

OPTIMAL LOCATIONS OF U.S. FAST CHARGING STATIONS FOR LONG-DISTANCE TRIPS BY BATTERY ELECTRIC VEHICLES

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ABSTRACT

Due to environmental and energy challenges, promoting battery electric vehicles (BEVs) is a popular policy for many countries. However, lack of fast recharging infrastructure and limitations on BEV range moderate their purchase and use. It is important to have a well-designed charging station network, so this paper uses U.S. long-distance travel data to place charging stations in order to maximize long-distance trip completions. Each scenario assumes a certain number of charging stations (from 50 to 250, across the U.S.) and vehicle range (from 60 mi to 250 mi).

The problem is formulated as a mixed integer program, and a modified flow-refueling location model (FRLM) model is solved via a branch-and-bound algorithm. Results reveal that all electric ranges (AER) longer than 250 miles offers little benefit to U.S. travelers, with station count offering impressive results. For example, at AERs of 200 and 300 miles, 93% and 99% of the nation's long-distance personal trips can be completed, with just 100 charging stations placed strategically. With a 60-mile AER, only 42% can be completed. The 60-mile-AER percentage varies between 31% and 65%, as one increases station count from just 50 stations to 250 stations. At least 100-mile range BEVs may be needed, to avoid long-distance-trip issues for the great majority of U.S. households, until more fast-charging stations can be added to the nation's network.

Key words: Battery electric vehicle, Optimal location, long-distance trips, Fast charging station

MOTIVATION

Alternative-fuel vehicles, especially electric vehicles (EVs), have acquired considerable attention over the past few decades. Many countries hope EVs will help resolve certain energy problems and actively promote EV adoption. Experts expect U.S. sales to be over 1.8 million plug-in hybrid electric vehicles (PHEVs) and 1.2 million battery-only electric vehicles (BEVs) from 2012 to 2020 (1, 2).

Unfortunately, EVs are relatively range-limited between recharges (3, 4, 5). Presently, the longest BEV driving range is 337 miles (Tesla Model S P100D), while the shortest range is 53 miles (Scion

1 iQ EV). Most BEVs have ranges between 60 miles and 100 miles. Even though the comparatively
2 priced 2017 Chevrolet Bolt EV and Tesla Model 3 can have a total range of 238 miles and 215
3 miles, respectively(6), the petroleum-fueled cars and trucks regularly go 400 miles or more.
4 Another challenge to widespread EV adoption is lack of charging station (CS) infrastructure. These
5 days EVs are generally charged through three types of Electric Vehicle Supply Equipment (EVSE):
6 Level 1 EVSE typically takes 10 – 20 hours to charge, restricting charging periods largely to a
7 vehicle’s home base. Level 2 (240 volt) chargers require about 4 to 8 hours, and are used in both
8 commercial and home charging settings (7). Level 3 constitutes a “fast charging station” and can
9 take as little as 20 minutes to charge to 170 miles, 40 minutes to charge to 270 miles, and 75
10 minutes to 330 miles, making en-route/mid-trip charging feasible for most travelers. Ignoring
11 power-supply costs, Level 1 EVSE costs less than \$1,000, Level 2 equipment costs between \$3,500
12 and \$6,000 for a single commercial/relatively public installation or \$1,000 for a residential/private
13 setup (8). Level 3 EVSE currently costs from \$60,000 to \$100,000 (8), making it difficult to
14 provide and rare in practice. As a BEV leader, Tesla is providing its own supercharging network
15 across the U.S., with an average total construction cost per supercharge station of roughly \$270,000
16 (9).

17 To address travelers’ range anxiety for intra-urban trips, as well as long, inter-regional trips, many
18 countries are investing in public charging stations. For example, in April 2017, the U.S. National
19 ZEV (zero emissions vehicle) organization announced a plan to establish a network of more than
20 2,500 non-proprietary EV chargers in 11 metropolitan areas and along major highways by 2019
21 (10). \$1.2 billion will be directed toward U.S. EV infrastructure and education programs, with an
22 initial goal of 240 highway-based inter-city sites installed or under development by 2020. Canada’s
23 British-Columbia province aims to build 570 charging stations (11). Such plans (and fast-charging
24 cost realities) present an important engineering problem: how many charging stations are needed,
25 and where are the best placements?

26 This paper provides and applies a workable method for “optimal” placements of 50 to 250 direct-
27 current fast charging (DCFC) stations across the U.S.’s extensive highway network, with all-
28 electric ranges (AERs) range from 60 miles to 300 miles. Optimality is defined here as maximizing
29 the share or number of long-distance (over 50-miles, one-way) car trips that Americans already
30 demonstrate.

31 LITERATURE SYNTHESIS

32 Many researchers have investigated the EV charging station (CS) location problem, with some
33 papers concentrating on slow-charge stations and mostly focused on small networks. Wang et al.
34 (12) specified a numerical method for locating CSs using a multi-objective planning model and
35 distributions of gas-station demands in Chengdu, China. Li et al. (13) formulated genetic
36 algorithms to estimate top locations for charging infrastructure while minimizing cost. Frade et al.
37 and Chen et al. used regression methods to estimate the potential demand by neighborhood. Frade
38 et al. (14) estimated nighttime versus daytime charging demands in each census block. Chen et al.
39 (15) used parking demand as a proxy for charging demand, and applied a mixed integer program
40 (MIP) to Seattle, Washington, based on a fixed-charge facility location model, minimizing walk
41 distances or access costs for vehicle owners. Wood et al. (16) presented a Battery Lifetime Analysis
42 and Simulation Tool for Vehicles (BLAST-V) to maximize potential utility to prospective EV
43 owners (defined as the share of household VMT accomplished via a BEV relative to that of a
44 conventional vehicle). Their simulation’s parameters include driver behavior, vehicle performance,
45 battery attributes, environmental conditions, and charging infrastructure. Shahraki et al. (17) used
46 large-scale vehicle-trajectory data in Beijing, China to minimize total distances traveled between
47 locations of estimated demand and slow-charge (overnight) stations. Capar et al. (18) introduced
48 a relatively efficient arc-cover-path-cover model to reflect vehicle range and trips between origin-
49 destination pairs. All these research efforts were confined to a city or a small, simulated network.
50 The maximum number of charging stations and network nodes considered were 40 and 750,
51 respectively. This paper considers up to 250 stations, across the U.S., with 846 nodes as potential
52 station locations, allowing for more realistic implementations.

