



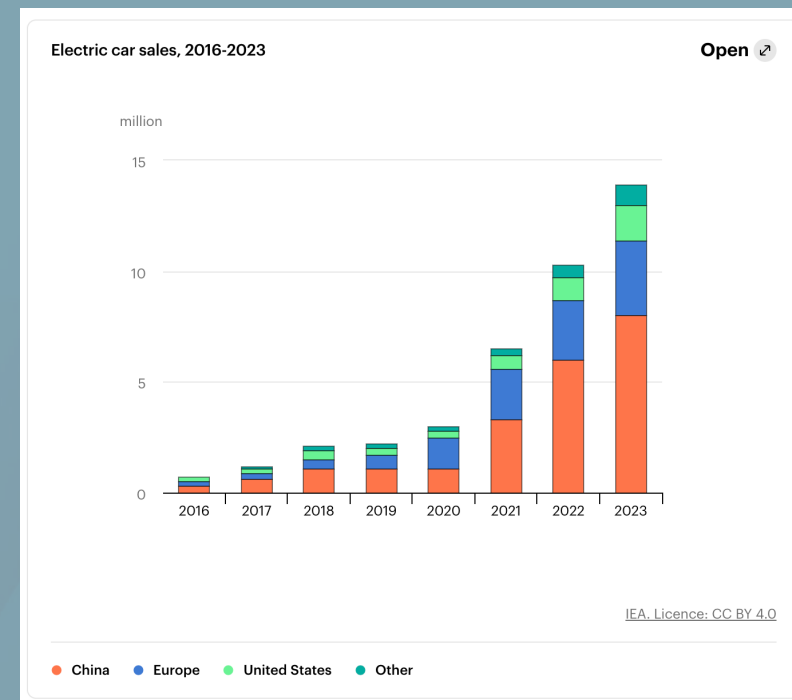
# Data-Driven Electric Vehicle Charging Demand Modeling and Charging Infrastructure Planning

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2023 CALPLUG Workshop, October 24, 2023



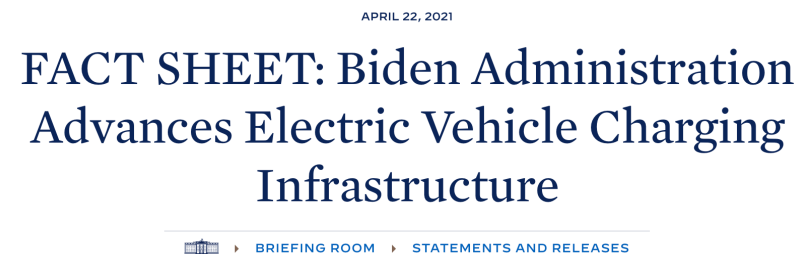
- ❑ Exponential growth in global PEV sales:
  - ❑ EV sales exceeded 10 million in 2022
  - ❑ EV share is more than tripled in three years, from 4% in 2020 to 14% in 2022
  - ❑ ~14 million in sales by the end of 2023, representing ~18% of total car sales
- ❑ Charging is a major concern for potential PEV buyers:
  - ❑ Recent survey shows that **6 in 10 Americans who aren't yet sold on PEVs were concerned about where and when they would charge** (61%) and how far that charge will take them (55%), i.e., “range anxiety”.
  - ❑ Early charging patterns are home- dominant (>80% of charging) but **many future PEV owners may not have access to a home charger.**



- ❑ EV charging a priority for federal government:
  - ❑ By 2030, 50% of LDV sales as ZEV, 500,000 PEV chargers
  - ❑ 2021 Bipartisan Infrastructure law includes \$7.5 billion to build out a national network of EV chargers
  - ❑ 2022 Inflation Reduction Act provides federal tax credits for EV infrastructure, EV purchases, and domestic mining and manufacturing.

**Major Uncertainty:** EV charging infrastructure requirements are hard to predict over time; challenging to plan for...

**Our Solution:** Data-driven EV charging demand modeling and charging infrastructure planning



## ☐ Passenger EVs:

- ☐ National Household Travel Survey (NHTS) data
- ☐ Real-world connected vehicle trip data
- ☐ Land use data
- ☐ Vehicle registration and EV adoption prediction

## ☐ Electric Transit Buses:

- ☐ General Transit Feed Specification (GTFS) data
- ☐ Electric bus deployment prediction
- ☐ Energy consumption prediction



## 1. Trip Data Acquisition & Preprocessing

Representative LDV travel data for region(s) of study is joined with geographically determined locational characteristics obtained from multiple data sources.

## 2. EV Adoption Modeling

For a given analysis year (2040), assign PEVs to households by vehicle model (battery size, ECR, & max kW acceptance required for simulation).

## 3. Travel Itinerary Synthesis

Vehicle trips from data aggregators typically do not contain persistent vehicle identifiers enabling analysis of multi-trip travel itineraries. Thus, an approach for generating synthetic travel itineraries is leveraged.

## 4. EV Charging Simulation

EV charging is simulated for synthetic travel itineraries considering: 1) EV adoption assumptions; 2) charging behaviors and location-specific EVSE availability; 3) home charging access assumptions.

## 5. EV Load Profile Generation

Charging demand for a given analysis year (2040) is assigned to specific locations (i.e., land parcels) by location type.

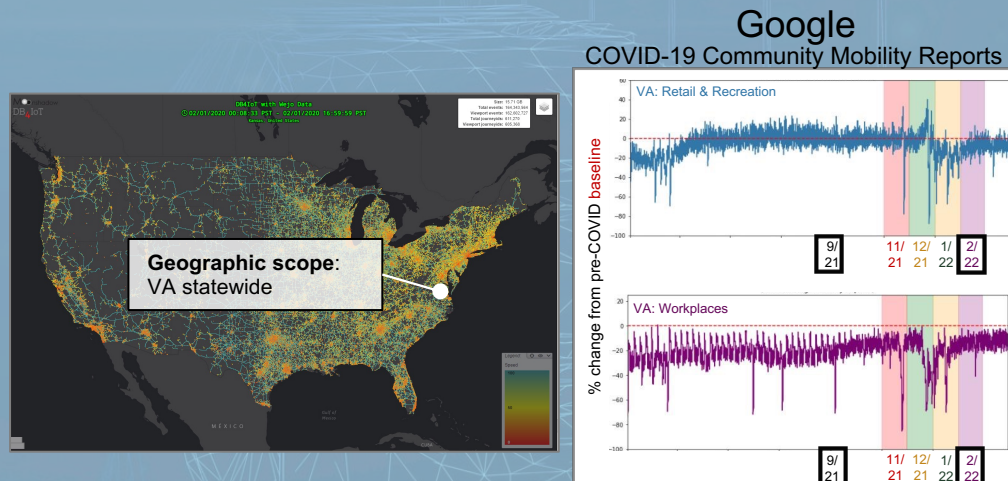
## Real-World Driving Data Set:

- ❑ Vehicle trips data acquired from Wejo for two months in the state of Virginia.
  - ❑ ~3% of passenger vehicle population
  - ❑ September 2021 and February 2022
  - ❑ **Richmond, VA** and **Newport News, VA** regions
- ❑ Trip O/Ds joined to land use data to infer trip purpose.

