Title: Long-term Strategic Planning of Inter-City Fast Charging Infrastructure for Battery Electric Vehicles

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ABSTRACT

This study introduces a multistage chance-constrained stochastic model for strategic planning of battery electric vehicle (BEV) inter-city fast charging infrastructure. A mixed integer programming model is developed to determine where and when charging stations are opened, and how many chargers are required for each station to meet the growing BEV inter-city demand. The model is applied to a case study in California and solved by genetic algorithm. This study showed that investment in inter-city charging infrastructure is vital to alleviate the range anxiety. Also, planning decisions depend on many factors, such as the design level of service and vehicle range.

KEY WORDS

Battery electric vehicle; inter-city charging infrastructure; charger capacity; chance-constrained stochastic model; genetic algorithm

1.0 Introduction

Promoting battery electric vehicles (BEV) is deemed an effective solution to help the United States reduce its dependency on imported oil and improve its competitive position in the emerging era of renewable energy market. Several agencies have enacted incentive policies to promote the mass adoption of BEVs. These policies include the Federal American Recovery and Reinvestment Act (ARRA) tax program, California's Zero Emission Vehicle (ZEV) Action Plan, and the Corporate Average Fuel Economy (CAFE) standards. Encouraged by these policies and standards, manufacturers are actively developing affordable BEVs with low manufacturing costs and plausible vehicle performance (e.g., vehicle range and power) (EPA et al., 2016). All these efforts by agencies and manufacturers contribute to success in the current BEV market. In particular, plug-in electric vehicles (PEVs, including both BEVs and plug-in hybrid electric vehicles (PHEVs)) garner about 1% of today's total sales (Davis et al., 2016). To be fully competitive with conventional vehicles (CVs, such as gasoline vehicles), "*range anxiety*" concerns have to be resolved.

Range anxiety, as the name suggests, is the fear of insufficient range to reach destinations (Eberle and von Helmolt, 2010). Unlike PHEVs, which can have unlimited range by running on conventional fuels, BEVs can run only on electricity. To alleviate range anxiety during trips, consumers need adequate charging infrastructure; this applies to both intra-city (short distance) and inter-city (long distance) travels. The intra-city travel problem has been well studied. Examples of effective solutions include establishing home and workplace charging systems (Huang and Zhou, 2015), and supporting intra-city public charging networks (NREL, 2017) that include level-1 (L1, 1.4 kW) chargers, level-2 (L2, 6.2 kW) chargers, and direct current fast chargers (DCFC, >50 kW).

However, the problem becomes more challenging for inter-city travels. First, inter-city travel distances can be longer than the vehicle range. Recharging is inevitable for long distance travel, and home or workplace charging cannot be relied upon. Second, unlike intra-city public charging during which travelers can tolerate relatively long recharging time by conducting other activities (e.g., shopping and dining), inter-city public charging may have stricter charging time limits as there are few activities available while charging along rural highway corridors. Therefore, a mature inter-city DCFC fast charging network with proper service capacity is necessary to satisfy the growing inter-city BEV trips. As building the DCFC charging network is costly (the facility can cost more than $50,000 per charger (NRC, 2013)), we need solutions to identify where to locate charging stations, when to install them, and how many chargers to allocate at each station in response to the changing BEV market.

To serve this need, this study aims to develop a multistage optimization modeling framework. The framework will gradually establish and expand DCFC charging infrastructure in terms of both *network coverage* and *service capacity* to alleviate increased range anxiety issue with growing BEV inter-city travel demand.

Existing literature describes two major modeling directions for problems related to facility location of refueling and charging infrastructure. One direction is to develop *node-based* facility location models stemming from p-median facility location problems (Daskin, 1995; Hakimi, 1964). Representative works include the studies (Ip et al., 2010; Jung et al., 2014; Momtazpour et

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al., 2014). However, Li et al. (2016) suggest that the node-based facility location model may not be well suit for charging location problems as it cannot properly model flows of goods or passengers in a network. Wide recognition of this issue has led to richer literature on the second direction, to develop *flow-based* facility location models that stem from flow-capturing location-allocation models (FCLMs) (Hodgson, 1990). Representative works include the studies (Berman et al., 1992; He et al., 2013; He et al., 2015; Hodgson, 1990; Huang et al., 2015; Kuby and Lim, 2005; Li and Huang, 2014; Li et al., 2016; Wang and Lin, 2009).

Few existing studies are available on BEV inter-city DCFC facility location models. Wang and Lin (2009) introduced a single-path set-covering model based on vehicle routing logic. Jochem et al. (2016) developed a single-path inter-city fast charging infrastructure planning model for a case study in Germany. To recognize the heterogeneity of BEV travelers in choosing paths, a multi-path (multi-deviated paths) flow based set covering model was proposed in the study by Li and Huang (2014). The model was later extended to a multistage formulation to capture topological changes in inter-city network over time (Li et al., 2016). Different from other node- or flow-based modeling efforts, Sathaye and Kelley (2013) developed a continuous facility location model that yields solutions on station densities instead of locations, and the model is less computationally intensive. Note that all these models do not consider charging station capacity.

However, long-term planning of inter-city DCFC charging infrastructure should consider both locations and charging capacity. Otherwise, charging congestion is inevitable and increases the frustration of using BEV for inter-city trips. There are several approaches to modeling charger capacity. One simple and direct method is to use deterministic capacitated facility location models (Sadeghi-Barzani et al., 2014; Upchurch et al., 2009). However, those models simplified the logic between charging activities and required charger capacity with assumed daily or annual capacity (e.g., vehicles per day). On the other hand, using the Global Positioning System (GPS)-based travel survey data, NREL (2017) determined the required number of chargers to avoid conflicts in charging activities by different vehicles at the same time and location. The method is straightforward to implement, but it may create the over-fitting bias as the decisions are only based on sampled trip data. Alternatively, Ge et al. (2011) and Jia et al. (2012) assumed charging demand is positively correlated with the traffic flow rate (vehicles/hour) and the share of BEVs in the flow. With this assumption, charging capacity can be determined if the average recharging frequency is

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known. All the prior studies neglect the stochasticity in charging activities at each station. To capture both randomness in charging demand arrivals and actual charging service time, an alternative approach is to model charger operations using stochastic queuing models (Fang and Hua, 2015; Gusrialdi et al., 2014; Said et al., 2013).

In this study, we propose a flow-based multistage (multi-period) chance-constrained stochastic modeling framework in planning long-term DCFC charging infrastructure expansion to serve growing BEV inter-city trips. The framework is built upon the multi-period multi-path refueling location model (M^2PRLM) (Li et al., 2016), and allows multistage expansions of the charging infrastructure and multiple deviated paths. In addition, we model charging station capacities by using the stochastic queuing theory (Fang and Hua, 2015; Gusrialdi et al., 2014; Said et al., 2013). In order to better reflect stochasticity in charging activities, we introduced the level of service concept formulated using stochastic chance constraints to determine charger capacity. Note that the M^2PRLM is a set-covering problem. We also relax the set-covering formulation by providing penalty terms for infeasible trips, so that the model can further investigate the tradeoff between the high investment cost in DCFC charging infrastructure and the high range anxiety cost caused by trip infeasibility. As the model is a facility location problem and is NP-hard, we developed a genetic algorithm based heuristic method to efficiently solve the model.

The model will be applied to a large-scale case study in California to understand long-term infrastructure requirements to meet the growing inter-city travel demand. Compared to previous modeling efforts, we expect the proposed framework to yield additional managerial insights and policy implications on future inter-city DCFC charging network in many ways. First, a complete set of decisions on both charger location and capacity can help stakeholders better understand when, where, and how much capital investment should be made on the charging infrastructure. Also, integration of the stochastic queuing models as well as the level of service concept gives policy makers detailed analyses of infrastructure requirements, such as the suitability of opening large or small charging stations at various conditions.

In the rest of the paper, we will first demonstrate the modeling framework and the solution method in section 2 and 3, respectively. In the remaining sections, we will describe the California case study, discuss the modeling results, and summarize the study in the conclusion.

2.0 Modeling

2.1 Multistage DCFC Infrastructure Planning Model

Within an inter-city transportation network, BEV trip demands are generated at origins (O) and end at destinations (D). Long-term planning of the DCFC charging infrastructure that will satisfy these trip demands requires both spatial and temporal considerations. In the spatial dimension, each O-D pair is interconnected with highway networks, along which trips can take multiple paths. Inter-city trips can be of much greater distance than short distance intra-city travels (e.g., longer than 100 miles). Solving where to locate DCFC charging stations becomes necessary to mitigate the short vehicle range of BEVs. In the temporal dimension, BEV trip demand may change over time with the emerging BEV market. This makes it important to understand how to expand charging station capacity, namely the number of chargers, to meet the growing demand.

