DEPLOYING FAST CHARGING INFRASTRUCTURE FOR ELECTRIC VEHICLES IN URBAN NETWORKS: AN ACTIVITY-BASED APPROACH

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ABSTRACT

This paper explores an important problem under the domain of network modeling, the optimal configuration of charging infrastructure for electric vehicles (EVs) in urban networks considering EV users' daily activities and charging behavior. This study proposes a charging behavior simulation model considering different initial state of charges (SOC), travel distance, availability of home chargers, and the daily schedule of trips for each traveler. The proposed charging behavior simulation model examines the complete chain of trips for EV users as well as the interdependency of trips traveled by each driver. Then, the problem of finding the optimum charging configuration is formulated as a Mixed-Integer Nonlinear Programming that considers travel time and travel distance dynamics, the interdependency of trips made by each driver, limited range of EVs, remaining battery capacity for recharging, waiting time in queue, and the detour to access a charging station. This problem is solved using a metaheuristic approach for a large-scale case network. A series of examples are presented to demonstrate the model efficacy and explore the impact of energy consumption on the final SOC and the optimum charging infrastructure.

KEYWORDS: Network Modeling, Charging Infrastructure Planning, Public Charging Station, Electric Vehicles, Chain of Trips, Charging Behavior Simulation, System Optimization

INTRODUCTION

Increased crude oil prices and concerns associated with vehicle emissions have led the car industry and users toward hybrid and electric vehicles (EVs). While hybrid vehicles are a step forward from gasoline vehicles, they cannot fully exploit the benefits of EVs as they still depend on their gasoline engine, especially on long-distance trips. EVs do not have any on-road emissions, and if charged with green energy, they can significantly mitigate air pollution and oil dependency. However, they currently suffer from a low range, long charging time, and lack of supporting charging infrastructure. These factors also affect the decision of potential EV customers in purchasing a vehicle (*1*, *2*). To address these challenges and increase the market share of EVs, it is proposed to build a dense network of direct-current fast chargers (DCFC) to ensure the feasibility of trips, alleviate range anxiety, and provide an acceptable level of service for EV users (*3*).

Building a charging infrastructure network requires consideration of charging demand, power supply, and budget limitation, resulting in a charging infrastructure planning problem, which seeks to optimize a charging configuration (i.e., supply) for a charging demand. Depending on how each component of the problem (i.e., supply, demand, and objective function) is defined, the final solution may vary significantly. For instance, the objective function may minimize travel time and system cost or maximize EV demand, and vehicle miles traveled (VMT). Regardless of the objective function, the charging infrastructure planning problem seeks a solution that can address the charging demand while considering human behavior, which is known to be probabilistic and hard to predict. The more complex user behavior and supply consideration, the more difficult the problem to solve, and the closer to real optimal the solution.

The charging infrastructure planning problem can be divided into two categories: intercity models and urban models. The main distinctions between these two categories are associated with the travel distance range and initial state of charge (SOC) distribution. The intercity trips are long-distance ones assumed to start fully charged as users plan in advance for them (*2*, *4*–*7*). On the other hand, urban trips can start with any SOC depending on home chargers availability, preceding trips, access to workplace chargers, and dwell time at the origin (*8*, *9*). One approach to finding the charging demand is to use travel surveys or stand-alone trips (*10*, *11*). In this approach, the energy demand of each trip is independently evaluated from its past or future trips; either by assigning an initial SOC and estimating the energy demand to reach the destination with an assigned SOC (*8*) or by assuming a fixed energy demand for all trajectories (*12*). However, trip-based approaches cannot track the travelers' activity and do not have information on past and future trips, two fundamental components of the EV users charging behavior. Since urban trips are part of a trip chain, their initial SOC at each trip depends on its preceding trips. Further, EVs might even charge during a feasible trip (i.e., a trip EV can finish without charging) to prevent charging during a future infeasible trip (i.e., a trip in which EV needs to charge to be able to reach the destination) (*13*). Therefore, considering the activity engagement and the chain of trips in the problem of urban charger placement can represent the users' behavior more realistically.

While OD demand tables are commonly available to planning agencies, using the classical four-step travel model, the trip chain data is more limited, and its acquisition usually requires a significant investment. One of the earlier studies in this domain incorporated trip chain data and trajectories acquired by installing GPS on taxis to identify locations with the highest dwell times as candidate locations for building charging stations (*14*). Later, they found the best locations, among the candidate locations, by maximizing the VMT on electricity (*15*). However, the EV trajectories data is still very limited, especially on large-scale networks, and the studies usually rely on simulation models as a proxy for the actual vehicle trajectories (*8*, *16*, *17*).

This study employs a state-of-the-art agent-based model, POLARIS, which has an embedded activity-based model and simulates the travel demand of users by providing daily vehicle trajectories. Then, it proposes a charging behavior simulation that considers the availability of home chargers, travel distance, preceding trips, and remaining scheduled trips to update the SOC after each trip. Next, the charging demand is fed to a charging optimization model, which finds the optimum charging infrastructure considering the battery capacity, feasible range, dynamic travel times and travel distances, and the EVs' battery performance. The main contributions of this study are as follows:

1) Proposing a comprehensive integration of the activity-based model with mathematical optimization that enables system planners to gain valuable insights into users' behavioral factors related to activities and charging, and understand its consequential impact on the optimal charging infrastructure configuration
2) Employing an activity-based approach to track the drop in EVs SOC during daily activities and estimate charging demand based on the remaining chain of trips
3) Considering the impact of home chargers on initial and desired SOC and EVs charging behavior
4) Extending the trip-based charging infrastructure planning optimization problem to a tour-based problem
5) Conducting a sensitivity analysis, using the extended framework, on the impact of initial SOC on the final SOC for different energy consumption rates.

While the above items might have been partially or solely considered in similar studies in the literature, there is no comprehensive study that captures all these features in one framework. This study proposes a framework that could realistically simulate EVs behavior by considering users' daily activities and their access to home chargers while accounting for station congestion, charging delay, and detour to charging stations. The rest of this paper is organized as follows. The next section introduces the research framework where different components of the problem are presented, the problem is formulated, and a solution approach is proposed. Then, the numerical experiment section presents the case study and provides insights into EV charging behavior. The last section concludes the paper and proposes future research directions.

LITERATURE REVIEW

The two main approaches in the literature to consider energy demands are point clustering (*18*) and the flow-based model (*19*). The former considers where vehicles run out of charge, calculates their charging demand, and clusters them at different nodes in the network. However, this approach cannot track individual trips or place charging stations considering the detour and feasible range. The latter treats the charging demand as flow and places the charging stations in locations to capture as much flow as possible, which is called the flow-capturing location model (FCLM) (*20*). While FCLM assumes a fixed flow pattern, other variants of this model assume more realistic behaviors such as round trips and multiple refueling (*21*) and deviation from the shortest path (*22*).

Hodgson's (*19*) work was among the first to utilize the FCLM method to capture as much traffic flow as possible in the charging station networks. This work assumes a single charging facility is enough to support all traffic flow on a given path. However, EVs may need multiple charging stops on long-distance travel due to limited driving range. Thus, Kuby and Lim (*21*) proposed the flow refueling location model (FRLM) to maximize the captured flow while assigning a combination of stations to cover an EV trip from origin to destination without running out of power. Studies with flow maximization objectives are best suited for projects aiming to increase EV demand coverage, given a fixed number of charging stations and a limited budget. On the other hand, cost minimization studies aim to build as many stations as needed to support EV trips without running out of energy while minimizing total system cost or maximizing investor profit from building charging infrastructure (*20*).

Some researchers (*23*, *24*) incorporated path deviation to capture the realistic driving behaviors of EVs in a network with sparse charging infrastructures. These studies allow EV users to detach from their predetermined path to a charging station in case they need to recharge their vehicles. Previous studies either included the amount of deviation from the shortest path in their objective function or considered a tolerance threshold for the detour. In addition, while the initial charging station planning models focused on finding the optimal location of charging stations assuming an unlimited service rate implicitly, another group of studies also accounted for the number of chargers by considering waiting time at charging stations and incorporating the queuing theory (*25*, *26*). The users' response to waiting time at charging stations varies among users (*27*) For instance, for some users, such as electric taxis, a long waiting time for charging could cost them to be out of business (*27*). Thus, it is vital to consider station capacity and queue when locating charging stations.

Recent studies have accounted for the charging station capacity and EVs' detours by incorporating a framework based on the user equilibrium concept (*4*, *12*, *28*). According to this concept, all the selected paths for an origin-destination (OD) pair should have the same travel time as the optimum path, in which the travel time includes the link travel times and waiting times in the queue (*29*, *30*). In this approach, the EV users' selection of charging stations impacts the resulting congestion on network links, which will further impact the assignment of other users to their best path (*31*). Huang and Kockelman (*28*) proposed a bi-level optimization framework that modifies travelers' route behavior based on traffic congestion and station queues to find charging station configurations that maximize owners' profit.