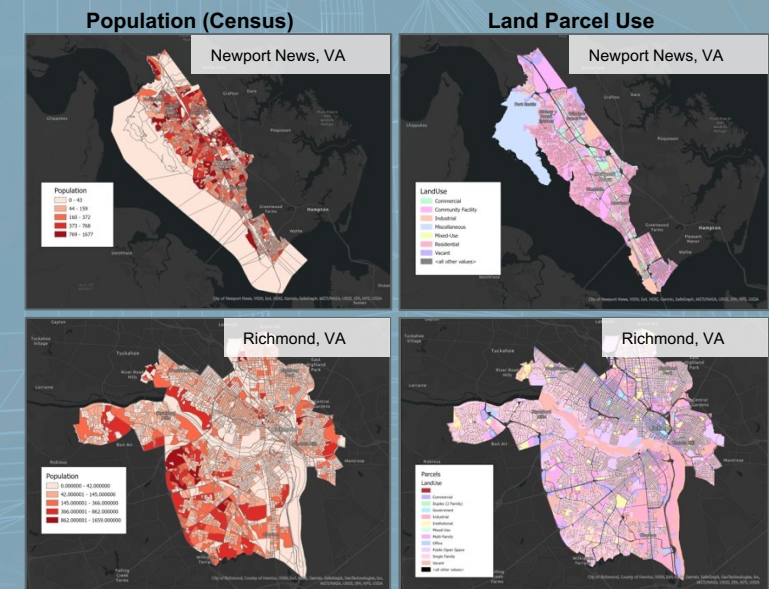
wejo

### Regional Trip Data Summaries:

Region	Sep. Trips	Feb. Trips	Sep. VMT	Feb. VMT
<b>Newport News, VA:</b> Newport News Hampton York county James City county	920k	720k	4.3M	3.3M
<b>Richmond, VA:</b> Richmond Henrico county Chesterfield county Hanover county	1.5M	1.3M	8.9M	7.2M



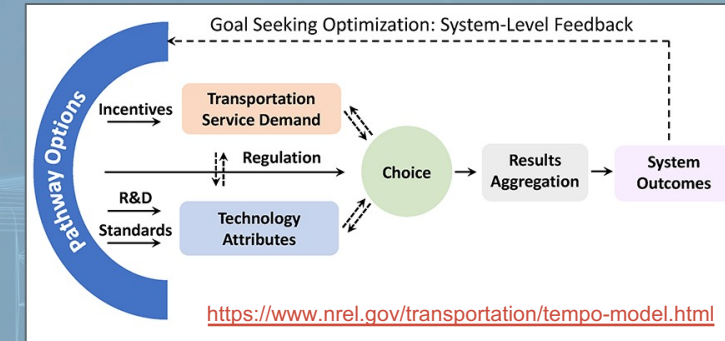
**Temporal scope:**  
September 2021 (summer)  
February 2022 (winter)



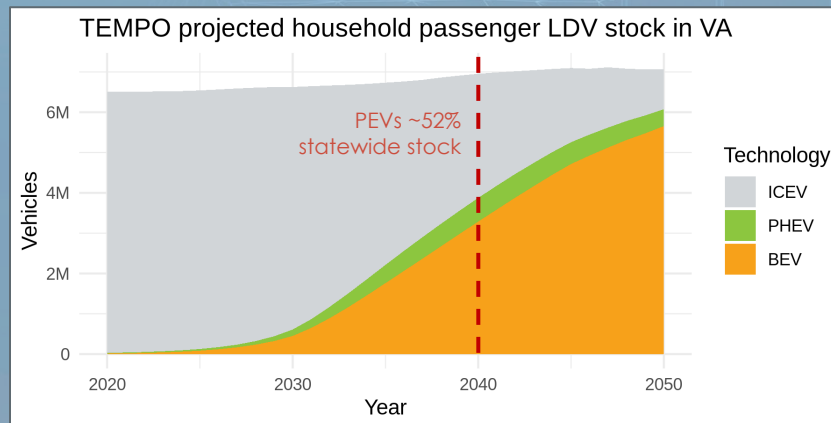


## EV Adoption Modeling – NREL TEMPO Model:

- TEMPO is an all-inclusive transport demand model that projects **household-level vehicle ownership** and technology choices based on heterogeneous consumer preferences.
- 2040 aggressive passenger EV adoption scenario assumes:
  - 50% national PEV sales by 2030
  - 100% national PEV sales by 2035
- TEMPO adoption outputs mapped to BEV/PHEV **archetype vehicles**
  - established for previous DOE projects



TEMPO Modeling Diagram



Map TEMPO PEV adoption to archetype vehicles for charging simulation

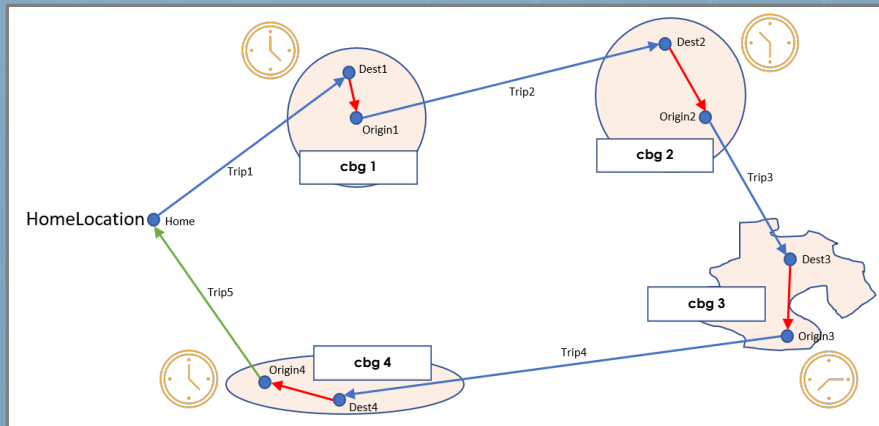
Archetype Vehicles for Simulation:

