



# Quantifying the Effect of Fast Charger Deployments on Electric Vehicle Utility and Travel Patterns via Advanced Simulation

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Eric Wood, Jeremy Neubauer, and Evan Burton  
*National Renewable Energy Laboratory*

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## Abstract

The disparate characteristics between conventional (CVs) and battery electric vehicles (BEVs) in terms of driving range, refill/recharge time, and availability of refuel/recharge infrastructure inherently limit the relative utility of BEVs when benchmarked against traditional driver travel patterns. However, given a high penetration of high-power public charging combined with driver tolerance for rerouting travel to facilitate charging on long-distance trips, the difference in utility between CVs and BEVs could be marginalized. We quantify the relationships between BEV utility, the deployment of fast chargers, and driver tolerance for rerouting travel and extending travel durations by simulating BEVs operated over real-world travel patterns using the National Renewable Energy Laboratory's Battery Lifetime Analysis and Simulation Tool for Vehicles (BLAST-V). With support from the U.S. Department of Energy's Vehicle Technologies Office, BLAST-V has been developed to include algorithms for estimating the available range of BEVs prior to the start of trips, for rerouting baseline travel to utilize public charging infrastructure when necessary, and for making driver travel decisions for those trips in the presence of available public charging infrastructure, all while conducting advanced vehicle simulations that account for battery electrical, thermal, and degradation response. Results from BLAST-V simulations on vehicle utility, frequency of inserted stops, duration of charging events, and additional time and distance necessary for rerouting travel are presented to illustrate how BEV utility and travel patterns can be affected by various fast charge deployments.

## Introduction

As automotive manufacturers continue to develop and market advanced technologies to satisfy consumer demand and government requirements for increasingly efficient vehicles, battery electric vehicles (BEVs) become an increasingly attractive option. By sourcing 100% of energy from an electric grid that becomes cleaner every year, BEVs are an effective option for reducing petroleum consumption, decreasing greenhouse gases, and improving air quality. While range and recharge time limitations make BEVs a difficult sell to many consumers, increased availability of high-power direct current fast charging (DCFC) is seen as one pathway to improving BEV utility and accelerating market adoption (utility is used in this paper to express the percent of travel accomplished with a BEV relative to a conventional vehicle or CV).

However, DCFC presents a myriad of technical challenges to battery manufacturers and electric utility operators. Increased cycling and elevated temperatures during fast charge events are cited as contributing factors to premature battery degradation. Battery packs unable to meet warranty requirements because of high DCFC utilization would prove mutually problematic for consumer, automotive, and battery stakeholders. Meanwhile, electric utilities are closely monitoring the impacts of residential Level 1 and 2 charging on distribution networks in neighborhoods with high BEV concentrations. Increased residential concentrations coupled with an evolving network of public DCFC stations leaves electric utilities with a high degree of uncertainty regarding future load profile projections.

Recent efforts by Idaho National Laboratory as part of the EV Project [1] have provided real-world DCFC usage statistics for early BEV adopters. The data reveal that 1% to 21% of all charge events from a subset of Nissan Leafs occurred at DCFC stations (with usage varying among vehicles and through time) [2]. While illuminating, this data does not lend to future projections of DCFC impacts under various infrastructure deployment and vehicle penetration scenarios.

Quantification of DCFC utilization relative to arbitrary combinations of infrastructure and travel behavior is a problem that lends itself nicely to a modeling and simulation approach. Researchers at the University of California, Davis have taken such an approach by linking spatial travel data with a simplified vehicle model in a geographic information system environment [3]. This geographic information system tool has been used primarily to evaluate and optimally locate public electric vehicle support equipment (EVSE) in California. Lawrence Berkeley National Laboratory has taken a similar approach in developing the V2G-Sim tool that, in addition to spatial travel data, leverages detailed powertrain simulation and battery life modeling to estimate impacts of various vehicle-to-grid communication and power flow scenarios [4]. Oak Ridge National Laboratory also has ongoing modeling and simulation activities related to assessing impacts of charging availability on electric vehicle utility and energy outcomes [5].

With support from the U.S. Department of Energy's Vehicle Technologies Office, the National Renewable Energy Laboratory (NREL) has developed BLAST-V—the Battery Lifetime Analysis and Simulation Tool for Vehicles. BLAST-V has been used in parallel with travel data from the Seattle, Washington metropolitan area to quantify vehicle utility and battery life outcomes resulting from various levels of charging availability [6]. However, this analysis was constrained to travel behavior data collected in

conventional vehicles (CVs) with driving range and refuel time characteristics drastically different than those allowed by current BEV technology. The static nature of travel data in previous BLAST-V studies did not allow for rerouting or impromptu stops to utilize fast charging and extend driving range mid-trip.

This paper discusses updated spatial capabilities within BLAST-V for evaluating utilization of and incremental utility afforded by various public DCFC deployment scenarios. The analysis focuses on quantifying impacts of several distinct rollouts of publically available DCFC stations in the Seattle metropolitan area. Publically available data on existing DCFC stations are also used as an input to BLAST-V with the resulting vehicle utility compared to a number of mock rollout scenarios. The discussion focuses on the estimated number of DCFC stations necessary to substantially increase vehicle utility and how stations can be strategically sited to maximize their potential benefit to prospective BEV owners.

## BLAST-V for BEV Utility Estimation

### Nominal Capabilities

BLAST-V is an electric vehicle simulator focused on computing the long-term effects of complex operational scenarios on vehicle utility and battery performance. It considers the vehicle powertrain, battery control strategy, driving and charging patterns, local climate, the vehicle-battery-environment thermal system, battery chemistry, and other factors in computing short-term vehicle and battery performance (e.g., vehicle range, battery voltage, state of charge (SOC), and temperature) and long-term vehicle utility and battery degradation. Figure 1 illustrates an approximate graphical representation of the key elements and flow of data within BLAST-V. Further details on the methods employed in this simulation are described in [7].

