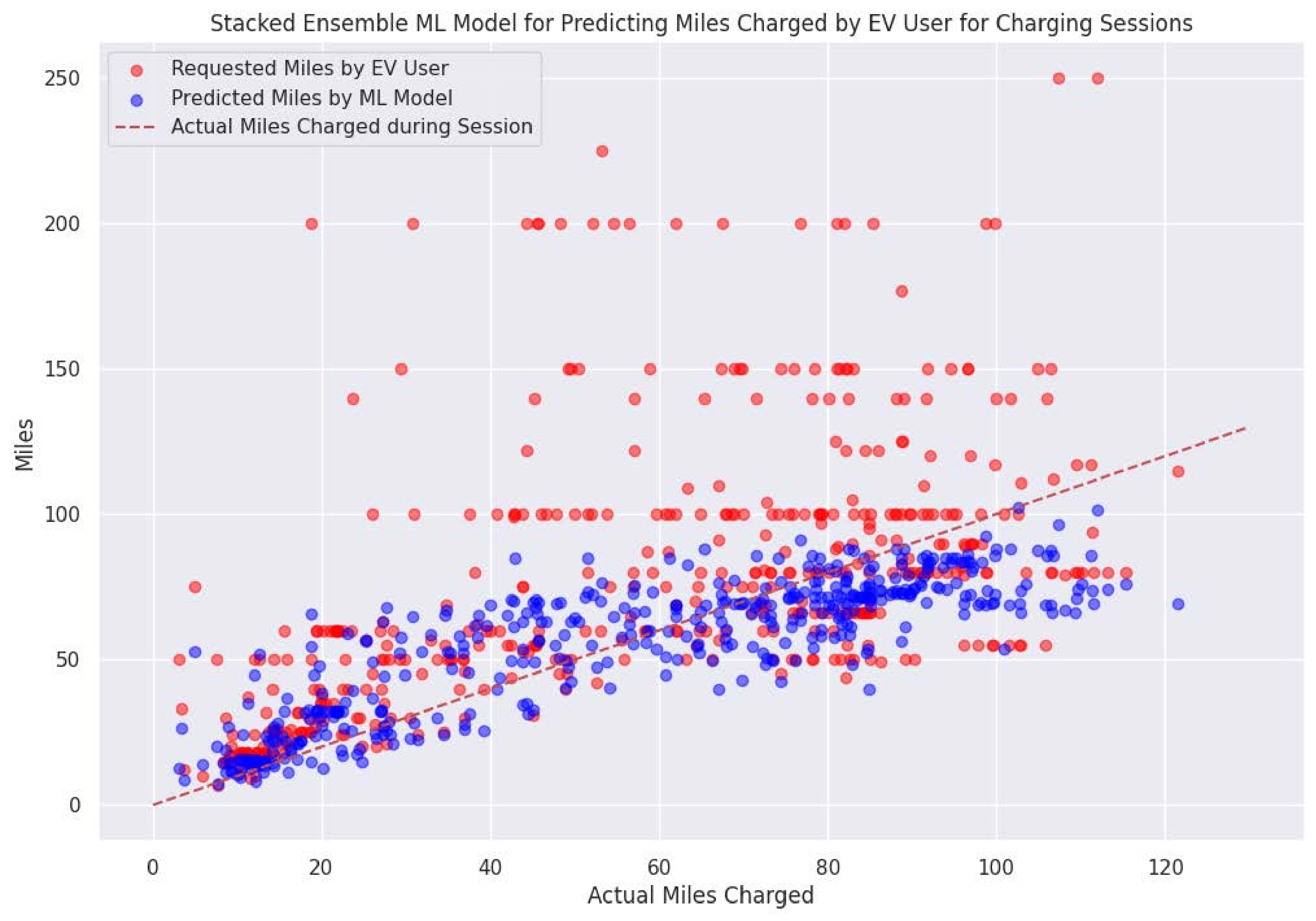
Can Actual Energy for Charging Sessions be Explained and Predicted?

- Stacked-ensemble Machine Learning model trained on EV User's historical attributes, such as:
    - *total number of sessions,*
    - *historical accuracy of requested miles*
- used to **predict energy requirements (in miles) for charging sessions**

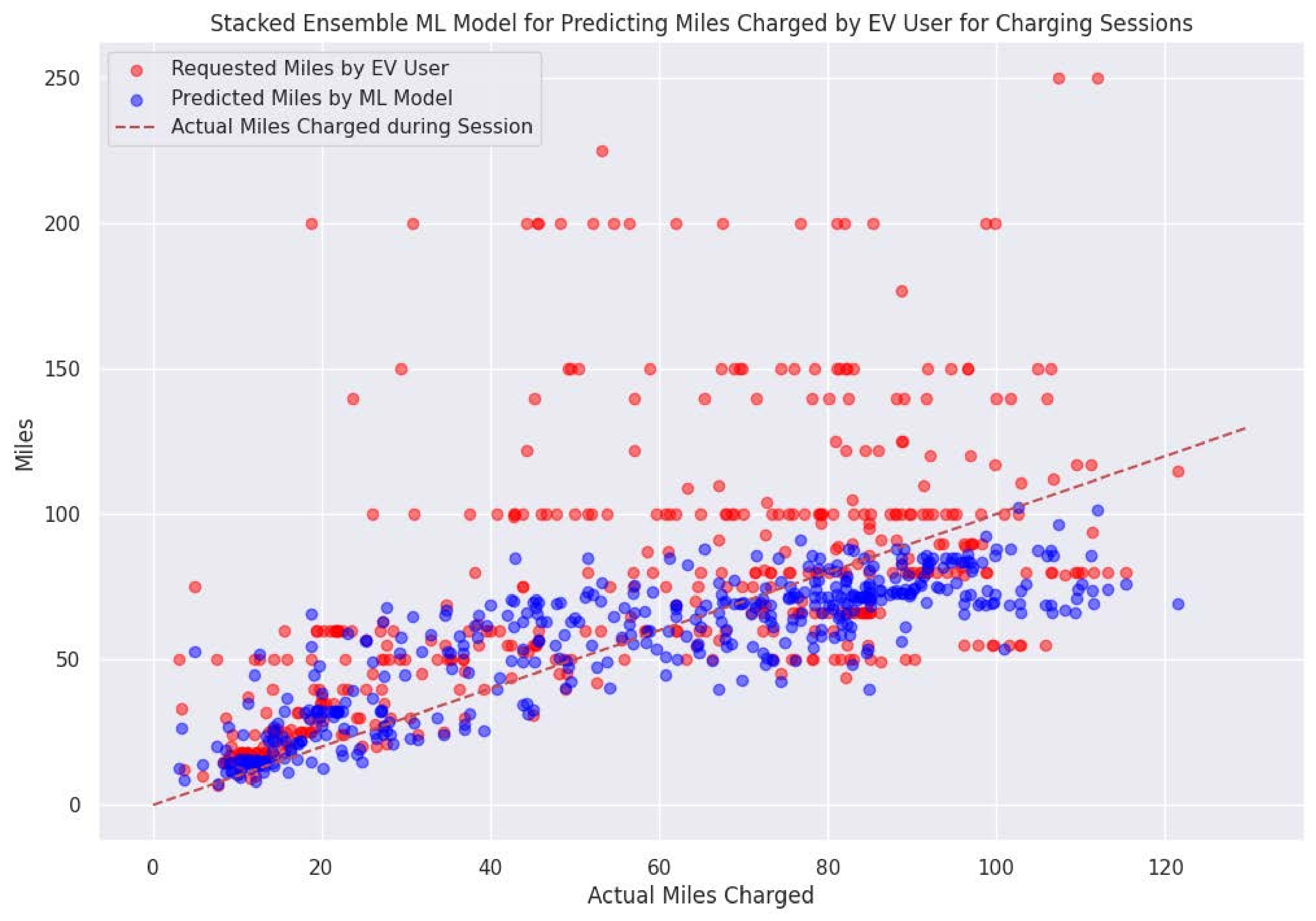
- Results show **ML can predict actual energy requirements significantly better than EV User's own expectations**

- **Mean Absolute Error (MAE)** improved by **47.3%** with ML-based predictions:
    - MAE for User Expectation: 34.8%
    - MAE for ML Predictions: 18.3%



Can Actual Energy for Charging Sessions be Explained and Predicted?

- Shows the potential for predictive power in historical EV user behaviour
- Larger dataset of Evrest user history with fine-tuned modelling could provide even more interesting results
- Predictions for energy required and user flexibility for charging sessions could become inputs for charge scheduling models and greatly improve impact



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Smart Charge Management and Vehicle Grid Integration: FUSE

- Predicting Requested Energy (Mileage) for Reservations using Machine Learning
- Smart Charge Scheduling

Salman Yousaf (yousaf@anl.gov)

Predicting Requested Energy (Mileage) for Reservations using Machine Learning

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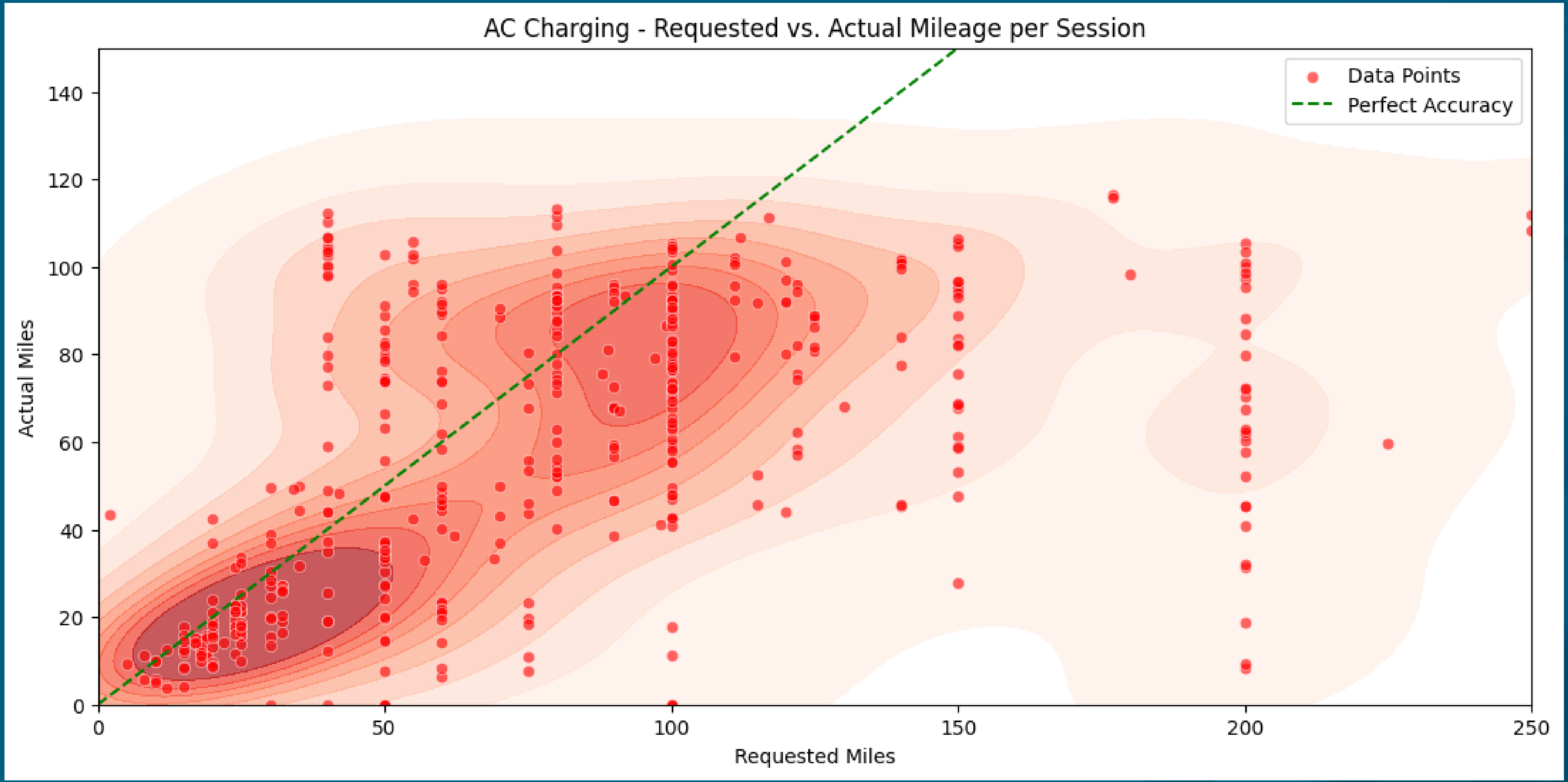
- EVrest user's own estimations for energy for charging reservations are inaccurate:
  - Root Mean Squared Error for AC Charging: ***51.23***



- Users often ***<u>overestimate</u>*** their energy requirements.
- Actual energy received during charging sessions is often ***<u>lower</u>*** than requested energy.

Predicting Requested Energy (Mileage) for Reservations using Machine Learning

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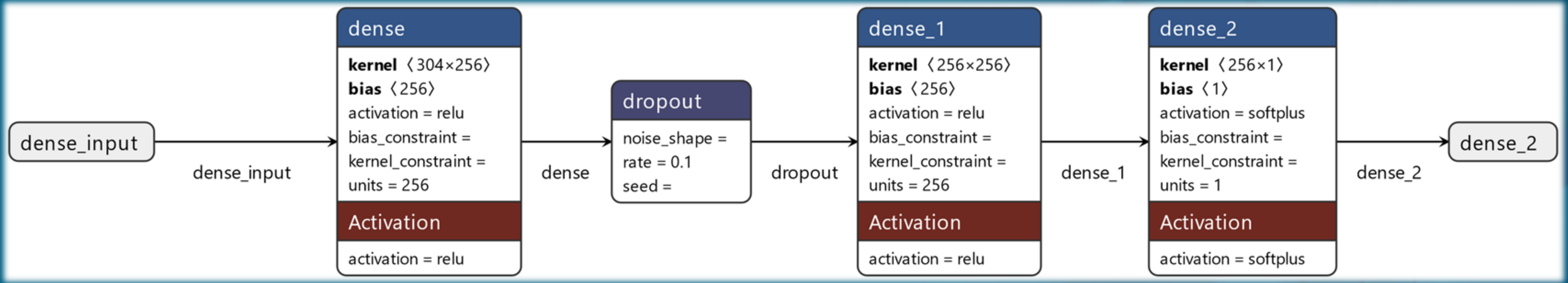
- Using historical reservation and charging sessions data, we developed a Deep Neural Network that **predicts requested energy (mileage) for an EV reservation**

- *Deep Neural Network Architecture*



Predicting Requested Energy (Mileage) for Reservations using Machine Learning

Training Data Overview

***Source*:** Real Time Data from EVrest reservations and charging session records

***<u>Data Features</u>*:**

- **User Information**
  - **EV User ID:** Unique identifier for each user.
  - **Historical User Characteristics:**
    - **Historical Average Energy Request Accuracy:** Assessment of user's past request accuracy, measured by comparing requested to actual energy needs.
    - **Total Number of Sessions**: Cumulative count of user's charging sessions, reflecting user experience and frequency
- **Vehicle Details**
  - **Vehicle ID:** Unique identifier for each vehicle.
  - **Make & Model:** Vehicle's brand and model name, providing insights into vehicle type and potential charging needs.
- **Reservation Metrics**
  - **Start Time:** Hour and day of the week when the charging session is reserved, highlighting peak usage times and patterns.
  - **Duration**: Length of reservation, offering insights into charging behaviour and station occupancy.
- **Reservation Type (AC / DC Charging)**

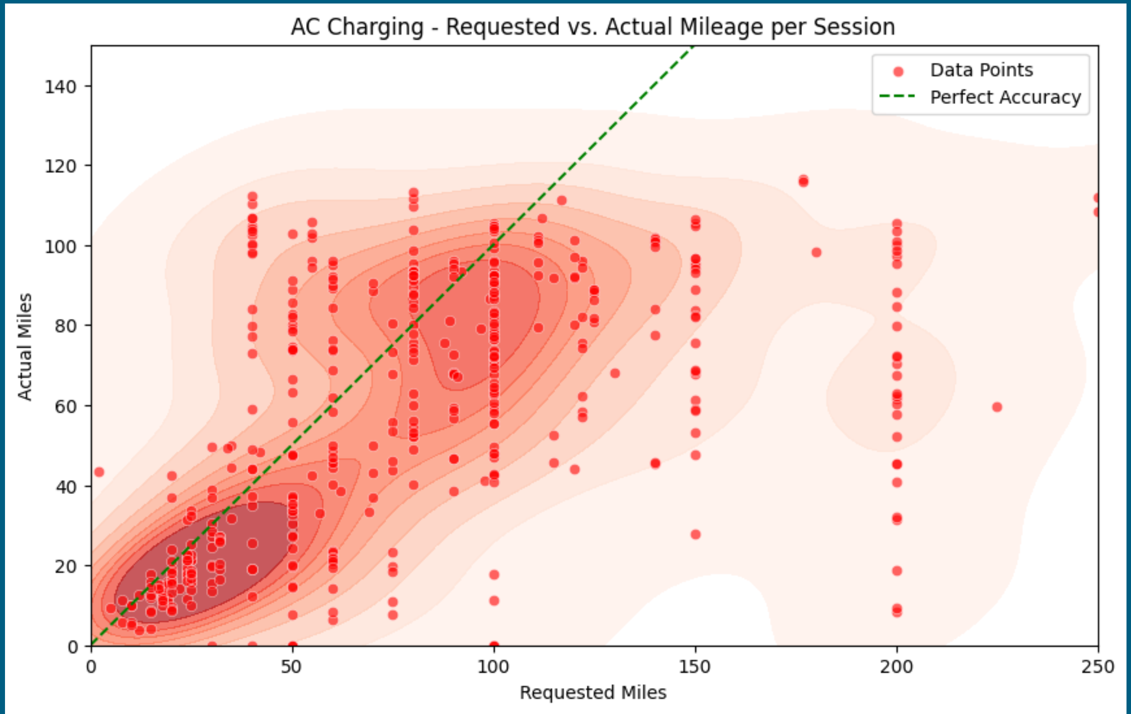
<u>Prediction Target</u>

- **Actual Miles Charged:** The actual mileage charged during the session, serving as the label for predicting user behavior and charging needs

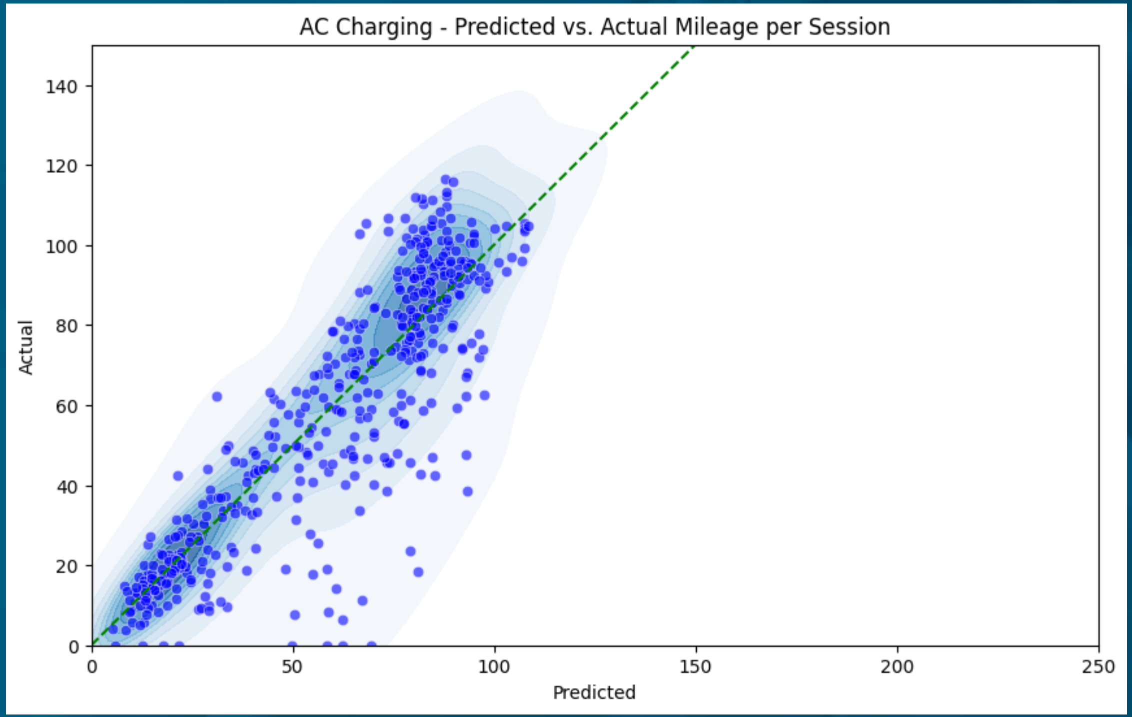
Predicting Requested Energy (Mileage) for Reservations using Machine Learning

- AC Charging: Improved RMSE (Root Mean Squared Error) by ~68%

EV User's Estimations



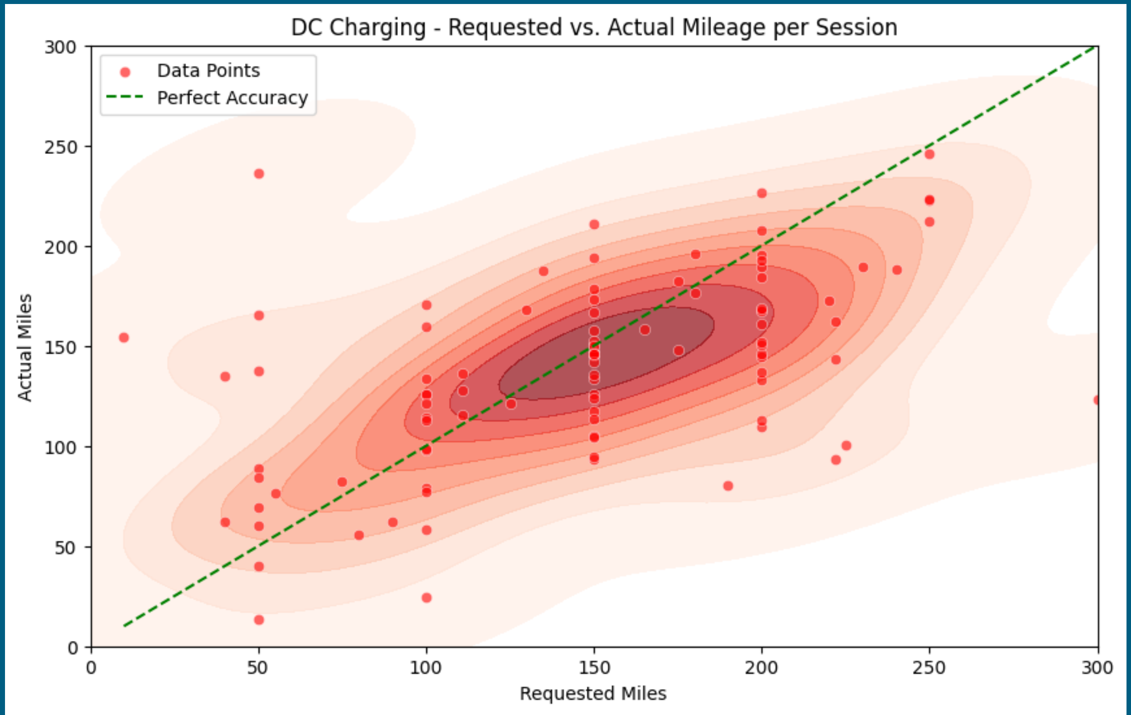
Model Predictions



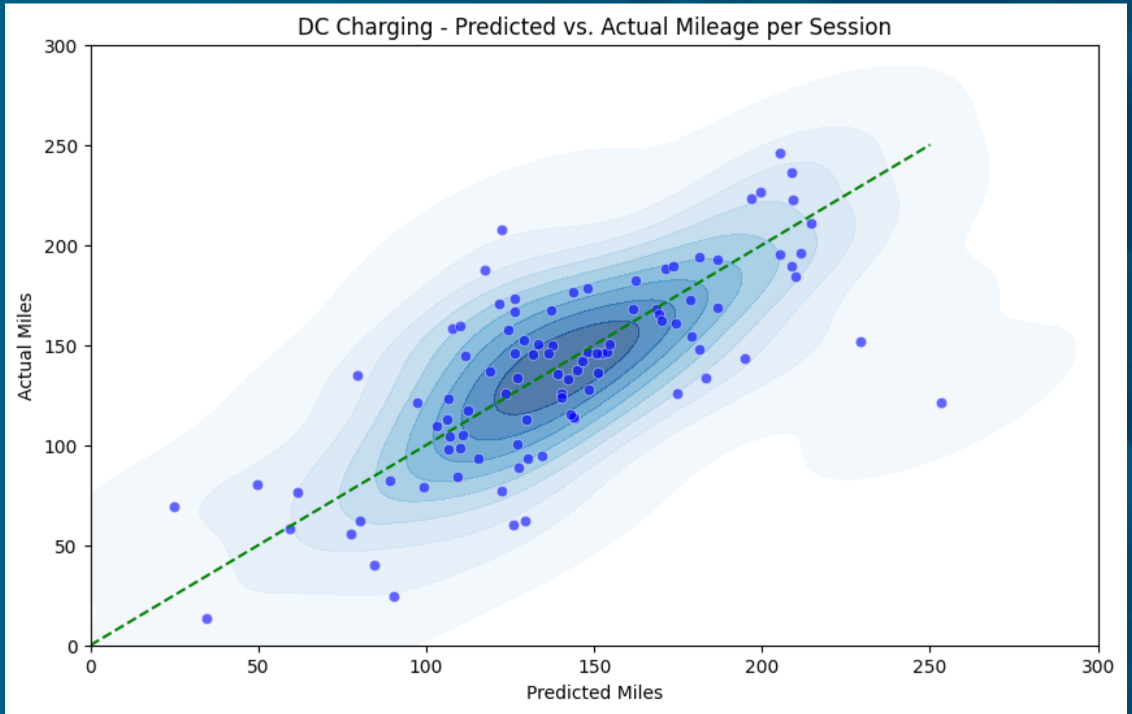
Predicting Requested Energy (Mileage) for Reservations using Machine Learning

- DC Charging: Improved RMSE (Root Mean Squared Error) by ~30%

EV User's Estimations



Model Predictions



Predicting Requested Energy (Mileage) for Reservations using Machine Learning

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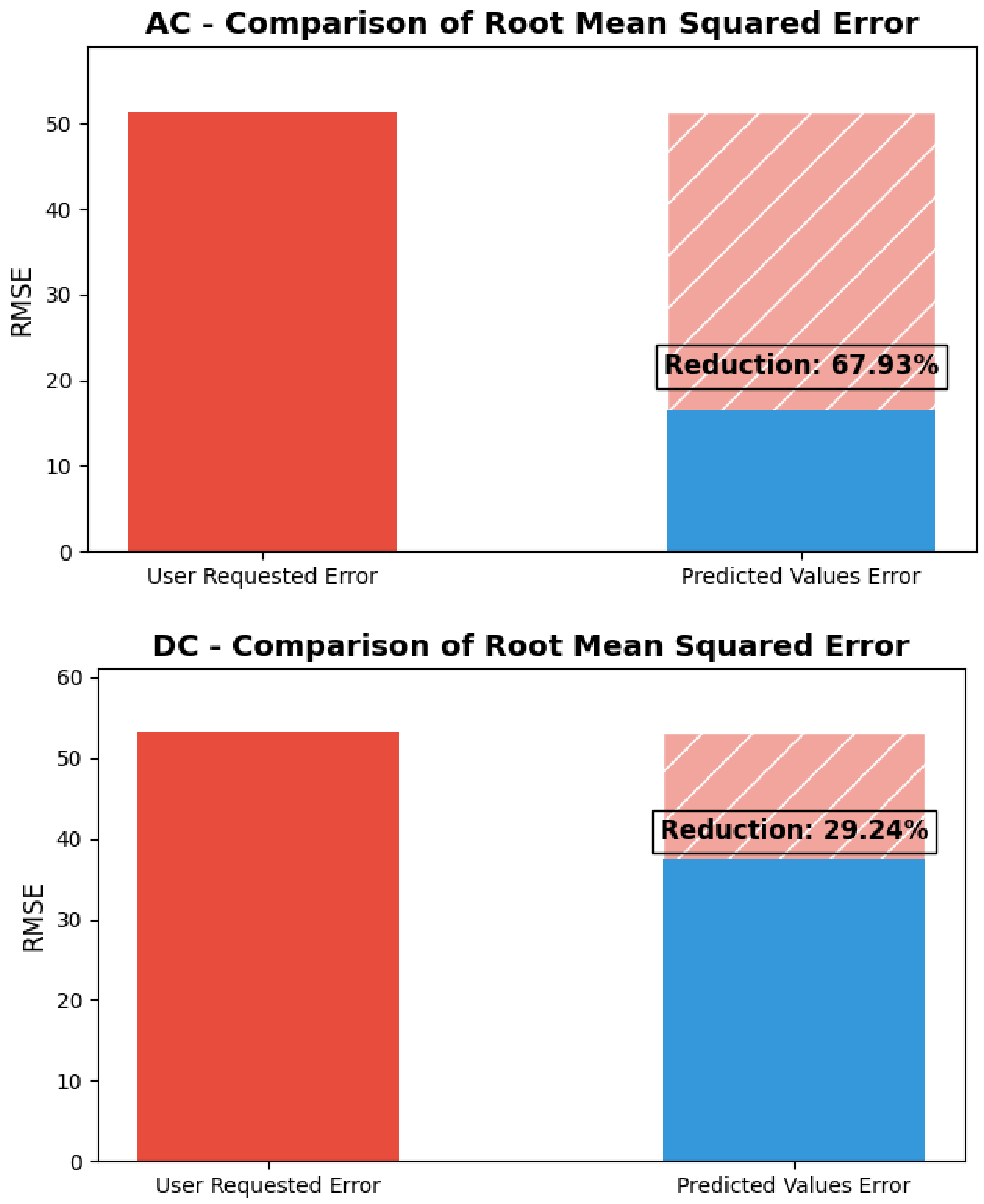
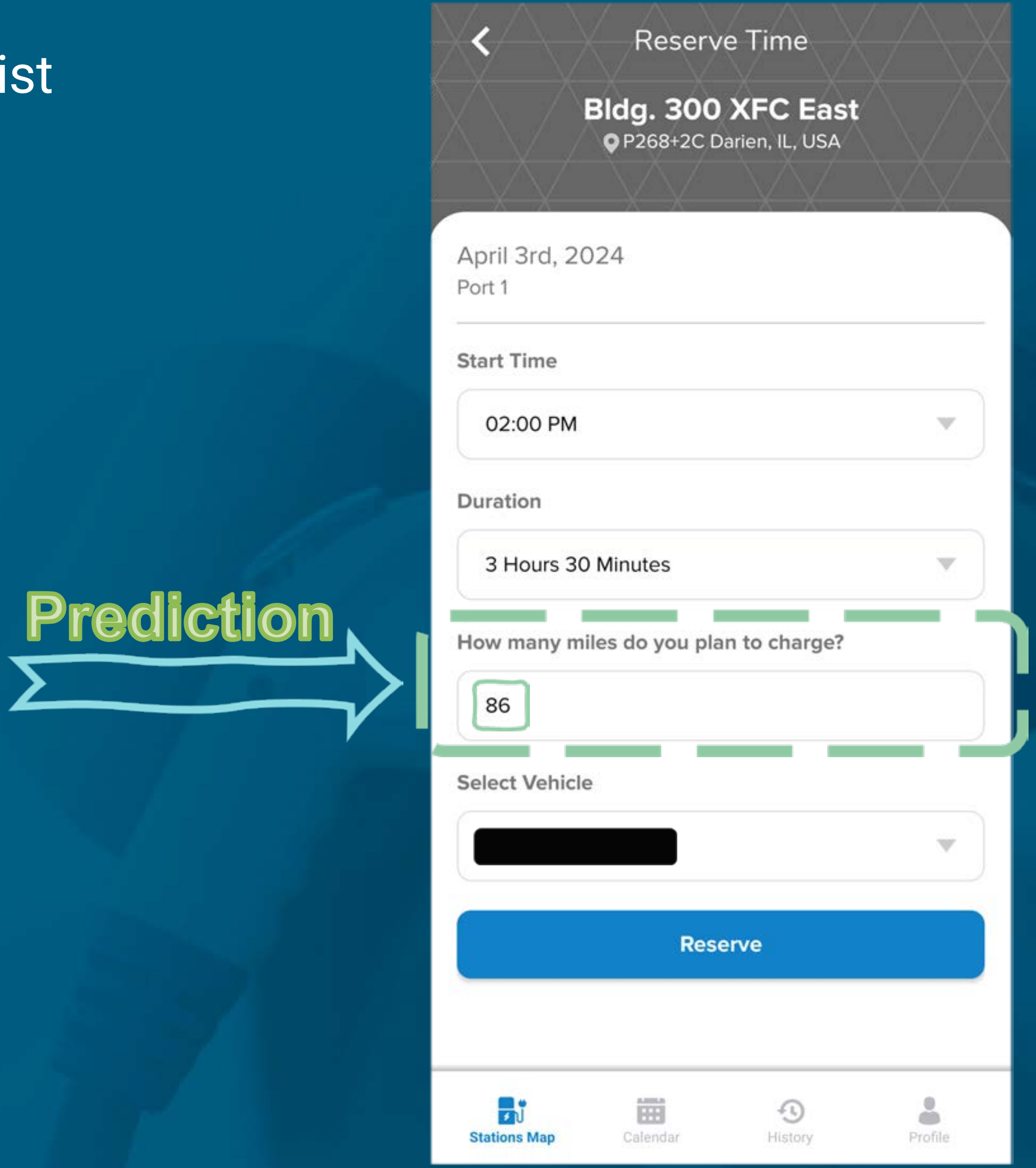
- Model's predictions reduced RMSE (Root Mean Squared Error) when compared with user's own predictions by:
  - *68%* for AC Charging
  - *29%* for DC Charging



Predicting Requested Energy (Mileage) for Reservations using Machine Learning

- <u>Prepopulate</u> predicted *'miles planned to charge'* to assist users while creating a reservation
- Users <u>can choose to change</u> the prepopulated value based on their needs
- ML-based prepopulated predictions take into account historical trends and attributes, such as:
  - *User's historical reservations*
  - *User vehicle's historical characteristics*
  - *Reservation timing and duration*
- *Deep Learning Model is trained with new data and new predictions are generated with a <u>daily frequency</u>*



Predicting Requested Energy (Mileage) for Reservations using Machine Learning

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User Enters Reservation Details on EVrest

Input Data Features

1. Driver's Attributes
   - ID
   - Historical Average Accuracy
   - Number of Completed Sessions
2. Vehicle's Attributes
   - ID
   - Make, Model
3. Reservation Start Time
   - Day of Week
   - Hour of Day
4. Reservation Duration
   - 15-minute increments

Deep Neural Network

Predicted Miles for Reservation

EVrest uses prediction to prepopulate requested energy for User

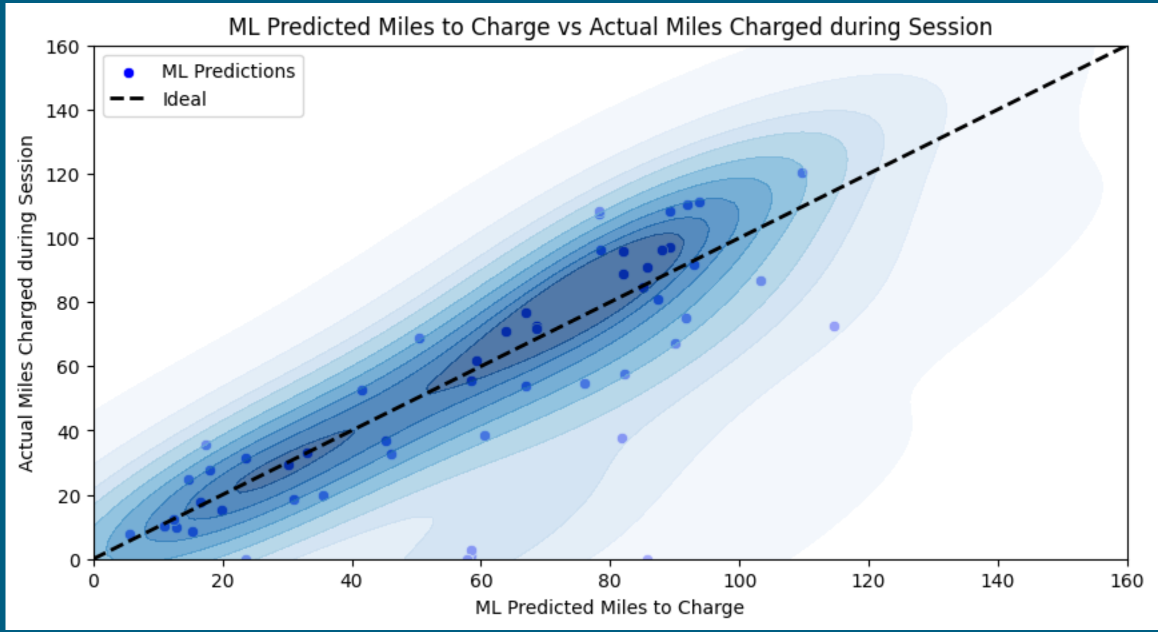
Deployment Insights:
Predicting Requested Energy (Mileage) for Reservations using Machine Learning

EVs@Scale
U.S. Department of Energy

From March 27 – April 3, 2024:

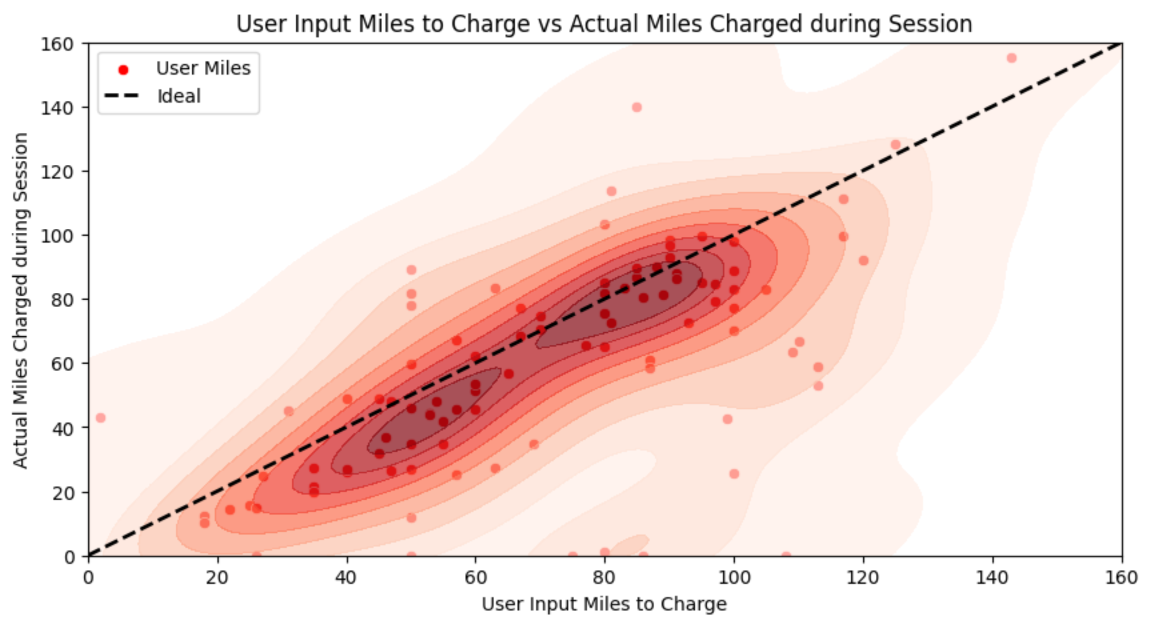
- Total of **158** Sessions
- **56.4%** of users chose to proceed with ML-prepopulated requested energy mileage while creating EVrest reservations
- Accuracy comparison:

Sessions with ML-Prepopulated Values



RMSE: **25.9**

Sessions with Users' Manually Entered Values



RMSE: **29.4**

- **Reservations that used ML-Prepopulated Requested Energy reduced (RMSE) error by ~30%**

Predicting Requested Energy (Mileage) for Reservations using Machine Learning

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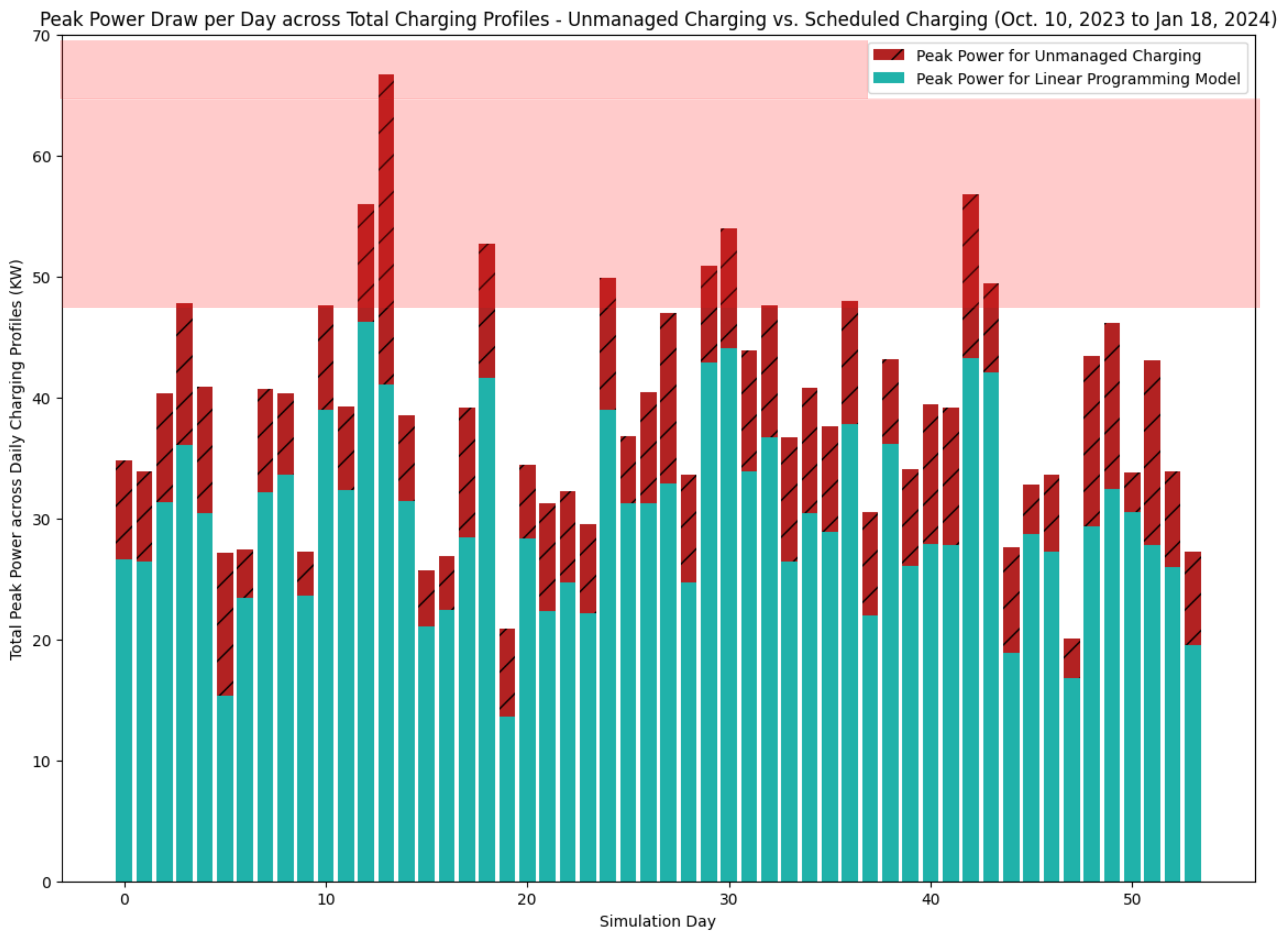
- Initial Deployment Insights:
  - The platform was launched 8 days ago, offering **early but valuable insights**.
  - **Continuous accumulation of usage data** will enrich our understanding and drive deeper analysis
- AI Model Evolution:
  - Our Machine Learning (ML) model is in **ongoing training with live data** from EVrest reservations and charging sessions.
  - This dynamic training approach ensures constant improvement and optimization of our Deep Neural Network, **adapting to evolving user needs and behaviors**.
  - **Continouous training** of ML Model allows us to **monitor and analyze the training and further optimization** of our Deep Neural Network
- User Experience and AI Integration:
  - User's confidence with ML-prepopulated energy requirements provides **insightful ideas on behaviour**
  - Exploring the **potential of making ML-prepopulated energy suggestions the default**, encouraged by their accuracy and user reception.
- Future Considerations:
  - Assess the long-term impact of AI-prepopulated options on user behavior and platform efficiency.
  - Continuously evaluate user feedback to refine and enhance the AI's accuracy and usefulness.