Veh. Gen.	Vehicle Type	EV Range (mi.)	ECR (Wh/mi.)	DC Charge Accept. (kW)	2040 NN fleet share (%)	2040 Rich fleet share (%)
Gen 3	BEV SUV/truck	300	475	575	37.5%	39.5%
	BEV midsize car	300	325	400	7.8%	6.3%
Gen 2	BEV SUV/truck	250	475	350	10.8%	13.5%
	BEV midsize car	300	325	300	3.5%	3.7%
	BEV compact car	150	300	150	19.7%	17.8%
Gen 1	BEV SUV/truck	200	475	150	1.3%	2.2%
	BEV midsize car	275	300	150	0.6%	0.7%
	PHEV SUV/truck	50	475	N/A	10.8%	9.7%
	PHEV midsize car	50	310	N/A	3.2%	2.4%
Gen 0	BEV compact car	150	300	50	0.5%	0.8%
	PHEV midsize car	20	250	N/A	4.3%	3.2%

202k passenger EVs  
470k passenger EVs

## Synthetic Vehicle Travel Itineraries:

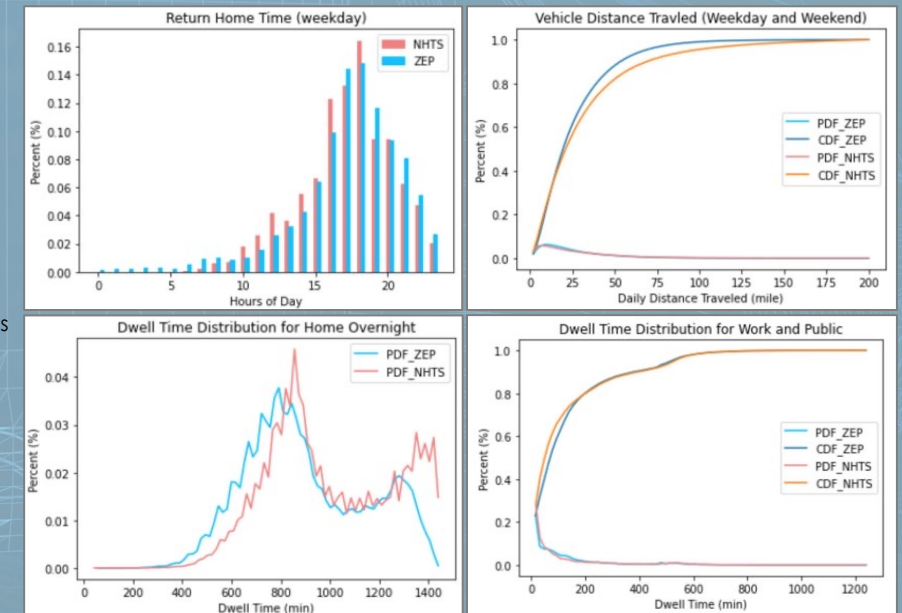
- ❑ Wejo travel data contained unlinked trips with no persistent vehicle identifier, thus a procedure for generating synthetic travel itineraries (through **trip chaining**) was leveraged.
- ❑ Locational dwell distributions (from 2017 NHTS) are used to infer vehicle dwells at each stop. Trips are chained based on **spatiotemporal alignment** of trip origins and destinations (+ dwell).
- ❑ Synthetic vehicle travel itineraries are validated against 2017 NHTS vehicle trip distributions.



Example trip chain

Validation plots:

ZEP = synth veh itineraries  
NHTS = ground truth





## EV Charging Simulation – NREL EVI-Pro Model:

- ❑ EVI-Pro takes EV adoption and travel demand data and simulates **EV charging behaviors, energy demands, and infrastructure requirements**.
- ❑ For this study, EV drivers are assumed to **prioritize home charging**, followed by workplace and public slow charging (supported by real-world charging data).
- ❑ Home charging access is derived from previous modeling, **72%** for the study region in 2040 scenario.
- ❑ 1-week charging demands are produced.

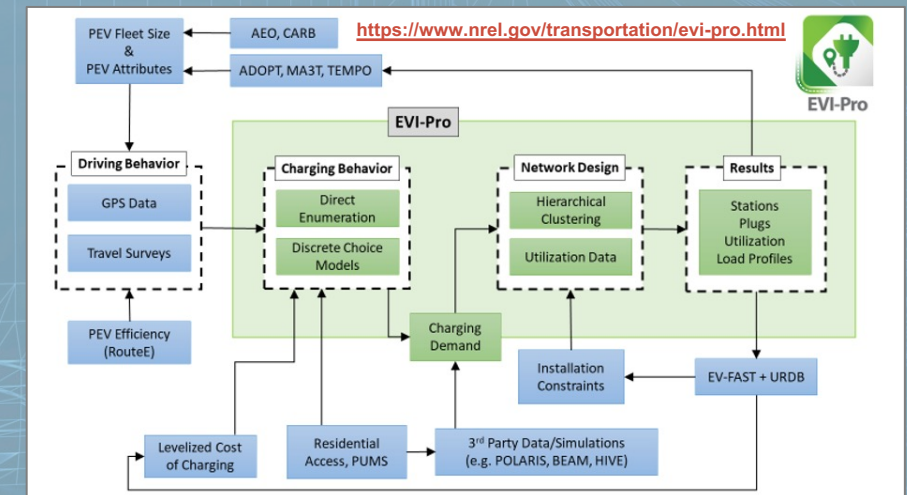


EVI-Pro

EVI-Pro ordered charge preference:

**Home > Work > Public > Public  
L2 DCFC**

*drivers prefer to destination charge during long dwell periods, maximizing opportunities for SCM...*