Above mentioned studies cannot capture the effect of charging station location on EV users' activities and chain of trips. In addition, they are not able to track the battery state of charge and user charging considerations when travelers create a sequence of trips. To address this limitation, some studies (*15*, *17*, *32*, *33*) utilized activity-based models to capture individual charging behavior in their daily schedules. Usman et al. (*13*) proposed a simulation framework to plan charging strategies for urban city trips considering recharging options available at home, work, or a fixed number of fast charging stations. The model does not suggest optimum charging infrastructure but rather seeks to optimize the daily schedule of EV users created by an agent-based model, assigning EVs to the charging station that results in the minimum detour, waiting, and recharging time. Khayati and Kang (*33*) utilize a variant of Household Activity Pattern Problem (HAPP) to simulate the changes in travel behavior of households when replacing conventioal vehicles by EVs. They developed four scenarios with different settings to investigate potential impacts of EV adoption including intra-household interactions, vehicle and activity assignment among household members, and decisions regarding activity starttime and sequencing. He, Yin, and Zhou (*34*) suggested a tour-based network equilibrium model searching for the optimum location of the charging station while considering the interdependency of multiple trips made by the same driver. The proposed bi-level mathematical model was applied to the Sioux Falls network. However, this model cannot consider charging station congestion and queueing and was only tested on a small-scale network. Zhang et al. (*35*) suggested a multi-day scenario analysis for EV feasibility assessment and charging planning as single-day data may lead to an overestimation in travelers' EV feasibility. However, obtaining multi-day data can be expensive or unavailable. To tackle this issue, they replicated single-day travel activities for several days to generate multi-day data. According to their results, home charging considerably decreases the need for level 3 charging, even for people with high travel demands, and for those whose trip purposes are usually leisure.

Since urban trips are usually part of a sequence of tours, the integration of activity-based tools and mathematical charging placement optimization models is a promising approach to simulate EV charging behavior and find the optimum number and location of EV charging stations. However, there are limited comprehensive studies considering individual EV users' characteristics in optimizing charger placement infrastructures that could be efficiently applied to large-scale networks. Therefore, this study proposes a framework for monitoring EVs' daily chain of trips, battery performance, access to home chargers, charging delay, and detour time while optimizing charging placement infrastructure.

RESEARCH FRAMEWORK

This section discusses the research framework as presented in Figure 1. This framework consists of an agent-based model, a charging behavior simulation module, and a mathematical optimization model. The agent-based model, POLARIS, considers travel demand, network supply, and network operations (*36*). Travel demand-related inputs to POLARIS include data from the American Community Survey that provides cross-tabulated information on the number of people in the household and demographics. This is supplemented with the data of activity generation rates, mode choice, and destination choice from the regional MPOs. Network supply inputs include road network properties. The network operation element connects the supply and demand using a dynamic traffic simulation module (*37*). The agent-based model outputs are vehicle daily trajectories, zone-to-zone travel distances, and travel times. The next element, the charging behavior simulation, analyses the daily chain of trips for each EV and evaluates its feasibility by tracking the state of charge along its trips. For the identified infeasible trip with the state of charge below the minimum acceptable threshold, it also estimates the energy demand considering the availability of the home charger, initial charge, desired charge upon arriving home at the end of the day, trip distances, location of charging stations, and the remaining trips. The third element, the charging optimization model, takes the charging demand from the charging behavior simulation and the average zone-to-zone travel times and travel distances from POLARIS and finds the optimum charging infrastructure that minimizes the total system cost, including the infrastructure cost and delay costs. The outputs of the optimization model are the location of charging stations and the number of chargers at each location. The approach to solving the optimization problem is also discussed, where the problem is decomposed into two subproblems. The first subproblem finds the location of charging stations and provides the spatiotemporal charging demand, an input to the second subproblem, which finds the number of chargers separately.

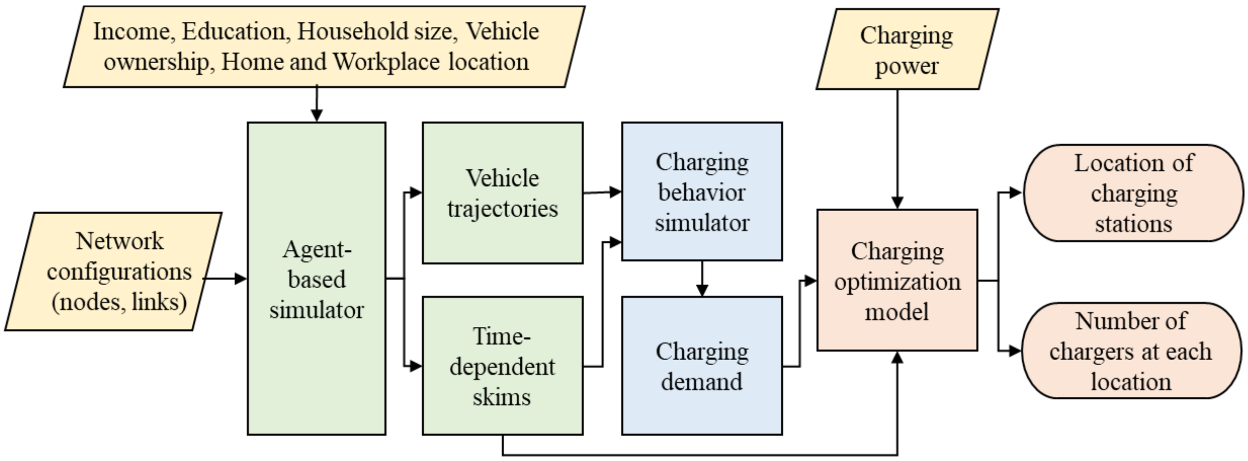


Figure 1- Research framework

Agent-Based Model

The agent-based modeling software used in this study, POLARIS, is a dynamic simulation tool that integrates the simulation of travel demand, network supply, and operations (*36*). Within the agent-based model framework of POLARIS, an activity-based model (ABM) is integrated that simulates the travel planning behavior. The ABM includes three steps; First, an activity-based travel demand model is implemented, including the agents' behaviors and actions during the simulation. After the simulation of activities and travels, the second component, i.e., the network simulation model, is tasked with assigning the travel demand and simulating the traffic. Finally, the traffic management component monitors the traffic information (e.g., accidents and weather conditions) and provides feedback to the other two components.

Charging Behavior Simulation Module

The charging behavior of EV users varies depending on the trip they make. Intercity trips are usually preplanned, where users fully recharge their EVs before departure. On the other hand, urban trips may include a constant daily schedule with some day-to-day variations. Depending on the availability of home chargers, length of trips, and daily schedule of trips, users may or may not preplan for their trips. EV users with home charger access are more likely to prepare for their upcoming trips by charging their vehicles overnight. This group tries to minimize the use of DCFCs, since charging at home is typically cheaper than charging at a public DCFC and helps them to avoid wasting their time waiting in queue or charging. On the other hand, EV users who do not have access to home chargers would more likely fully recharge their vehicles whenever they have to recharge them to minimize the number of charging incidences, similar to the behavior of conventional vehicle users. To provide a charging configuration that can address the EV charging demand, it is essential to consider the EV users' charging behavior. The more realistic the charging demand estimation, the better service EVs will receive, promoting their adoption.

Several behavioral factors may impact EV charging behavior. Considering such factors in a mathematical optimization model makes the EV charging infrastructure problem more complex and expensive to solve. Therefore, the common approach in the literature is to recharge EVs with a fixed energy (*12*, *28*) or to their full capacity (*2*, *38*). However, depending on the availability of home chargers and the travel distance of the remaining trips, the charging behavior changes, and assuming the same behavior for them cannot realistically reflect the heterogeneity in the charging behavior of EV users. Thus, this study estimates the EV charging demand considering the remaining daily schedule, home-charger availability, energy consumption, battery size, and minimum charge acceptable by users. The charging behavior simulation considers the following intuitive assumptions:

I) EV users recharge their batteries during any infeasible trip that results in a state of charge below the minimum acceptable value at their destination (without charging)
II) The remaining trips of EV users' daily schedules beyond the infeasible trip are known to them.
III) EV users try to minimize the number of charging events and costs.
IV) EV users comply with their scheduled chain of trips and do not visit their homes to recharge their batteries between their daily tours due to the slowness of their home chargers relative to DCFCs. In addition, it is assumed that the cost of charging at DCFC stations is much higher than the cost of charging at home, typically during the off-peak

The first assumption determines the trip in which the users would recharge their batteries based on current practice in the literature. The second and third assumptions imply that users want to minimize the number of recharging events (e.g., they do not want to recharge on each trip). Therefore, they consider their remaining trips in their schedule and charge enough to reach their final destination (i.e., home) with their desired state of charge. In addition, users would like to spend as little as possible on their charging costs (i.e., EV users who have access to a home charger would not fully charge their vehicle as they have a cheaper charging alternative option at home). On the other hand, EV users who do not have access to home chargers would fully charge their vehicle once they have to recharge it, as they would not like to visit a charging station every day. The fourth assumption says EV users can only charge their vehicle at home after finishing their daily activities.