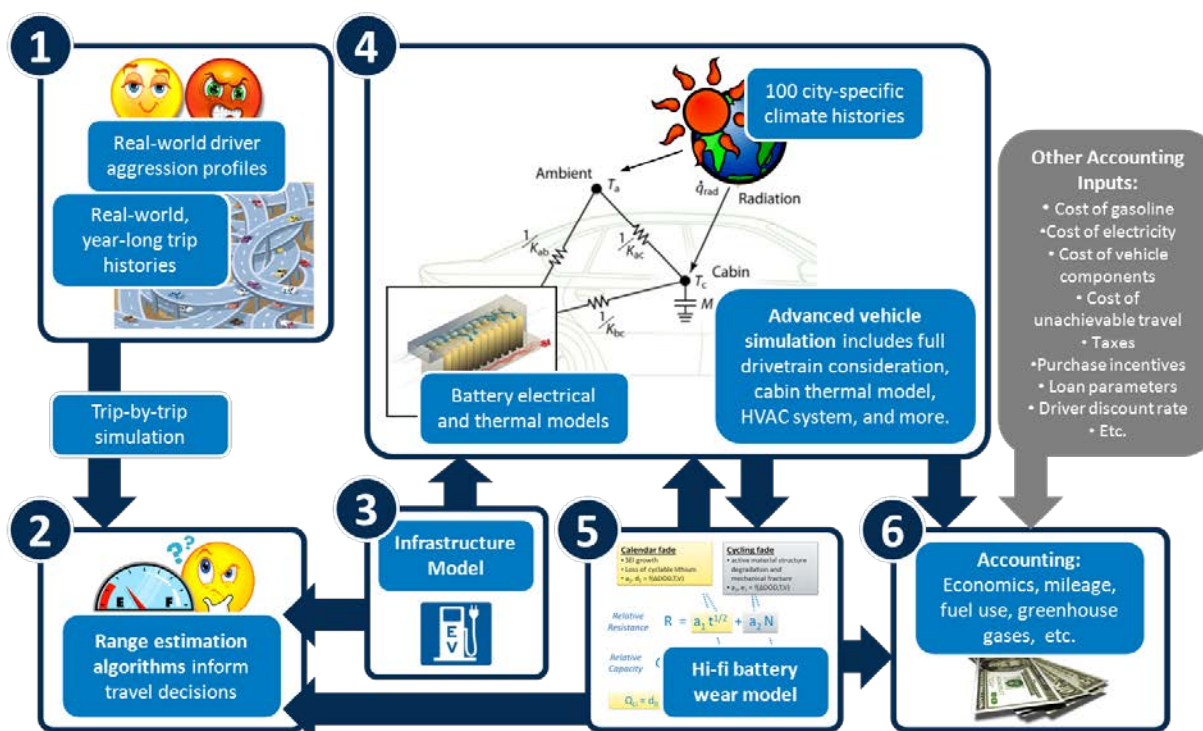


Figure 1. Graphical illustration of BLAST-V simulation algorithms.

Determination of which trips to take with a BEV and which to forgo is a key to BLAST-V. As input driving patterns are generally sourced from real-world operation of CVs, certain trips (and sequences of trips) will exceed the driving range of the simulated BEV and result in full battery depletion. Given the cost and inconvenience associated with stranded vehicles, BLAST-V assumes BEV drivers will rely on conservative estimates of vehicle range and detailed knowledge of travel itineraries to avoid running out of charge mid-trip.

BLAST-V structures travel data as a sequence of tours. Each tour consists of consecutive trips with the first trip beginning and the last trip ending at the vehicle's home location (with assumed access to charging). Prior to the start of each tour, BLAST-V considers the battery's current SOC, distance and expected duration of pending trips in the tour, historical depletion rates from similar trips, and availability of work/public EVSE to estimate battery SOC throughout the potential tour. This estimation informs a go/no-go decision at the

beginning of each tour. If the estimated SOC is maintained above a specified threshold for the entire tour, the simulated driver selects the BEV for travel and the tour is simulated in greater detail considering electrical, thermal, and life models of the battery pack. However, if the SOC is estimated to become depleted below the specified threshold, the driver forgoes use of the BEV and electrical, thermal, and life models of the battery pack are simulated with the vehicle in its parked mode for the duration of the tour. While BLAST-V is not primarily concerned with alternate travel modes in situations where BEV travel is dismissed, it is reasonable to assume that real-world drivers would coordinate use of a secondary household vehicle (likely a CV), arrange for a short-term rental vehicle, utilize some form of public transportation, plan a carpool, or potentially omit the tour entirely.

BLAST-V's go/no-go decision for determining BEV travel is believed to mirror the way that real-world drivers make personal

travel decisions. By implementing a low-order planning model prior to tour evaluation, BLAST-V simulates the hundreds of tour decisions a driver makes every year when determining whether their BEV is suitable for a particular tour.

### ***Upgrades to Consider Rerouting and DCFC Stops***

In situations where estimated battery SOC is not predicted to be maintained above the driver's required threshold, BLAST-V now includes the capability to consider alternate paths of travel and stops at available DCFC stations. Tours requiring rerouting leverage the Google Maps API [8] (application programming interface) to generate one to three potential paths of travel for each trip in the prospective tour. BLAST-V then considers combinations of potential trip paths, DCFC station availability, and estimated battery SOC to satisfy the constraint of maintaining the minimum SOC above the required threshold while minimizing the number of DCFC stops. The rerouting algorithm employs several rules regarding driver behavior at DCFC stations. The following rules are employed:

- Stations requiring more than a 1-mile excursion from the path of travel are not considered.
- Drivers only dwell at stations long enough to charge their batteries to 95% of full capacity.
- Dwell time at stations must be at least 5 minutes and no more than 60 minutes.
- Vehicle must arrive at the station before the driver's minimum allowable SOC constraint is exceeded.
- Each rerouted trip, which may imply additional travel time and includes a stop at a DCFC up to 60 minutes long, must be completed prior to the start time of the subsequent trip from the original travel data.

Of these rules, the most restrictive in terms of limiting achievable BEV miles is the requirement that the original trip start times remain intact. For example, consider a tour consisting of two 100-mile trips with a 75-mile BEV and DCFC stations available at tour miles 50, 100, and 150. In theory, this tour could be rerouted into four 50-mile trips with DCFC stations at the end of the first three trips and home charging available after the fourth (home charging is available at the end of every tour by definition). However, if the original data specified a dwell time of only one minute after 100 miles of driving, that would only allow for one minute of dwell at the first DCFC

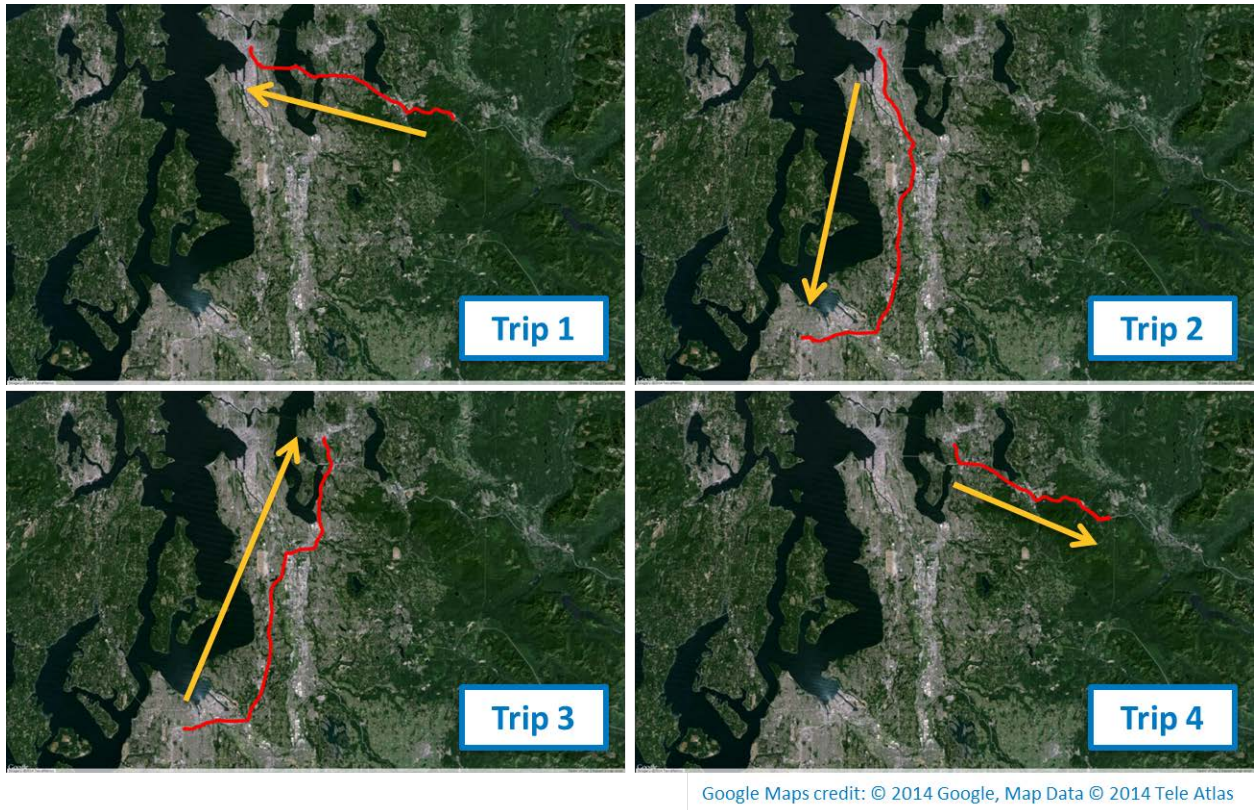
station after 50 miles of driving. Not only does a one-minute DCFC station dwell violate another rerouting rule, but the vehicle would not be able to recoup enough battery SOC in one minute of fast charging to reach its next destination.

