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NREL FY14 Vehicle Technologies AOP
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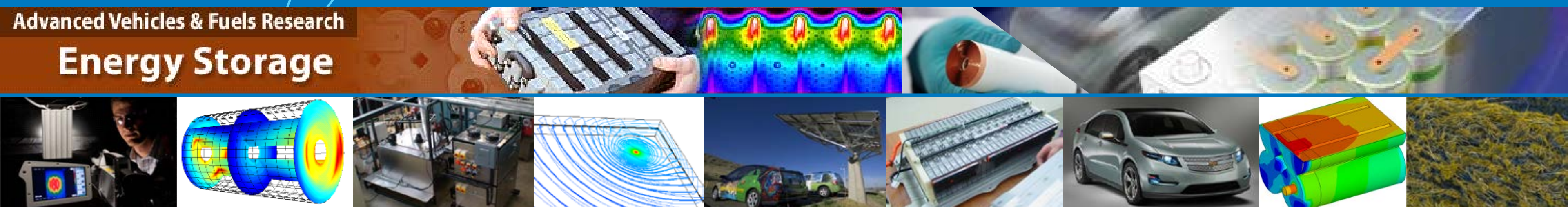
DOE Agreement: #22252
Office of Vehicle Technologies
U.S. Department of Energy

FY14 Milestone:

Simulated Impacts of Life-Like Fast Charging on BEV Batteries



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NREL/MP-5400-63386

Motivation & Objective

- **Motivation: Deployment of fast charging networks could significantly improve the utility of BEVs, but the impact of fast charging on batteries is not well understood under real-world conditions.**

- **Objective: Assess the impact of realistic fast charging scenarios on battery response, including thermal and degradation effects.**

Outline

- **Capabilities Added in FY14**
  - Cell-level evaluation of electrical, thermal, and life models
  - Rerouting travel data to include stops at fast charge stations
- **Baseline Simulations**
  - Vehicle Specs, drive profile and infrastructure availability assumptions
  - Compare simulated fast charger utilization with real-world data
- **Fast Charge Impact Analysis**
  - Evaluate impact of fast charging on battery packs under three thermal management scenarios
  - Consider cell heterogeneity in hot climate subject to fast charging
  - A closer look at how fast charging impacts max battery temperatures
- **Summary**

Capabilities added in FY14

Cell-level evaluation of battery electrical, thermal, and life models

Multi-cell pack modeling

- **Motivation:** Availability of fast chargers can result in much longer sequences of back-to-back drive-charge-drive events. This is expected to create greater heat generation, thermal gradients, and peak temperatures within the pack. Thermal gradients can lead to heterogeneous degradation of cells within a pack, and thereby lower available capacity and battery lifetime.

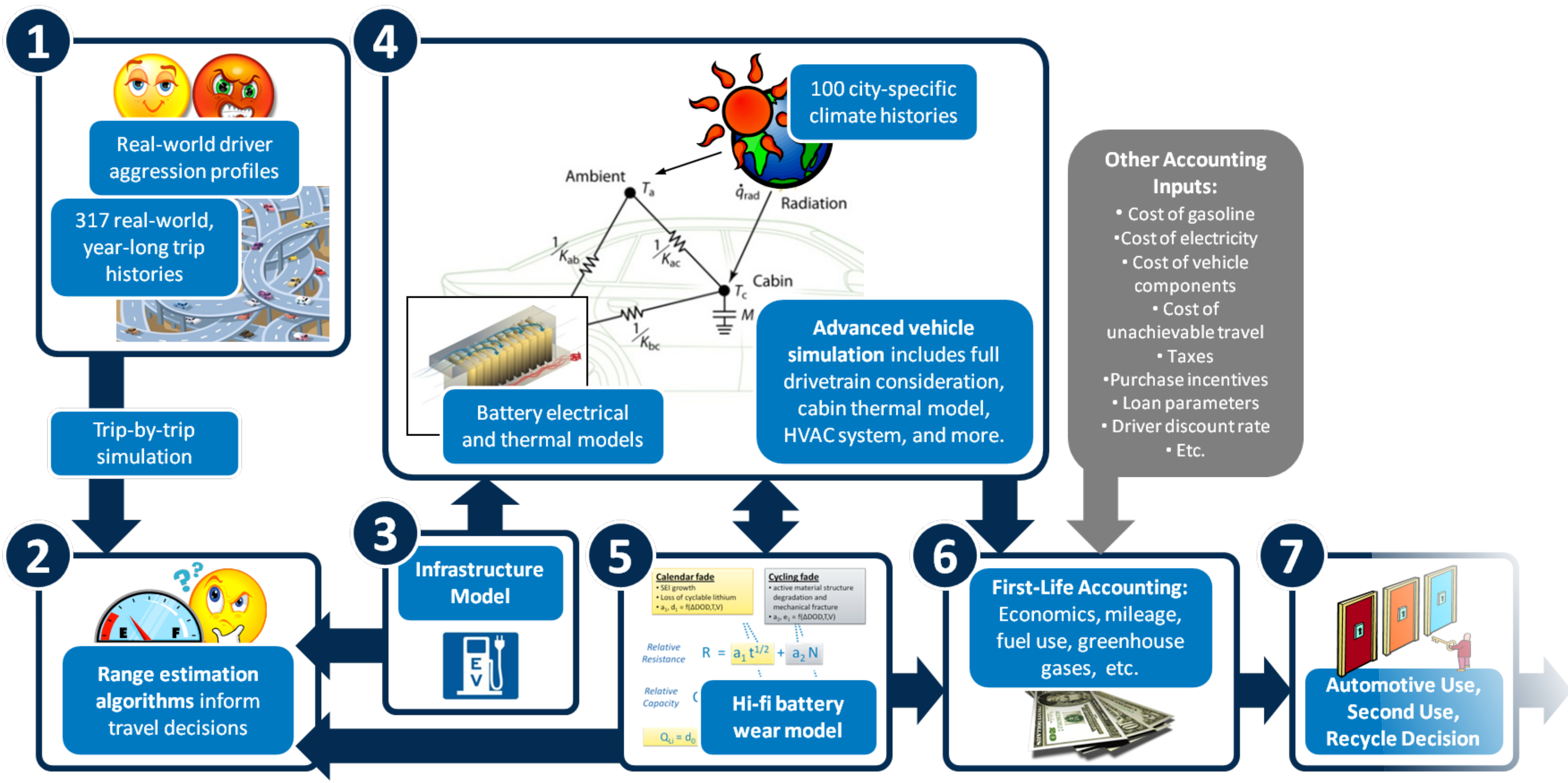
- **Objective:** Add the ability to simulate individual cells within the BLAST-V software package, creating a more accurate depiction of peak battery temperatures and degradation under aggressive fast charge conditions than would otherwise be possible.

- **Approach:**
  - Divide previously “lumped” battery mode into flexible electrical and thermal subsets
  - Include ability to randomize initial conditions of SOC, capacity and resistance values
  - Simulate temperature, voltage, and SOC for each individual cell
  - Calculate degradation for each individual cell

- **March 2014 Milestone:** Complete addition of multi-cell code

BLAST-V

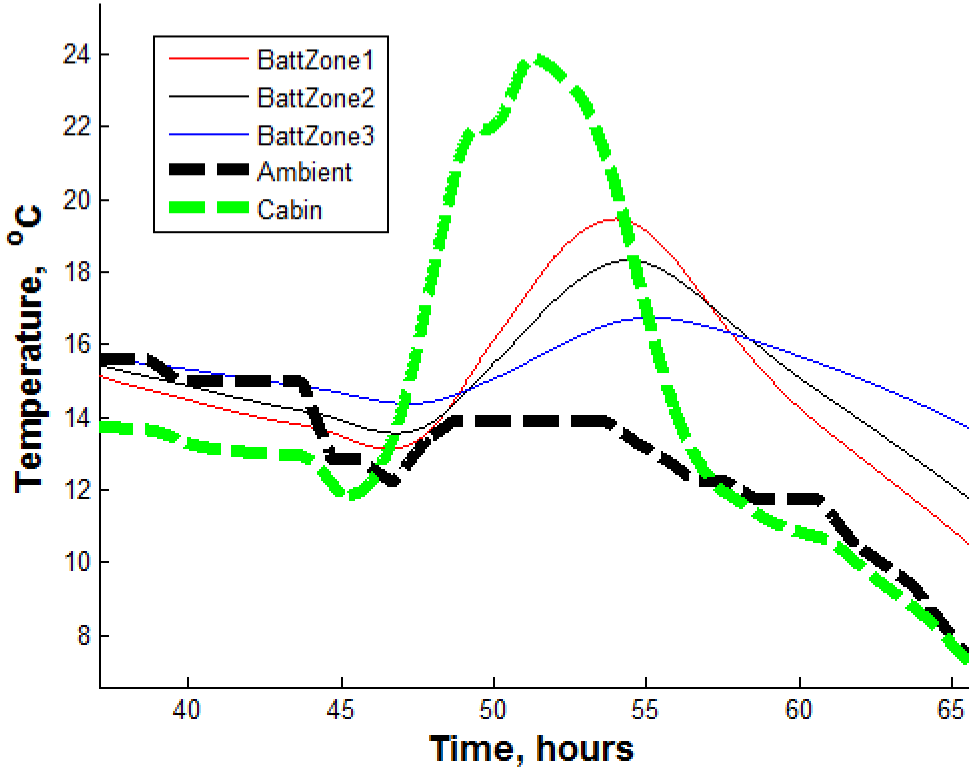
- **B**attery **L**ifetime **A**nalysis and **S**imulation **T**ool for **V**ehicles
- **Objective:** Perform accurate techno-economic assessments of HEV, PHEV, and BEV technologies and operational strategies to optimize consumer cost-benefit ratios, petroleum use reductions, and emissions savings



Thermal and Electrical Model Separation

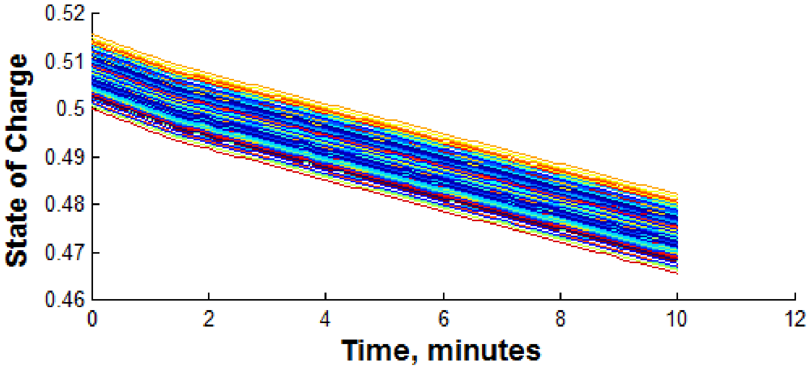
- **Thermal model can be separately discretized from electrical model. This can be beneficial for accelerating simulation speed and/or simplifying model validation**
- **In this example, a 100-node electrical model and 3-node thermal model is employed**

Three-node BEV battery thermal response during a parking event

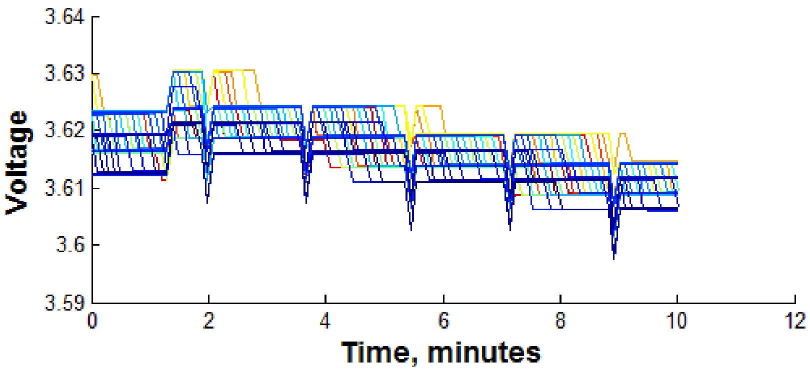


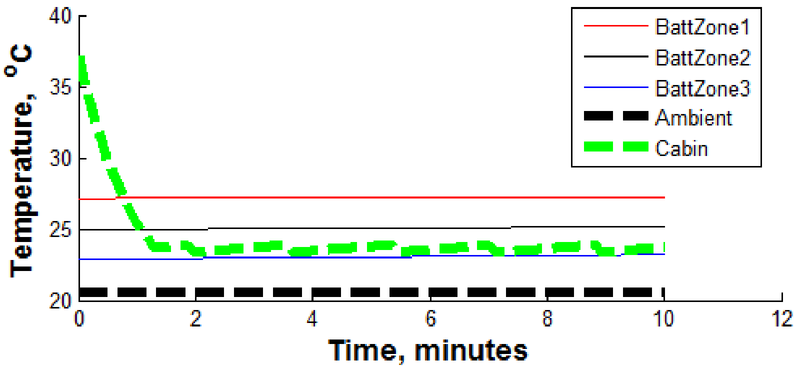
Example Electrical Response

- **Electrical model calculates voltage and SOC separately for each individual cell**
- **The example below shows a closely matched pack at beginning of life**



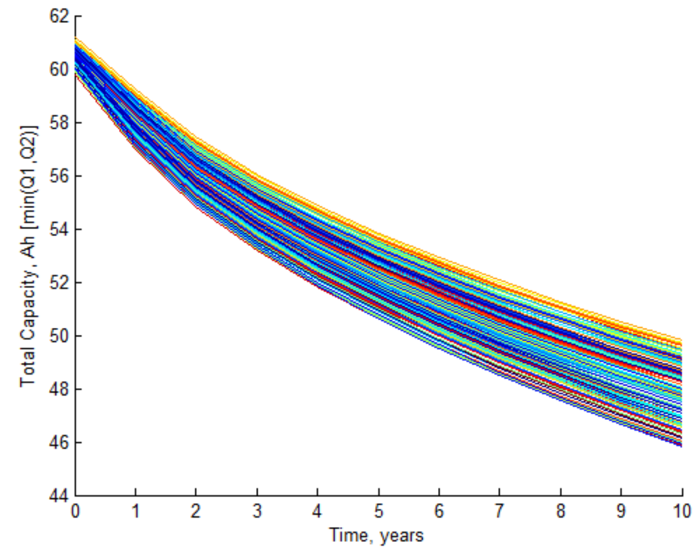
Three-node BEV battery thermal and 100 node BEV battery electrical response during a drive event

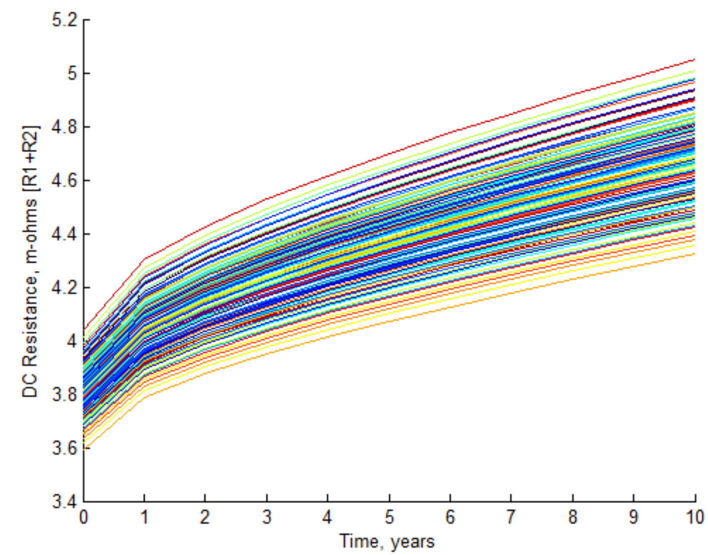




Example Degradation Response

- **Different thermal and electrical conditions at each cell implies different degradation rates.**
- **Thus, cell level calculation of degradation has been included as well**

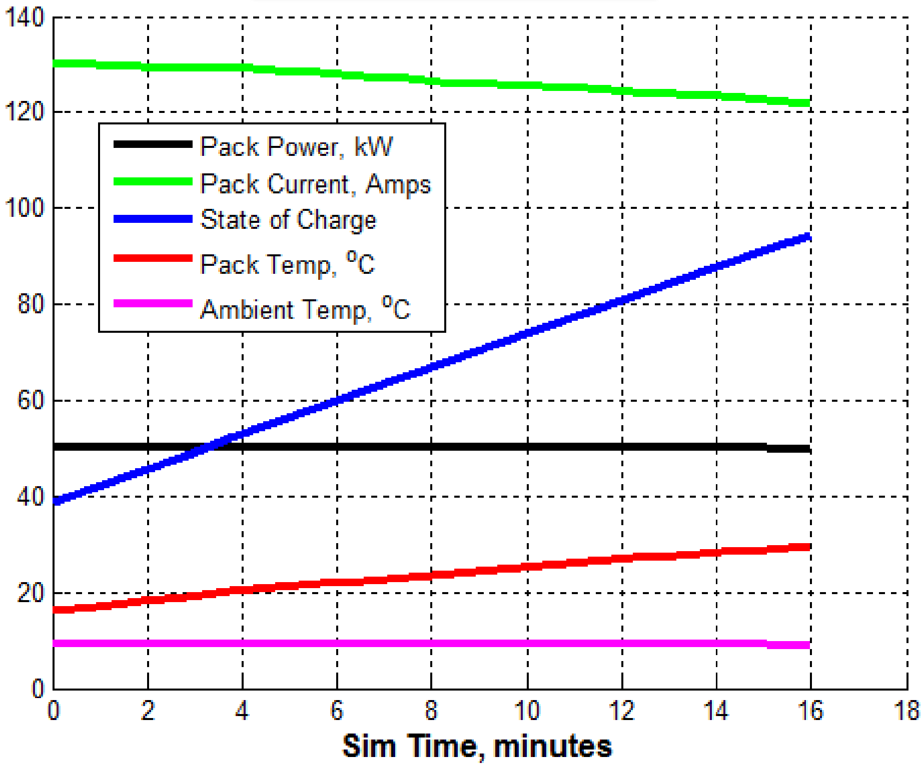




Example ten-year capacity loss and resistance growth in a 100-cell BEV battery model

Example Fast Charge (50kW)

Single Cell Model

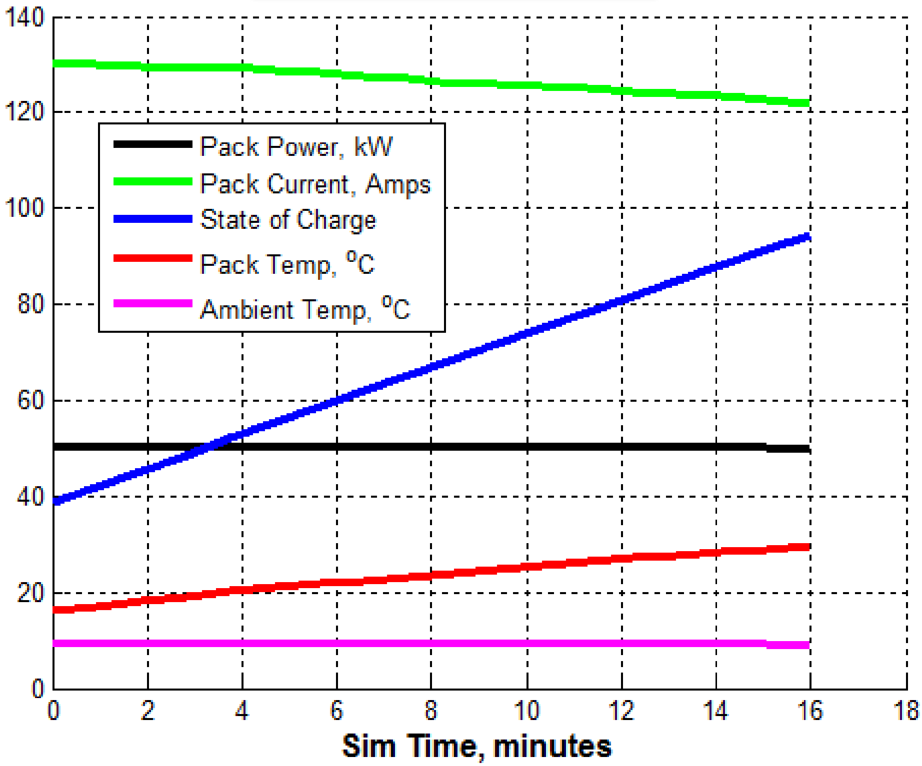


- **Simulated pack electrical and thermal response to FC event at beginning of life**
  - Good charge acceptance behavior with taper not occurring until ~90% SOC
  - Significant heat generation with thermal model predicting 13°C increase over 16-minute charge

