Electric Vehicle Fast Charger Planning for Metropolitan Planning Organizations

Adapting to Changing Markets and Vehicle Technology

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Presented is a tool to estimate fast charger demand and sample results on a current and future battery electric vehicle (BEV) scenario. The results highlight the data and methods needed to plan for fast charger demand. To plan for existing BEVs, origin and destination data are necessary for identifying which traffic is relevant to assess fast-charging demand. Also, as the battery size for BEVs increases, demand shifts from primarily inside metro areas to long-distance corridors outside metro areas. The sample results show the interactions of battery size, frequency of charging, and energy needed per charge. Although energy per charge increases with battery size, overall electricity demand per vehicle decreases with larger batteries.

To achieve the 2025 Corporate Average Fuel Economy standards of 54.5 mpg average fuel economy, there is growing interest in battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). PHEVs have a significant advantage over BEVs in regard to long-distance travel since PHEVs have gasoline as an energy source, while a BEV's range is restricted by battery capacity. Improving charging infrastructure is crucial to support BEVs for long-distance trips and to give range confidence. Recognizing this, the U.S. Department of Energy announced 16 electric vehicle planning grants totaling $8.5 million in 2011 to help prepare for plug-in electric vehicles (PEVs) and charging infrastructure in 24 states (*1*). These plans were quite successful in engaging stakeholders, but the science of fast charger placement was not well developed in many cases. Many plans either did not focus on this aspect or dealt with it in generalities. By building on this stakeholder engagement, these plans should be revisited to produce better guidance on fast charger needs. More recent behavior data, vehicle growth projections, and battery size projections make better planning possible.

There are three common charging levels: alternating current (AC) Level 1 uses a standard 120 volt alternating current to provide slow charging (typically of 1.4 kW to 1.9 kW); AC Level 2 uses a 208/240 volt alternating current to provide charge power from about 1.5 kW to 19.2 kW; and fast charging typically refers to direct current (DC) Level 2 and uses a high voltage direct current to provide power from 36 to 90 kW, although DC Level 1, which is less than 36 kW, could be considered fast charging as well (*2*). To provide EV drivers access to longer-range trips, more fast charging stations will be needed.

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BACKGROUND

There are various DC fast chargers that siting strategy planners have used to site fast charging stations (*3–5*). For example, the Metropolitan Transportation Commission in the San Francisco Bay Area, California, derived trips by potential PEV adopters on the basis of their own regional transportation demand model, and used it to choose sites for fast charging stations (*6*). The San Diego Association of Governments in California identified sites based on locations of existing Level 2 chargers and a list of siting requirements (*7, 8*). The Sacramento, California, Area of Council of Government assessed locations by analyzing existing and forecasted PEV owner demographics, corresponding driving patterns, and land uses (*9*). California's North Coast Region built an agent-based model to identify PEV infrastructure sites (*10, 11*). The West Coast Electric Highway Project proposed by the State of Washington and the Oregon Department of Transportation is an extensive charging network with fast charging stations located every 25 to 50 mi along Interstate 5 and other major roadways (*12*). However, a lack of consistency among these strategies makes comparing results difficult. Further, the data used to create these scenarios use regional travel data or simple traffic counts and do not have long distance travel, raising two issues. First, demand from outside a metropolitan area is not well represented. Many times, there is an aggregate inflow of traffic from outside an area, but not how far they traveled before drivers arrive at a metro area boundary. This makes assessing demand difficult in both the likelihood of this traffic being a BEV, and in what energy might be needed. Some corridors, such as highways away from cities, have primarily long-distance trips, while other highways have a mix of long- and short-distance trips. Second, when the origin of a trip is not known, there is no opportunity to match known vehicle sales data to trip origin. Knowing in detail the origin gives modelers the opportunity to identify trips originating in areas with a high PEV density. Knowing the destination shows how far the vehicle traveled and where along the journey they would need to charge.

This paper presents a model that uses long-distance data and addresses demand coming from outside a metro region in the context of any battery size. The model will be free for any modeler to use, providing consistency in modeling fast charging, given sufficient travel data. The model incorporates the latest behavior data, can assess the potential usage of current stations, and can assess proposed sites based on future growth and increase in battery size. A detailed explanation of the model is given. It is followed by two scenarios showing the ability to model any distribution of demand and battery size and what effects those parameters may have on any analysis.

MODEL

A model was built to evaluate BEV charging demand and to assess the usage of current and proposed charger locations based on that demand. Use of this model is predicated on having access to long-distance travel data, and it can be used for two analysis purposes: to evaluate charging demand based on current and proposed chargers; and to propose new locations based on unmet gaps in demand. The demand is presented in charge events per day or utility of proposed charger locations. Data on California statewide travel in gasoline vehicles are provided by a statewide survey done by the California Department of Transportation (Caltrans) in 2012 (*13*).

Charge Windows

Two main concepts are used to evaluate fast charger utility: tours and charge windows. A tour is made up of all the travel from the time a vehicle leaves home to the time it returns home. This is done because charging is likely to be available at home, making it easier to assess which travel might require public charging. The concept of a charge window is proposed. It refers to a section of a long-distance tour such that if a charger were placed anywhere in the window, the vehicle could make it to its destination. The inputs that define the charge window are chosen by the modeler. For the scenario, a safety buffer of 20% state of charge is assumed, such that a vehicle will need a charge if it falls below that level. Batteries are assumed to charge only to 80% state of charge matching the point where charge rate begins to taper on most BEVs. This means that at any fast charger, only 60% of a battery can be recovered (48 mi in the BEV 80 case). For large batteries the safety buffer can be lowered so that more than 60% can be recovered.

Charge windows are shown in Figure 1. Assuming that a BEV driver wants to travel from Elk Grove to Livermore, California, the distance is 85 mi, as Route D in Figure 1 shows. The BEV has a range of 80 mi, so one fast charge is needed to reach the destination. With a safety buffer of 20%, the vehicle can go only 64 mi before needing to charge, creating an upper limit to the charge window. The maximum number of miles that can be traveled from a fast charger is 48 (from 80% to 20% state of charge), so the lower limit of the charge window is 85 – 48, or at mile 37. Thus, the charge window for this trip is from mile 37 to mile 64.

Although trips shown in Figure 1 are single trips, most travel in the model is round trip to home, creating a tour. For an 85-mi tour, the same principles apply, with a slight modification if work charging is incorporated in the middle of a charge window. Routes A, B, and C are important for evaluating utility of multiple tours and are explained later.