Figure 2 shows the impact of the chain of trips on the charging behavior. The EV starts fully charged, and its SOC drops because of the trip it makes. As the third trip is not feasible for the user, the EV user must make a detour and recharge the vehicle to get to its next stop. The amount of charge to be acquired via a detour in trip 3 depends on the distance between the charging station and trip 3 destination, the length of trip 4, and desired state of charge at the final destination, which varies significantly depending on the home charger availability.

Figure 2- Charging decision in a chain of trips

Mathematical Optimization Model

This section introduces the developed modeling framework to minimize the cost of charging infrastructure and user delays. Table 1 presents the notation used in the study.

Table 1 – Notations

Sets	
$i \in I$	Set of zones
$\tau \in T$	Set of time intervals that vehicles get to charging stations
$\theta \in T$	Set of time intervals that vehicles leave charging stations
$j \in J$	Set of electric vehicles/trip chains
$k \in K_j$	Set of trips by vehicle *j*
Parameters	
T_0	Duration of a time interval in this study
$O(j,k)$	Origin zone of trip *k* by vehicle *j*
$D(j,k)$	Destination zone of trip *k* by vehicle *j*
t'_{jk}	Exact time of departure for vehicle *j* in trip *k*
t_{jk}	Time interval of departure for vehicle *j* in trip *k*
$d^{t_{jk}}_{(O(j,k),D(j,k))}$	Distance from origin to destination in trip *k* by vehicle *j* (mile)
$t^{t_{jk}}_{(O(j,k),D(j,k))}$	Travel time from origin to destination in trip *k* by vehicle *j* (hour)
$s_{j,k}$	State of charge for vehicle *j* at the beginning of trip *k*
s_{max}	Maximum state of charge that EVs can reach to in a charging station
ζ_j	Minimum acceptable state of charge for vehicle *j*
F_j	Battery capacity of vehicle *j* (kWh)
β_j	Battery performance of vehicle *j* (mile/kWh)
C_i^s	Fixed cost of building and maintaining a charging station at zone *i*, converted to depreciation cost per day ($)
C_i^p	Cost of installation and maintenance of one charger at zone *i*, converted to depreciation cost per day ($)
γ	Value of time ($/hour)
P	Charging power (kW)
α	Charger efficiency
M	An arbitrary large number
State Variables	
$E_{j,k}$	Energy demand of vehicle *j* at the end of trip *k* (kWh)
$E_{j,k,i}$	Energy demand of vehicle *j* charging in zone *i* during trip *k* (if it is selected as the charging station) (kWh)
$E^{\theta}_{i,j,k}$	Energy demand of vehicle *j* charging in zone *i* during trip *k* and departs after charging at time interval θ (kWh)
π_i^{τ}	Total charging and queuing time experienced by EVs reaching to the charging station in zone *i* at time interval τ (hour)
$TTd_{j,k}$	Detour travel time of vehicle *j* in trip *k* to access a charging station (hour)

$Q_{i,j,k}^{\tau,\theta}$	Binary variable, equal to 1 if vehicle *j* in trip *k* arrives to charging station in zone *i* at time interval τ and departs after charging at time interval θ; and 0 otherwise
y_i^τ	Total number of EVs visiting charging station in zone *i* at time interval τ
v_i^τ	Total energy demand of EVs visiting charging station in zone *i* at time interval τ (kWh)
$\overline{W}_i^\tau$	Average waiting time in charging station of zone *i* for EVs arriving at time τ (hour)
$R_{i,j,k}^{\theta}$	Refueling time for vehicle *j* recharging at zone *i* during trip *k* and departs after charging at time interval θ (hour)
Decision Variables	
x_i	Binary variable, equal to 1 if a charging station is built at zone *i* and 0 otherwise
z_i	Integer variable, number of chargers to be built at location *i*

This study considers a set of zones ($i \in I$) and a set of time intervals ($\tau \in T$) specifying the times EVs arrive at charging stations. T_0 represents the duration of each time interval in this study. Each trip chain ($j \in J$) includes multiple trips ($k \in K_j$) with known origins ($O(j,k)$), destinations ($D(j,k)$), exact departure times (t'_{jk}), departure time intervals (t_{jk}), lengths ($d_{(O(j,k),D(j,k))}^{t_{jk}}$), travel times ($t_{(O(j,k),D(j,k))}^{t_{jk}}$), initial state of charge ($s_{j,k}$), and acceptable minimum state of charge (ζ_j).

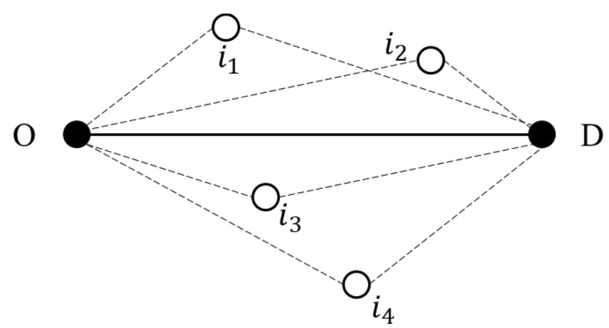
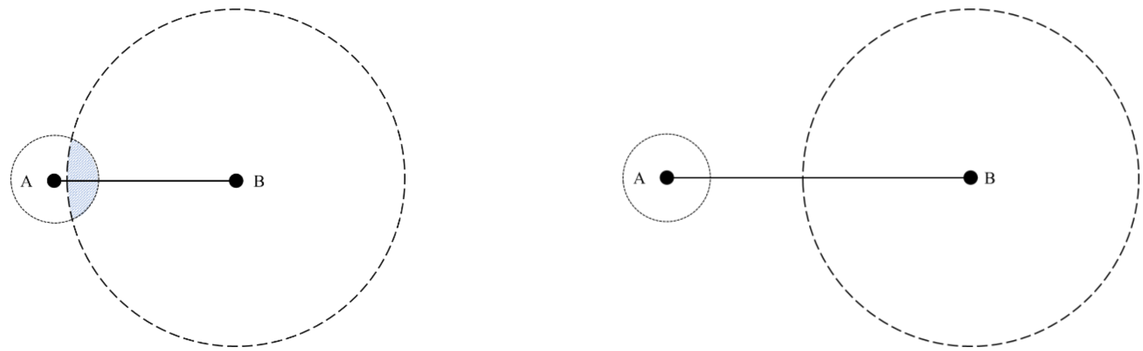


Figure 3- Electric vehicle's charging-routing decision

The feasibility of trip k for EV j between O and D in Figure 3 can be calculated using the below equation:

$$E_{j,k} = \frac{1}{\beta_j} d_{(O(j,k),D(j,k))}^{t_{j,k}} + \zeta_j F_j - s_{j,k} F_j \,, \qquad \forall\, j \in J, k \in K_j \tag{1}$$

Where E_{jk} is the energy demand of vehicle j at the end of trip k, F_j is the battery capacity, and β_j is the battery performance ($\frac{mile}{kWh}$) for vehicle j, which is the inverse of energy consumption rate. The energy demand is calculated assuming the minimum state of charge at the destination, the initial state of charge, and the distances from the origin zone to the destination zone. $E_{j,k} \le 0$ shows that energy demand is negative, i.e., the trip is feasible, and the EV would end its trip with a state of charge higher or equal to its minimum acceptable threshold. On the other hand, $E_{j,k} > 0$) means that the EV needs to recharge its battery and would select one of its charging options (i.e., $i_n, n = 1 \dots 4$ in the example shown in Figure 3). This study assumes that EV users would like to minimize the number of times they recharge their EVs (assumption III). Therefore, when EV users need to recharge their battery, they consider the remaining daily trips to estimate their required charge for the entire day. Depending on the availability of the home charger, the initial state of charge, and the remaining distance to home, this study considers two charging scenarios, as illustrated in Figure 4.



(a) (b)

Figure 4- Charging scenarios depending on the initial state of charge and the remaining distance to home. (a) Feasible area to do a single recharge and reach the destination (2) No feasible area to reach the destination based on a single recharge.