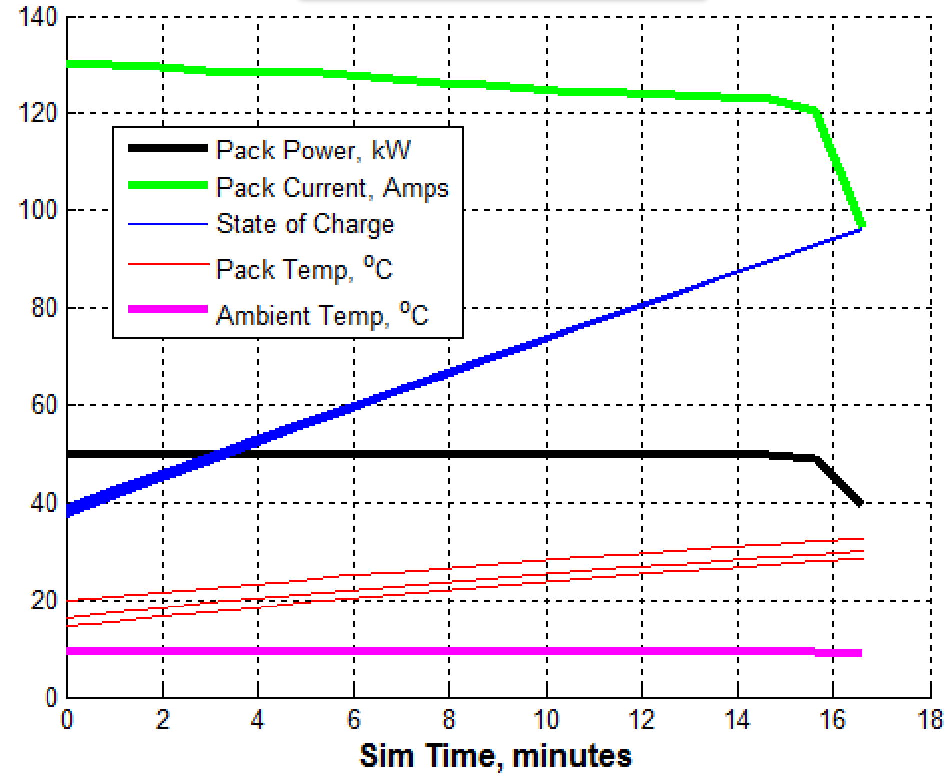
Example Fast Charge (50kW)

- **Single and multi-cell models contrasted**
  - Multi-cell pack power capability limited by weakest cell
  - Power tapering occurs slightly earlier in fast charge event
  - Predicted max temperature is notably higher

Single Cell Model

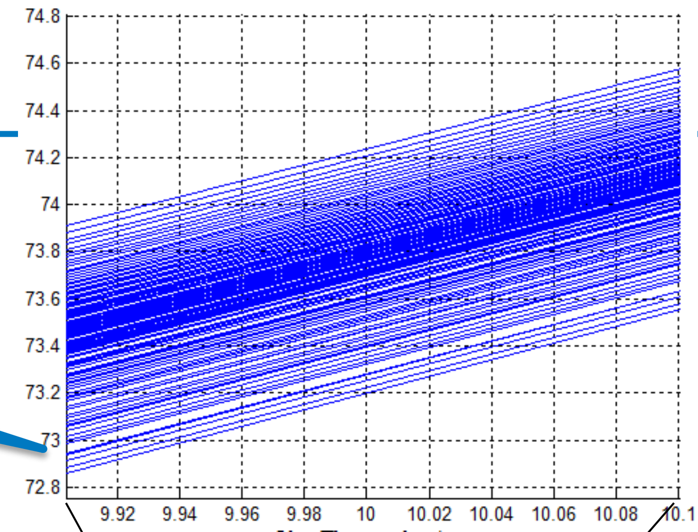


Multi Cell Model

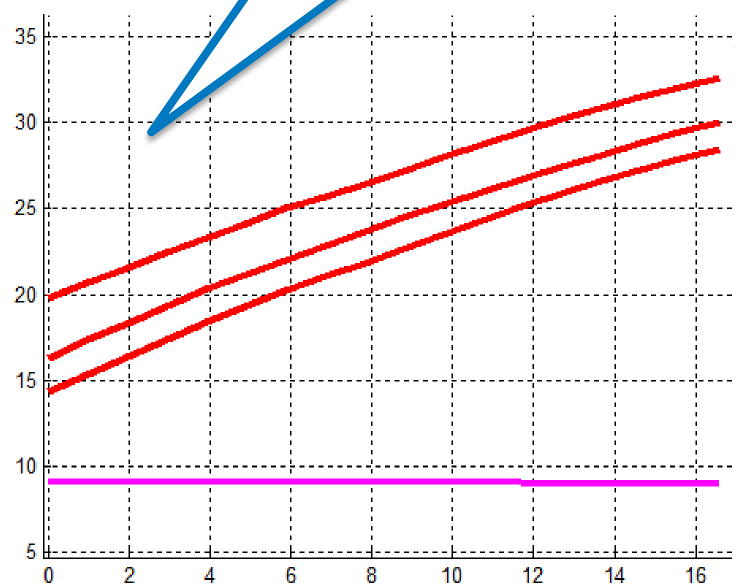


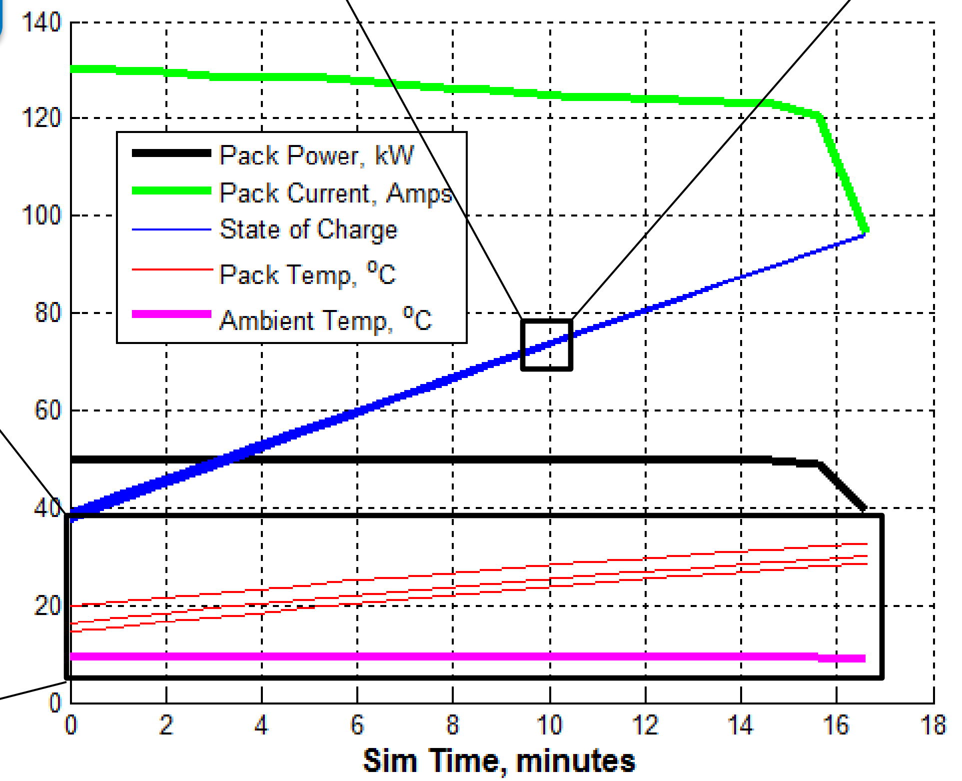
Example Fast Charge

100-cell electrical model



3-node lumped thermal model





Capabilities added in FY14

Rerouting travel data to include stops at fast charge stations

Tour Planning in BLAST

BLAST estimates BEV utility by making a go/no-go decision before each tour (sequence of trips beginning and ending at home)

A reduced-order electrical model of the battery is used to estimate SOC at the end of each trip in the proposed tour based on initial state of the vehicle, anticipated road and cabin loads, and available charging infrastructure

If estimated SOC is determined to dip below a pre-defined driver tolerance at any point during the tour, the driver elects not to take their BEV on said tour

If estimated SOC stays above tolerance, driver elects to take BEV and high-resolution simulation of battery electrical, thermal, and life behavior is conducted

Tour Planning in BLAST

Example Tour 1

Depart / Arrive	Miles	Minutes
8:31am / 9:07am	21.2	36.3
4:33pm / 4:48pm	9.9	15.6
5:39pm / 6:10pm	13.7	30.9

Group trip data into tours, where each tour starts and ends at home

(Assume L2 charging at home)

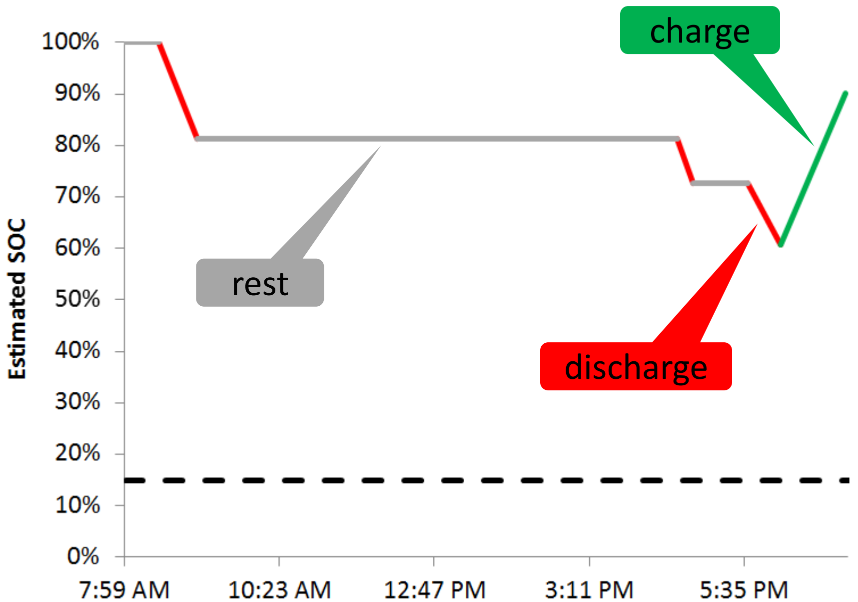
For each tour, the driver must decide whether or not to take BEV based on estimated range

Assume drivers require battery stay above 15% SOC (or about 15 miles) to select travel via BEV

Tour Planning in BLAST

Example Tour 1

Depart / Arrive	Miles	Minutes	Estimated SOC
8:31am / 9:07am	21.2	36.3	100% → 81%
4:33pm / 4:48pm	9.9	15.6	81% → 73%
5:39pm / 6:10pm	13.7	30.9	73% → 61%



BLAST estimates SOC through tour using reduced order battery model

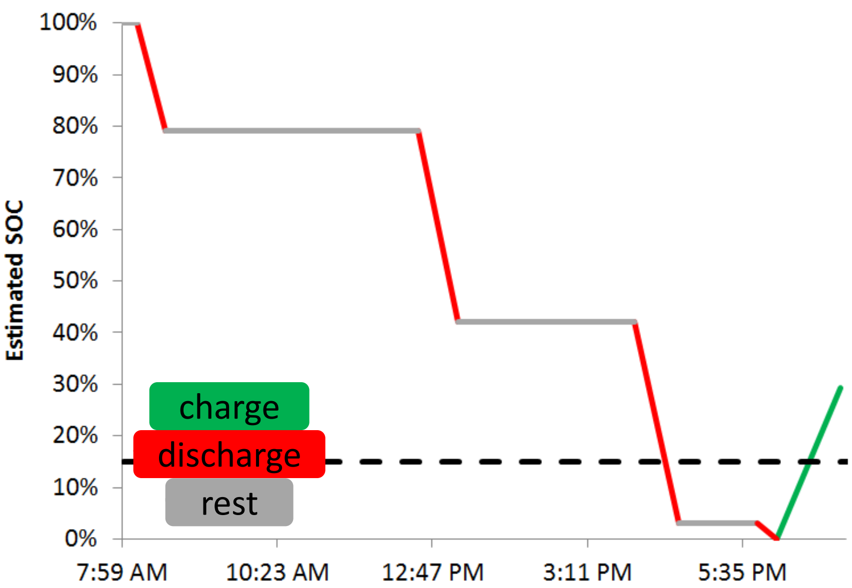
If minimum estimated SOC is above driver's range tolerance, BLAST proceeds with simulating the tour, otherwise tour is evaluated as single parked event

Many tours stay above range tolerance without work/public charging

Tour Planning in BLAST

Example Tour 2

Depart / Arrive	Miles	Minutes	Estimated SOC
8:14am / 8:40am	20.0	26.3	100% → 79%
12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:36pm	37.3	41.2	42% → 3%
5:49pm / 6:07pm	13.6	19.0	3% → 0%



Consider a different example tour from the BLAST travel data

If minimum estimated SOC drops below range tolerance, BLAST has the option of rerouting select trips to include stops at fast charge stations

All fast charge stations assumed 50kW in this analysis

Rerouting for Stops at FC Stations

BLAST considers two data sources when rerouting tours

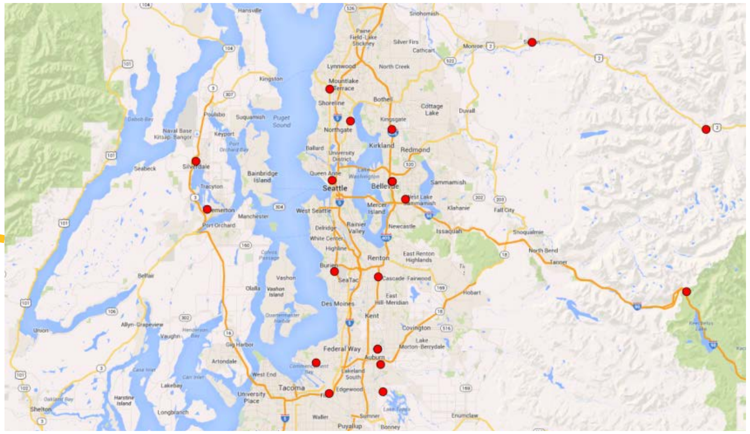
1. Alternate path of travel combinations using O/D pairs from original travel data and Google Maps Directions API
2. User-defined EVSE networks

Using said input data, BLAST reschedules the original tour while attempting to:

- Keep minimum estimated SOC above driver tolerance
- Minimize number of stops and time spent at FC stations

***Constraint is applied that all trip start times be preserved from original travel data**

Google Maps Directions API



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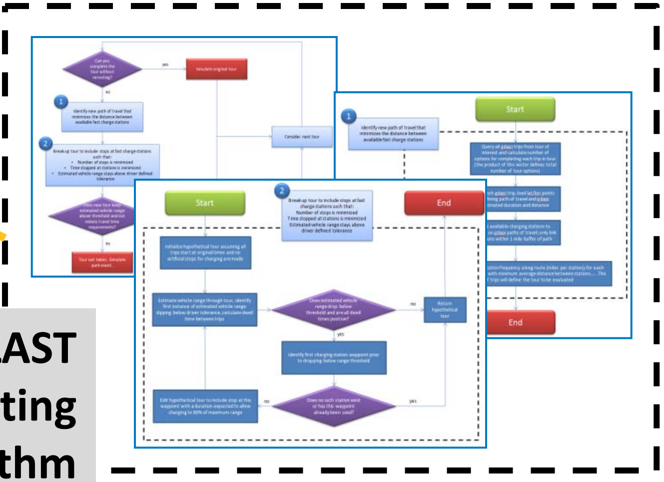
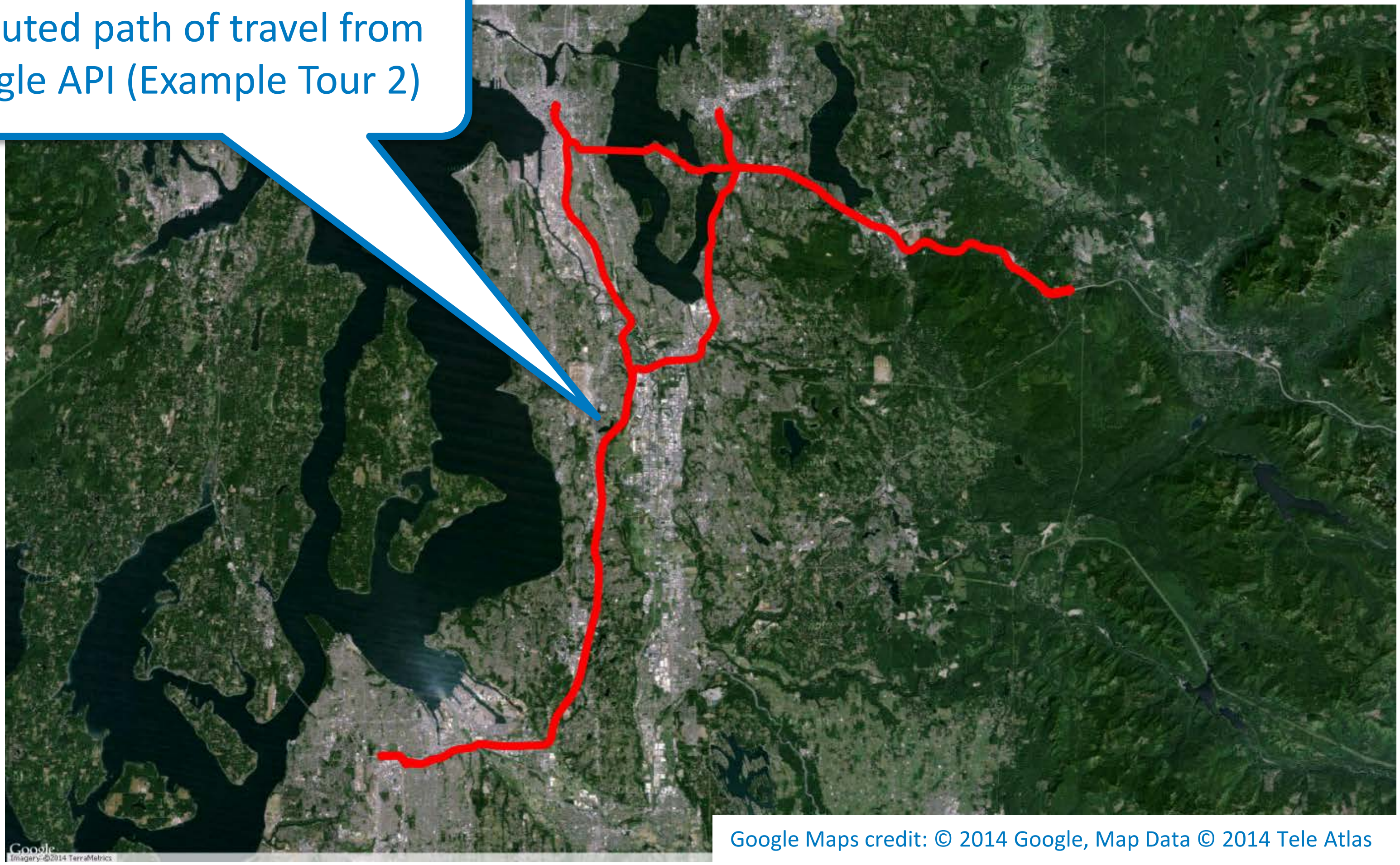


BLAST Rerouting Algorithm

Rerouting for Stops at FC Stations

Rerouted path of travel from Google API (Example Tour 2)