1 Models for fast-charge locations do differ, in that they should emphasize longer trips (those most
 2 likely to run out of range in route) and thus inter-city settings. Their charging demand is usually
 3 estimated as a function of number of EVs on the road, and/or trip endpoints. Hanabusa and
 4 Horiguchi (19) used stochastic user equilibrium to estimate EV flows and then sought to minimize
 5 travel times while ensuring EV-trip completions. They ignored range limitations, but allowed
 6 routing choice impacts. Lam et al. (20) applied a flow model for small networks with implicit
 7 range anxiety considerations. Lee et al. (21) developed a bi-level optimization model (with user
 8 equilibrium on route choices, and range limitations explicit) to locate stations in a 24-node network.
 9 Chung and Kwon (22) formulated a multi-period optimization model based on a flow-refueling
 10 location model (FRLM) for maximizing network coverage across tolled South Korea freeways.
 11 Sadeghi-Barzani et al. (23) used genetic algorithms to solve a mixed-integer non-linear problem
 12 to minimize total cost of EV travel. Ghamami et al. (24) solved a general corridor model for
 13 optimally configuring charging infrastructure to support long-distance (LD) inter-city travel, with
 14 flow-dependent charging delays, but for just three OD pairs.

15 Kuby and Lim (25) developed the first flow-refueling location model (FRLM) to optimally locate
 16 refueling facilities for range-limited vehicles. The FRLM's objective is to maximize traffic flow
 17 served or completed via a specific number of refueling (or battery-charging) stations. Many authors,
 18 like Wang and Lin (26) proposed a set-covering FRLM to minimize facilities costs while refueling
 19 100% of vehicles. Wang and Wang (5) extend Wang and Lin's model to a multi-objective case,
 20 with the second objective maximizing the served flow. Lee et al. (21) introduced a stochastic model
 21 for route-choice, endogenously within the FRLM. MirHassani and Ebrazi (27) proposed a network
 22 expansion method to improve FRLM's computation times and opportunities for application to
 23 more realistic networks.

24 Across these investigations, only two have investigated placement of both slow and fast charging
 25 stations, together. Huang et al. (7) estimated the public Level 2 charging demand using traffic
 26 analysis zones and public Level 3 charging demand using network links. Liu (28) used an ad hoc
 27 method to place slow charging stations in home neighborhoods and fast charging stations based
 28 on current gas station locations. Table 1 summarizes all cited models, with most focused on
 29 maximizing served demand or minimizing access or distance costs. Table 1's fifth column shows
 30 how only Capar et al., Ghamami et al., and Chung & Kwon (18, 22, 24) study the layout problem
 31 of charging stations for an inter-city setting, but not for a national setting, as done here. For slow-
 32 charging stations, past researchers use polygon centroids to represent demand locations and rely
 33 on parking lots as candidate locations. For fast charging studies, network nodes or gas stations are
 34 typically used as candidate locations.

35 **TABLE 1 Literature Review and Classification**

Prior Studies	Decision Model	Objective	Demand Representation	Spatial Scope	Station Type	Candidate Locations
Frade et al. (2011)	IPM	Maximize covered demand	point	INC	SC	Car parks
Chen et al. (2013)	FC-FLM	Minimize total access cost	point	INC	SC	Car parks
Wood et al. (2015)	BLAST-V	Maximize EV travels' utility	point	INC	SC	Public destination
Wang et al. (2010)	MOPM	Minimize total access cost	network	INC	SC	Gas stations
Shahraki et al. (2015)	MILM	Minimize total access distance	point	INC	AFC	Gas stations
Capar et al. (2013)	AC-PC	Maximize covered demand	network	ITC	AFC	OD nodes
Hanabusa & Horiguchi	MOPM	Minimize total travel time	network	NC	FC	Network nodes

(2011)						
Lee et al. (2014)	BLOM	Minimize total failure cost	network	INC	FC	Network nodes
Chung & Kwon (2015)	FRLM	Maximize covered demand	network	ITC	FC	Tollgate nodes
Sadeghi et al. (2014)	MINLM	Minimize total operational cost	point	INC	FC	Nodes
Ghamami et al. (2016)	MINLM	Minimize total system cost	point	ITC	FC	Nodes
Liu (2012)	Ad hoc	Minimize the number of charging stations	polygon	INC	SC&FC	Gas stations
Huang et al. (2016)	FC/SC-GS	Minimize total access cost	polygon	INC	SC&FC	Gas stations

1
2 Note: NC = not considered, EV = electric vehicle, INC = inner-city, ITC = inter-city, SC = slow charging, FC = fast
3 charging, IPM = linear programming model, FC-FLM = fixed-charge facility location model, BLAST-V = battery
4 lifetime analysis and simulation tool for vehicles, MOPM = multi-objective planning model, MILM = mixed integer
5 linear model, AFC = alternative-fuel charging, AC-PC = arc cover-path cover, OD = origin-destination, BLOM = bi-
6 level optimization model, FRLM = flow-refueling location model, MINLM = mixed-integer non-linear model. GS =
7 geometric segmentation,

8 Paper Overview

9 This paper expands upon existing research by tackling a problem of national scope, utilizing large-
10 scale vehicle trip data for deciding the location of DCFC stations across the U.S. highway network.
11 The objective is to maximally serve long-distance, highway-based travel demand, subject to
12 station-count and EV range limitations. The framework can be applied in other country or regional
13 contexts by using comparable data: simply a network file and trip table.