Figure 4 shows two different charging scenarios considered in this study. In Figure 4(a), the small circle shows the range of the EV at location A assuming a given state of charge, s_A. The radius of this circle is $(s_A - \zeta_j)F_j\beta_j$, which is the available range for the EV from origin A. The larger circle shows the area that if the EV recharges there, it can reach B with the minimum charge. The radius of this circle is $(1 - \zeta_j)F_j\beta_j$. In scenario (a), the distance between A and B is less than the range of a fully charged EV plus the EV available range, i.e., $d_{(A,B)} < \left(1 + s_A - 2\zeta_j\right)F_j\beta_j$ If the vehicle recharges within the highlighted area, it can fulfill its trip with just one charge (Assumption III). If the EV has access to home charger, it would only charge enough to make the trip feasible. The energy demand for this vehicle can be calculated based on the following equation:

$$E_{j,k,i} = \frac{1}{\beta_j}[d^{t_{j,k}}_{(O(j,k),i)} + d^{t_{j,k}}_{(i,D(j,k))} + \sum_{m=k+1}^{K_j} d^{t_{j,k}}_{(O(j,m),D(j,m))}] + \zeta_j F_j - s_{j,k}F_j \qquad (2)$$

Where $E_{jk,i}$ shows the energy demand of vehicle j in its trip k at location i (if it is selected as the charging station) and $s_{j,k}$ shows the state of charge of vehicle j at the beginning of trip k. $\sum_{m=k+1}^{K_j} d^{t_{jk}}_{(O(j,m),D(j,m))}$ shows the remaining trip distances in the schedule of vehicle j. Contrarily, vehicles without home chargers fully recharge in their infeasible trip. The energy demand for these vehicles can be calculated as follows:

$$E_{j,k,i} = \frac{d^{t_{jk}}_{(O(j,k),i)}}{\beta_j} + F_j - s_{j,k}F_j \qquad (3)$$

In the second charging scenario, presented in Figure 4 (b), the EV cannot reach the destination with a single charge. This scenario can happen when the size of the battery is small, the battery performance is low, or the trip length is significantly long, which may happen in large-scale networks. In this case, the EV user, regardless of its home charger availability, will fully recharge the battery, based on Eq. 3, until the user reaches a point where the EV can get to the destination with just one recharging. At that point, the EV user determines the required charge according to Eq. 2 and Eq. 3, considering the home charger availability. In this case, the location of each charging would depend on the previous charging, which makes the problem highly nonlinear and expensive to solve. This study proposes an algorithm to preprocess the trips and prevent extensive computation by breaking the long-distance trips into smaller trips and addressing the charging demand at each trip separately. The algorithm to determine the energy demand for such vehicles is provided below.

Algorithm to estimate charging demand

(1) **For** each vehicle j in J
(2) **While** each trip k in K_j
(3) **If** $s_{j,k} - \frac{1}{\beta_j} d^{t_{j,k}}_{(O(j,k),D(j,k))} < \zeta_j F_j$ **then**
(4) **While** $d < \beta_j (1 - \zeta_j) F_j$ **and** $k \leq K_j$ **then**
$d \leftarrow d + d^{t_{j,k}}_{(O(j,k),D(j,k))}$
$k \leftarrow k + 1$
End While
(5) Check Figure 4a and 4b
(6) **If** Figure 4a **then**
(7) **If** home charger available **then**
$E_{j,k,i} = \frac{1}{\beta_j} [d^{t_{j,k}}_{(O(j,k),i)} + d^{t_{j,k}}_{(i,D(j,k))} + \sum_{m=k+1}^{K_j} d^{t_{j,k}}_{(O(j,m),D(j,m))}] + \zeta_j F_j - s_{j,k} F_j$
Else $E_{j,k,i} = \frac{d^{t_{jk}}_{(O(j,k),i)}}{\beta_j} + F_j - s_{j,k} F_j$
End if
(8) **Else**
$E_{j,k,i} = \frac{d^{t_{jk}}_{(O(j,k),i)}}{\beta_j} + F_j - s_{j,k} F_j$
Break the trip into two smaller trips and update the SOCs and indices and K_j accordingly
$k \leftarrow k + 1$
Go to (3)
End if
End if
End While
End For

Based on the estimated charging demand, the activity-based optimization model can be formulated as below:

$$min \sum_{i \in I} (C_i^s x_i + C_i^p z_i) + \gamma (\sum_{i \in I} \sum_{\tau \in T} \pi_i^\tau + \sum_{j \in J} \sum_{k \in K_j} TTd_{j,k}) \qquad (4)$$

The objective function (4) consists of two main terms. The first term calculates the total infrastructure investment cost, including the costs associated with the availability of charging stations, x_i, and the integer variable z_i that represents the number of chargers at each location i. The next term provides the monetary value of the total delay of all EV travelers that need recharging, including those related to the queueing and charging delays, π_i^τ, at all charging stations for different arrival time intervals and those related to the detour travel time, TTd_j, experienced by EV users to access a charging station. These delays are multiplied by the value of time (VOT), γ, to calculate their monetary values. While a fixed value of time is considered for simplicity here, the assumption can easily be updated to account for different values of time for different users. The objective function (4) is subject to the constraints (1-3) and (5-23):

$$x_i \in \{0,1\}, \qquad \forall\, i \in I \tag{5}$$

$$z_i \in \{0,1,2,\dots\} \qquad \forall\, i \in I \tag{6}$$

$$z_i \leq x_i M, \qquad \forall\, i \in I \tag{7}$$

$$\sum_{i\in I}\sum_{\tau\in T}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta} = 1, \qquad E_{j,k} > 0, \forall\, j \in J, k \in K_j \tag{8}$$

$$\sum_{i\in I}\sum_{\tau\in T}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta} = 0, \qquad E_{j,k} \leq 0, \forall\, j \in J, k \in K_j \tag{9}$$

$$s_{j,k+1}F_j = s_{j,k}F_j - \frac{1}{\beta_j} d_{(O(j,k),D(j,k))}^{t_{j,k}} + \sum_{i\in I}\sum_{\tau\in T}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta} E_{i,j,k}^{\theta}, \qquad \forall\, j \in J, k \in K_j, k > 1 \tag{10}$$

$$\sum_{\tau\in T}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta} E_{i,j,k}^{\theta} \leq s_{max}F_j - s_{j,k}F_j + \frac{d_{(O(j,k),i)}^{t_{j,k}}}{\beta_j}, \qquad \forall\, j \in J, k \in K_j, i \in I \tag{11}$$

$$\sum_{i\in I}\sum_{\tau\in T}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta} d_{(O(j),i)}^{t_j} \leq \beta_j (s_{j,k} - \zeta_j) F_j, \qquad \forall\, j \in J \tag{12}$$

$$\sum_{\tau\in T}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta} \leq x_i, \qquad \forall\, i \in I, \forall j \in J, k \in K_j \tag{13}$$

$$TTd_{j,k} = \sum_{\tau\in T}\sum_{\theta\in T}\sum_{i\in I} Q_{i,j,k}^{\tau,\theta} \left(t_{(O(j,k),i)}^{t_{j,k}} + t_{(i,D(j,k))}^{\theta} - t_{(O(j,k),D(j,k))}^{t_{j,k}} \right), \qquad \forall\; j \in J, k \in K_j \tag{14}$$

$$t'_{j,k} + t_{(O(j),i)}^{t_{j,k}} - T_0\tau \leq \left(1 - Q_{i,j,k}^{\tau,\theta}\right) M, \qquad \forall\, \tau \in T, \theta \in T, i \in I, j \in J, k \in K_j \tag{15}$$

$$t'_{j,k} + t_{(O(j),i)}^{t_{j,k}} - T_0(\tau - 1) \geq \left(Q_{i,j,k}^{\tau,\theta} - 1\right) M, \qquad \forall\, \tau \in T, \theta \in T, i \in I, j \in J, k \in K_j \tag{16}$$

Constraint (5) shows the problem is an integer programming, and each candidate location can be equipped with a charging station ($x = 1$) or not ($x = 0$). Constraint (6) shows that the number of chargers at each location must be an integer value. Constraint (7) shows that chargers can only be placed where a charging station is built. Constraints (8-9) enforce a charging incidence only when a trip become infeasible and the energy demand is positive ($E > 0$); otherwise, no charging is required. Constraint (10) tracks the state of charge. If a vehicle is not recharged during a trip, it updates the EV's SOC based on its preceding SOC and traveled distance. Otherwise, it updates the EV's SOC based on its preceding SOC, traveled distance, and the charged energy. Constraint (11) limits the feasible locations to charge by not letting the EV charge more than its battery capacity. Constraint (12) ensures that EVs will only recharge at locations within their feasible range. Constraint (13) ensures that EVs cannot charge at locations with no charging stations. Constraint (14) calculates the detour travel time by considering the difference between the preplanned trip distance and the summation of distances from the origin to the charging station and from the charging station to the destination. Constraints (15-16) find the time interval in which EVs would enter a charging station.