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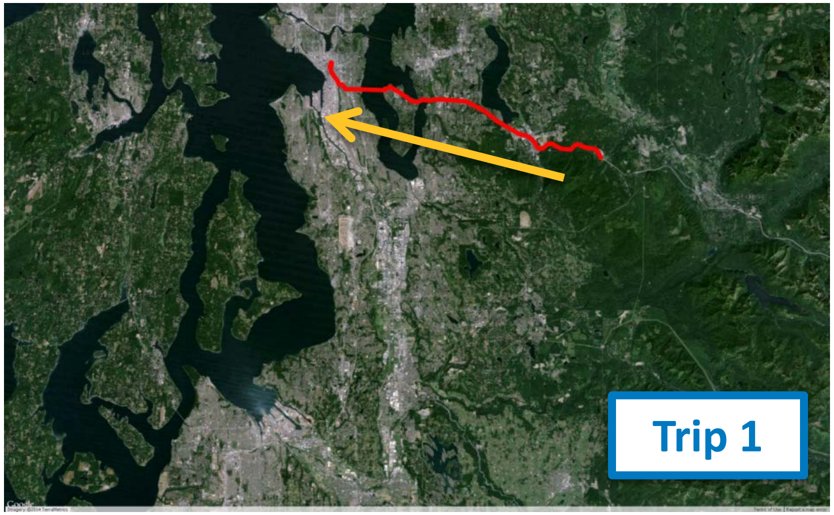
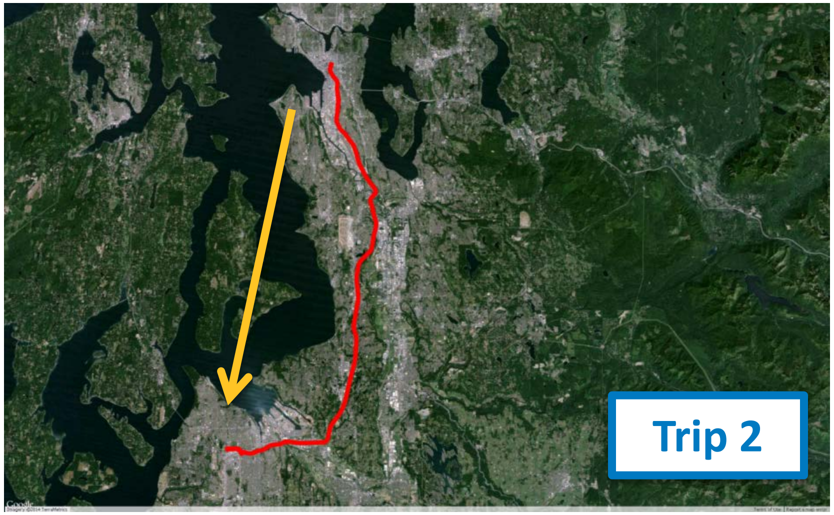
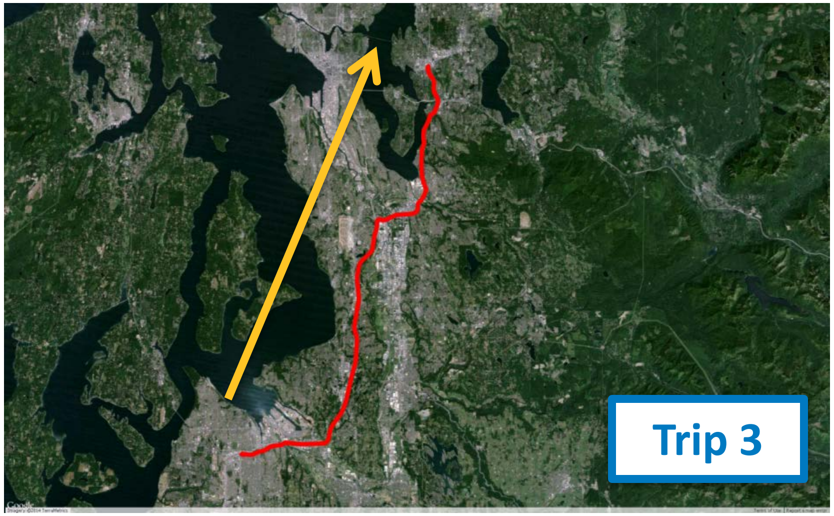
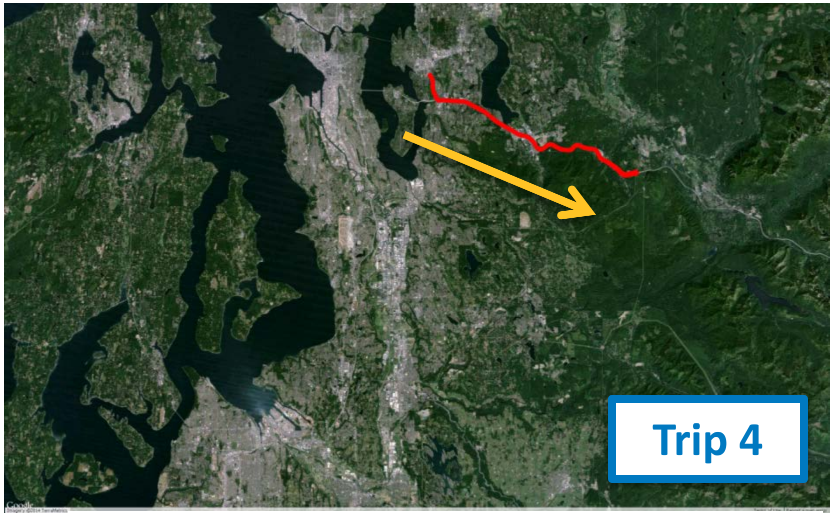
*Map does not reflect actual travel data;
trip coordinates have been synthesized for illustrative purposes.

Rerouting for Stops at FC Stations









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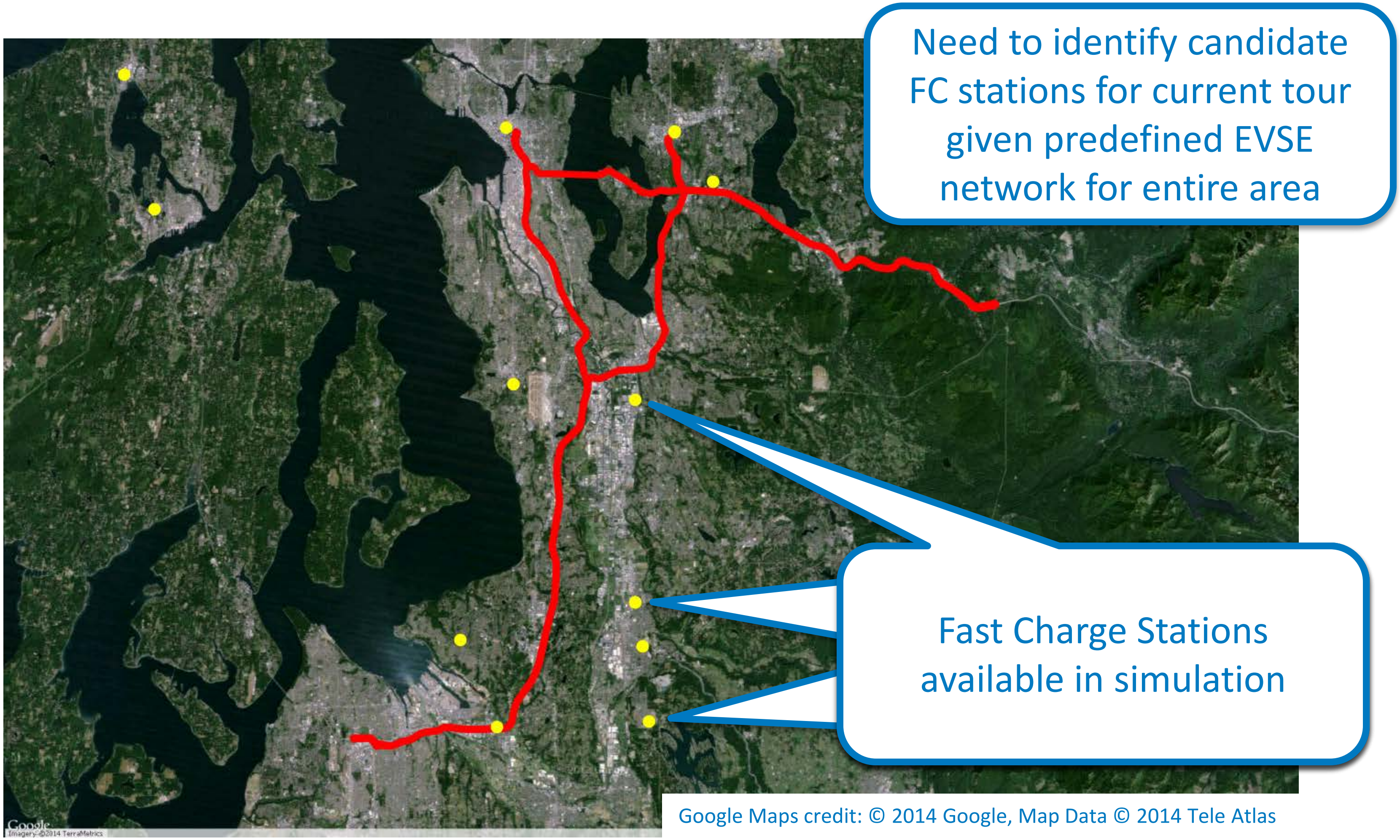
Rerouting for Stops at FC Stations



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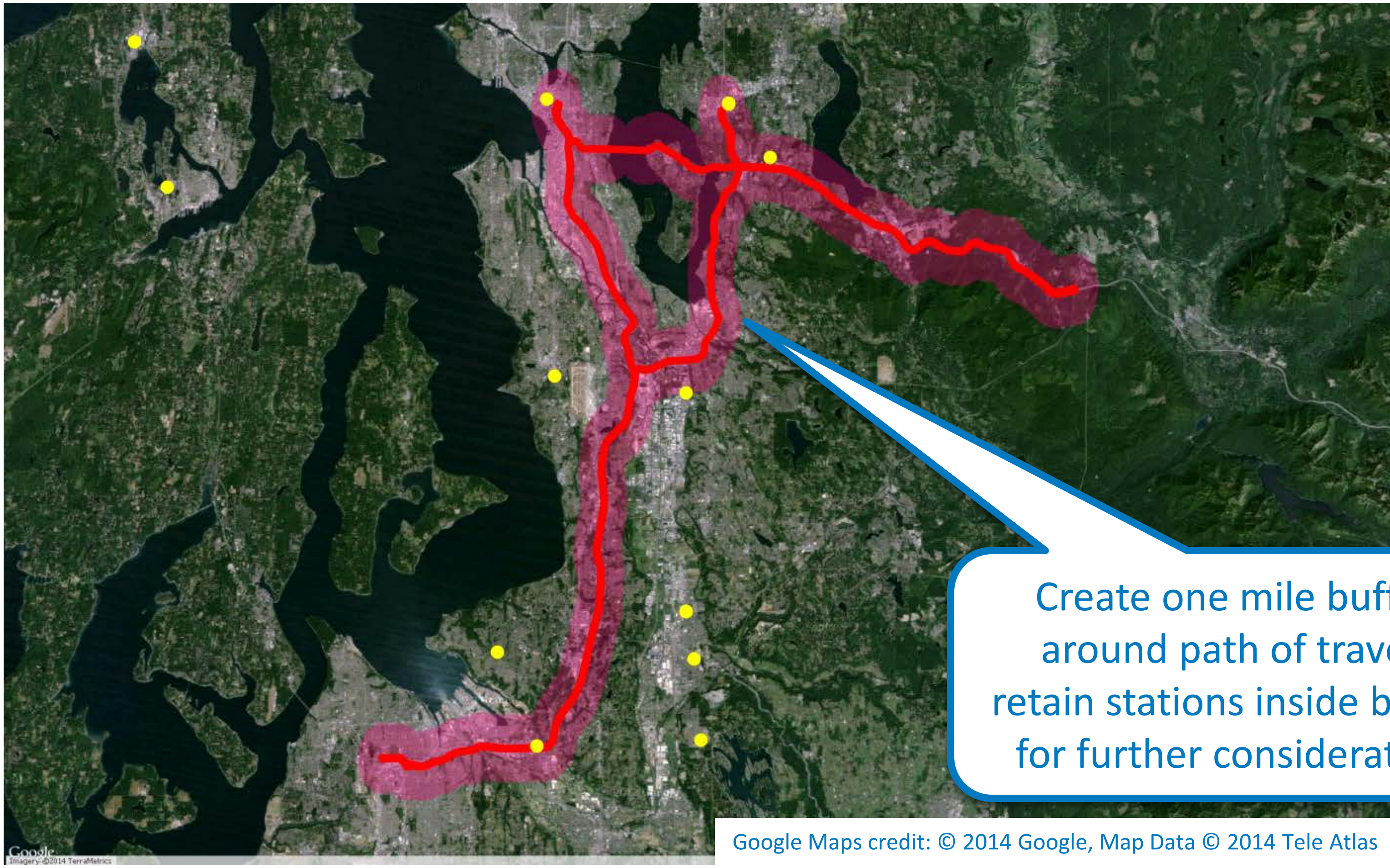
Rerouting for Stops at FC Stations



Create one mile buffer around path of travel; retain stations inside buffer for further consideration

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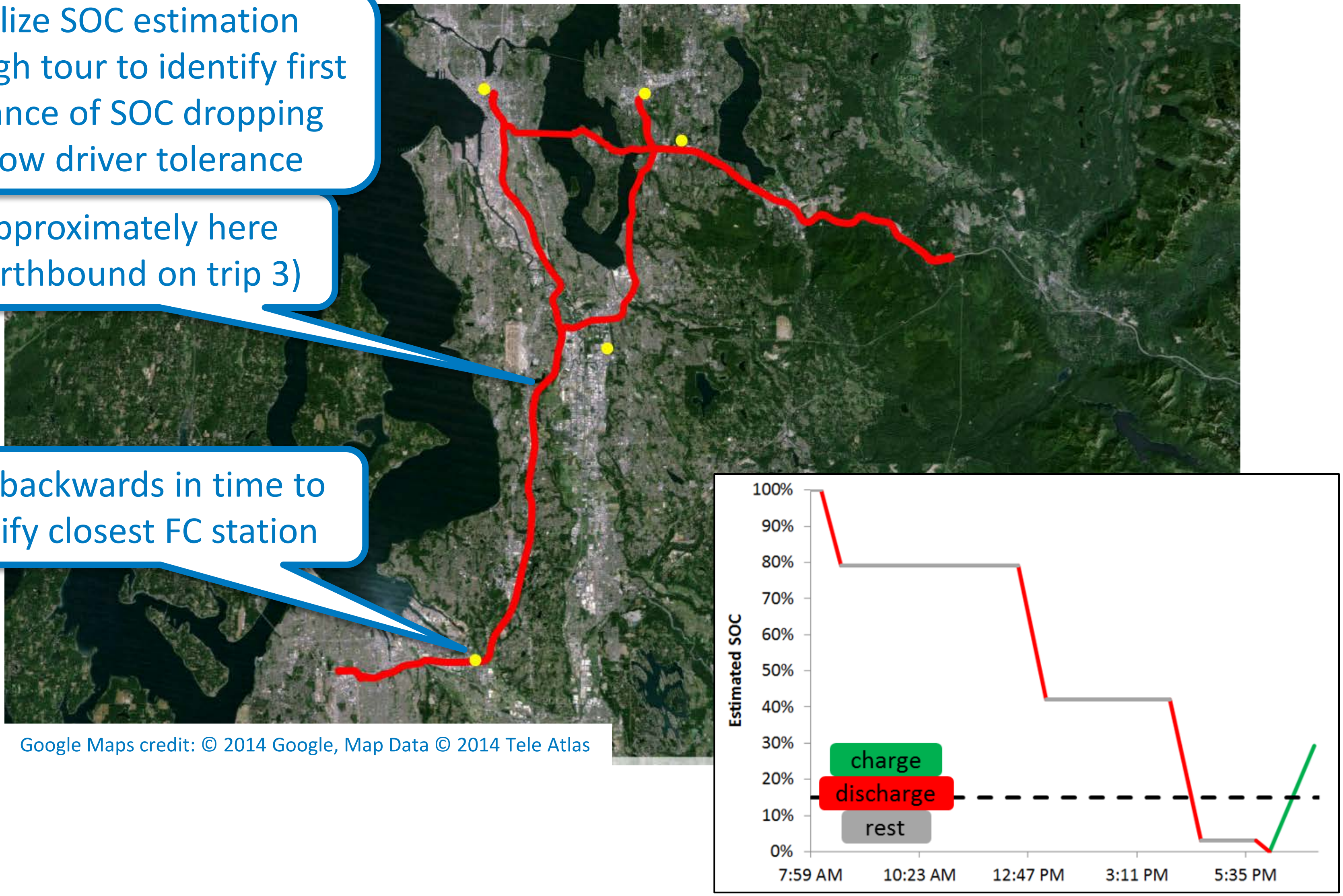
Rerouting for Stops at FC Stations

Utilize SOC estimation through tour to identify first instance of SOC dropping below driver tolerance

Approximately here (northbound on trip 3)

Walk backwards in time to identify closest FC station



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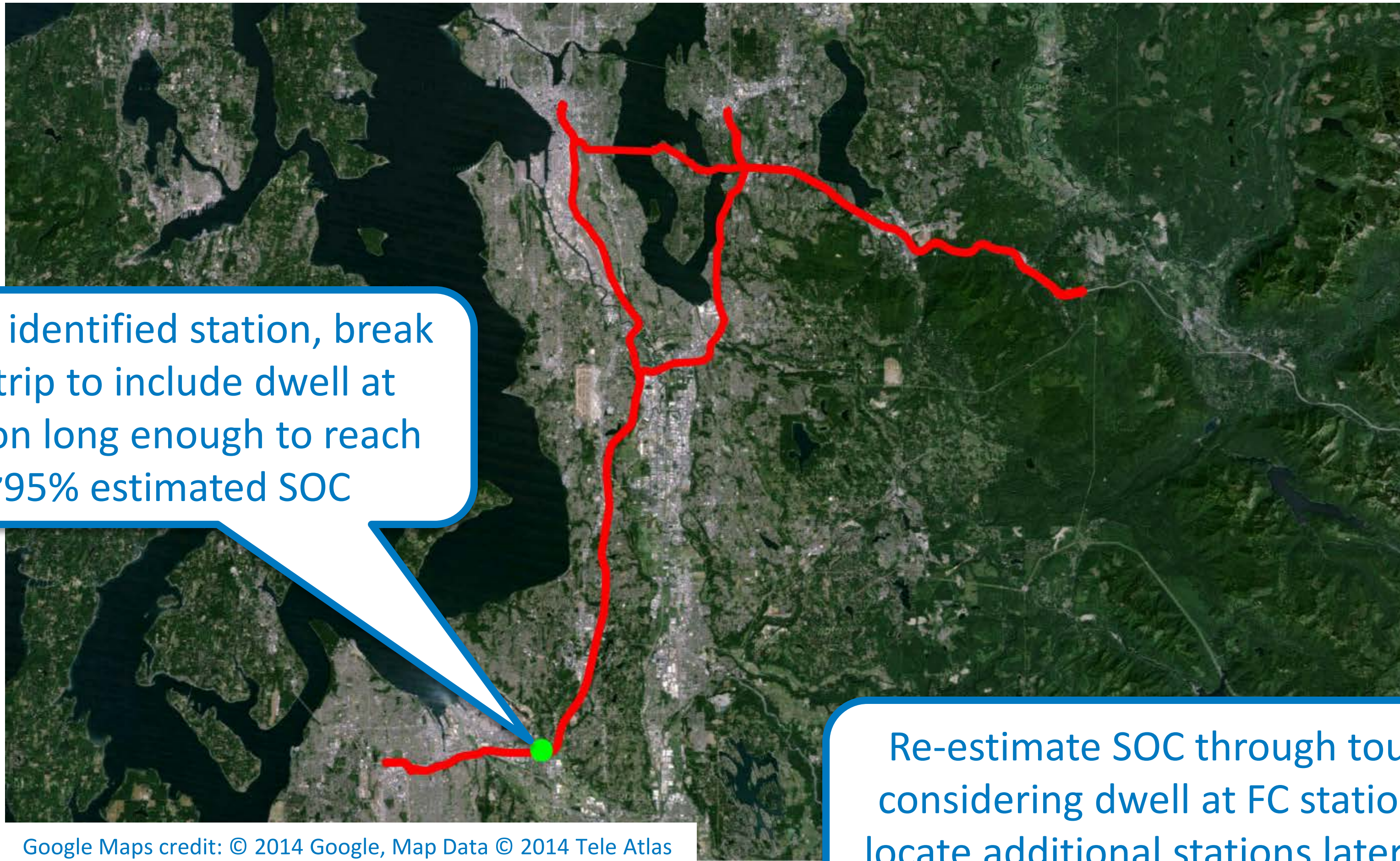
Rerouting for Stops at FC Stations