To reflect these spatial and temporal requirements, we propose a multistage DCFC infrastructure planning model, which is built upon the M^2PRLM (Li et al., 2016). The two models have similarities. Both are multistage flow based facility location models, and they all consider multi-path flows. However, the proposed model extends the M^2PRLM, at the following aspects:

1. The M^2PRLM is an un-capacitated facility location model that only provides decisions on station location and ignores station capacity, while the proposed model is a capacitated facility location model that can provide richer information on both station location and capacity (measured by number of chargers).
2. The M^2PRLM is a set-covering model that requires full coverage of all O-D trips. In contrast, the proposed model will be formulated to allow partial coverage of the network with penalty costs on un-covered O-D trips. This feature allows additional managerial insights on the tradeoff between the high infrastructure investment cost and the high range anxiety cost caused by trip infeasibility.
3. The M^2PRLM captures only the binary condition of O-D demand (i.e., whether an O-D pair has trip demand), and cannot distinguish between high (e.g., trips between metropolitan areas) and low (e.g., trips between far apart rural towns) O-D demands. On the other hand, the proposed model will consider the actual trip demand.

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4. The M^2PRLM allows relocation of charging stations. Practically, relocation is possible in operations when unexpected geographical shift in travel demand occurs. However, in planning, it is extremely difficult to project this shift, and thus is not considered in the proposed model.
5. The M^2PRLM is a deterministic model. The proposed model is a chance-constrained stochastic model and will introduce a new concept of the level of service to model charging capacity. In particular, a certain traveler satisfactory level, measured by waiting time and probability of finding a charger, is maintained to allow normal charging operations.

As in the proposed model, the long-term planning horizon is partitioned into multiple stages or periods (e.g., one or five years per stage), during which planning and operational decisions are made. Sequential planning decisions are made on where and when to locate charging stations and how many chargers per station are needed to satisfy the growing inter-city trip demand by BEV users. With the charging infrastructure setting, operational decisions on trip path selection and charging scheme are made for each O-D pair. In any stage, if trips along one O-D pair cannot be accommodated because of a lack of infrastructure support, a penalty cost will occur, which is defined as the range anxiety cost due to trip infeasibility. Note that there are two possible causes of range anxiety (Lin, 2014). The first reason is the fear of exhausting vehicle range due to unanticipated reasons (e.g., congestion and extreme weather). This part is difficult to quantify and therefore is not considered in this study. The second reason is the infeasibility of a planned trip without adequate infrastructure support. The penalty cost in this study is associated with the second type of range anxiety, and is assumed to be the cost of arranging an alternative vehicle (e.g., car rental cost). In the rest of this paper, this penalty cost is denoted as the range limitation cost. Descriptions on decision variables and assumptions are shown as follows.

- Decision variables:
    - Where to open charging stations in each time stage;
    - How many chargers are open at each station in each time stage;
    - Which O-D pair BEV travel demand can be satisfied in each time stage; and
    - Path selection and charging scheme along each feasible O-D pair in each time stage.

- Assumptions:
    - Each charging station and its chargers will not be shut down once opened;
    - Single design maximum state of charge (SOC) measured by the vehicle range (e.g., 100 miles) is applied to all BEVs;
    - BEVs are fully charged at origins and destinations (i.e., the dwell time at origins and destinations is sufficient for recharging); and
    - O-D travel demands remain the same at one stage[2] (e.g., average travel demand is considered within the stage).

The proposed model is formulated in (1) to (17). The notations for the model are listed in Table 1.

Table 1. Notations

Indices	
i	index of candidate sites for charging stations in the network, $i \in \tilde{N} \subseteq N$, where $\tilde{N}$ is the set of candidate sites and N is the node set,
t	index of time stages, $t \in T$
r	index of origins in the network, $r \in R \subset N$
s	index of destinations in the network, $s \in S \subset N$
k	index of the paths for an O-D pair, k=1, 2, …, K^{rs}, where K^{rs} is maximum number of deviated path allowed between an O-D pair (r,s)
a	index of arc set A, $a=(i,j)\in A$
Parameters	
c_{it}^F	Fixed capital cost ($) of opened charging station at node i in time stage t
c_{it}^V	Variable capital cost ($) per charger at the charging station at node i in time stage t

[2] The O-D travel demand is for planning purpose only. The actual O-D travel demand can vary within a stage. An average demand is considered in the model.

q_t^{rs}	Range limitation cost (\$/trip) when a trip cannot be satisfied between O-D pair *r*-*s* in time stage *t*
D_t^{rs}	Number of BEV inter-city trips between O-D pair *r*-*s* in time stage *t*
$\overline{B}$	Maximum SOC measured by vehicle range (miles)
M	a sufficiently large number
$P^{rs,k}$	the sequence of nodes on the k^{th} path between O-D pair *r*-*s*
d_{ij}	Distance (miles) between node *i* and *j*
Variables	
Z_{it}	=1 if a charging station is open at node *i* in time stage *t*; 0 otherwise
$Y_t^{rs,k}$	=1 if the k^{th} path between *r* and *s* is taken in time stage *t*; 0 otherwise
$\overline{Y}_t^{rs}$	=1 if at least one path is satisfied for an O-D pair *r*-*s* in time stage *t*; 0 otherwise
$I_{it}^{rs,k}$	=1 if trips along the k^{th} path between *r* and *s* will be charged at the station at node *i* in time stage *t*; 0 otherwise
X_{it}	Number of chargers are installed at the station at node *i* in time stage *t*; 0 otherwise
$B_{it}^{rs,k}$	remaining SOC (miles) on a PEV at node *i* on the k^{th} path of an O-D pair *r*-*s* in time stage *t*
$l_{it}^{rs,k}$	Restored SOC (miles) to an PEV at node *i* on the k^{th} path of an O-D pair *r*-*s* in time stage *t*

Objective:

$$\text{Minimize } \sum_{t\in T}\sum_{i\in \tilde{N}} c_{it}^{F} Z_{it} + \sum_{t\in T}\sum_{i\in \tilde{N}} c_{it}^{V} X_{it} + \sum_{t\in T}\sum_{r\in R}\sum_{s\in S} q_t^{rs} D_t^{rs}\left(1-\overline{Y}_t^{rs}\right) \tag{1}$$

The objective function in (1) is to minimize the total systems cost for the BEV inter-city travel network across the entire planning horizon. The total systems cost includes the fixed capital cost of charging stations (which may be location specific), the variable capital cost of charging stations (depending on the number of chargers per station), and the total range limitation cost in cases where BEV trips cannot be satisfied. The objective function (1) is subject to constraints in (2) to (17).

Subject to

$$X_{it} \leq MZ_{it} \qquad \forall t \in T; i \in \tilde{N} \tag{2}$$

$$X_{it} \geq X_{it-1} \qquad \forall t \in T \setminus 1; i \in \tilde{N} \tag{3}$$

Constraint (2) is the logic constraint stating that no chargers can be installed unless there is a charging station open. Constraint (3) assures that a charging station once open will not shut down or relocate.

$$\Pr\left(W\left(\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} D_t^{rs} I_{it}^{rs,k}, X_{it} \right) \leq \alpha \right)_{it} \geq \beta \qquad \forall t \in T; i \in \tilde{N} \tag{4}$$

Constraint (4) is the capacity logic constraint formulated as a stochastic chance constraint setting up the relationship of the required number of chargers to meet a certain level of charging capacity, where $W\left(\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} D_t^{rs} I_{it}^{rs,k}, X_{it} \right)$ represents the waiting time before a BEV finds an available charging spot. Waiting time is a function of the total number charging demands $\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} D_t^{rs} I_{it}^{rs,k}$ and the number of chargers X_{it} at the station. As suggested in the chance constraint, charging capacity is modeled as the level of service, namely the required probability β (e.g., 95%) of finding a vacant charger within time α (e.g., 10 mins). The inequality chance constraint is developed based on queuing theories. Note that, as demonstrated later in Section 2.2, this constraint is originally in a non-linear form, but can be represented in a piecewise linear form.

$$\bar{Y}_t^{rs} \leq \sum_{k\in K^{rs}} Y_t^{rs,k} \leq 1 \qquad \forall r \in R, s \in S; t \in T \tag{5}$$

$$I_{it}^{rs,k} \le Y_t^{rs,k} \qquad \forall r \in R, s \in S; i \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{6}$$

$$l_{it}^{rs,k} \le M I_{it}^{rs,k} \qquad \forall r \in R, s \in S; i \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{7}$$

$$B_{it}^{rs,k} + l_{it}^{rs,k} \le M(1 - Y_t^{rs,k}) + \overline{B} \qquad \forall r \in R, s \in S; i \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{8}$$

$$B_{it}^{rs,k} + l_{it}^{rs,k} - d_{ij} - B_{jt}^{rs,k} \le M(1 - Y_t^{rs,k}) \qquad \forall r \in R, s \in S; (i, j) \in A; i, j \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{9}$$

$$-(B_{it}^{rs,k} + l_{it}^{rs,k} - d_{ij} - B_{jt}^{rs,k}) \le M(1 - Y_t^{rs,k}) \qquad \forall r \in R, s \in S; (i, j) \in A; i, j \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{10}$$

$$B_{rt}^{rs,k} = \overline{B} \qquad \forall r \in R, s \in S; t \in T; k = 1,..., K^{rs} \tag{11}$$