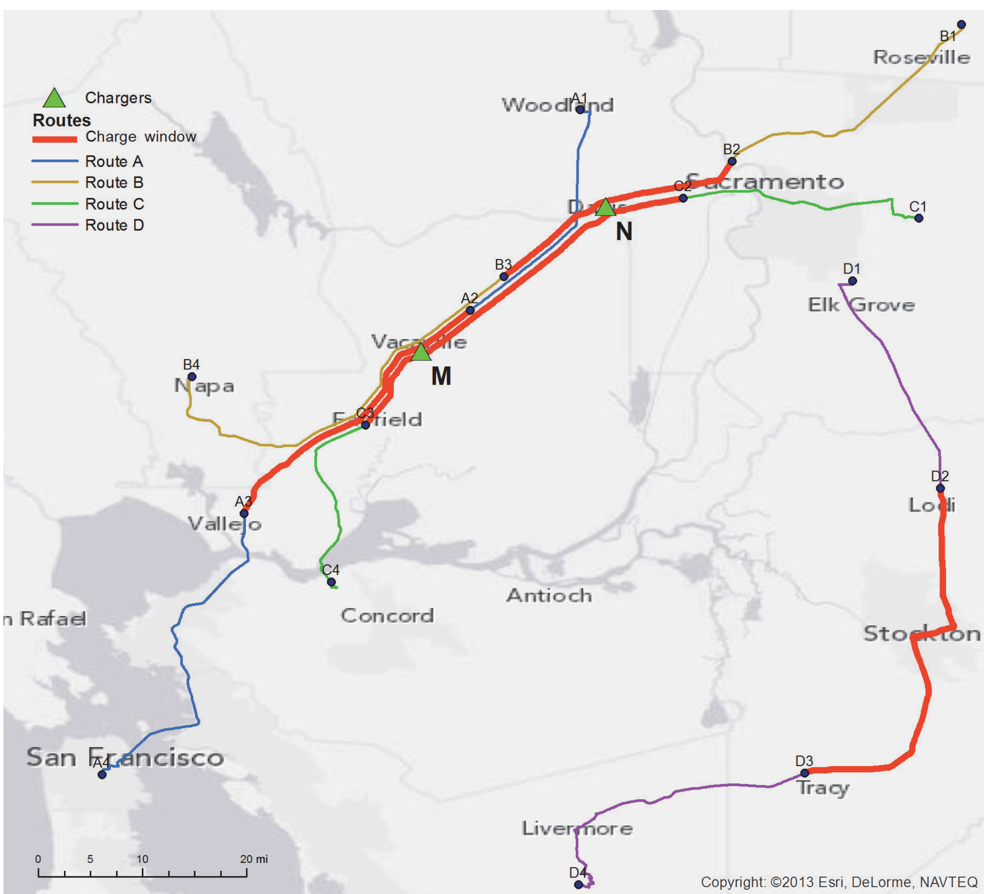

FIGURE 1 Illustration of charge window.

Input Parameters

Travel diary or other origin–destination data are necessary to support this model. A travel diary consists of respondents' trip information on an assigned survey date, including the location of origin and destination, departure and arrival time, travel mode, trip purpose, and so on. It is widely used to analyze travel behavior. The ultimate goal of building a charging infrastructure is to enable travel to consumers' chosen destinations. Therefore, the model uses travel in the Caltrans survey from trips that are currently taken in gasoline vehicles. However, alternate data sets that include origin and destination data can be used.

To prepare the data, the origin and destination trip data must be converted to tour-based data, which, as previously defined, is travel done between the time the vehicle leaves home and returns home. AC Level 1 and Level 2 charging can also be incorporated, for travel diary data include dwell times at locations as well as trip purpose. Different Level 1 and Level 2 scenarios can be used to test the effect on DC fast charging demand or can be used as analysis outputs themselves.

Currently, there are various models of BEVs with different ranges available in the market. For example, the 2013 Nissan Leaf has an Environmental Protection Agency (EPA) range of 75 mi; the 2012 Mitsubishi i-MiEV has an EPA range of 62 mi; and the Tesla Model S has an EPA range of 208 mi and 265 mi for the 60-kW-h and 85-kW-h battery, respectively (*14*). The model can evaluate the charging demand of a mix of BEV models by allowing users to define county-level ownership of different ranges of BEVs.

In this study, constant BEV range and vehicle efficiency are used to calculate charging demand. However, BEVs could have different vehicle efficiency on highways and local streets. For example, the 2013 Nissan Leaf has a miles per gallon equivalent, or mpge, of 129 in the city and 102 on highways (*14*). Further analysis will focus on improving this evaluation.

Scaling

The scaling factor for each BEV model is calculated as the ratio of the number of corresponding BEVs to the number of households in each county, so that the product of this scaling factor and the household weight is the number of BEVs that each sample household represents. For example, if there are 1,000 county respondents in the survey and the county has 100 vehicles in existence, then each household would represent about 1/10th of a vehicle. This of course varies since each household's scaling factor is a little different to account for underrepresented or overrepresented groups.

BEV charging is time consuming compared with refueling a conventional vehicle, so consumers' willingness to choose a BEV for a certain trip decreases as the number of charging events necessary to complete the trip increases (Figure 2) (*15*). Thus, the model has another scaling factor to account for BEV drivers' choosing other modes as the number of fast charging events increases per tour.

As a result, the weight of each tour is

$$W_{kx} = C_{ij} \frac{B_{ix}}{\sum_{j=1}^{N_i} C_{ij}} R_k \tag{1}$$

where

- W_{kx} = final weight of tour$_k$ for BEV with a range of x mi;
- C_{ij} = household weight of corresponding household from county$_i$, and each household from county$_i$ has a unique identification marked as j;
- N_i = total number of sample households from county$_i$$B_{ix}$ is equal to the number of BEV$_x$ in county$_i$; and
- R_k = scaling factor of number of required charging events within tour$_k$.