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Using identified station, break up trip to include dwell at station long enough to reach ~95% estimated SOC

Re-estimate SOC through tour considering dwell at FC station; locate additional stations later in tour if necessary

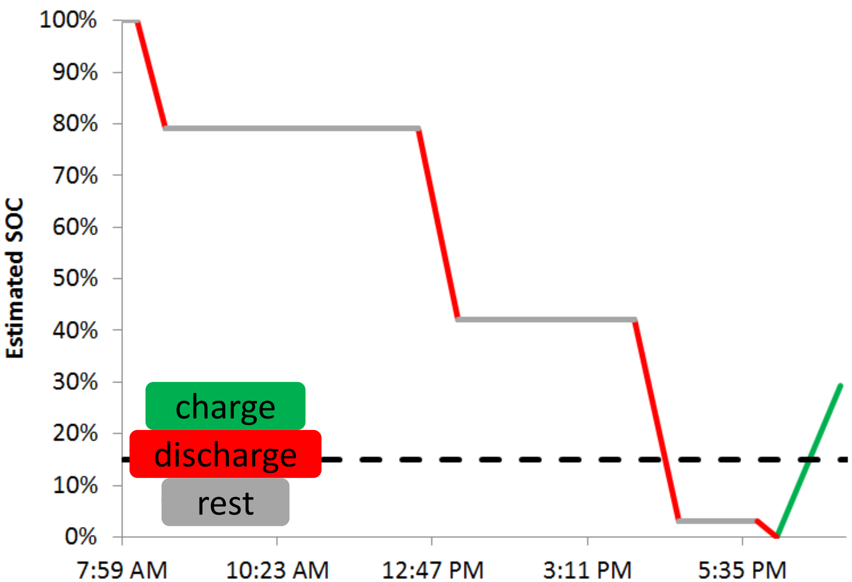
Tour Planning in BLAST

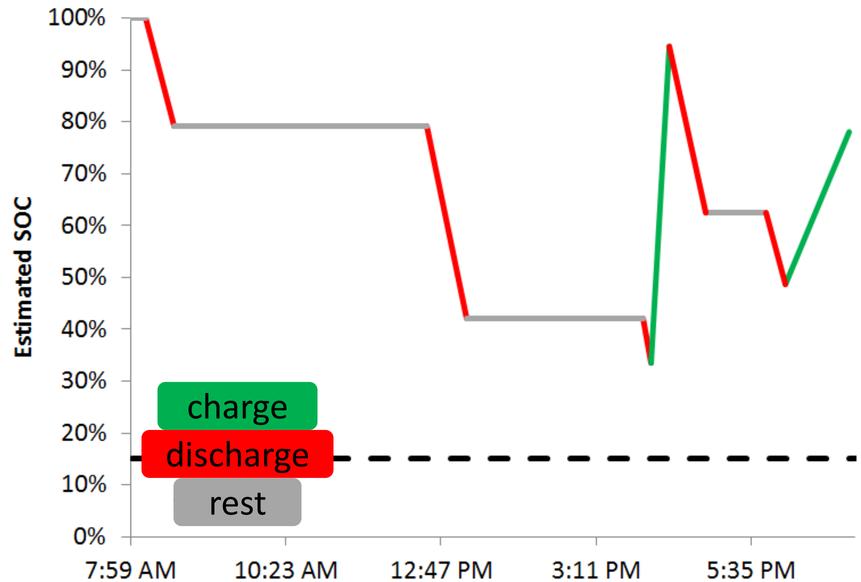
Original Tour

Depart / Arrive	Miles	Minutes	Estimated SOC
8:14am / 8:40am	20.0	26.3	100% → 79%
12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:36pm	37.3	41.2	42% → 3%
5:49pm / 6:07pm	13.6	19.0	3% → 0%

Rerouted Tour w/ stop at FC station

Depart / Arrive	Miles	Minutes	Estimated SOC
8:14am / 8:40am	20.0	26.3	100% → 79%
12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:03pm	7.8	8.3	42% → 34%
17 minute FC			
4:20pm / 4:53pm	30.0	32.9	95% → 62%
5:49pm / 6:07pm	13.6	19.0	62% → 49%





Tour Planning in BLAST

Original Tour

Depart / Arrive	Miles	Minutes	Estimated SOC
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12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:36pm	37.3	41.2	42% → 3%
5:49pm / 6:07pm	13.6	19.0	3% → 0%

Rerouted Tour w/ stop at FC station

Depart / Arrive	Miles	Minutes	Estimated SOC
8:14am / 8:40am	20.0	26.3	100% → 79%
12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:03pm	7.8	8.3	42% → 34%
17 minute FC			
4:20pm / 4:53pm	30.0	32.9	95% → 62%
5:49pm / 6:07pm	13.6	19.0	62% → 49%

All trips in rerouted tour start on time (per original data)

Tour Planning in BLAST

Original Tour

Depart / Arrive	Miles	Minutes	Estimated SOC
8:14am / 8:40am	20.0	26.3	100% → 79%
12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:36pm	37.3	41.2	42% → 3%
5:49pm / 6:07pm	13.6	19.0	3% → 0%

Rerouted Tour w/ stop at FC station

Depart / Arrive	Miles	Minutes	Estimated SOC
8:14am / 8:40am	20.0	26.3	100% → 79%
12:34pm / 1:11pm	35.0	37.0	79% → 42%
3:55pm / 4:03pm	7.8	8.3	42% → 34%
17 minute FC			
4:20pm / 4:53pm	30.0	32.9	95% → 62%
5:49pm / 6:07pm	13.6	19.0	62% → 49%

BLAST records statistics on incremental driving time and distance resulting from rerouting and FC stops

Tour Planning in BLAST

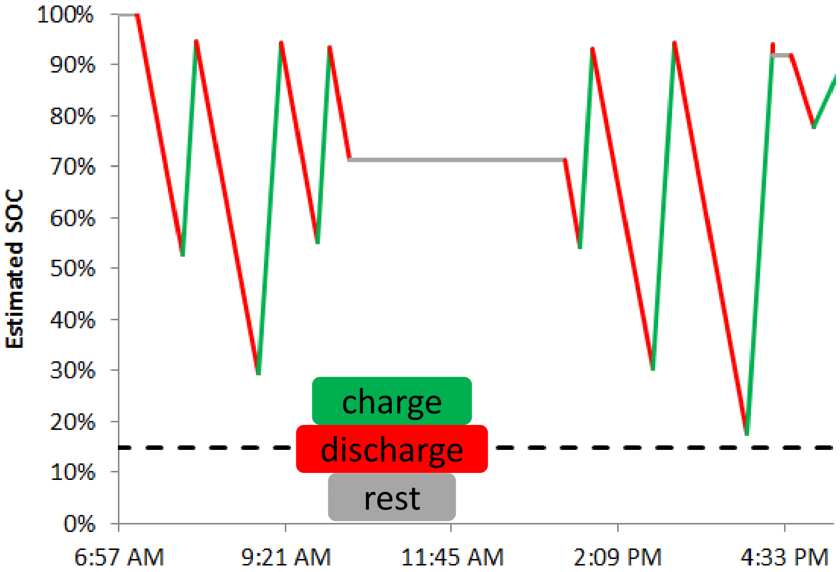
Algorithm can also enable very long tours that require several stops at fast charge stations

Example 3 - Original Tour

Depart / Arrive	Miles	Minutes	Estimated SOC
7:13am / 9:55am	140.1	162.0	100% → 0%
1:23pm / 3:29pm	135.2	125.8	0% → 0%
4:40pm / 5:05pm	13.7	25.6	0% → 0%

Example of a tour between Tacoma, WA and Portland, OR

Tour Planning in BLAST

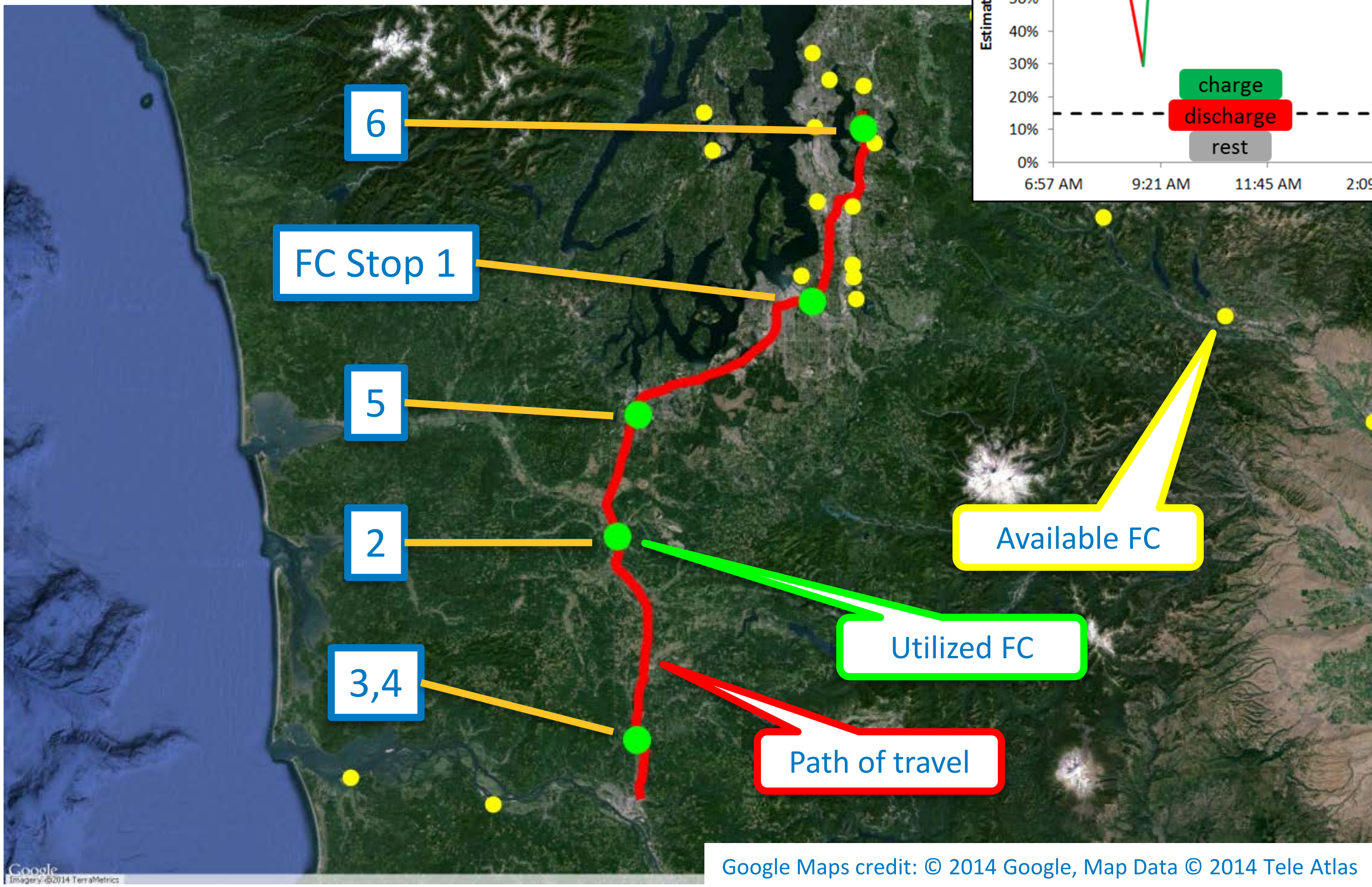


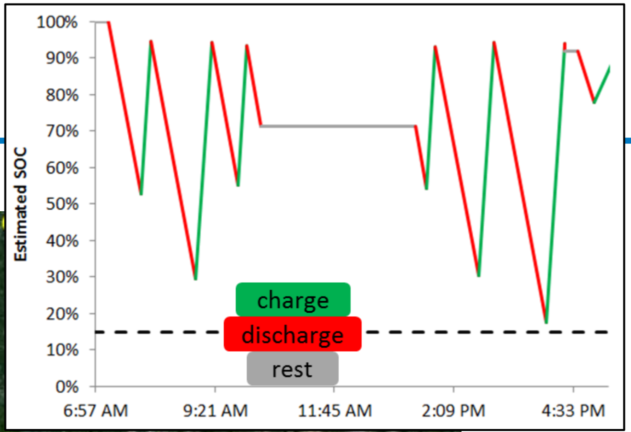
Rerouted Tour w/ stops at FC stations

Depart / Arrive	Miles	Minutes	Estimated SOC
7:13am / 7:52am	39.7	39.1	100% → 53%
12 minute FC			
8:04am / 8:59am	55.9	54.7	95% → 30%
18 minute FC			
9:17am / 9:49am	33.4	31.8	94% → 55%
11 minute FC			
10:00am / 10:17am	18.7	17.3	93% → 71%
1:23pm / 1:37pm	14.3	13.4	71% → 54%
11 minute FC			
1:48pm / 2:40pm	53.9	52.3	93% → 30%
18 minute FC			
2:58pm / 4:02pm	66.0	63.3	94% → 18%
21 minute FC			
4:23pm / 4:24pm	1.5	0.6	94% → 92%
4:40pm / 4:59pm	13.7	19.0	92% → 78%

While such tours are deemed feasible during tour planning, BLAST will additionally evaluate the thermal and life impacts of such an aggressive cycling profile

Tour Planning in BLAST





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*Map does not reflect actual travel data; trip coordinates have been synthesized for illustrative purposes.

Baseline Simulations

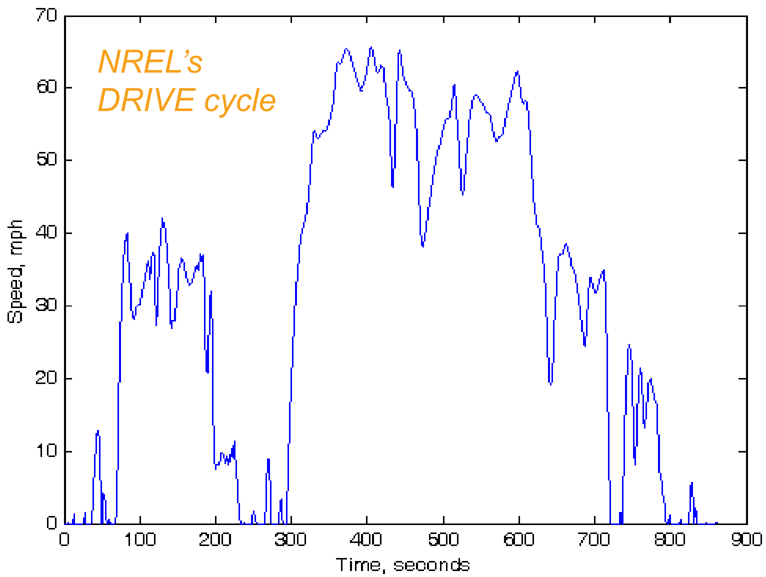
Vehicle Specs, Driving Profiles, & Infrastructure Availability Assumptions

Vehicle Design & Efficiency

- **Employing NREL's DRIVE cycle for real-world efficiency prediction**
  - See Neubauer & Wood, *Accounting for the Variation of Driver Aggression in the Simulation of Conventional and Advanced Vehicles*, SAE 2013 World Congress
  - Note: does not account for grade.

- **Assuming a year 2020 mid-size sedan for the vehicle platform**

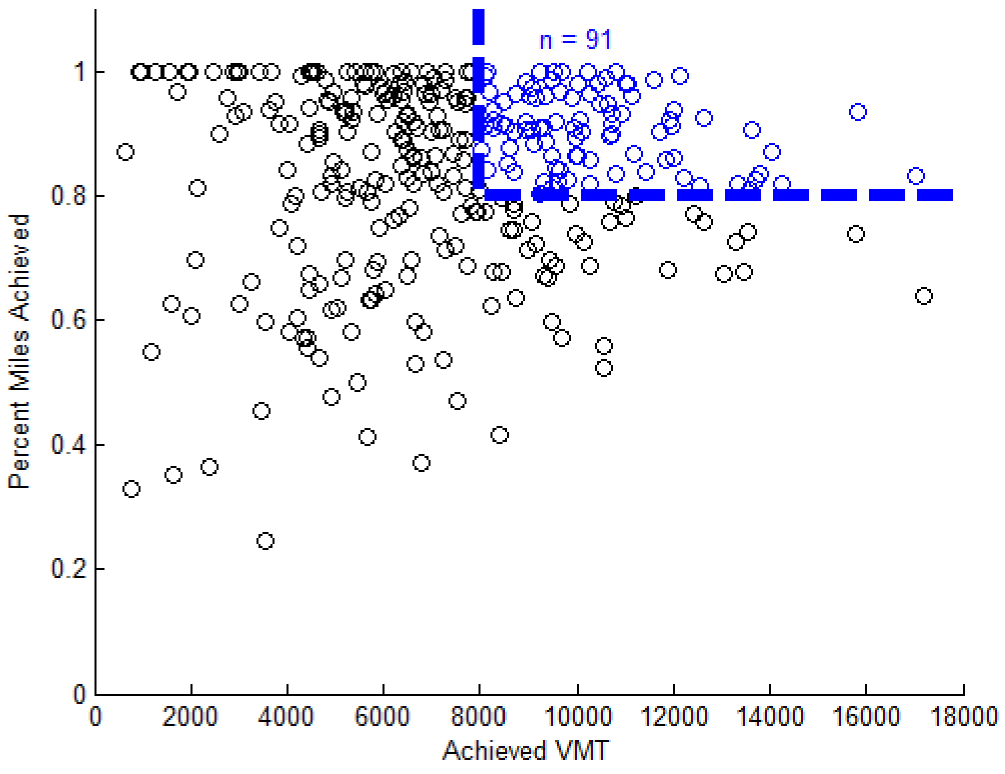
- **Apply FASTSim to design specific drivetrains**
  - NOTE: We apply a 300 W aux load for EPA based sizing, but remove the aux load for DRIVE efficiency calculation. Aux loads are then added as appropriate within the BOM simulations.