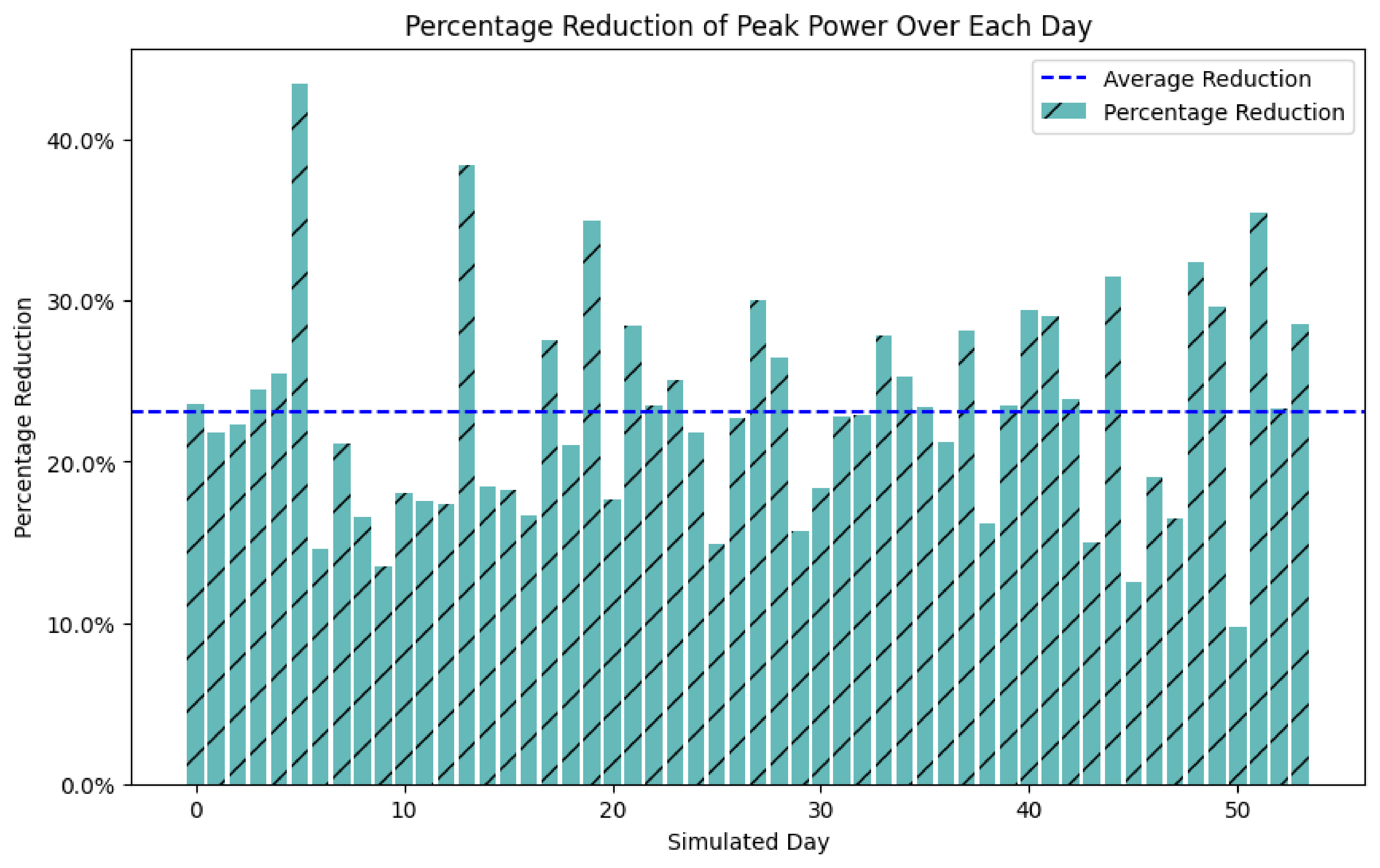
Smart Charge Management

- **Argonne's Building 300** – Peak charging loads are becoming unsustainable, and can potentially lead to hardware failures
- Simulations on historical charging data using a Linear Programming scheduling algorithm shows:
  - smart charge management can successfully reduce peak demand to stay within constraints



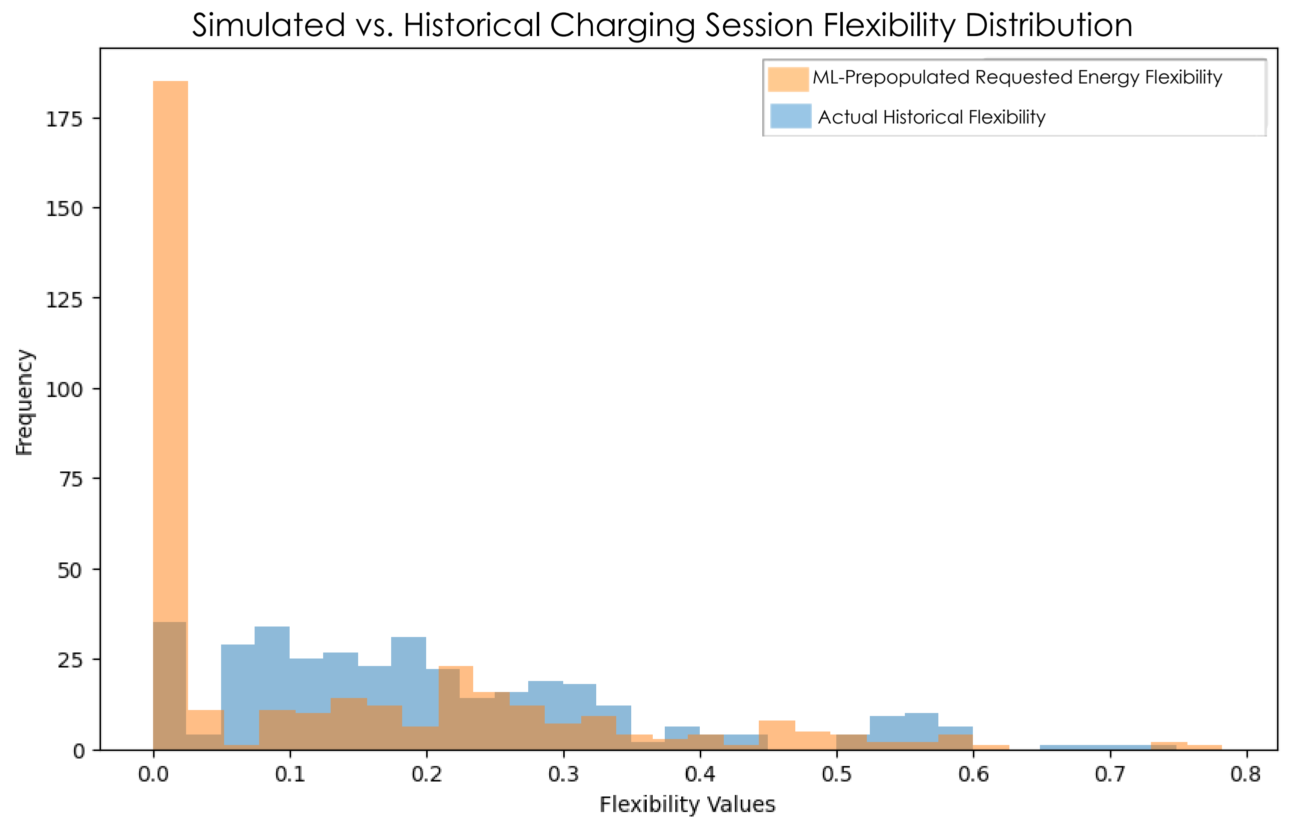
Smart Charge Management

- Simulations using smart charge scheduling show average peak power reduction of ~22% across days where charging is above 20kW



ML-based Requested Energy (Mileage) Predictions to drive Smart Charge Management

- ML-based requested energy predictions for reservations **can be used to drive** Smart Charge Management
- Analysis on historical data shows ML-based requested energy predictions for reservations **improve flexibility**:
    - Average Original Flexibility: **0.127**
    - Average ML Predictions Flexibility: **0.206**
    - Average Flexibility Change: **+61.6%**
- Flexibility offered through ML-based requested energy predictions is **sufficient for managing peak demand** for ANL Building 300
- Next steps include **deploying** a Smart Charge Management platform integrated with ML-based requested energy predictions



Thank You

Salman Yousaf

yousaf@anl.gov

Nithin Manne

nmanne@anl.gov

Jason D. Harper

jharper@anl.gov

EVs@Scale

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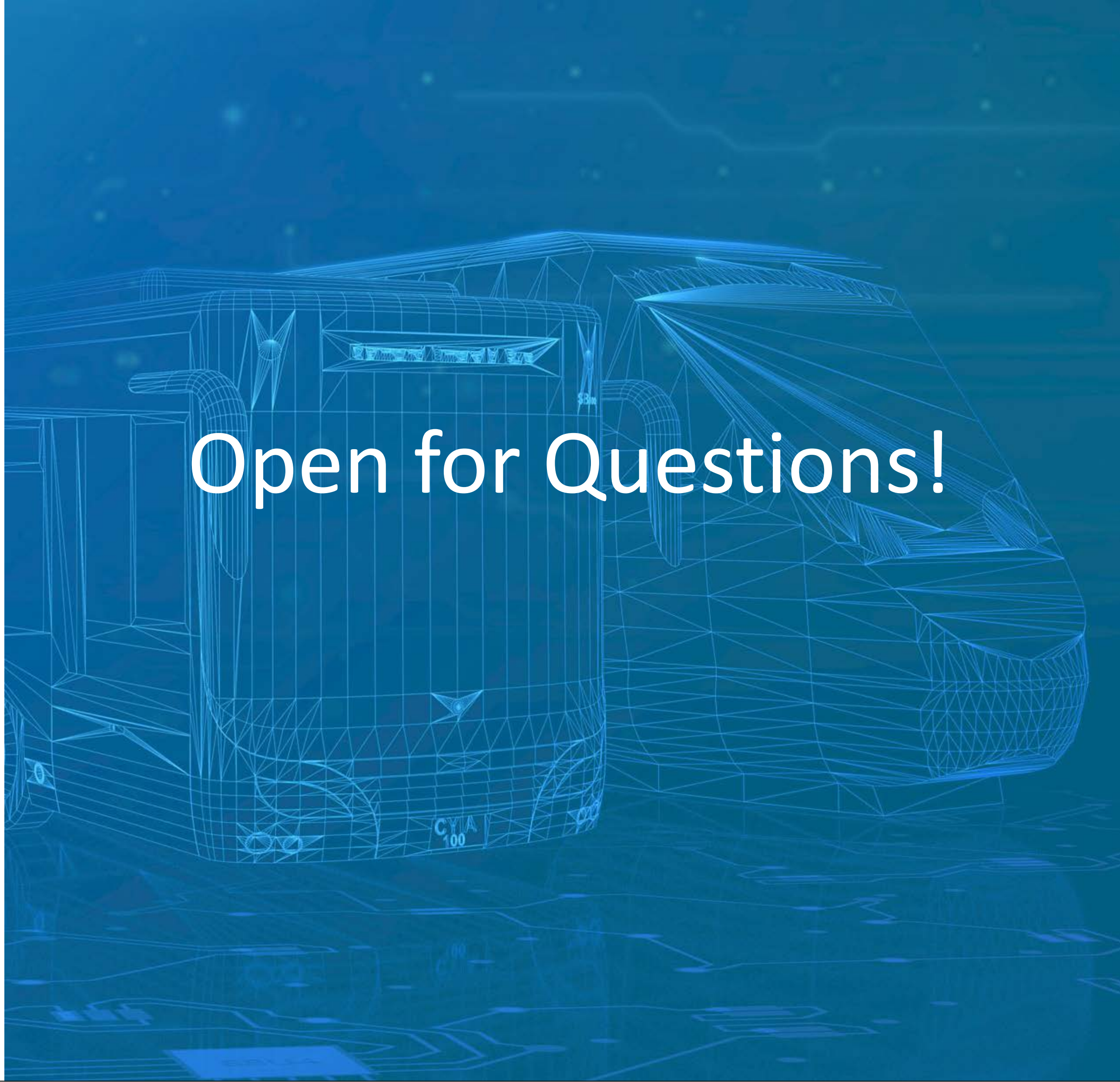

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Bryan Nystrom

ANL EV-Smart Grid Interoperability Center

Advanced Mobility and Grid Integration Technology

April 4th, 2024

Smart Charge Management and Vehicle Grid Integration: FUSE

OCPP 2.0.1 development work

OCPP 2.0.1 Node-Red nodes

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OCPP "101"

What is OCPP?

- Open Charge Point Protocol (OCPP) is a communication standard for electric vehicle (EV) charging stations.
- Think of it as a common language for chargers and charging network software to talk to each other.

Problem OCPP Solves:

- Promotes interoperability: Any OCPP-compliant charger can work with any OCPP-compliant network software, regardless of manufacturer.
- Avoids vendor lock-in: Businesses are not limited to using a single provider for chargers and software.
- Simplifies network management: OCPP allows for centralized control and monitoring of charging stations from different vendors.

OCPP 2.0.1: Node-Red Nodes

OCPP Message Types

Message examples

Message Request (CALL)

Msg Type (2)	Unique ID	Command Name	Json Payload

[2, "19223201", "BootNotification", { "reason": "PowerUp", "chargingStation": { "model": "SingleSocketCharger" , "vendorName": "VendorX" } }]

Message Response (CALLRESULT)

Msg Type (3)	Unique ID	Json Payload

[3, "19223201", { "currentTime": "2013-02-01T20:53:32.486Z", "interval": 300, "status": "Accepted" }]

Error Message (CALLERROR)

Msg Type (4)	Unique ID	Code	Description	Details

[4, "162376037", "NotSupported", "SetDisplayMessageRequest not implemented", {}]

OCPP 2.0.1: Node-Red Nodes

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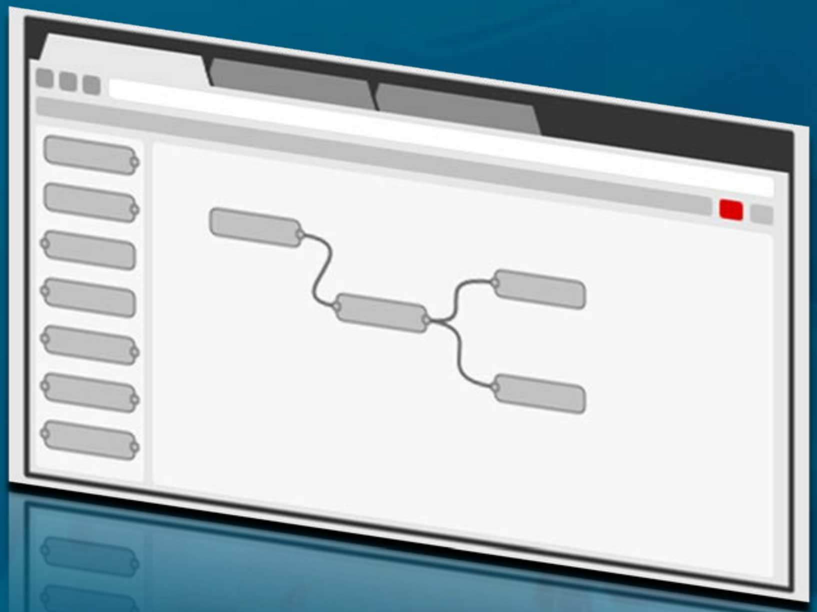
Node-Red "101"



What is Node-RED?

- A visual programming tool for wiring together hardware, APIs, and online services.
- Uses a web browser interface - no complex coding required!
- Great for building event-driven applications.

Why Node-RED? Perfect for Prototyping and Production

- **Rapid Prototyping:** Quickly test your ideas by dragging and dropping nodes to create workflows.
- **Easy to Learn:** Intuitive interface lowers the barrier to entry for non-programmers.
- **Wide Range of Nodes:** Pre-built functionality for common tasks saves development time.
- **Scalable:** Start small and scale your applications to production use.
- **Deployment Ready:** Flows can be deployed with a single click.
- **Customizable:** Create your own nodes to extend functionality for your specific needs.

OCPP 2.0.1: Node-Red Nodes

Node-Red OCPP2 Nodes “101”

What it is:

- Node-Red “nodes” that support the sending and receiving of OCPP messages, including the connection and authentication of the underlying WebSocket layer.
- Separate “nodes” for implementation by either a charge station (CS) or a charge station management system (CSMS).
- Support for OCPP 2.0.1.
- Packages OCPP message arrays based on a defined Json structure
- Handles tasks like creation of unique message Ids and can direct OCPP responses based on those Ids to the appropriate functions/nodes.
- Can be used in addition to the existing Node-Red OCPP 1.6 nodes previously available.

What it isn’t:

- They do not implement a fully functional CS or CSMS.
  - It is not a full software stack like the Linux Foundation EVerest project.
  - It is up to the user/developer to implement the full business logic based on the OCPP message being passed and the available hardware and data storage.
- Usage requires the user/developer to have an understanding of the OCPP protocol.
- Nodes do not interpret or act upon OCPP messages themselves.

OCPP 2.0.1: Node-Red Nodes

OCPP 1.6	OCPP 2.0.1
• Security not required but supported (see OCA OCPP Security White Paper)	• Security Profiles • **#1 Basic (user/password)** • #2 Basic + TLS CSMS • #3 Basic + TLS CSMS + TLS CS
• SOAP </> & JSON [{}]	• JSON [{}] only
• Multiple OCPP nodes for message handling	• Single node for message handling
• OCPP SOAP schema validation only	• OCPP JSON schema validation
• Custom dynamic commands (non-ocpp commands like connect, disconnect, etc.)	• OCPPCommCtrlr and SecurityCtrlr dynamic variable settings for WebSocket and security functionality
• Open Source for 6 years used by other labs, open-source projects, and 3rd parties • CS server (CSMS) • Used for **ANL Smart Energy Plaza CSMS** prior to EVrest rollout • CP client (CS) • Used in **ANL OptiQ EVSE** project.	

OCPP 2.0.1: Node-Red Nodes

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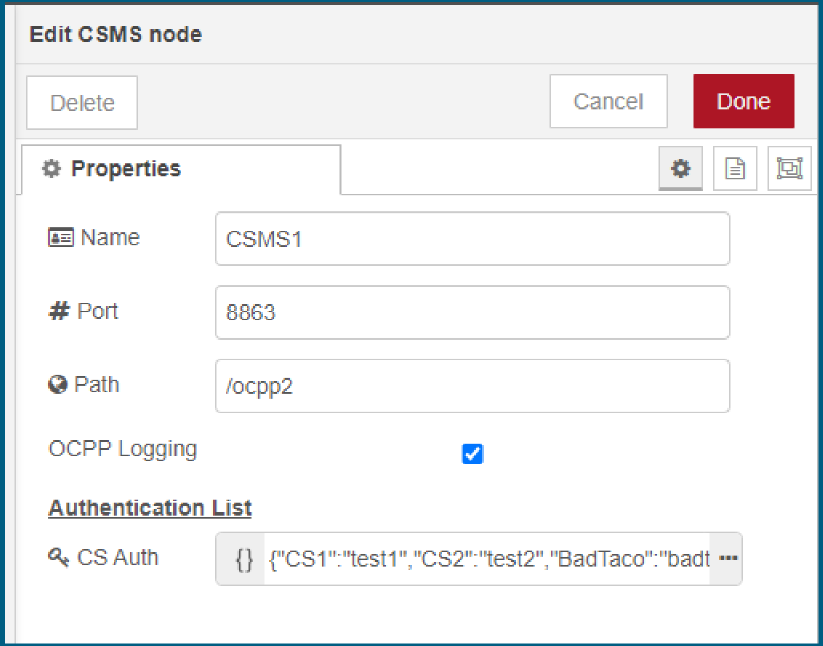
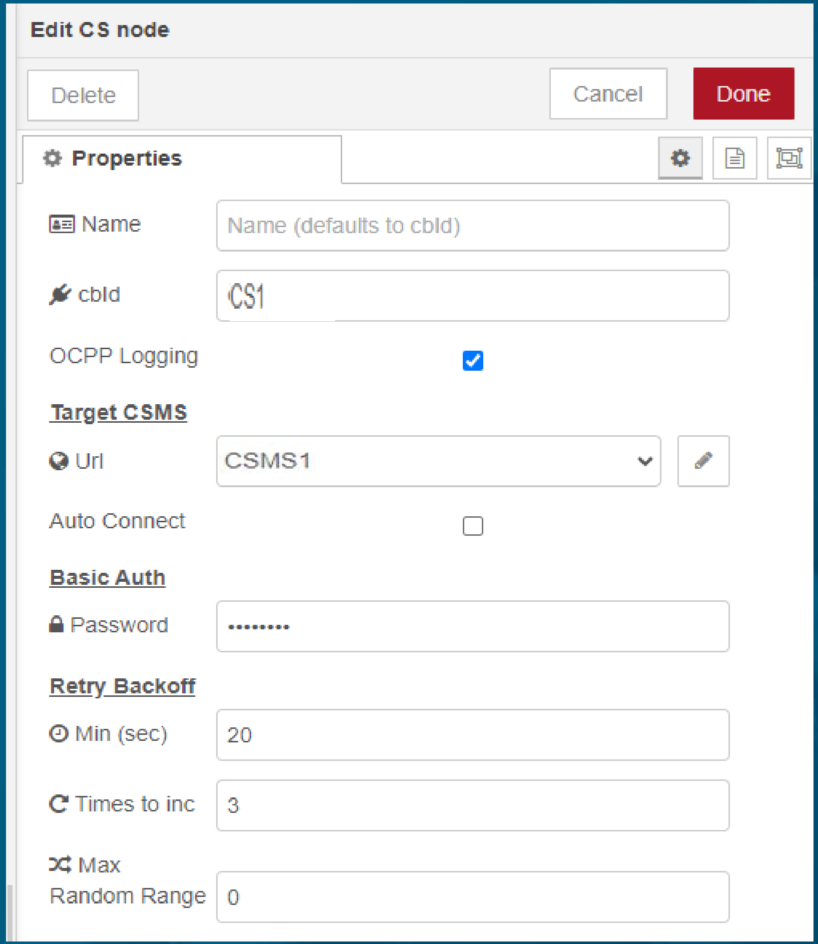
Node Setup

CSMS Node Config



CS Node Config



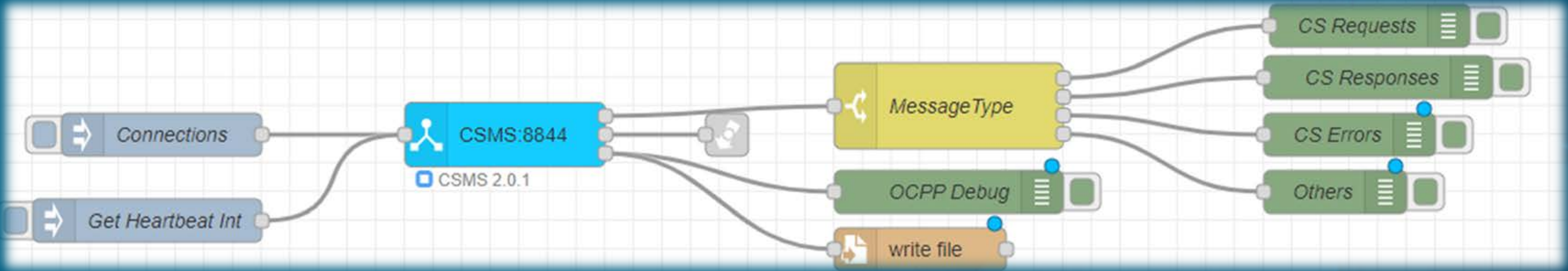
OCPP 2.0.1: Node-Red Nodes

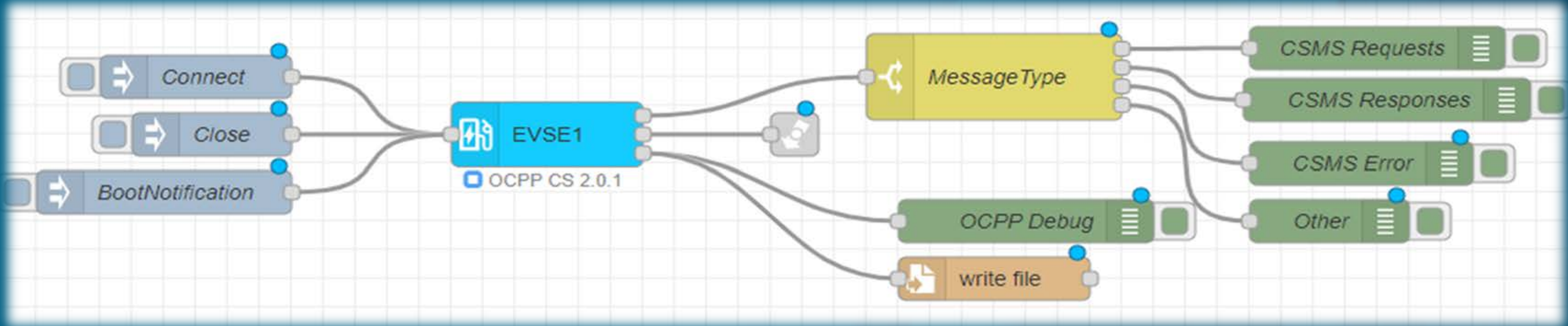
Output ports:

1. Standard non-directed
2. Dynamically linked
3. Optional OCPP logging

Recommendation:

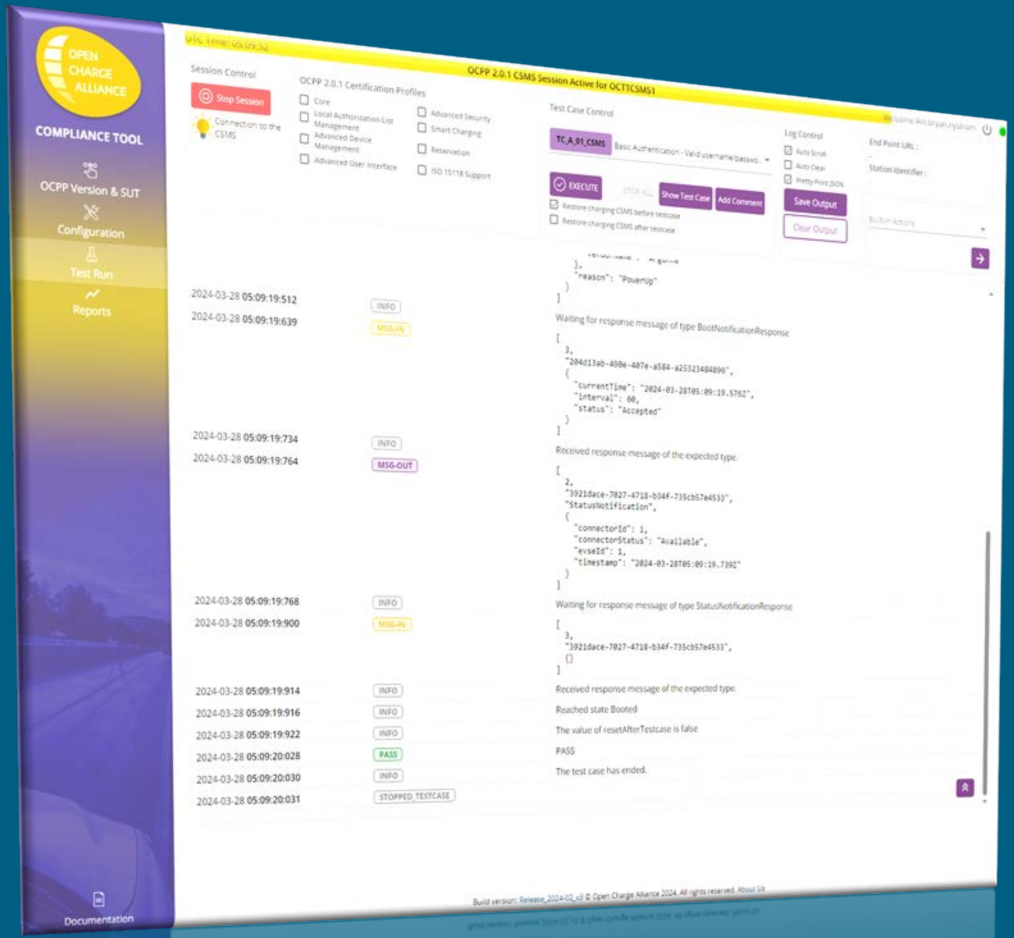
Make use of the new Node-Red "Link" node capabilities like dynamic linking



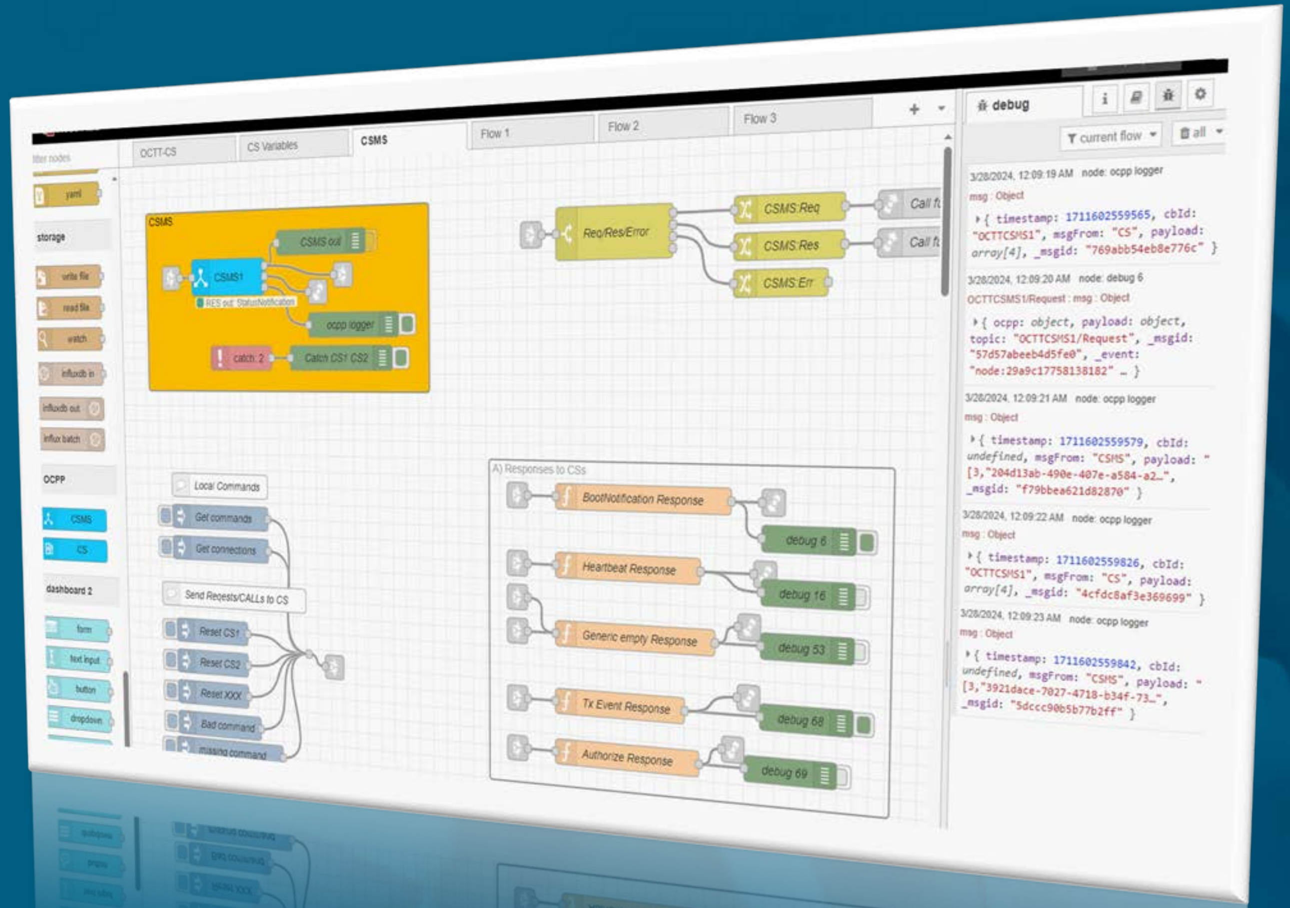


OCPP 2.0.1: Node-Red Nodes

OCTT tested



OCTT test tool



Node-Red CSMS proto

OCPP 2.0.1: Node-Red Nodes

Installation in Node-Red:

- Use the "Manage Palette" menu
- Search and Install
  - node-red-contrib-ocpp2

-or-

- cd ~/.node-red installation folder
- npm install @anl-ioc/node-red-contrib-ocpp2

Git Repository:

- github.com/Argonne-National-Laboratory/node-red-contrib-ocpp2

Bryan Nystrom

- bnystrom@anl.gov

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Concentrated charging infrastructure: reconstructing trip sequences from traffic data that reflect use patterns

Jeewon Choi, Thad Haines, Matt Lave, Andrea Mammoli, Emily Moog, Will Vining

EV@Scale Deep Dive Meeting, April 4, 2024

U.S. DEPARTMENT OF ENERGY | Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

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Overview

- **Why we need synthetic trip generation**
- **Required characteristics of a synthetic trip**
- **What the trip sequences look like in reality**
- **Methodology to reconstruct trips that respect statistics and also look like typical routes**
- **What synthetic trip sequences look like**
- **Distinguishing between EV users with different charging access**
- **Do the synthetic trip sequences look like the real ones?**
- **Dealing with trips that cross boundaries**
- **Trip endpoints to actual routes, including real addresses and speed**
- **What changes for MHDV – schedules**
- **Reconstructed MHDV trips**
- **Hesitant EV driver workshop – what we expect to get out of it**
- **How we plan to use this in our simulations**

Why we need synthetic trip generation

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- We are interested in the interplay of charging opportunities at home, at work and en-route
- We want to model when, where and why drivers charge their vehicles, via a Markov Chain-based ABM
- We need to generate large numbers of synthetic trip sequences that match the statistics
- From traffic "big data", we can extract origin-destination pair distributions
- Problem - how to reconstruct trips in a realistic way, that reflect commuting behavior and daily / weekly schedules?