Two further scaling factors are applied for each tour. Based on the travel survey data, not all vehicles were used on the assigned day; that could be influenced by many factors, such as vehicle type, travel day, and residential location (*16*). However, for a statewide model, one constant vehicle usage rate is acceptable and the idle factor, consisting of the households that drive on a certain day are divided by the total households in the survey (78% of respondents did not travel by car in the California sample). Also, a factor is applied to decrease the demand from any one household, since there may be two or more drivers and vehicles in the household, only one of which may be a PEV. This factor is the number of households that drive divided by the number of total tours (48%). That results in a combined scaling factor of 36.5% for this analysis. This last scaling

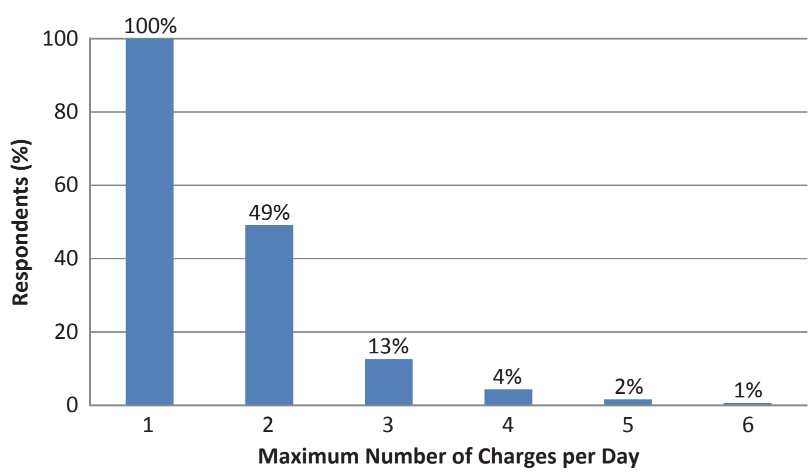

FIGURE 2 Maximum number of times per day that subjects are willing to fast charge.

factor will be updated, for it is a slightly imprecise method of reducing BEV tour probability. Using only one vehicle in a household is also an option, but since there are so few tours, keeping the variety of tours—but reducing their value—was preferred.

Evaluation of Charging Demand

Charging demand can be represented as a heat map created with charge windows. For each tour, charge windows are generated for each respective BEV range. The final weight of each charge window is the same as the tour it belongs to. A total charging demand density can be calculated as the line density of charge windows multiplied by the scaling factor, divided by the length of the charge window to normalize long- and short-charge windows. The value of each cell represents the number of charging events per unit area.

Assessment of Charger Utility

The utility of each charger is the combined weights of all charge windows within a user-defined search radius from the charger. However, the tool takes two assignment strategies when assessing the utility of existing and proposed chargers versus predicting potential chargers. Different from existing chargers, the proposed ones have been approved to build but not yet been used.

Existing and Proposed Chargers

When assessing the utility of existing and proposed chargers, charging demand will be assigned evenly to all chargers within the charge window. For instance, there are two existing chargers, M and N, that can serve the charge windows of Routes A, B, and C (Figure 1). The charge window of Route A has a weight of 4, the charge window of Route B has a weight of 3, and the charge window of Route C has a weight of 6. Charge windows of Routes A and C are within the search radius from Charger M, and charge windows of Routes B and C are within the search radius from Charger N. Thus, the utility of Charger M is $4 + 6/2 = 7$, and the utility of Charger N is $6/2 + 3 = 6$.

Potential Chargers

At times, modelers want to find which potential sites are the best choices. When predicting the utility of potential chargers, all unserved charge windows are assigned to all potential chargers. Then the charger with the highest utility will get all charge windows assigned to it, and the two steps will repeat to assign charge windows to the next highest utility Charger, until no more charge windows can be assigned. Assuming both Chargers M and N in Figure 1 are potential Chargers after the first round assignment, the utility of Charger M is $4 + 6 = 10$, and the utility of Charger N is $6 + 3 = 9$. Charger M has higher utility, so both charger windows of Routes A and C are assigned to Charger M, and the final utility of Charger M is 10. In the next round assignment, only charge window of Route B is assigned to Charger N (since charger window of Route C has been assigned to Charger M), so the final utility of Charger N is 3. After the desired number of chargers is chosen by the tool, the final assignment of demand is again distributed among nearby chargers as described in the existing and proposed chargers.

DATA

Data Set of California Household Travel Survey

Scenario analysis in this paper uses the data set of the 2010–2012 California Household Travel Survey conducted by Caltrans, including 42,431 households from all of California's 58 counties (*13*). Since the travel diary does not have detailed information about route choice of each trip, the route with the fastest network distance between origin and destination is used to analyze respondents' travel patterns. Each trip is represented by a line, and the line density is the traffic density. The highest traffic density is located in the Bay Area and Sacramento in Northern California, and Los Angeles and San Diego in Southern California (Figure 3).

A potential limitation of the fastest path method is that it might not reflect the true traffic demand when there are parallel paths. Considering traffic congestion, user equilibrium traffic assignment can be a better approximation to real traffic. For example, there are three parallel paths from the Bay Area to Los Angeles, including Interstate 5, California State Route 99, and U.S. Route 101. According to the fastest path method, all traffic will be assigned to Interstate 5 because it is the fastest path assuming normal speeds. But such assignment could cause heavy congestion on Interstate 5 and make U.S. Route 101 a quicker path than Interstate 5. A user equilibrium algorithm can assign traffic more evenly and better simulate the travel pattern. However, travel could be completed with the assigned paths, and if a modeler has access to actual paths, the tool can reflect this demand.

By converting the travel diary into home-based tours, a total of 70,917 tours can be put into two categories: one has at least one trip for work purpose and is called work tour; and the other that has no trip for work purposes, so it is called nonwork tour. There are 47,288 nonwork tours, twice more than work tours. A study about Atlanta commute trips has a similar conclusion about the share of work and nonwork tours (*17*). Few work tours are longer than 160 mi, a distance requiring more than one extra charge within a day for a BEV with a range of 80 mi or less (accounting for most of the popular BEV models, except for Tesla). Because users are not expected to fast charge every day, work tours are treated separately in the tool. They can be included later, included with workplace charging available, or excluded. The scenarios that follow mostly show the demand from nonwork tours to reflect the nonhabitual use of fast chargers.

BEV Ownership

According to the Clean Vehicle Rebate Project (CVRP) from the California Air Resources Board, 22 BEV models are available in California. The Nissan Leaf and the Tesla Model S are the two most popular models; the Nissan Leaf accounts for nearly half of the BEV market share, and the Tesla Model S accounts for around a quarter of the share. Currently, most BEV models have a range of around 60 to 80 mi except for the Tesla Model S. Further, most current fast chargers support only the Nissan Leaf and Mitsubishi i-MiEV. Therefore, the present scenario considered only the Mitsubishi i-MiEV and Nissan Leaf. There are a total of 16,961 Leafs and i-MiEVs combined in the analysis, representing those who received a rebate from the CVRP. As battery and powertrain technology improve, more long-range BEV models are expected to be available in the future, so the future scenario with 500,000 BEVs is interpolated by using a combination of buying patterns from the Leaf and Tesla (*18*).