14 The problem is formulated as a mixed integer program (MIP), based on a flow-refueling location
15 model. To solve the problem efficiently, a modified FRLM model was proposed to accommodate
16 a wider scope than was achieved through previous studies. The model is solved by a branch and
17 bound algorithm, as discussed below.

18 The remainder of this paper is organized as follows: the nation's long-distance travel data are
19 introduced, followed by a discussion of the paper's methodology. A location model of DCFC
20 stations based on the modified FRLM model is formulated, and an optimization algorithm is
21 designed to efficiently solve the problem. Research results are discussed for various scenarios, and
22 the paper concludes with some suggestions for future research directions.

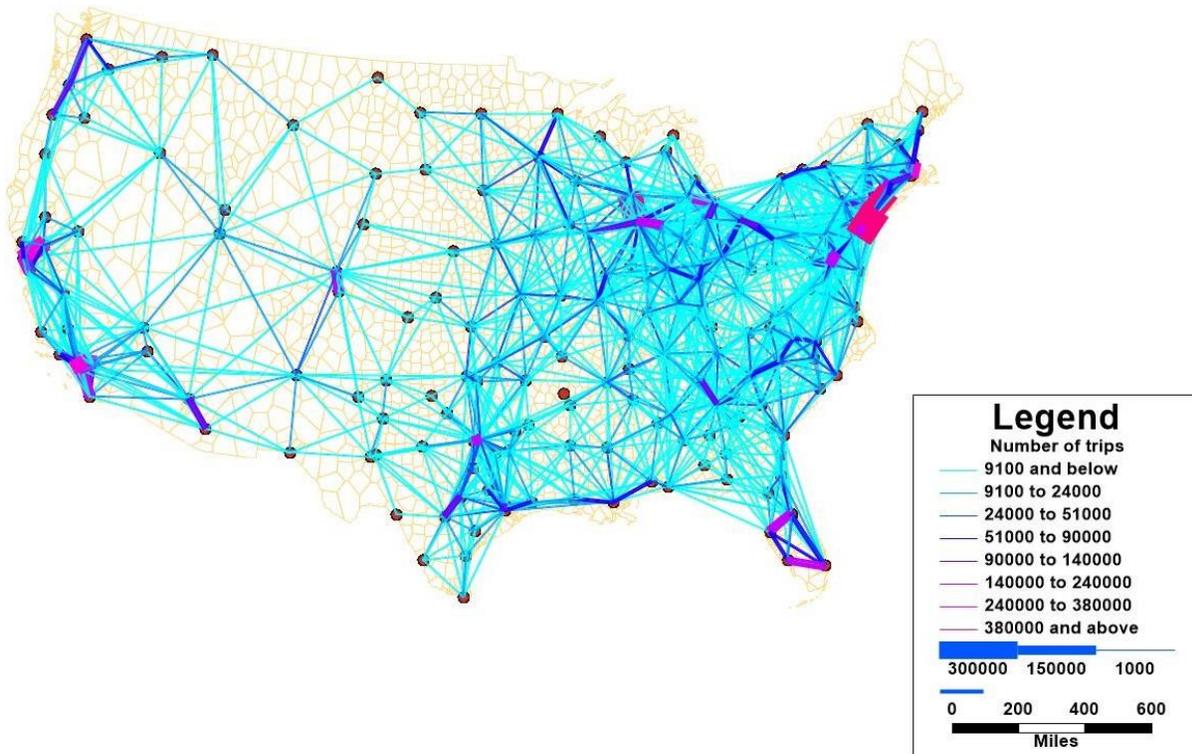
23 DATA SET

24 To determine optimal charging station locations, one must first appreciate the spatial distribution
25 of travel demands. Here, the FHWA's rJourney data set is used, as developed by Outwater et al.
26 (29). They estimated long-distance travel for all 117 million U.S. households or 309 million
27 Americans (based on the 2010 US Census). These are 820,389,992 trips over 50 miles in one-way
28 distance (actual driving distance), and tie to nearly all pairwise combinations of the nation's 4486
29 NUMAs (National Use Microdata Areas, based on over 3,000 counties and various cities and
30 census tracts) as well as four modes, using cross-nested logit (CNL) models: automobile/passenger
31 vehicle, bus, rail and airline modes (29, 30).

32 This research emphasizes long-distance trips by EVs, so only rJourney's automobile mode trip
33 table (for year 2010) is considered here. 48.67% of those trips are under 100 miles distance, and
34 68.5% are under 150 miles. Shortest-path distances for each NUMA pair are based on the National
35 Highway Planning Network, with connectors added to NUMA centroids. The 4486 x 4486
36 matrices of trip counts, travel times, costs, and distances (by each of 5 trip purposes) are too
37 extensive to model explicitly (with over 25 million OD pairs). To enable station-location solutions,

1 the problem's dimensionality was reduced to 200 x 200, using the K-means method (31) to cluster
 2 trip ends over space, as shown in Figure 1. Cluster centers were located in the member NUMA
 3 with the highest total density (households + jobs per square mile). Four cluster points in Alaska
 4 and Hawaii were removed, due to lack of contiguity with the other 48 states, resulting in a 196 x
 5 196 final matrix of automobile-based travel demands (and thus 38,220 shortest paths for the
 6 station-location solution algorithm to keep track of). Using this simplified setup for a complex
 7 system of OD pairs, Figure 1 highlights the nation's most popular travel corridors.