Vehicle Model:
9 sec 0-60 mph
75 mile EPA range
22.1 kWh battery
106 kW motor
1576 kg curb weight
220 Wh/mi on DRIVE cycle w/o aux

Real-World Driving Data: Trip Distribution Set A

- **317 vehicle-specific, year-long data records were pulled from the Puget Sound Regional Councils Traffic Choices Study**
  - Records selected based on availability of 365 consecutive days of data without significant error
- **Not all drivers are likely to purchase BEVs; total mileage and percent-achievable mileage may be good indicators of likely BEV drivers**
- **We chose to analyze drive patterns that meet the following criteria:**
  - 80% of their year-one driving is achievable with the BEV *without infrastructure support*
  - More than 8,000 miles are achieved with the BEV in year one
- **With these criteria, 91 of 317 (29%) drivers were selected as stand-alone BEV drivers (shown in blue).**

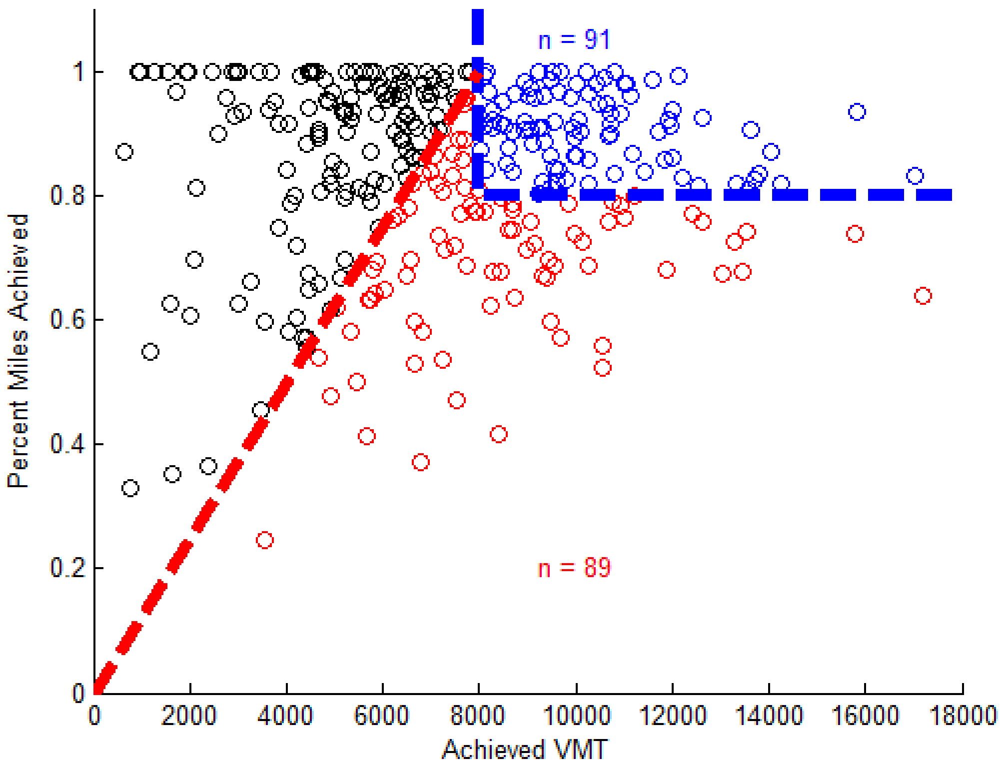


Real-World Driving Data: Trip Distribution Set B

- **The previous 80% utility factor counts out some high mileage drivers that could benefit from infrastructure**

- **We therefore created and added a second set of drive patterns that met the following criteria:**
  - Not included in Set A
  - More than 8,000 miles per year are driven with a CV

- **With these criteria, an additional 89 of 317 (28%) drivers were selected (shown in red).**



Baseline EVSE Scenario

- **For analysis of fast charging impact on batteries, it was necessary to select a baseline public infrastructure scenario**
- **The Pacific Northwest has fairly good geographic coverage of existing FC stations already in the ground**
    - 34 existing FC stations in Washington State

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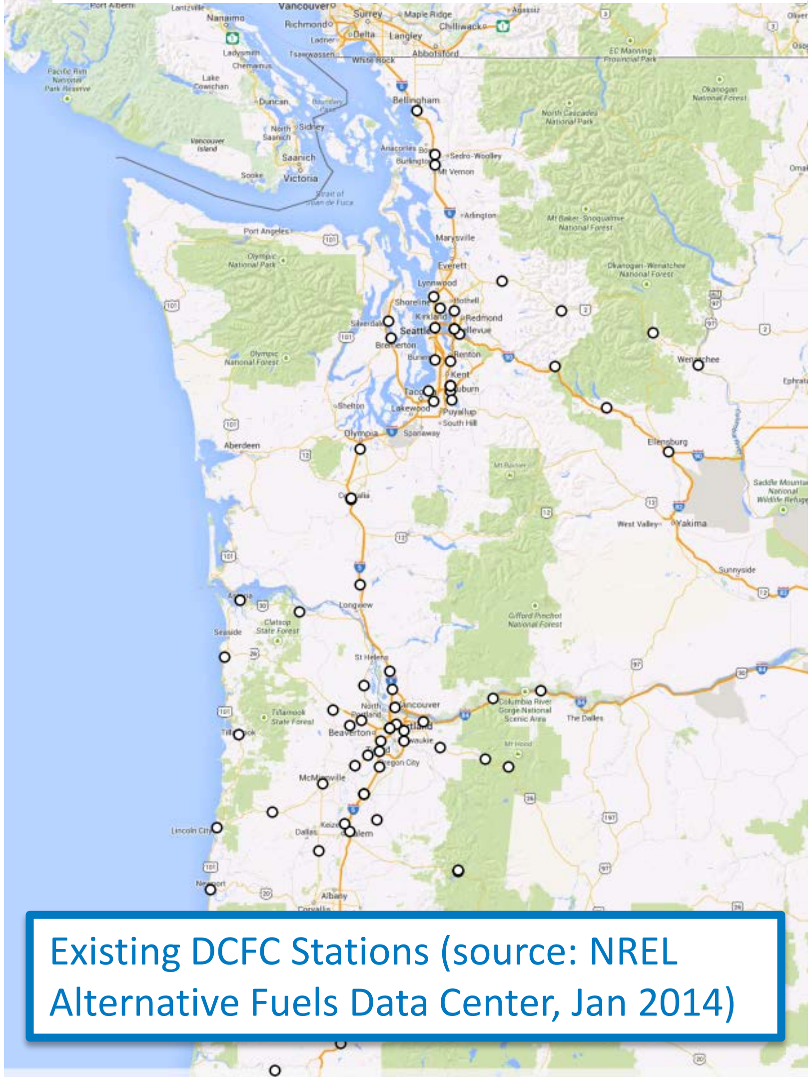
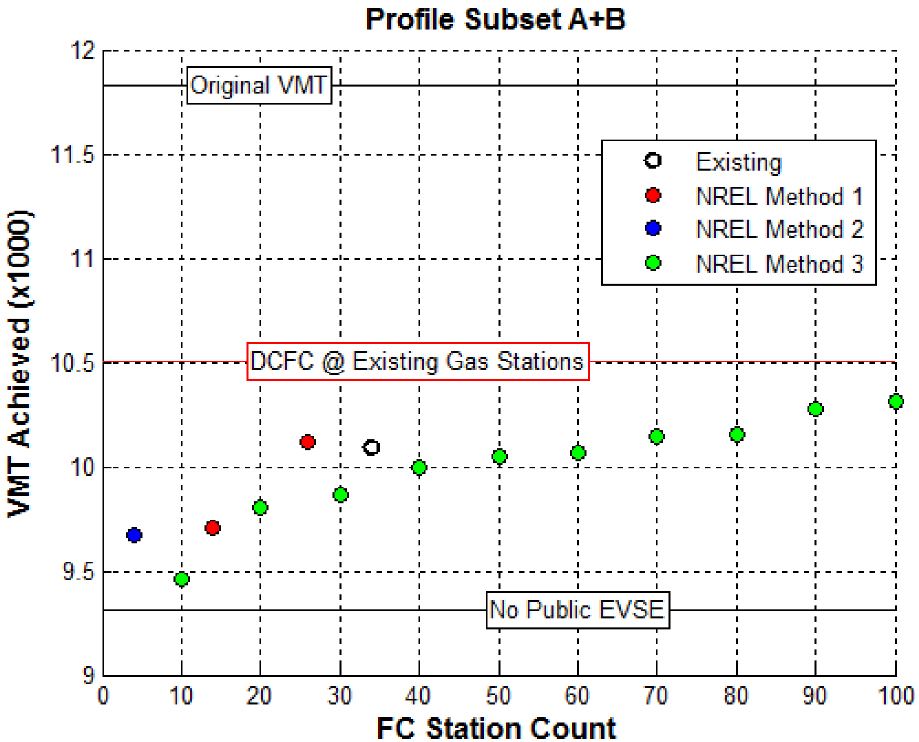


Existing DCFC Stations (source: NREL Alternative Fuels Data Center, Jan 2014)

Baseline EVSE Scenario

- **Incremental utility afforded by existing FC stations was compared to a number of artificial rollouts**
- **Found existing infrastructure scenario to be sufficient at improving BEV utility with a relatively small number of stations**



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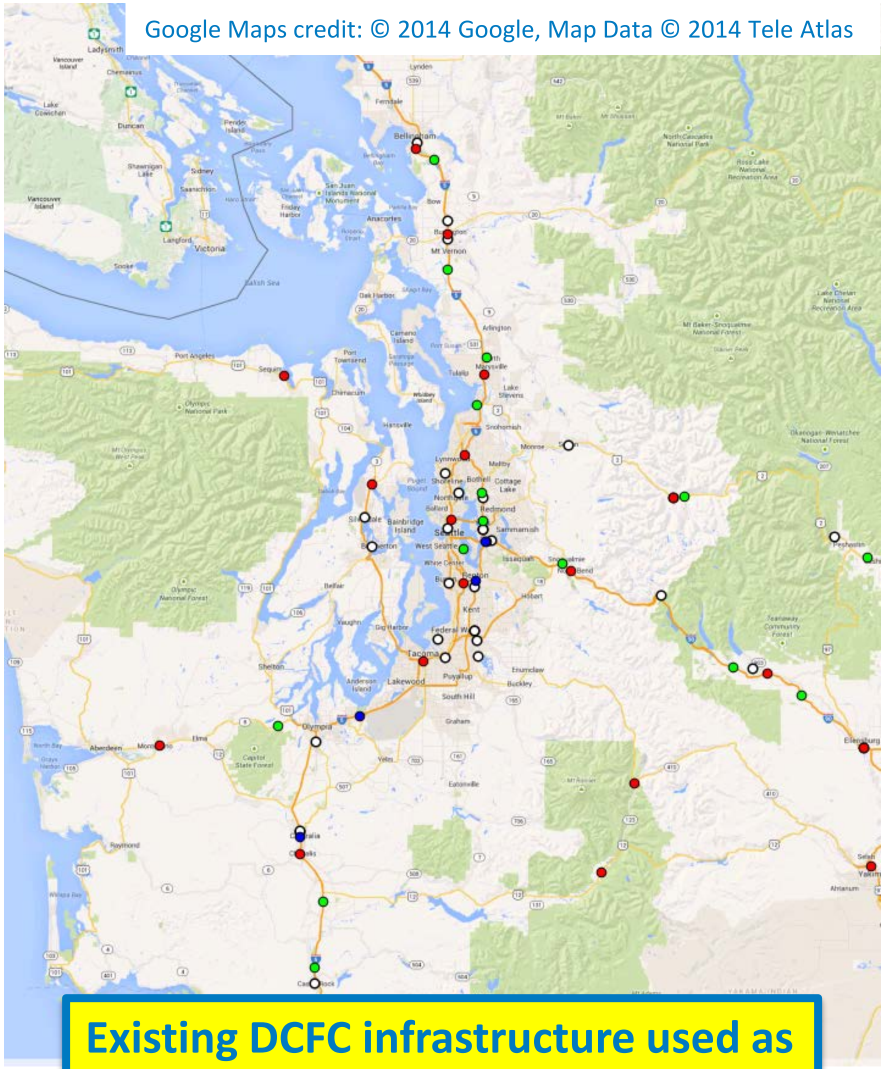


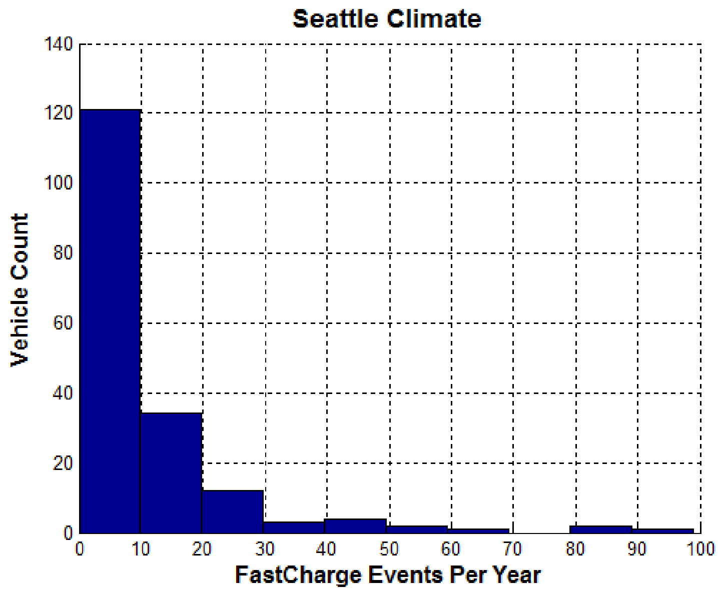
Existing DCFC infrastructure used as default for remainder of analysis

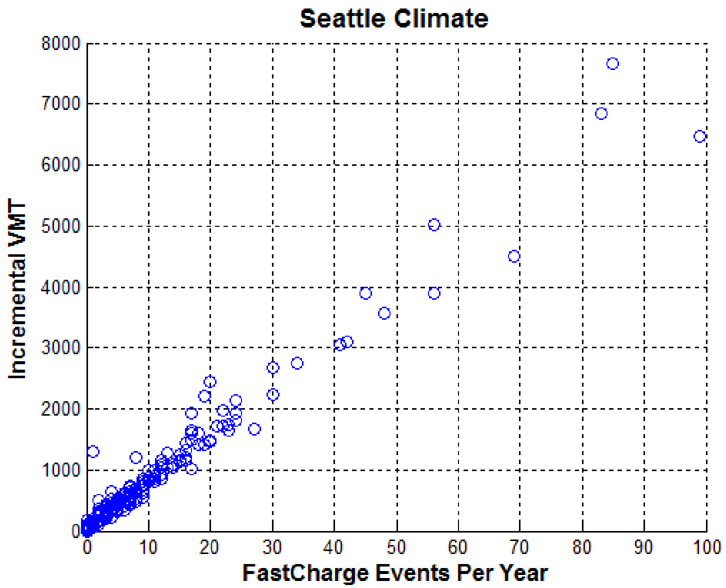
Baseline Simulations

Compare Simulated Fast Charger Utilization to Real-World Data

FC Utilization & Validation

- **Average driver utilized FC 10 times in first year of life**
  - Extreme case driver utilized FC at an average rate of 8 times a month
- **FC utilization correlates well with incremental VMT**
- **Some drivers complete 100% of travel w/o need for FC**

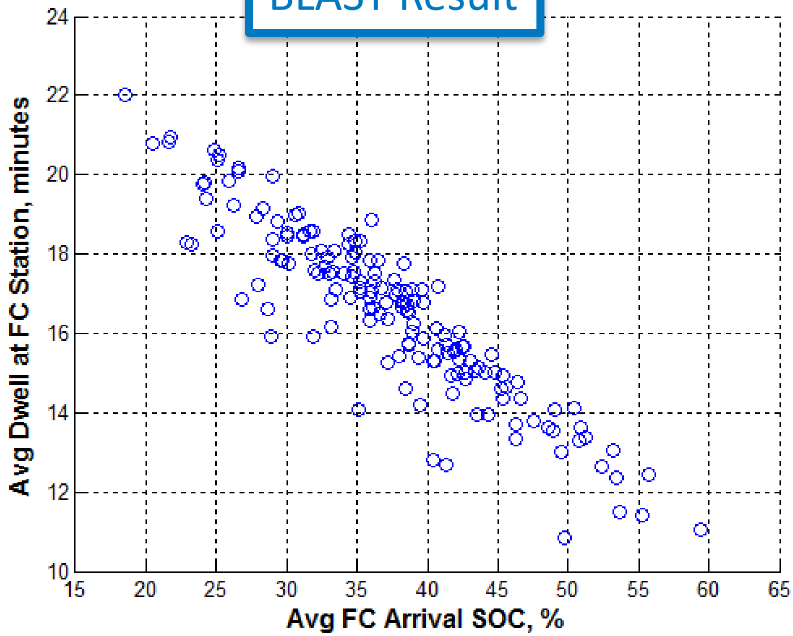




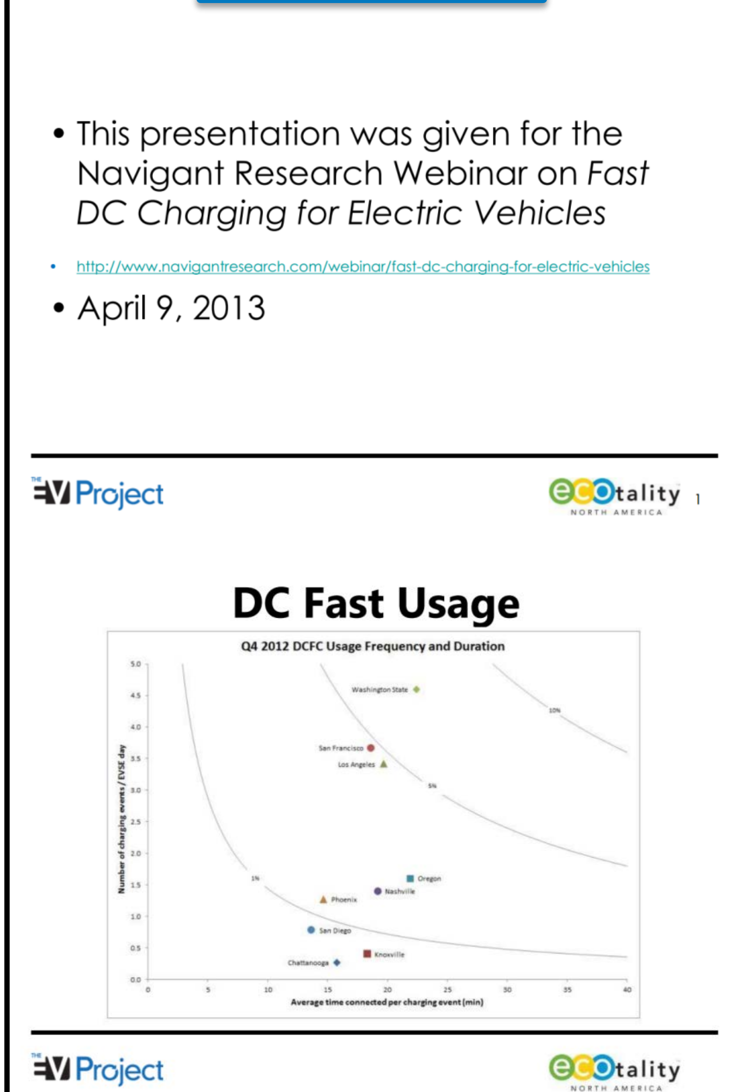
FC Utilization & Validation

- **BLAST runs reveal average FC connection times of 10-22 minutes**
  - Dependent on arrival SOC
- **EV Project data indicated average FC connection times of 14-24 minutes**

BLAST Result

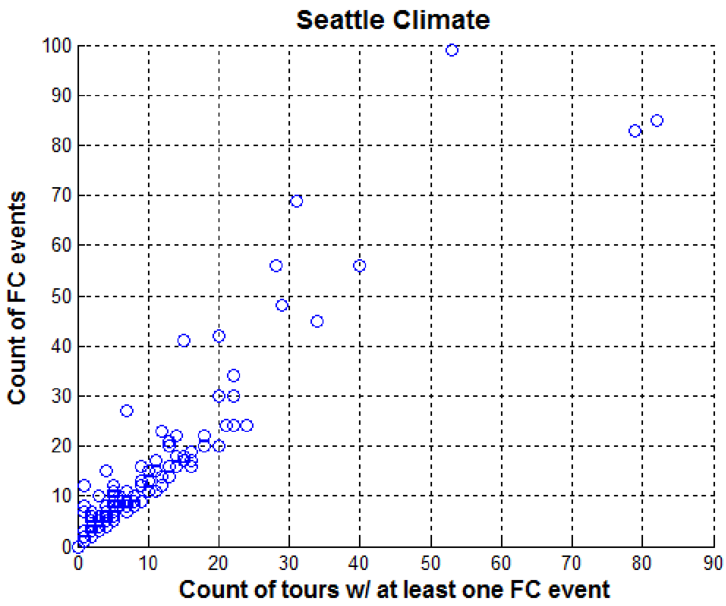


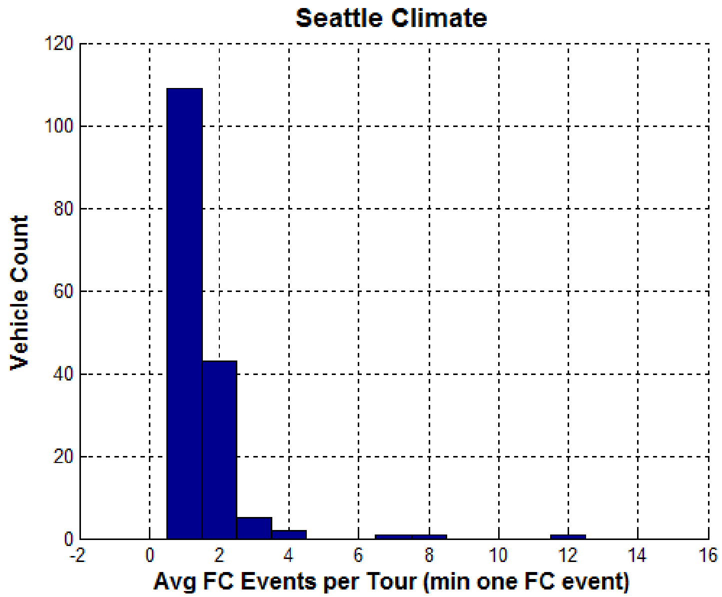
EV Project Data



FC Utilization & Validation

- **BLAST predicts the majority of tours enabled by fast charging to require 1-2 FC events**
- **One outlying vehicle utilized fast charging 12 times on its average FC-enabled tour**