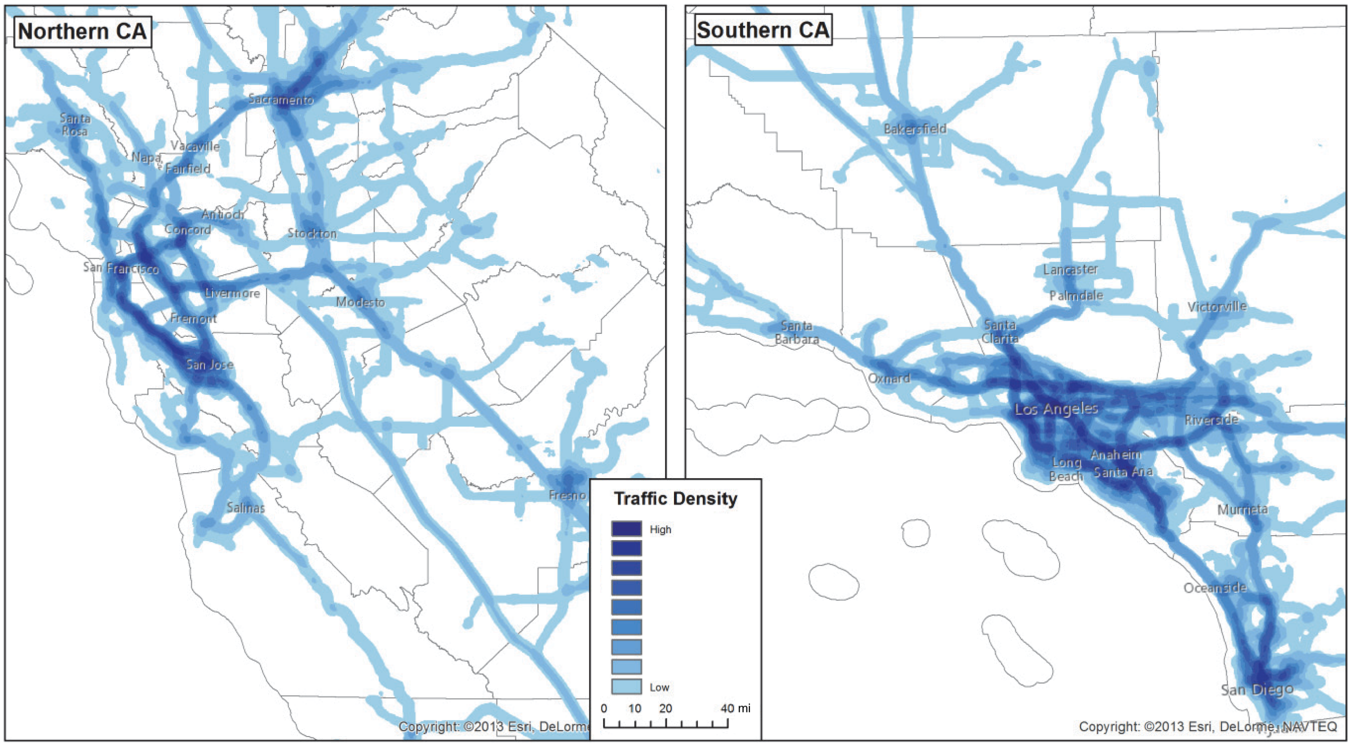

FIGURE 3 Traffic density of nonwork purpose tours in California (CA).

PEV households have higher income than the general population does. According to a previous study about the PEV market in California, there is a significant difference in household income between internal combustion engine buyers and PEV buyers. Findings are that 51% of new internal combustion engine car buyers (or leasers) reported an annual income lower than \$100,000, while only 11% of PEV owners reported similar income (*19*). Detailed explanations about the BEV types used in the study will be given later in the description of each sample scenario.

SAMPLE SCENARIOS AND RESULTS

Present Scenario

The present scenario highlights the ability of the tool to perform gaps analysis to show where chargers may be needed in the context of existing chargers. Connecting the origins with the destinations allows the tours originating in areas with more BEVs to be weighted accordingly and reflects where people in those regions would like to travel. This is important, because getting spatially resolved demand by road segment any other way is difficult. In the present scenario, actual BEV ownership is sourced from CVRP rebates and used together with travel diaries from the California Household Travel Survey to analyze the demand of fast charging.

According to the U.S. Department of Energy, there are 148 existing CHAdeMO (a trade name for DC quick charging method) fast charging stations in California (*20*). Additionally, at least 53 more fast charging stations have been proposed to be built in the near future. Locations of these chargers are used to assess potential use of these stations. Using these inputs, statewide fast charging demand was generated by the tool (Figure 4). For the current scenario, ranges of 80 and 60 were used, with a 20% buffer. The range of vehicles decreases with highway speed, but the buffer gives the model some margin for error when computing actual vehicle range. Based on the tool's assessment, the average utilization of fast chargers in San Francisco is 3.9 events per charger per day; that conforms to the real utilization, which is about 4.2 charging events per day per charger (*21*). The modeled usage is expected to fluctuate up or down depending on a host of factors, including price, nearby services, Level 2 availability, nearby homes of PEV customers, and season.

Based on the present scenario's result, the highest fast charging demand density (indicated by colors on the map) is 0.27 charging events per square mile. Most fast charging demand is in the Bay Area, Los Angeles, and San Diego. A close-up view of fast charging demand in the Bay Area indicates that most demand is on the north–south corridors of U.S. Route 101, Interstate 880, and Interstate 680. From the travel survey, these are the routes most likely to be used by BEV owners. However, demand on these three freeways is not equal. Interstate 680 (center right of Figure 4) has less demand than the parallel route on Interstate 880 (center). It could be the real charging demand, or it could represent the parallel route problem caused by the fastest path method as mentioned earlier. The model indicates that the most popular charger locations have a potential demand of up to 10 charging events per day.

After demand is served by existing chargers in the model, the tool reports the unserved fast charging demand for which there is no fast charger within 1 mi of the charge windows. The unserved demand in Figure 5 shows the need for chargers south from San Jose connecting to Santa Cruz and Gilroy, and east from Livermore to Tracy, California.