The charging demand at a charging station includes 1) the number of vehicles recharging and 2) energy demand. The constraints (17-18) find the spatiotemporal charging demand for all selected charging stations. Finally, the equations (19-23) are related to deterministic queuing at charging stations.

$$y_i^{\tau} = \sum_{j\in J}\sum_{k\in K_j}\sum_{\theta\in T} Q_{i,j,k}^{\tau,\theta}, \qquad \forall\, \tau \in T, i \in I, \tag{17}$$

$$v_i^{\tau} = \sum_{j\in J}\sum_{k\in K_j}\sum_{\theta\in T} Q_{i,j}^{\tau,\theta}\, E_{i,j,k}^{\theta}, \qquad \forall\, \tau \in T, i \in I\,. \tag{18}$$

$$\bar{W}_i^{\tau} = \Phi(y_i^{\tau}, v_i^{\tau}, z_i, P), \qquad \forall\, \tau \in T, i \in I. \tag{19}$$

$$R_{i,j,k}^{\theta} = \alpha \frac{E_{i,j,k}^{\theta}}{P}, \qquad \forall\, i \in I, j \in J, k \in K_j \tag{20}$$

$$\pi_i^{\tau} = y_i^{\tau}\bar{W}_i^{\tau} + \sum_{\theta\in T}\sum_{j\in J}\sum_{k\in K_j} Q_{i,j}^{\tau,\theta} R_{i,j,k}^{\theta}, \qquad \forall\, \tau \in T, i \in I \tag{21}$$

$$t'_{j,k} + t_{(o(j,k),i)}^{t_{j,k}} + R_{i,j,k}^{\theta} + \bar{W}_i^{\tau} - T_0\theta \le \left(1 - Q_{i,j,k}^{\tau,\theta}\right)M, \qquad \forall\, \tau \in T, \theta \in T, i \in I, j \in J, k \in K_j \tag{22}$$

$$t'_{j,k} + t_{(o(j,k),i)}^{t_{j,k}} + R_{i,j,k}^{\theta} + \bar{W}_i^{\tau} - T_0(\theta - 1) \ge \left(Q_{i,j,k}^{\tau,\theta} - 1\right)M, \qquad \forall\, \tau \in T, \theta \in T, i \in I, j \in J, k \in K_j \tag{23}$$

Where equation (19) summarizes the deterministic queuing formula is a function of the number of visiting EVs, energy demand, number of chargers, and charging power (Please refer to (*8*) for more in-depth discussion on the deterministic queuing formula constraints). Equation (20) finds the charging time considering the electricity loss, α, and charging power. Equation (21) calculates the total delay in the charging station, including the charging time and waiting time in a queue. The constraints (22-23) find the time interval that an EV would leave the charging station.

Solution Approach

The proposed problem is a Mixed-Integer nonlinear programming and cannot be solved with commercial solvers when the size of the problem increases. Similar to (*8*), this problem can be decomposed into two subproblems where the location of charging stations and the number of chargers are found separately. The decomposition approach assumes that vehicles do not experience significant queuing delays at charging stations that can affect the charging station allocation; this assumption is verified in (*8*). Note that the formulated problem in this study is highly non-linear, and no exact solution method could be applied to solve this problem. In a previous study, Kavianipour et al. (*8*) compared the heuristic approach with the implicit enumeration method and showed the merit of the decomposition technique in terms of accuracy and run-time. In the next section, the subproblems of finding the location of charging stations and the number of chargers are formulated.

Charging station location problem

The first subproblem ignores the queuing at charging stations and allocates the charging stations to EVs minimizing the station costs, charging delay, and detour delay. As the problem is system optimal and there is no constraint to limit the number of chargers, the number of chargers will be determined in the next section based on the charging demand at each station and the trade-off between queuing delay and charger costs. The mathematical model of the first subproblem is formulated through equations (24-26).

$$\min \sum_{i\in I}(C_i^s x_i) + \gamma\Big(\sum_{\tau\in T}\sum_{\theta\in T}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_j} Q_{i,j,k}^{\tau,\theta} R_{i,j,k}^{\theta} + \sum_{j\in J}\sum_{k\in K_j} TTd_{j,k}\Big) \tag{24}$$

Subject to (2-3), (5-16), (20) and

$$t'_{j,k} + t^{t_{j,k}}_{(o(j,k),i)} + R^{\theta}_{i,j,k} - T_0\theta \leq \left(1 - Q^{\tau,\theta}_{i,j,k}\right)M, \qquad \forall\, \tau \in T, \theta \in T, i \in I, j \in J, k \in K_j \tag{25}$$

$$t'_{j,k} + t^{t_{j,k}}_{(o(j,k),i)} + R^{\theta}_{i,j,k} - T_0(\theta - 1) \geq \left(Q^{\tau,\theta}_{i,j,k} - 1\right)M, \qquad \forall\, \tau \in T, \theta \in T, i \in I, j \in J, k \in K_j \tag{26}$$

Constraints (25-26) find the time interval that an EV leaves the charging station, assuming that EVs charge upon their arrival to charging stations and no waiting is required to access an available charger.

This problem is a Mixed-Integer Programming (MIP) and can be solved using commercial solvers (e.g., CPLEX and Gurobi) for small to medium-sized problems. However, these problems become computationally expensive once the problem size increases. For large-scale networks (e.g., the full regional network of Chicago), which is used as the case study in this research, only heuristic algorithms can yield a solution. Kavianipour et al. proposed a heuristic algorithm based on the simulated annealing concept, which is used in this study to solve the problem of locating the charging stations (*8*). Kavianipour et al. (*8*) showed that applying the proposed heuristic method to the network in Detroit, MI decreased the run-time by 50% and memory requirement by 96% while yielding acceptable accuracy compared to results generated by commercial solvers.

Number of chargers at charging stations

The second subproblem finds the number of chargers at each location i and is formulated as in equation (27).

$$\min C^{p}_{i} z_i + \gamma \sum_{\tau \in T} y^{\tau}_{i} \bar{W}^{\tau}_{i} \tag{27}$$

Subject to
(17-19)

The objective function (27) considers the trade-off between the number of chargers and the monetary value of the deterministic waiting time to access a charger. This problem is Mixed-Integer nonlinear programming but is proven to be convex (*8*) and can be solved using a commercial solver (e.g., knitro) or the Golden-section search technique (*39*). In addition to deterministic queuing, stochastic queuing can also be incorporated, assuming a Poisson distribution for the arrival rate of vehicles and an exponential distribution for the service rates (For a more in-depth discussion on this topic and accessing the required formulation, please refer to (*8*)). It should be noted that the proposed mathematical model can consider existing charging infrastructure or minimum charger requirement at candidate locations by modifying a sub-set of station set x_i, and/or charger set z_i to model parameters instead of decision variables.

NUMERICAL EXPERIMENTS

In this section, the case study and its network specifications are presented. Next, the impact of the initial SOC on the final SOC is investigated for different battery performances. Based on these analyses, a base scenario is defined and solved, where the convergence of the solution algorithm is explored. Next, a few sensitivity analyses are conducted to investigate the impact of charging power,battery performance, and VOT on the optimum charging configuration to provide insights for policymakers.

Case Study and Assumptions

The Chicago full regional network, shown in Figure 5, is selected as a large-scale network for this study. This network includes a part of three states: Illinois, Indiana, and Wisconsin. The network consists of about 85,000 links, 36,000 nodes, 8,000 signals, and 2,000 traffic analysis zones (TAZ). The centroids of the TAZs are represented by the blue dots in the figure.