8



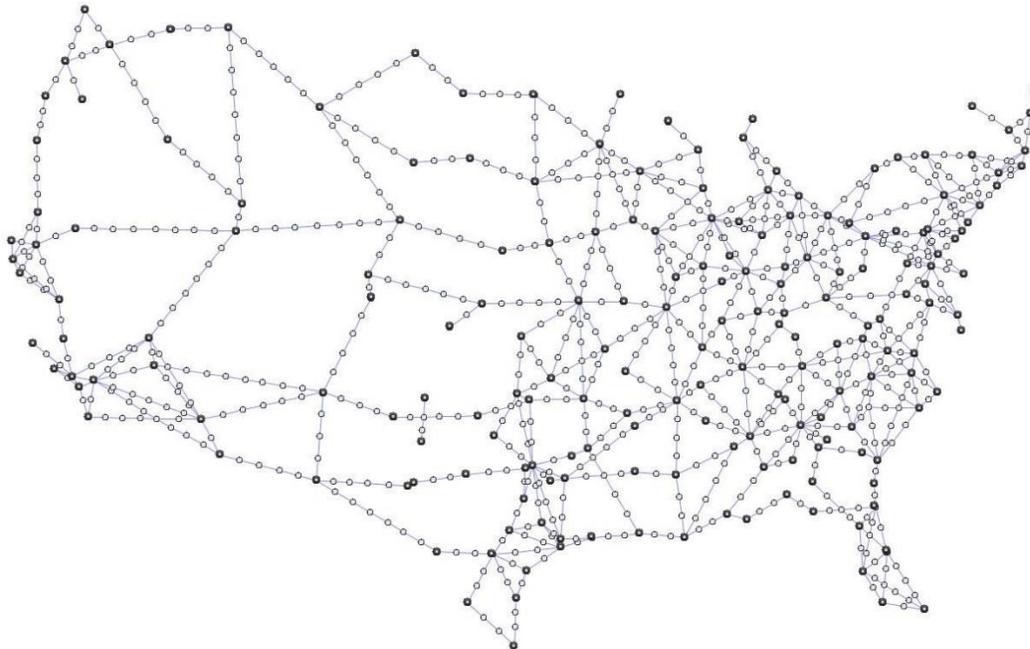
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 10 **FIGURE 1 U.S. map of long-distance trips, with 196 clustered trip-ends and one-way**
 11 **vehicle-volumes per week.**

12 **METHODOLOGY**

13 To thoughtfully select charging station sites across this almost 3-million square-mile region with
 14 over 38,000 OD pairs, a network was defined using the U.S. interstate highway system and Figure
 15 1's demand-map. The resulting network connects all 196 clusters nodes with links roughly
 16 following actual highways. To ensure that the length of each link between any two consecutive
 17 nodes is less than the minimum AER scenario (with a range of 60-mile), 650 nodes were added
 18 to break up any link over 60 miles in length. Figure 2 shows the resulting network, with 846 nodes
 19 and 1071 bi-directional links; black nodes represent the 196 cluster centers, and other nodes are
 20 shown in white. All 846 nodes are candidates for charging station placements.

21 In light of the still-massive U.S. network scope and limitations on the research team's
 22 computational resources, many OD pairs and their paths were filtered out initially. Low-use paths
 23 were dropped, in order to achieve solutions on a UT Austin supercomputer. As Table 2 shows, 89.7%
 24 of paths have a comparatively low demand at fewer than 18,240 vehicle-trips during the entire
 25 base year. (long-distance, by automobile) in the U.S. Just 3,940 paths (or 10.3%) of all 38,220
 26 paths account for 90.8% of the nation's total long-distance person-trip demand (as estimated by
 27 Outwater et al. (29)), so popular OD pairs are rather concentrated. These 3,940 paths were

1 therefore use to identify optimal charging-station placement across 30 different station-plus-range
 2 scenarios.



3
 4 **FIGURE 2 U.S. network of 846 nodes, for major highways with 60-mile maximum link**
 5 **length. (196 OD trip ends shown in black)**

6 **TABLE 2 Percentage of Total Paths and Corresponding Trip Volume**

Demand threshold (#LD car trips per year)	Number of OD pairs	Percent of the total paths	Number of LD Trips by car per year	Percent of total trip volume
Demand ≥ 0 LD trips per year	38,220 shortest paths	100%	820,389,992	100%
Demand ≥ 18240	3,940	10.3%	745,088,708	90.8%
Demand ≥ 30000	2,878	7.53%	720,414,075	87.8%
Demand ≥ 150000	1,003	2.62%	596,393,814	72.7%
Demand ≥ 300000	564	1.48%	505,295,078	61.6%

7 Note: LD stands for long-distance trip, which is over 50 miles (one-way).

8 The proposed model is an uncapacitated facility location problem to maximally serve long-
 9 distance demands between clusters origins and destinations. It is a modification of FRLM model
 10 and leverages the network expansion technique proposed by MirHassani and Ebrazi (27).

11 **Basic Assumptions**

12 There are several important behavioral assumptions in this paper’s solution framework. First, every
 13 OD pair has a single path that all its EV users will select (rather than deviating, to find a charging
 14 station off the shortest path). Moreover, all trips start or end near Figure 2’s black nodes, and
 15 charging stations can only be sited at any of the network’s 846 nodes (rather than in between).
 16 These two starting assumptions mean that the more flexibility exists, so presumably more trips can
 17 be completed than the solution algorithms will suggest.