The tool can also evaluate proposed chargers in the context of existing chargers. A comparison of unserved fast charging demand before and after the installation of the 53 proposed chargers taking Los Angeles as an example is given in Figure 5. The highest unserved demand density is 0.082 charging events per square mile, which is around one-third of the highest served demand density. With

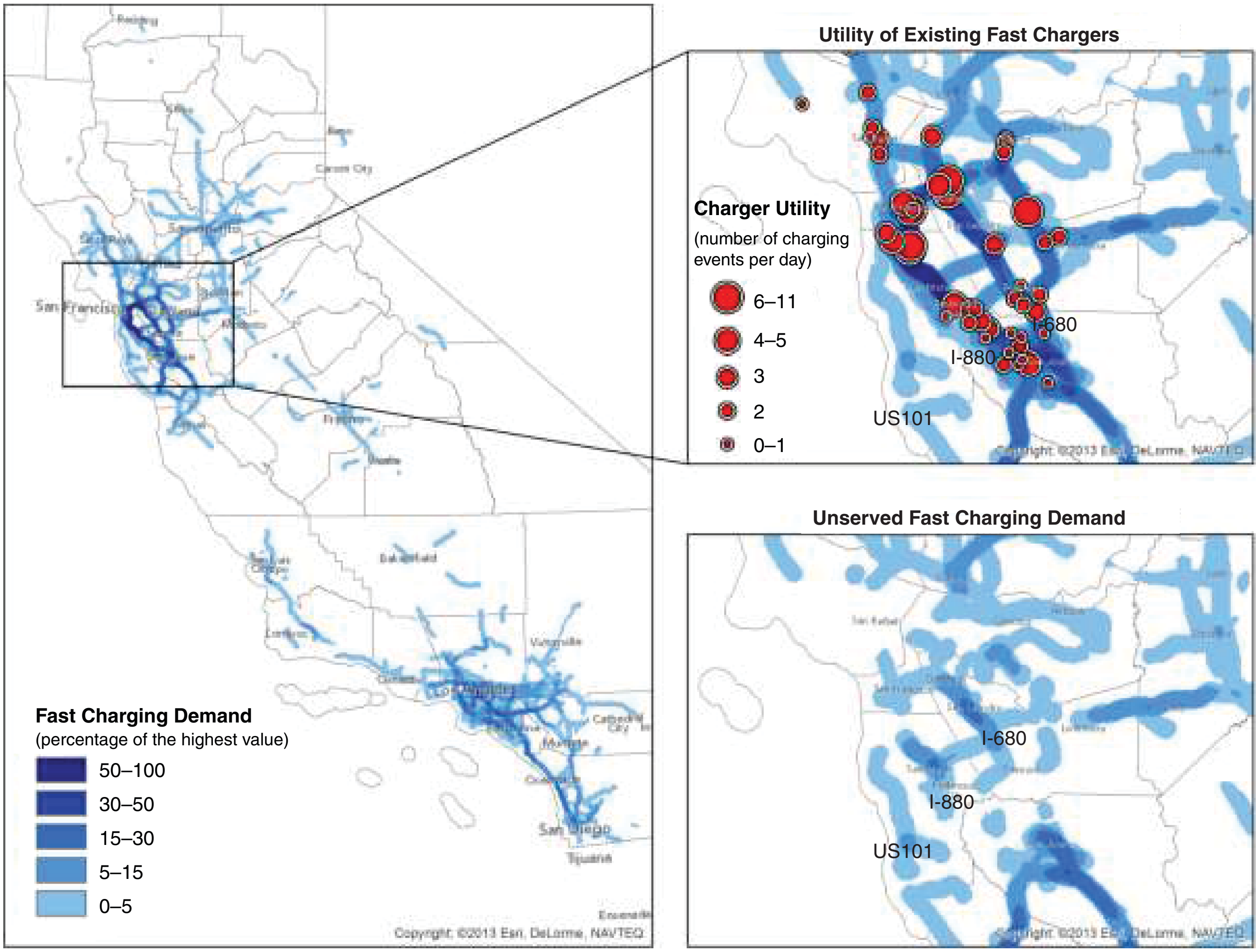

FIGURE 4 Result of present scenario with existing fast chargers.

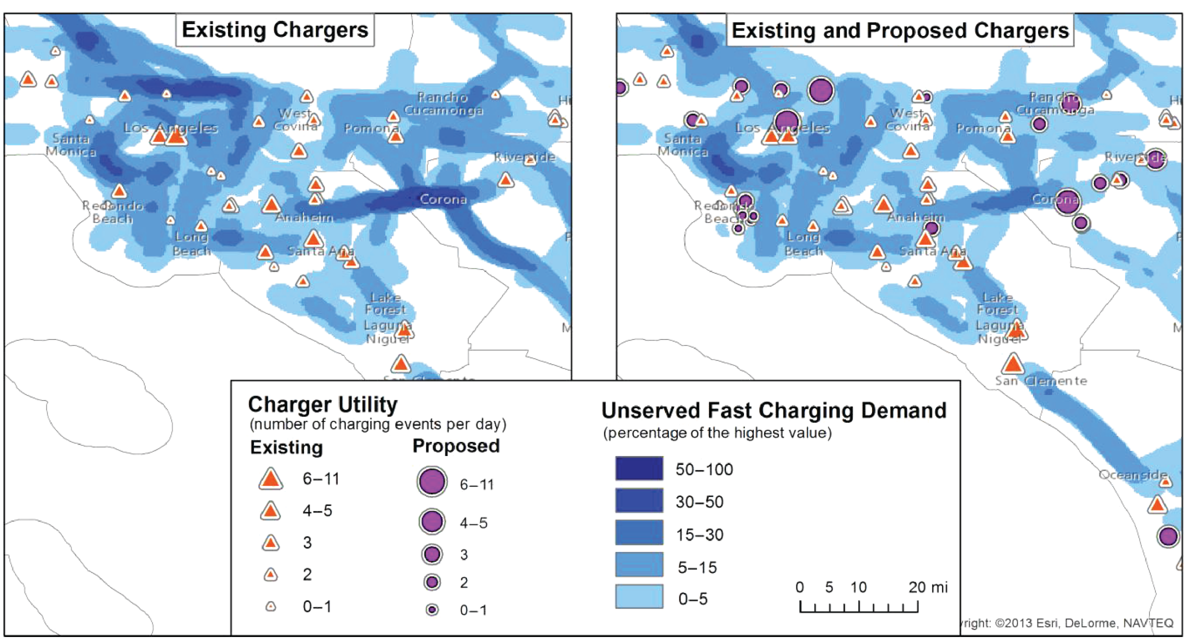

FIGURE 5 Results of present scenario with existing versus existing and proposed chargers in Los Angeles with utility in charging events per day.

only the existing chargers, most unserved fast charging demand is in northwest Los Angeles and Corona, California. But both areas have proposed chargers to be installed, and these proposed chargers can relieve charging demand to a great extent, according to the results.