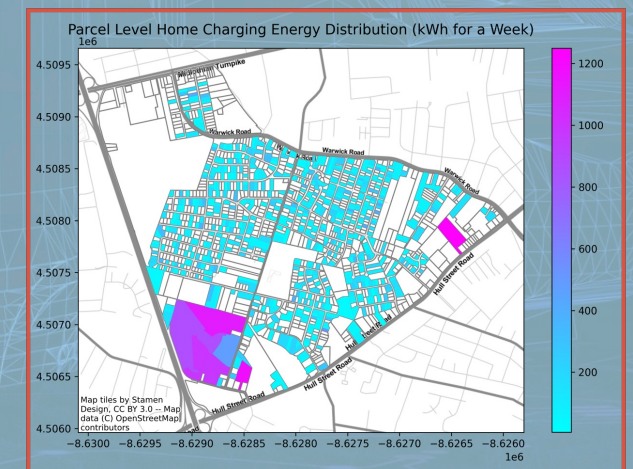
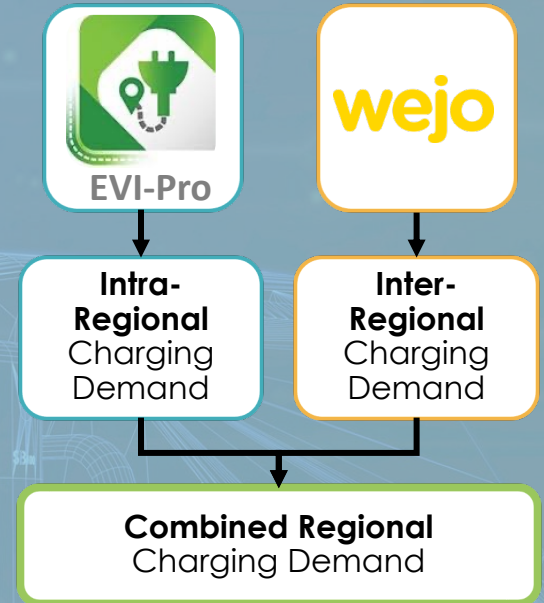


EVI-Pro Modeling Diagram

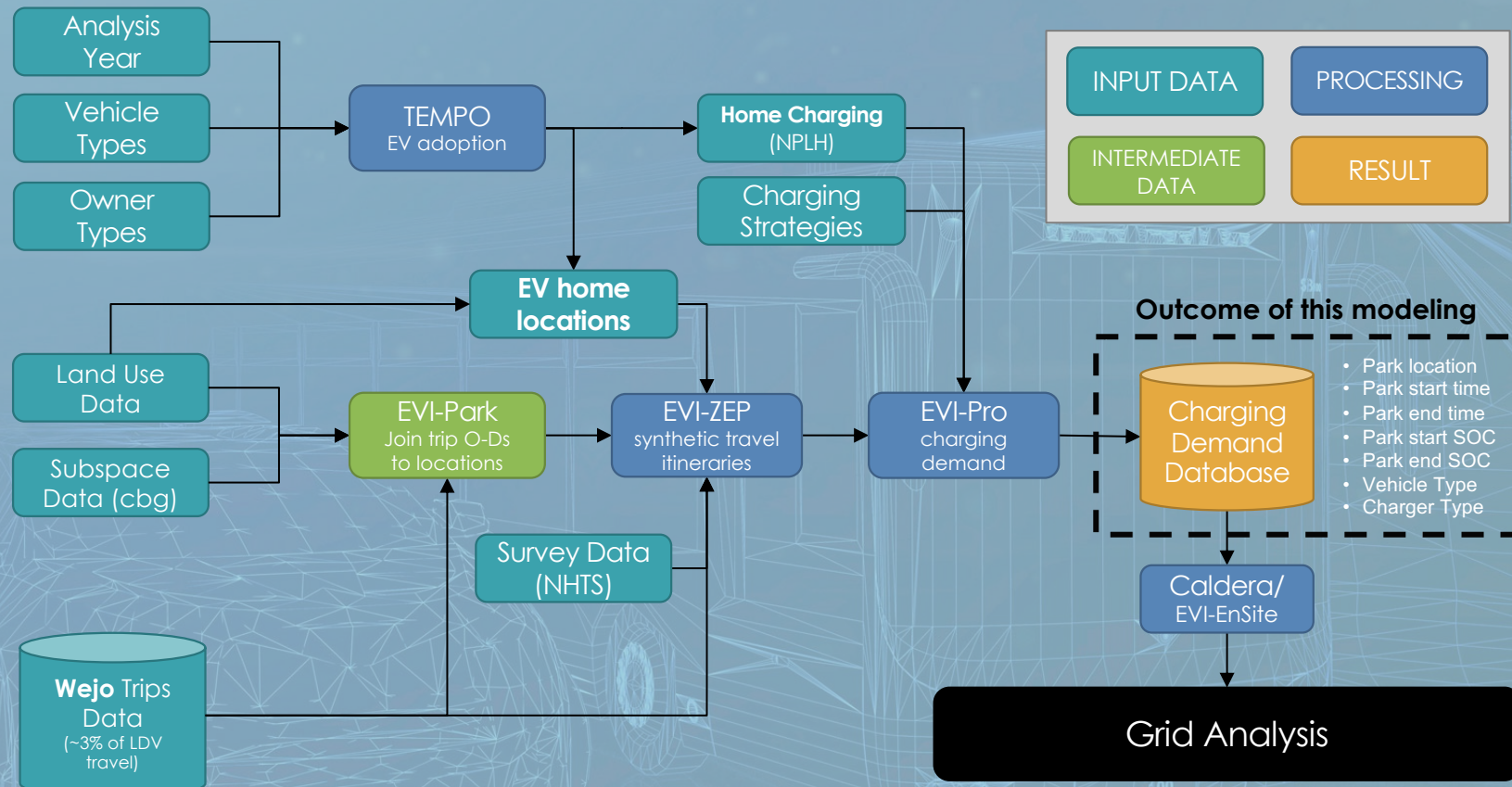


## EV Load Profiles:

- ❑ EV charging demand is combined from two sources:
  - ❑ **Intra-regional charging demand** is determined from EVI-Pro simulations
  - ❑ **Inter-regional charging demand** is determined by separately simulating charging for long-distance trips (>100-mi.) that end within the region of interest.
- ❑ EV charging events are assigned spatial coordinates depending on their location type:
  - ❑ **Home charging locations** = EV adoption projections + residential land use data.
  - ❑ **Workplace charging locations** = census tract of charging demand + commercial land use data.
  - ❑ **Public charging locations** = census tract of charging demand + commercial land use data.
- ❑ EV charging events can be assigned to **individual stations** depending on EVSE type(s), station size, and port utilization assumptions.