18 The algorithms also assume that EV users begin their trips with less than a full charge (speculated
 19 to be 30 miles less than their AER) unless there is a charging station at placed at their start node
 20 (in which case they are assumed to begin their trip fully charged). This allows travelers to use up

1 some of their battery before entering Figure 1's coarsened/simplified network, recognizing that
 2 travelers come from all over a NUMA cluster, which requires some energy to enter. As one can
 3 imagine, the work also assumes that EV users will stop at a charging station, if one exists, to avoid
 4 running out of charge. And the algorithm focuses on completing the highest number of vehicle-
 5 trips, rather than paying attention to vehicle occupancies (which tend to be higher on longer-
 6 distance trips).

7 Model Specification

8 This sub-section presents a toy network with just one path to introduce MirHassani and Ebrazi's
 9 (27) expansion technique to the standard FRLM model. The path is an ordered set of nodes and
 10 links from origin node O to destination node D with an associated trip volume, or demand. If there
 11 is a feasible combination of fast-charging stations that enables each EV to reach D , the path and
 12 trips that use this path are considered "covered" or served. The single path p is denoted as $G(U^p,$
 13 $A^p)$. U^p represents its node set, and A^p represents its link set. $d_p(i,j)$ denotes the distance between
 14 any two nodes i and j on the path p and $ord_p(i)$ is an order indexing of node i along path p . For
 15 instance, if i is the second node from the origin node on path p , $ord_p(i) = 2$.

16 Under the expanded FRLM model system, a virtual source and sink node were added for each path,
 17 so path p is now denoted as $G(\hat{U}^p, \hat{A}^p)$, in the expanded network, constructed in 4 steps:

18 **Step 1:** Add source node s (before the origin node O) and sink node r (after the destination node
 19 D) to the path nodes. Connect s and O via a pseudo-link (s, O) , and D and r via a pseudo-link $(D,$
 20 $r)$. Then,

$$21 \quad \hat{U}^p = U^p \cup \{s, r\}, \hat{A}^p = A^p \cup \{(s, O), (D, r)\}$$

22 **Step 2:** Connect s to any other node, say i , on path p , by adding a pseudo-link (s, i) if the length
 23 between node i and origin node O is no more than the vehicles' AER minus 30 miles, which means
 24 that:

$$25 \quad \text{AER} - 30 \text{ miles} = T$$

$$26 \quad \forall i \in U^p: (s, i) \in \hat{A}^p \text{ if } d_p(O, i) \leq T$$

27 **Step 3:** Connect sink node r to any other node, say j , on path p , by adding a pseudo-link (j, r) if
 28 the length between node j and destination node D are no longer than the T miles, which means that

$$29 \quad \forall j \in U^p: (j, r) \in \hat{A}^p \text{ if } d_p(j, D) \leq T$$

30 **Step 4:** Connect any two nodes i and j along path p , if i 's ordering index is less than that of j and
 31 the EV can arrive at j with a fully charged battery from i . Thus,

$$32 \quad \forall (i, j) \in U^p: (i, j) \in \hat{A}^p \text{ if } d_p(i, j) \leq \text{AER} \wedge ord_p(i) < ord_p(j)$$

33 This paper uses the same processing method described above for all potential paths to establish
 34 the modified expanded FRLM model, producing two new path sets:

$$35 \quad \hat{U} = \bigcup_{p \in C} \hat{U}^p \quad \text{and} \quad \hat{A} = \bigcup_{p \in C} \hat{A}^p$$

36 where C is the set of all potential paths. Binary variable y_i is also introduced to indicate whether
 37 node i is selected for a charging station ($y_i = 1$ if chosen; otherwise, $y_i = 0$). Traveler flow through
 38 link $(i, j) \in \hat{A}^p$ of path p is denoted as x_{ij}^p . Since this research distributes a given number of charging
 39 stations to maximize served trips, the objective function of the expanded FRLM model becomes:

$$40 \quad \max Z = \sum_{p \in C} f_p (1 - x_{sr}^p)$$

41 where f_p is the trip demand of a specific OD pair on its shortest path p . For each path p , an additional

1 and important link (s, r) is added in the new link set \bar{A} , which means $\bar{A}^p = \{(s, r)\} \cup \hat{A}^p$. x_{sr}^p is the
 2 link-flow variable for the pseudo-link (s, r) . If $x_{sr}^p = 0$, path p 's travelers are served (i.e. they can
 3 complete their long-distance trip); if $x_{sr}^p = 1$, path p travelers cannot complete their trip without
 4 additional charging stations. The final model of this paper can be specified as follows:

$$5 \quad \max Z = \sum_{p \in C} f_p (1 - x_{sr}^p) \quad (1)$$

$$6 \quad \text{s.t.} \quad \sum_{\{j|(i,j) \in \bar{A}^p\}} x_{ij}^p - \sum_{\{j|(j,i) \in \bar{A}^p\}} x_{ji}^p = \begin{cases} 1 & i = s^p \\ -1 & i = r^p \\ 0 & i \neq s^p, r^p \end{cases} \quad \forall p \in C, \forall i \in \hat{U}^p \quad (2)$$

$$7 \quad \sum_{\{j|(i,j) \in \bar{A}^p\}} x_{ij}^p \leq y_i \quad \forall p \in C_i, i \in U^p \quad (3)$$

$$8 \quad \sum_{i \in U} y_i = N \quad (4)$$

$$9 \quad x_{ij}^p \geq 0 \quad \forall p \in C, (i, j) \in \bar{A}^p \quad (5)$$

$$10 \quad y_i \in \{0, 1\} \quad \forall i \in U \quad (6)$$

$$11 \quad \alpha_i \leq y_i \leq \beta_i \quad \forall i \in U \quad (7)$$

12 where p indexes the shortest path of a specific OD pair, C = set of all OD pair paths to be considered
 13 serving, C_i = subset of OD pair paths that includes all the path crossing nodes i , U = set of all
 14 network nodes, U^p = set of nodes on path p , $\hat{U}^p = U^p \cup \{s^p, r^p\}$, $\bar{A}^p = \{(s, r)\} \cup \hat{A}^p$; $\hat{A}^p = A^p \cup \{(s^p,$
 15 $O), (D, r^p)\}$; A^p = set of links on path p , N = number of charging stations to install across network,
 16 $y_i = 1$ if a DCFC station is located at node i & 0 otherwise, f_p = travel demand of a specific OD pair
 17 on its shortest path p , and x_{ij}^p = flow through the link $(i, j) \in \hat{A}^p$ of path, $\forall p \in C$.