Constraint (5) ensures that trips along an O-D pair in each stage can be fulfilled if at least one path is taken. Also, to avoid double counting, no more than one path is taken for each O-D pair. Constraints (6) and (7) convey two principles on charging activities: charging activities can occur along one path of a trip only if the path is taken; and a BEV can receive a positive amount of energy at a station only if the charging activity occurs at the station. For each selected path (when $Y_t^{rs,k} = 1$), constraint (8) ensures the onboard battery's SOC does not exceed the battery capacity while constraints (9) and (10) concurrently enforce the energy consumption conservation. Constraints (8) – (10) are relaxed for paths that are not taken (i.e., $Y_t^{rs,k} = 0$). Constraint (11) assumes that all BEVs start with a full battery SOC at origins.

$$Z_{it} \in \{0,1\} \qquad \forall t \in T; i \in \tilde{N} \tag{12}$$

$$Y_t^{rs,k} \in \{0,1\} \qquad \forall r \in R, s \in S; t \in T; k = 1,..., K^{rs} \tag{13}$$

$$\overline{Y}_t^{rs} \in \{0,1\} \qquad \forall r \in R, s \in S; t \in T \tag{14}$$

$$I_{it}^{rs,k} \in \{0,1\} \qquad \forall r \in R, s \in S; i \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{15}$$

$$X_{it} \text{ Integer } \ge 0 \qquad \forall t \in T; i \in \tilde{N} \tag{16}$$

$$B_{it}^{rs,k} \ge 0, l_{it}^{rs,k} \ge 0 \qquad \forall r \in R, s \in S; i \in P^{rs,k}; t \in T; k = 1,..., K^{rs} \tag{17}$$

Constraints (12) to (17) are binary, integer, and nonnegativity constraints.

The proposed model is a mixed integer program. Generally, the objective of the model is to minimize the total capacitated facility location cost while allowing the penalty cost, namely the range limitation cost to penalize un-covered trips. As the model is essentially a flow-based capacitated partial set-covering problem with path deviations, it is a facility location problem and is NP-hard (Daskin, 1995; Könemann et al., 2011).

2.2 Charger Capacity with the Stochastic Queuing Model

To determine charging station capacity, we adopted queuing theories to simulate the stochastic charging activities (Fang and Hua, 2015; Gusrialdi et al., 2014; Said et al., 2013). Each station is considered a queuing node with multiple servers (each charger is one server). Incoming BEV charging demands are the jobs to be served at each charging station. The charging activities at each charging station $i \in \tilde{N}$ in time $t \in T$ can be approximated as follows: (1) the arrivals of BEVs at each station are simulated by a Poisson process with expected arrival rate of λ_{it} (vehicles/hour); (2) the charging time, namely, the service time of each BEV, follows exponential distribution with expected service time μ (hours); and (3) the station has X_{it} number of chargers or servers and obeys the "first-in, first-out" (FIFO) service rule. This systems can be represented as the M/M/c queuing model with Erlang C formula (Chromy et al., 2011). As shown in the chance constraint in (4), this study models charging capacity in terms of the required level of service, namely the design or minimum probability β for a BEV user to find a vacant charger within time α. Based on Erlang C formula (Chromy et al., 2011; Tanner, 2000), we can formulate the probability of finding a vacant charger within time α in (18).

$$\Pr(\text{waiting time} \le \alpha)_{it} = 1 - \frac{\dfrac{(\lambda_{it}\mu)^{X_{it}}}{X_{it}!}}{\dfrac{(\lambda_{it}\mu)^{X_{it}}}{X_{it}!} + \left(1 - \dfrac{\lambda_{it}\mu}{X_{it}}\right)\displaystyle\sum_{k=0}^{X_{it}-1}\dfrac{(\lambda_{it}\mu)^{k}}{k!}} \cdot e^{-(X_{it}-\lambda_{it}\mu)\frac{\alpha}{\mu}} \quad \forall t \in T; i \in \tilde{N} \qquad (18)$$

To maintain target level of service, the probability $\Pr(\text{waiting time} \le \alpha)_{it}$ in the left-hand side of (18) shall be smaller than the design probability β (i.e., $\Pr(\text{waiting time} \le \alpha)_{it} \le \beta$), which corresponds to the chance constraint in (4). Note that the "*waiting time*" in (18) is related to $W\left(\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} D_t^{rs} I_{it}^{rs,k}, X_{it}\right)$ in (4). For simplicity, the expected service time μ in (18) is assumed to be exogenously determined (e.g., 30 mins/vehicle). Then, only two variables, namely λ_{it} and X_{it}, in (18), are inter-related that should satisfy the chance constraint. Note that the arrival rate λ_{it} is assumed to be linearly correlated with the total charging demand $\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} D_t^{rs} I_{it}^{rs,k}$ in each stage. We assume each charging station will serve 14 hours a day (i.e., 6:00 am to 8:00 pm), 365 days a year, and the arrival rate remains the same during the open window. Also, as in the case study demonstrated later, we assume that each time stage consists of five years. Then, the arrival rate λ_{it} can be calculated in (19).

$$\lambda_{it} = \frac{1}{14\times 365\times 5}\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} D_t^{rs} I_{it}^{rs,k} \qquad \forall t\in T; i\in \tilde{N} \tag{19}$$

With the non-linear relationship in the formula (18), the chance constraint in (4) is in a mixed integer non-linear form and may make the model difficult to solve. Alternatively, we managed to determine the maximum charging demand that can be served for each level of infrastructure development (i.e., number of chargers). With formulation (18), we simulated five sets of relationships based on different levels of service shown in Figure 1. The highest level of service is to guarantee 99% probability for BEV users to find to a vacant charger within 0 minutes (i.e., immediately after arriving at the station), labeled as "99%+0 minutes", and the lowest level of service, "90%+30 minutes", is to guarantee 90% probability for BEV users to find a vacant charger within 30 minutes. Among the five scenarios, we chose the middle one, "95%+10 minutes" (i.e., 95% possibility to find a vacant charger within 10 minutes), as the baseline case. Note that the step relationship between charging demand and number of chargers in Figure 1 can be

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formulated using piecewise linear functions with only mixed integer variables. Then, the problem in (1) to (17) becomes a mixed integer program.

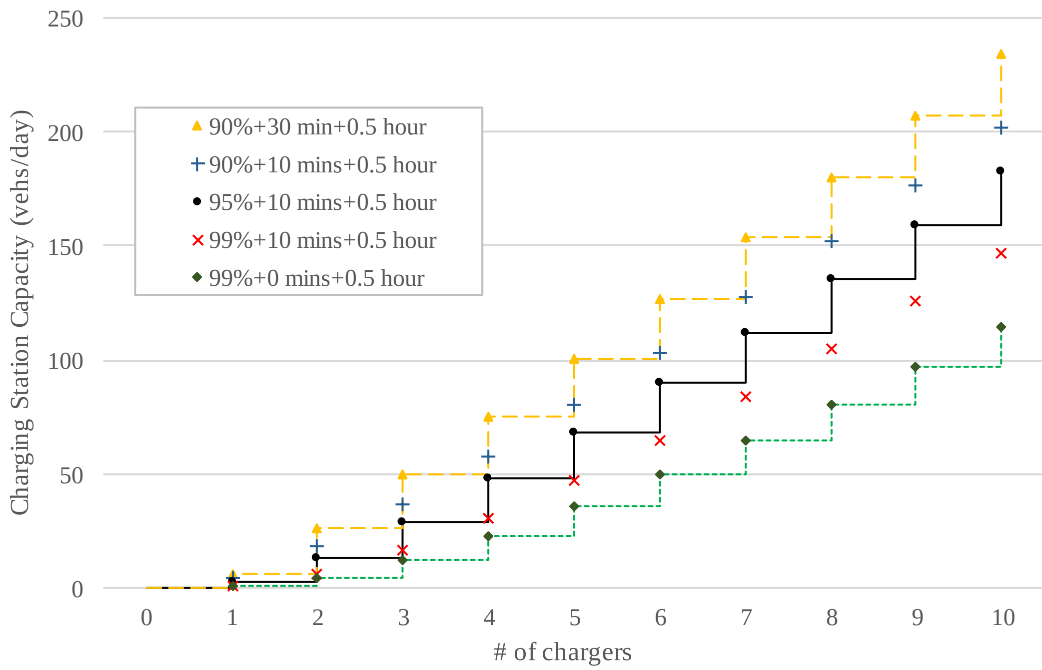

Figure 1. Relationship of Maximum Charging Demand and the Number of Chargers

Remarks on Queuing Models. This study considers the M/M/c queuing model to model charger capacity. As additional data are available or new technologies emerge, other types of queuing models may also be applicable. For example, with connected automated vehicles (CAVs), vehicles have potential to automatically enter and leave charging stations. Then, the charging time may be deterministic, and charging activities can be simulated with M/D/c queues. Explorations of the potential impacts with other queuing models can be our future studies.