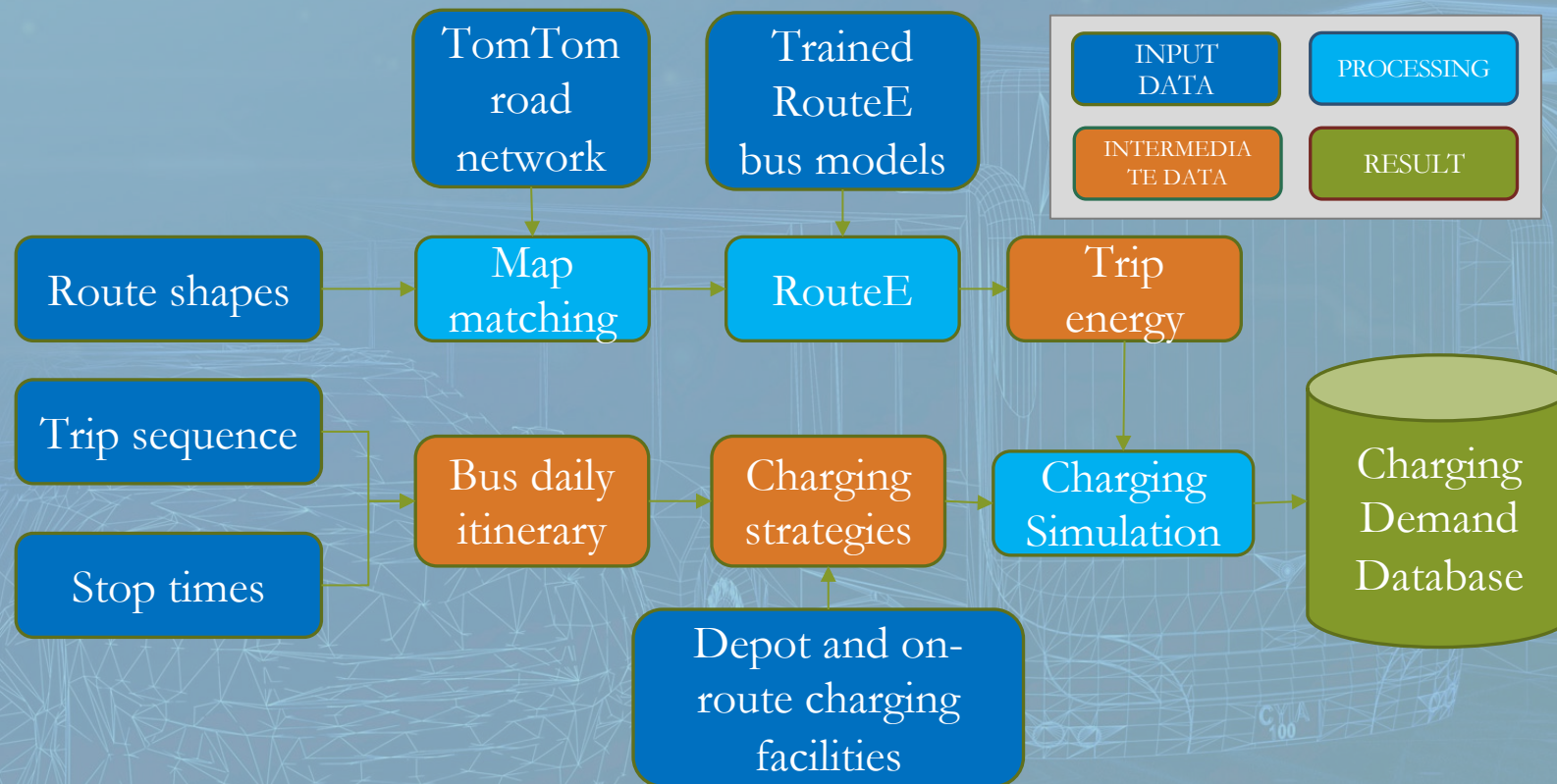


## Complete Modeling Framework:





- ❑ GTFS-based transit bus system analysis
- ❑ Transit system has relatively fixed routes and timetables, and its depot and terminal locations are known



## Real-World Transit System Data:

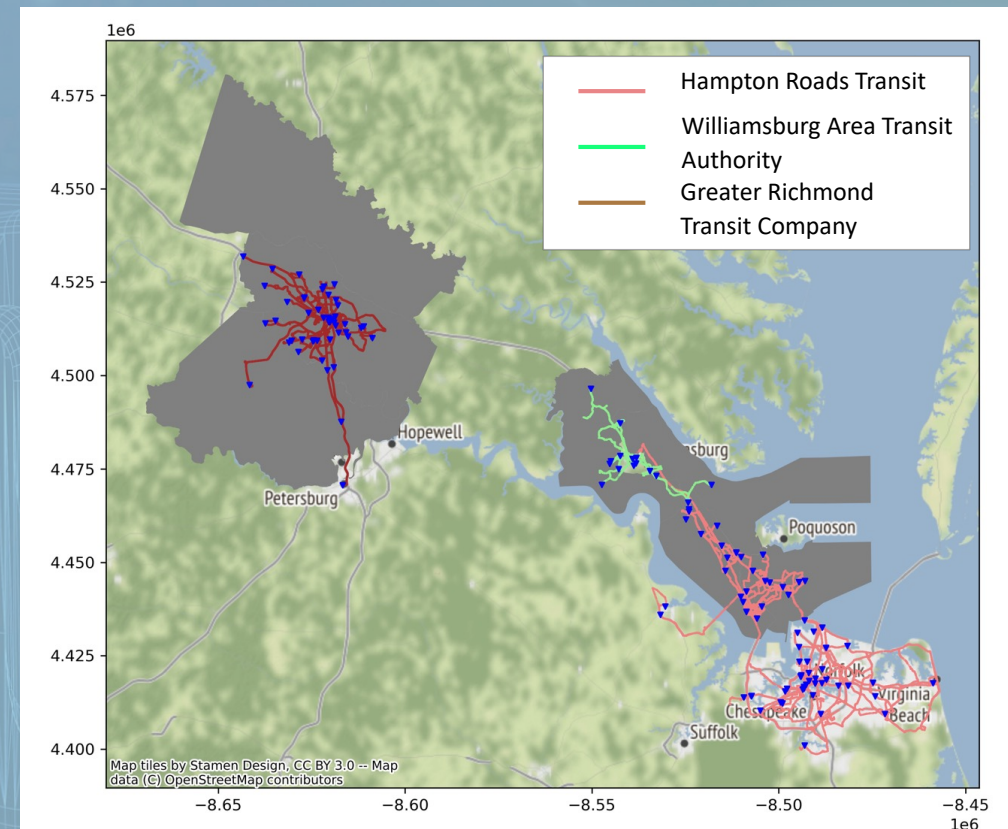
- ❑ GTFS, General Transit Feed Specification or Google Transit Feed Specification, defines a common format for public transportation schedules and associated geographic information.
- ❑ A series of standardized, text files that can be easily shared, read, and used by anyone
- ❑ Contains all information relating to the fixed schedules
- ❑ Geospatial and scheduling information from “shapes”, “trips”, “stops”, and “stop times” files.
- ❑ Depot locations are from the National Transit Database (NTD)
- ❑ Deadhead trips from and to the depot and between trips are based on shortest path algorithm