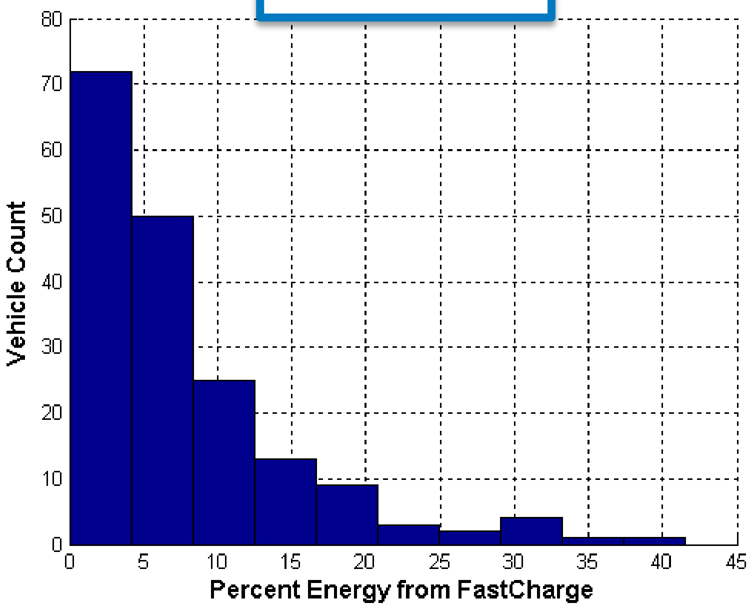




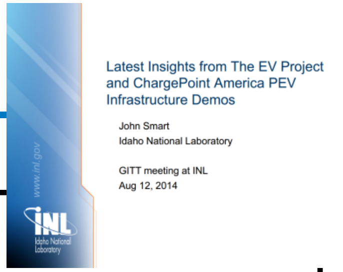
FC Utilization & Validation

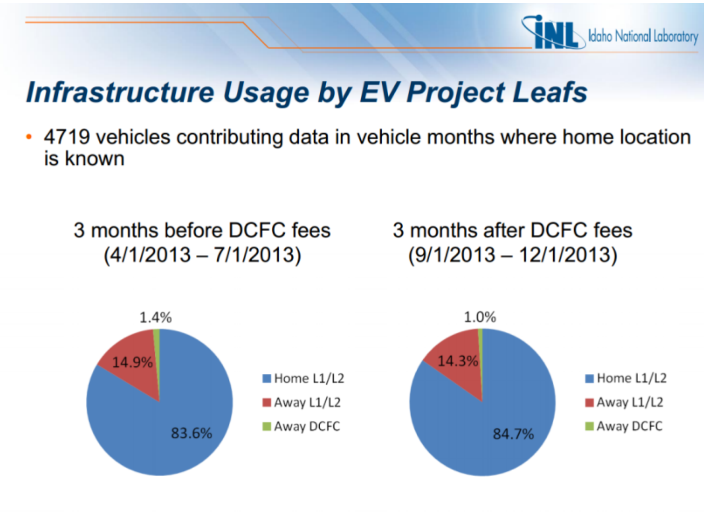
- **BLAST aggregates charge energy by location**
- **Group all FC locations together and average driver receives 7.6% of energy from fast charging**
  - Max: 41.5%
  - Min 0.0%
- **EV Project reports fast charges accounting for 1-21% of all charge events for Nissan Leaf's under study that frequently used fast chargers**
  - Where a cost for fast charging was present, **8%** of charging energy came from fast charging for Nissan Leaf's under study

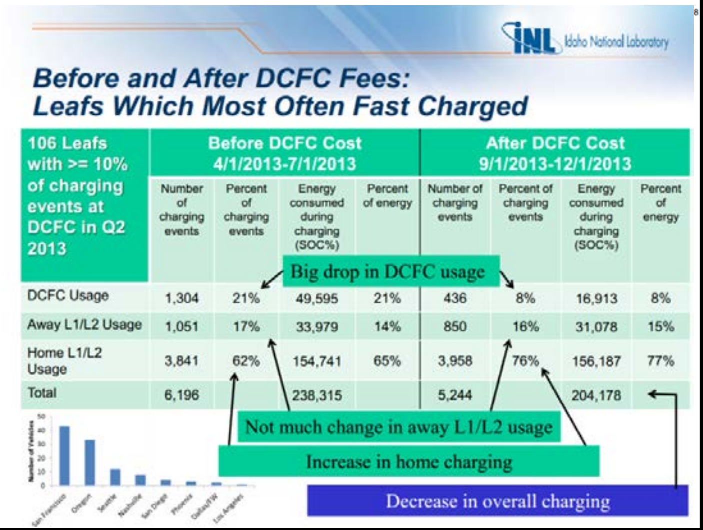
BLAST Result



EV Project Data







Before and After DCFC Fees: Leafs Which Most Often Fast Charged

106 Leafs with >= 10% of charging events at DCFC in Q2 2013	Before DCFC Cost 4/1/2013-7/1/2013				After DCFC Cost 9/1/2013-12/1/2013			
	Number of charging events	Percent of charging events	Energy consumed during charging (SOC%)	Percent of energy	Number of charging events	Percent of charging events	Energy consumed during charging (SOC%)	Percent of energy
DCFC Usage	1,304	21%	49,595	21%	436	8%	16,913	8%
Away L1/L2 Usage	1,051	17%	33,979	14%	850	16%	31,078	15%
Home L1/L2 Usage	3,841	62%	154,741	65%	3,958	76%	156,187	77%
Total	6,196		238,315		5,244		204,178	

Big drop in DCFC usage

Not much change in away L1/L2 usage

Increase in home charging

Decrease in overall charging

Fast charge impact analysis

Evaluate impact of fast charging on battery packs under three thermal management scenarios

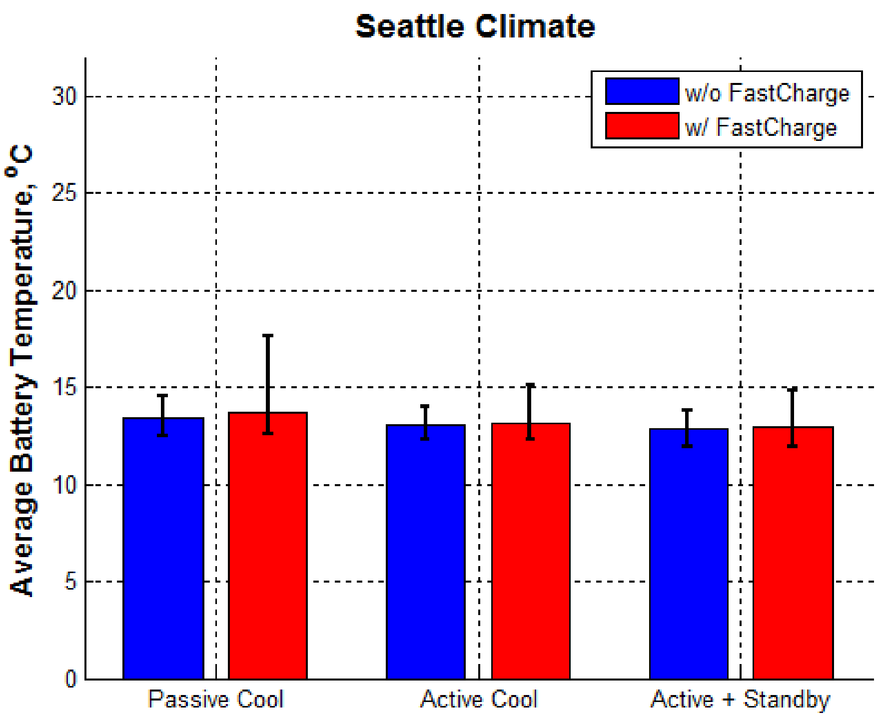
Simulation Sweep

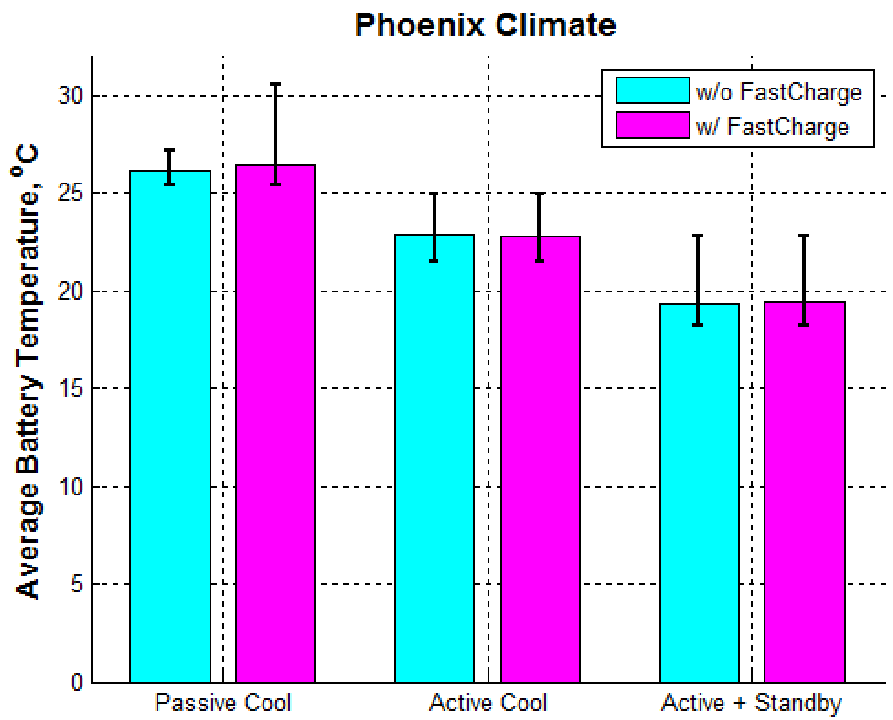
- **Perform 10 years of battery simulations for 180 driving profiles given…**
  - EVSE:
    - L2 home charging
    - L2 home charging + present day FC station availability
  - Climate:
    - Seattle (coincident with travel data)
    - Phoenix (worst case thermal management)
  - Battery Thermal Management System:
    - Passive cooling
    - High-power liquid cooling (active only when driving)
    - High-power liquid cooling (active when driving & charging)

Results: Average Battery Temp

- **In Seattle, neither average FC utilization rates nor increased levels of pack cooling capability significantly impacted average battery temperature**
    - Exception: Drivers with very high FC utilization saw slightly elevated impact

- **However, subject to a Phoenix climate, we begin to see the impacts of aggressive battery cooling systems on average battery temperatures**

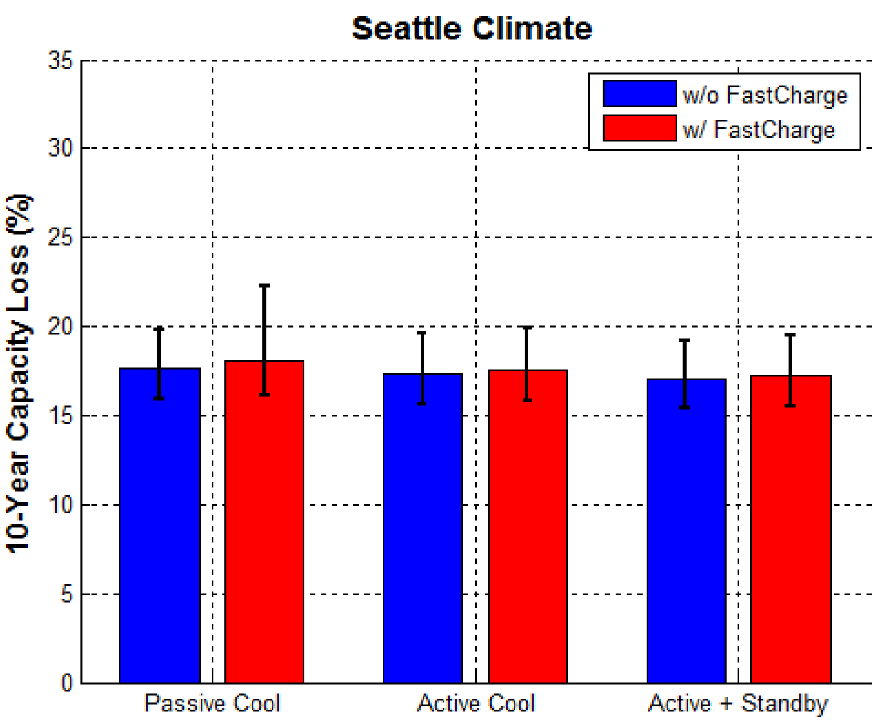


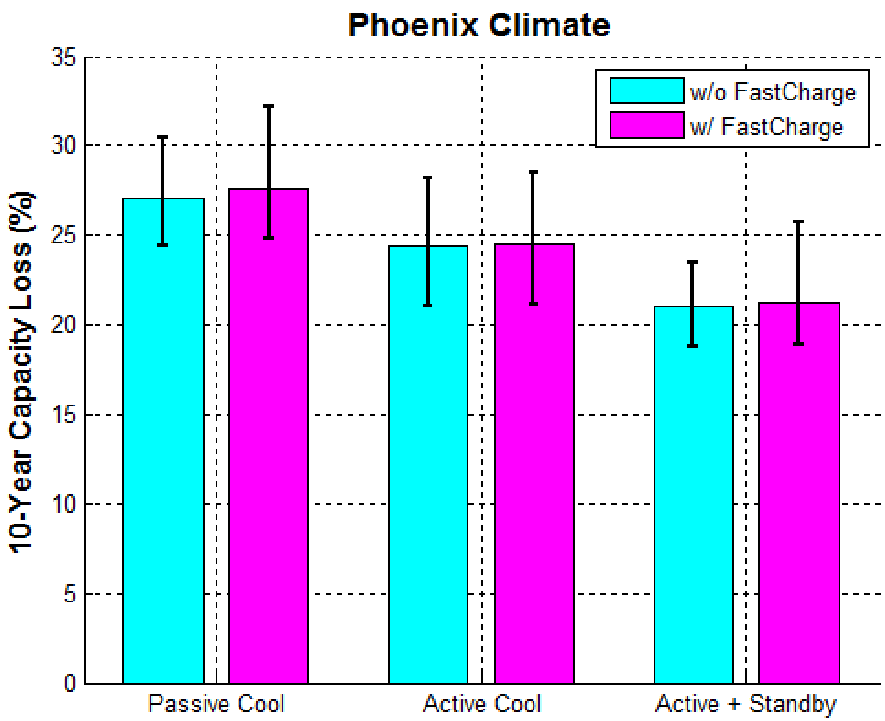


Bar = average across 180 driving profiles; Whiskers = max/min value across 180 driving profiles

Results: Battery Life

- **Correlating well with average battery temperature trends, battery degradation is largely unaffected by fast charging and battery cooling systems in the Seattle climate, but is strongly affected by battery cooling systems in the Phoenix climate**
  - 10-year capacity fade reduces from ~28% to ~21% in the presence of active cooling during driving and charging





Bar = average across 180 driving profiles; Whiskers = max/min value across 180 driving profiles

Real-World Comparison

- **Compare INL field study with BLAST simulations from Phoenix with fast charging and passive battery cooling**

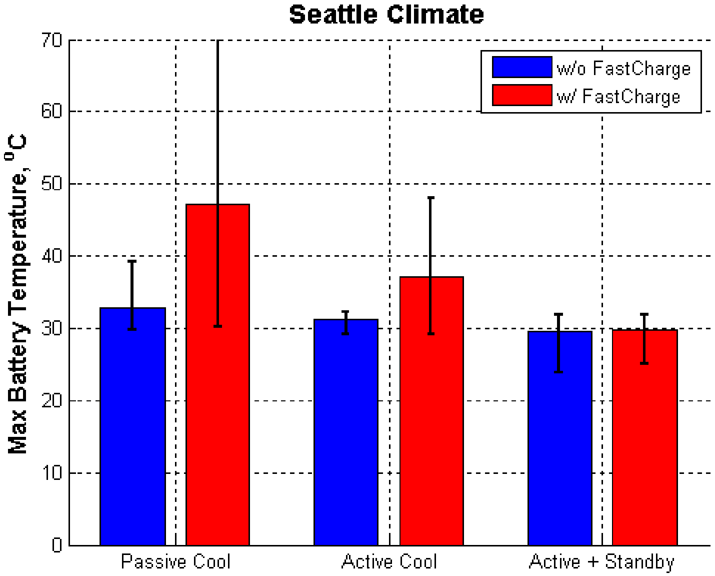
	Years	Odometer Avg, mi	Avg FC Events	Avg Capacity Loss w/o FC	Avg Capacity Loss w/ FC
INL Field Test	1.5	50,000	526	24.8%	27.4%
BLAST Simulation	10	97,157	155	27.0%	27.6%

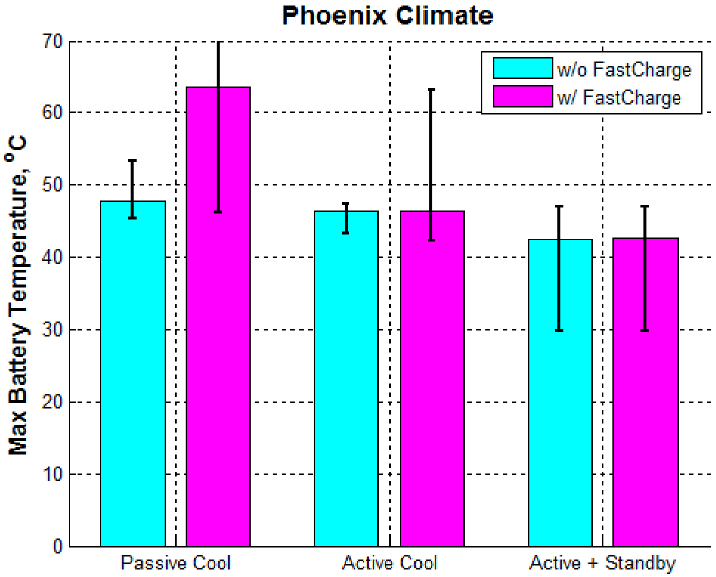
- **While experimental and simulated conditions differ in terms of duration, mileage, and fast charge utilization, the common outcome is that fast charging has a relatively minor impact on battery life in both cases**

Results: Battery Max Temp

- **Impact of FC was most observable in maximum pack temperatures from passively cooled packs**
  - Back-to-back sequencing of drive-FC-drive produces significant heat generation resulting in dangerous thermal conditions

- **Simulated packs with aggressive cooling systems were able to mitigate heat generation on FC tours and maintain safe thermal conditions**





Bar = average across 180 driving profiles
Whiskers = max/min value across 180 driving profiles

Fast charge impact analysis

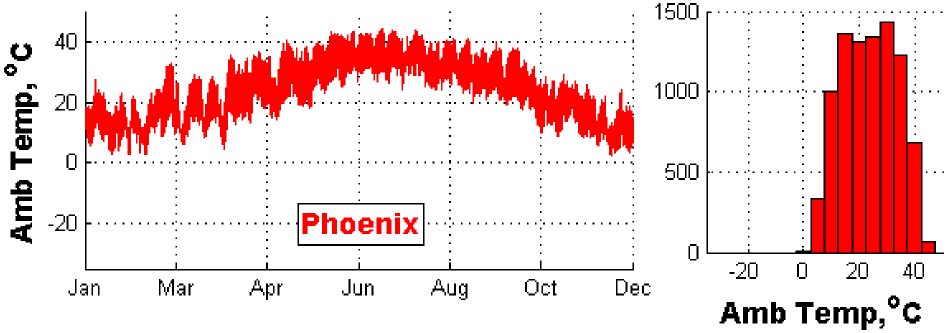
Consider cell heterogeneity in a hot climate subject to fast charging

Model Parameters

- **Consider identical vehicle model from previous section with the pack disaggregated into individual cell models with distinct characteristics**