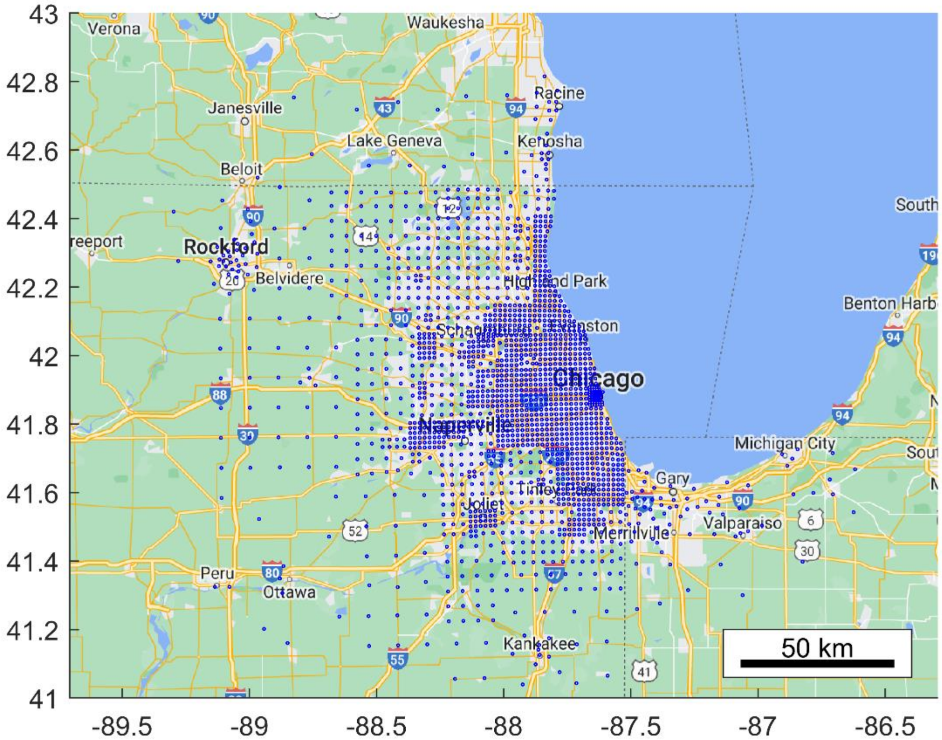


Figure 5- Chicago regional network

Based on the Chicago travel survey data, the POLARIS agent-based model is estimated and calibrated against the observed data. It employs population and vehicle synthesis and the ABM to simulate the traffic and performs the traffic assignment considering the scheduling of all users. In this study, there are 9,247,846 trips, 2,601,734 persons, and 2,644,118 vehicles available in total where 1,906,526 trips are EV trips traveled by 582,236 persons and 504,771 vehicles (25% market share). Influenced by ABM inputs such as sociodemographic characteristics, household size, income, and education level, 5% of multi-unit buildings and 61% of single-family homeowners are assumed to have access to home chargers. Considering mixed building settings in Chicago regional network, this assumption results in 41% of EVs having home chargers. This study considers three levels of charging powers 50 kW, 150 kW, and 300 kW. Table shows the station and charger costs for each charging power. A VOT of $18/hour converts the user's delay to its monetary equivalent

Table 2 Station and charger costs for different charging power

Charging power (kW)	50	150	300
Station Cost	$48,437	$80,125	$135500
Charger Cost	$33,750	$76,250	$155000

SOC Analyses

The SOC at the end of the day depends on the initial SOC and charging behavior. Considering the range of current EVs, if an EV starts the day with a fully charged battery, it would hardly need to recharge. However, the ability to fully recharge the EV every night depends on different factors (e.g., the availability of a home charger and available charging time). EV users who live in single-family residentials can purchase home chargers and install them easily. This group of users will only charge enough to make their trips feasible if they need to recharge during the day, as they can access cheaper charging at home. Therefore, the charging vehicles would finish their daily trips with a SOC close to their minimum acceptable charge. Regardless of charging, it can be expected that this group of EVs would start the day with an almost fully charged battery.

On the other hand, residents of multi-family units might not have access to chargers in their parking spaces. Therefore, they cannot start every day with a fully-charged battery. Their charging behavior also varies from the other group as they will fully recharge their vehicle once they have recharged their EV, similar to gasoline vehicles. Figure 6 investigates the impact of the initial SOC on the final SOC (upon finishing the daily trips and considering recharging between trips) for the second group considering different battery performances. The average initial SOC on the horizontal axis represents the average of a truncated normal distribution (e.g., if the lower bound and upper bound of a distribution are 0.3 and 0.8, the average SOC would be 0.55). Therefore, for an average initial SOC, there are different average final SOC in each figure.

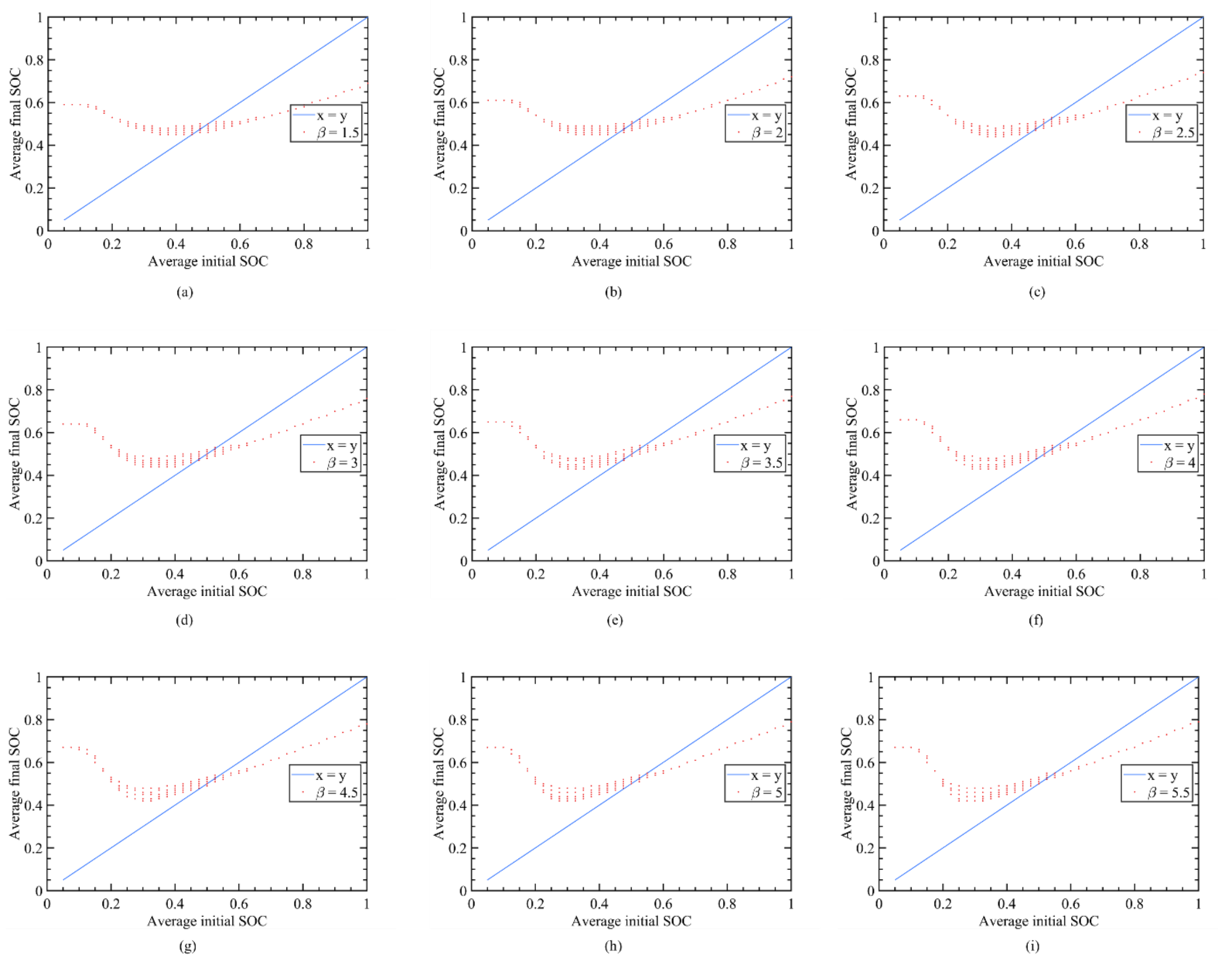


Figure 6- Average final SOC based on battery performance and initial SOC

Figure 6 considers nine different battery performances, ranging from $\beta = 1.5\frac{mile}{kWh}$ to $\beta = 5.5\frac{mile}{kWh}$, assuming that the energy consumption rate of all EVs is the same. As the β increases from Figure 6 (a) to (i), vehicles can travel longer distances using the same energy. Each node in the figure represents an average initial SOC, and an average final SOC estimated through the charging behavior simulation. In the figure, the line $y = x$ shows that the initial SOC is the same as the final SOC, which represents the energy conservation concept on average for this group of users. A node above this line indicates that the final SOC is higher than the initial SOC; hence the total energy is increased during the day, which is not possible. On the other hand, a node below the line shows that the total energy has decreased. As shown in the figure, EVs starting their daily trips with a very low initial SOC finish their activities with an average SOC significantly higher than the initial SOC. The reason is that these vehicles cannot fulfill their trips due to their very low initial SOC and have to recharge their batteries. As they do not have a home charger, they fully recharge their battery and have a high SOC once they arrive home. On the other hand, EVs starting with a very high initial SOC hardly need to recharge their vehicles during the day and return home with a SOC lower than what they started. The average initial energy level of EVs without any home charger should remain the same on different days to maintain the energy balance in the network. Thus, the nodes close to the line can represent real-life scenarios.