The assumption that trip departure times are inelastic is likely inaccurate in many instances. In reality, some trips have inelastic departure times, arrival times, both, or neither. In the absence of additional travel data describing the nature of each trip requirements, the trip start time constraint is applied as a reasonable compromise. While limiting BEV utility in some scenarios, the "start on time" requirement is implemented to prevent egregious manipulations of the original travel data.

If BLAST-V's rerouting algorithm is able to successfully identify a revised travel plan that maintains estimated battery SOC above the driver's minimum requirement, statistics on the rerouted tour are recorded (e.g., number of DCFC stops, duration of DCFC stops, incremental distance relative to original tour) and the rerouted tour is simulated in greater detail considering electrical, thermal, and life models of the battery pack. However, if an adequate alternate tour is not identified, the driver forgoes use of the BEV and electrical, thermal, and life models of the battery pack are simulated with the vehicle in its parked mode for the duration of the tour.

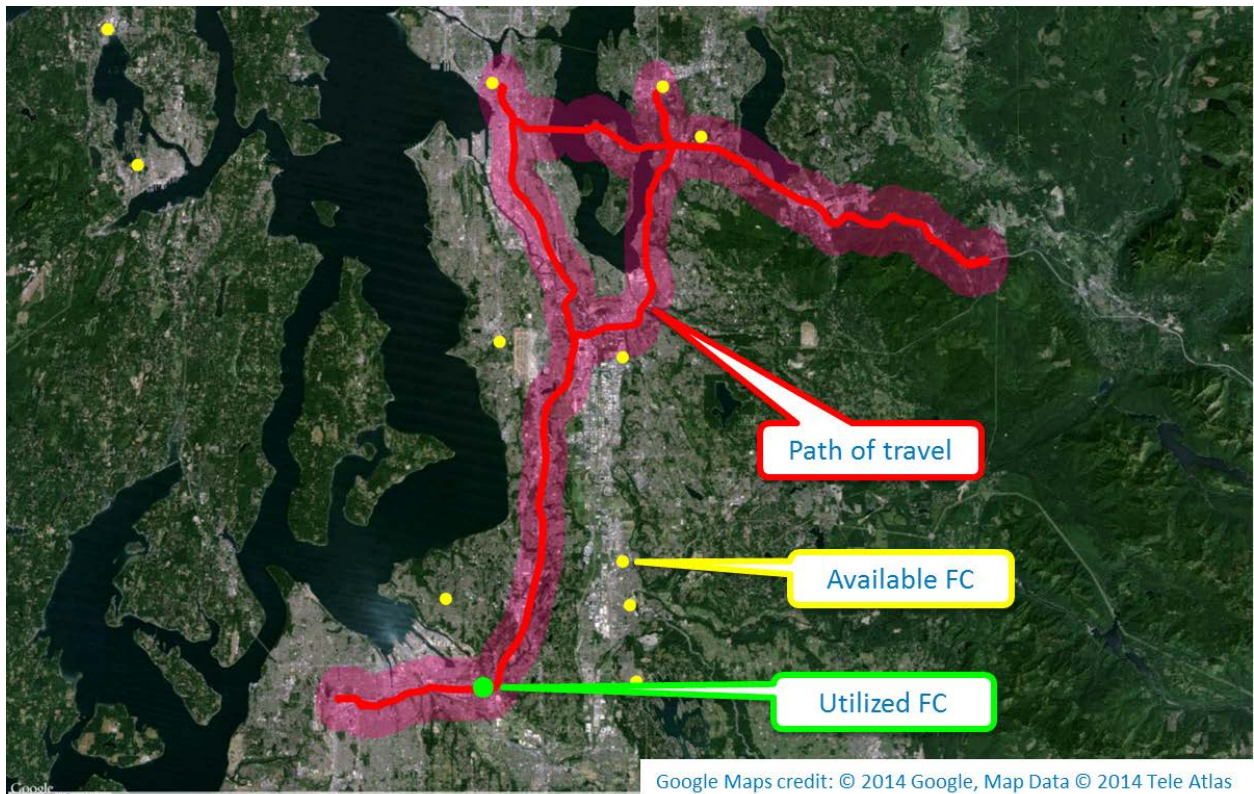
### **Rerouting Example 1**

For illustrative purposes, consider details of the rerouted tour shown in Figures 2–4. Figure 2 shows the rerouted tour path of travel consisting of four separate trips for a total of 106 miles. When simulated with a 75-mile BEV, the estimated battery SOC falls below a driver tolerance of 15% midway through Trip 3 (see the data for the original tour in Figure 4). Because the estimated battery SOC does not stay above the driver's required threshold, BLAST-V considers potential mid-trip stops at DCFC stations for charging. Figure 3 summarizes the rerouting output by showing the rerouted path of travel, a one-mile buffer around the path of travel (only stations within this buffer are considered), all available DCFC stations in the simulation, and DCFC stations selected for mid-trip charging stops. Travel itineraries and estimated battery SOC for the original tour and the rerouted tour with one DCFC stop are shown in Figure 4. By inserting a 17-minute DCFC stop midway through Trip 3, the estimated battery SOC is maintained above the driver's required threshold for the entire tour.



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Figure 2. Rerouting example 1: Rerouted tour mapped by trip. Actual trip destinations in all maps have been modified as a privacy precaution.



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Figure 3. Rerouting example 1: Rerouted tour overlaid with available and utilized DCFC stations. Actual trip destinations in all maps have been modified as a privacy precaution.