18 The objective function (1) is designed to maximize the network's or nation's number or share of
 19 completed/served long-distance trips. Balance constraints (2) expand the scope to all potential
 20 paths, considering all those paths' situations. Constraints (3) guarantee that EVs can pass the node
 21 i smoothly following the corresponding path when there is a charging station placed at node i .
 22 Equation (4) simply restricts the total number of stations installed, while constraints (5) and (6)
 23 ensure non-negative and valid solution values.

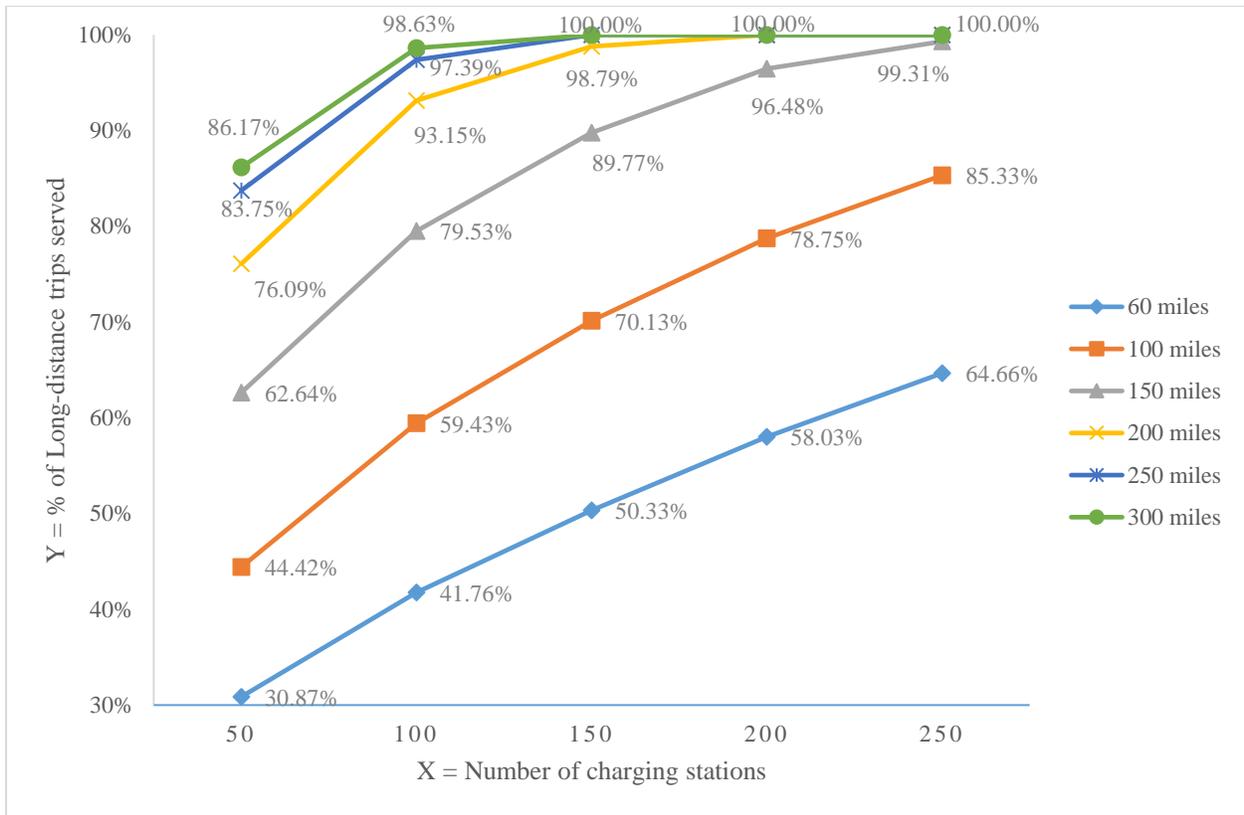
24 The model's last, massive constraint (7) provides several realistic options for decision-makers.
 25 Both α_i and β_i are binary variables. If an adequate charging station already exists at zone i (thanks
 26 to Tesla's supercharging system, for example), then both α_i and β_i may be set to 1. When a charging
 27 station is not permitted at node i (due to local implementation costs, jurisdictional or other
 28 constraints, for example), α_i and β_i can both be set to 0. If all locations/nodes are feasible, Equation
 29 (7) constraints can be ignored. Either way, for this type of problem setup, a branch and bound
 30 algorithm tends to perform well, and was applied here, with results described below.

31 RESULTS

32 The optimization model was implemented using one node of the Texas Advanced Computing
 33 Center's (TACC's) Wrangler parallel computer and MATLAB's Optimization Toolbox MILP
 34 solver. The files containing matrices for each AER total 5 GB in size. Filesystem I/O exceeded 12
 35 minutes for each large matrix, and total computation time for all 30 scenarios was around 6 hours.