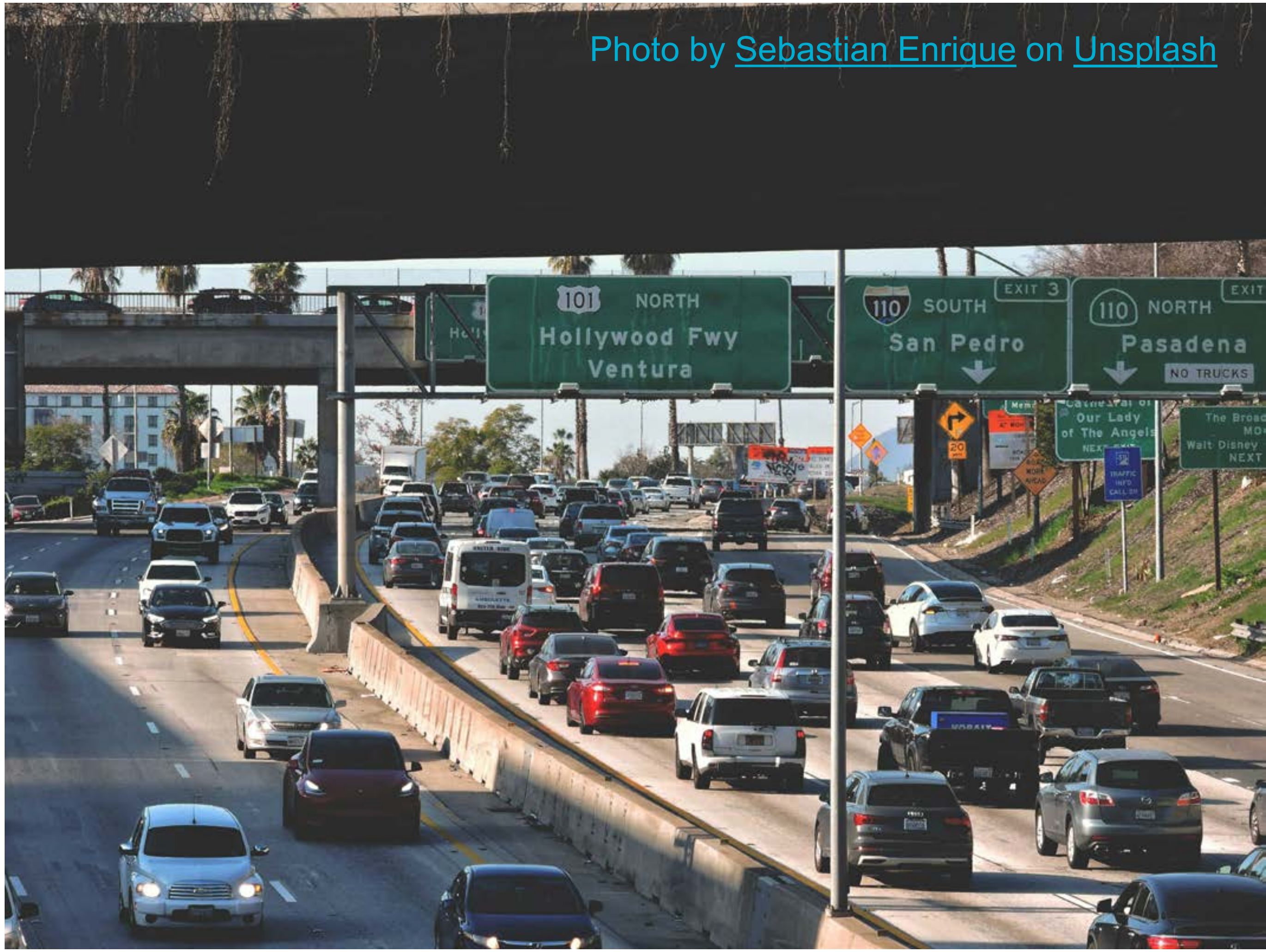

Photo by Sebastian Enrique on Unsplash

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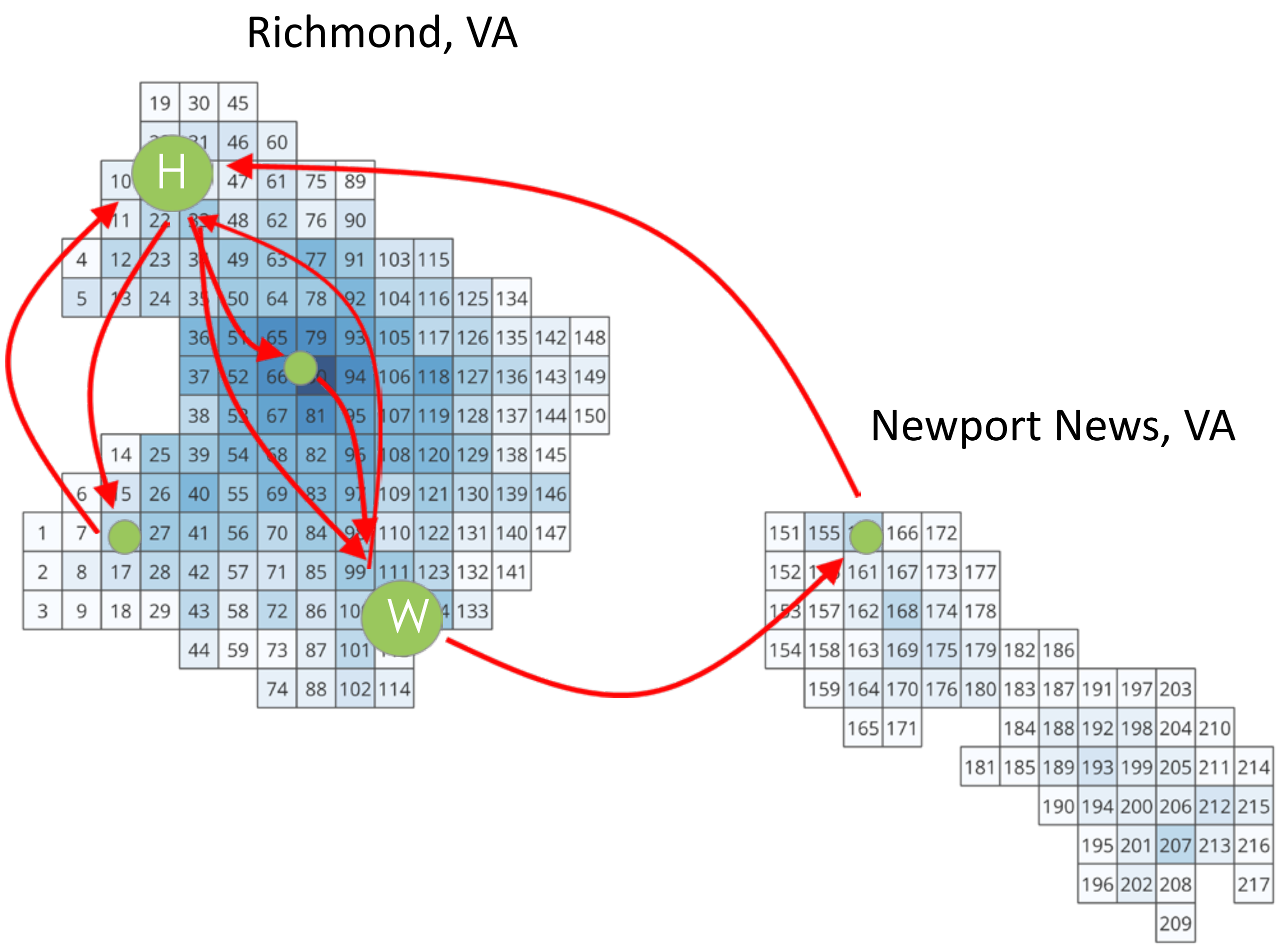
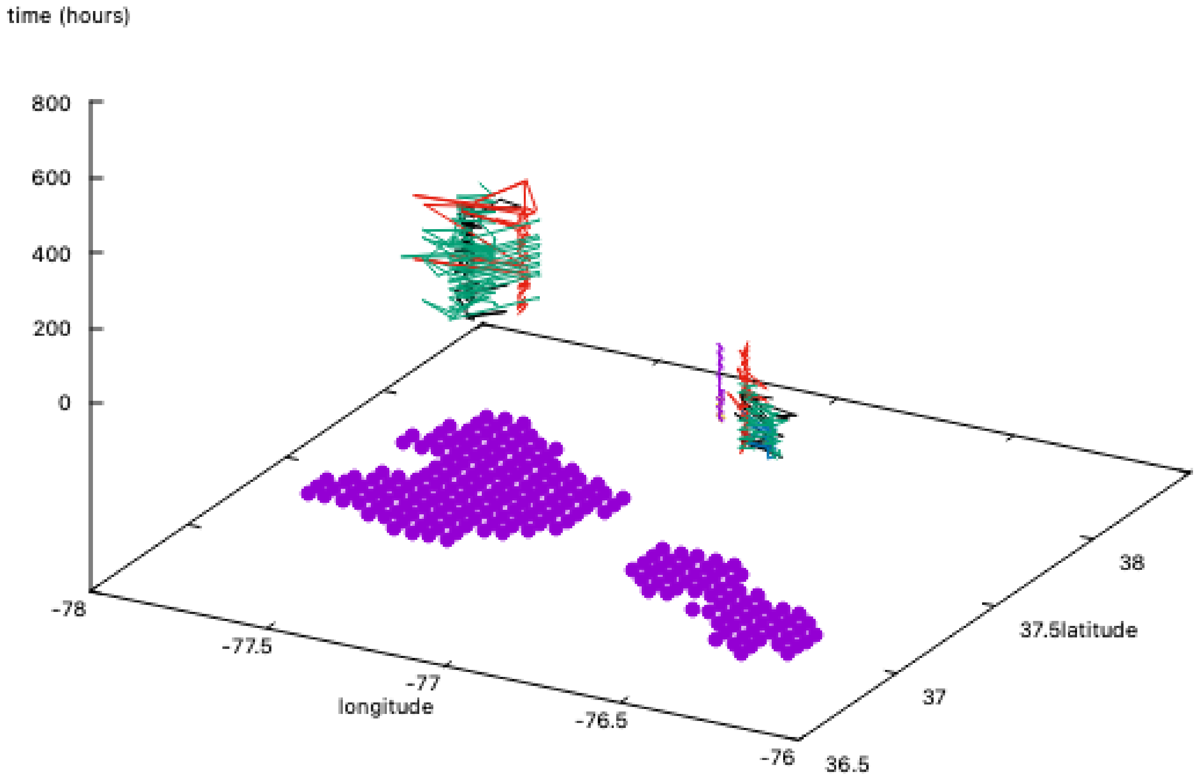
Required characteristics for synthetic trips

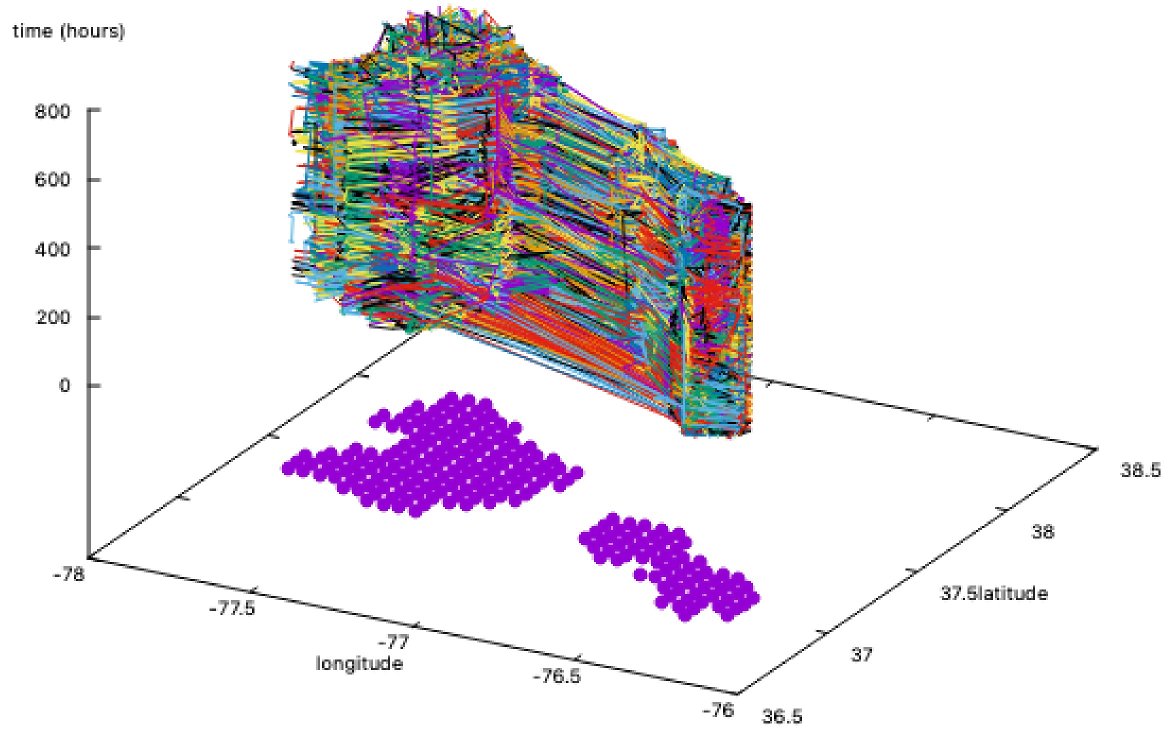
- **Collectively, synthetic trips should reflect the OD pair statistics, that can be extracted from datasets such as Wejo, Geotab or cell phone data**
- **Synthetic trips should reflect real driving spatial patterns: repeated trips between home and work (anchor points) and occasional trips to other destinations**
- **Synthetic trips should reflect temporal characteristics of real trips – work schedules, average speed due to congestion**



What the trip sequences look like – wejo data



A few trips in 8 counties



All trips in 8 counties

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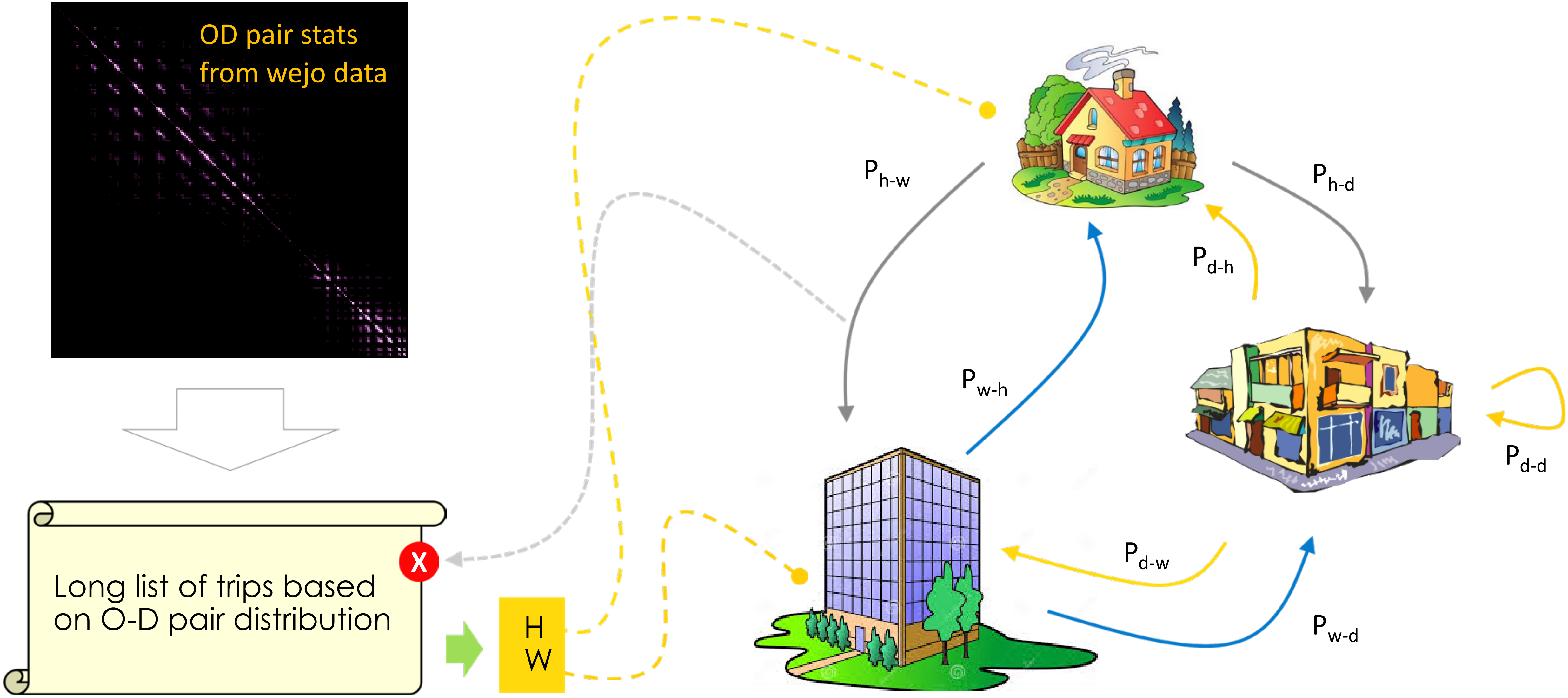
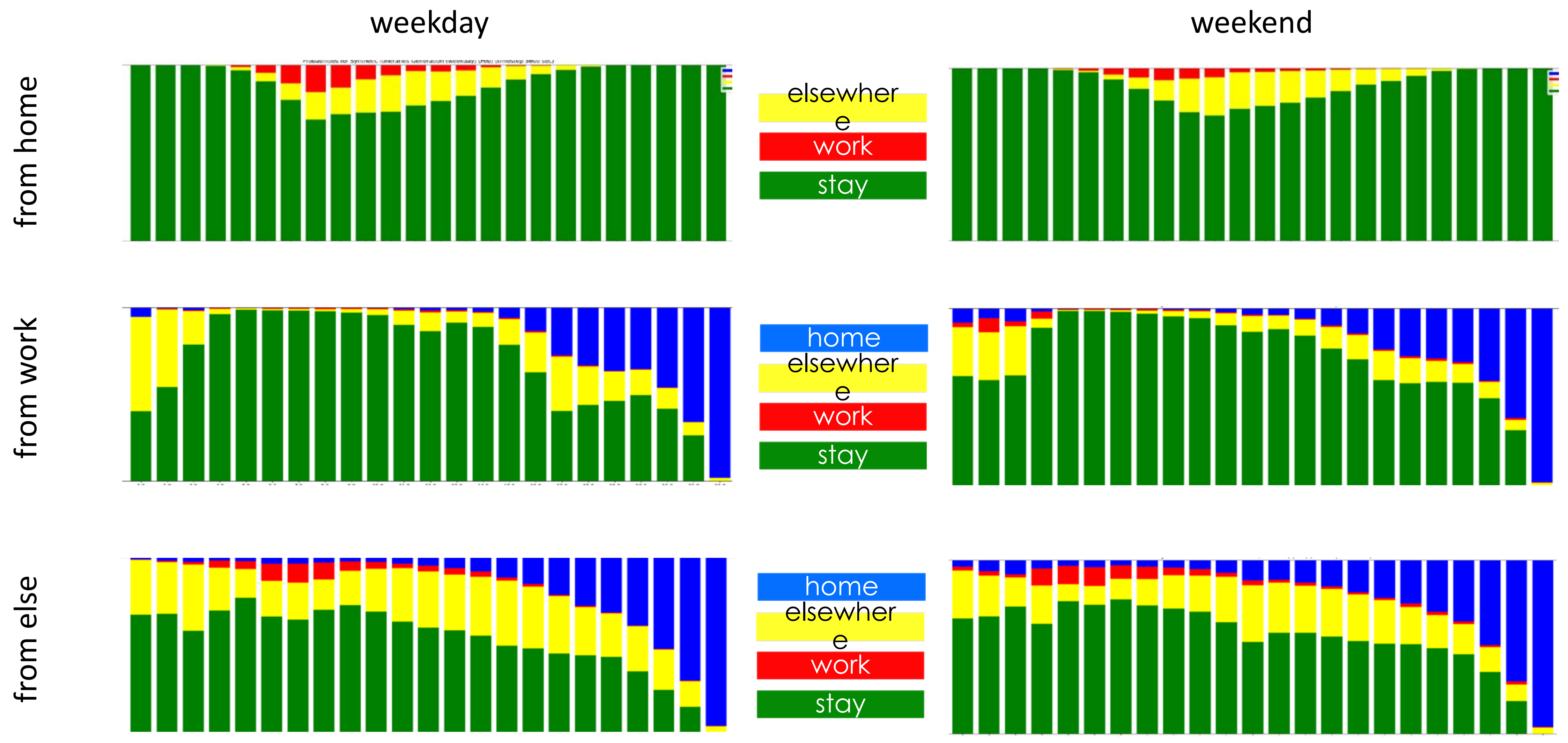
List-constrained Markov chain trip sequence generation



Trip probabilities are also derived from real data



Probabilities courtesy of Steven Schmidt INL

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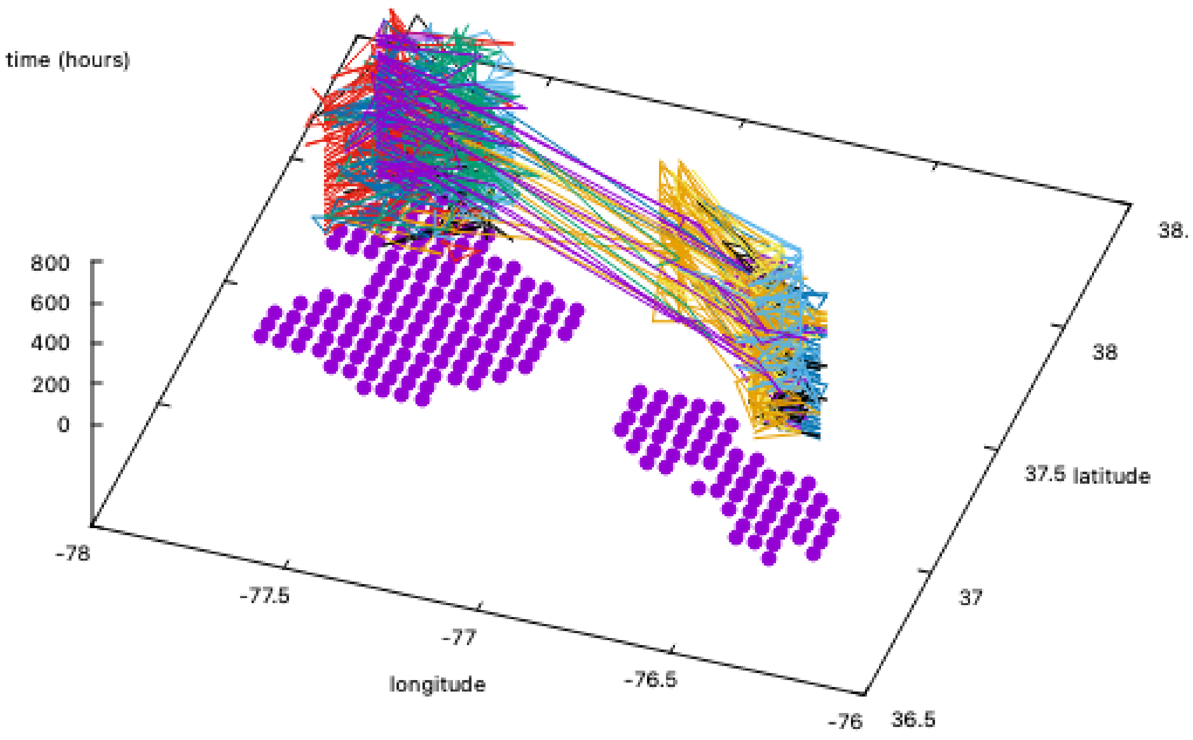
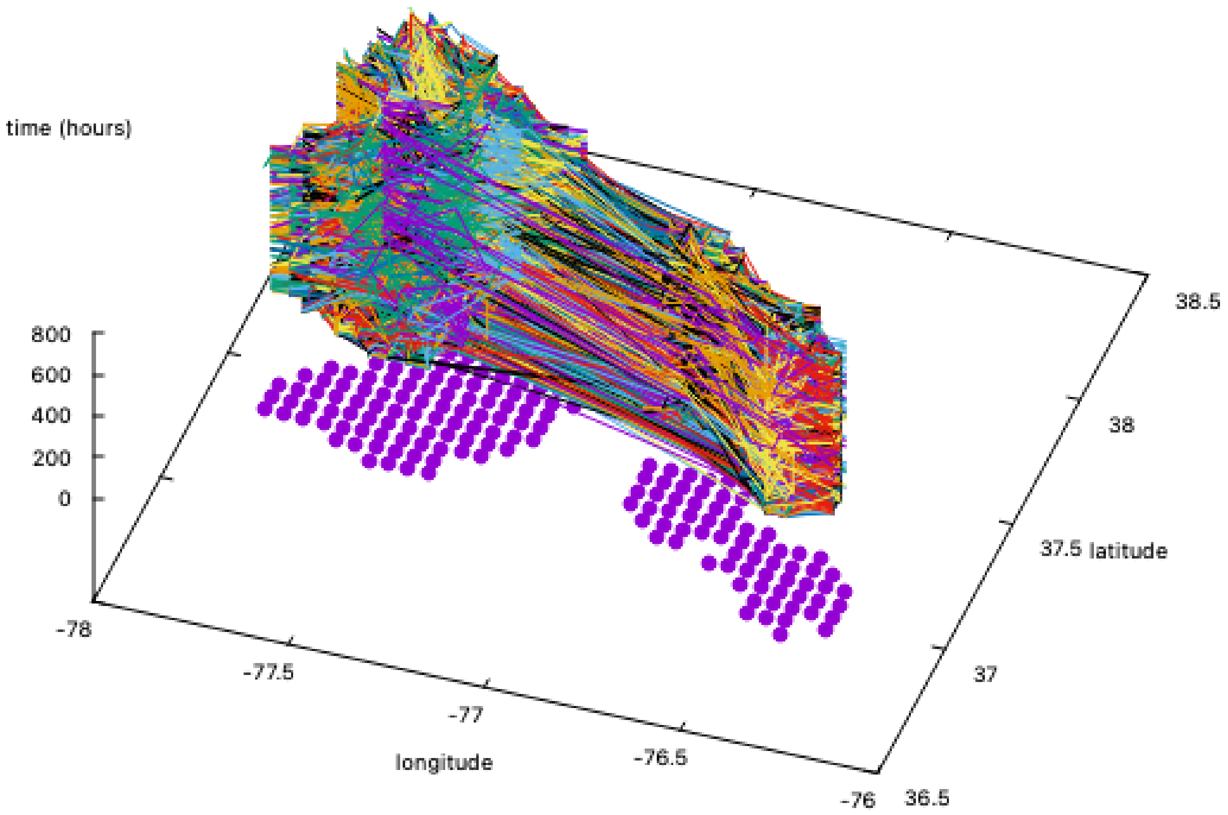
What the synthetic trip sequences look like



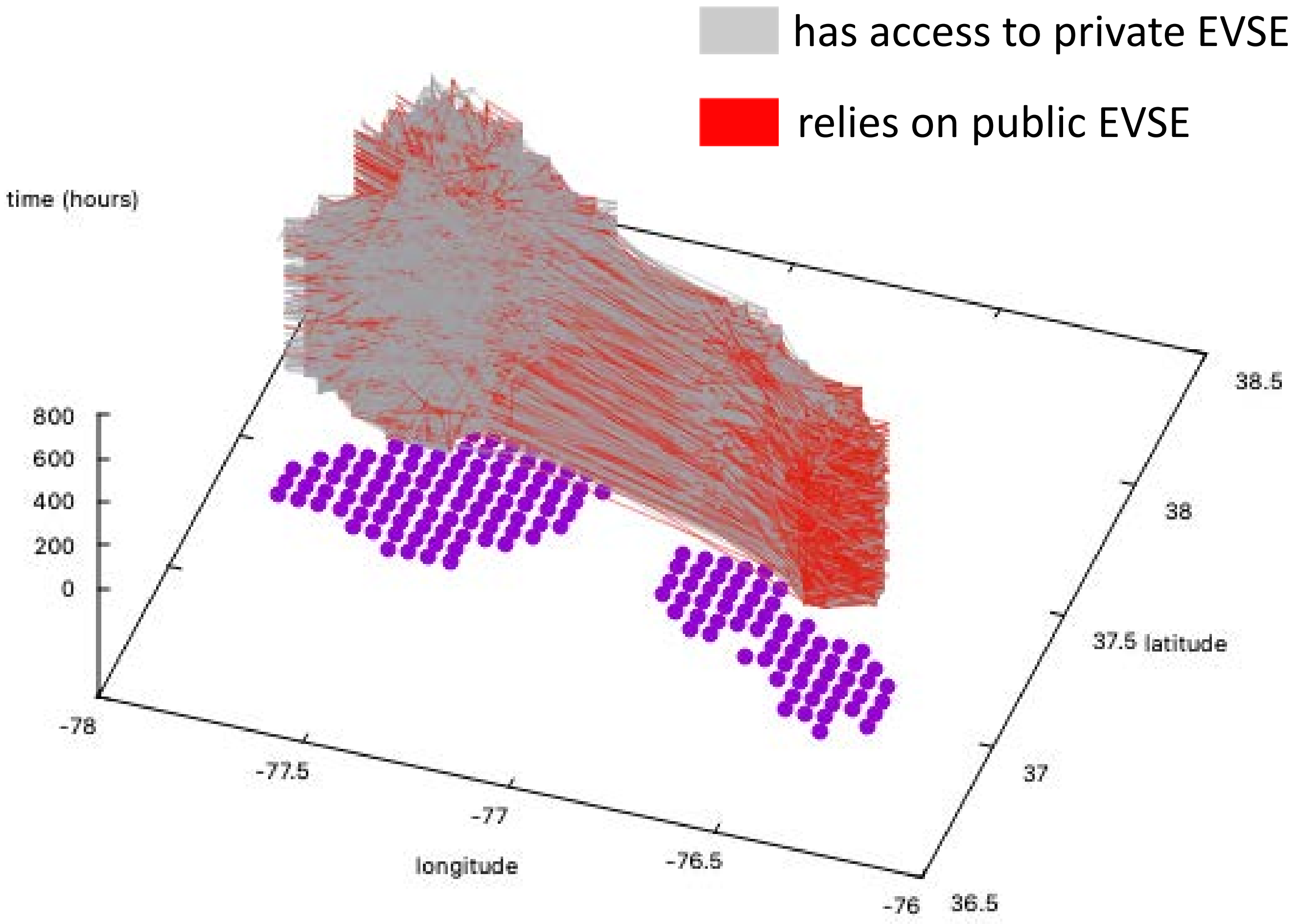
16 trips



10000 trips

Differentiating between EV users by access to private charging

- **Use census block data to assign probability of driver either renting or living in MUD**
- **Information provided in "No Place Like Home" report links likelihood of private EVSE to rental vs. owned**
- **Use this information to determine whether driver has access to private EVSE**



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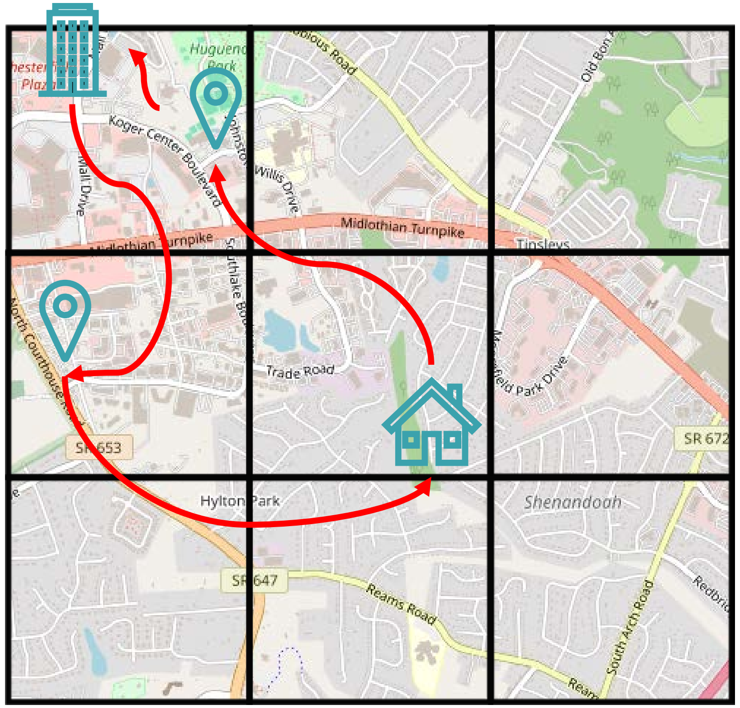
Turning coarse trips in a sequence into specific trips

- **Trip chains are based on a square grid**
- **Each agent has a home and work grid square that are fixed. A random address, chosen from a list of all addresses in the box, is chosen within the grid to be the specific home/work location**
- **The home and work addresses remain fixed for the entire trip chain**
- **For all trips ending somewhere else (not at home or work) a random address is chosen within the grid square where the trip ends**



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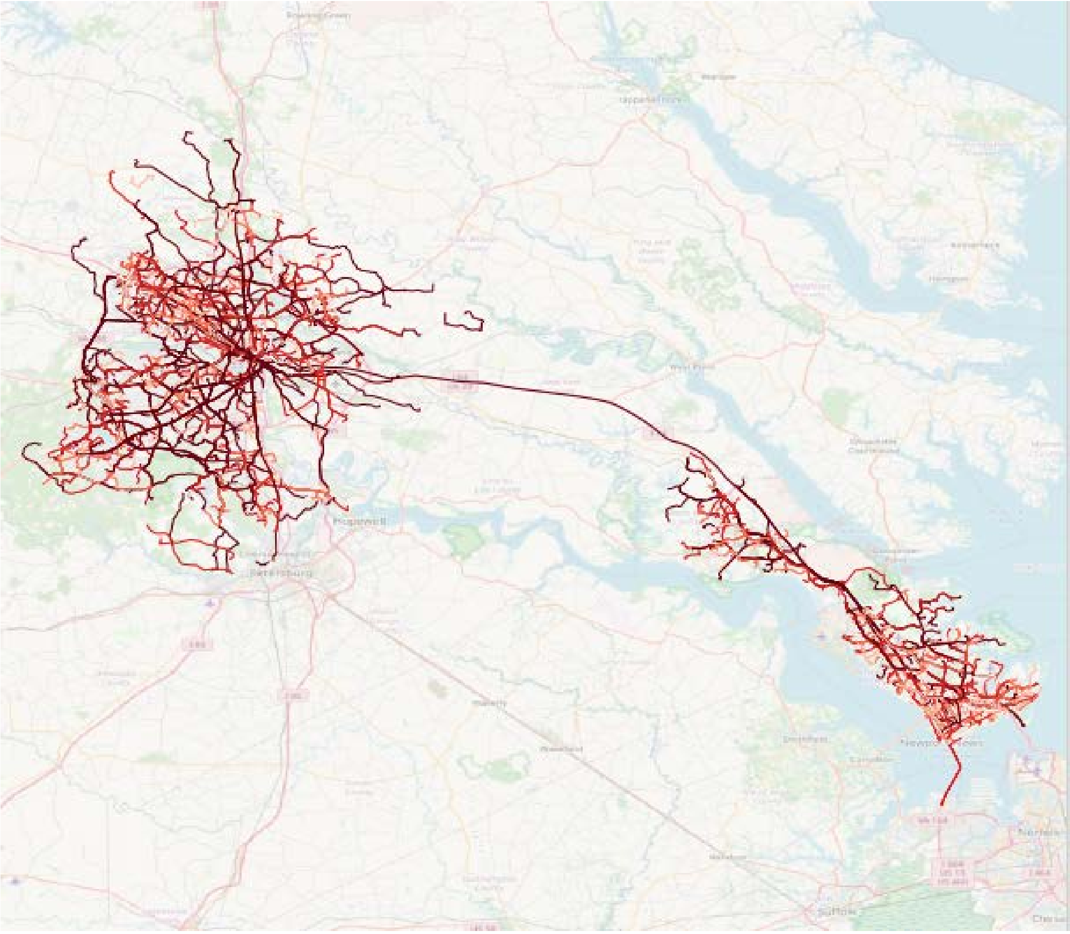
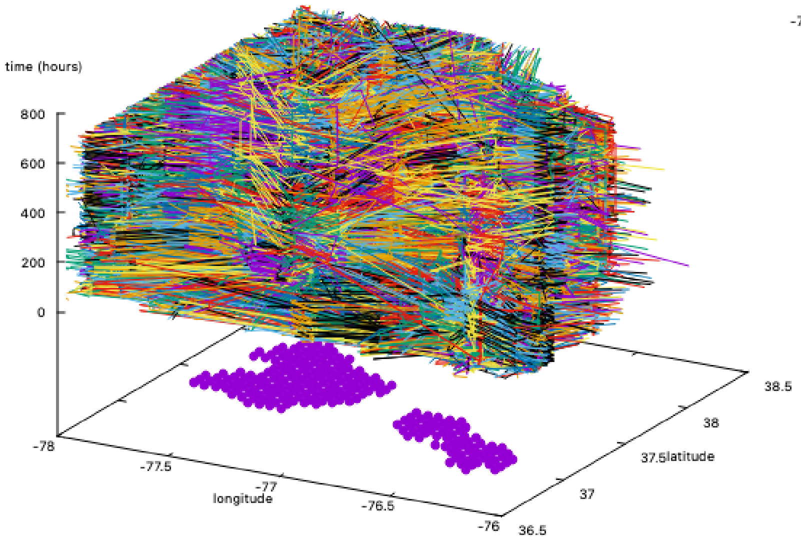
Differentiating between EV users by access to private charging

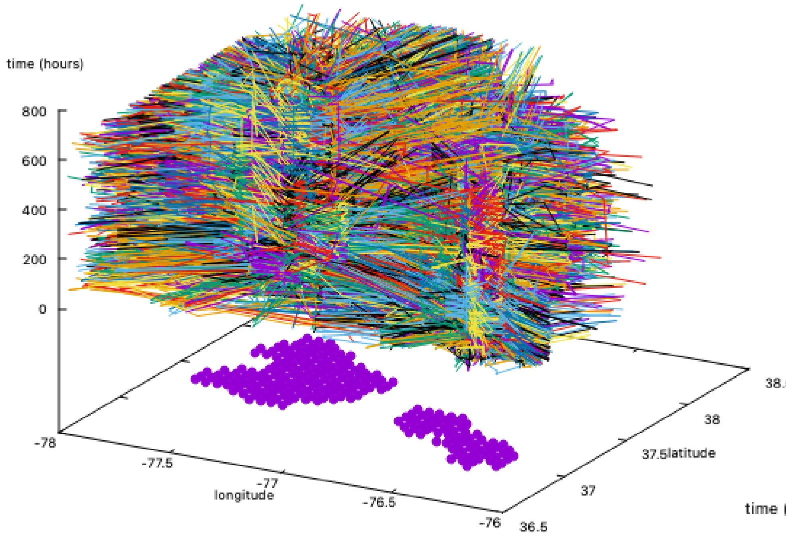
- **Once the trip endpoints are transformed from grid squares into addresses we can find the route, travel time, and energy required for each trip.**
- **Using the Open Street Map road network and speed limit data we use the A* algorithm to find the route with the shortest travel time.**
- **For each route we calculate the energy required to drive that route.**



What about trips that cross boundaries?