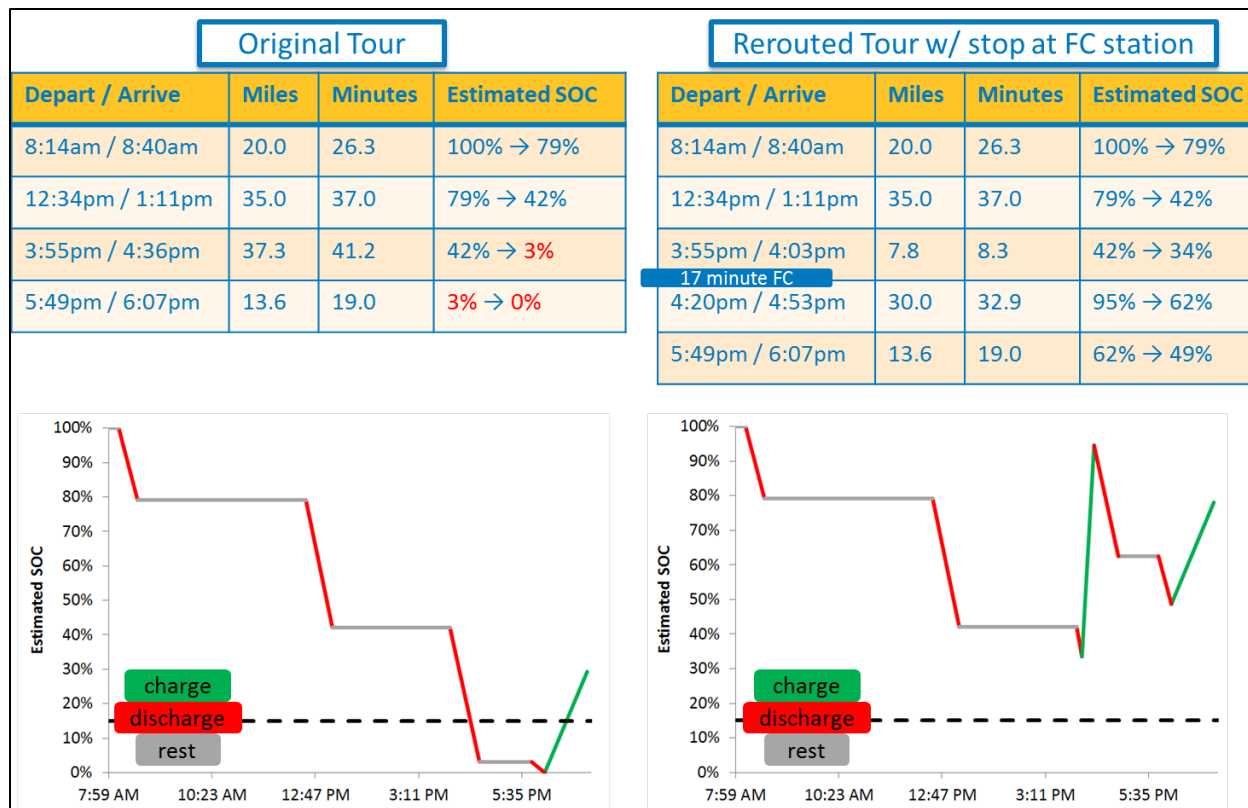


Figure 4. Rerouting example 1: Original and rerouted travel itineraries and estimated battery SOC.

## Rerouting Example 2

BLAST-V's rerouting algorithm also supports tours requiring multiple DCFC stops. Figure 5 shows a rerouted path of travel, available DCFC stations, and selected DCFC stops for a 289-mile tour between Tacoma, Washington, and Portland, Oregon. The estimated battery SOC from the rerouted tour with DCFC stops is shown in Figure 6. This example highlights the potential of fast charging both to 1) enable long-distance travel in otherwise range-limited BEVs, and 2) accelerate battery degradation via aggressive cycling profiles and the resultant heat generation. A detailed analysis of simulated impacts of DCFC on battery life is available in a parallel publication [9].

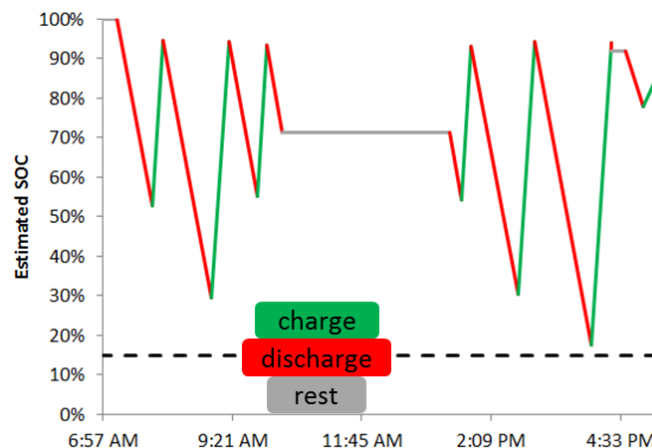


Figure 6. Estimated battery SOC for rerouting Example 2 with DCFC stops.

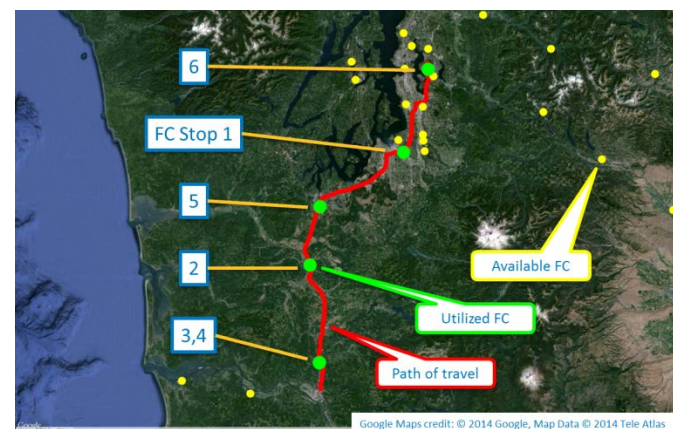


Figure 5. Rerouting example 2: Rerouted tour overlaid with available and utilized DCFC stations. Actual trip destinations in all maps have been modified as a privacy precaution.

## Analysis

### Simulation Parameters

Having established a methodology for estimating BEV utility that is sensitive to user-defined rollouts of public DCFC stations and dynamic tour rerouting, we now wish to investigate various deployments of high-power public charging infrastructure. In doing so, a number of simulation parameters must be defined, including travel profiles, driver behavior, vehicle performance, battery attributes, environmental conditions, and charging infrastructure.

## Travel Profiles

For the travel profiles, we used historical travel data from the Puget Sound Regional Council's (PSRC's) Traffic Choices Study [10], processed per [7] to yield 317 real-world travel histories, each consisting of 365 continuous days of uninterrupted data. The resulting histories provide trip distance, trip and park durations, and destination data for each trip event (including codes such as home, work, and public in addition to precise latitude/longitude coordinates). Relevant statistics for the 317 vehicle sample are shown in Figure 7.

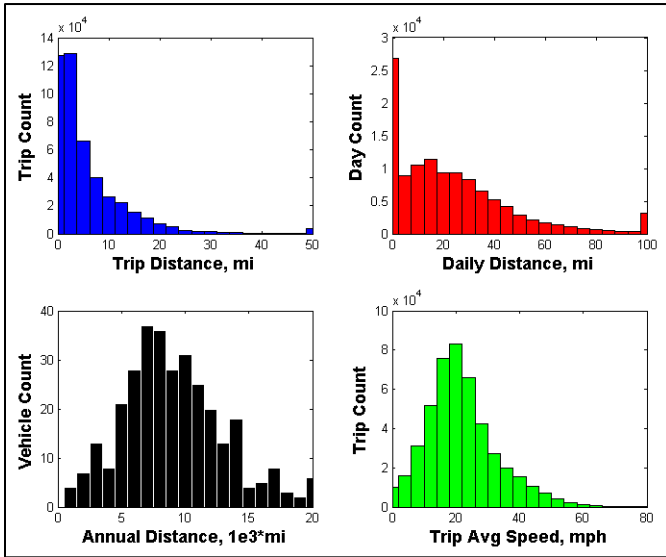


Figure 7. Trip distance, daily distance, annual distance, and trip average speed distributions for all 317 PSRC vehicle histories.