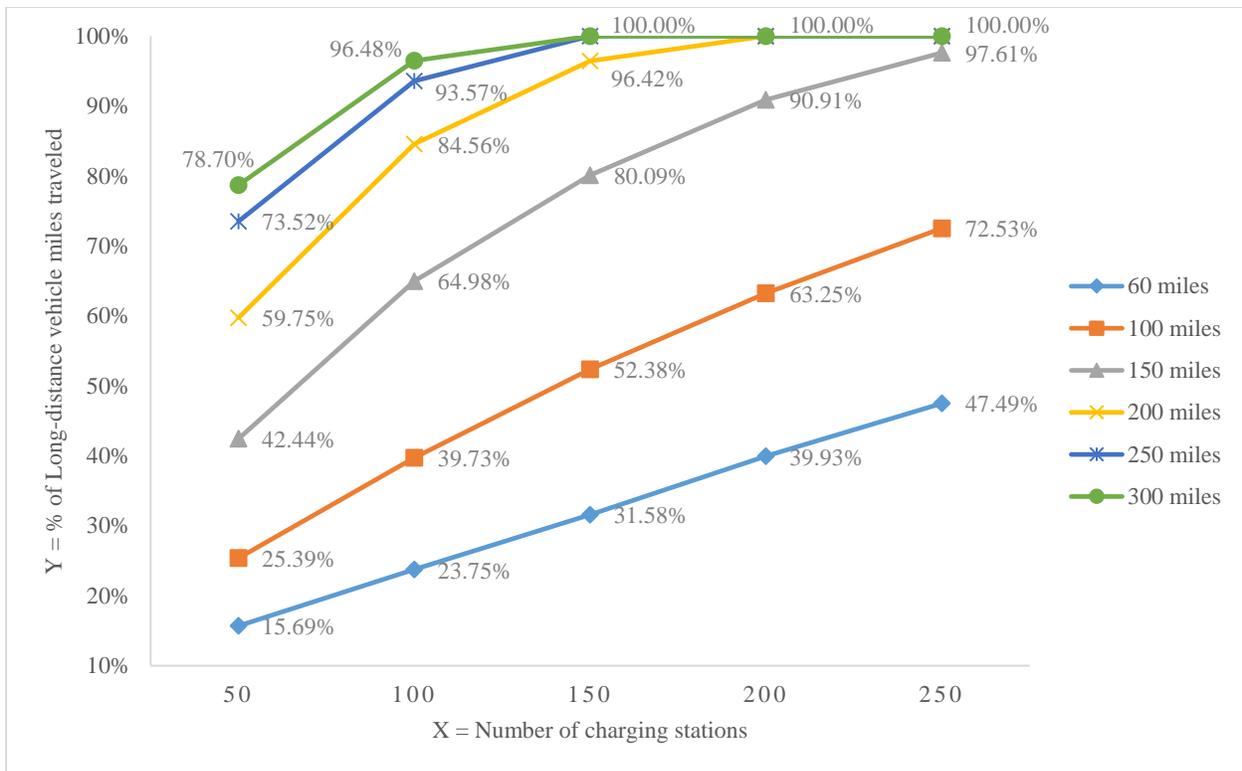
36 Figure 3 summarizes results across the 30 scenarios. Part (a) shows how BEVs with AERs of 200
 37 or more miles can serve almost all of the nation's long-distance, ground-based trips with rather
 38 few (just 100) charging-station installations. With just 100-mile range, 250 stations will be needed,
 39 and thoughtfully located, to serve a similar number of long-distance trips. At 60-mile and 100-mile

1 AER, each added station serves roughly another 0.2 percent of trips. The added trip share does
 2 start to fall as station count increases, with the most dramatic contributions coming between the
 3 60-mile and 150-mile AER cases. Part (b) displays the percentages of long-distance vehicle-miles
 4 traveled (LD VMT) served by these various scenarios. While the sets of results are very similar,
 5 somewhat lower VMT shares are served than are LD trips completed (since it is more difficult to
 6 complete each of the longest trips taken across the U.S.).



7

8 **a. Long-distance trips completed by different number of charging station and AER scenarios**



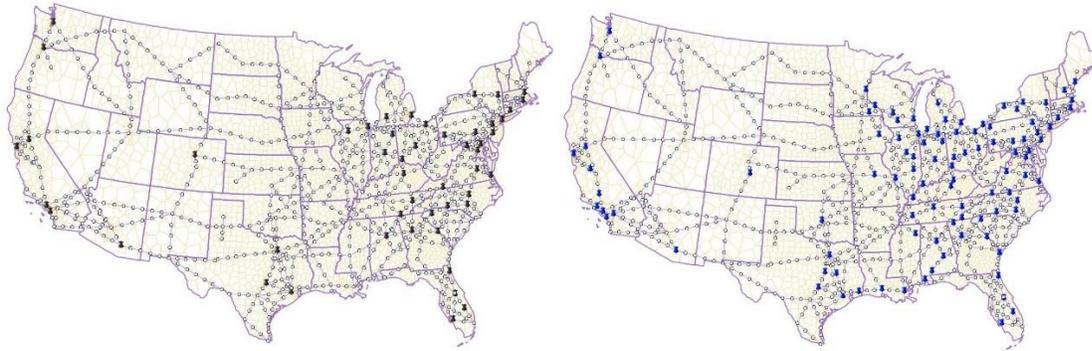
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2 **b. Long-distance VMT served by different number of charging station and AER scenarios**

3 **FIGURE 3 U.S. Covered percentage versus charging station count, at different AER values.**

4 Figure 4 displays the 5 station-location cases with AER values of 150 miles (and all path demands
 5 over 18,240 vehicle-trips per year, with the final case showing Tesla’s supercharging station
 6 locations (32). Looking from map (a) to map (e), one quickly senses the nation’s most important
 7 corridors for ensuring that most long-distance trips can be met, and how that pattern of optimal
 8 locations evolves as budgeted station counts rise. Apparently, most charging stations should be
 9 located in the eastern half and central region of U.S., where much of the population (and those
 10 most trip-making) is located. As for the western region, California is also key for long-distance
 11 trip-making and station locations.