Future Scenario

The tool also helps inform policy surrounding future growth in the market with larger battery BEVs, and it helps answer the question of what sort of infrastructure may be needed and where. The scenario presented here provides insights into what may come. With the improvement of battery and powertrain technology, more long-range BEV models are expected to be available in the future (*18*), so BEVs with ranges of not only 80 mi but also of 150 mi and 300 mi were considered in the future scenario. The scenario in this study assumes that there are a total of 500,000 BEVs in California, among which 50% are BEV 80s, 25% are BEV 150s, and 25% of are BEV 300s. The distribution of the 250,000 BEV 80s among California's 58 counties is assumed to be similar to today's Nissan Leaf customer characteristics, while the characteristics of Tesla Model S owners were used to predict the distribution of BEV 300s. The distribution of BEV 150s was a combination of Leaf and Tesla owner demographics. In general, the distribution of vehicles was much more widespread than in the present scenario because there was not a geographic filter in the model. If the household fit the model in regard to income, commute, garage, and more, then that household would be equally likely to buy as would any other household with similar characteristics.

A prediction of future fast charging demand is given in Figure 6. The highest fast charging demand density in the future scenario is 4.67 charging events per square mile, about 18 times the maximum in the present scenario.

To highlight the change in demand location between the present and future scenario, the colors were normalized so that the highest demand in each scenario is represented by red. In the future scenario, there is relatively more charging demand on long-distance corridors such as Interstate 80 and Interstate 5, reflecting large-battery BEVs used for longer-distance trips, such as from the Bay Area to Los Angeles, or from Sacramento to Oregon. Such trips can be made by a BEV 300 with one or two fast charges. Conversely, in the near-term scenario, only SR-99, or CA-99, shows up with any significant demand, signaling that for a near-term north–south corridor in California, CA-99 is the clear choice.

To examine the interaction between battery size and number of charging events scenario results are shown in Table 1. Since it is hypothesized that nonwork tours are more likely to incorporate fast charging, they are separated from nonwork tours. Of statewide tours, 67% are nonwork tours. Out of 250,000 BEV 80s, they would generate 6,731 charging events on any given day on nonwork tours, assuming there were no public Level 2. However, comparison of the BEV 80 with the BEV 150, shows some important interactions:

1. Events per vehicle per day decrease by 63%,
2. Electricity dispensed per charge increases by 87%, and
3. Energy needed per event in the state decreases by 31%.

Even though the battery size of the BEV 150 is nearly double that of the BEV 80, the consumption per day per car decreased by only about 31%. This decrease is not only because batteries are bigger, but also because trips that are too long for BEV 80s are more palatable to BEV 150 customers, since they have to stop fewer times, as shown in other studies (*3*).

When one looks at work trips in Table 1, one sees a large apparent potential for fast charging based on distance, but it is hypothesized

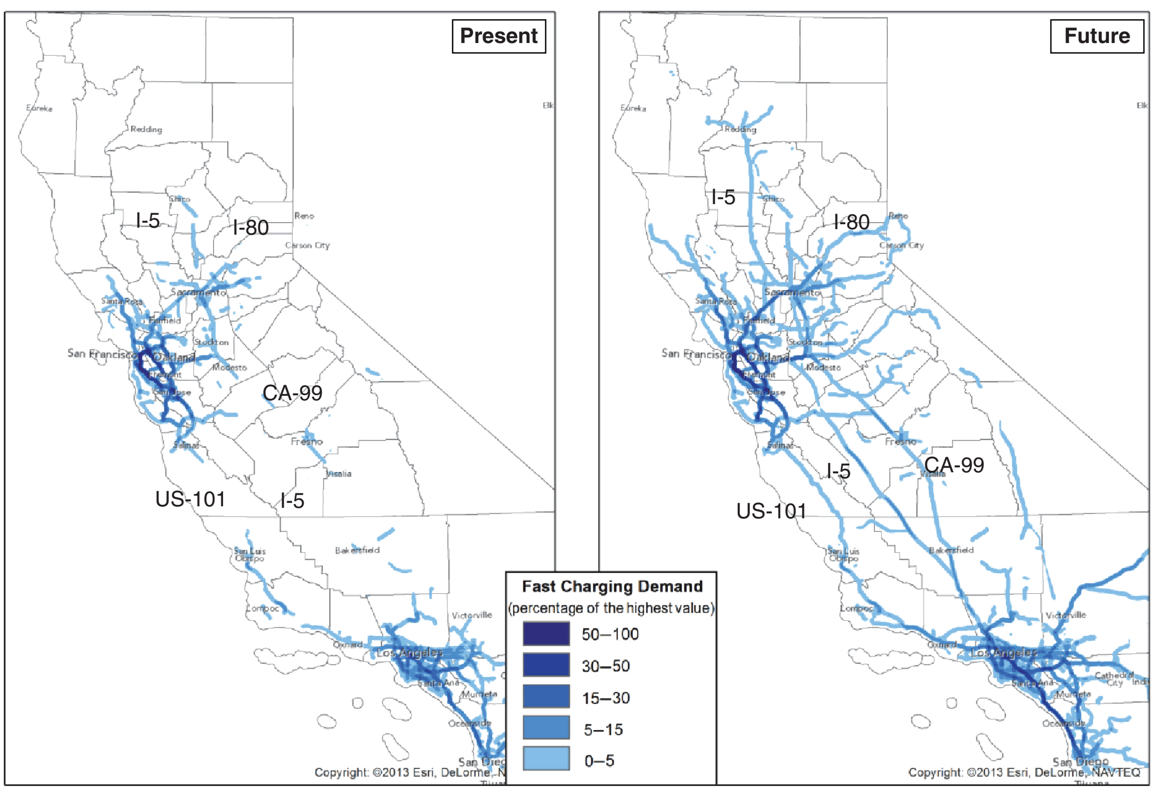

FIGURE 6 Results of fast charging demand in present scenario versus future scenario.

TABLE 1 Results of Future Scenario

Tour Purpose	BEV Range (mi)	Number of Cars	Total Charge Events	Total Consumption (kW-h)	Average Consumption (kW-h/car/day)	Average Consumption (kW-h/charge)	Average Charge Events/Car
Nonwork	80	250,000	6,731	83,562.61	0.33	12.42	0.0269
	150	125,000	1,244	28,906.56	0.23	23.25	0.0099
	300	125,000	296	13,167	0.11	44.41	0.0024
Work	80	250,000	8,040	117,486.88	0.47	14.61	0.0322
	150	125,000	474	12,176.45	0.10	25.71	0.0038
	300	125,000	73	3,411	0.03	46.31	0.0006
All	80	250,000	14,770	201,049.48	0.80	13.61	0.0591
	150	125,000	1,717	41,083.01	0.33	23.92	0.0137
	300	125,000	369	16,578	0.13	44.93	0.0030

that this demand will not materialize to this degree if workplace charging is available as an alternative to fast charging. Owing to this large potential demand, some work-based fast charging could be expected occasionally in lieu of Level 2.