We then filter these histories to those that accrued 8,000 miles or more over this one-year period for simulation to focus on higher-mileage drivers. In Figure 8, we plot all 317 histories to show the utility factor and the annual mileage they would achieve driving a 75-mile BEV without fast charging. The black points to the upper left of the diagonal line represent the 137 drivers that completed fewer than 8,000 miles in a CV and were therefore excluded from this study. These profiles are of lesser interest to this study, as the low annual mileage implies they are unlikely to (1) benefit significantly from public EVSE, or (2) accumulate sufficient fuel savings to justify the upfront price premium of a BEV. Accordingly, they were not simulated. The 91 drivers boxed in the upper right corner of the plot represent those that both completed more than 8,000 miles and achieved a utility factor greater than 80% in the 75-mile BEV. Arguably, these drivers are well suited to such a BEV without fast charging. The remaining 89 drivers are high-mileage drivers that achieve low utility factors with a 75-mile BEV. Because Profile Set A has the potential to reach 100% utility with the addition of fast charging infrastructure, and Profile Set B has the potential for large absolute gains in vehicle utility, both sets will be examined.

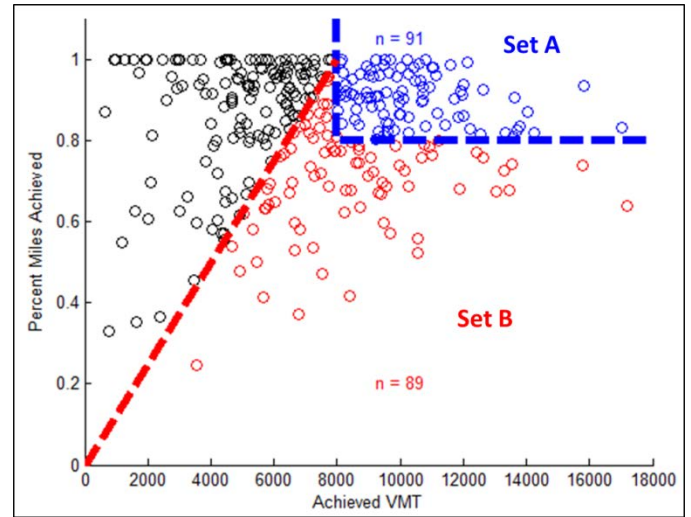


Figure 8. Simulated utility and achieved vehicle miles traveled (VMT) for PSRC travel histories in a 75-mile BEV.

## Driver Behavior

It is assumed that all drivers in this study operate BEVs with “normal” levels of driver aggression (25<sup>th</sup> to 75<sup>th</sup> percentile) per previous BLAST-V studies [7, 11].

For the purposes of making a go/no-go decision prior to the start of each tour, it is assumed that all drivers impose a range tolerance of 15% battery SOC (or about 11 miles) per the previous discussion of BLAST-V's “Nominal Capabilities,” which is to say that drivers will only elect to travel with their BEV on tours where the estimated battery SOC is greater than 15% for the entire tour. This SOC tolerance provides a reasonable buffer in situations where simulated driving range turns out to be less than the pre-tour estimate.

## Vehicle Performance

We employ a mid-size sedan with technology and performance levels anticipated for a 2020 model year vehicle. We utilize FASTSim (Future Automotive Systems Technology Simulator) [12] to simulate the vehicle response to the Urban Dynamometer Driving and Highway Fuel Economy Driving Schedules, the results of which are weighted and combined per [13] to approximate the U.S. Environmental Protection Agency-rated range. We further employ FASTSim to simulate the vehicle's response to NREL's DRIVE cycle to calculate the vehicle's real-world efficiency [11]. Note that within BLAST-V simulations, auxiliary loads for the vehicle's cabin heating, ventilation, and air conditioning and battery thermal management system are added separately and the efficiency computed from the DRIVE cycle is adjusted for the speed and distance of each trip. The vehicle parameters are given in Table 1.



Table 1. Vehicle Parameters.

0-60 mph Acceleration	9 sec
Approximated U.S. Environmental Protection Agency-rated Range	75 miles
Battery Energy	22.1 kWh (100% usable)
Motor Power	106 kW
Vehicle Curb Weight	1,576 kg
Vehicle Efficiency	220 Wh/mi on DRIVE cycle (excludes auxiliary loads accounted for during BLAST-V simulations)

### Battery Attributes

All battery electrical, thermal, and life calculations in the study employ a single-node battery model, which assumes uniform response between all cells in the pack. Electrical modeling is done using a zero-order equivalent circuit approach with open circuit voltage and internal resistance parameters based on a lithium-ion cell with a nickel-cobalt-aluminum cathode and graphite anode. Thermal modeling considers battery response to ambient and cabin temperatures in the presence of an active battery cooling system. Life modeling is implemented via a physically justified and empirically fit system of equations for describing calendar- and cycling-induced resistance growth and capacity fade based on a thru-life nickel-cobalt-aluminum data set. While battery degradation calculations are included in this analysis, the duration of simulations (all one-year long) and moderate climate (Seattle) resulted in a negligible impact on results. A detailed investigation of the thermal impacts of fast charging in more demanding climates, as well as the degradation response thereof, is performed in a parallel study [9]. For more extensive documentation on BLAST-V pack modeling approaches, please refer to [7].

### Environmental Conditions

Seattle was selected because it has ambient temperature and solar irradiation input data available, and it has coincident PSRC travel data and represents a relatively moderate climate. Typical meteorological year data for Seattle is taken from [14] and is illustrated in Figure 9.

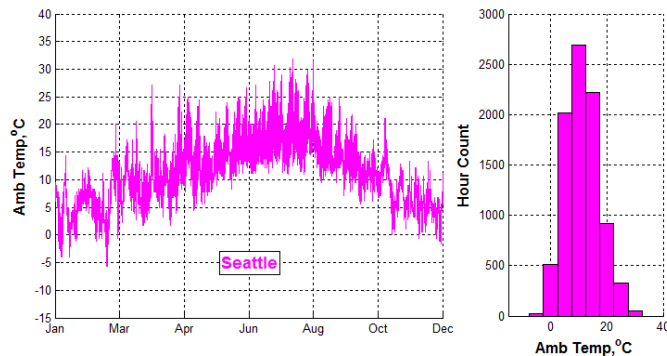


Figure 9. Ambient temperature data from Seattle, Washington.

### Charging Infrastructure

For vehicle charging, we assume a Level 2 charger (6.6 kW AC) is installed at each driver’s home and used in an “opportunity” mode (i.e., whenever the driver is at home, the vehicle is plugged in and charging).

All public charging networks in this study employ 50-kW DCFC stations. A public charging network representative of existing DCFC locations is shown in Figure 10 with three synthetic rollout scenarios. Location of existing DCFC stations references the U.S. Department of Energy’s Alternative Fuels Data Center [15] (sourced Jan 2014). The existing DCFC network includes 34 DCFC stations in Washington State in addition to 306 DCFC stations outside of Washington State. Synthetic infrastructure rollouts are labeled as NREL Methods 1–3 and have been generated using combinations of heuristics, systems optimization, and operations research techniques. Each synthetic method offers the ability to prioritize station deployments in terms of estimated incremental BEV utility enabled (only one iteration of each synthetic method is shown for mapping purposes).