## ❑ Transit agencies:

- ❑ Williamsburg Area Transit Authority (WATA)
- ❑ Greater Richmond Transit Company (GRTC)
- ❑ Hampton Roads Transit (HRT)

Transit Agency	Fleet Size	Routes	Weekday Blocks	Saturday Blocks	Sunday Blocks
WATA	20	13	20	12	10
GRTC	142	38	110	81	63
HRT	294	71	293	236	136





## □ Assumptions:

□ Two electric bus options from Proterra

Model	Battery (kWh)	Efficiency (kWh/mi)	Range (mi)	Charging power (kW)
ZX5 + 40-feet	492	1.8-2.5	160-240	150/180/450
ZX5 MAX 40-feet	738	1.9-2.8	220-340	150/180/450

□ Simulation logic:

- Depot charging > terminal charging
- Smaller battery is better
- Lower charging power is better

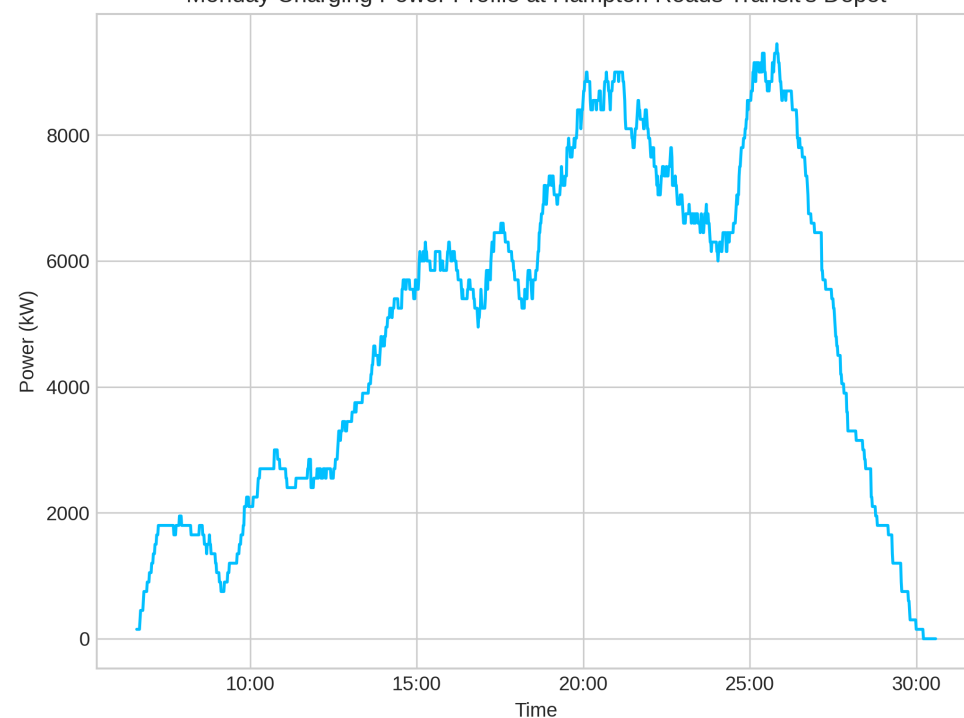
## Winter Charging Energy

Transit Agency	Depot Charging Energy (kWh)			Terminal Charging Energy (kWh)		
	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday
WATA	13358	11578	7363	1610	1638	959
GRTC	36191	35125	21586	38552	25276	26349
HRT	117661	95267	52395	53124	49787	25648

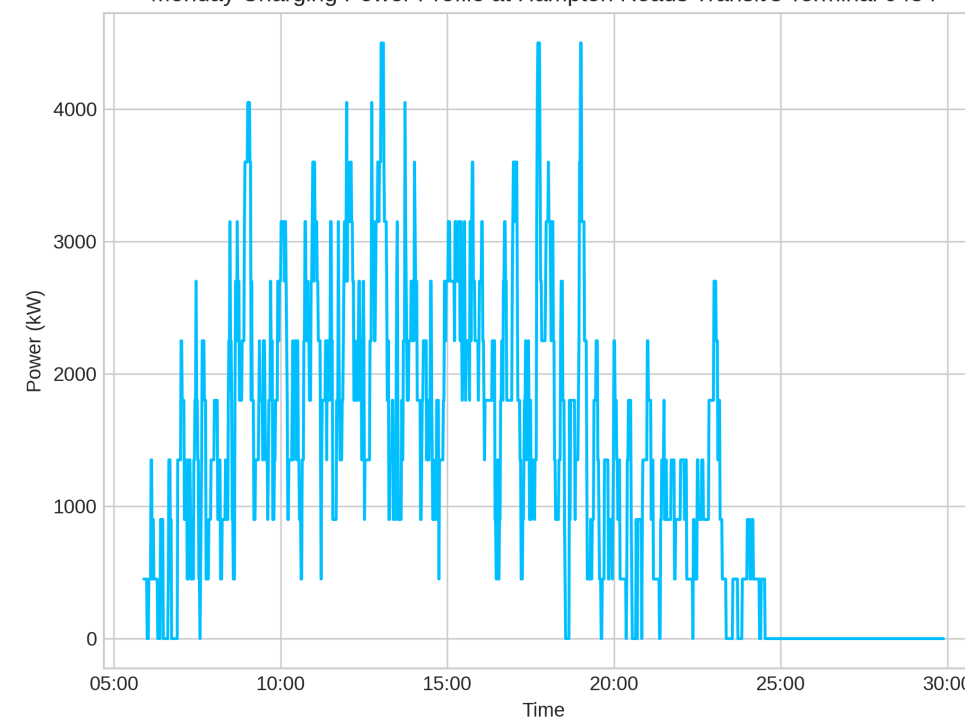
## Summer Charging Energy

Transit Agency	Depot Charging Energy (kWh)			Terminal Charging Energy (kWh)		
	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday
WATA	10647	9178	5883	1610	1638	959
GRTC	27266	27400	15395	34189	22263	24018
HRT	93914	74787	41923	46507	44506	22245