3 Genetic Algorithm

Even though charger capacity can be formulated as piecewise linear relationship, the mixed integer program is still hard to solve optimality. We developed a genetic algorithm based heuristic method

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(Vose, 1999) to solve the model. Generally, the genetic algorithm involves a pool of chromosomes. Each chromosome represents one candidate solution to the problem, and the fitness of each candidate solution is measured by the cost objective value of (1). Between chromosomes, the one with a lower objective value indicates better fitness. The algorithm has an iterative process, during which chromosomes with bad fitness are more likely to be removed from the pool while chromosomes with good fitness have more chances to survive and give birth to a new child. The whole process mimics natural selection. It is generally observed that through multiple iterations the genetic algorithm can help find near-optimal or relatively satisfactory solutions.

3.1 Implementation Details

Two features are important to efficiently apply a genetic algorithm. One is the simplicity in coding the solution with chromosomes, and the other is to be able to easily determine fitness given the genetic information of one chromosome. However, both features are hard to maintain for the proposed model. First, as in Li et al. (2016)'s study, only two-dimension infrastructure related decision variables, i.e., where and when charging stations are opened, are needed to be encoded in the chromosome. However, this task is more challenging for this study because the model requires another dimension on capacity-related decisions, i.e., how many chargers per station. That creates challenges in coding all decision information in each chromosome. Second, as capacity is considered for each charging station, the heuristic approach to check path feasibility with infinity capacity (Li et al., 2016) is not applicable to this study. Instead, mixed integer programming sub-models need to be solved, which makes it difficult to efficiently determine fitness for each chromosome generated in the solution process.

To tackle the two challenges in this complex model, in addition to the assumptions shown in Section 2.1, we made the following assumptions to simplify the BEV users' charging behavior:

- *Last-minute charging*: A BEV will only be charged at the last possible moment to have the full SOC before beginning of the rest trip.

- *Guaranteed Service*: If an O-D path at one stage is feasible and selected given particular charging infrastructure deployment, charging stations along the path will have sufficient chargers to satisfy all O-D traffic demands along the path in the same time stage.

The first assumption is adopted from the study by Kelly et al. (2012). The assumption indicates that when a BEV reaches an opened charging station, the necessity for charging is determined based on whether the BEV can reach the next opened charging station with the current SOC. This assumption is a reasonable one for BEV users who rationally prefer to minimize the number of charging events. Note that, in the real-world operations, it may happen that the level of service at a station is guaranteed and a BEV cannot be properly serviced. To avoid or alleviate such risk, the maximum vehicle range $\overline{B}$ will be set at a level to allow sufficient SOC reserve for traveling additional miles after the range is depleted.

The second assumption is already inherently built into the proposed model, which considers only the feasibility of each O-D pair instead of each O-D trip. This assumption is reasonable to provide equity for all travel demand along each O-D pair.

These two assumptions simplify the solution process for the model in the following ways. First, it will significantly simplify the determination of fitness of each chromosome with heuristic methods. Given the setting of charging stations at each time stage encoded in each chromosome (where and when to open stations), the heuristic approach (Li and Huang, 2014; Li et al., 2016) can be used to efficiently check path feasibility of all O-D pairs. Then with the *Last-minute charging* assumption, we can efficiently determine the charging strategy (i.e., where to charge) for each feasible O-D pair and the total charging frequency (number of charging activities per stage) at each station. Following the *Guaranteed Service* assumption, we can determine the number of chargers needed for each station to satisfy all charging demand. Finally, the fitness of the chromosome can be calculated using the objective function in (1). Second, as suggested in the first benefit, the number of chargers per station can be post-calculated. Therefore, only decisions on where and when charging stations are opened need to be encoded in each chromosome. That simplifies the representation of each chromosome.

The *Last-minute charging* assumption may yield sub-optimal solutions for the proposed model as it relaxes the model's potential capability to better coordinate charging strategies.

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However, such capability can be realized only when a central decision maker makes the systems-wide optimal decisions for all travelers, which is currently not practical. However, with emerging CAV technologies, a central decision maker becomes possible in future transportation. How to solve the model to gain additional social benefits is a future research question.

3.2 Settings of Genetic Algorithms

Based on the above properties and assumptions of the problem, we made the following settings to apply the genetic algorithm to solve the proposed model.

3.2.1 Encoding of Chromosome

As mentioned, only decisions on where and when charging stations are opened need to be encoded into each chromosome. Since each opened charging station will remain open once it is in operation, only the time when the charging station is first opened needs to be recorded. Therefore, we used a single dimension integer valued string to represent such information. Each digit entry along the chromosome string represents one specific candidate location. Then, the total length of the string is $|\tilde{N}|$ (the number of candidate locations). Each digit can take non-negative integer values. When the digit takes a value of 0, it indicates no charging station is opened at the location throughout the time horizon. When the digit takes a positive value of i, it indicates the charging station is first opened in time stage i.

We used a simple example chromosome string "01020" to demonstrate its meaning on charging infrastructure planning decisions as follows:

- Five digits in the string indicate five candidate locations ($|\tilde{N}| = 5$) for charging stations;
- No charging station is opened at candidate locations 1, 3, and 5;
- One charging station is opened at candidate location 2 in time stage 1; and
- Another charging station is opened at candidate location 4 in time stage 2.

3.2.2 Fitness of Chromosome

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Figure 2 shows the pseudocode used to determine fitness of each chromosome. There are five major steps along the pseudocode: step 1 is the initialization that translates genetic information of the chromosome into corresponding charging location decisions; step 2 is to check feasibility and select a path for each O-D pair in all stages; for all feasible O-D pairs, step 3 is to determine charging activities based on the *last-minute charging* assumption (demonstrated in Section 3.1); for each opened charging station, step 4 is to determine the total number of charging activities and the corresponding required number of chargers based on the design level of service (demonstrated in Section 2.2); and finally, step 5 is to calculate the fitness of the chromosome with objective function in equation (1) in Section 2.1.

```
// Step 1 - Initialization:
Translate genes of the chromosome into charging location decisions Z_it,
∀t ∈ T; i ∈ Ñ;

// Step 2 – Feasibility Check:
For (each O-D pair in each stage, ∀r ∈ R, s ∈ S; t ∈ T) {
        Check feasibility of all paths, k = 1,..., K^rs :
                If Feasible for at least one path, then mark the O-D pair feasible (i.e.,
                Ȳ_t^rs = 1), and the shortest feasible path is selected;
                Else, then mark the O-D pair infeasible (i.e., Ȳ_t^rs = 0);
}

// Step 3 – Refining Charging Activities:
For (each feasible O-D pair in each stage, ∀r ∈ R, s ∈ S; t ∈ T, s.t. Ȳ_t^rs = 1) {
        Determine charging activity ( I_it^rs,k ) based on the "Last-minute charging"
        assumption;
}

// Step 4 – Determination of Station Capacity:
For (each opened station in each stage, ∀t ∈ T; i ∈ Ñ, s.t. Z_it = 1) {
        Determine total number of charging activities Σ_{r∈R} Σ_{s∈S} Σ_{k∈K^rs} D_t^rs I_it^rs,k ;
        Determine required number of chargers X_it to meet the level of service;
}

// Step 5 – Determination of fitness of Chromosome:
Determine fitness with objective function in (1);
```

Figure 2. Pseudocode to determine fitness of each chromosome

3.2.3 Population Pool

At beginning of the algorithm, we initialized a pool of chromosome strings with a population size of N (e.g., 500). The pool is defined as the population pool where crossover, mutation, and replacement are applied through an iteration process.

3.2.4 Parent Selection

For each iteration, four candidate chromosomes are randomly selected from the population pool. The four chromosomes are partitioned equally into two groups, and one chromosome will be selected from each group. The chromosome with better fitness (lower objective value) has a better chance to be selected, and the selection probability is set to be inverse to its objective value. The final selected two parents are defined as $P1$ and $P2$.

3.2.5 Crossover

The crossover is then applied to the two selected parents ($P1$ and $P2$) to give birth to a new child chromosome *C*. Let f_{P1} and f_{P2} be the objective values of the parents $P1$ and $P2$, respectively, and let *i* indexes digits of each chromosome, $i = 1, \ldots, |\tilde{N}|$. Then the chromosome *C* is created as follows:

1) if $P1_i = P2_i$, then set $C_i := P1_i \text{ } or \text{ } P2_i$;
2) otherwise, then set $C_i := P1_i$ with probability $p = f_{P2} / (f_{P1} + f_{P2})$, and $C_i := P2_i$ with probability $1 - p$.

3.2.6 Mutation

Once a child chromosome *C* is created, each element C_i, $i = 1, \ldots, |\tilde{N}|$, has a probability (e.g., 5%) to mutate. Let t' be a random integer value selected among $1, \ldots, |T|$ with equal probability. If the element C_i is selected to mutate, then it has two possible ways to change depending the original value of C_i:

1) if $C_i = 0$, then set $C_i := t'$;
2) otherwise, then set $C_i := 0$ with probability of 50%, and $C_i := t'$ with probability of 50%.