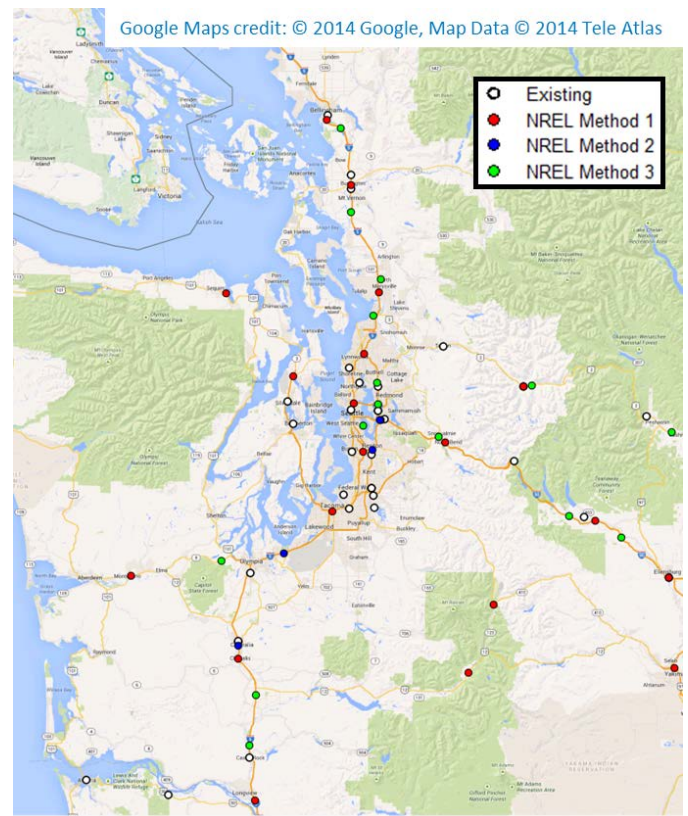


Figure 10. Existing DCFC locations shown alongside three synthetic rollout scenarios.

### Simulation Results

Although some parameter uncertainties exist in the underlying historical drive and climate data employed in this study, the main source of uncertainty is structural. The principal structural uncertainties include our approach to modeling human tour decisions, our method of computing vehicle energy consumption, and the battery performance and life models employed. Quantifying the level of uncertainty present in our modeling of human tour decisions is challenged by the need for large amounts of data on the real-world tour decisions of BEV drivers.

The second factor, computation of vehicle energy consumption, is applied consistently across all scenarios. Thus, while it is expected to affect the absolute vehicle utilities calculated herein, it should not significantly affect the relative impacts of different public charging scenarios. Improving the accuracy of battery performance and life models to account for cell-to-cell variation within a pack and better ascertain the impacts of fast charging on battery wear is a major focus of a parallel study [9]. Despite these uncertainties, however, the following findings are telling as to the relative impact of public charging impact on overall BEV utility.

### Existing DCFC Infrastructure

Simulation results using existing DCFC infrastructure reveal that the average BEV utilized DCFC stations fewer than 10 times per year. Figure 11 shows a relatively linear trend between DCFC utilization and incremental utility (represented in addition to vehicle miles traveled (VMT)). The trend line of this plot reveals that approximately 75 miles of additional travel are enabled by each fast charge event. Note that this does *not* imply that each DCFC event charged the battery from 0% to 100% SOC. For example, brief use of a fast charger to partially charge a battery after 50 miles of travel could have enabled a 75-mile tour.

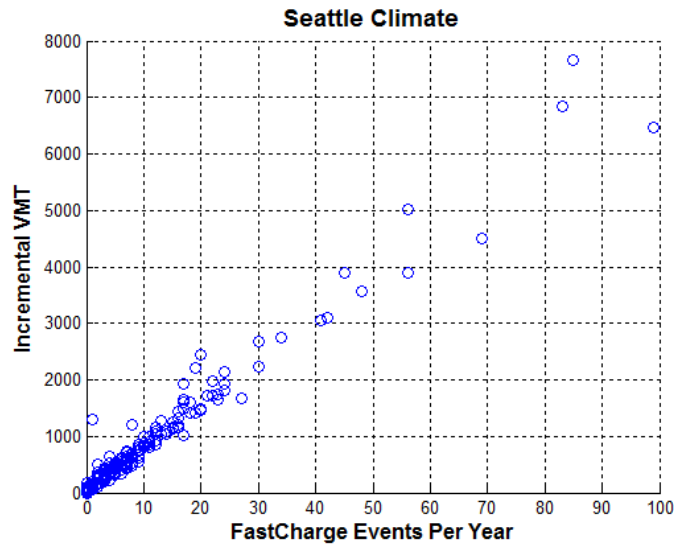


Figure 11. Incremental VMT afforded by existing DCFC for simulated 75-mile BEV vs. the count of fast charge events per year for each simulated vehicle.

In Figure 12, we see that it is most common for vehicles utilizing DCFC stations to require only one or two additional stops for charging per tour. This result is significant in light of a University of California, Davis consumer survey in which 100% of respondents reported finding one DCFC stop per day reasonable on an occasional basis (51% found two stops per day reasonable) [16].

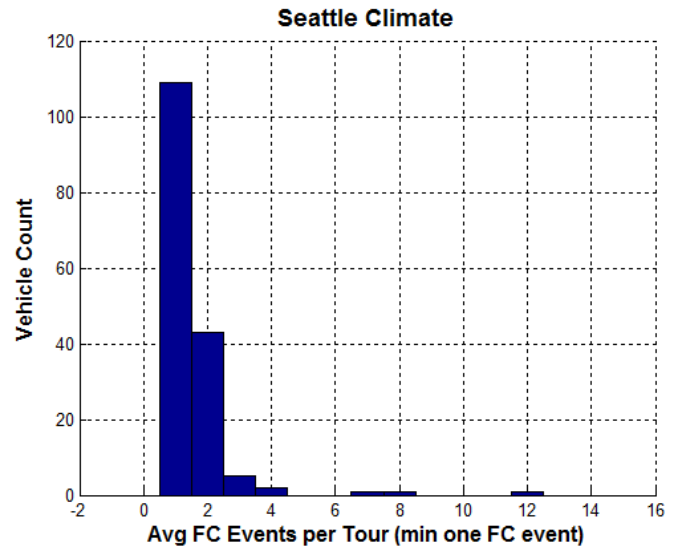


Figure 12. Distribution of average fast charge events per tour by vehicle (for tours with at least one fast charge event).

### Validation to EV Project

While identifying appropriate validation data for BLAST-V’s rerouting and behavior modification algorithms is difficult, some confidence can be gained by evaluating BLAST-V outputs from runs with existing DCFC infrastructure and data reported by the EV Project. For instance, Figure 13 shows average dwell times at DCFC stations as a function of average arrival battery SOC. The correlation between these outputs is a byproduct of BLAST-V’s tour rerouting algorithm determining DCFC dwell times based on estimated time required to charge to a specified SOC (95% in this analysis). BLAST-V’s simulated dwell times of 11 to 22 minutes agrees well with EV Project data showing real-world charger connection times of 14 to 24 minutes [17].