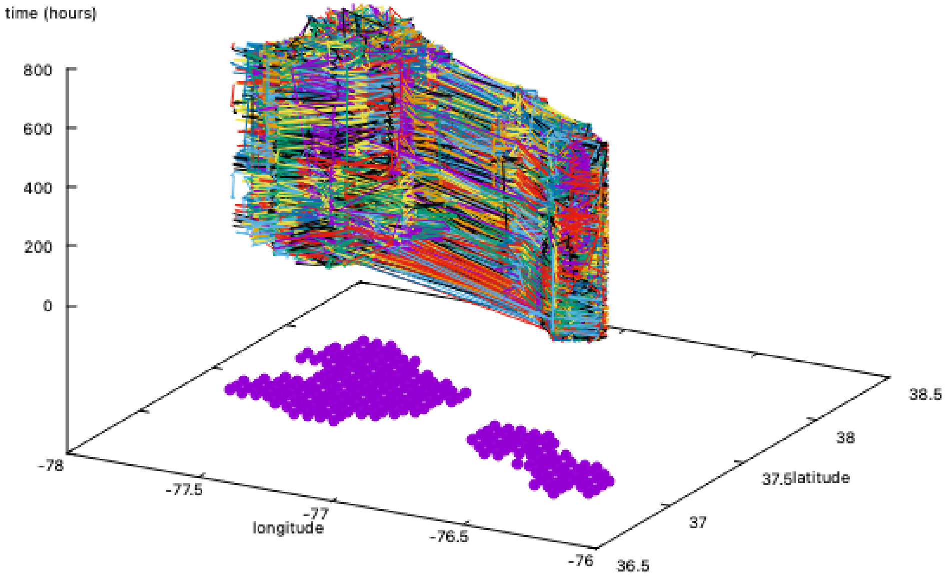
All wejo trip sequences that enter area of interest at least once – 166825 sequences



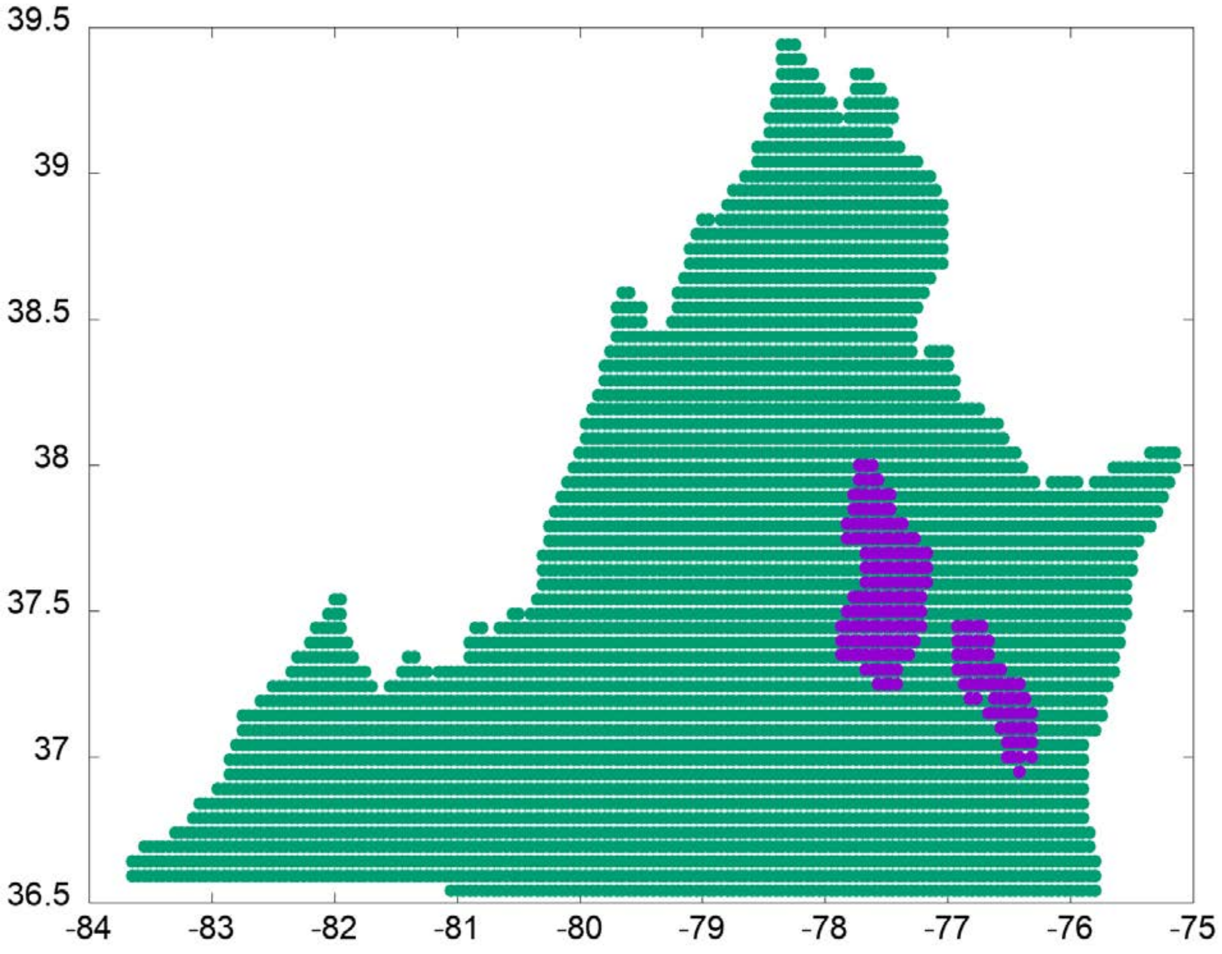


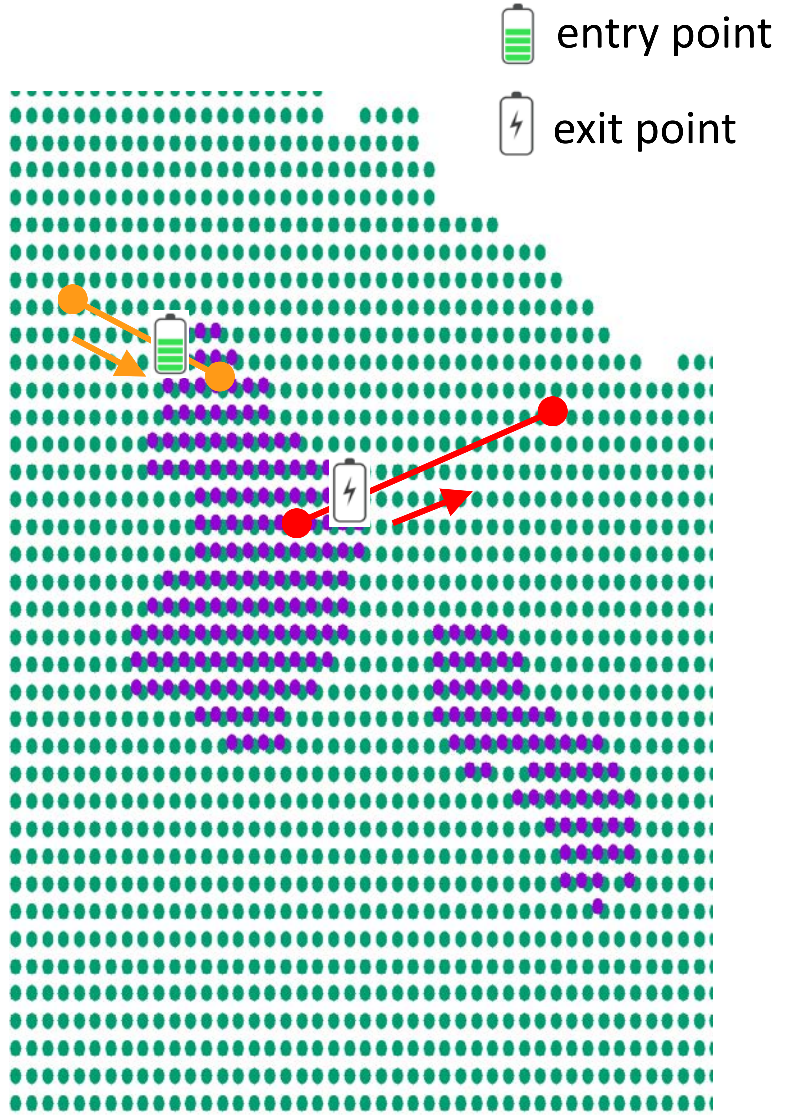
All wejo trip sequences with at least 50% of trips in area of interest – 128586 sequences

All wejo trip sequences with at 100% of trips in area of interest – 90083 sequences



Dealing with trips that cross boundaries



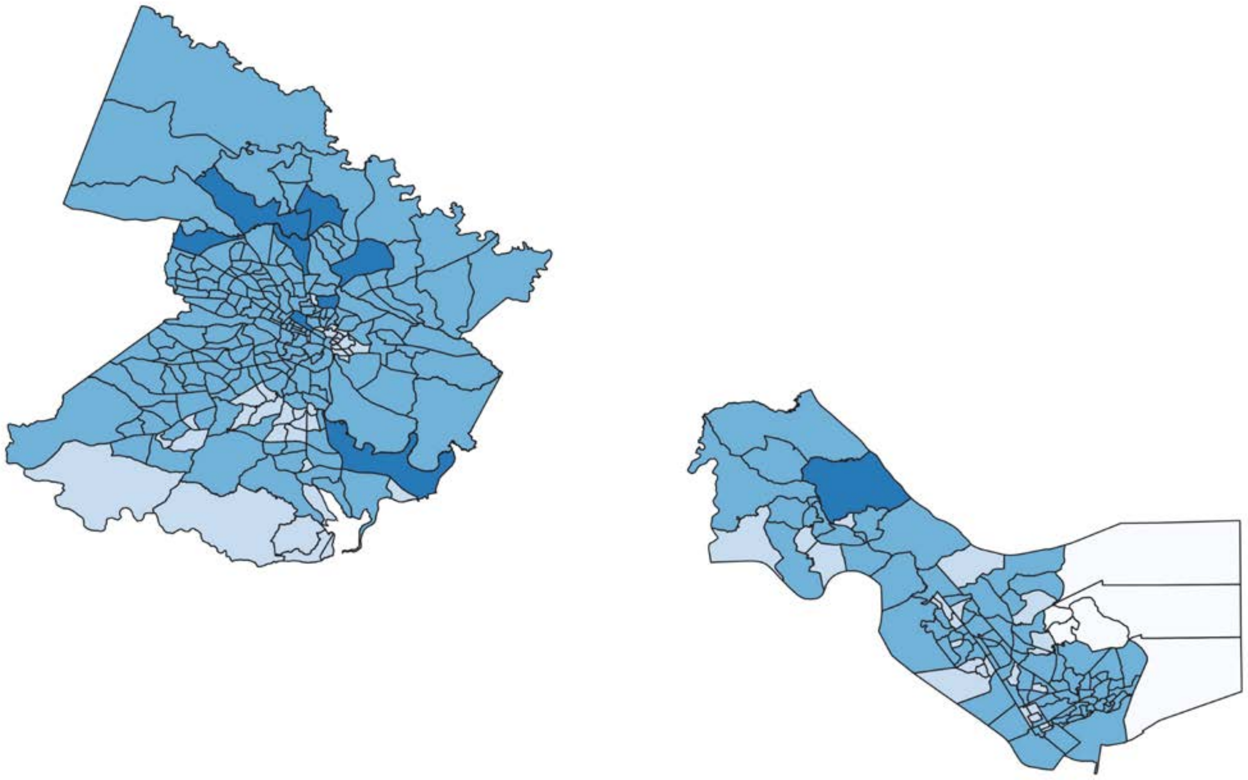


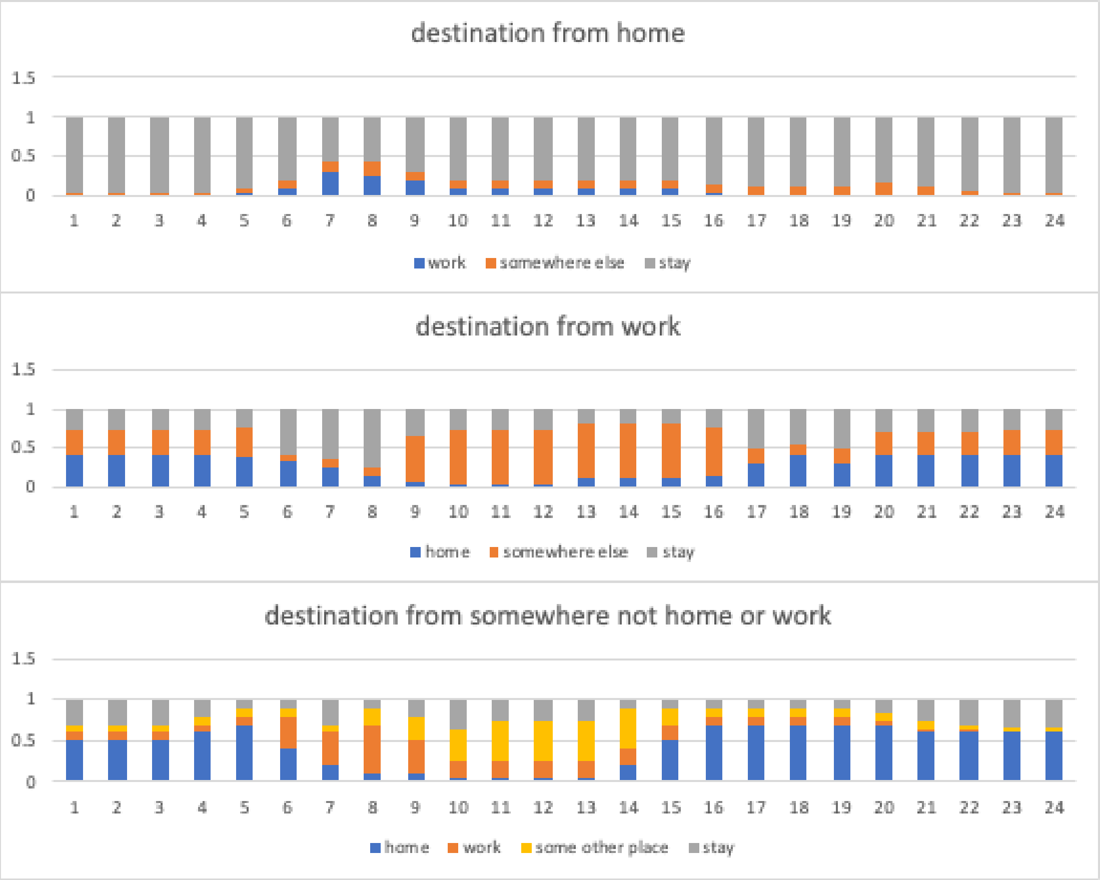
Small business traffic simulation

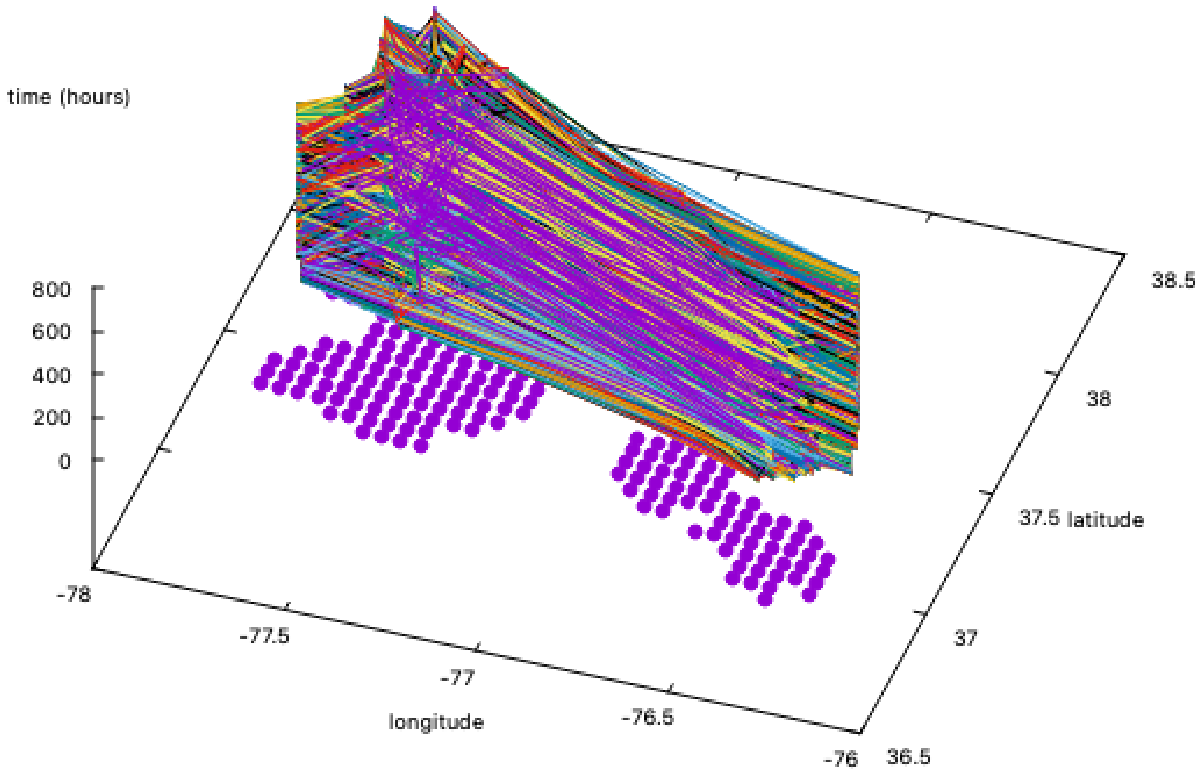
- Typical annual miles driven range from ~ 15K miles to ~ 90K miles per year for service trucks / vans
- At least 500,000 establishments with 1-5 vehicles in their fleet
- Most small business employees take their trucks home after work
- Using an EV could improve profits for a small business by better tracking, lower fuel cost and lower downtime
- Charging may be an issue for trucks that cover many miles

Photo by Brian on Unsplash

- **Geotab data used for MHDV trip analysis**
- **Geotab provides OD pairs directly**
- **Process to build synthetic trips similar to the one used for wejo data, with similar issues**







hourly trip probabilities adapted for service vehicles

Planned workshop at UTK and national survey – what we hope to learn

- **From the workshop**
  - What are good questions to ask in a survey?
  - Are small businesses interested in operating EVs?
  - Is our research useful to city planners, community organizations and other stakeholders?
  - Unknown unknowns
- **From the national survey**
  - How do potential EV users with limited access to charging with acquiring and owning an EV?
  - What is the expected charging behavior for these potential new users, in personal transportation?
  - What is the expected charging behavior for these potential new users, in business use?


Photo by Jason Goodman on Unsplash

Where we go from here and thank you!

- Trip sequences that cross boundaries gracefully
- Hourly probabilities obtained from survey results and / or data
- Integrate data with EVIPro and Caldera
- Implement ABM to model charging response to external pressures

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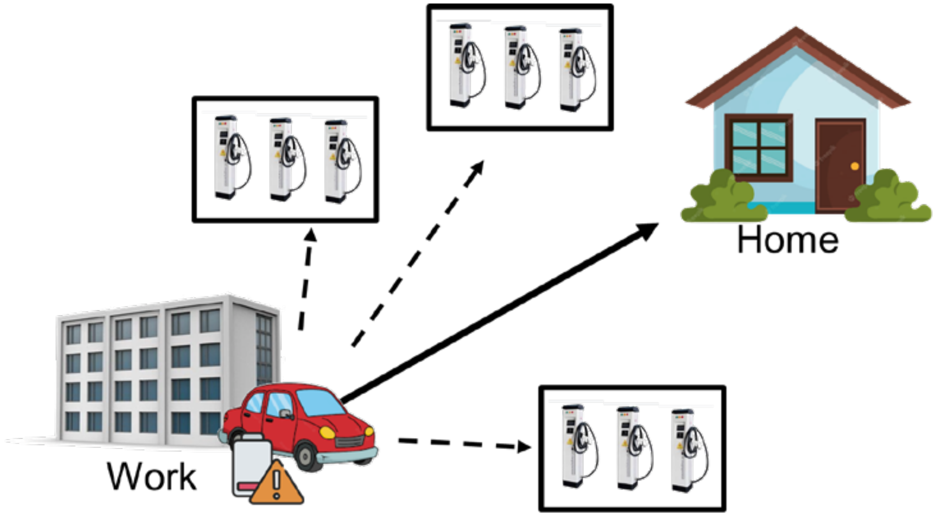
Smart Charge Management (SCM) and mid-route charging

Manoj Sundarrajan
Steven Schmidt

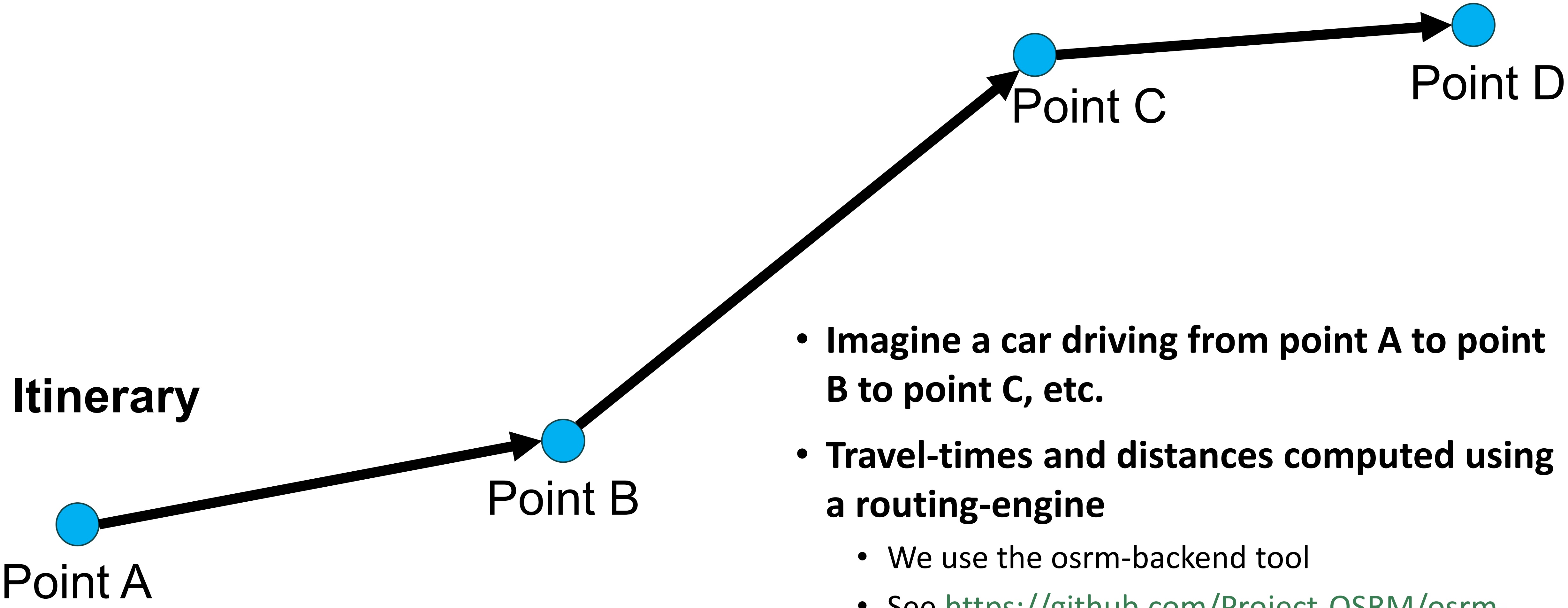
April 4, 2024

- **Each EV is modeled as its own agent driving and charging as needed within Caldera.**
- **Process**
  - Input a large number of vehicle itineraries
    - Point A to Point B to Point C, etc. Several days or even several weeks of data.
  - Track SOC of each vehicle each leg of itinerary
  - When needed, deviate from itinerary to charge at public high-powered station
  - Utilize routing-engine tool osrm-backend (akin to Google Maps)
    - See https://github.com/Project-OSRM/osrm-backend
  - Collect charge events and model using Caldera Grid or Caldera ICM
- **Modes**
  - ***Unscheduled*** charging mode (Base-case)
    - Go directly to station without checking availability, first-come-first-serve
  - ***Scheduled*** charging mode
    - Remote communication with multiple stations to determine best choice
    - Lowest opportunity-cost



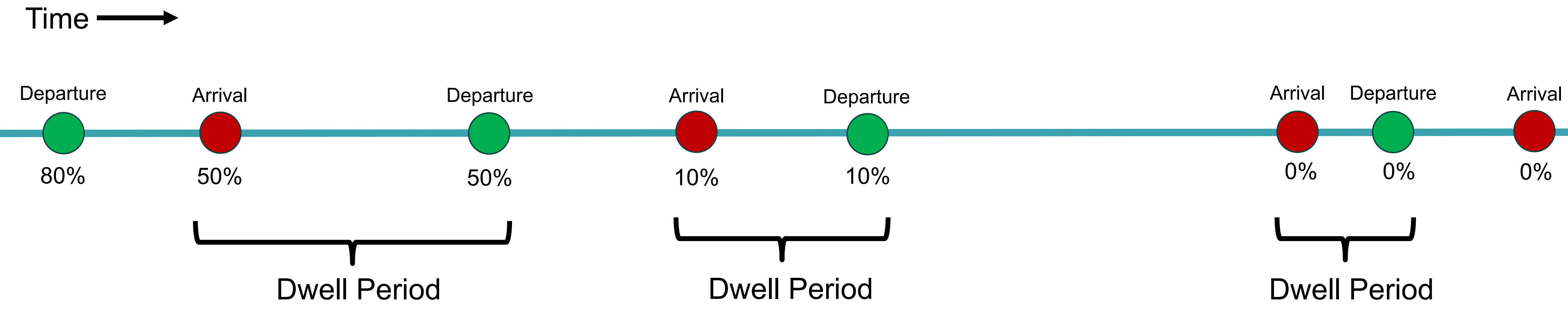
Agent-based modeling

Itinerary

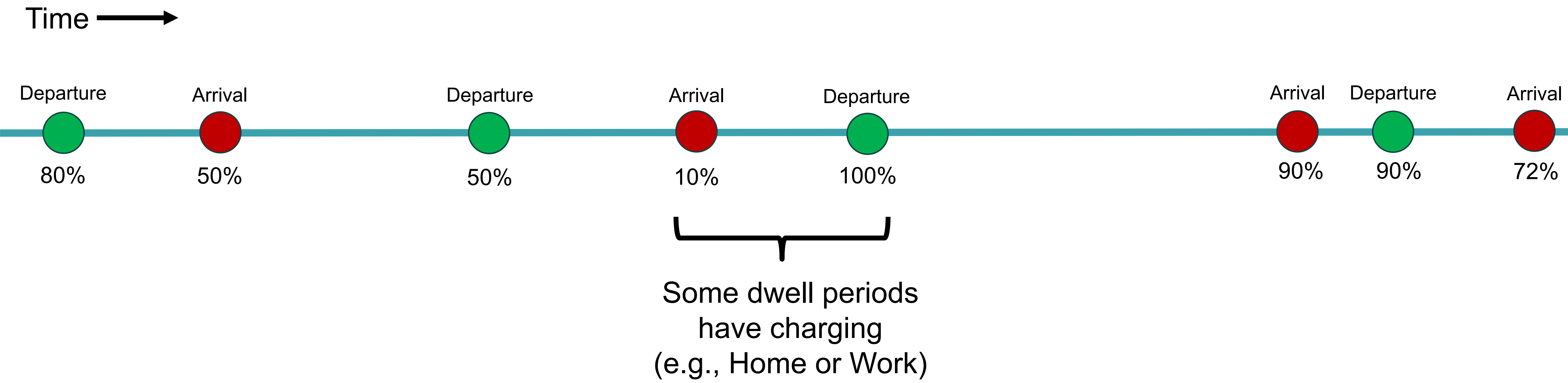


- **Imagine a car driving from point A to point B to point C, etc.**
- **Travel-times and distances computed using a routing-engine**
  - We use the osrm-backend tool
  - See https://github.com/Project-OSRM/osrm-backend

Agent-based modeling, Short-dwell/Mid-Route

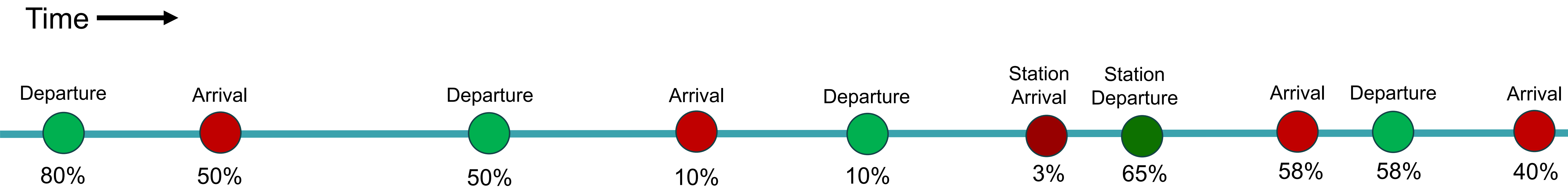


Agent-based modeling, Short-dwell/Mid-Route



Agent-based modeling, Short-dwell/Mid-Route

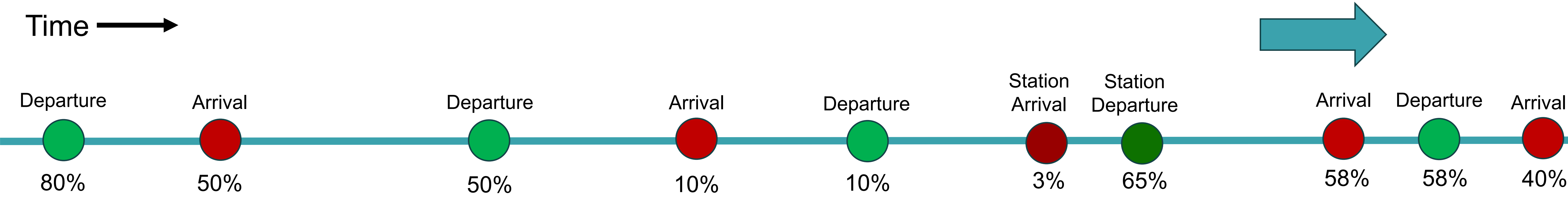
Sometimes we need mid-route charging



Inserted Mid-route Charging Waypoints

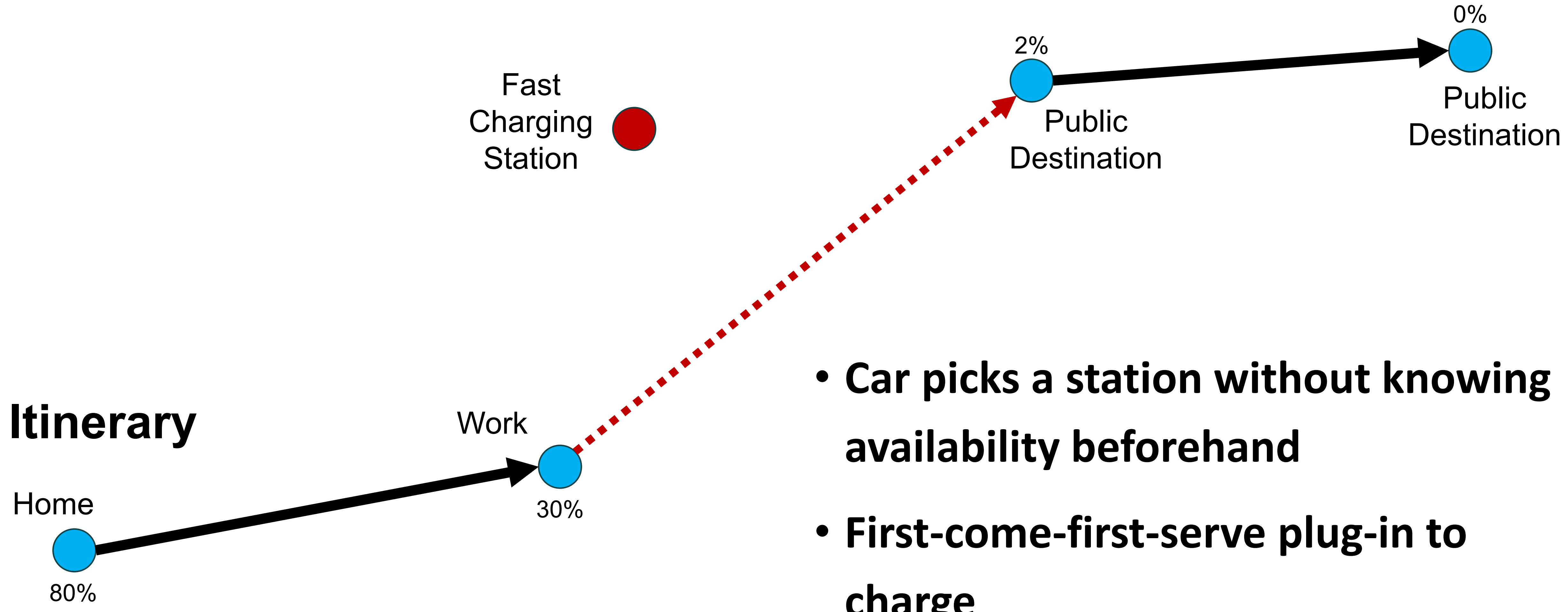
Future SOC values updated

Agent-based modeling, Short-dwell/Mid-Route



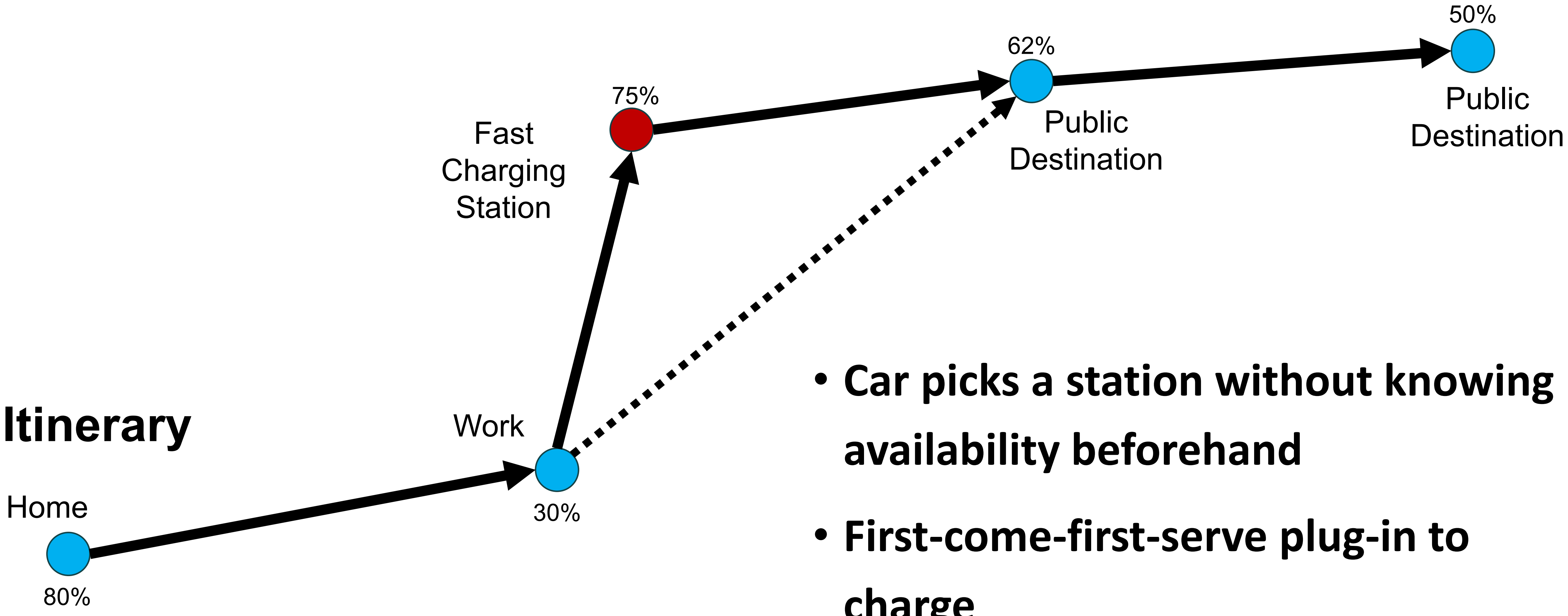
Future waypoints shifted into the future if needed

(Travel times and distances computed using a routing engine)



- **Car picks a station without knowing availability beforehand**
- **First-come-first-serve plug-in to charge**

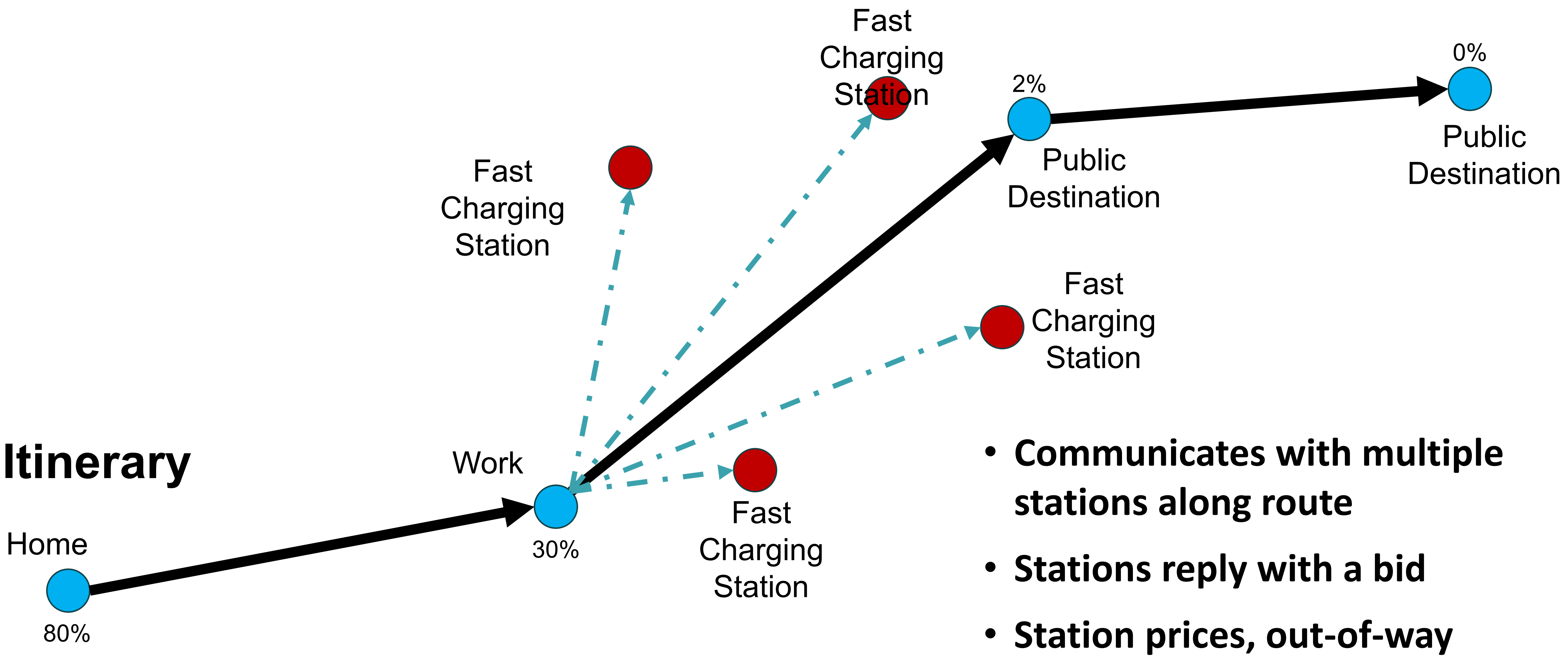
Unscheduled Charging



- **Car picks a station without knowing availability beforehand**
- **First-come-first-serve plug-in to charge**

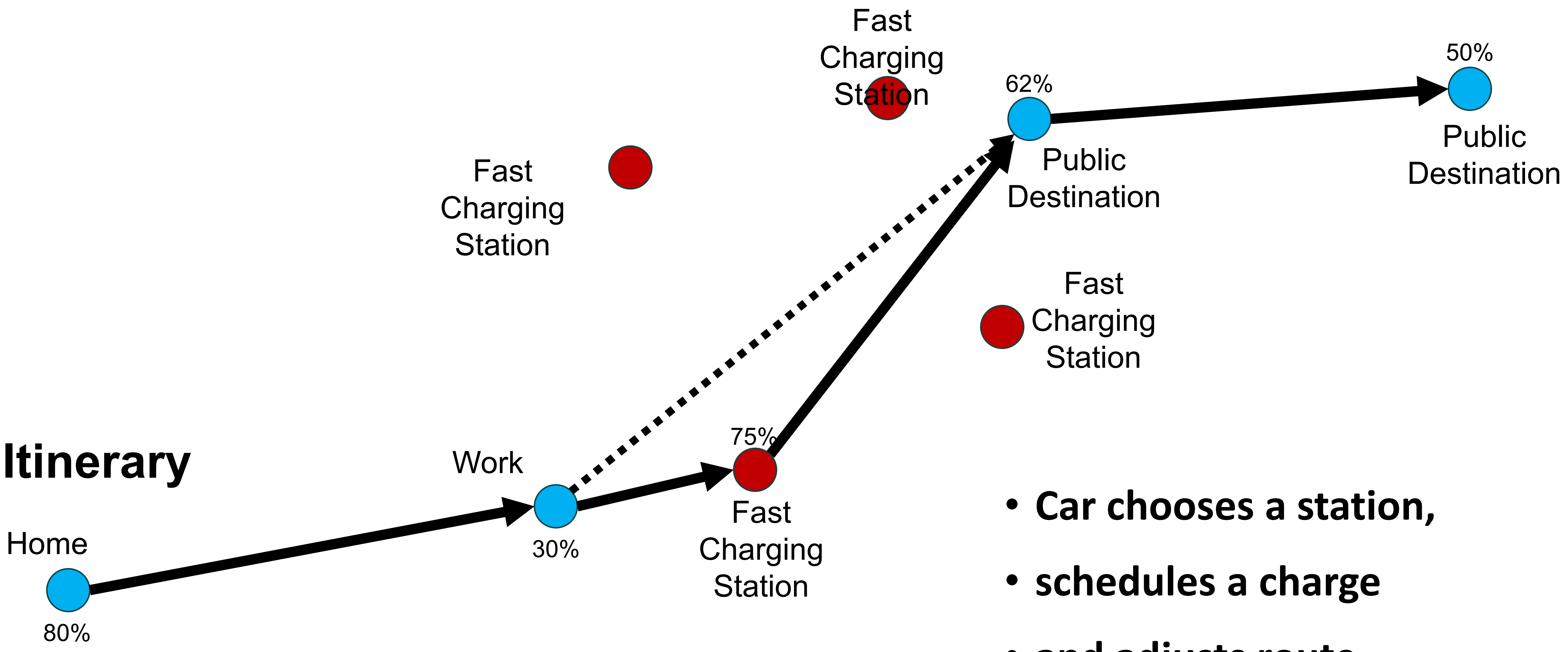
Scheduled Charging

Itinerary



- **Communicates with multiple stations along route**
- **Stations reply with a bid**
- **Station prices, out-of-way distance, etc., affects choice.**
- **Lowest opportunity-cost**

Scheduled Charging



Itinerary

- **Car chooses a station,**
- **schedules a charge**
- **and adjusts route accordingly.**

Itinerary Data

- **Characteristics of Itinerary Data**
  - **Input**: Collection of move-events:
    - Itinerary unique-id and vehicle type
    - Start and end time, start and end location (lat, lon)
    - Destination type (Home, Work, Public, etc)
    - EVSE available at destination
  - **Input**: Initial SOC for each itinerary
  - Additional requirements:
    - Arrival and departure location must match (no teleportation)
    - Each itinerary must have exactly one home and one work location
    - Itineraries always depart from home in the morning and return to the same home at the end of the day
  - At run-time:
    - Travel times computed using osrm-backend routing engine
    - SOC at each waypoint computed based on travel distances and vehicle efficiency (wh-per-mile)

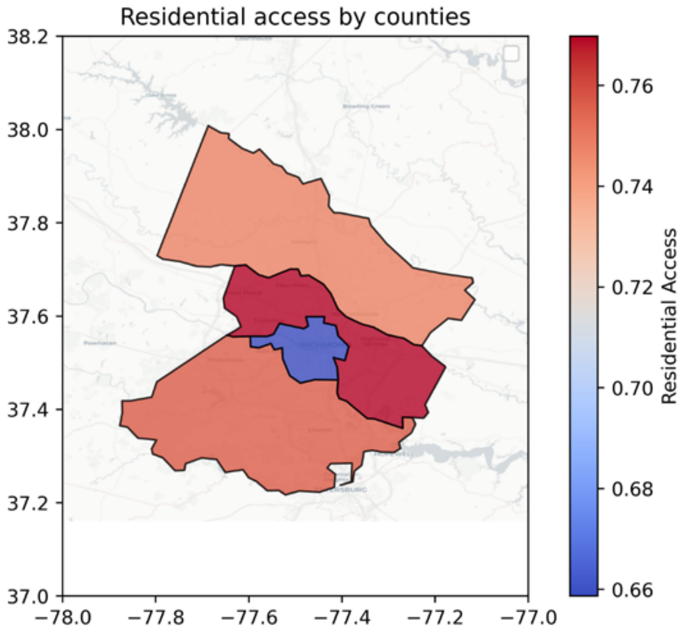
Itinerary Data

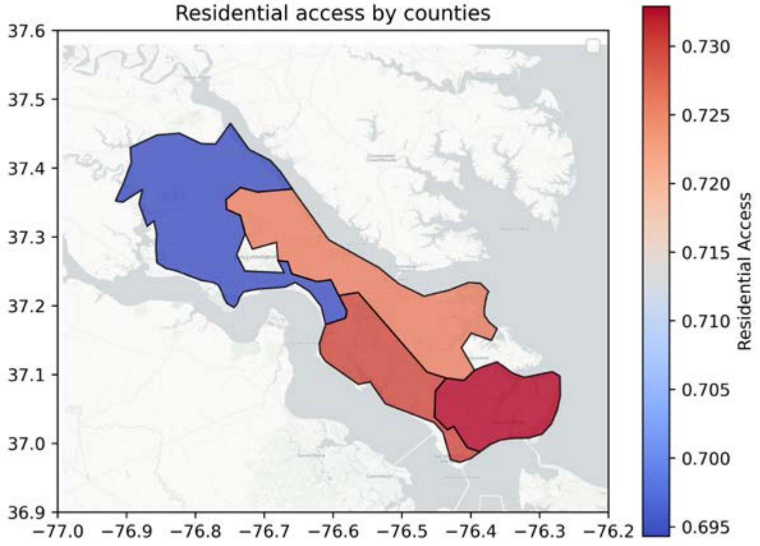
- **Itineraries from NREL**
  - Real world trips in Virginia purchased from WEJO, trip chained to form individual vehicle itineraries.
- **Itineraries from Sandia**
  - Plan:
    - Sandia team will stochastically-generate itinerary data
    - INL team will run simulations with Sandia's itineraries to compare with Sandia's analysis.