3.2.7 Replacement

After a new individual is added to the population (e.g., a child created with both the crossover and mutation processes), it will replace an existing individual in the population pool. Specifically, *n* (e.g., n = 3) candidate individuals are randomly selected from the pool, and the one with the highest objective cost is removed from the pool.

The entire genetic algorithm for the problem can be demonstrated using the pseudocode as follows:

Generate an initial *population pool* of chromosomes;
Do
    Conduct *parent selection* among the population pool;
    Apply the *crossover* with the parents and yield a new child;
    Apply the *mutation* to the child;
    Apply the *replacement* to the population with the child;
Until the maximum number of iterations or the time limit is reached

The final solution is the best chromosome achieved with the lowest objective value from the population.

4.0 Case Study Inputs

We chose the state of California as the case study for demonstrating charging infrastructure planning. Note that California dominates today's BEV sales in the U.S. (ICCT, 2016) and its ZEV action plan (Brown, 2013) is expected to further increase the BEV market in the future. Therefore, the systematic planning of BEV inter-city DCFC charging infrastructure is especially crucial to support the growing demand in California. Also, the success of the case study may yield important policy implications for developing the alternative fuel infrastructure systems for other regions and other fuel technologies. We demonstrate case study inputs for the baseline case in this section.

4.1 Planning Horizon

The planning horizon is set at 15 years, from 2015 to 2029, and the model will initiate and expand the inter-city DCFC charging infrastructure systems to support long-distance (longer than 100

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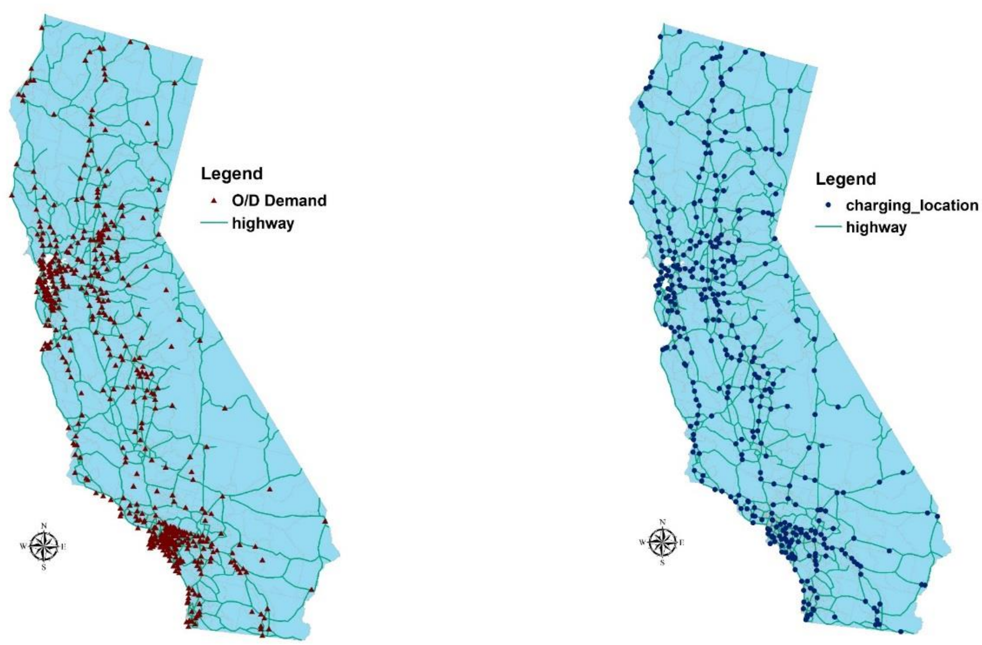
miles) travel demands of BEV users. The 15 years planning horizon is divided into three five-year planning stages (Stage 1: 2015–2019, Stage 2: 2020–2024, and Stage 3: 2025–2029).

4.2 Inter-city DCFC Charging Network

The origins and destinations of inter-city travel demands are aggregated over at least 5,000 Traffic Analysis Zones (TAZs) in California, defined by the California Statewide Travel Demand Model (CSTDM) (California Department of Transportation, 2014). About 4,700 TAZs belong to 482 different municipalities and are aggregated based on their municipal boundaries. The remaining 300 rural TAZs are clustered into 50 nodes using the fuzzy c-mean algorithm (Bezdek et al., 1984). There are 532 demand nodes in total, and each node serves as both trip origin and destination. To serve the inter-city trip demands along all O-D pairs, 389 locations, with clusters of demand nodes and rest areas, are selected as the candidate charging locations. California highway systems (Caltrans, 2016) are considered the transportation network where trips are made. The maps in Figure 3 show the O-D demand nodes, candidate charging locations, and the highway network.



(a) O-D Demand Nodes (b) Candidate Charging Locations

Figure 3. Origin-Destination Nodes and Candidate Charging Locations

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4.3 BEV Travel Demand

With O-D demand nodes, another important task is to estimate BEV O-D travel demands over the 15 years planning horizon. The estimation procedure is illustrated in Figure 4 and breakdowns of the procedure are detailed as follows.

- Step 1: Estimate the base year (2015) light duty vehicle (LDV) O-D demands ($\bar{D}_0$, unit: vehicles/year) between each O-D pair. Note that the LDV includes CVs, BEVs, and other fuel technology types. We assumed that BEV users have the same inter-city travel behaviors as other LDV travelers. Therefore, the BEV O-D traffic demands can be proportionally determined later based on its market share among the LDV population. The LDV O-D demands along the 532 demand nodes are mapped and aggregated with the travel demands of at least 5,000 TAZs from the CSTDM model (California Department of Transportation, 2014).
- Step 2: Estimate the base year BEV market share among the LDV population (η, unit: %) at demand nodes. Specifically, the BEV population at each demand node is estimated using the Clean Vehicle Rebate Project (CVRP) database (CARB, 2015), while the LDV population is estimated based on the number of households (United States Census Bureau, 2010) assuming each household owns two vehicles (Crane et al., 2002). Then, the BEV market share η is determined as the BEV population size divided by the LDV population size.
- Step 3: Determine the base year BEV O-D travel demand between each O-D pair. As shown in Figure 4, the BEV demand can be determined as $\eta \times \bar{D}_0$, where η is determined in step 2 and $\bar{D}_0$ is determined in step 1. Along an O-D pair, BEV market shares may be different at the two demand nodes, and the average of the two will be taken.
- Step 4: Project BEV O-D demands in each year *t* along the planning horizon. We assumed that the growth in O-D demands is proportional to the growth (ρ_t relative to base year, unit: %) in the BEV population size. Then, year *t* BEV O-D demand is determined as

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$\eta \times \bar{D}_0 \times (1+\rho_t)$. Assuming the BEV market share (currently 24%) remains the same in the ZEV fleet (CARB, 2015), the growth rate in the BEV fleet size is approximately equal to the growth rate in the entire ZEV population size. According to the ZEV program (Brown, 2013), the ZEV population in California will reach 1 million by 2020 and 1.5 million by 2025. Proportionally, the BEV population is expected to reach 0.24 (1×24%) million by 2020 and 0.36 (1.5×24%) million by 2025. BEV population in other years can be interpolated.

Note that the travel demand determined above is at an aggregated level. The actual demand in terms of the arrival rate at each charging station varies over a day. As noted in the equation (19) in Section 2, a 14-hour service time window is assumed for each station, which moderately recognizes the design hour operations at each station. It is equivalent to magnifying the aggregated travel demand by a factor of 1.7 (24 hours flows are assumed to be only allocated to 14 hours' time window).

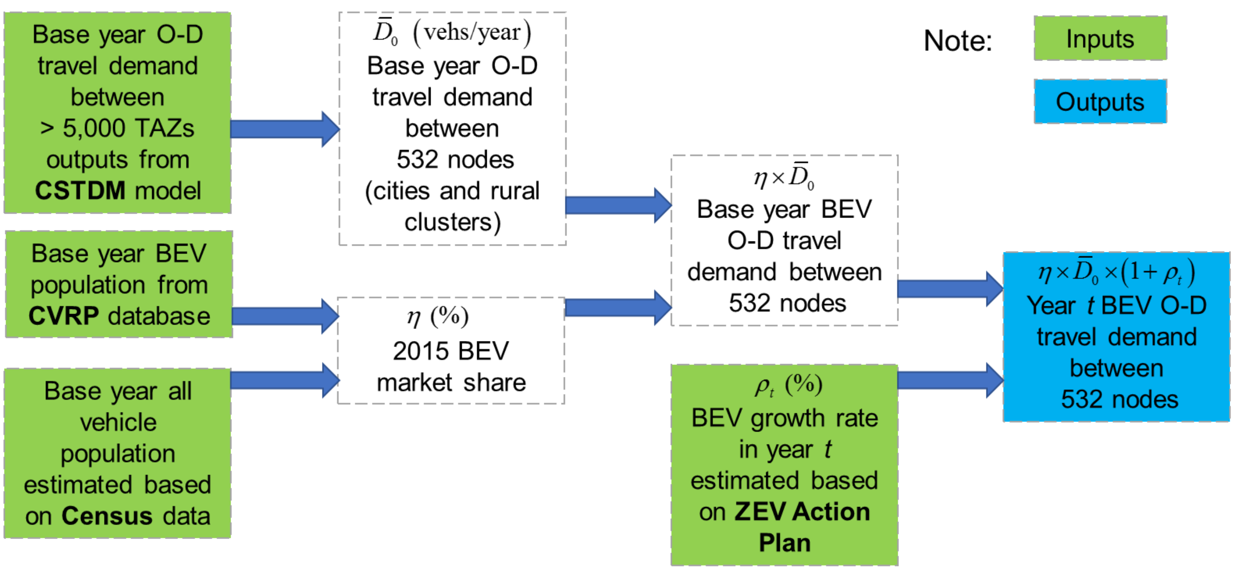

Figure 4. Yearly BEV travel demand estimation procedure

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4.4 DCFC Charging Station Infrastructure Cost