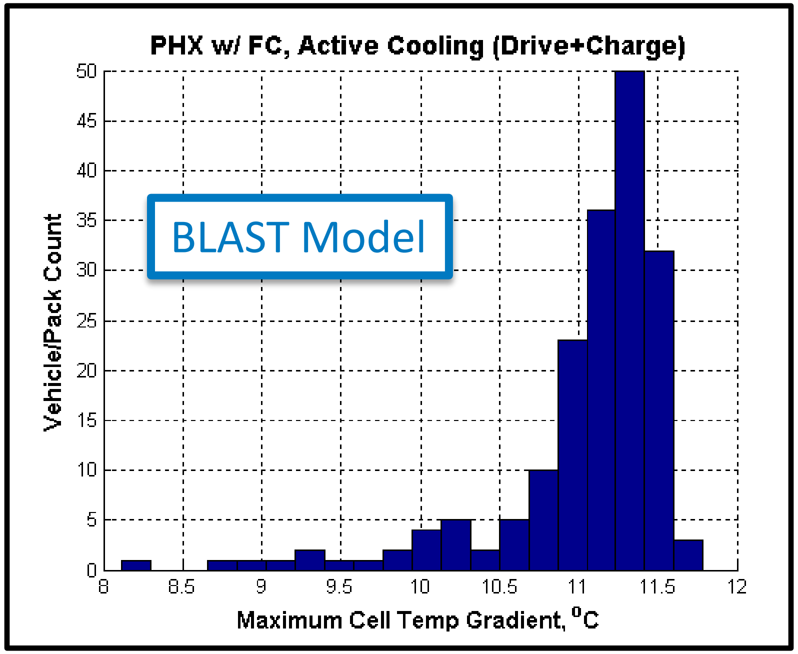
Vehicle Model:	**Battery Model:**
9 sec 0-60 mph	100S1P configuration
75 mile EPA range	±2% BOL capacity variation
22.1 kWh battery	±5% BOL internal resistance variation
106 kW motor	±10% life coefficient variation
1576 kg curb weight	3 node thermal model
220 Wh/mi on DRIVE cycle w/o aux	Active cooling BTMS (drive+charge)

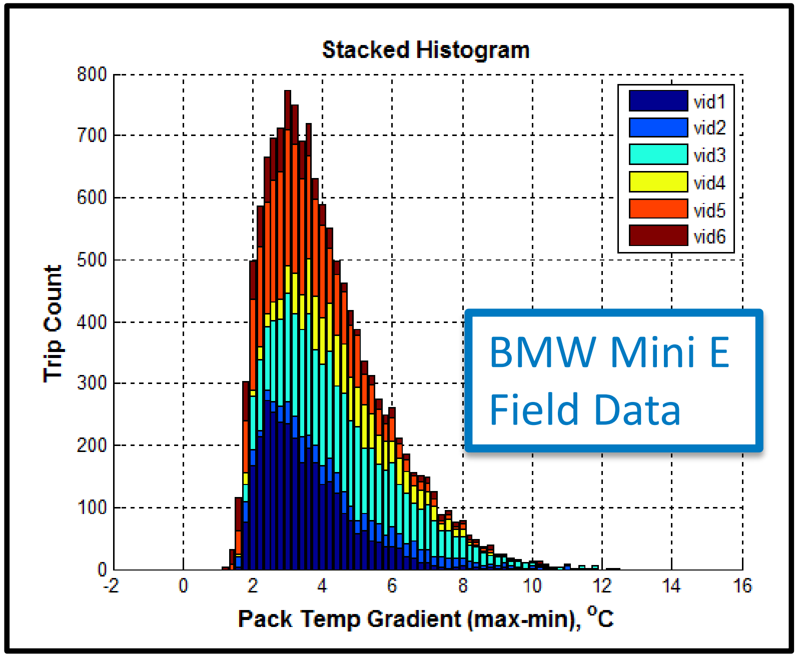
- **Simulate 10 years life in Phoenix subject to as-necessary fast charging**



Pack Thermal Gradients

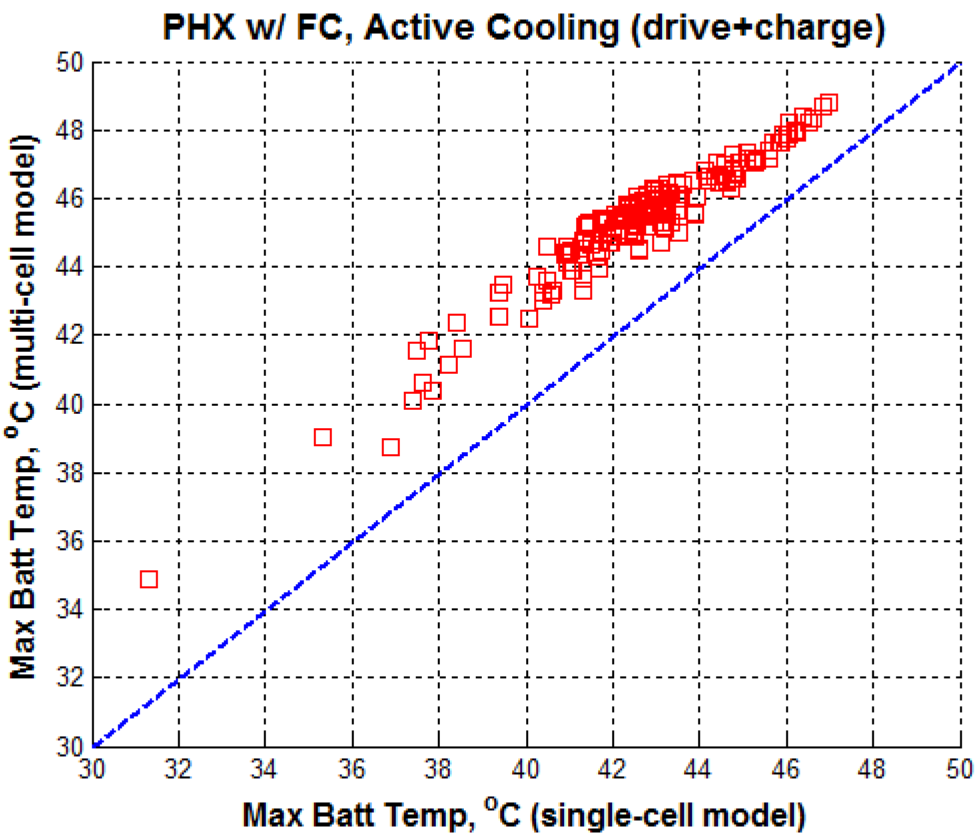
- BLAST simulations resulted in maximum cell-to-cell temperature variation of 11°C on average
- Modeled behavior compares favorably with small field dataset collected by BMW on the Mini E platform

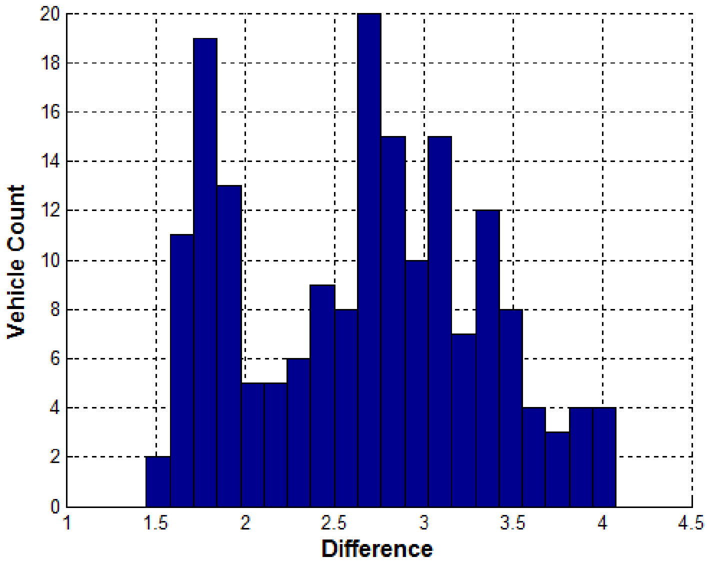




Value of Multi-cell Thermal Model

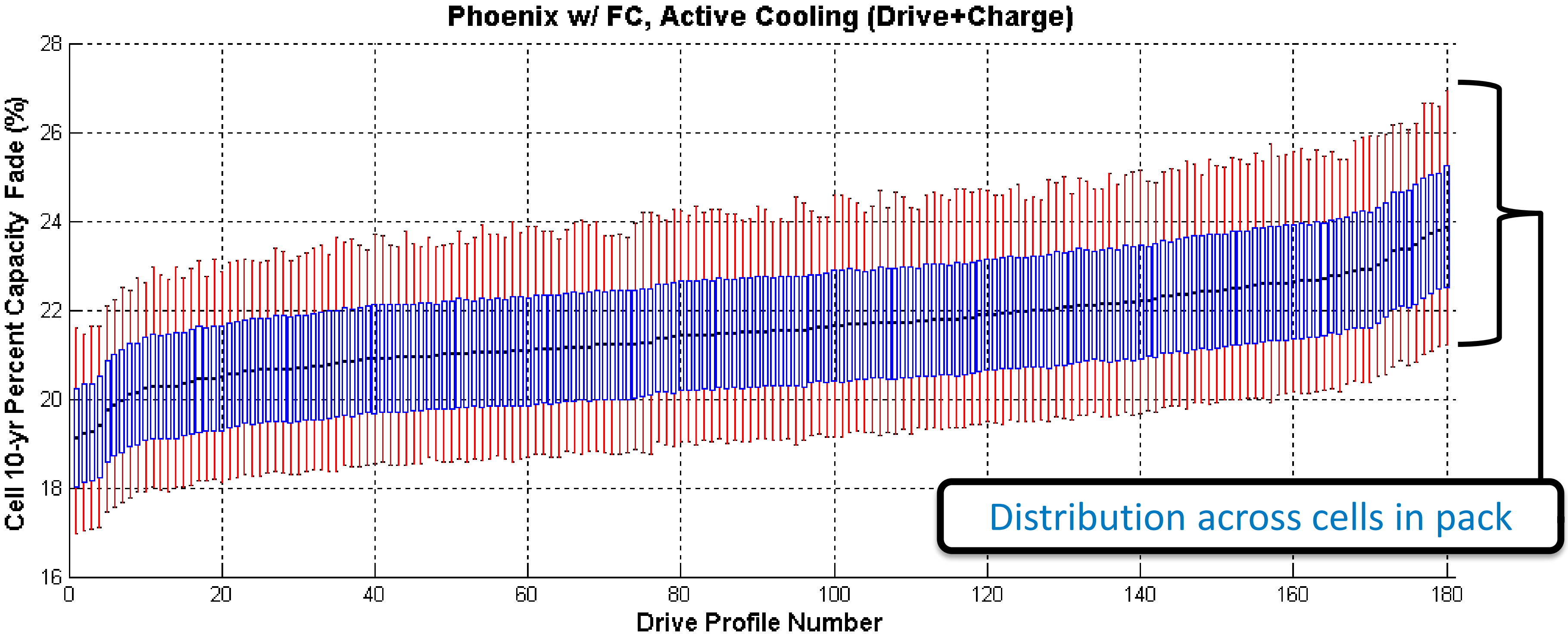
- **Multi-cell modeling predicts peak temperatures 1.5°C to 4°C warmer than single-cell model**





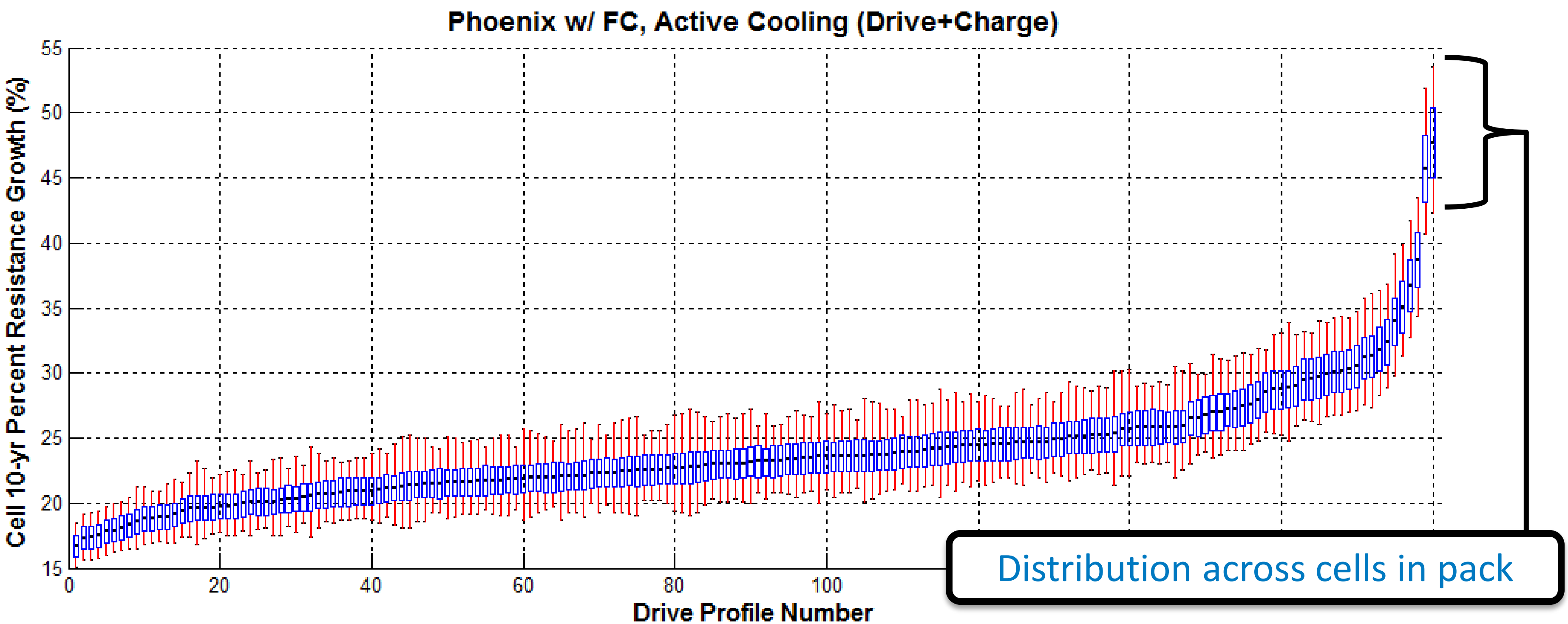
Capacity Loss Results

- **Average cells lost 19% to 24% of BOL capacity**
  - Best case vehicle/cell combination lost 17% BOL capacity
  - Worst case vehicle/cell combination lost 27% BOL capacity
- **Difference in capacity across cells in a pack is typically ~5%**
- **Capturing minimum cell capacity is important, as this is what will limit range and vehicle utility without advanced balancing**



Resistance Growth Results

- **Average cells saw 17% to 48% resistance growth**
  - Best case vehicle/cell combination saw 15% resistance growth
  - Worst case vehicle/cell combination saw 54% resistance growth
- **Difference in resistance across cells in a pack is typically ~6%**
- **Capturing maximum cell resistance is important, as this is what will limit power (in combination with thermal gradient) without advanced balancing**



Fast charge impact analysis

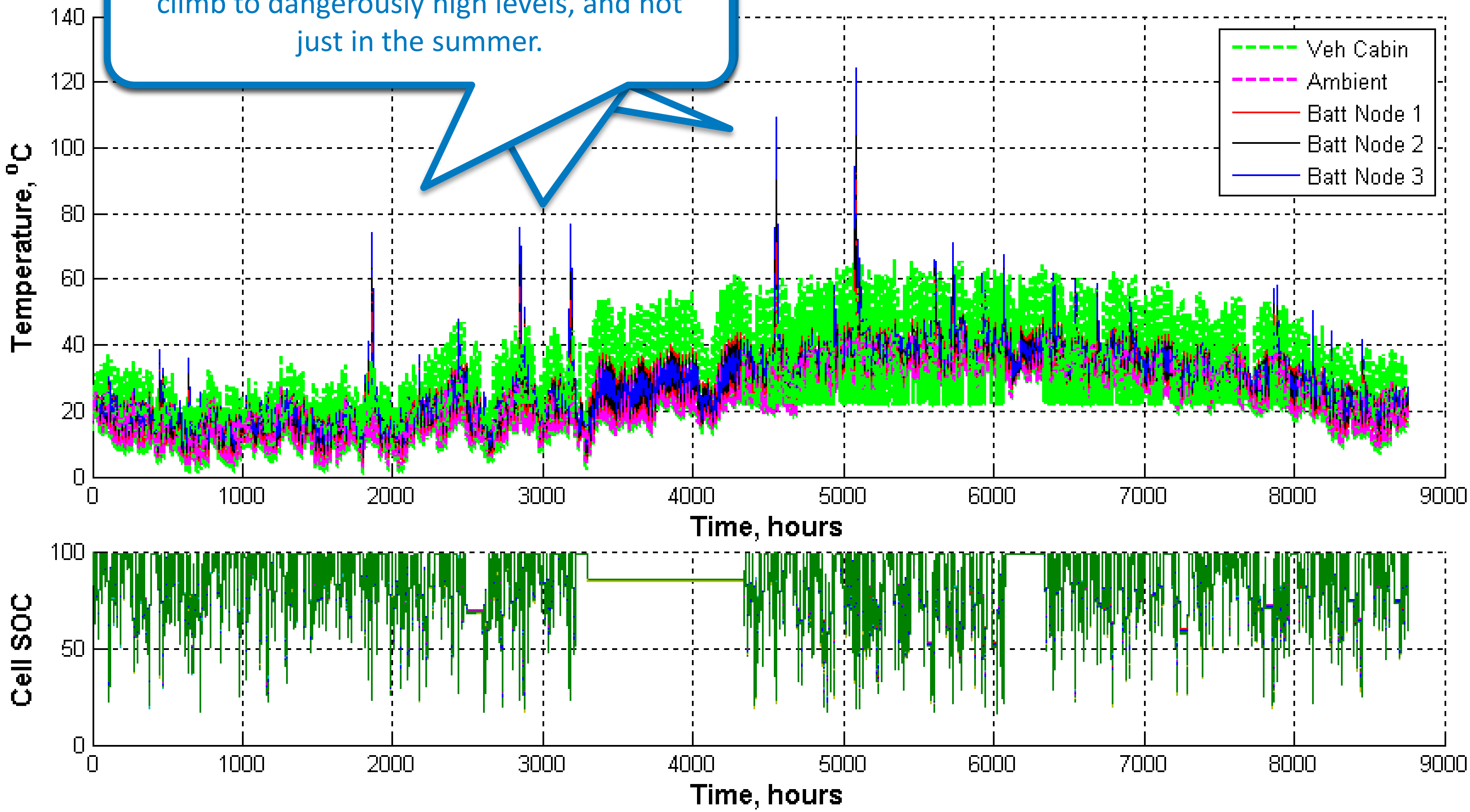
A closer look at how fast charging impacts max battery temperatures

Example Vehicle: Full Year

Passive Battery Cooling

Thermal history of battery w/ passive cooling and fast charging

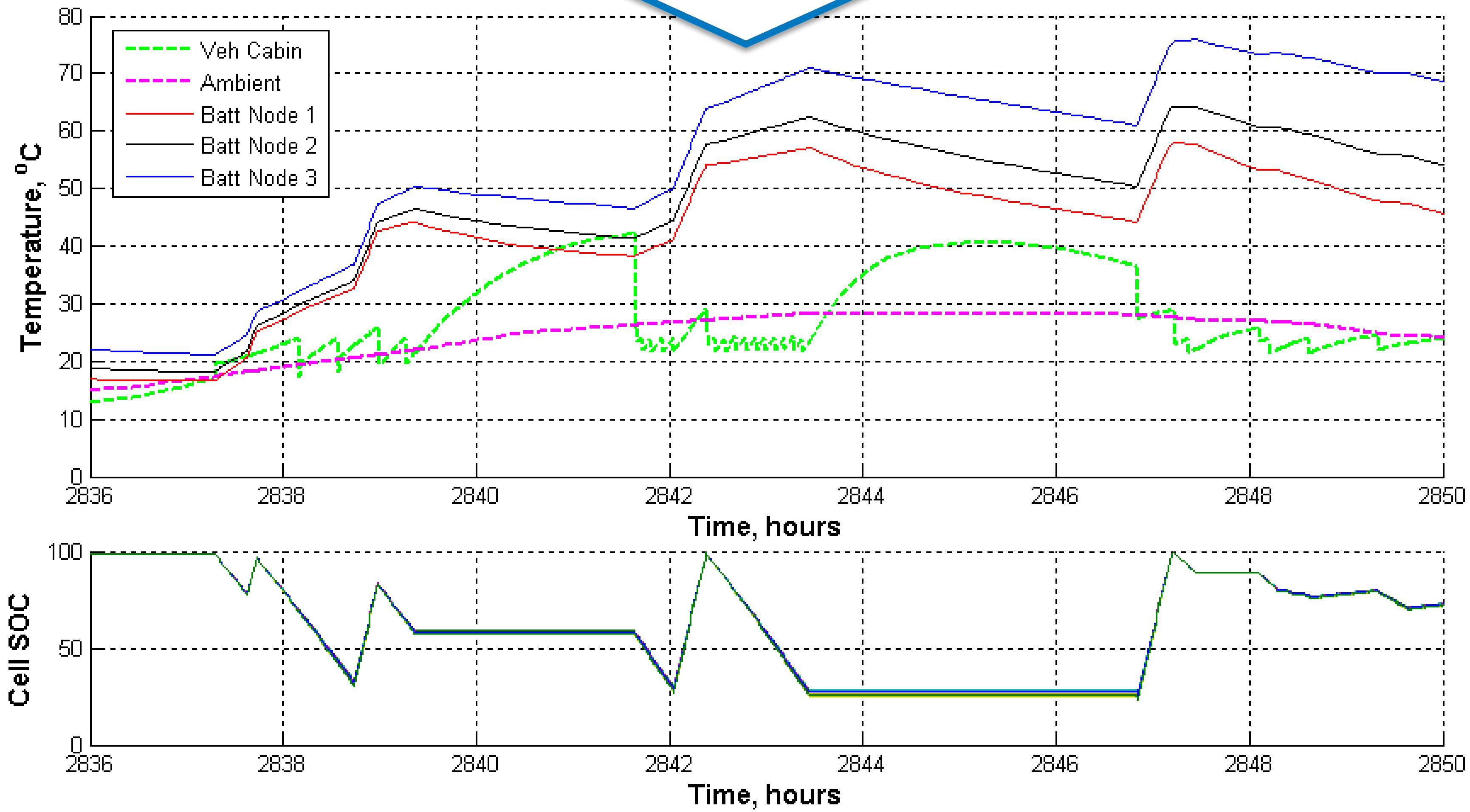
On multiple occasions, pack temperatures climb to dangerously high levels, and not just in the summer.