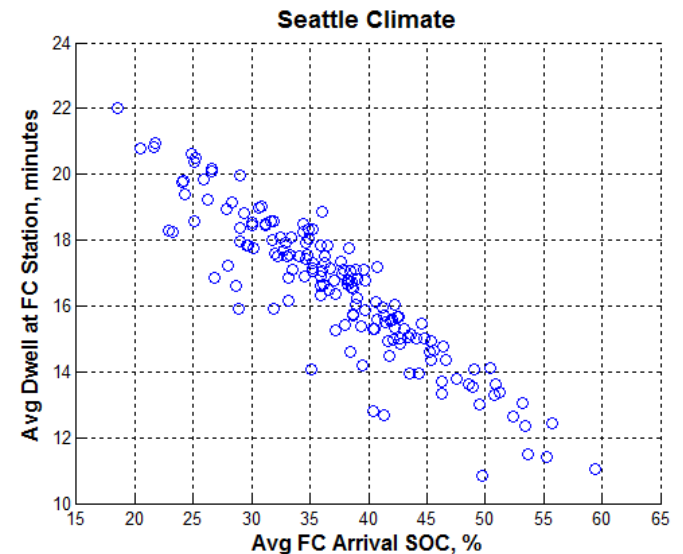


Figure 13. Average dwell time at DCFC station versus average arrival SOC (by simulated vehicle).

Another metric comparing BLAST-V outputs and EV Project reported data is percent of energy sourced from DCFC stations. Figure 14 shows a distribution of simulated vehicles with the average vehicle sourcing 7.6% of total energy from fast charging. This value falls well within EV Project reported bounds of 1% to 21% of real-world BEV energy originating from DCFC stations [2].

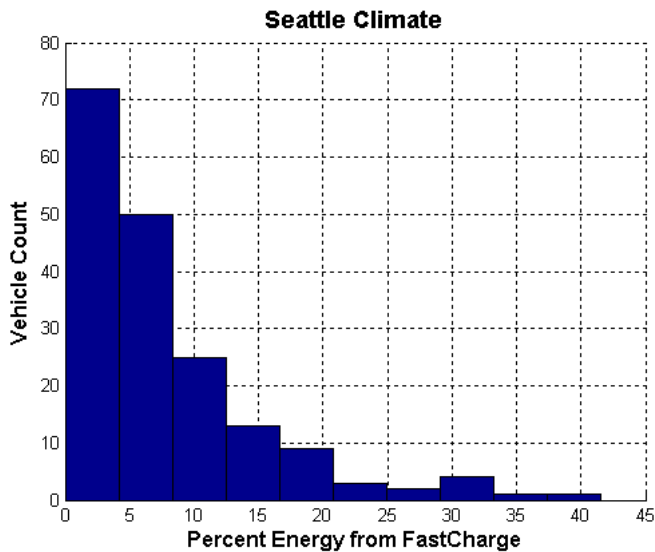


Figure 14. Distribution of percent of total energy sourced from DCFC by vehicle.

### Synthetic DCFC Rollout Scenarios

BEV utility with respect to existing DCFC infrastructure is now compared to multiple iterations of the three NREL-developed deployment methods. Figure 15 shows average achieved VMT in a 75-mile BEV from 180 year-long driving profiles (the union of Profile Sets A and B) in the Seattle metropolitan area. Average utility is plotted against the number of available DCFC stations in each simulation (i.e., NREL Method 3 at the 40-station level resulted in an average annual VMT of 10,000 miles achieved). Considering the incremental utility afforded by existing DCFC stations alongside that of multiple distinct synthetic rollouts provides context for the effectiveness of existing infrastructure. The 34 existing stations in Washington State resulted in a simulated average utility of 10,090 miles per year, which compares favorably with synthetic rollouts of similar volume. While simulated utility from various segmentations of travel histories (e.g., all profiles, set A, set B, set A+B) was found to impact baseline utility values, relative benefit of DCFC availability was largely insensitive to travel history segmentation.

Also included in Figure 15 are reference lines for utility afforded by no DCFC stations (9,310 miles per year) and VMT of original CV travel profiles (11,830 miles per year). The reference line at 10,500 miles per year reflects average annual VMT from a simulation where DCFC stations are made available at every gasoline refueling station in the United States (123,703 unique locations [18]). The “existing gas station” scenario provides an upper bound for the potential utility of our simulated 75-mile BEV. By densely populating a BLAST-V simulation with DCFC stations, we ensure that unachieved tours are not a result of public charging availability. Instead, unachieved tours in the “existing gas station” scenario are attributed to the aforementioned original trip start time constraint. By enforcing the condition that all trips start “on time” relative to the original travel data, we find that the final increment of BEV utility is potentially constrained by human behavioral norms.

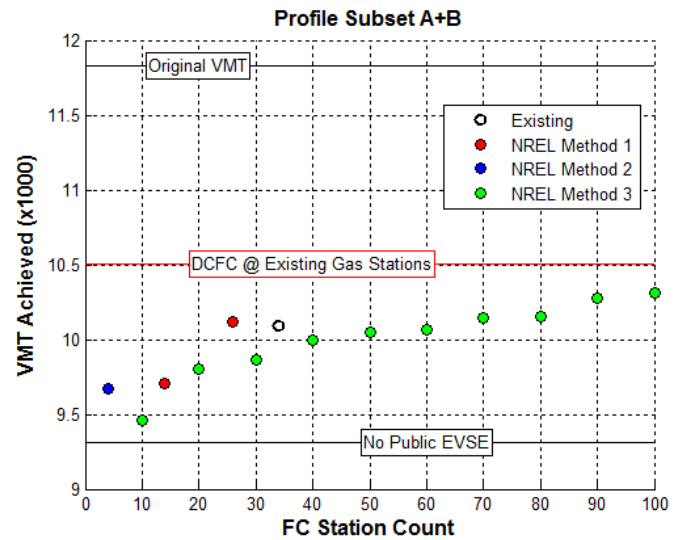


Figure 15. Average achieved VMT in a 75-mile BEV from 180 year-long driving profiles in the Seattle metropolitan area relative to various DCFC deployments.

### Additional Battery Sizes

It is also of interest to explore the effects of installed battery size on utility when fast charging is available. To study this, we employed the existing DCFC deployment for simulation of six vehicles with different size batteries. The baseline data of Table 1 were applied in all cases, with the exception that the battery energy was changed from a low of 16 kWh (corresponding to approximately 58 miles of range) to a high of 60 kWh (approximately 218 miles of range). Vehicle efficiency was not altered to accommodate the changes in mass expected from the different battery sizes. The 60-kWh case would add 380 kg of battery mass (assuming 100 Wh/kg technology) to our baseline vehicle, which is anticipated to affect energy consumption by less than 10%, which was judged to be acceptable for the purposes of this investigation.

Looking first at results for the largest range vehicle, we see that increasing the battery size encourages BEVs to arrive at DCFCs with lower SOC and dwell there for a longer period of time. This can be observed by comparing Figures 16 and 13. The longer vehicle range effectively presents more options for fast charging within a given tour, enabling drivers to wait to charge until the battery is further depleted, ultimately making fewer additional stops.

Figure 17 compares the simulated utility across all travel histories (driver sets A and B), battery sizes (16 to 60 kWh), and charging options (with and without fast charging). The box plot for each combination of battery size and charging option provides the maximum, 75th percentile, median, 25th percentile, and minimum utility simulated across the set A and B travel histories. The data show that the added utility of fast charging diminishes as battery size is increased. It also enables comparison of the merits of additional battery capacity and additional infrastructure. For example, the utility provided by adding accesses to the elected DCFC infrastructure deployment to our baseline 22-kWh BEV is approximately equivalent to increasing the battery size to 38 kWh in the absence of DCFC infrastructure. Similarly, operation of a 60-kWh BEV without fast charging is approximately equivalent to operating a 30-kWh BEV with fast charging. In all cases, however, the median and 25th percentile drivers achieve significantly less than 100% utility.