In the future scenario, a fast charger location might have more than 170 charging events per day (Figure 7), so multiple chargers are needed for certain areas. Although this demand is represented at one point, most likely, the demand will be spread over several locations near the point. Charging likewise is not expected to happen evenly throughout the day, and charging a Nissan Leaf battery to 80% is up to 25 min, assuming use of a 50 kW charger (*21*). Higher capacity chargers corresponding to larger-battery vehicles preserving the 20- to 30-min charge times are assumed, so each charger is expected to serve an average of 15 charging events per day (*3*). Therefore, a location with 170 charging events needs about 12 chargers to satisfy all charging demand.

Another feature of the model is to select the best sites from possibilities input by the user. Analysis for this study used 800 possible

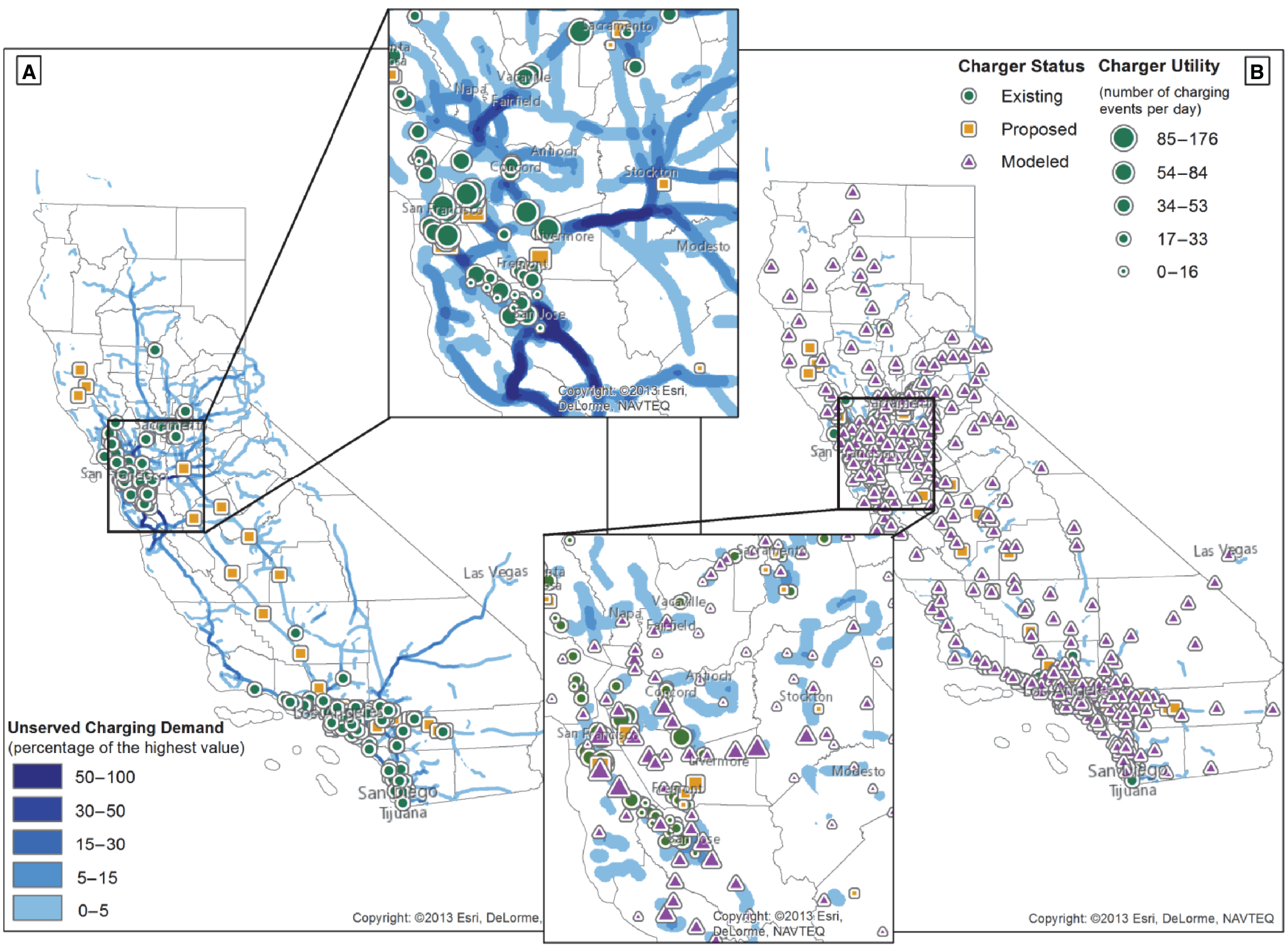

FIGURE 7 Future scenario using the model to select 300 additional sites based on potential use.

locations beyond the planned and existing sites. The model assessed their potential utility based on the method outlined in the section on assessing charger utility. The top 300 locations with the most utility are presented in Figure 7 as modeled. With the 300 modeled locations, there will be little significant fast charging demand in California based on the input data. This compares well with previous studies (*3*).

Work Charging

Many Californians will have workplace charging in the future. Since people are not as likely to fast charge regularly to or from work, work tours were taken out of the foregoing analysis. They can be included, however, with or without work charging. Fast charging demand reduces because the highest level of demand in the case of without work charging does not appear in the case of with work charging (Figure 8). Including work charging allows the possibility that drivers may have nonhabitual trips starting from work that may require fast charging in combination with Level 2 work charging.

The number of charge windows can give a rough estimation of fast charging demand. For the present scenario, the number of charge windows for work tours decreased by 39.8% after implementation of work charging. In the future scenario, work charging can reduce fast charging demand by 25.8%. Since the future scenario has more long-range BEVs, it is reasonable that work charging has less influence on fast charging demand.

Limitations of Regional Data

As mentioned before, analysis of fast charging demand benefits from travel data beyond a regional context. To illustrate this benefit, the results from the future scenario were separated as either coming from those living inside a region or from those coming from outside a region. The regions were identified by the census urbanized area, and four were analyzed: Los Angeles area, San Francisco Bay Area, San Diego area, and Sacramento area. The percentage of fast charger demand coming from inside the region varies with battery size (Figure 9) (*22*).