Example Vehicle: Half Day

Passive Battery Cooling

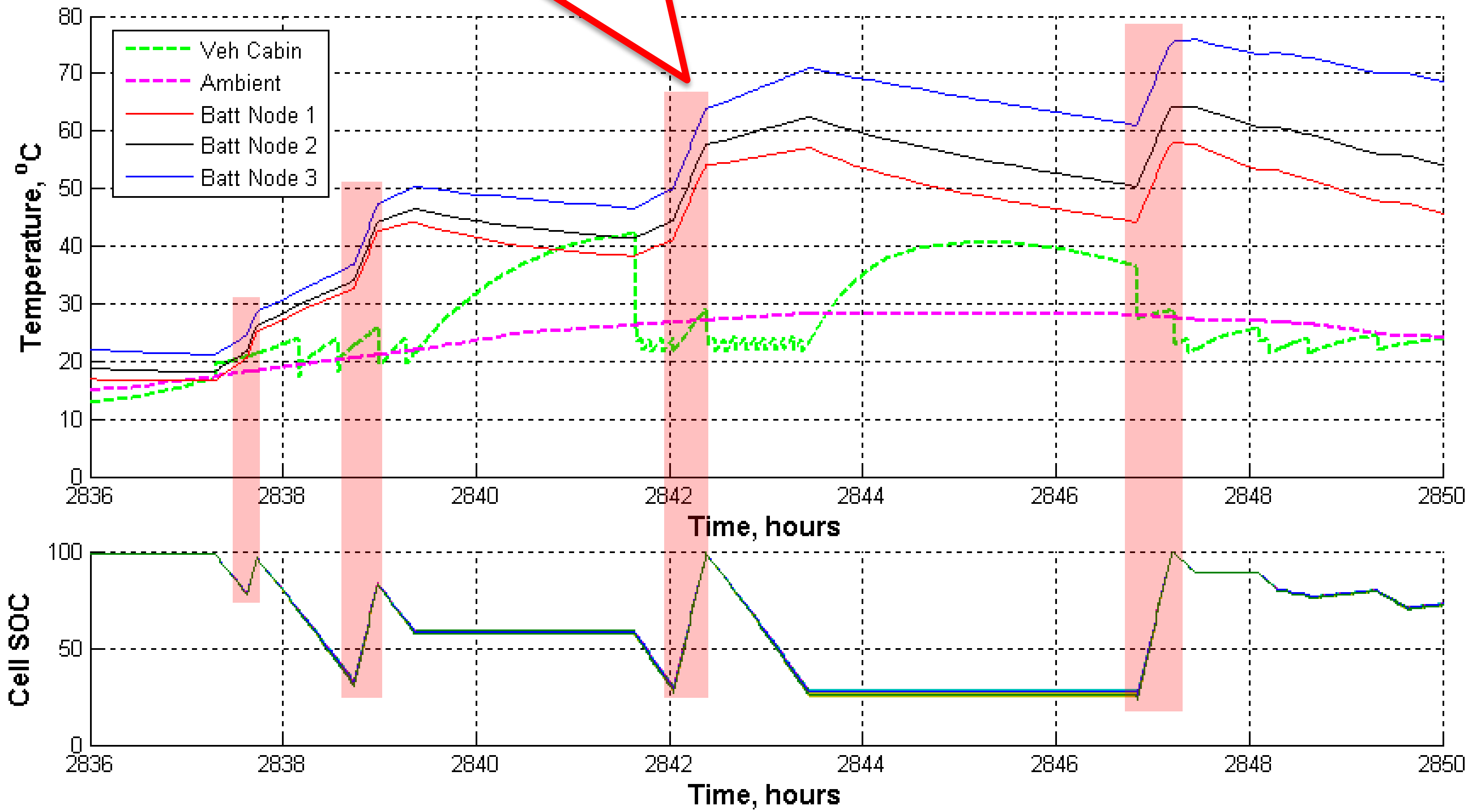
Zoom in on these temperature peaks and we find sequences of multiple back-to-back drive-then-fast-charge-then-drive-again events (4 fast charge events in <12 hours)



Example Vehicle: Half Day

Passive Battery Cooling

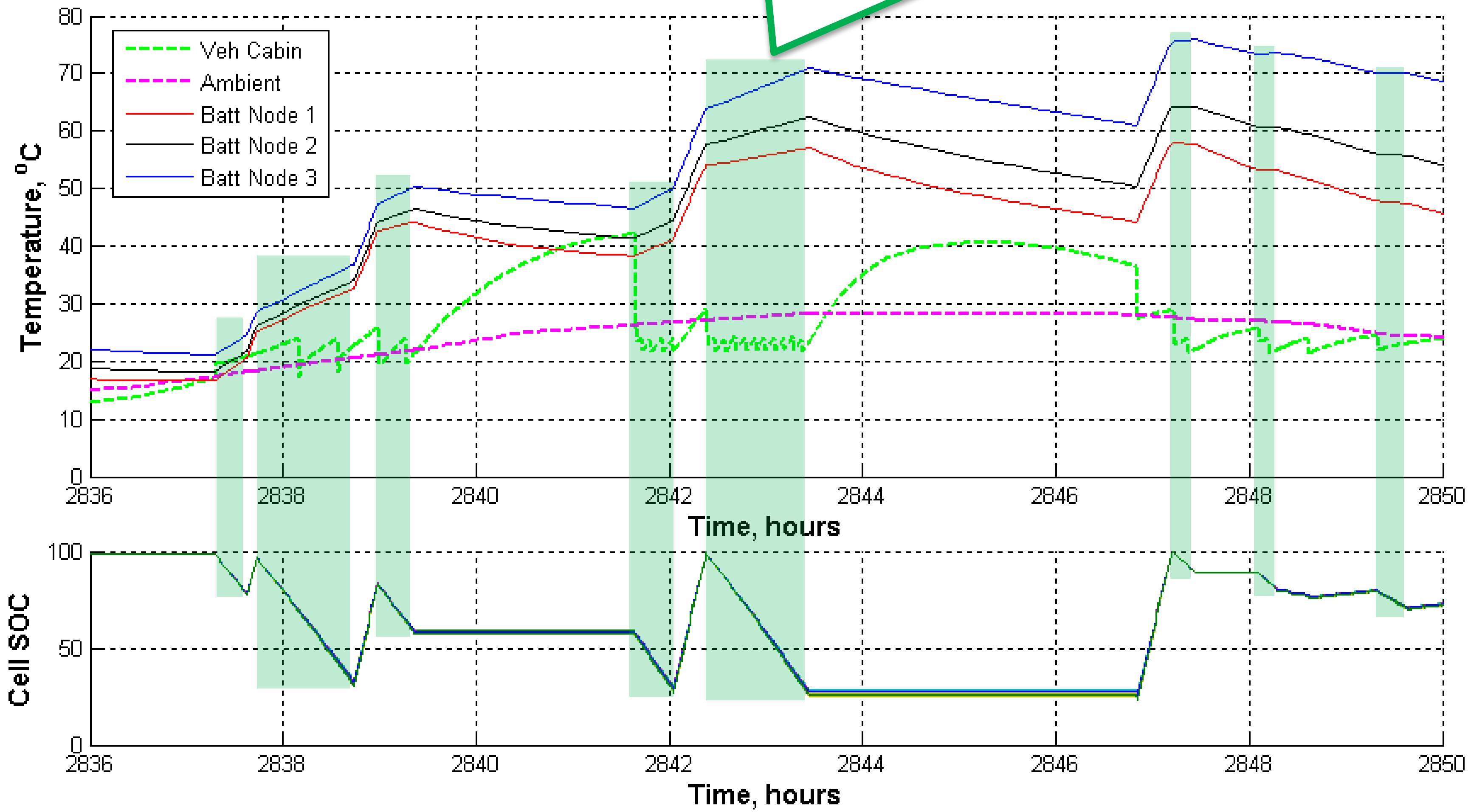
Large amount of battery internal heat generation during fast charge events



Example Vehicle: Half Day

Passive Battery Cooling

Heat generation during driving also plays a big role.
These are “fast charge enabled” miles

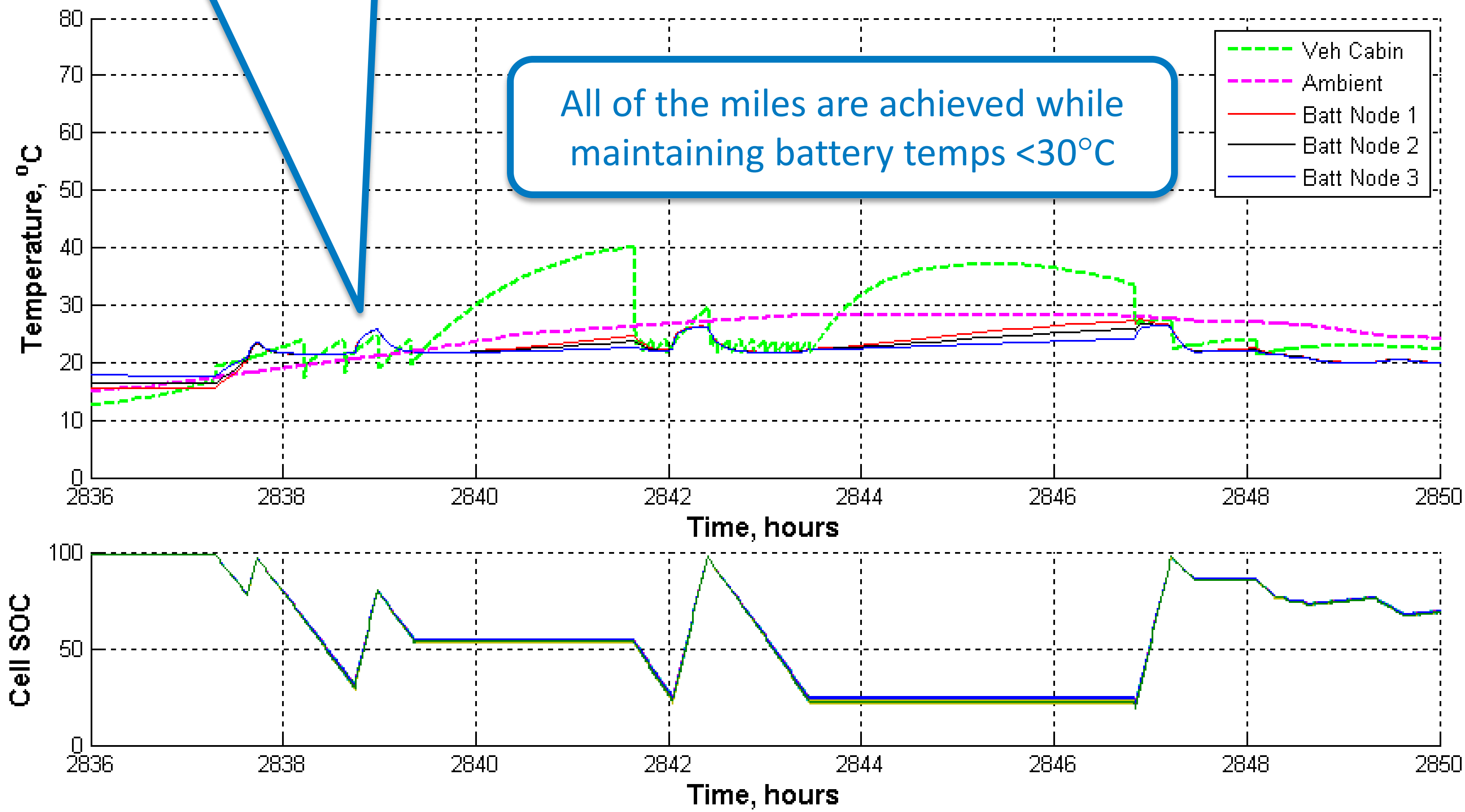


Example Vehicle: Half Day

Active Battery Cooling

Consider the same profile w/ active battery cooling and fast charging

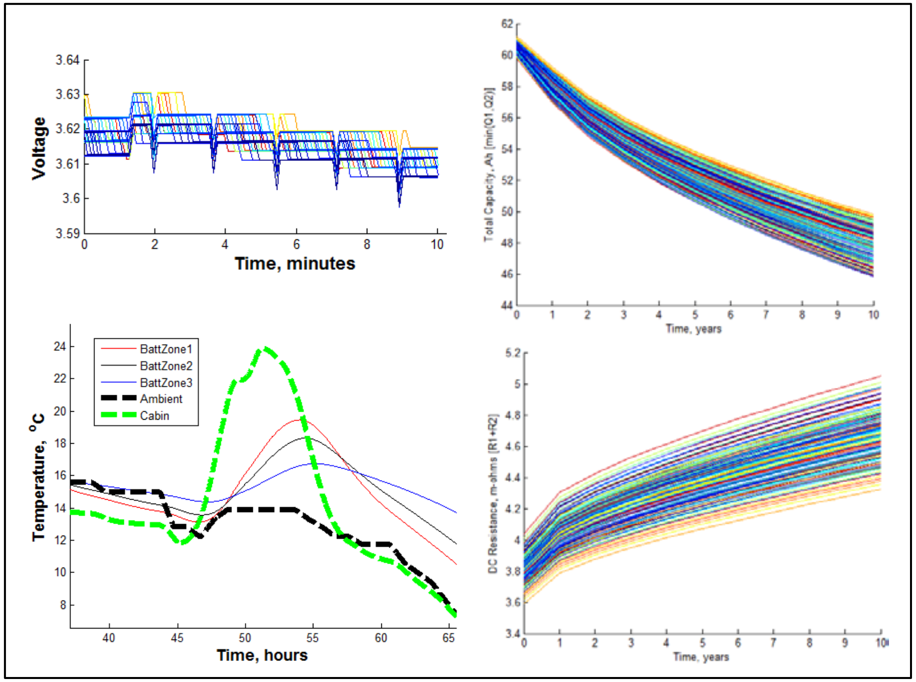
All of the miles are achieved while maintaining battery temps <30°C

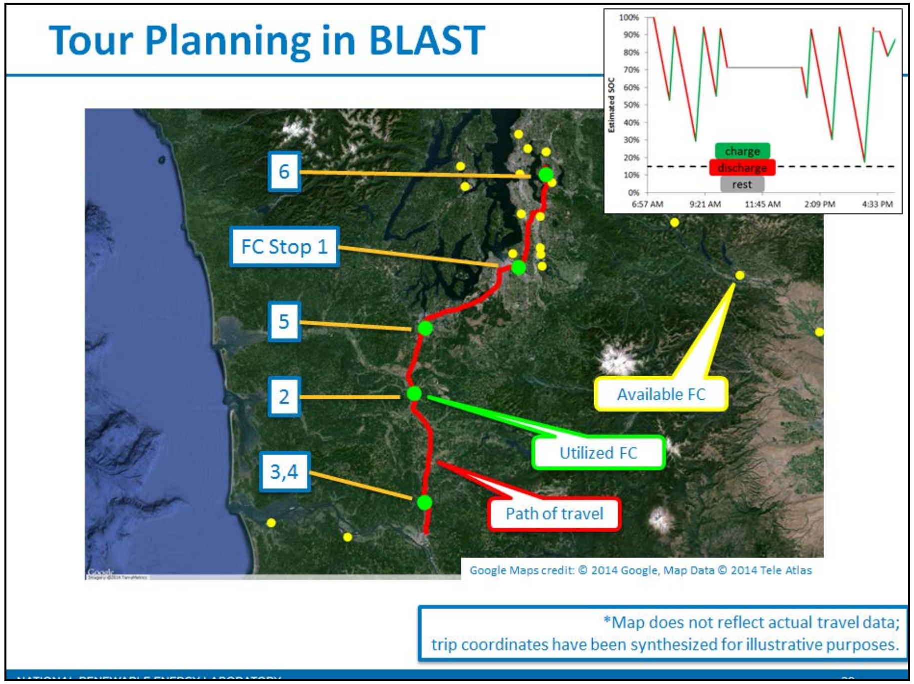


Summary

Summary

- **FY14 New Capabilities**
  - Demonstrated ability to capture cell level electrical/thermal/life effects in comprehensive ownership analysis
  - Developed architecture for evaluating impact of public charging on vehicle and infrastructure stakeholders while accounting for spatial station availability and temporal vehicle demand





Summary: Correlation with Real World Data

- Our new-for-FY14 routing logic produces fast charge usage statistics – particularly time at stations and energy from stations – that agree well with EV Project data

- Our degradation data agrees well with INL's fast charge degradation tests, in that the difference in degradation between cases with and without fast charging is small

- BLAST-V simulations predict much higher maximum battery temperatures than INL's BEV fast charging experiments, but these experiments have multi-hour rests in between fast charging and subsequent driving events

Summary: Analysis Results

- **Aggressive active battery cooling is important for constraining maximum battery temperatures, particularly for long fast-charge-enabled tours in hot climates**
  - Such conditions could pose a safety risk without aggressive active cooling, though it is more likely that the BMS will intervene to reduce available charging and driving power
- **Active battery cooling can also positively impact battery lifetime in hot climates when utilized while parked at a charger in addition to while driving**
- **Use of multi-cell thermal and electrical models provide additional insight into battery thermal and degradation responses**

Moving Forward

- We've completed simulation of multiple cases (multiple drivers, climates, vehicle range, etc.) that can be used to assess the additional utility of fast charging

- Analysis thereof will be conducted in the remaining 2014 calendar year to provide additional information on the overall benefits of fast charging and our expectations for its importance in electrifying the vehicle fleet

- These results and those described herein will be compiled into papers and presentation for the 2015 SAE World Congress

Acknowledgments

- **This activity is funded by the DOE Vehicle Technologies Office, Energy Storage Technology**

- **We appreciate the support provided by our DOE program managers**
  - David Howell
  - Brian Cunningham

- Special thanks to **NREL's Vehicle Systems Analysis** team for supporting this effort with FASTSim

- **Technical questions regarding this work should be directed to Jeremy Neubauer at 303-275-3084 or jeremy.neubauer@nrel.gov.**