Home Charging Levels

- **A probability of home charging availability is computed for each county.**
  - Based on the NREL study:
    - *"There's No Place Like Home: Residential Parking, Electrical Access, and Implications for the Future of Electric Vehicle Charging Infrastructure"*.
  - Estimates levels of home charging access based on housing attributes
    - National data on vehicle ownership
    - Residence type
    - Housing density
    - Housing rent or own
    - Data supported with survey of 3772 U.S. individuals
  - County-level data

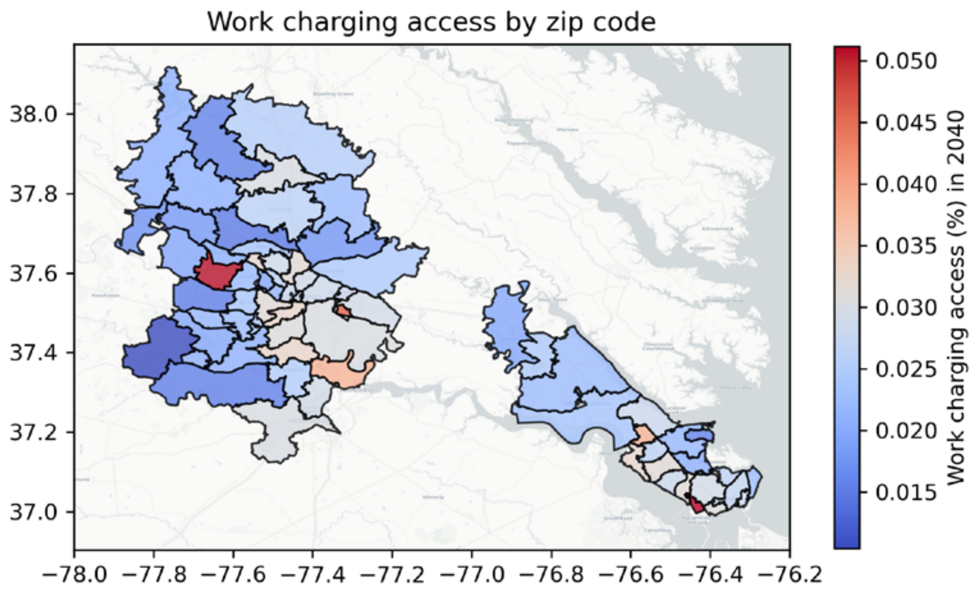
- **If an itinerary's home has L2 charging:**
  - Upon arrival at home, a L2 charge event occurs if:
    - SOC < 80%
    - The driver remembers to plug-in (95% chance)





Work Charging Levels

- **A probability of work charging availability is computed for each zip code.**
  - A generalized linear model is used to estimate the probability that a business establishment has workplace charging available
    - Based on:
      - Population density,
      - Establishment density,
      - Company size distribution,
      - Median income,
      - Average Annual payroll,
      - Average company size.
    - Zip-code level
  - Zip-codes with sufficient data are used to fit the model (Alternate Fuel Data Center AFDC data)
  - The fitted model is used to estimate all zip codes in the country.
  - Availability is scaled up for 2040 scenario with 1.03% annual establishment growth and 485k workplace chargers based on NREL's 2030 charging needs assessment.



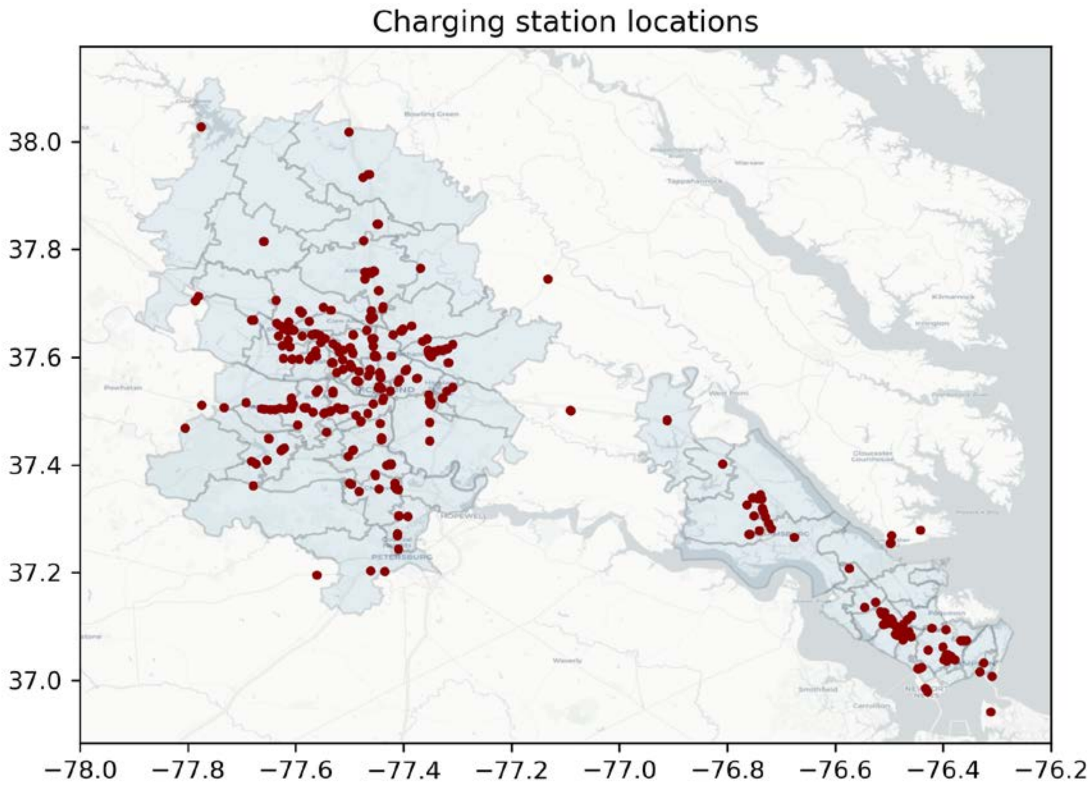
- **If an itinerary's work has L2 charging:**
  - Upon arrival at work, a L2 charge event occurs if:
    - SOC < 65%
    - The port is available (66% chance)
    - The driver remembers to plug-in (95% chance)

Public (Destination) Charging Levels

- **6.7% of public destination locations have L2 charging available**
  - From EVI-Pro lite online tool.
- **If a public destination has L2 charging:**
  - Upon arrival, a L2 charge event occurs if:
    - SOC < 50%
    - Driver remembers to plug-in (95% chance)

XFC Charging Stations

- **318 number of public charging stations.**
  - Charging station locations based on current charging stations and gas station locations.
  - 1500 total plugs based on EVI-pro lite tool.
  - Plugs distributed to stations based on how busy a station is.
  - Currently, all plugs support up to 350kW.
- **Public charging stations are used by a vehicle when certain conditions are met**
  - Itinerary is adjusted to allow vehicle to go to public charger before continuing on its way
  - Range anxiety metrics



Range Anxiety Metrics

- **When to divert to a public charging station?**
  - Depends on if an upcoming waypoint has destination-charging available
  - Depends on if we're going to work, home, or a public destination
- **If an upcoming waypoint has destination charging (home,work,public):**
  - Allow lower SOC before public charging is desired
- **If SOC will fall below the threshold:**
  - Divert to a public station to charge.

- **Threshold values (specific values are still debatable):**

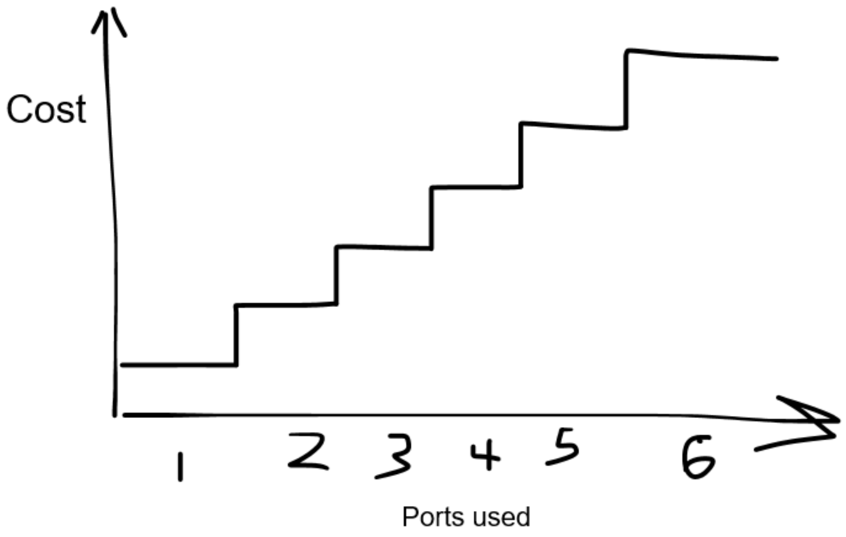
	Upcoming destination has L2 charging	No upcoming destination charging
Arriving at home	**7% SOC** or **15 miles range**	**14% SOC** or **40 miles range**
Arriving at public destination	**7% SOC** or **15 miles range**	**12% SOC** or **35 miles range**
Arriving at work	**7% SOC** or **15 miles range**	**10% SOC** or **30 miles range**

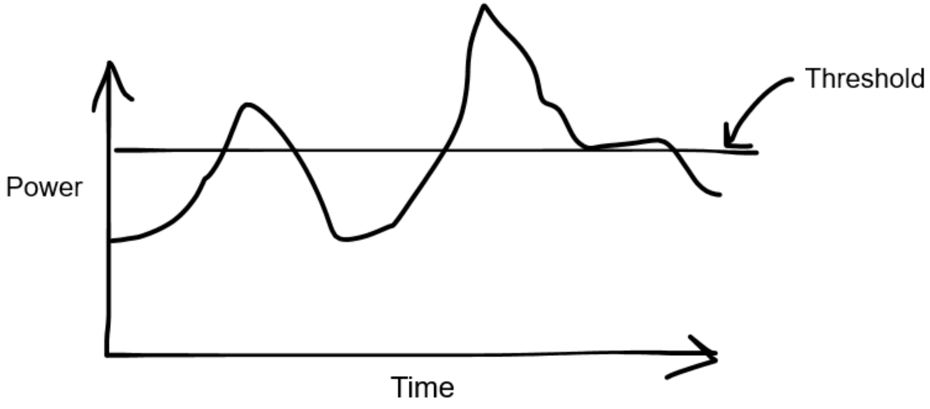
NOTE: ***When going to work, the driver is more anxious to make it on time, so threshold allows a lower SOC when going to work.***
Whereas, when going Home or to a Public Destination location, the driver is assumed to have more flexibility.

Smart Charge Management

- **Scheduling Mode:**
  - Unscheduled Charging:
    - Looks into the future only one leg at a time
  - Scheduled Charging:
    - Looks multiple travel-legs into the future

- **Station Pricing Mechanisms:**
  - Constant pricing
  - Station-busyness based pricing
  - Station peak-power-usage based pricing





Cost metrics

- **Costs can be used to influence vehicle behavior**
  - Spatial and Temporal Shifts
  - Shift from busy station to less-busy
  - Help alleviate station overage-charges
- **Prevent slow-charging vehicles from clogging up fast-chargers**
  - If time and energy costs are set appropriately
- **Additional fixed costs may be different for each station**
  - Control for unique scenarios
  - Make sure the station near Mr. Trump's resort is never full so he never gets mad.
- **Varying station cost based on station demand (busyness)**
  - Lower-bound vs upper-bound cost
  - Linear interpolation based on station-usage

Possible Values (not set in stone):

EVSE Type	Cost While Charging					
	Time ($/min)		Energy ($/kWh)		Connection Cost ($)	
	Low	High	Low	High	Low	High
L2 1440	0.02	0.52	0.10	1.50	0.00	1.00
L2 17280	0.07	0.57	0.10	1.50	0.00	1.00
DCFC 50	0.10	0.60	0.10	1.50	0.00	1.00
XFC 350	0.20	0.70	0.10	1.50	0.00	1.00

Vehicle Class	Cost While Driving	
	Time ($/min)	Distance (Wear and Tear) ($/mile)
Default	1.00	0.05

Extreme Cases

- **What do cars do when all stations are busy?**
  - Unscheduled:
    - Cars go from station to station looking for a place to charge until they are stranded.
  - Scheduled:
    - Cars wait and wait, trying to schedule again and again every few minutes, until they can’t wait any longer and are declared stranded.

Simulations

- **Questions we want to answer:**
  - How effectively can we influence cars to shift XFC charging?
    - **Spatially**: Influence cars to charge at a different public charging station
    - **Temporally**: Influence cars to charge earlier or later
  - What specific cost controls are most effective at influencing charging behavior?
    - Peak-power vs. station-busyness controls
    - Different controls have different benefits
  - Benefits to:
    - Electrical grid – avoid charging during peak power usage
    - Station operators – avoid demand charges
    - EV drivers – avoid full/busy stations, and minimize cost, time charging

Initial Results

- **Pending a currently-running simulation**

FUSE EV charge load modeling update: “Short-dwell” vehicle travel itinerary development

Matthew Bruchon, Yi He, Zhaocai Liu, Jesse Bennett

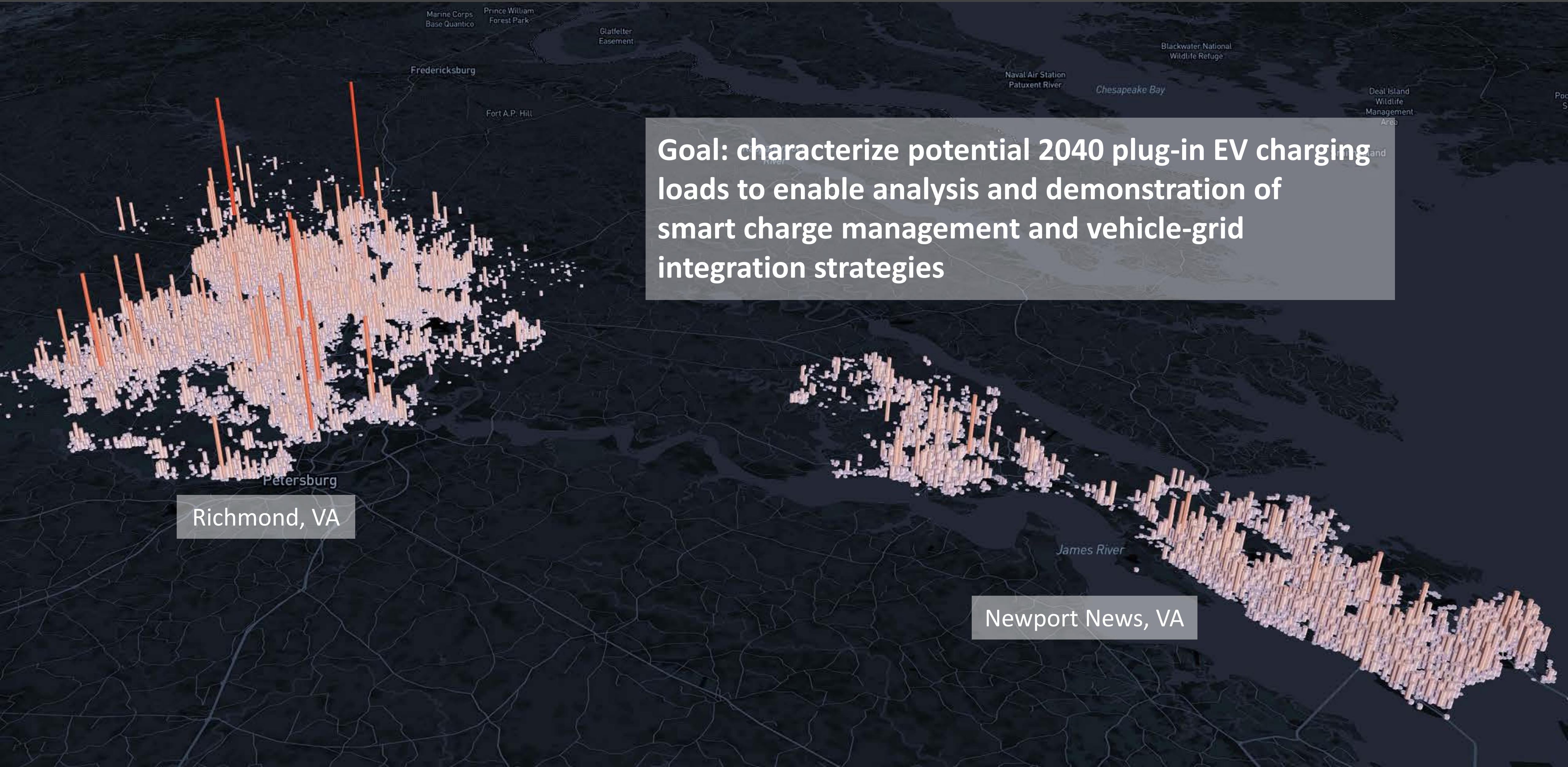
March 2024

U.S. DEPARTMENT OF ENERGY | Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

FUSE EV charge load modeling overview

EVs@Scale
U.S. Department of Energy

Goal: characterize potential 2040 plug-in EV charging loads to enable analysis and demonstration of smart charge management and vehicle-grid integration strategies



FUSE EV charge load modeling to date

- Analysis began with **light-duty passenger vehicles**
- We then considered medium- and heavy-duty vehicles (MHDV) with charging needs fully met by **long-dwell depot charging**

Summary statistics for Richmond and Newport News, VA (2040 estimates)

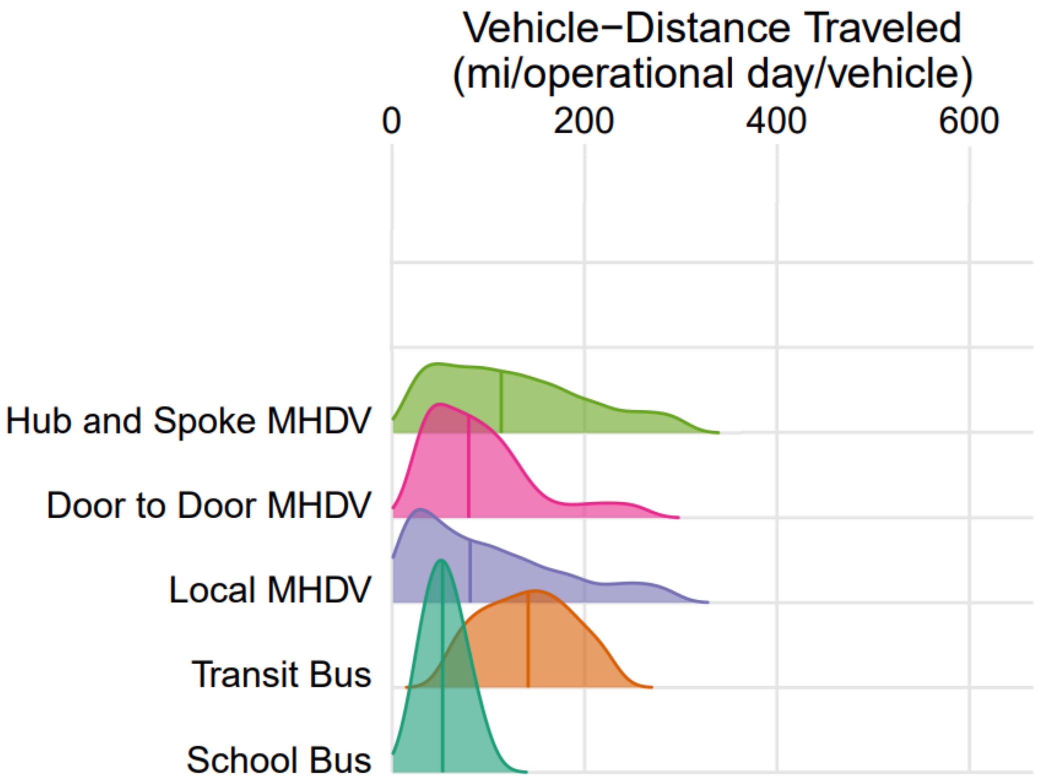
	Projected EV count	Regional daily energy	Peak power per h9 hex cell*	Peak load time of day
Passenger cars	700,000	1.50 GWh	600 kW	5 – 10 PM
Local freight	17,000	410 MWh	1.4 MW	5 – 9 PM
School buses	3,000	670 MWh	900 kW	5 – 11 PM
Transit buses	500	250 MWh	9.0 MW	3 PM – 2 AM

*h9 hex cells are approx. 0.04 mi^2 (0.1 km^2)

Short-dwell charging needs vary by vocation

Typical nationwide vocational travel patterns

Modeled in earlier stages of FUSE
(not pictured: light-duty vehicles)



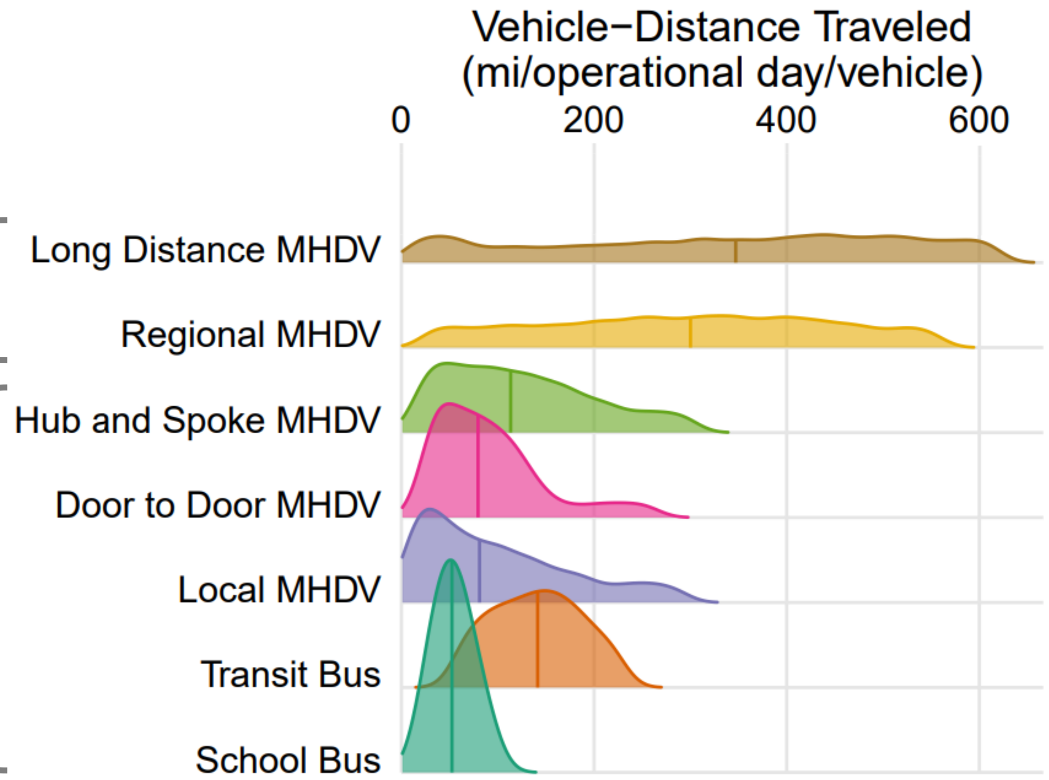
Bruchon, Matthew, Brennan Borlaug, Bo Liu, Tim Jonas, Jiayun Sun, Nhat Le, Eric Wood. “Depot-Based Vehicle Data for National Analysis of Medium- and Heavy-Duty Electric Vehicle Charging”. National Renewable Energy Laboratory. NREL/TP-5400-88241. February 2024.

Short-dwell charging needs vary by vocation

Typical nationwide vocational travel patterns

Modeled in short-dwell analysis
(not pictured: drayage)

Modeled in earlier stages of FUSE
(not pictured: light-duty vehicles)



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Short-dwell charging needs vary by vocation

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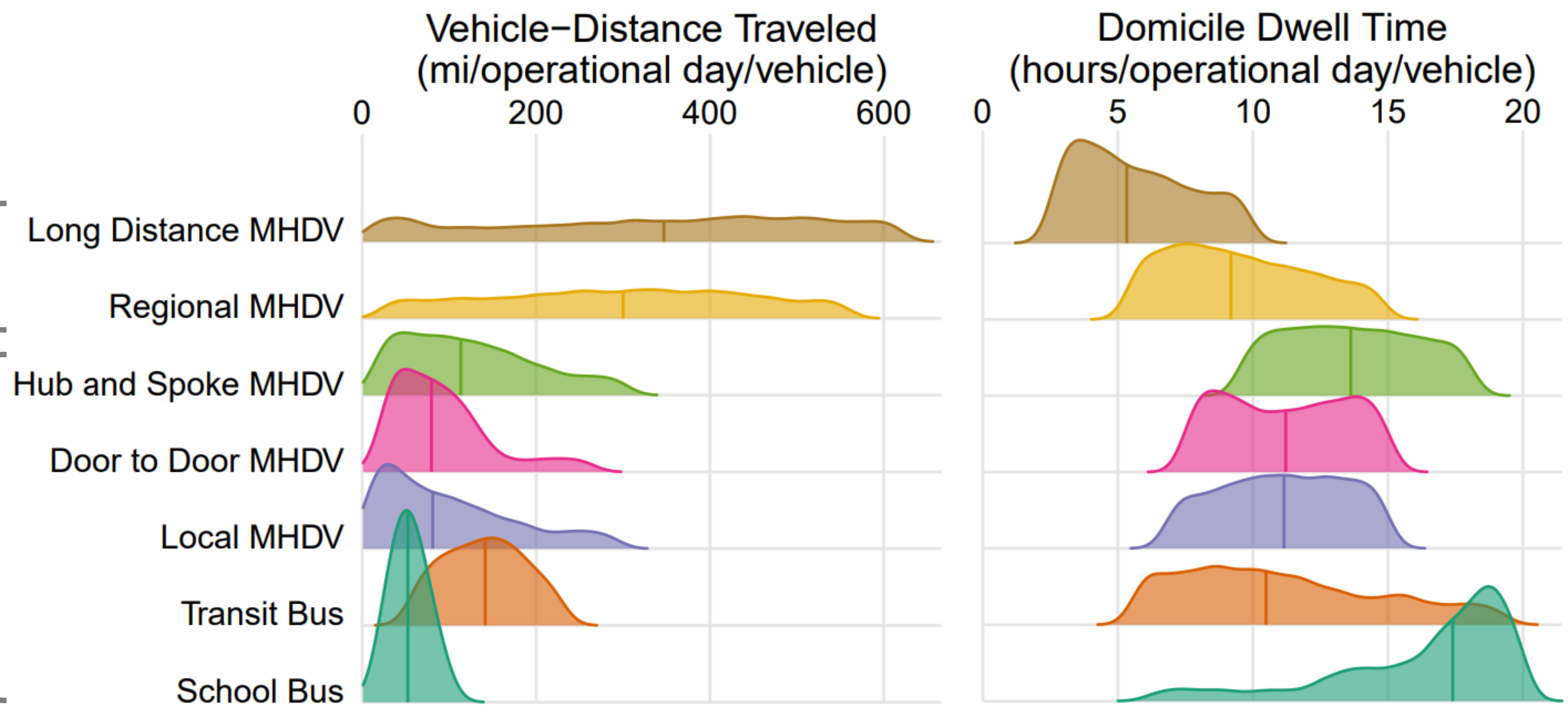

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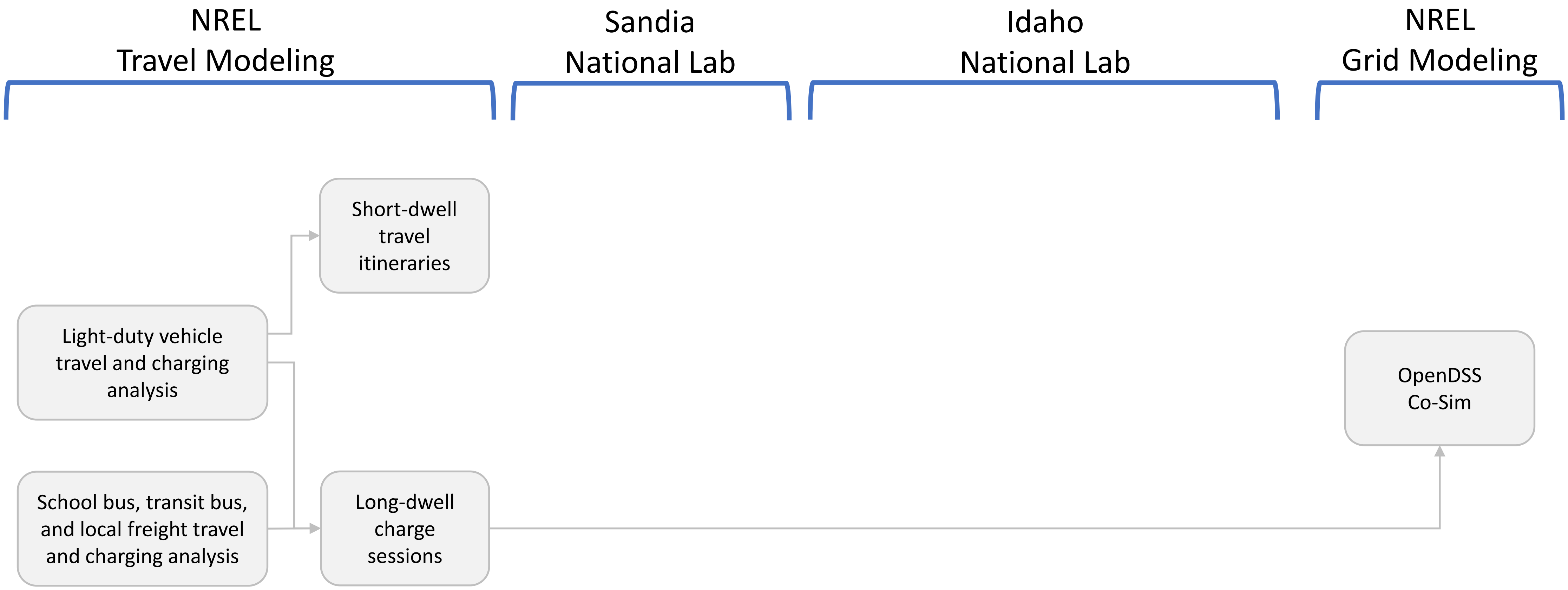
Multiple labs are coordinating to model short-dwell charging demands



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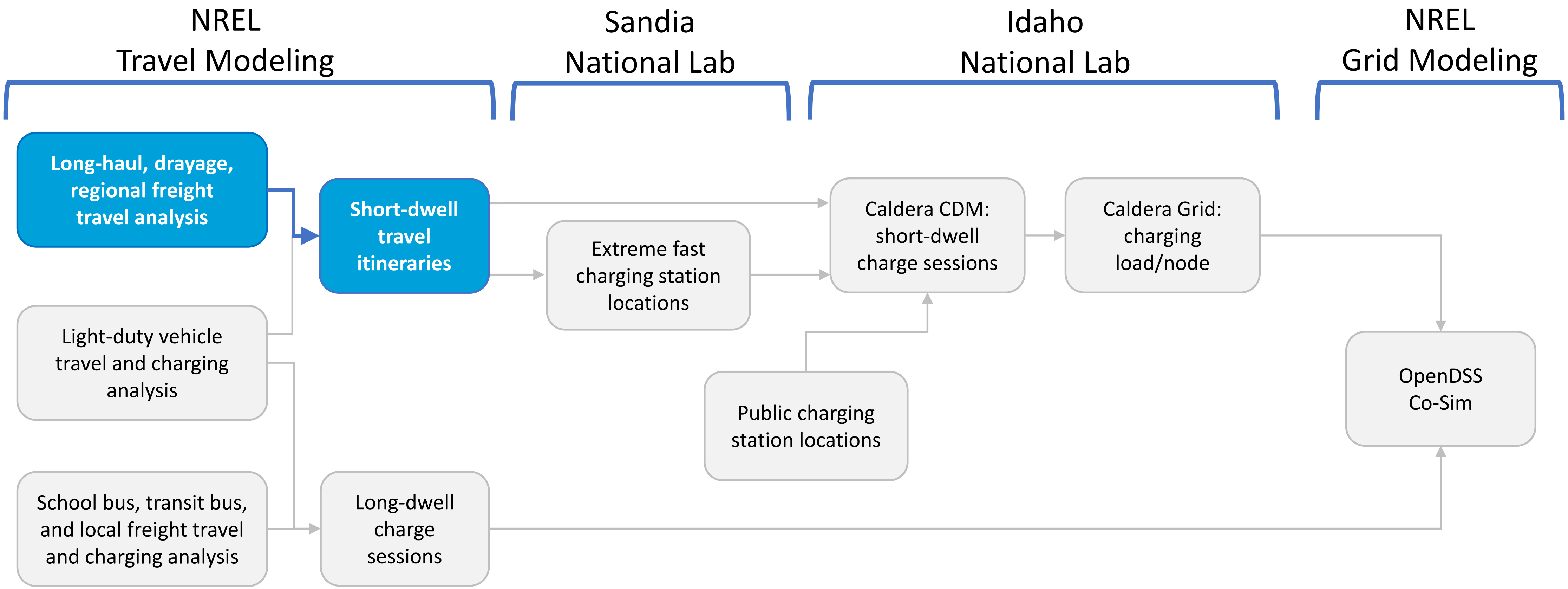

We model three short-dwell medium- and heavy-duty vocations

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Long-haul	Drayage	Regional freight
Class 7-8 tractors	Class 7-8 tractors	• Class 3-6 cargo vans, step vans, straight trucks • Class 7-8 tractors
Largely interstate freight	Freight delivered to/from ports	Operating radius over 150 miles
Less consistent domicile location	More consistent domicile location	More consistent domicile location
Modeled using FAF and Geotab	Modeled using Port of Virginia data and Geotab	Modeled using Geotab

Long-haul modeling approach

Freight Analysis Framework (FAF) and Geotab based approach

Obtain entry and exit road links from FAF network

↓

Obtain entry and exit volume (2040 long-haul) from FAF truck volume data

↓

Obtain stop location and time information from Geotab

↓

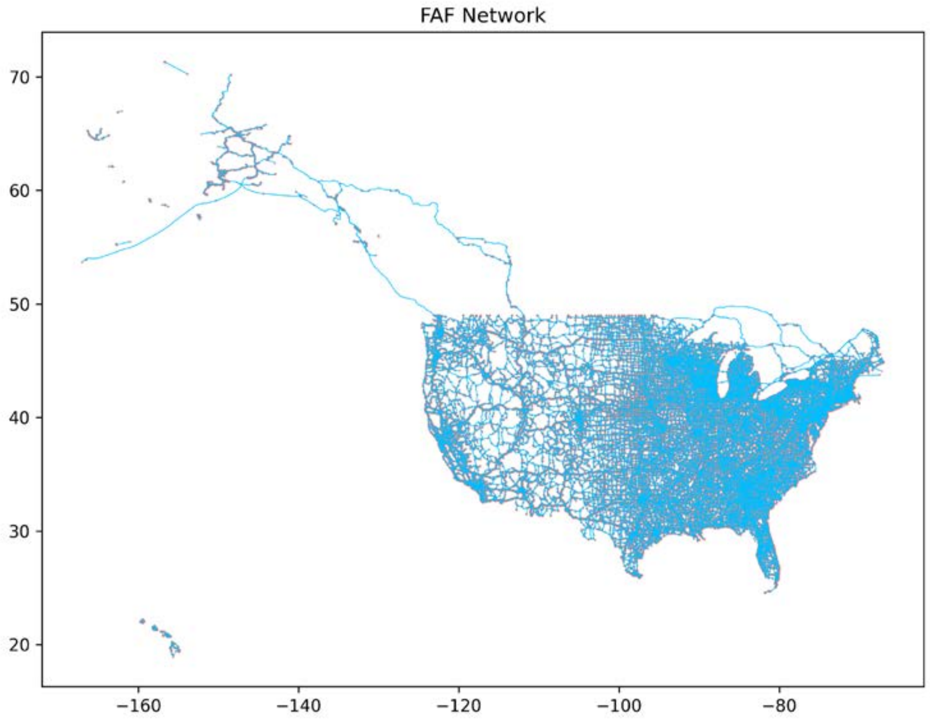
Generate synthetic travel itineraries within the study region by matching entry points, exit points, and stops