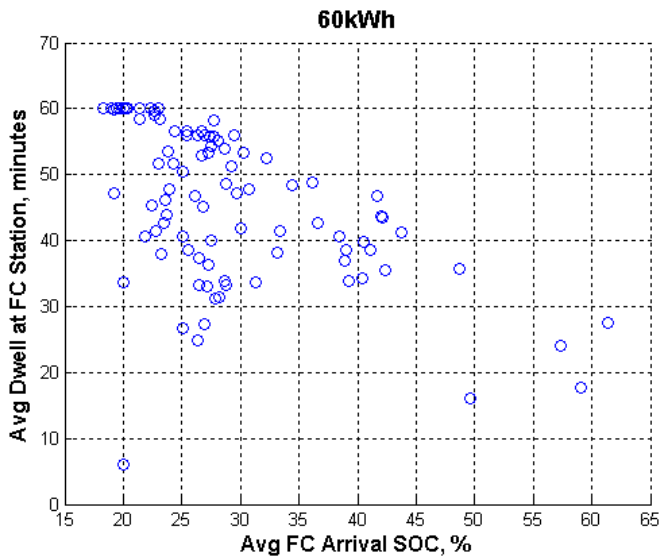


Figure 16. Average dwell time at DCFC station versus average arrival SOC (by simulated vehicle). Data from simulation of 60kWh battery size.

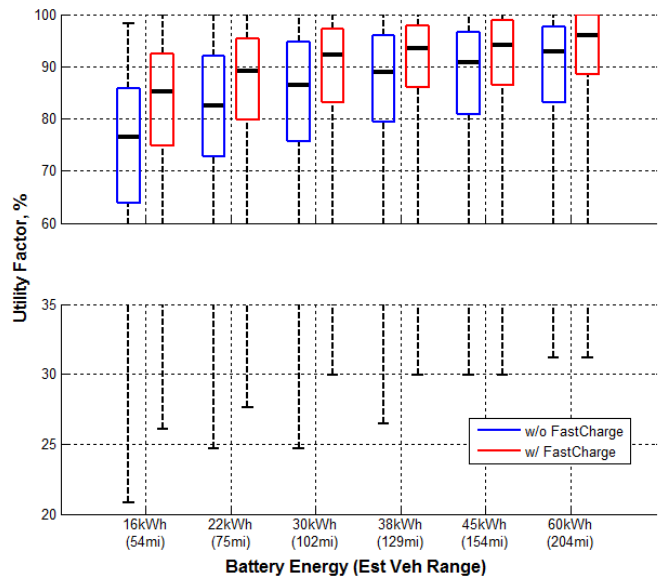


Figure 17. Simulated utility factor distributions with and without fast charging for a range of battery sizes.

Figure 18 shows the absolute annual mileage enabled by the addition of fast charging. Again, the benefits of adding fast charging are seen to diminish as installed battery size increases. This plot better illustrates the immense value that fast charging can have for select drivers: for our smallest battery case, fast charging enables more than 11,000 miles of additional BEV travel each year for the most benefitted driving profile. As battery capacity increases, however, this benefit falls sharply. It also shows that the benefit of fast charging to our median driver becomes largely insensitive to installed battery capacity at and above 38 kWh, at which point 25% of our investigated travel patterns achieve no benefit from fast charging.

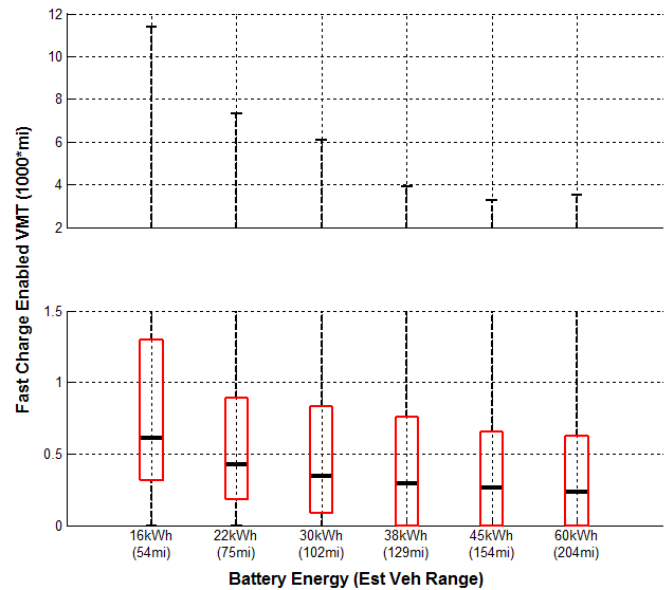


Figure 18. Simulated VMT enabled by fast charging for a range of battery sizes.

## Summary

A novel method for estimating real-world utilization of DCFC has been developed in BLAST-V, allowing rerouting of original travel data to facilitate mid-trip stops for charging at predetermined DCFC locations as necessary. Simulated utilization rates of DCFCs have been shown to agree well with real-world data from the EV Project, suggesting the employed rerouting algorithms adequately reflect real-world driver behavior. This tool has been applied to study both the effect of different fast charger deployments and the additional vehicle utility afforded thereby for BEVs of different ranges.

We found that Seattle's existing public DCFC infrastructure was shown to compare favorably with various synthetic rollouts of DCFC stations. Under Seattle's existing DCFC deployment, we have found that use of fast charging can greatly increase the achieved annual mileage of select drivers operating BEVs. However, the vast majority of travel patterns we studied observed a benefit of less than 1,000 DCFC-enabled miles per year, decreasing as the installed range of the vehicle is increased.

Where much larger deployments of DCFCs are available (e.g., approaching the prevalence of gas stations), we find that our imposed constraints on adjusting travel timing becomes the limiting factor for utility improvements. This implies that more flexible adjustments to travel profiles (e.g., moving trips between tours, altering the destinations of trips, or adjusting travel times, as real drivers may be prone to do when operating a range-limited BEV) could reveal greater benefits of fast charging. Analyzing the effects of such behavior will require a greater understanding of both the nature of individual trips and human travel behavior.

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## Contact Information

Transportation and Hydrogen Systems Center  
National Renewable Energy Laboratory  
15013 Denver West Pkwy MS 1634, Golden, CO 80401

Eric Wood (303) 275-3290 [eric.wood@nrel.gov](mailto:eric.wood@nrel.gov)  
Jeremy Neubauer (303) 275-3084 [jeremy.neubauer@nrel.gov](mailto:jeremy.neubauer@nrel.gov)  
Evan Burton (303) 275-3664 [evan.burton@nrel.gov](mailto:evan.burton@nrel.gov)

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## Definitions/Abbreviations

<b>BEV</b>	battery electric vehicle
<b>BLAST-V</b>	Battery Lifetime Analysis and Simulation Tool for Vehicles
<b>CV</b>	conventional vehicle
<b>DCFC</b>	direct current fast charging
<b>DRIVE</b>	Drive-Cycle Rapid Investigation, Visualization, and Evaluation Analysis
<b>EVSE</b>	electric vehicle support equipment
<b>FASTSim</b>	Future Automotive Systems Technology Simulator
<b>FC</b>	fast charge
<b>NREL</b>	National Renewable Energy Laboratory
<b>PSRC</b>	Puget Sound Regional Council
<b>SOC</b>	state of charge
<b>VMT</b>	vehicle miles traveled