The construction cost of each DCFC charger is set to be $54,200, which includes both equipment and installation cost (NRC, 2013). As each DCFC charger occupies one parking space, the annual parking space cost of $1,686 is also included as part of charger cost (Snyder, 2012). We assume that the lifetime of each charger is 10 years with 7% discount rate. Then, five-year capital cost for each charger is $47,014.

4.5 BEV Range, Charging Level of Service, and Range Limitation Cost

In reality, BEV range differs between vehicle models. For simplicity, one BEV range of 100 miles is assumed for all BEVs on the road throughout the planning horizon. As noted in Section 2.2, the baseline charging level of service at each station is set as follows: when a BEV user arrives at a charging station, there will be at least a 95% probability of finding a vacant charger within 10 minutes.

When the charging infrastructure cannot meet the required level of service between particular O-D pairs, all trips along the O-D pair are considered infeasible or unsatisfied. Then, BEV travelers are expected to seek alternative transportation choices to avoid such range anxiety. In this study, this inconvenience is penalized at a flat rate of $50 per unsatisfied trip that approximates the average daily rental cost for alternative vehicles (Lin, 2014).

5.0 Result Analysis

5.1 Performance of the Genetic Algorithm

To evaluate the solution performance of the genetic algorithm, we considered both small and large networks. With small networks, we aimed to evaluate the solution quality of the genetic algorithm by comparing its solution with the optimal solution yielded by the CPLEX (an off-the-self optimization solver). We also considered one large network, namely the California network in the baseline case, to test the convergence performance of the genetic algorithm. We used Java to implement the genetic algorithm on an HP desktop with Intel Core I7 CPU (3.6 GHz with 4 cores)

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and 16 GB DDR3 memory. To obtain optimal solutions with the CPLEX, we coded the model in AMPL (Fourer et al., 2003) and solved it on the NEOS server (Czyzyk et al., 1998).

Table 2 shows the solution performance with 10 small network scenarios. These small networks are randomly generated. Each one contains a subset of the California network with: (1) 10% of all O-D pairs, (2) 50 candidate charging locations, and (3) two stages' infrastructure expansion (i.e., 2015-2019 and 2020-2024). As shown in Table 2, we obtain the optimal objective value for each scenario using the CPLEX. The time limit for the genetic algorithm is set at one minute per scenario, and Table 2 (columns 4-6) shows the best achieved objective value, corresponding solution time, and the optimality gap. Compared to the CPLEX, the genetic algorithm could be more efficient in solving the small network problems while maintaining high solution quality (i.e., optimality gap < 1%).

Table 2. Comparison in Solution Performance between CPLEX and Genetic Algorithm on Small Networks

Scenarios	CPLEX[1]		Genetic Algorithm[2]		
	Opt. Obj. Val.	Sol. Time (sec)	Best Obj. Val.	Sol. Time (sec)	Gap
#1	$29.3M	598	$29.5M	18	0.4%
#2	$30.2M	1004	$30.4M	50	0.6%
#3	$31.2M	404	$31.3M	43	0.1%
#4	$32.9M	129	$32.9M	28	0.1%
#5	$29.1M	612	$29.2M	30	0.6%
#6	$33.5M	64	$33.6M	42	0.3%
#7	$32.3M	141	$32.3M	22	0.1%
#8	$33.2M	228	$33.3M	36	0.2%
#9	$32.8M	3600[3]	$32.8M	46	0.1%
#10	$32.4M	450	$32.5M	29	0.3%

1. Time limit for the CPLEX is 3,600 seconds
2. Time limit for the Genetic Algorithm is 60 seconds
3. The solution time for the ninth scenario exceeds 3,600 seconds' time limit, and the best integer is obtained

To further evaluate the convergence performance in large-scale problems, we ran the baseline case 10 times with the genetic algorithm and the solution time is set at three hours per run. Table 3 shows the convergence performance for the 10 runs. Note that each row shows a time stamp when the solution performance is evaluated. With three-hour limit, the 10,800 seconds in the last row indicates the final solution evaluation for each run. The table showed that the genetic algorithm can efficiently identify solutions with better fitness over time. Especially at earlier stages of the solution process, the average objective value could be reduced by about $20 million or 22.5% during the first 2,000 seconds of solution time (i.e., row 3 compared to row 2 in Table 3). In the same time period, relative changes in objective values for both best and worst cases also decreased significantly, and remained at a relatively low value later (within 1% relative to the average objective value when the solution time reached the three-hour limit).

Table 3. Average Convergence Performance for 10 Runs on California Case Study (three hours' limit)

Solution time (secs)	Average objective value	Best case relative change[1]	Worst case relative change[1]
100	$ 88.15m	-4.67%	7.18%
2,000	$ 68.32m	-0.84%	1.70%
4,000	$ 65.21m	-0.69%	0.82%
6,000	$ 63.73m	-0.75%	0.86%
8,000	$ 62.86m	-0.57%	0.87%
10,000	$ 62.07m	-0.44%	0.81%
10,800	$ 61.86m	-0.57%	0.94%

1. relative to the average objective value $61.86m at 10,800 secs

All these analyses indicated that the genetic algorithm can efficiently solve the California case study and provide consistent solution quality.

5.2 Baseline Results

Figure 5 shows the charging infrastructure layouts by time stage for the baseline case. In the figure, locations of circles represent the geographic distributions of charging stations, and the size of each circle indicates the station size in terms of number of chargers. This shows that the charging infrastructure is expanding over time as the BEV inter-city travel demand grows. At stage 1, 56 stations with 226 chargers are opened. At stage 3, the total number of stations and chargers increases to 176 stations and 618 chargers, respectively. The trip coverage (satisfied trips/all trips) remains at high levels in all stages (>99%), as the range limitation cost for each trip is set at a high of $50 per trip. Expanding charging infrastructure is an appealing strategy for all demand levels.

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For all cases, charging stations are mainly clustered along highways between the San Francisco Bay area and Los Angeles, which are the major traffic demand centers. Note that this geographic distribution pattern is also observed in the study (Arslan and Karaşan, 2016).