DCFC infrastructure

In this section, the battery performance is considered $\beta = 3\frac{mile}{kWh}$. A truncated normal distribution for the initial SOC of vehicles with a home charger is selected with a lower bound of 0.5 and an upper bound of 1. For vehicles without a home charger, a truncated normal distribution with a lower bound of 0.15 and an upper bound of 0.8 is selected for the initial SOC. The results are presented for three charging powers, 50 kW, 150 kW, and 300 kW. First, Figure 7 shows the convergence of the metaheuristic algorithm to find the optimal optimization problem solution. The figure shows that after 15,000 iterations, the solution has converged as it does not change significantly regardless of the increase in the number of iterations.

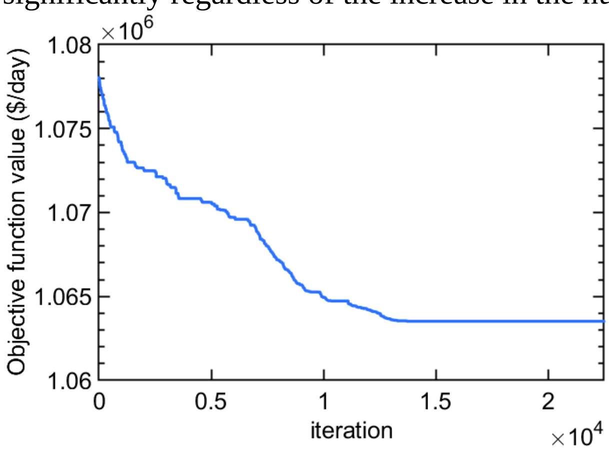
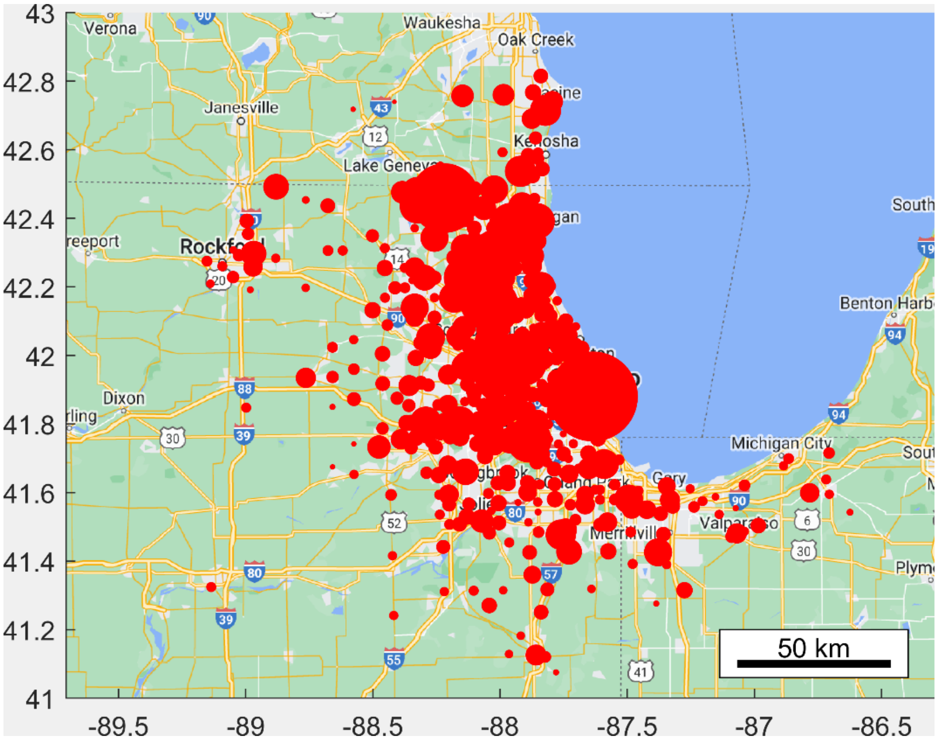


Figure 7- Convergence of the optimum solution

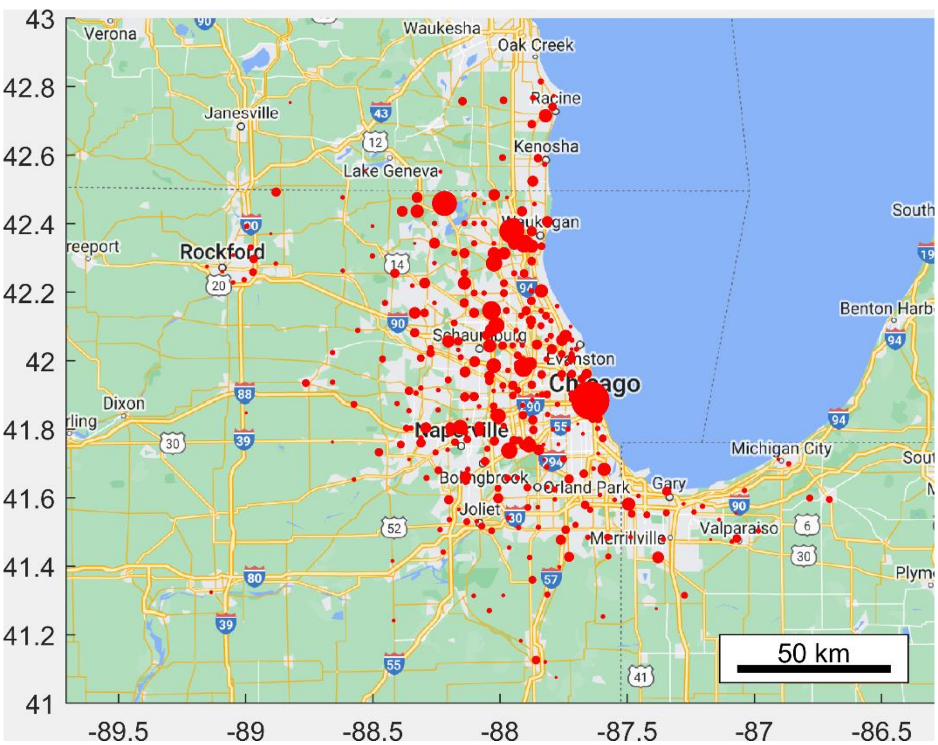
Next, provides the estimated charging infrastructure for the selected charging powers. According to Table 3, the scenario with the 150 kW power yielded a lower infrastructure cost and experienced delay, although the charging stations and chargers are more expensive per unit than the scenario with the 50 kW power, a result consistent with prior studies for other networks (*4*, *6*). Also, although the scenario with 300 kW powers results in a faster average charging time compared to the 150 kW scenario, due to the high cost of station and chargers in this scenario number of station decrease resulting in higher detour and wasting time. Also, no significant investment cost gained moving from 150 kW to 300 kW. Table 3 also shows that although with the increase in the charging powers user experienced delays at stations decrease, users have to travel longer to reach the charging station, which results in higher total detour times. As station and charger costs increase with the increase in charging powers, the models suggest building lower numbers and more scattered distribution of stations over the network, which increases the total user-experienced detour time. Figure 8 shows the estimated charging configurations for each charging power. The size of the circles relates to the number of chargers in stations, and a larger circle represents a higher number of chargers than a smaller circle. According to **Error! Reference source not found.**, the charging stations are distributed more densely in downtown Chicago with a higher number of chargers; this complies with the fact that many trips are generated or absorbed from downtown, and a charging station there can address significant charging demand. It should be noted that each TAZ is represented with one potential node for charging stations to be built. Such simplicity is considered to diminish the complexity of solving the problem in a macro-level optimization model for the entire regional network of Chicago.