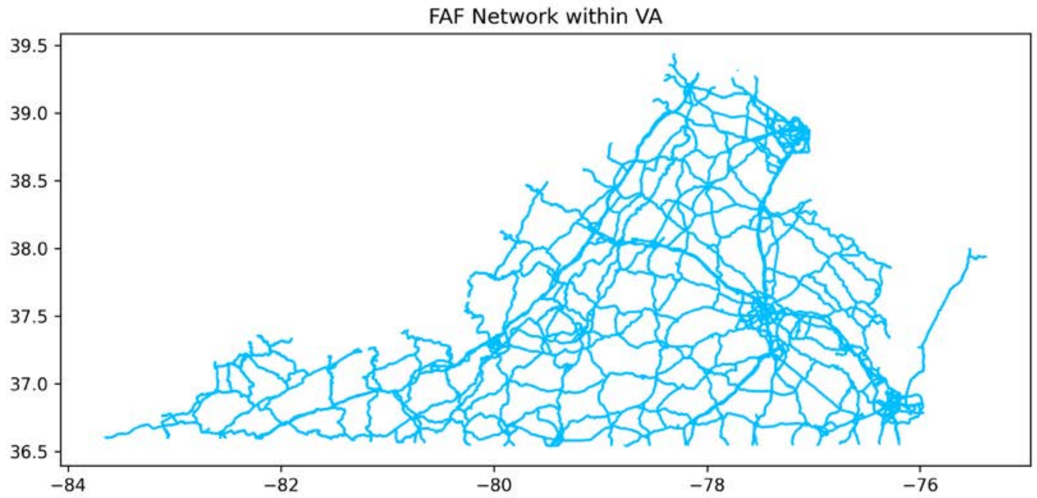
↓

Assign vehicle characteristics to travel itineraries

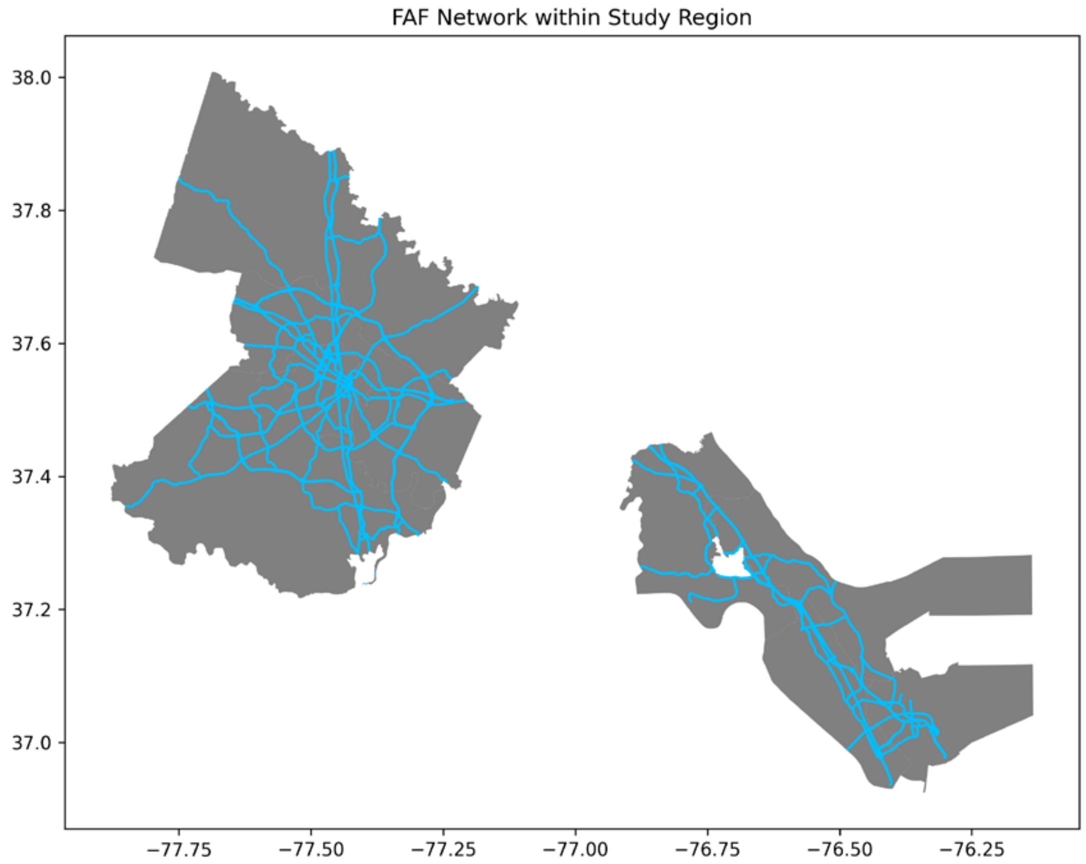
Long-haul modeling step 1:
Obtain entry and exit road links from FAF network

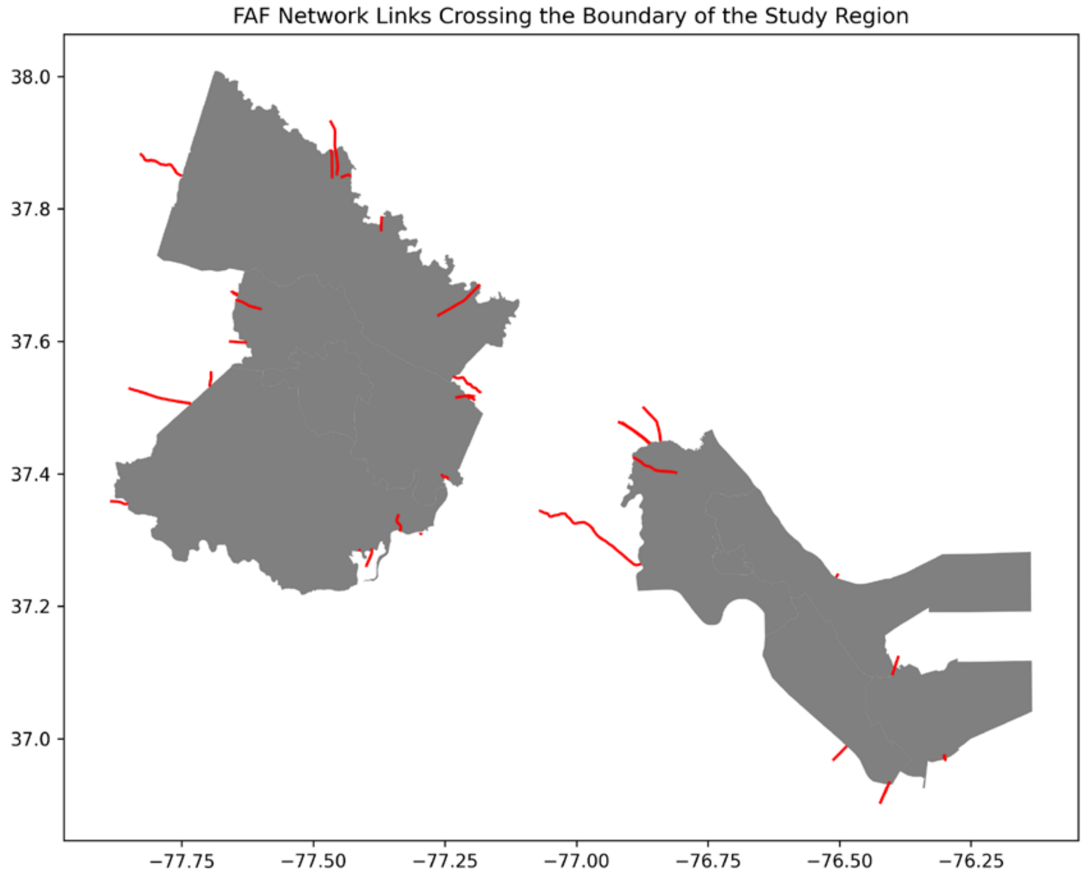
- FAF database has estimates of US freight flows for states and metropolitan areas
- Flows include all modes of transportation and 42 commodity types
- The Bureau of Transportation Statistics (BTS) produces the FAF with support from the Federal Highway Administration (FHWA). The main FAF5 input is the 2017 CFS.





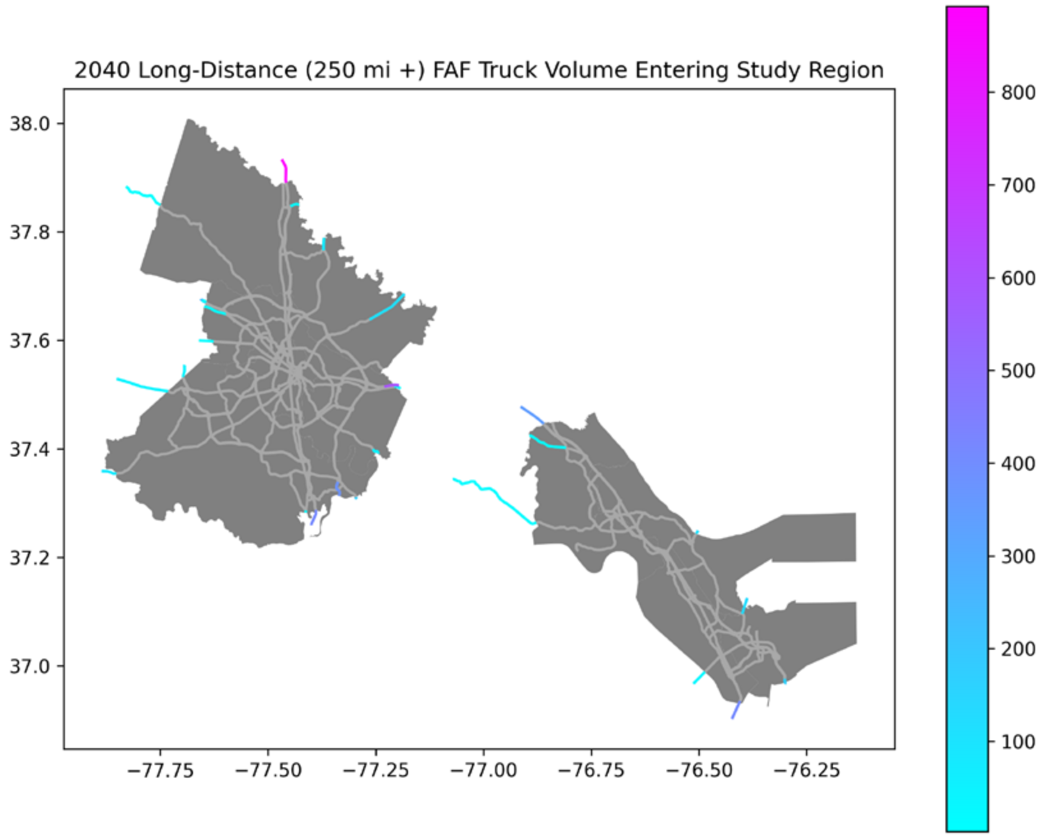
Long-haul modeling step 1:
Obtain entry and exit road links from FAF network

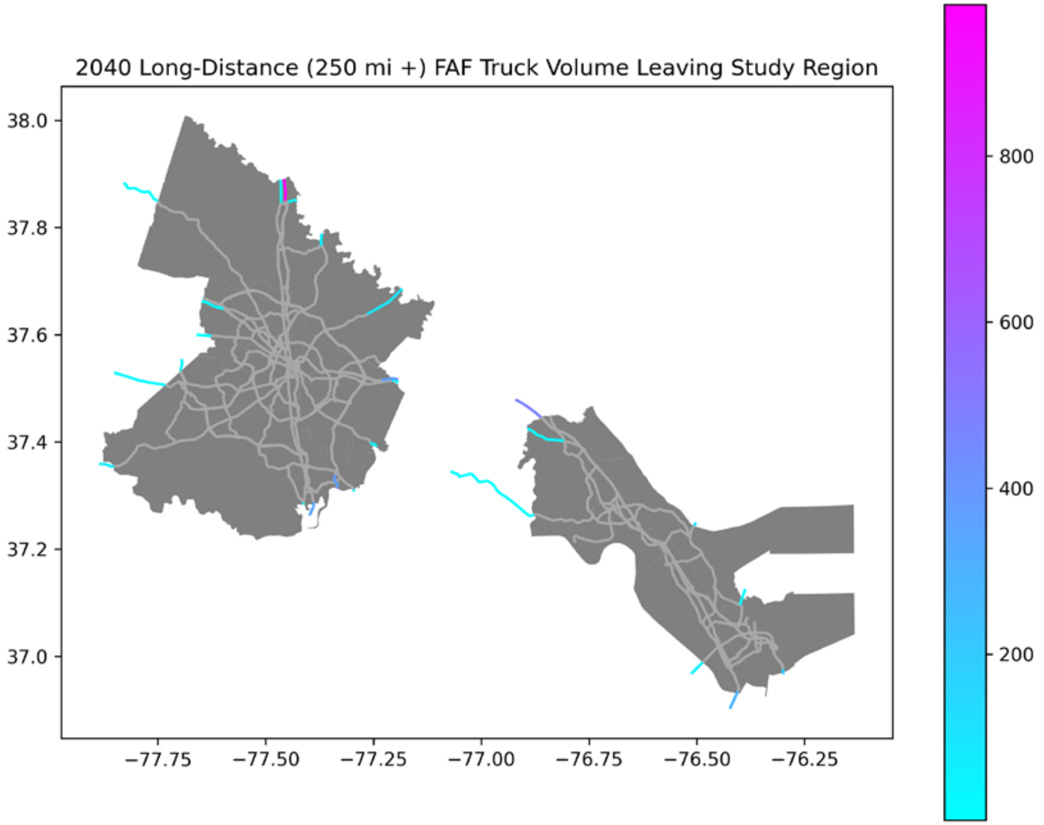




Long-haul modeling step 2:
Obtain 2040 entry and exit volumes from FAF truck volume data

FAF long-distance truck volume for each link with direction for year 2040





Long-haul modeling step 3:
Obtain stop location and time information from Geotab

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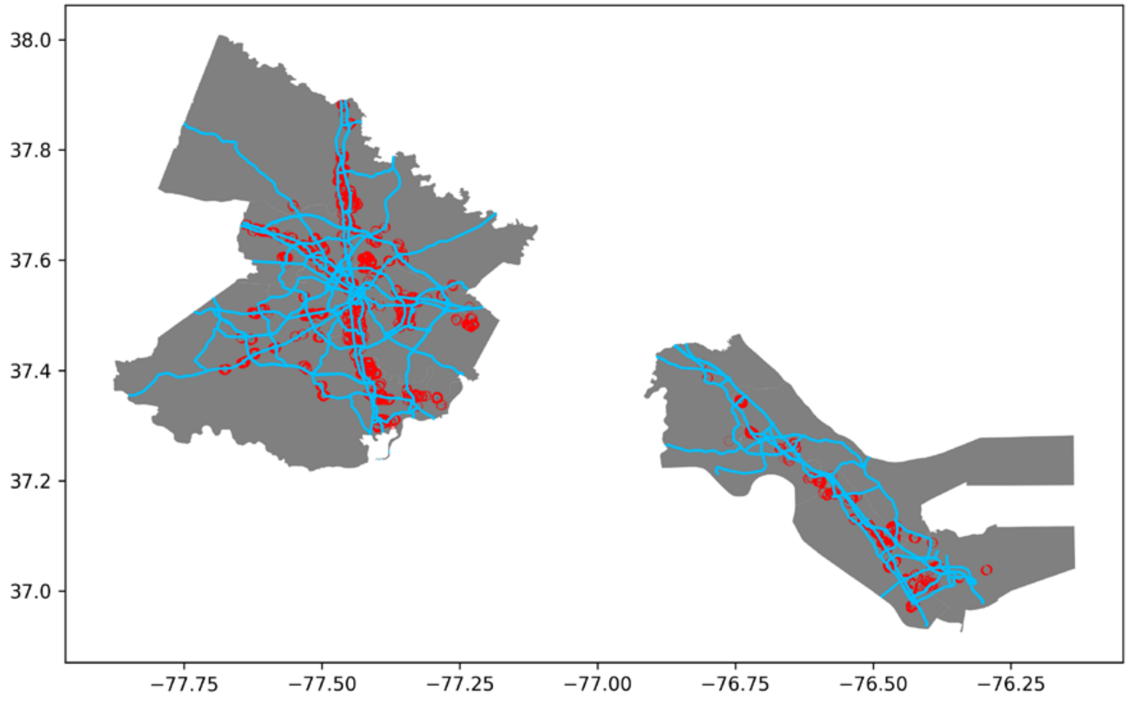
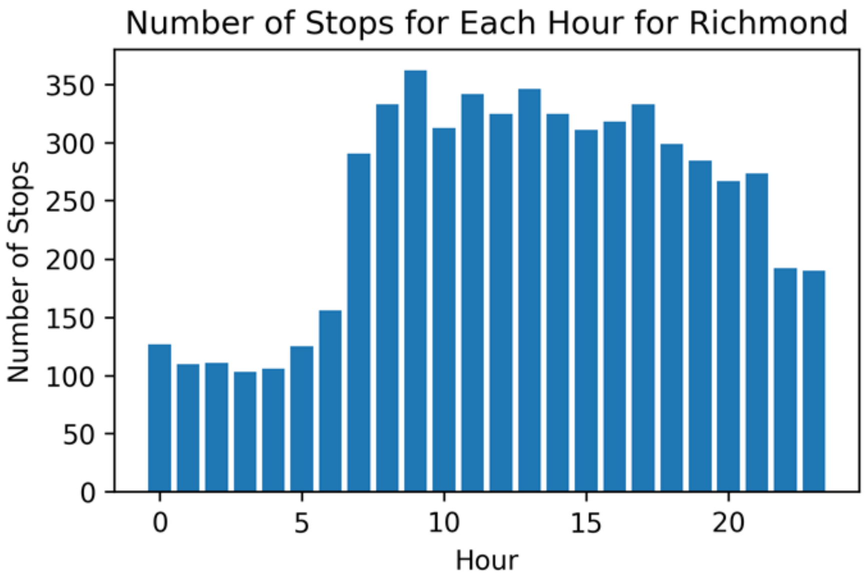
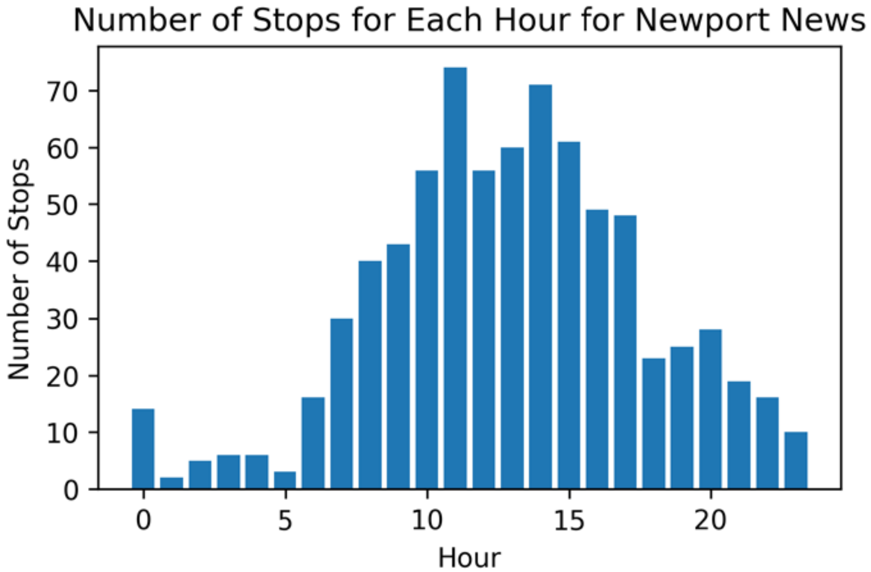
Stop analysis from Geotab can provide stop location and time information







Long-haul modeling step 4:
Generate itineraries by matching entry points, exit points, and stops

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Annual average volumes are scaled using monthly and weekly scaling factors

Region	Daily Trips	Mean Travel Distance	Mean Dwell Time
Richmond	3187	55 miles	6.2 hours
Newport News	1208	59 miles	2.6 hours

Monthly Activity Scalers

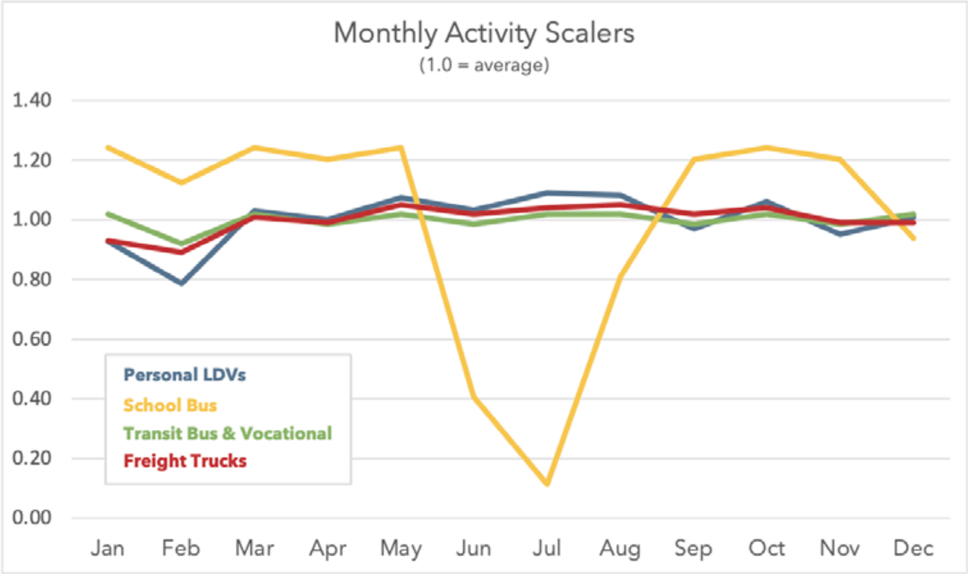


Chart: NREL; Data sources: NHTS17 (personal LDVs, school bus), Cass Info. Systems (freight trucks)

Weekly Activity Scalers (1.0=average day)

Day Type	Truck_Local	Truck_Regional	Truck_LongHaul	Bus_School	Bus_Transit	Vocational	Personal_LDV
Weekday	1.22	1.21	1.10	1.25	1.18	1.22	1.13
Weekend	0.44	0.47	0.75	0.36	0.52	0.44	0.68
Source:	*HD telematics*	*HD telematics*	*HD telematics*	*Fleet DNA*	*NTD*	*Truck_Light*	*2017 NHTS*

Source: NREL DECARB analysis (Brennan Borlaug et al.)

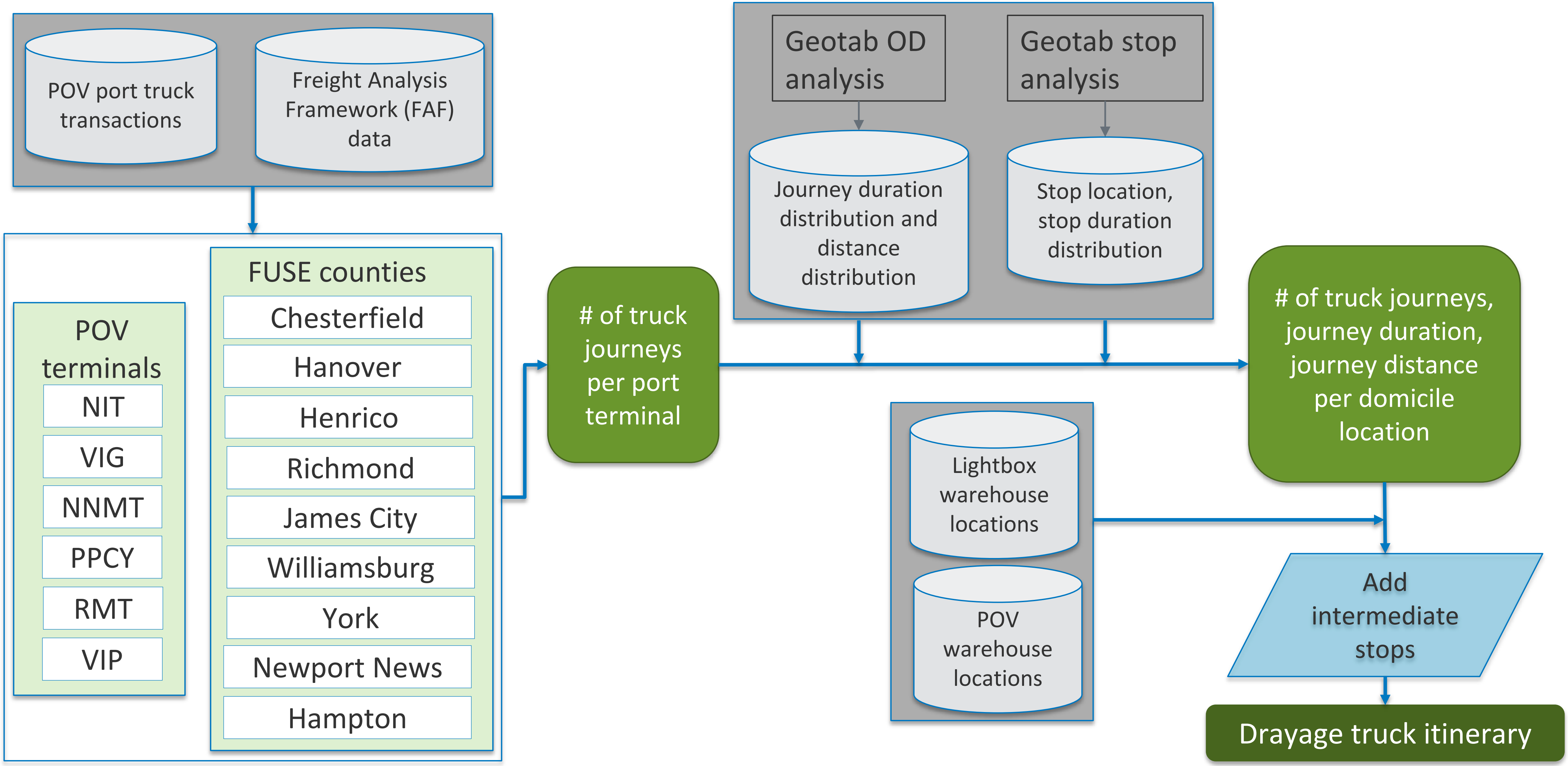
Step 5:
Assign vehicle characteristics to travel itineraries

- From TEMPO: 0% EV-150, 2.6% EV-300, 5.8% EV-500, 91.6% non-EVs[1]

Vehicle Class	Battery Range (mi)	Battery Size (kWh)[2]	Fuel Economy (kWh / Mile)[2]	Depot kW	Opportunity kW	En-Route kW
Heavy (Classes 7-8)	150	289 kWh	1.804	30	110	500
Heavy (Classes 7-8)	300	578 kWh	1.804	60	220	1000
Heavy (Classes 7-8)	500	963 kWh	1.804	100	360	1500

1. Catherine Ledna, Matteo Muratori, Arthur Yip, Paige Jadun, Christopher Hoehne, Kara Podkaminer. Assessing total cost of driving competitiveness of zero-emission trucks. *iScience* 27 (4), 2024.
2. Ehsan Sabri Islam, Daniela Nieto Prada, Ram Vijayagopal, Charbel Mansour, Paul Phillips, Namdoo Kim, Michel Alhajjar, and Aymeric Rousseau. Detailed Simulation Study to Evaluate Future Transportation Decarbonization Potential, 2024.

Drayage modeling approach



Drayage modeling step 1:
Determine daily drayage truck visits

- Average daily truck transactions for NIT, VIG, RMT, PPCY are obtained from Port of Virginia (POV) website statistics.
- Port features obtained from POV and online sources.
- Estimate daily truck transactions for NNMT and VIP based on port features.

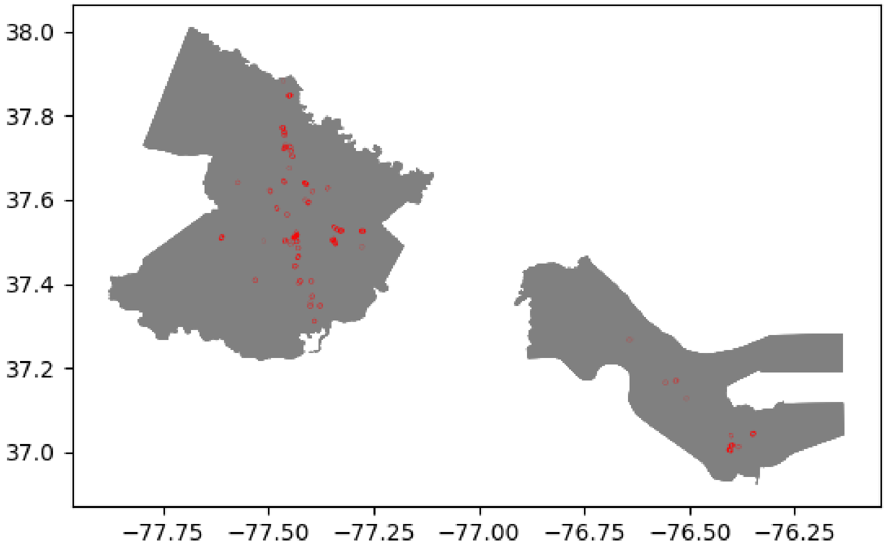
POV terminal	Current throughput TEU capacity	Operating acres	Forklift capacity	On-dock rail track (linear feet)	**Average daily truck transactions**	Truck data source
Norfolk International Terminal (NIT)	2.2M	378	/	27,416	**2307**	Port of Virginia
Virginia International Gateway (VIG)	2.2M	291	/	19,644	**3088**	Port of Virginia
Newport News Marine Terminal (NNMT)	/	165	65K	18,990	**221**	Estimation
Richmond Marine Terminal (RMT)	86,000	121	52K	19,640	**170**	Port of Virginia
Virginia Inland Port (VIP)	78,000	161	13K	17,820	**154**	Estimation
PPCY	/	/	/	/	**2333**	Port of Virginia

Drayage modeling steps 2-3:
Geotab Origin-Destination (O-D) and Stop Analysis

Geotab analysis parameters

	O-D Analysis parameter	Stop Analysis parameter
Vehicle class	Class 7-8 trucks	
Industry	Retail trade, transportation and warehousing, and wholesale trade	
Zones (of stops or origin-destination pairs)	Richmond & Newport News counties	
Stop duration threshold	< 360 minute stops chained into journeys	360 min (domiciles), 120 min (other stops)
Connector	Port of Virginia ports	N/A
Vocation	All	Hub and Spoke

Domicile locations



O-D Analysis outputs:

- Journey counts per combination of O-D pair and connector zone
- Journey distance distribution
- Journey duration distribution
- Running speed

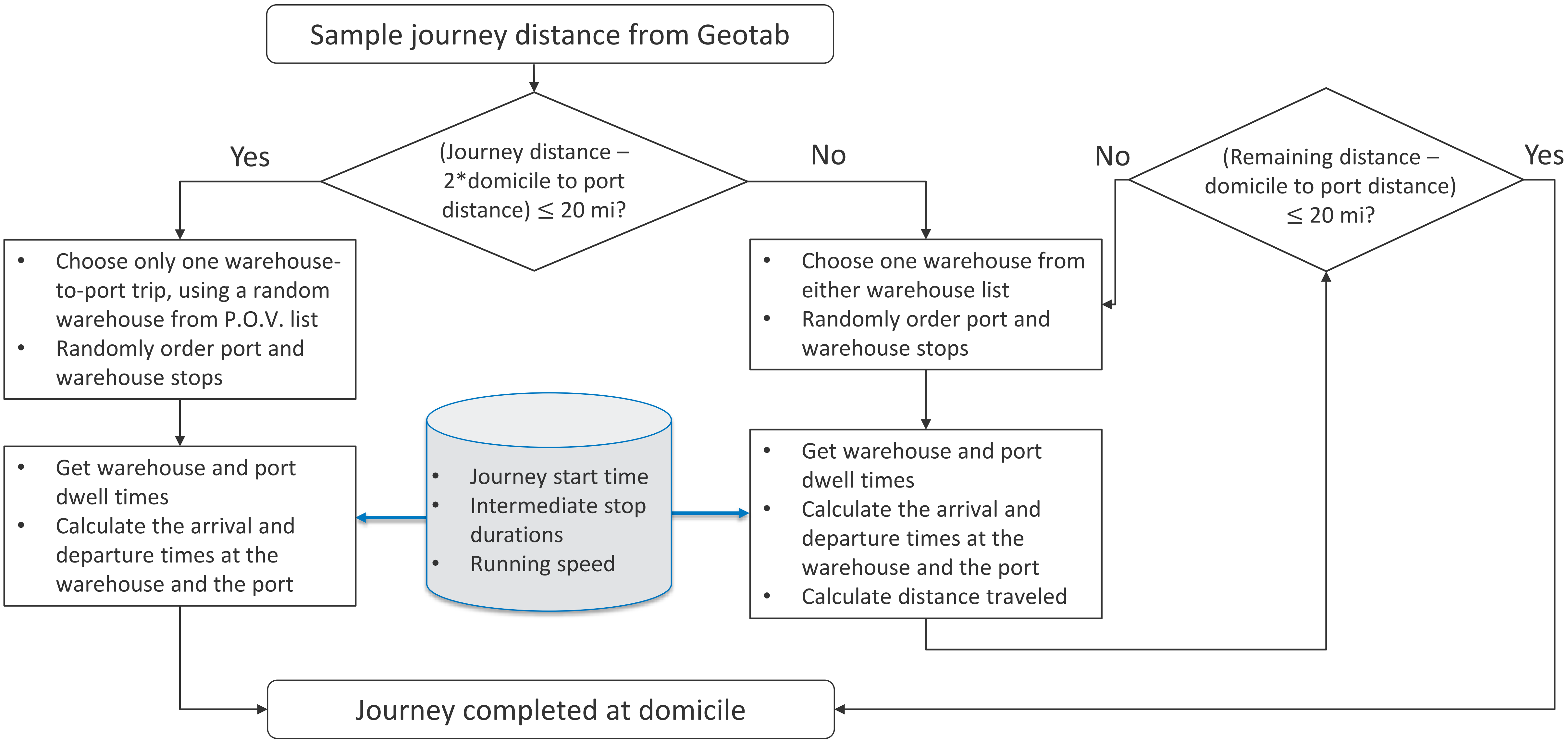
Stop Analysis outputs:

- Vehicles per stop location
- Stop duration distribution
- Arrival time at the stop location

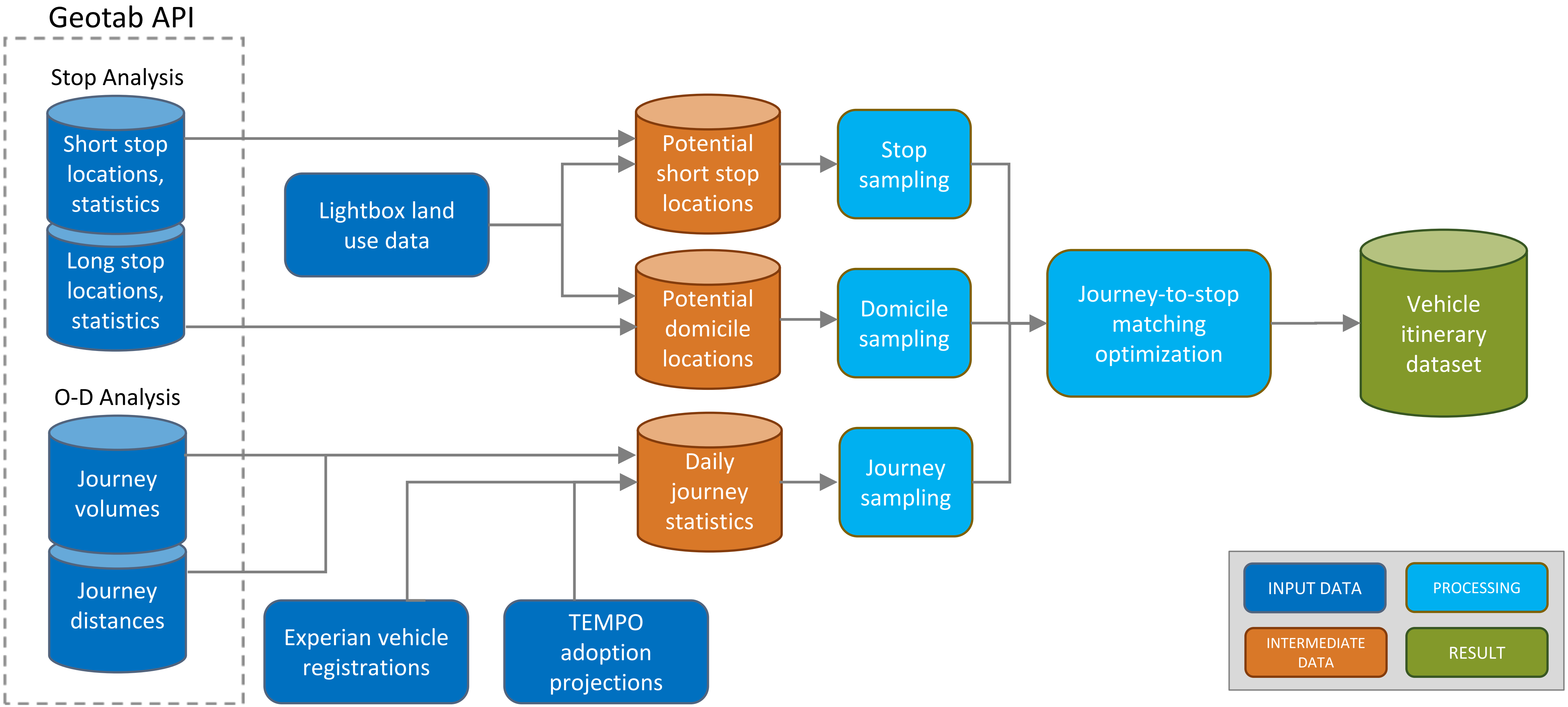
Modeling steps:

1. Assign journeys to each domicile location
2. Get dwell time of each vehicle at the domicile location
3. Calculate journey start time based on arrival time and dwell time at the domicile location
4. Get intermediate stop duration distributions

Drayage modeling step 4: Determine intermediate stop locations and build itineraries



Regional freight modeling approach



Regional freight modeling: Geotab Origin-Destination (O-D) and Stop Analysis

Geotab analysis parameters

	O-D Analysis parameter	Stop Analysis parameter
Vehicle class	Class 3-8 trucks	
Vocation	Regional	
Zones (of stops or O-D pairs)	Counties in VA, states in 250-mile radius	Richmond & Newport News counties
Connector	Richmond & Newport News counties	N/A
Excluded connector	Port of Virginia ports	N/A
Stop duration threshold	< 360 minute stops chained into journeys	360 min (domiciles), 15-360 minutes (other stops)

O-D Analysis outputs:

- Journey counts per combination of O-D pair and class
- Journey distance distribution per O-D pair and class
- Journey duration distribution per O-D pair and class

Stop Analysis outputs:

- Long stop cluster locations and durations for each class
- Short stop cluster locations and durations for each class

Regional freight modeling: stop location characterization

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- We query stop locations from Geotab. However:
  - For regional freight, some mid-route stops may happen outside of the nine-county region
  - Geotab data does not cover the full population of fleets or potential stops
- To add synthetic stop locations, we use third-party land use data (Lightbox):
  1. Pull shapefiles of stop clusters from Geotab
  2. For each type of vehicle, build a frequency table of land uses within stop clusters
  3. Randomly sample additional parcels matching the observed distribution of land uses

Stop location types per weight class

Land Use Category	Weight Class 3	4 & 5	6 & 7	8	Total
Commercial Retail	54%	35%	51%	40%	46%
Commercial/Industrial and Offices	8%	22%	16%	17%	15%
Heavy Industry and Transportation	9%	5%	4%	21%	12%
Industrial/Manufacturing/Warehouses	5%	9%	8%	15%	11%
Government and Related	7%	15%	8%	2%	6%
Residential	8%	9%	6%	2%	4%
Vacant Land	5%	3%	5%	3%	4%
Miscellaneous	2%	1%	1%	1%	1%
Recreational	2%	1%	1%	0%	1%
Agricultural	0%	0%	0%	0%	0%
	100%	100%	100%	100%	100%

Regional freight modeling: journey-to-stop sampling

For each combination of weight class and origin-destination pairing, the following steps are run:

1. Define journey start and end locations
   a) Sample journey distances from that O-D and weight class's Geotab distribution
   b) Sample within the origin and destination counties to determine locations of long stops (≥ 6 hours) from which to begin and end the journey
2. Sample short (< 6 hour) stops to serve as candidate mid-route stops
3. Conduct a matching optimization
   – Objective: minimize fleetwide travel distance, subject to:
     - Each vehicle's travel distance ≥ its defined journey distance
     - Network flow preservation constraints
4. Convert matched sets of stops into a dataset of move events

Next Steps

- Support the integration of short-dwell travel itineraries into Caldera agent-based modeling framework
- Development of additional modeling scenarios for long-dwell and short-dwell charge loads
  - Generate week-long light-duty vehicle itineraries with revised charger availability assumptions (e.g., workplace) to investigate additional community charging demand
  - Additional charger configurations
  - Additional EV adoption scenarios to test different levels of grid loading
- Ongoing support for grid impact and smart charge management analysis

Thank you!