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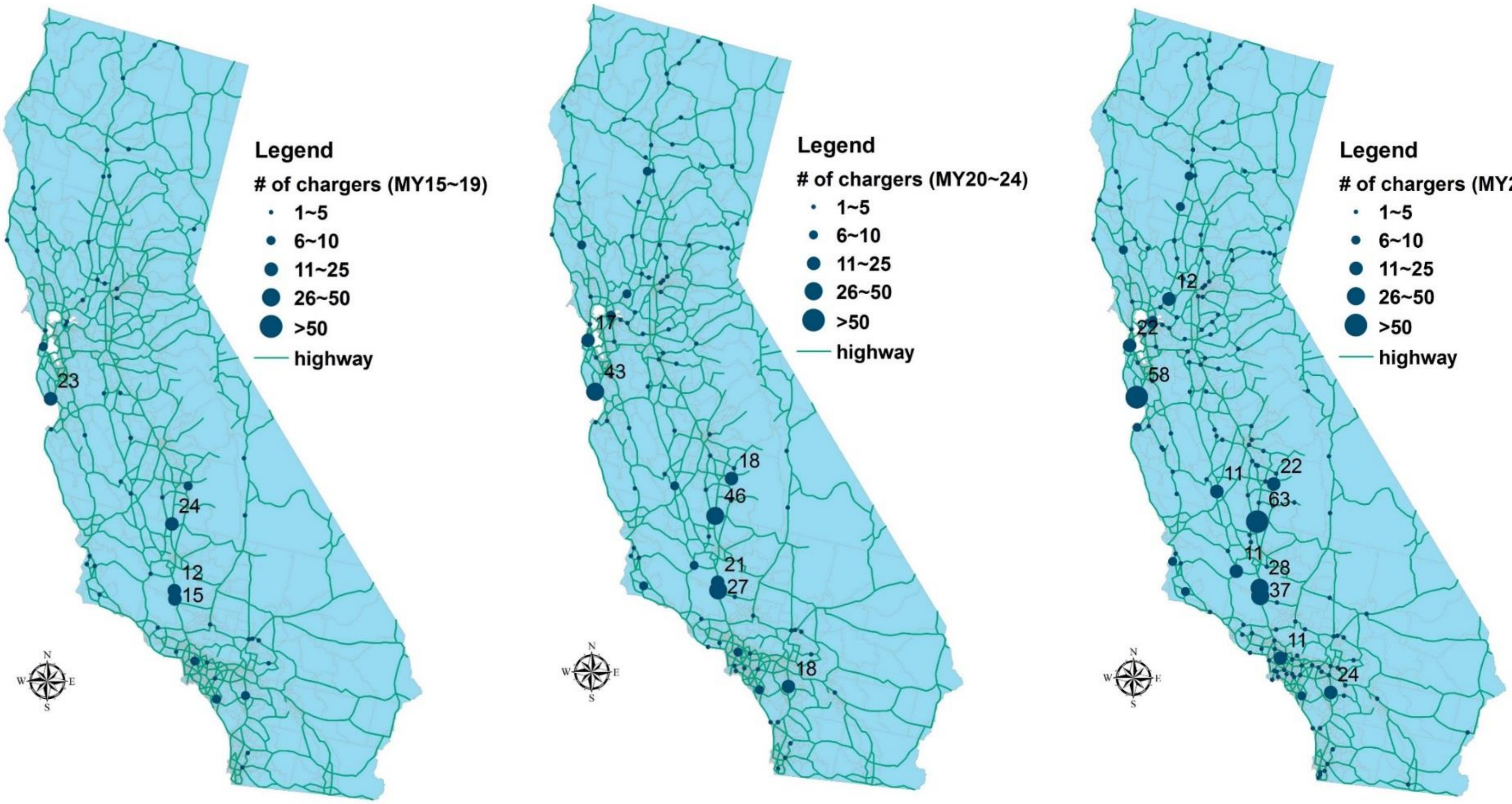

- 56 stations / 226 chargers
- Trip coverage: 99.2%

(a) Stage I (2015–2019)

- 104 stations / 423 chargers
- Trip coverage: 99.8%

(b) Stage II (2020–2024)

- 176 stations / 618 chargers
- Trip coverage: 99.8%

(c) Stage III (2025–2029)

Figure 5. Layouts of charging stations

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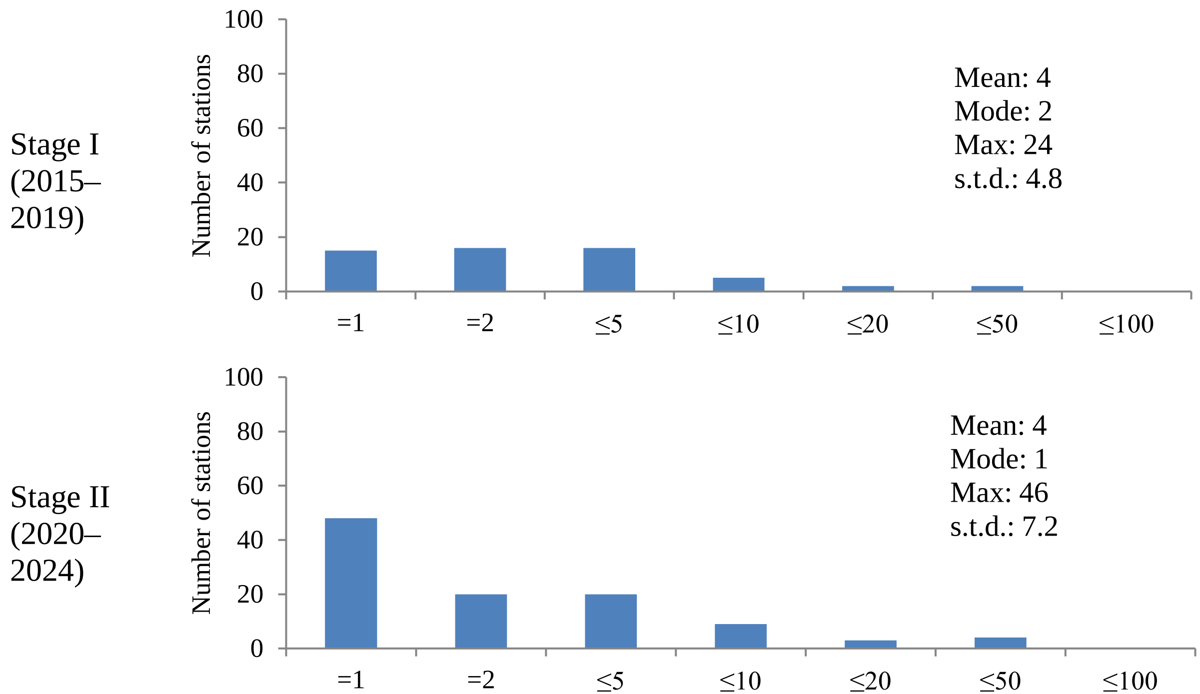
Figure 6 shows more details on the distribution of station sizes along the three stages. For stage 1 (2015–2019) when BEV inter-city travel demand is relatively low, the station size is normally small, with the largest station in stage 1 being 24 DCFC chargers. The most common configuration is two chargers per station (modal value). When BEV travel demand increases in stages 2 and 3, charging stations expand in both quantity and capacity. A large number of single-charger stations are opened. Although the capacity is low per station (on average 1.9 charging activities per day from Figure 1), they can provide widespread charging support and can complement each other in serving demand. At later stages, large charging station centers (e.g., 63 chargers at one station in stage 3) also appear, which can serve high BEV travel demand along busy corridors. It is noted that the average charging station size remains similar (around four chargers per station) across all travel demand levels. However, the variation in size does increase as the demand grows (standard deviation is increased in Figure 6). That indicates that the charging infrastructure expands in both coverage (small stations) and capacity (large stations).



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Stage III (2025–2029)

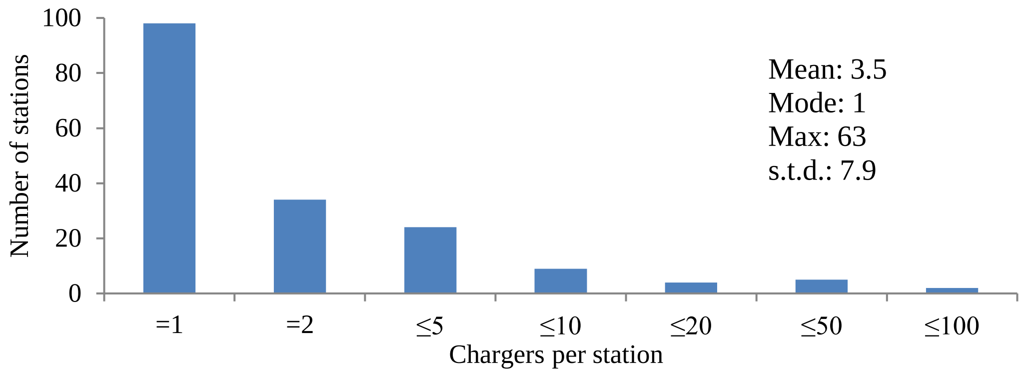

Figure 6. Histograms of chargers per station by stage

5.3 Sensitivity Analysis

The baseline case is defined by using moderate assumptions on important parameters, such as the level of service, demand flow, battery size, and range limitation cost levels. However, the actual parameters may change, and are subject to uncertain technology improvements and changes in other social and economic requirements. Therefore, we provide sensitivity analysis on several key parameters as follows.

5.3.1 Impacts of Level of Service

In the baseline case, the level of service is defined to allow BEV users to have at least a 95% probability of finding a vacant charger within 10 minutes ("95%+10 mins"). Charging infrastructure requirement may change with different level of services. Table 4 shows the impacts on charging infrastructure and trip coverage at different levels of service for stage 3 (2025–2029). It is noted that the infrastructure development level in terms of the number of stations does not differ (169–176 stations) significantly between scenarios on level of service. However, there is an obvious trend in increasing the average station size with the level of service. As the station capacity is conservatively downplayed with higher level of service (see Figure 1), more chargers are required to serve the same charging demand. The average station size increases from 3.1 chargers per station at "90%+30 mins" level to 4.4 chargers per station at "99%+0 mins" level. For all scenarios, the most common is the single-charger station, which can provide coverage for the majority less-populated rural areas in California. Note that the trip coverage rate remains high

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(>99%) for all scenarios because expanding infrastructure is preferred with high range limitation cost on infeasible trips.