For larger regions such as Los Angeles, the inside demand reaches nearly 80% in the BEV 80 case, meaning that a reasonably good estimation should be possible with only regional data. As the regions get smaller and battery size gets bigger, predicting demand becomes more difficult. For example, in Sacramento for BEV 80s, only 32% of demand is from local traffic, thus showing the value of statewide or greater-region data.

CONCLUSIONS

This paper presents a tool that uses travel survey data to evaluate fast charging demand and to assess the utility of proposed charger locations. Compared with other existing regional planning processes, this model can provide a statewide assessment with great consistency, and results are comparable among regions. The analysis also shows the importance of data on long-distance trips to analyze fast charging. Even for small-battery BEVs, a significant portion of demand originates outside of a region, making analysis with regional data incomplete.

The scenario analysis highlights several aspects important for planners. First, planning for today's vehicles is different from planning for tomorrow's vehicles. If the distributions of vehicles shift from today's concentrations to a more even distribution, and battery size grows, the demand shifts to more areas, and some demand appears on long-distance corridors where before there was little. The demand in kW-h from fast charging per vehicle decreases as the battery size grows

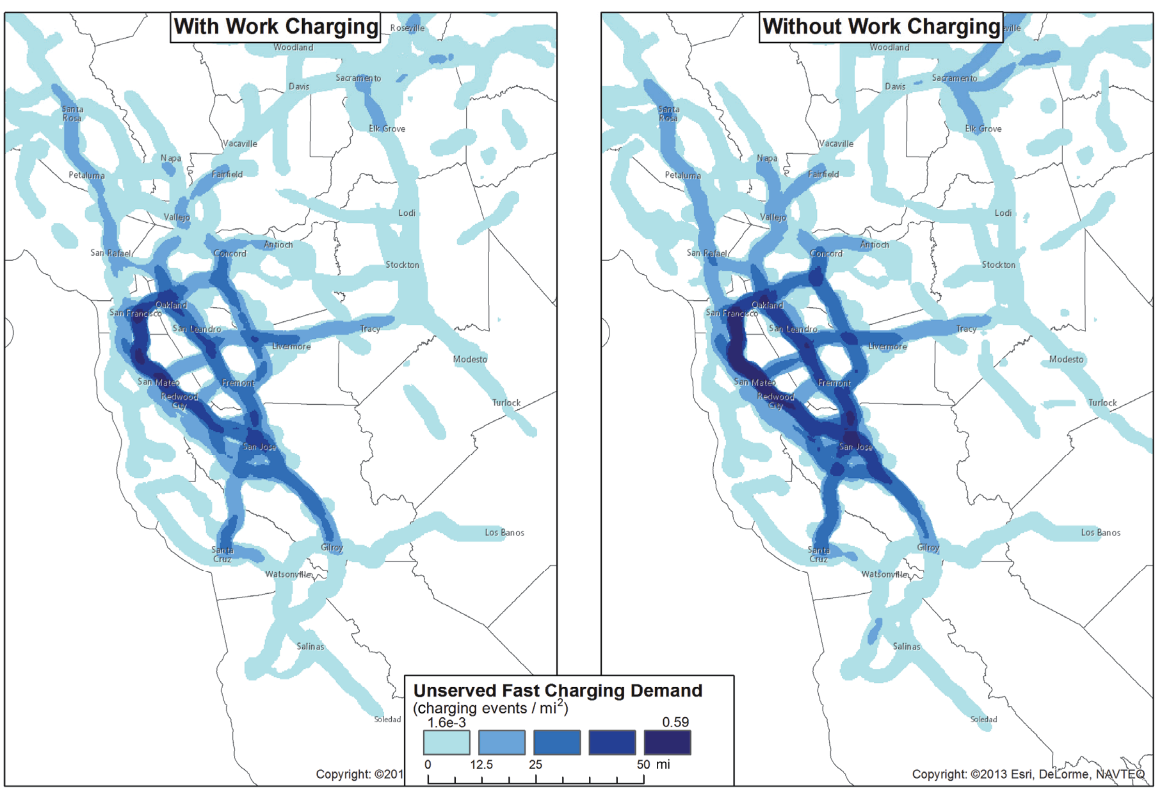

FIGURE 8 Influence of work charging on fast charging demand.

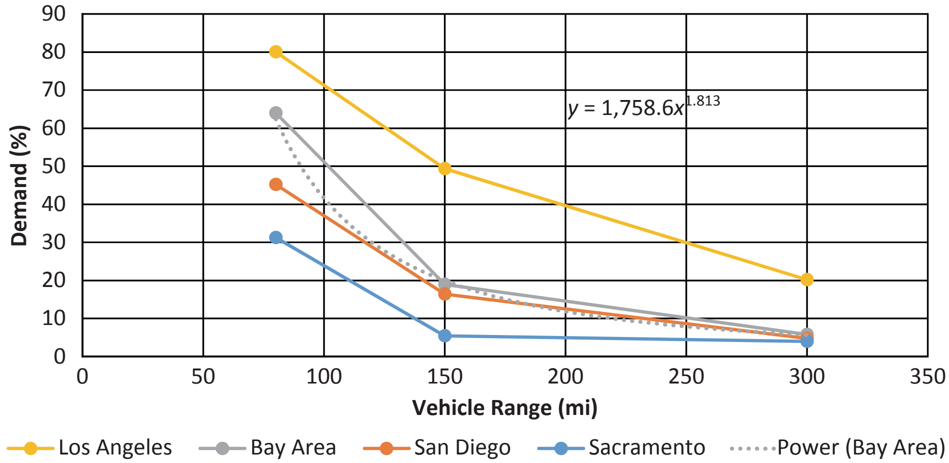

FIGURE 9 Fewer trips originating from within a metro area as battery size grows.

owing to the lower number of events, although per-session energy grows. Work-based demand shows an apparent high potential, but this demand may not materialize with reliable workplace charging. If the number of chargers needed at work is insufficient, fast charging may provide an important bridge to ubiquitous Level 2 in the case of BEV 80s.

The analysis focuses mostly on corridor charging. Although the tool incorporates survey data on willingness to stop, there are still many further factors that may affect demand that are not reflected. This analysis does not consider Level 2 demand outside of work, but this can be included in future scenarios. Likewise, some demand for fast charging will come from nearby homes or apartment dwellers who have poor access to charging. However, the tool and analysis should help identify places where fast chargers are needed, to enable longer trips in BEVs.

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