Matthew.Bruchon@nrel.gov

EVs@Scale
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EVs@Scale

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Coincidence Analysis

Polina Alexeenko, Matt Bruchon, Jesse Bennett

U.S. DEPARTMENT OF ENERGY | Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

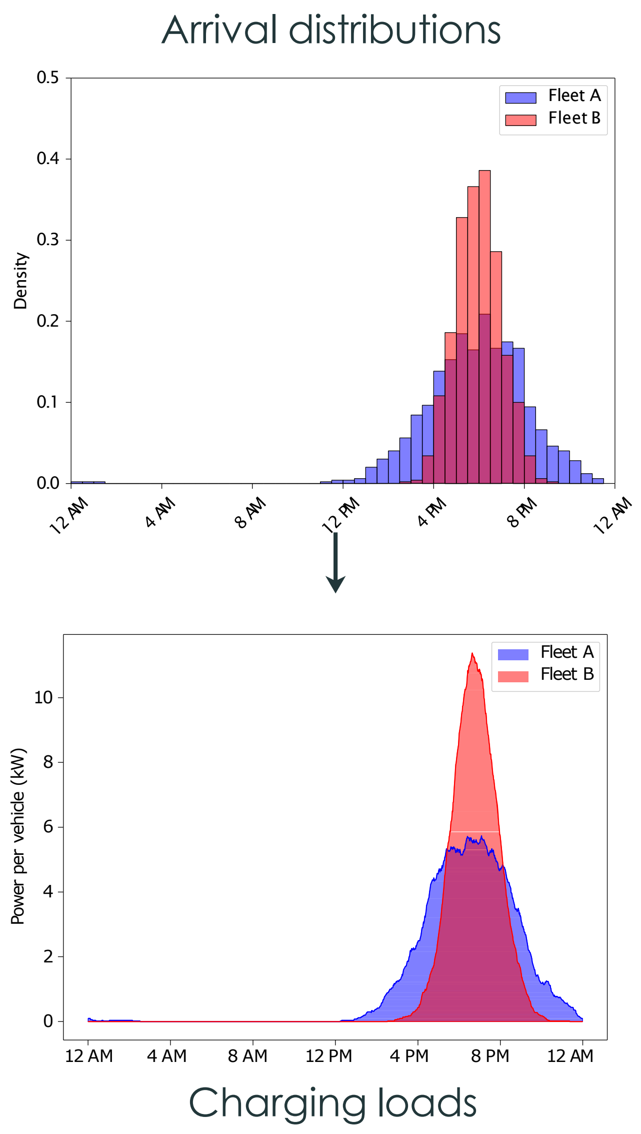
Motivation

FUSE Project

- Goal: develop SCM and VGI approaches for high EV penetration
- Challenges:
  - optimal approach depends on multiple factors (e.g., vehicle mobility, vocation)
  - detailed SCM/VGI simulation is complex
- This study:
  - "bridge" between direct SCM/VGI analysis and fleet characteristics
  - examines **coincidence**: the extent to which EV loads align
  - uses coincidence to heuristically evaluate SCM/VGI potential

Factors impacting coincidence

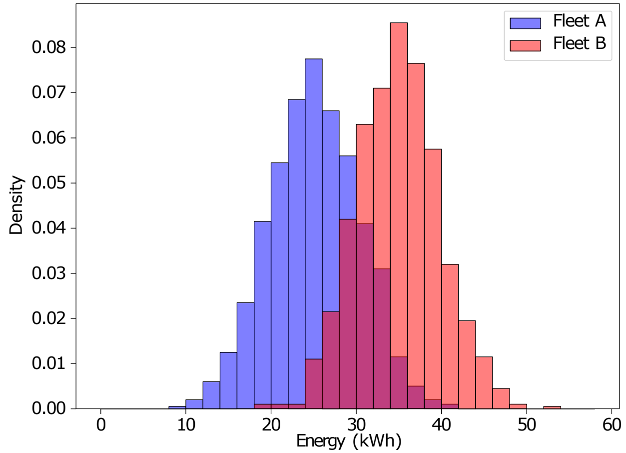
- **When** vehicles connect
  - Arrival at EVSE
  - Departure from EVSE
  - Lower variance → greater coincidence

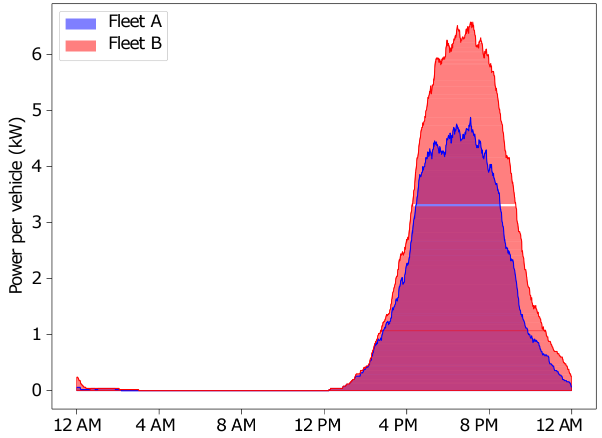


Factors impacting coincidence

- **When** vehicles connect
  - Arrival at EVSE
  - Departure from EVSE
  - Lower variance → greater coincidence
- **How** vehicles charge
  - energy consumption (kWh)
  - charging rate (kW)
  - Greater energy → greater coincidence

Energy distributions

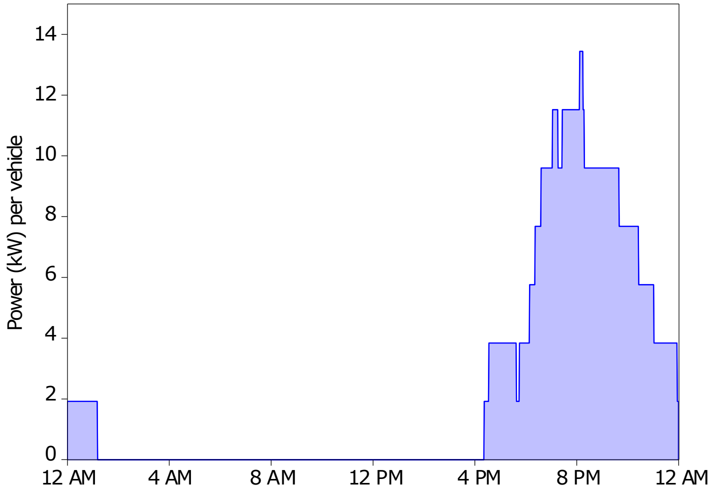




Charging loads

Types of coincidence

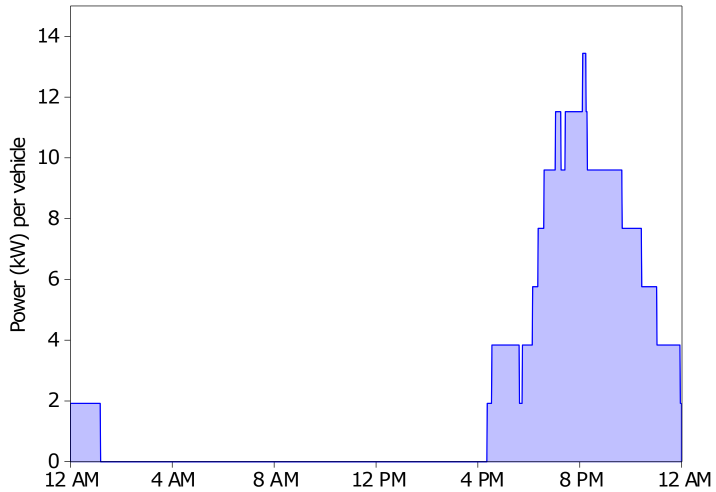
Charging Coincidence



- Depends on arrival, energy, and rate
- Measured in power (kW) per vehicle
- Quantifies timing and magnitude of peaks

Types of coincidence

Charging Coincidence



- Depends on arrival, energy, and rate
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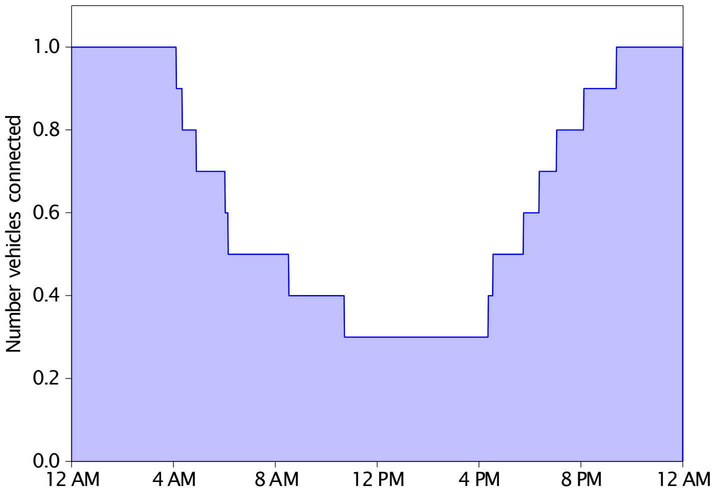
- Quantifies timing and magnitude of peaks

Dwell Coincidence



- Depends on arrival and departure
- Measured in fraction vehicles (0-1)
- Identifies load shifting opportunities

Vehicle groups studied

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Freight

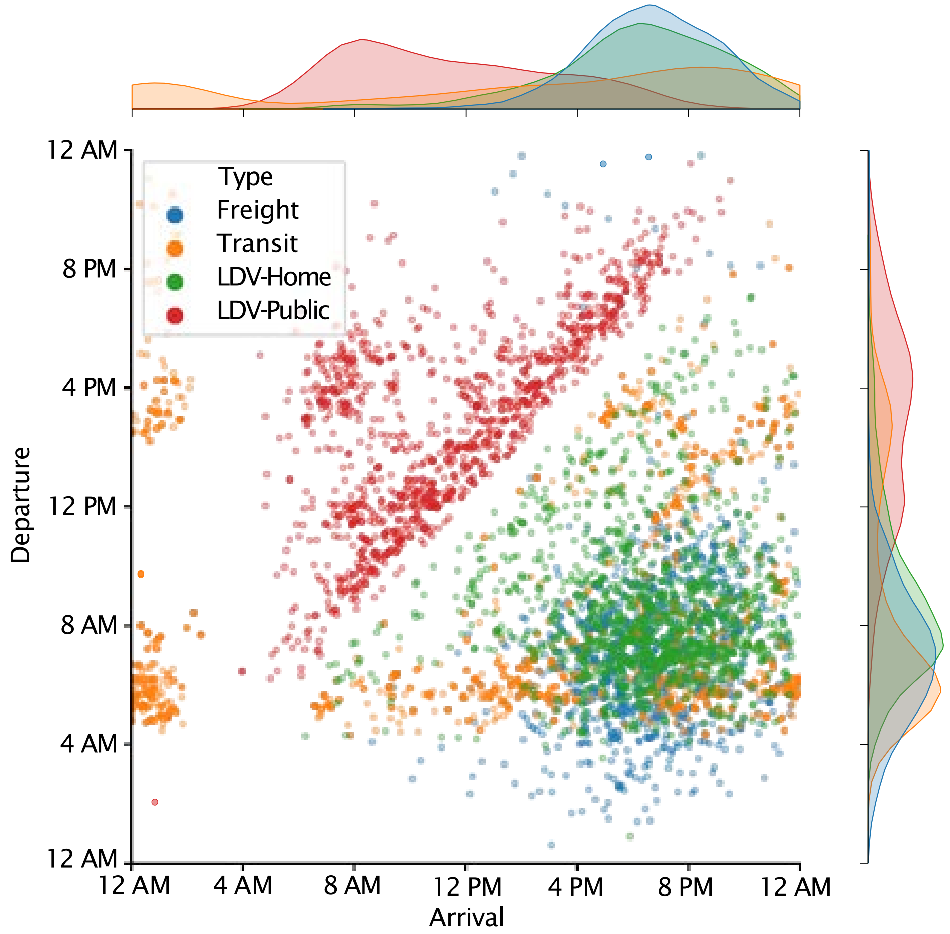
- 16,000 vehicles
- Cargo van, cutaway, straight truck, and step vans
- Average energy 50 kWh

Transit

- 423 vehicles
- Three transit agencies
- Average energy 367 kWh

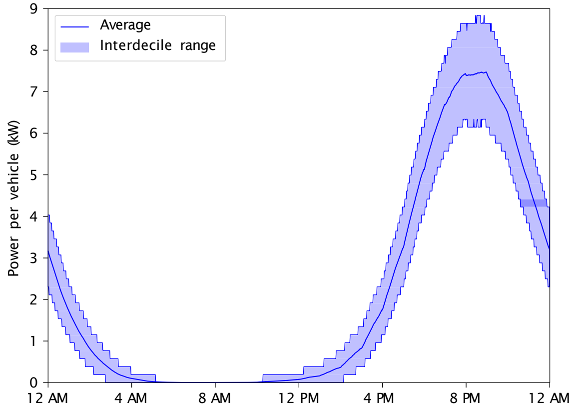
Light-duty vehicles (LDV)

- 935,000 vehicles
- Includes public (35%) and home charging (65%)
- Average energy: 26 kWh (home), 11 kWh (public)

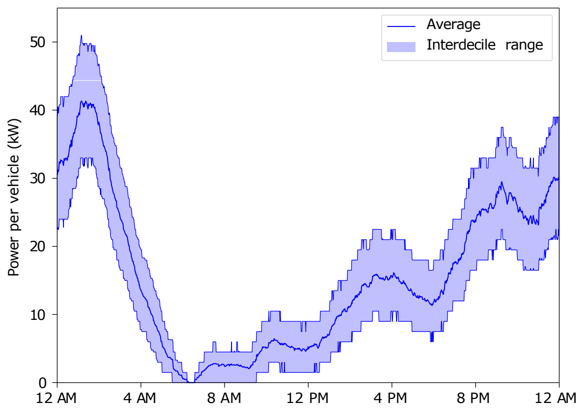


Arrival and departure distributions by group

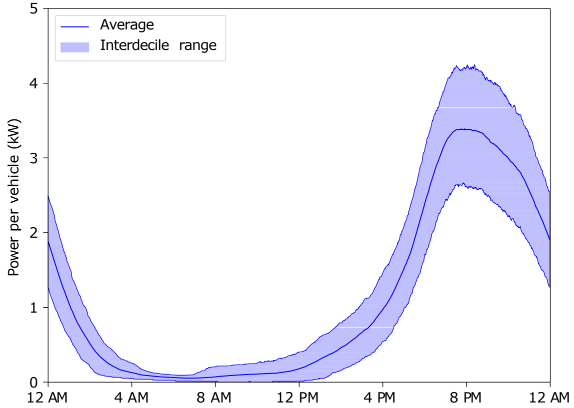
Results: charging coincidence



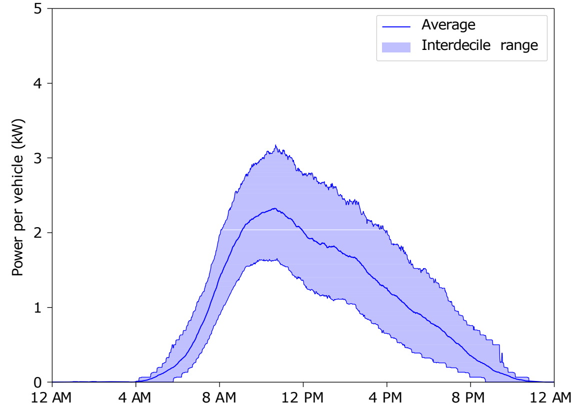
Freight



Transit



LDV-Home

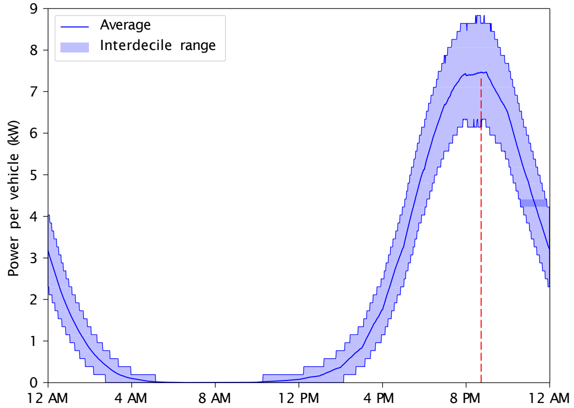


LDV-Public

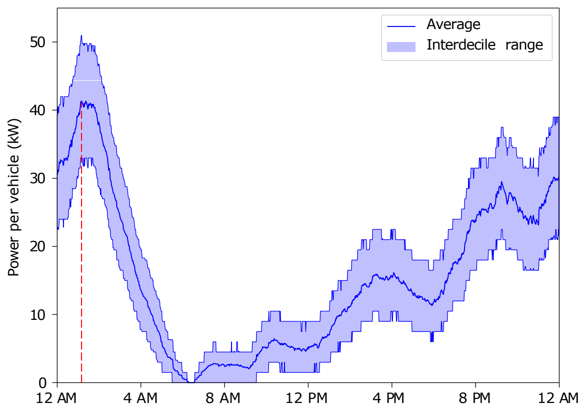
Results: charging coincidence

Peak timing

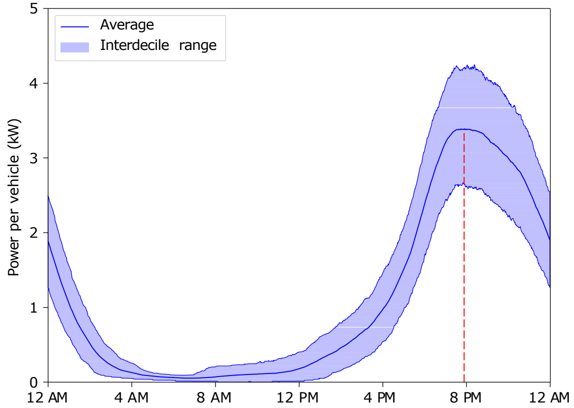
- Evening (~8 PM) for freight and LDV-Home
- Early morning for transit bus
- Late morning for LDV-Public



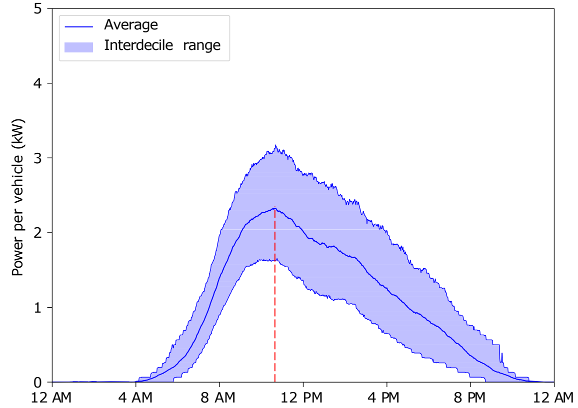
Freight



Transit



LDV-Home



LDV-Public

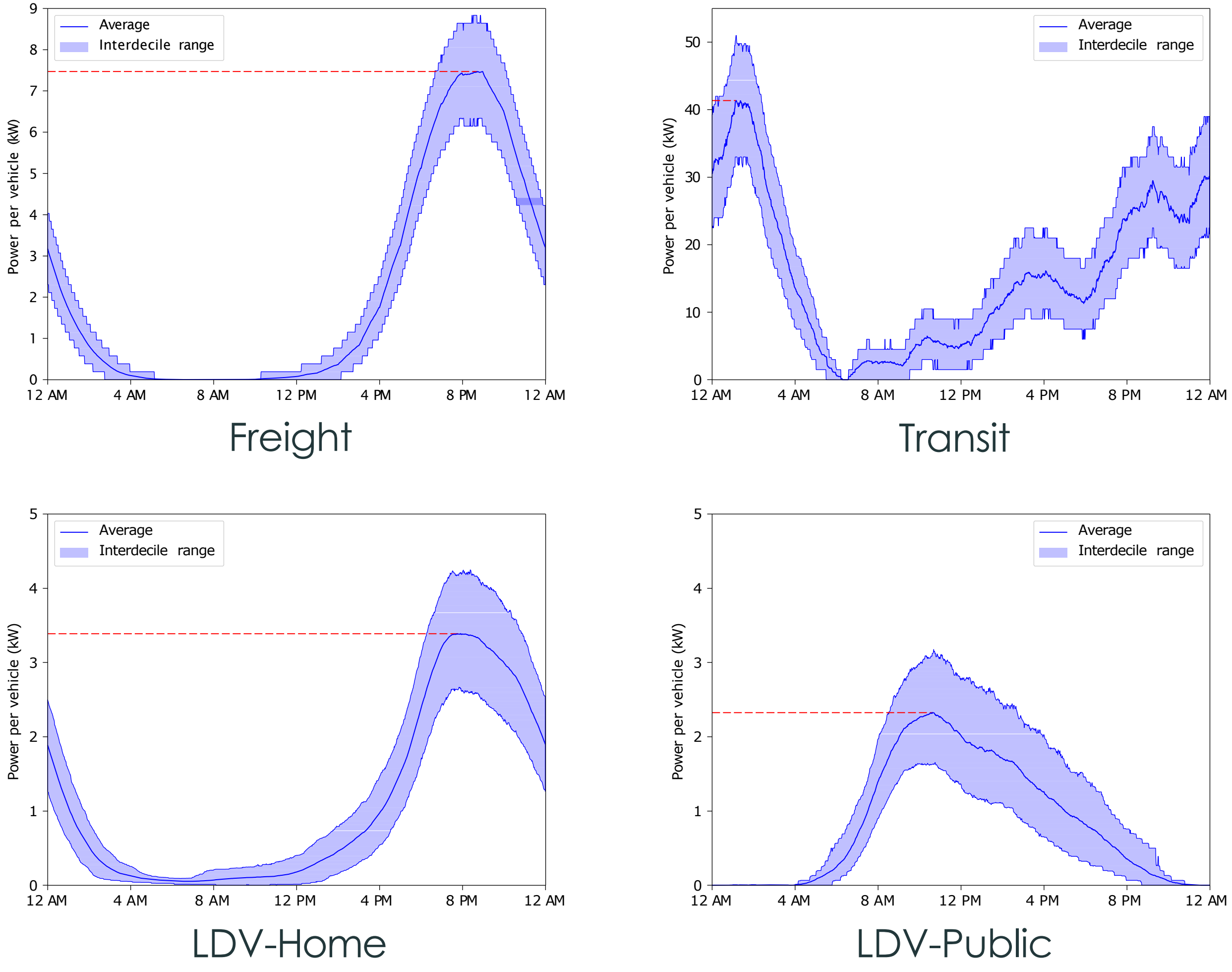
Results: charging coincidence

Peak timing

- Evening (~8 PM) for freight and LDV-Home
- Early morning for transit bus
- Late morning for LDV-Public

Peak magnitude and duration

- Highest magnitude: transit (~40 kW)
- Lowest magnitude: LDV (<4 kW)
- Peak duration (time within 90% of peak) similar across LDV, freight
- Duration shortest for transit buses



Results: charging coincidence

Peak timing

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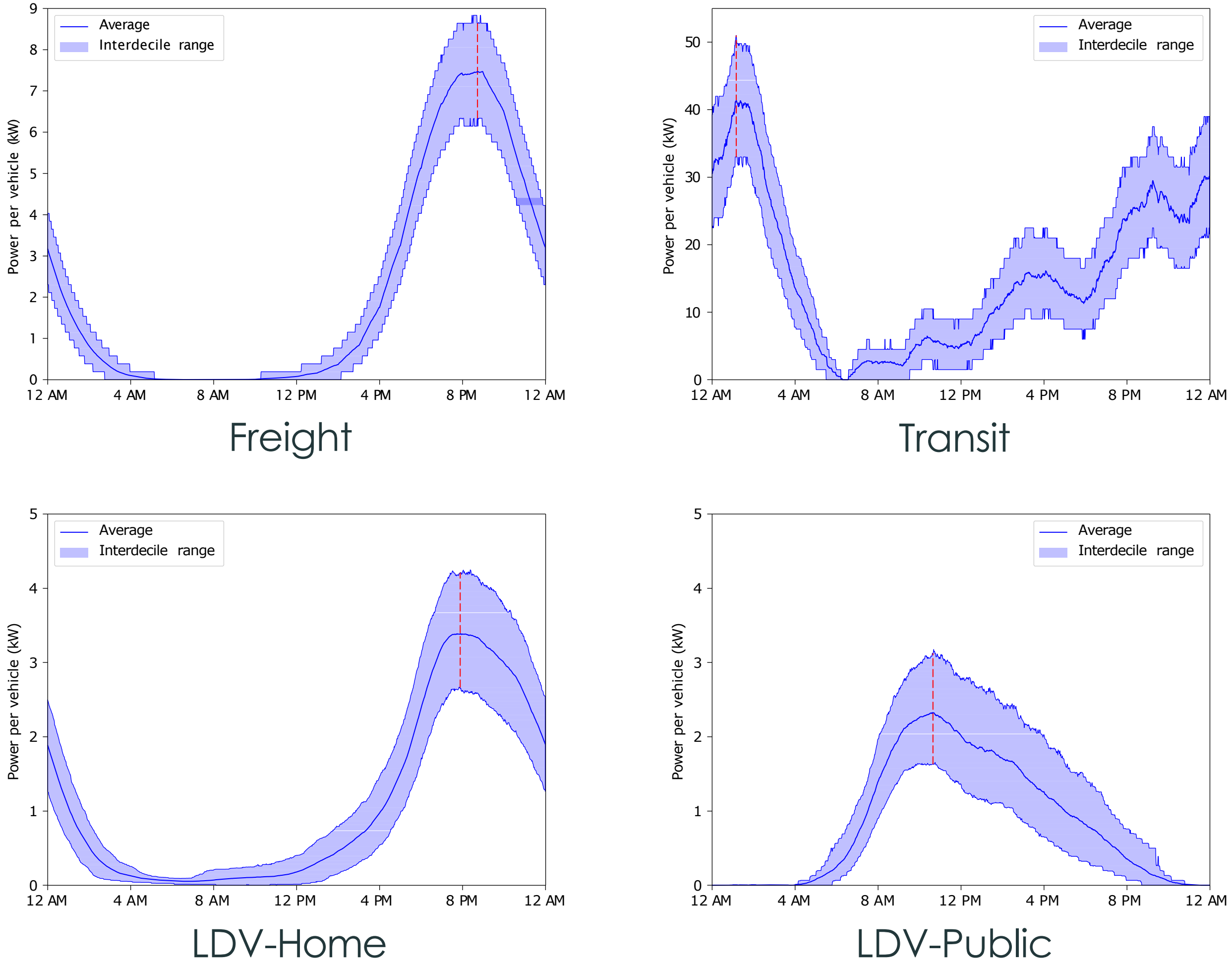
Peak magnitude and duration

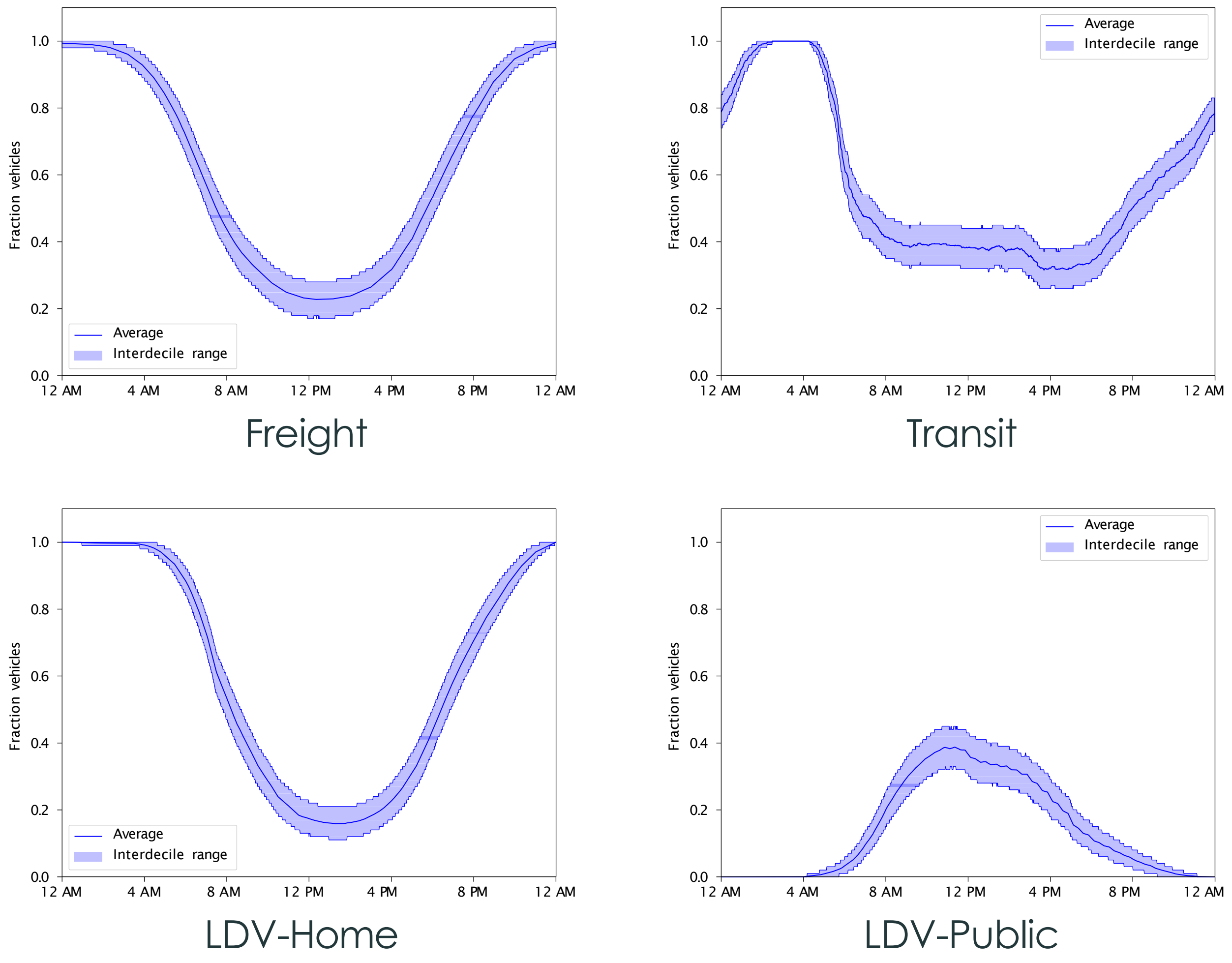
- Highest magnitude: transit (~40 kW)
- Lowest magnitude: LDV (<4 kW)
- Peak duration (time within 90% of peak) similar across LDV, freight
- Duration shortest for transit buses

Peak variability

- Highest (~60%) for LDV-Public
- Lowest (~33%) for freight



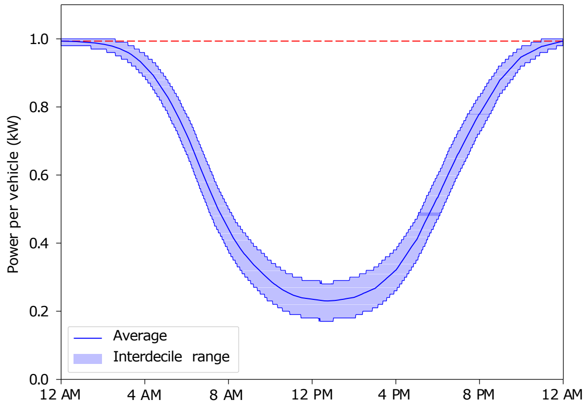
Results: dwell coincidence



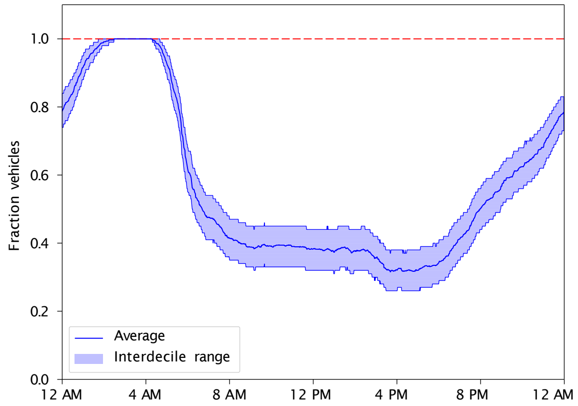
Results: dwell coincidence

Maximum dwell coincidence

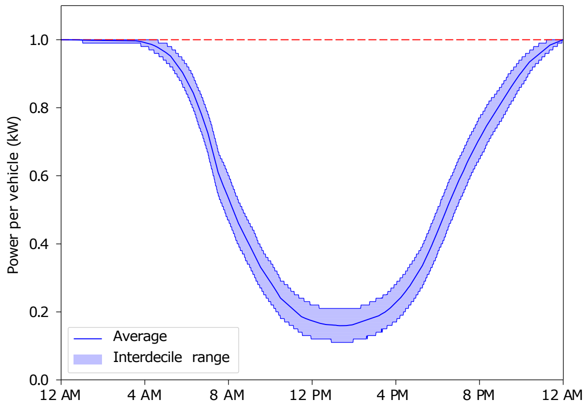
- 40% for LDV-Public
- 100% (full coincidence) for all others



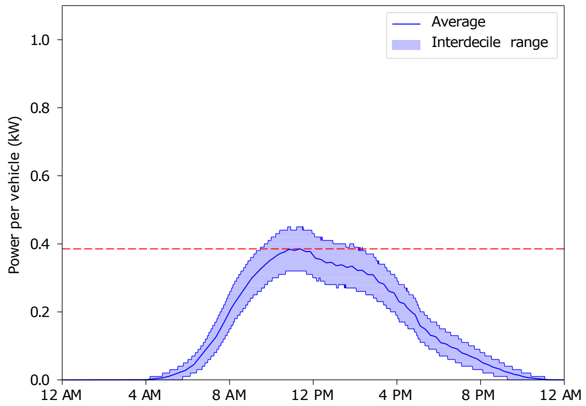
Freight



Transit



LDV-Home



LDV-Public

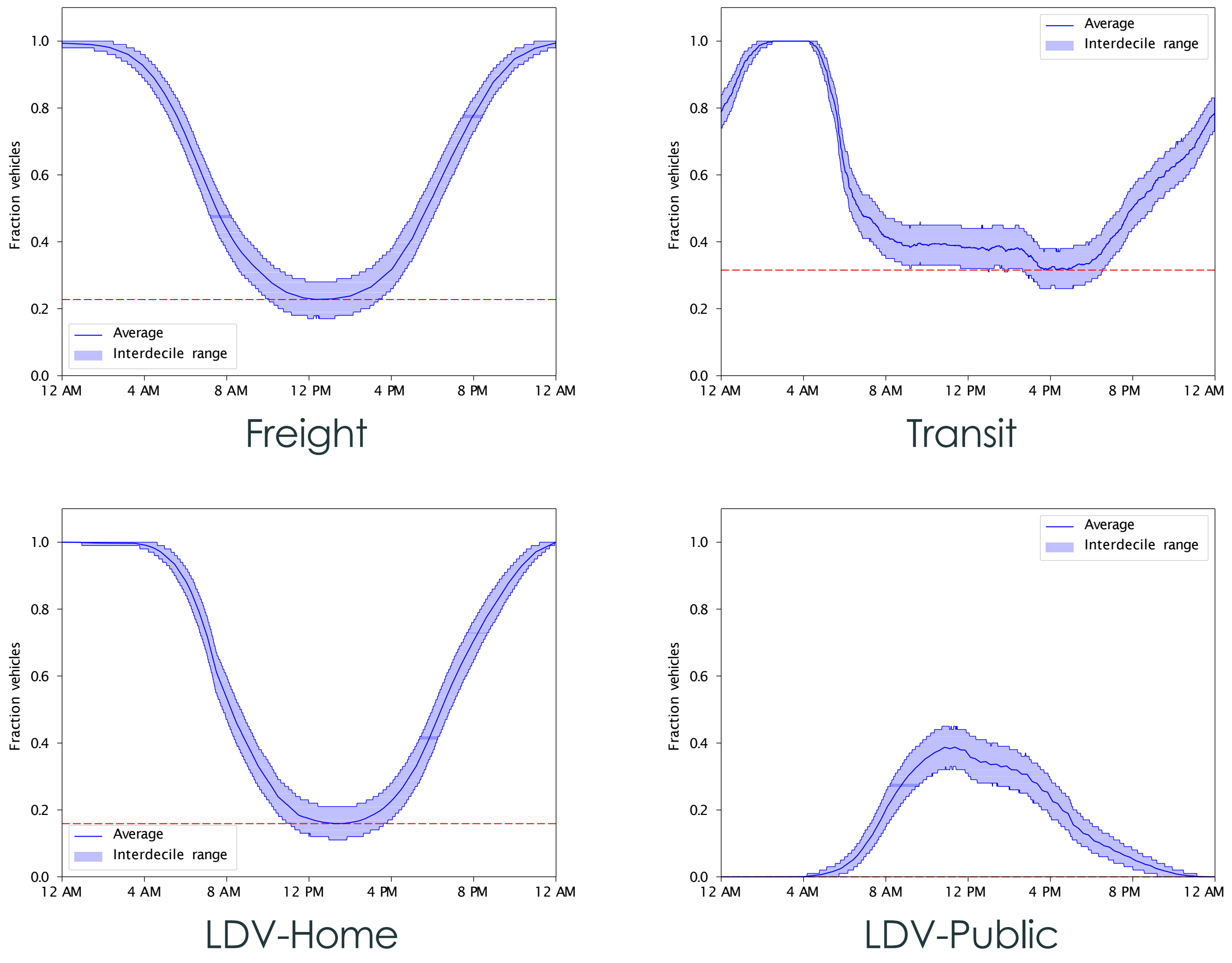
Results: dwell coincidence

Maximum dwell coincidence

- 40% for LDV-Public
- 100% (full coincidence) for all others

Minimum dwell coincidence

- 0% for LDV-Public
- Highest for transit (30%)



Results: dwell coincidence

Maximum dwell coincidence

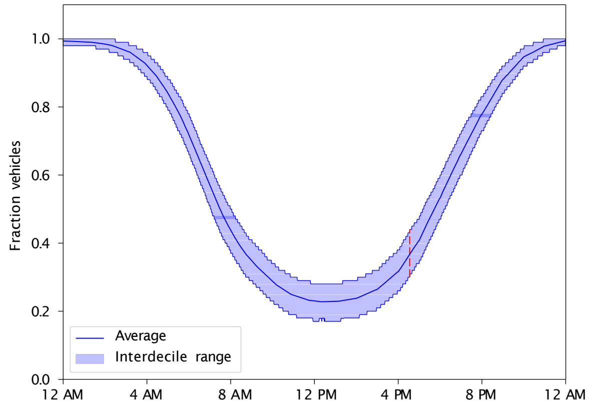
- 40% for LDV-Public
- 100% (full coincidence) for all others

Minimum dwell coincidence

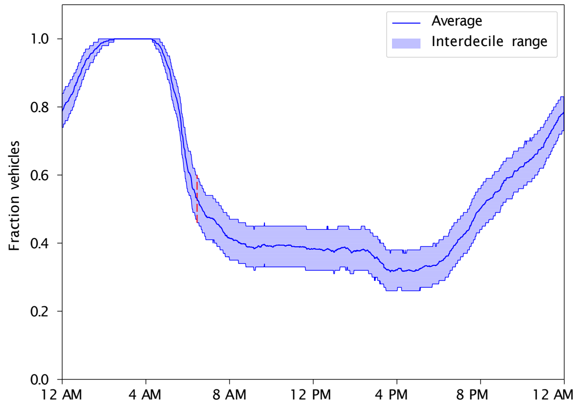
- 0% for LDV-Public
- Highest for transit (30%)

Dwell variability

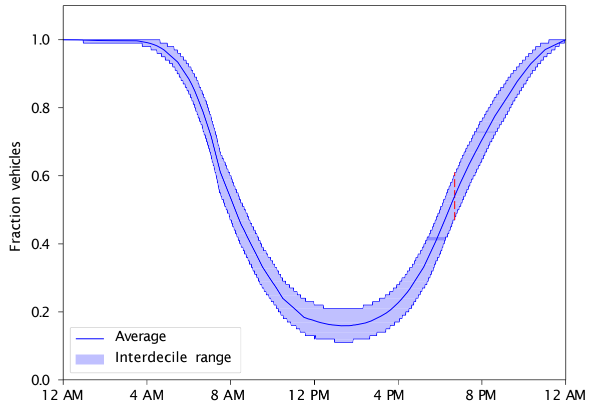
- Maximum interdecile range (IDR) around 14%
- Similar across vehicle groups
- Max IDRs occur in evening and morning