Table 4. Charging Infrastructure Statistics and Trip Coverage at Different Levels of Service (Stage 3 – 2025–2029)

Category	90%+30mins	90%+10mins	95%+10mins	99%+10mins	99%+0mins
average # of chargers/station	3.1	3.3	3.5	4.2	4.4
Number of stations	169	176	176	169	175
Number of chargers	526	575	618	707	776
Maximum station size	59	61	63	63	76
Most frequent station size	1	1	1	1	1
Trip coverage level (%)	>99%	>99%	>99%	>99%	>99%

5.3.2 Impacts of Vehicle Range

The inter-city DCFC infrastructure requirement also depends vehicle range, which affects the frequency of charging activities for BEVs. The baseline case assumes a 100-mile range. In long-term planning, the actual design vehicle range may be increased as larger batteries become affordable for the public, and may also be decreased for conservative reasons such as weather impacts (e.g., batteries have reduced performance in cold weather), traffic congestions, and users' insecurity about low battery SOC. Therefore, we also conducted a sensitivity analysis on impacts of vehicle range.

As shown in Table 5, when design vehicle range increases, the infrastructure requirement is decreased in all three measures: (1) average number of chargers per station, (2) number of stations, and (3) number of chargers. The covered trips remain at high levels for all long vehicle range scenarios (longer than 100 miles), especially in the cases of 200- and 300-mile ranges. The lower vehicle range scenario (i.e., 75 miles), while greatly reducing trip coverage, can still maintain the trip coverage at a high level (94%). From the systems' points of view, expanding the charging infrastructure is favorable for all these BEV range levels.

Table 5. Charging Infrastructure Statistics and Trip Coverage at Different Design Vehicle Range (Stage 3 – 2025–2029)

Item	75 miles	100 miles	150 miles	200 miles	300 miles
average chargers per station	4.2	3.5	2.8	2.3	1.7
Number of stations	197	176	138	110	100
Number of chargers	818	618	384	256	166
Maximum station size	65	63	41	44	26
Most frequent station size	1	1	1	1	1
Trip coverage level (%)	94%	>99%	>99%	100%	100%

5.3.3 Impacts of Range Limitation Cost

All above analyses are based on the assumption of the high range limitation cost of $50 per trip (Lin, 2014). We are also interested in understanding impacts of potential lower range limitation costs, which can arise from many factors, such as emerging ride and car share programs (Martin and Shaheen, 2016) and convenient multimodal transport (e.g., inter-city or regional buses and trains). These factors also help to alleviate range limitation costs of BEV users, and may reduce the infrastructure requirement.

Figure 7 shows impacts of range anxiety costs on the charging infrastructure deployment as well as trip coverage levels for stage 3 (2025–2029). For most of scenarios, relative to penalizing infeasible inter-city trips with the range limitation cost, it is economical to expand the charging infrastructure. Even though the range limitation cost can reach at an extremely low level of $5 per trip, the model still suggests opening 500 chargers to cover about 70% of trips. The results indicate that it is worthwhile to invest in capital-intense inter-city public charging infrastructure.

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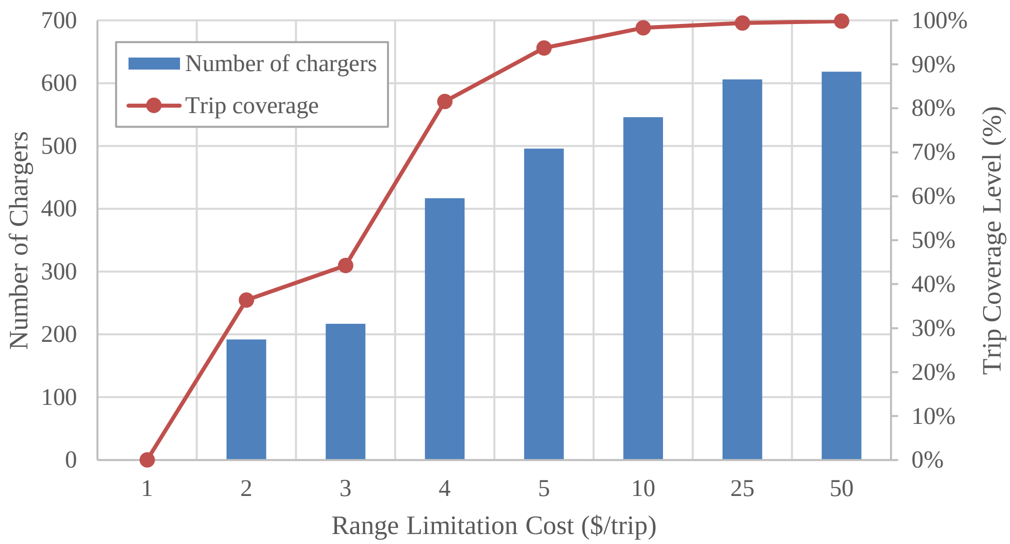

Figure 7. Impacts of range limitation costs (stage III – 2025–2029)

5.3.4 Relationship between Charging Deployment and Charging Opportunity

Following the sensitivity analysis on the range limitation cost in Section 5.3.3, we further investigated the inter-city charging deployment-opportunity relationship, a concept introduced in the study (Liu et al., 2017) to represent the relationship between charging deployment level and the charging opportunity provided to BEV users. In this study, the charging deployment level is defined as the number of chargers in the systems, and the charging opportunity is defined as the trip coverage level (percentage of trips covered). By modifying the range limitation cost at different levels, we simulated this relationship as shown in Figure 8 for three demand levels at the three stages. Results show that higher charging deployment levels will contribute to higher trip coverage levels. This relationship is time- or demand-dependent. In the near-term scope (stage 1 – 2015–2019), it requires a low infrastructure deployment level to reach a satisfying trip coverage level. For example, by opening 100 chargers, the systems can cover more than 50% of inter-city trips. However, as the travel demand increases, more chargers are needed. In stage 3 (2025–2029), a deployment level of 100 chargers can only cover about 20% of inter-city trips.

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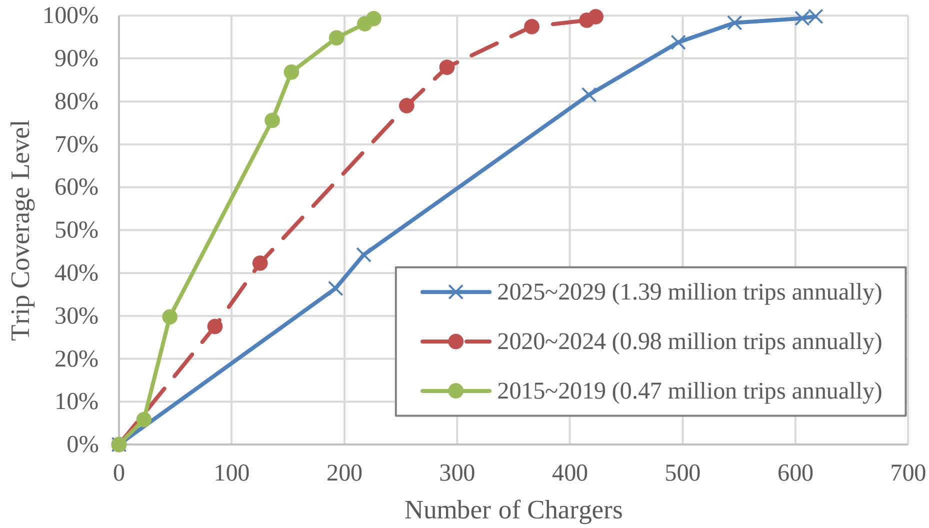

Figure 8. Charging deployment (number of chargers) – opportunity (trip coverage level) relationship.

6.0 Conclusions

We successfully developed a flow-based multistage inter-city DCFC charging infrastructure expansion planning model. In response to the growing demand of BEV inter-city travels, the model integrates both an optimization model to manage facility locations of charging stations and a stochastic queuing model to determine station capacity. A genetic algorithm based heuristic method was developed to efficiently solve the problem. The model was applied to a large-scale, real-world study in California to understand the infrastructure expansion requirement in a long-term planning scope.

We found that the charging infrastructure, in terms of both location and capacity, is gradually expanded over time to meet the growing demand of BEV inter-city travels. In the baseline case, the average station size remained similar (about four chargers per station), and the most common station configuration was the single-charger station, which can provide wide spread charging infrastructure support. The actual layout strategy depends on many factors, including the actual BEV electrified range, the required level of service, and the range limitation cost. However, for most simulated scenarios, the model suggests that it is economical systems-wide to invest in inter-city DCFC charging infrastructure, even though the range limitation cost is at the low end.

One immediate extension of this study is to integrate the model with an advanced vehicle market model, such as the Market Acceptance of Advanced Automotive Technologies (MA3T) (Lin and Greene, 2010; Lin and Greene, 2011; Liu and Lin, 2017), to understand the impacts of the expanded charging infrastructure on the BEV market share. Then, a complete analysis can be conducted to evaluate inter-relationships between the BEV market share and the charging infrastructure. Another extension is to develop an efficient global optimization solution algorithm to solve this large-scale model. One immediate benefit is to be able to fully evaluate the solution quality with an attainable optimality gap. Also, this effort can help to relax the "Last-minute charging" assumption, and we can further investigate the benefits of "central decision maker" in the infrastructure requirement.

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