12 Figure 4’s final map (f) compares the 368 Tesla Supercharger station locations to the 60-mile,
 13 FRLM solution that recognizes the original Supercharge stations and adds another 100 DCFC
 14 stations. Map (f) shows 275 black nodes for spots where Tesla Superchargers are reasonably
 15 consistent with the FRLM’s “optimal” locations in a 150-mile AER, 250-station scenario. Tesla
 16 has placed far more stations than the model would suggest is optimal in the western U.S.,
 17 presumably to help potential Tesla buyers see regional and national connectivity that may be more
 18 valuable to the company than enabling frequent service on more heavily used routes. Tesla is based
 19 in California, and that state leads the nation in BEV purchases. Most Tesla owners have battery
 20 packs with 300+ miles of range, so they are not subject to much range limitation (versus a
 21 conventional vehicle). The added 100 stations, presuming a short (60-mile) AER, help take the
 22 solution from just 25.0% trip-completion rate (with Tesla’s Supercharger system, assuming just
 23 60-mile range) to 61.1% LD-trip completion rate. This 144% increase in completion rate, with just
 24 27% more stations demonstrates how Tesla’s Supercharger location choices may not be optimal
 25 for U.S. BEVs of shorter range. Regardless, it is a useful demonstration of this model that existing
 26 station locations can be easily accounted for, before adding new stations. That is the situation of
 27 many countries: some stations already exist, so we need to be strategic in new station locations.



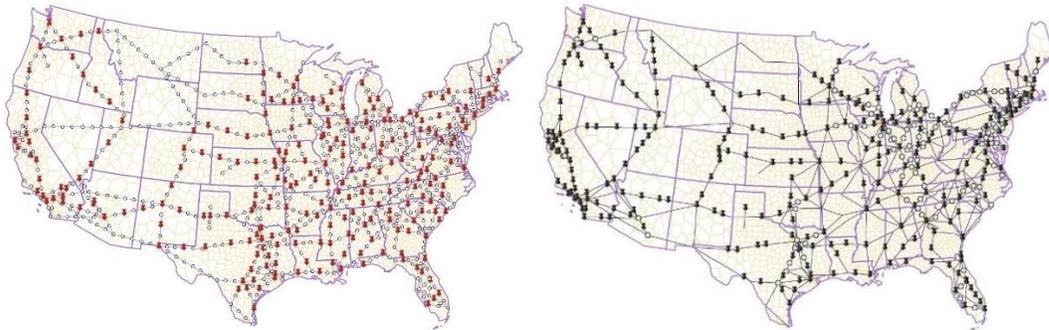
1
2 **a. 150 miles – 50 stations**

b. 150 miles – 100 stations



3
4
5 **c. 150 miles – 150 stations**

d. 150 miles – 200 stations



6
7 **e. 150 miles – 250 stations**

f. 368 Tesla stations and 100 added charging stations

8 **FIGURE 4 Optimal placements of charging stations across U.S. (for different station**
9 **counts).**

10 **CONCLUSIONS**

11 This work formulates a new flow-refueling location model (FRLM) to identify optimal sites for
12 charging stations, to maximize the share of U.S. long-distance highway travel that can be achieved
13 by BEV owners. To handle the very-large-scale input data that exist for this unusually massive
14 problem, origin and destination locations were clustered into 196 points (starting from over 4,000
15 NUMA centroids), and only heavily used paths were tracked between these over 38,000 OD pairs
16 (reflecting over 90 percent of the nation’s long-distance automobile travel).

17 Results recommend copious station placement across the eastern U.S. (starting with the Dallas Ft-
18 Worth Metroplex and Interstate Highway 35 corridor, for example). Interstate 5 along the western

1 edge of the nation is also important, and other locations are filled in as the number of permitted
2 stations rises from 50 to 250, or AER on the BEVs rises to 200+ miles. Of course, more charging
3 stations means that the nation's vehicle owners can invest in smaller car batteries and shorter AER,
4 while still being able to complete their long-distance trips. Building long-range BEVs with current
5 technology (and carrying heavy batteries around empty, for example) may not be socially optimal.
6 Smaller batteries with denser charging networks may be much more cost effective (23). Cost
7 analysis of this tradeoff is a worthwhile extension of this work. Assuming that each fast charging
8 station costs \$60,000 and every added 10 miles of AER adds \$500 to a BEV's cost (8), a cost-
9 effective investment for U.S. BEV owners and suppliers appears to be 200 stations coupled with
10 100-mile range vehicles.

11 This paper expands past work to a truly national scope, on an unprecedented scale, necessitating
12 the processing of larger scale traffic data amid a comparatively complex network. The processing
13 logic in this paper realizes the utilization of FRLM for long-distance trips across a range of settings.
14 The new model used describes the framework for others to pursue research on more efficiently
15 locating distribution centers and other important investments, not just charging stations. The paper
16 results are also meaningful for and closely related to the nation's new National ZEV Investment
17 Plan, to be implemented by Electrify America, which aims to invest \$1.2 billion of the VW
18 Dieselgate award between 2017 and 2027 in ZEV infrastructure (10). Approximately 240 charging
19 station sites will be installed nationwide, with many between cities, for long-distance trip-making,
20 and this research offers an important reference for the coming national plan.

21 This work can be extended, using faster computers or smarter algorithms to allow for more OD
22 pairs, more network details, and trip scheduling information (to determine charging station time
23 of use and power-grid demands, for example). A key challenge is tools that can read and process
24 the enormous input data sets, overcoming supercomputer memory limitations. Another direction
25 for further research is in introducing the capacity of each station and route choice. This paper
26 neglects congestion feedbacks (taking routes as exogenously given) and the model requires
27 significant input data preparation. A more efficient, greedy algorithm, using heuristics and/or
28 simulated annealing, for example, may work faster, for larger-scale settings.

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