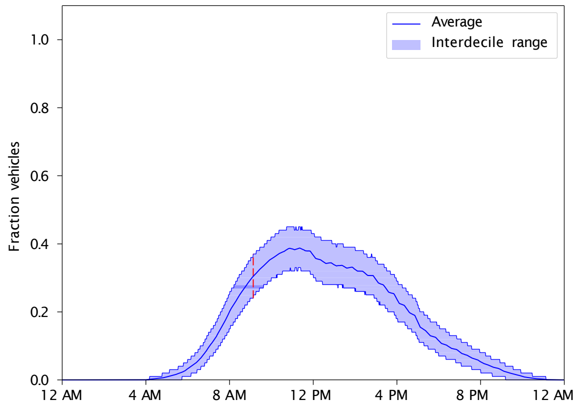
Freight



Transit



LDV-Home



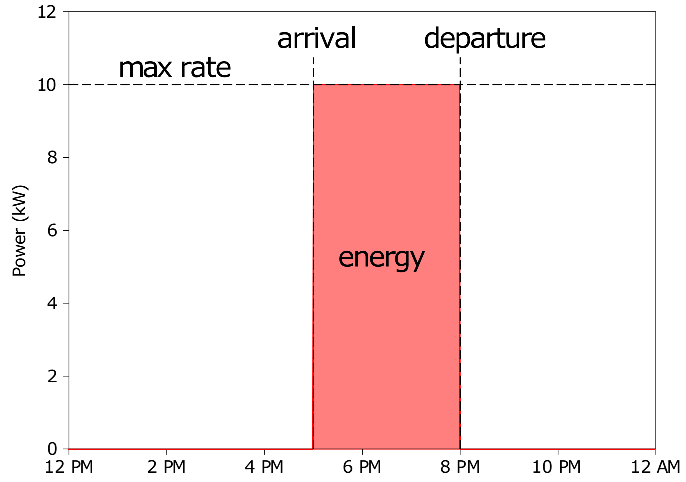
LDV-Public

Measuring flexibility

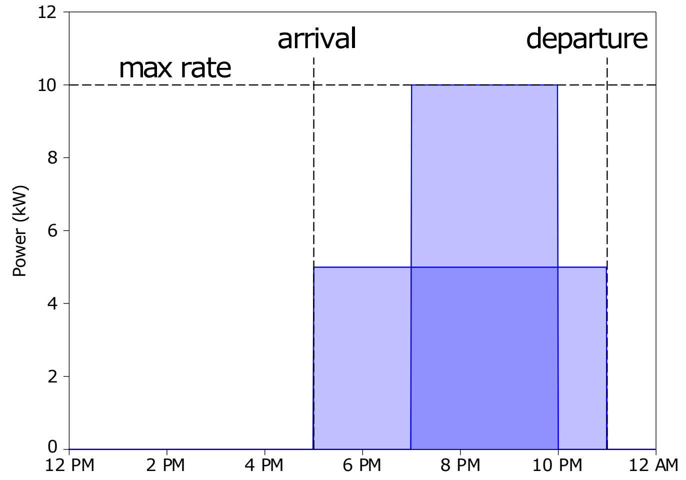
- **Flexibility: the extent to which loads can be reshaped**
  - **Depends on when vehicles connect and how they charge**
  - **Exact characterization of flexibility is complex**
  - **Goal: develop intuitive measure of flexibility**

Value of flexibility depends on

- When loads are flexible
- Magnitude of achievable load reduction
- Duration of load reduction



Inflexible load



Flexible load

Measuring flexibility

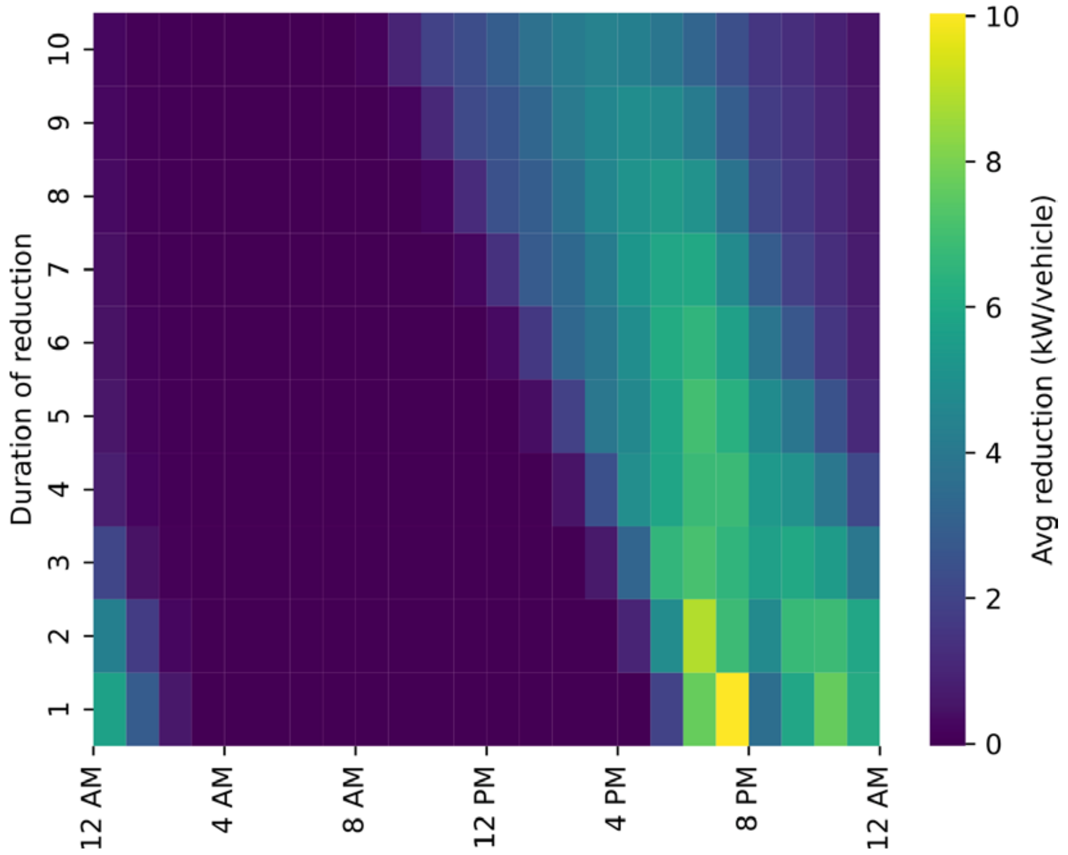
- The flexibility matrix M: a heuristic for flexibility
- Measures load reduction potential at each time interval
- $M \in \mathbb{R}^{T \times D}$ where
  - T number of time periods
  - D number duration periods
- $M(t, d)$: maximum possible load reduction between times t and $t + d$

$$M(t, d) = \frac{1}{d} \sum_{i=0}^{d-1} (u_{t+i} - m_{t+i})$$

where

- u_t is uncoordinated load at t
- m_t minimum possible load at t

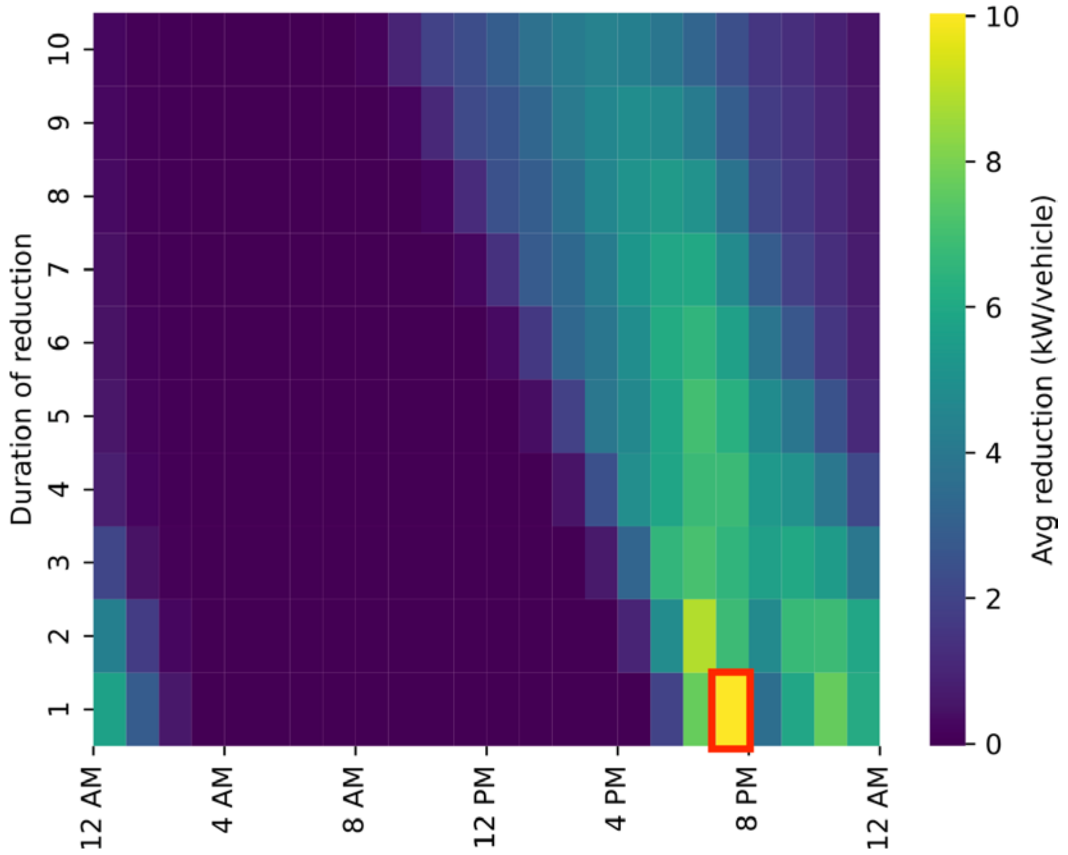
Interpreting the flexibility matrix: examples



Flexibility of 10-vehicle freight fleet

Interpreting the flexibility matrix: examples

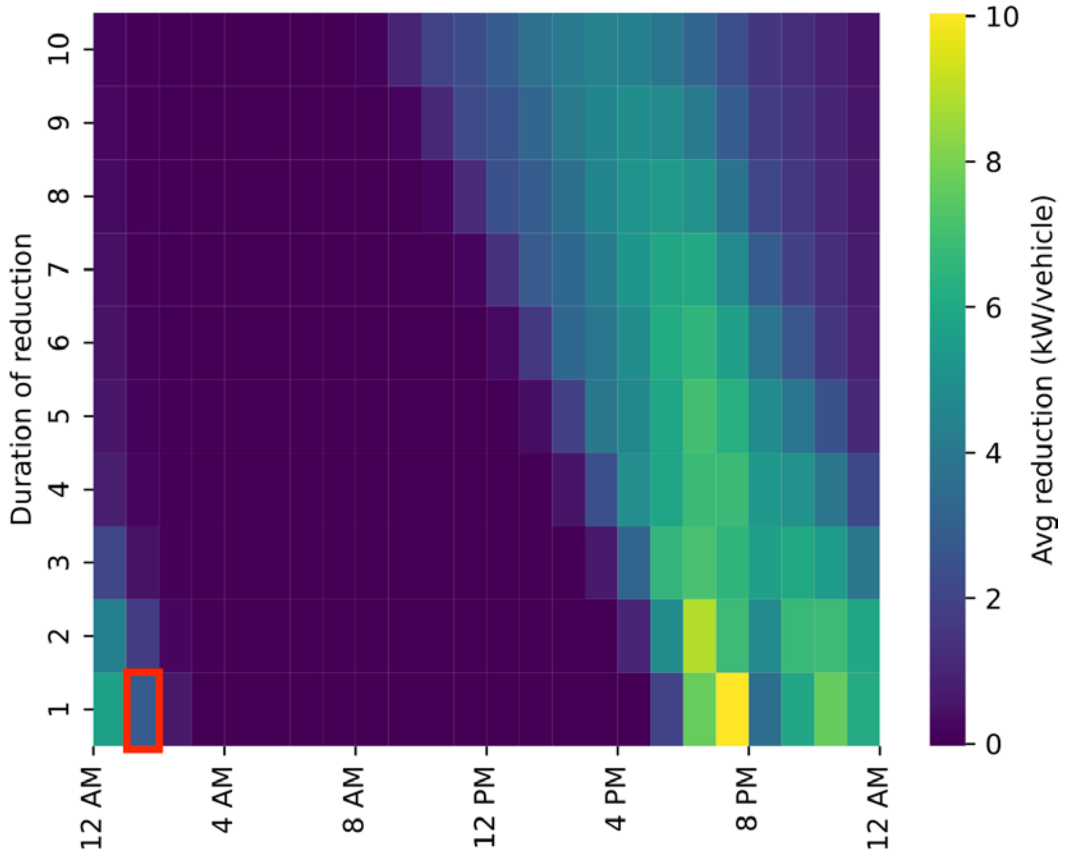
- $M\ (7\ \mathrm{PM}, 1)$: 10 kW/vehicle reduction potential between 7 PM - 8 PM



Flexibility of 10-vehicle freight fleet

Interpreting the flexibility matrix: examples

- $M\,(7\ \mathrm{PM}, 1)$: 10 kW/vehicle reduction potential between 7 PM - 8 PM
- $M\,(1\ \mathrm{AM}, 1)$: potential for 3 kW/vehicle reduction between 1AM - 2AM
- $M\,(7\ \mathrm{PM}, 1) > M\,(1\ \mathrm{AM}, 1)$ because few vehicles charge at night (in uncontrolled setting)



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Interpreting the flexibility matrix: examples

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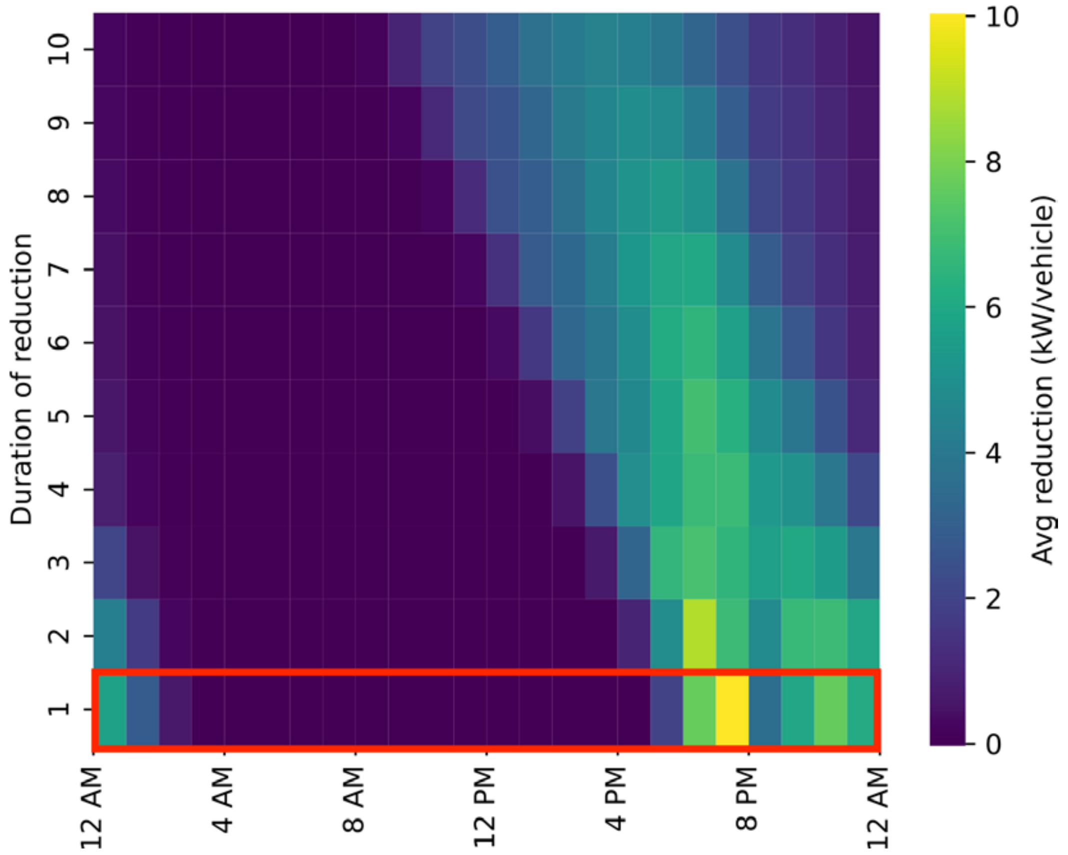
- Reading across bottom row reveals (flexible) peak number and duration



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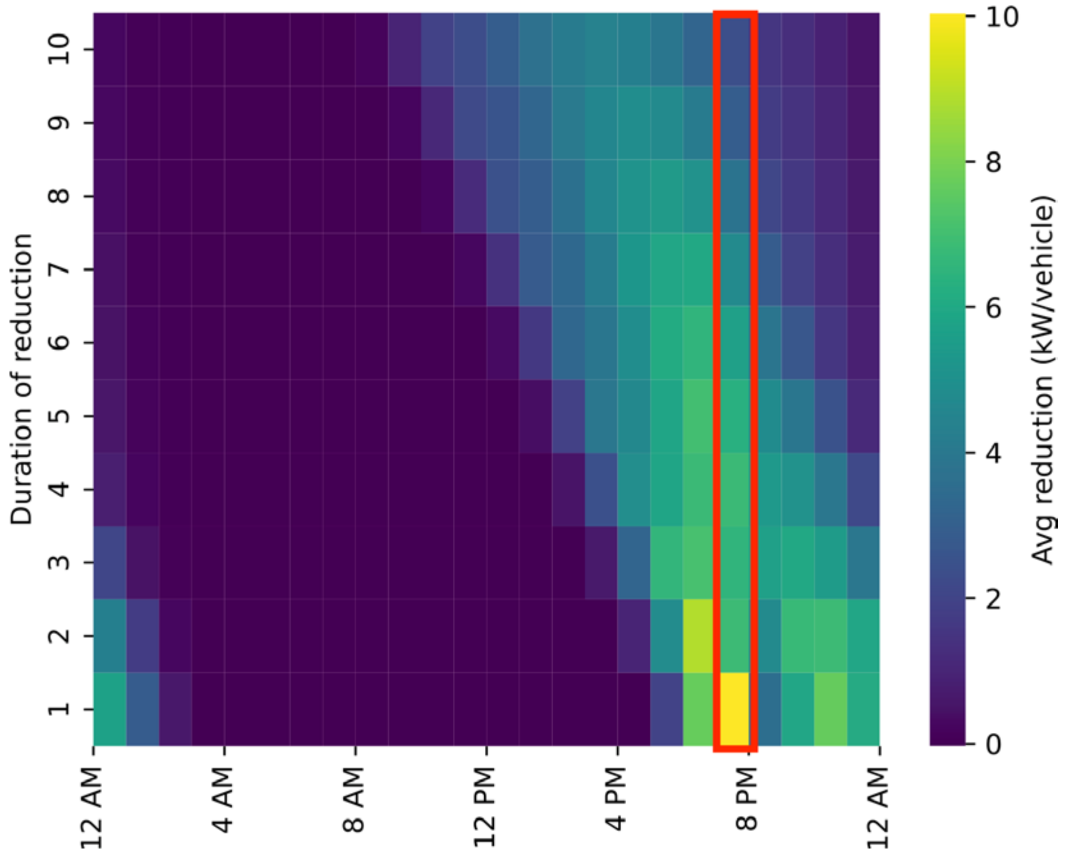
- Reading across bottom row reveals (flexible) peak number and duration
- Reading across column reveals flexibility duration



Flexibility of 10-vehicle freight fleet

Results: flexibility & reduction potential

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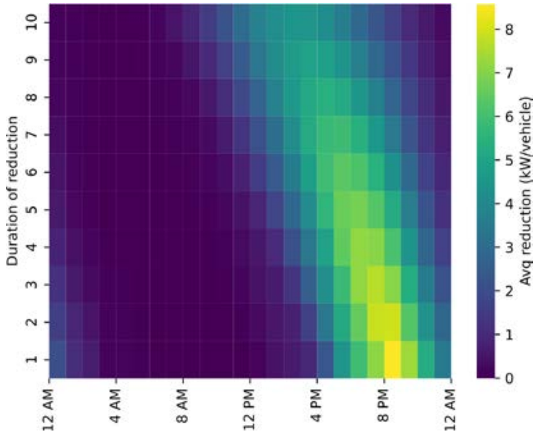
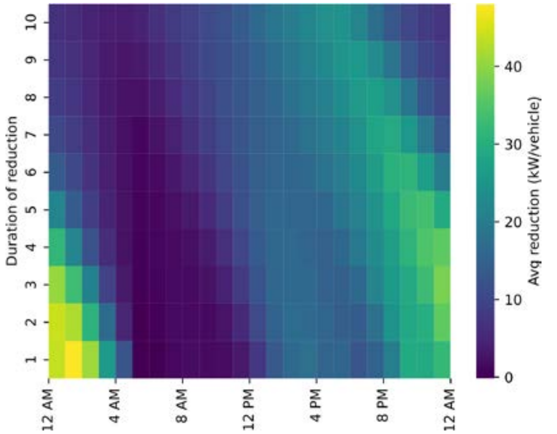
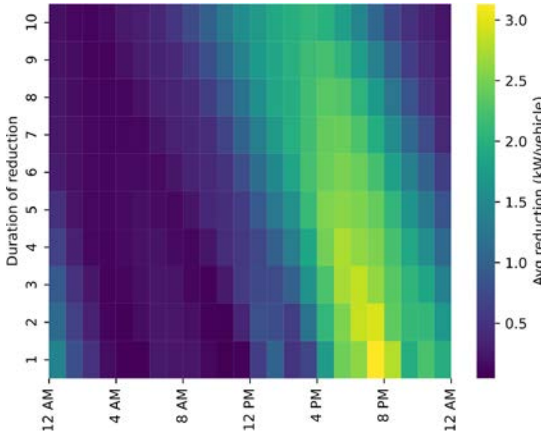


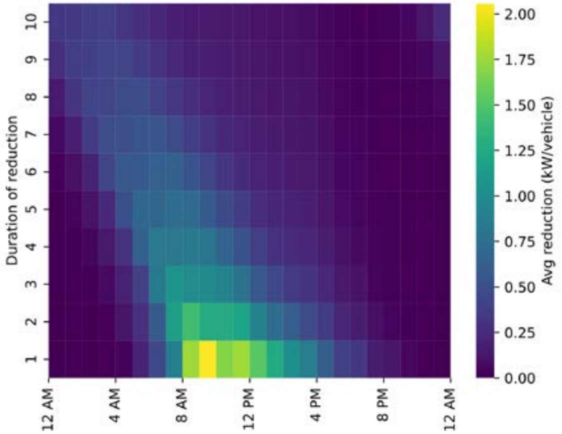
Freight



Transit



LDV-Home

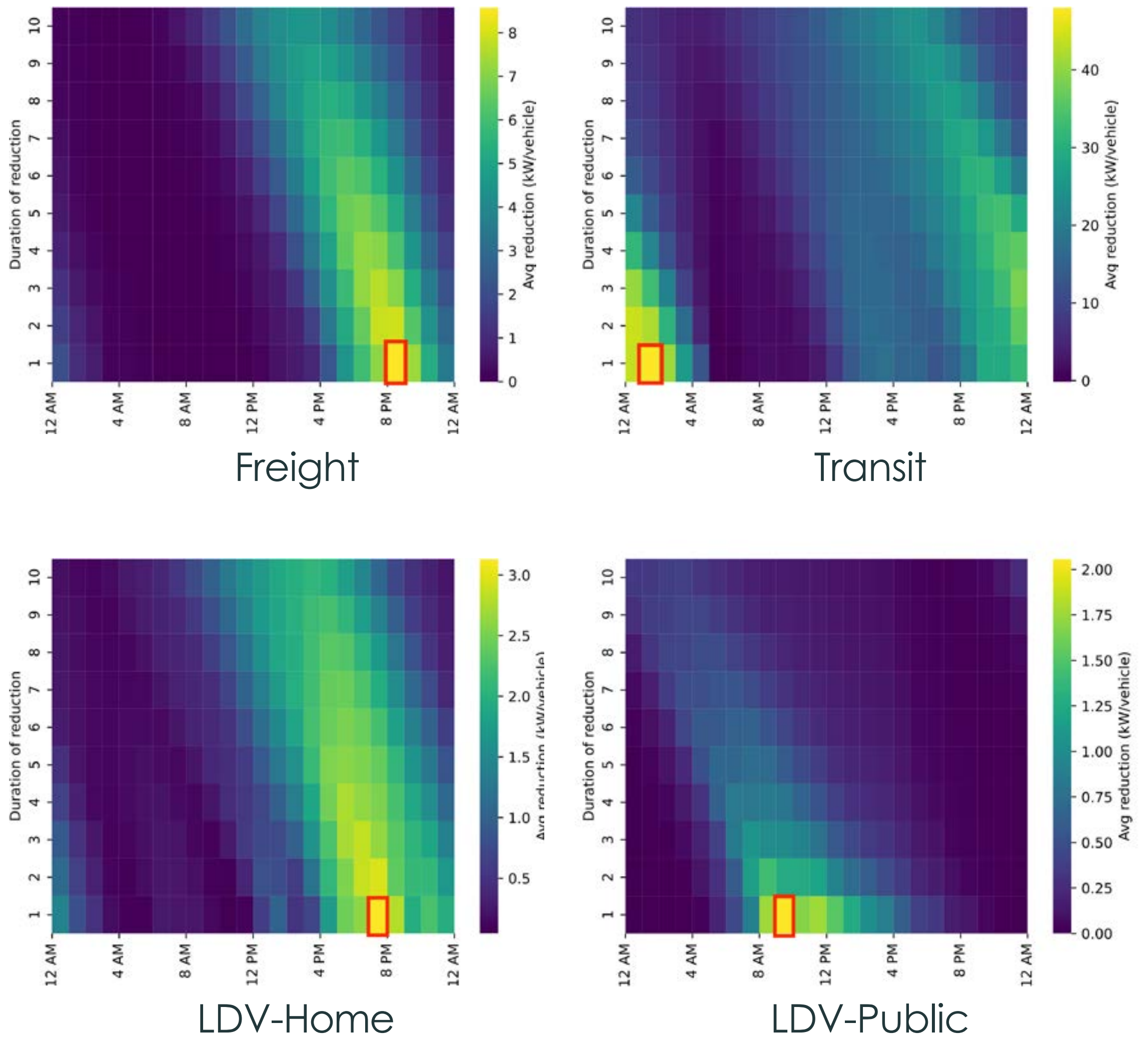


LDV-Public

Results: flexibility & reduction potential

Maximum reduction potential

- Occurs at uncoordinated peak times
- Close in magnitude to uncoordinated peak



Results: flexibility & reduction potential

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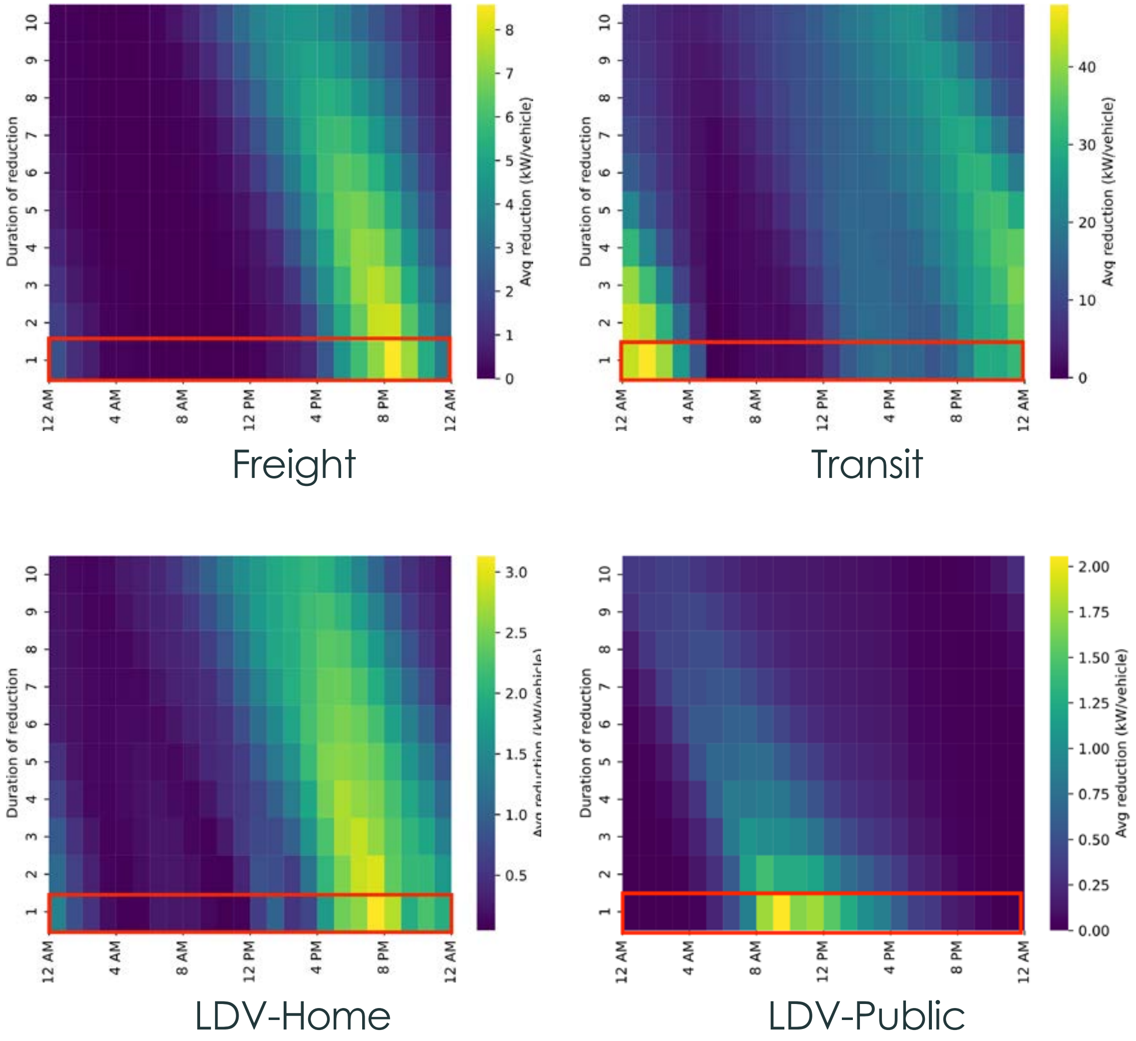
Reduction potential timing

- LDV-Public: reduction potential only in daytime
- All others have night-time reduction potential



Results: flexibility & reduction potential

Maximum reduction potential

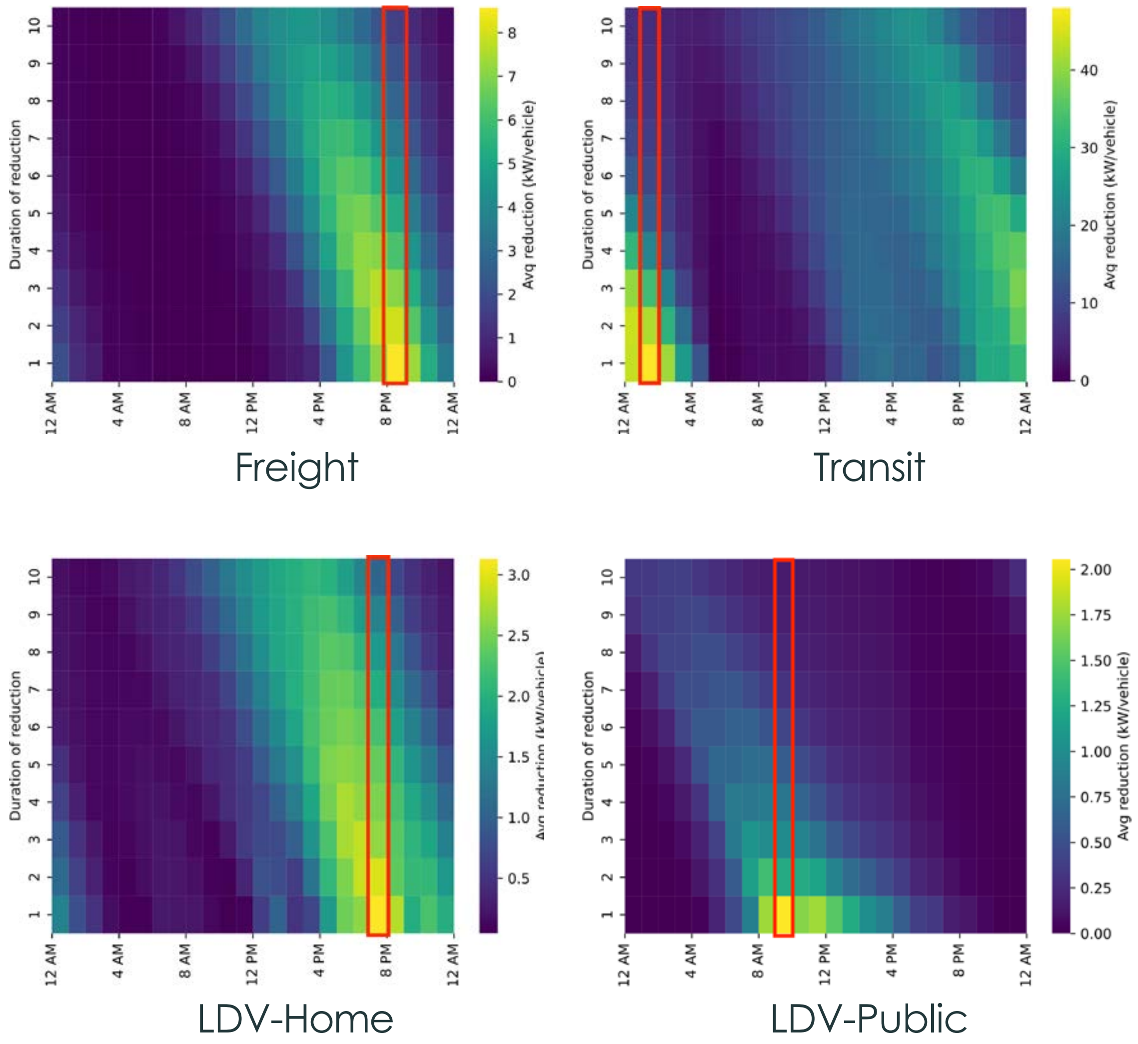
- Occurs at uncoordinated peak times
- Close in magnitude to uncoordinated peak

Reduction potential timing

- LDV-Public: reduction potential only in daytime
- All others have night-time reduction potential

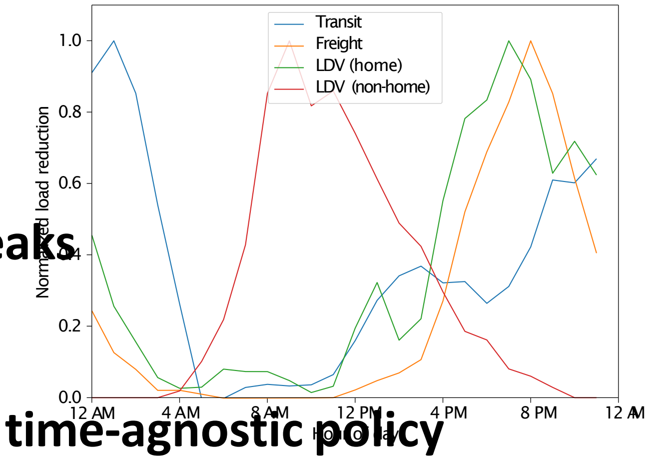
Reduction potential duration

- Potential decays rapidly with duration for LDV-Public, Transit
- LDV-Public, Transit are less flexible
- Potential decays slowly for freight, LDV-Home
- Freight, LDV-Home more flexible



Flexibility: control implications

- **Control timing**
  - **Freight/LDV Home peaks align with typical high-price periods**
  - **Dynamic pricing (e.g., real-time or TOU) may reduce freight/LDV-Home peaks**
  - **Transit and LDV-Public loads peak during typical low-price periods**
  - **Transit/LDV-Public load reduction requires alternative pricing schedule or time-agnostic policy (e.g., demand charges)**



Load reduction potential over day

Flexibility: control implications

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  - **Dynamic pricing (e.g., real-time or TOU) may reduce freight/LDV-Home peaks**
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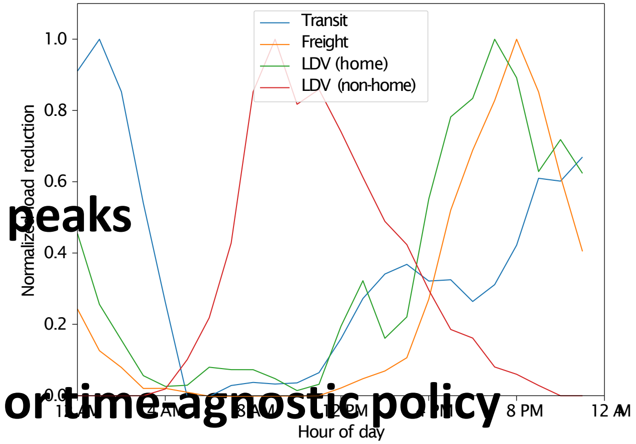
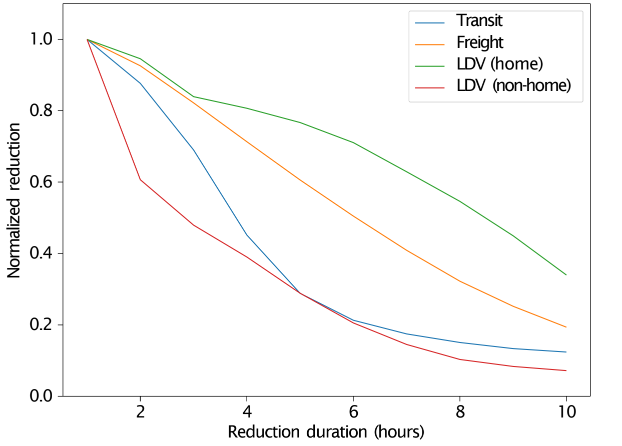


Load reduction potential over day

Control duration

- Magnitude of reduction potential decays with reduction duration
- Speed of decay captures value of sustained control
- Can inform duration of control signals (e.g., length of DR event)
- Short-duration control may be more effective for LDV-Public/Transit
- Longer-duration control effective for Freight/LDV-Home



Load reduction vs reduction duration

Summary

Coincidence analysis

- Consider four vehicle groups: transit, freight, light-duty home, and light-duty public
- Examine uncoordinated charging and dwell coincidence
- Quantify cross-temporal load flexibility for each vehicle group

Findings

- Peak times vary: freight, LDV-Home peak in evening while transit, LDV-Public peak in morning
- Dwell coincidence high for freight, LDV-Home, and trasnit; low for LDV-Public
- Effective control strategies different across vehicle groups

Next steps

- Study mixed composition fleets
- Incorporate models of geographic coincidence
- Study impacts of multi-resolution geographic coincidence on resultant load

Polina Alexeenko (NREL)

polina.alexeenko@nrel.gov

EVs@Scale

U.S. Department of Energy

Smart Charge Management Stakeholder Feedback

- Discussions from the Semi-Annual Stakeholder Meeting on Codes and Standards, Use Cases, and Valuation of SCM
- Strong need for **end-to-end standards certification**, enforcement, and interoperability testing
- Need for SCM use cases with **large fleets,** travel centers, emergency response and resilience, **V2X**, widespread residential applications
- Value of SCM in avoided **service transformer** and distribution feeder upgrades, avoided **long lead-times** for interconnection, need for parallel processing of soft costs

Thank You!

Please mark your calendars for the next Semi-annual Stakeholder Meeting:

September 25-26

Idaho National Laboratory

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Fall Deep Dive Focus Topics:

- SCM/VGI Controls
  - New SCM/VGI and HELICS Updates
  - Broad Analysis Results
- Grid Impact Assessments
  - L/M/HDV Controlled/Uncontrolled
  - Highlight Cost Tradeoff Benefits
- Demonstrations
  - Lab Testbed: Multi-EVSE, OCPP 2.0.1
  - Field Demo in Utility Environment

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