Monday Charging Power Profile at Hampton Roads Transit's Depot

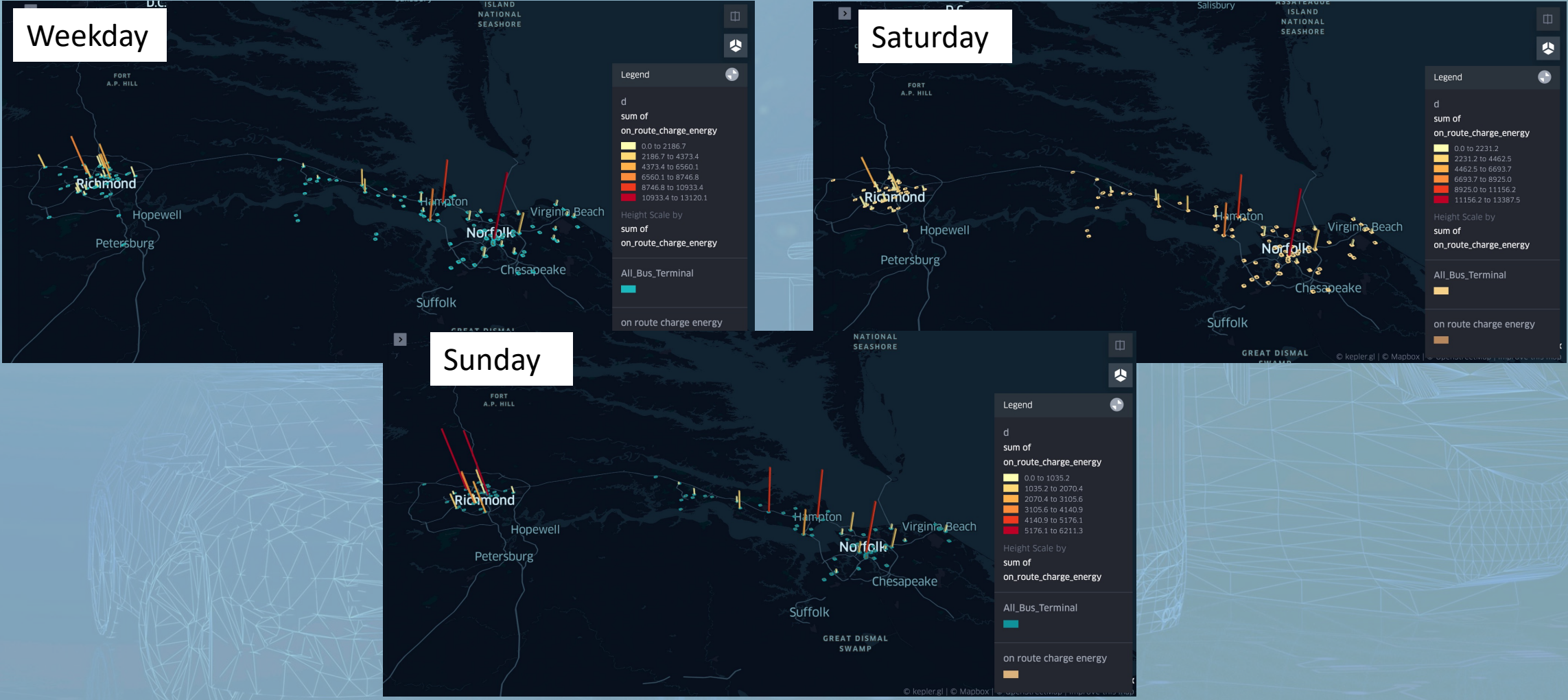


Monday Charging Power Profile at Hampton Roads Transit's Terminal 0454

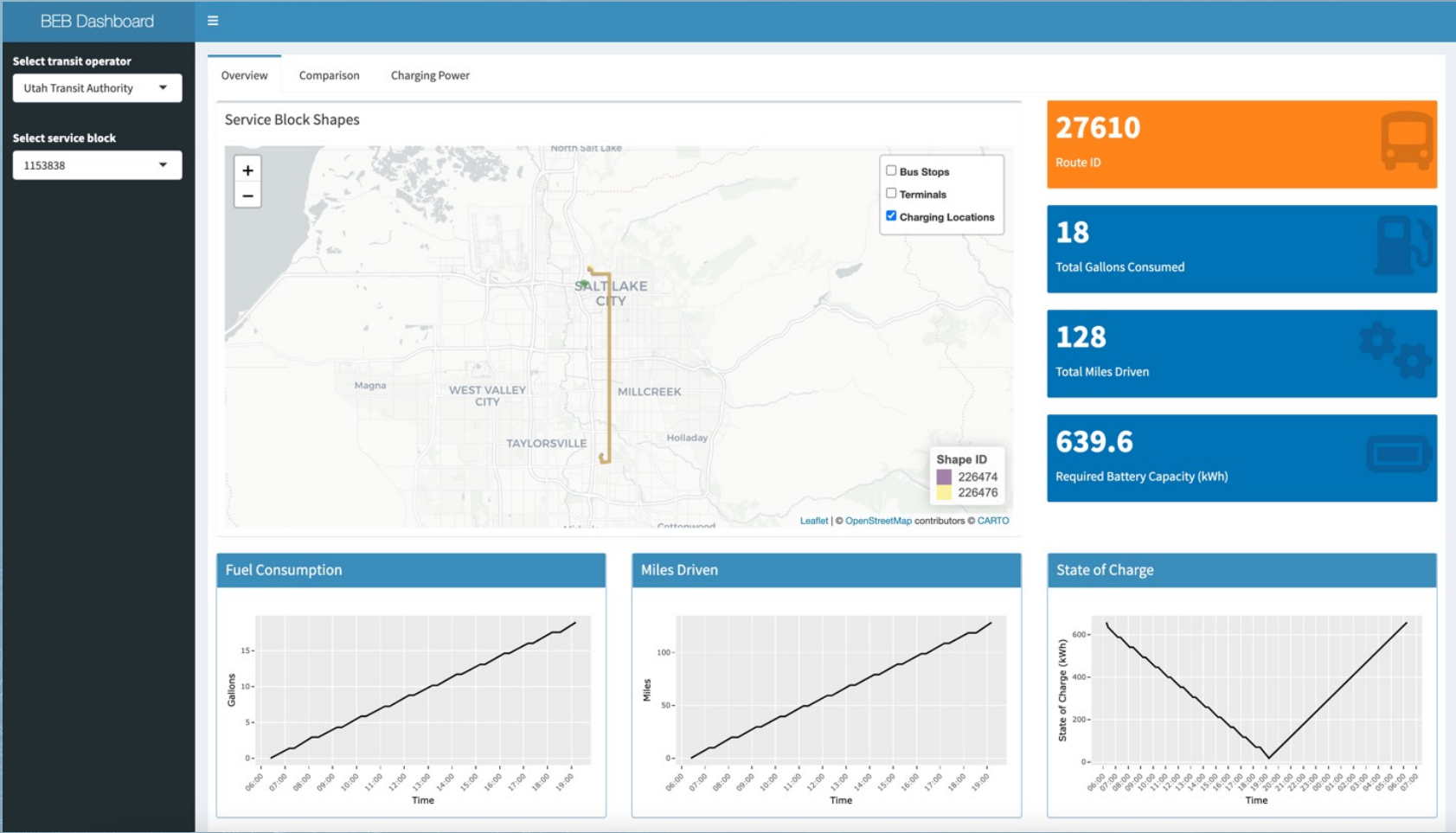




## Daily Charging Energy Needs for Opportunity Charging All Agency- Winter



## R-Shiny Based User-Friendly Dashboard



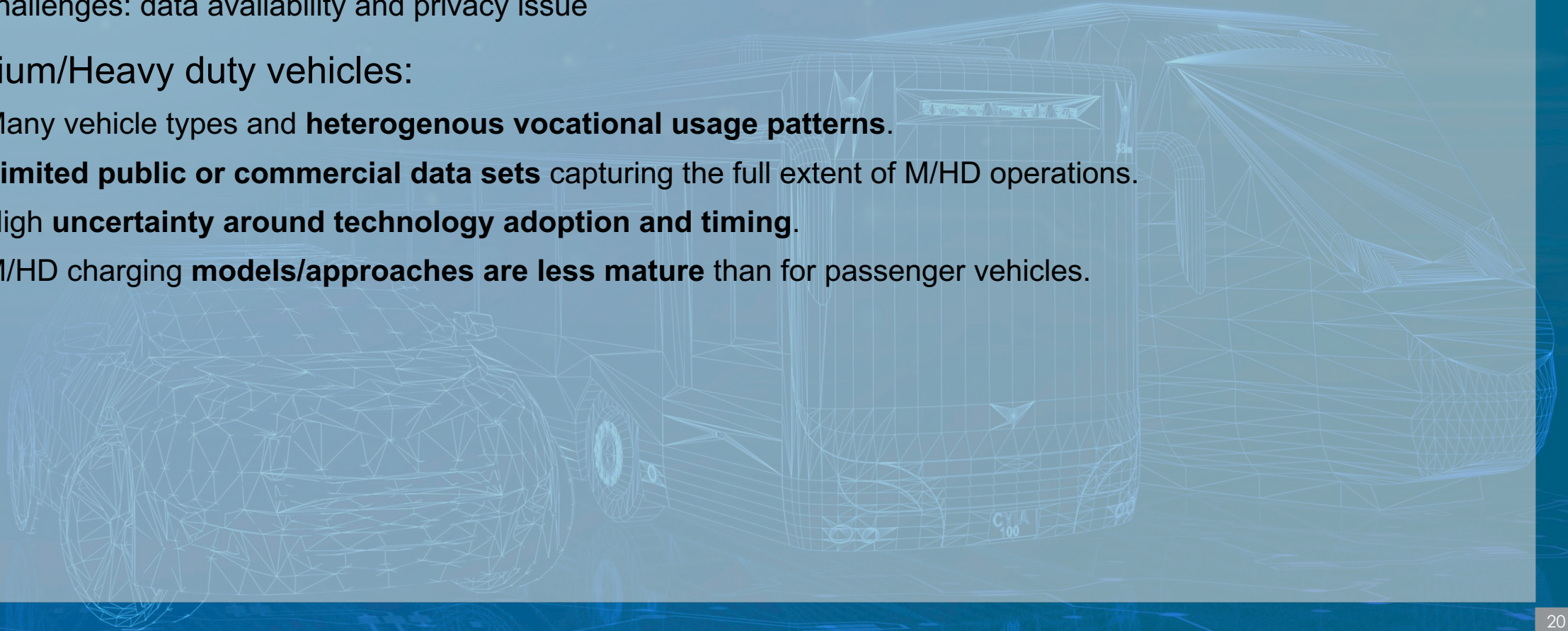


## ❑ Private vehicles:

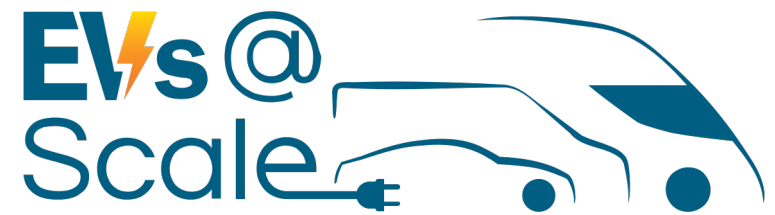
- ❑ Higher resolution: more high-quality data
- ❑ Higher fidelity: refine assumptions around EV user behaviors
- ❑ Challenges: data availability and privacy issue

## ❑ Medium/Heavy duty vehicles:

- ❑ Many vehicle types and **heterogenous vocational usage patterns.**
- ❑ **Limited public or commercial data sets** capturing the full extent of M/HD operations.
- ❑ High **uncertainty around technology adoption and timing.**
- ❑ M/HD charging **models/approaches are less mature** than for passenger vehicles.







U.S. Department of Energy

Thank you!