Table 3- Results under different charging power

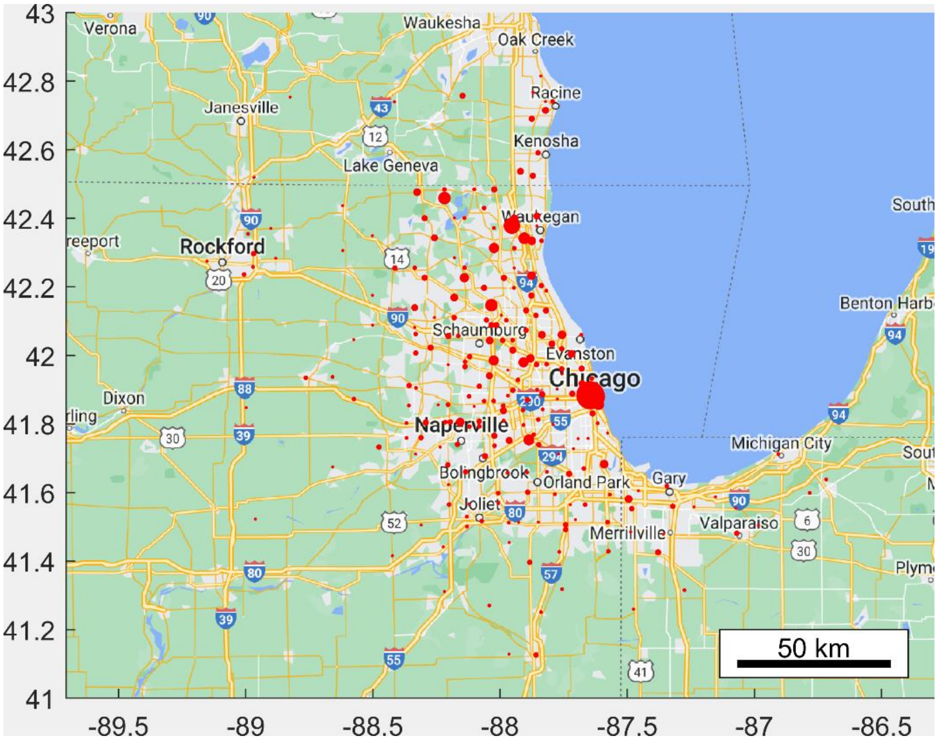
Charging station (kW)	50	150	300
Number of zones	1,961	1,961	1,961
EV trips (per day)	1,906,526	1,906,526	1,906,526
Charging events (per day)	38,648	38,648	38,648
Charging vehicles (per day)	38,366	38,366	38,366
Number of stations	438	345	246
Number of chargers	10,088	3,494	1,679
Average charging time (min)	58.57	19.54	9.77
Average waiting time (min)	0.63	0.64	0.67
Average detour (min)	4.11	4.39	4.79
Total daily charge (MWh)	1,887.19	1,887.74	1,888.44
Total station cost (m$)	25.65	31.14	35.83
Total charger cost (m$)	349.97	269.71	261.82
Total infrastructure cost (m$)	375.62	300.85	297.65



(a) 50 kW



(b) 150 kW



(c) 300 kW

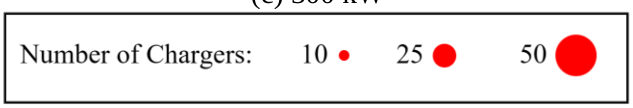


Figure 8- Optimum charging infrastructure configuration (a) 50 kW charging power (b) 150 kW (c) 300 kW charging power

SENSITIVITY ANALYSIS

Battery Performance

In order to explore the impact of battery performance on the optimum charging infrastructure, a sensitivity analysis is conducted, changing the values of battery performance from $\beta = 1.5\frac{mile}{kWh}$ to $\beta = 5\frac{mile}{kWh}$ considering a charging power of 50 kW; the results are provided in Table 4.

Table 4- Results under different battery performance with 50 kW charging power

Battery performance (mi/kWh)	**1.5**	**2**	**2.5**	**3**	**3.5**	**4**	**4.5**	**5**
Charging events (per day)	112,823	73,532	51,576	38,648	30,122	24,309	20,154	17,322
Charging vehicles (per day)	105,488	71,185	50,792	38,366	30,025	24,271	20,130	17,312
Number of stations	837	642	534	438	385	342	307	284
Number of chargers	25,806	17,662	13,057	10,088	8,216	6,704	5,691	4,996
Average charging time (min)	54.41	55.81	57.51	58.57	59.68	60.15	60.47	60.73
Average waiting time (min)	0.55	0.58	0.59	0.63	0.64	0.64	0.68	0.65
Average detour (min)	3.87	3.94	4.05	4.11	4.25	4.42	4.54	4.61
Total daily charge (MWh)	5,115.20	3,419.67	2,471.90	1,887.19	1,498.07	1,218.57	1,015.61	876.59
Total station cost (m$)	49.02	37.60	31.27	25.65	22.55	20.03	17.98	16.63
Total charger cost (m$)	895.25	612.72	452.97	349.97	285.03	232.57	197.43	173.32
Total infrastructure cost (m$)	944.27	650.32	484.24	375.62	307.58	252.60	215.41	189.95

According to Table 4, the number of charging events decreases with the increase of battery performance, which is intuitive. While the size of the batteries for vehicles is not changing between scenarios, the required infrastructure to address the charging demand increases significantly when the battery performance decreases. When the battery performance increases, the number of charging stations decreases, but this decrease is not as steep as the decrease in the number of chargers. This is due to the fact that there is no cap on the maximum number of chargers in the model, and for the hot-spot charging stations, the model provides as many chargers as needed.

VOT

Table 5 shows the sensitivity analysis conducted on VOT variables for the scenario with 50 kW charging powers, and $\beta = 3\frac{mile}{kWh}$. While the modeling always provides as many stations and chargers as needed to ensure the feasibility of all EV trips, VOT is an essential variable determining how much emphasis will be on minimizing user experience delays and detours in finding optimum charging infrastructure configuration. Table 5 shows that with VOT equal to 1 ($/hour), the model provides as low as possible number of stations and chargers to minimize the total infrastructure cost resulting in excessive user time spent in the system. As VOT increases in each scenario, the number of stations, chargers, and total infrastructure costs will increase to minimize user time spent on refueling, waiting in the queue, and detour time. With VOT 18 ($/hour), the model has already provided enough charging infrastructure to minimize user time spent in the charging stations (refueling and waiting time) and increasing VOT from this point on could only decrease the users' detour time by providing more charging stations.

Table 5- Results under different VOT with 50 kW charging power

VOT ($/hour)	1	10	18	30
Charging events (per day)	38,648	38,648	38,648	38,648
Charging vehicles (per day)	38,366	38,366	38,366	38,366
Number of stations	92	303	438	589
Number of chargers	4,884	8,450	10,088	11,479
Average charging time (min)	58.76	58.61	58.57	58.59
Average waiting time (min)	5.50	0.99	0.63	0.49
Average detour (min)	6.77	4.50	4.11	3.91
Total daily charge (MWh)	1,892.39	1,887.86	1,887.19	1,886.81
Total station cost (m$)	5.39	17.75	25.65	34.50
Total charger cost (m$)	169.43	293.14	349.97	398.22
Total infrastructure cost (m$)	174.82	310.89	375.62	432.72

EV Market Share

Table 6 presents the model results under different EV market shares of 5, 15, and 25% considering 50 kW charging power. Table 6 highlights that an increase in the EV market share leads to a proportional increase in the number of charging events, chargers, and total infrastructure cost. Charging stations are to be provided to ensure feasibility of trips and reducing detour travel time. Therefore, even with a low EV market share, a significant number of stations are required in a large-scale network like Chicago to prevent users from experiencing high detour time or energy depletion. Thus, although, increasing EV demand would increase the number of stations and decrease the detour time, the relationship was found to be more complex and non-linear.

Table 6 demonstrates that as EV market share grows users benefit from lower charging, waiting, and detour times. As discussed in the methodology section, the system provider aims to minimize both the total infrastructure cost and user time spent in the charging system. As the number of EVs grows, the user time spent in the system becomes a more influential factor compared to the total cost. Thus, the system provider gains higher benefits by reducing the user time spent and enhancing their charging experience. This finding suggests that as more users adopt EVs, policymakers and system providers give more priority to this group resulting in an overall improved charging experience for all EV users.

Table 6- Results under different EV market share with 50 kW charging power

EV Market Share (%)	**5**	**15**	**25**
Charging events (per day)	7,810	22,994	38,648
Charging vehicles (per day)	7,747	22,818	38,366
Number of stations	161	320	438
Number of chargers	2,292	6,146	10,088
Average charging time (min)	59.24	58.66	58.57
Average waiting time (min)	0.75	0.62	0.63
Average detour (min)	5.18	4.46	4.11
Total daily charge (MWh)	385.54	1,123.98	1,887.19
Total station cost (m$)	9.43	18.74	25.65
Total charger cost (m$)	79.51	213.21	349.97
Total infrastructure cost (m$)	88.94	231.95	375.62

Home Charger Ownership

Table 7 presents the model result under different shares of home charger ownership for the scenario with 50 kW charging powers, and 25% EV market share. Users with access to home charging tend to start their daily trips with a higher initial State of Charge (SOC) and require a lower desired SOC. Consequently, this group experiences a significantly lower number of charging events and total daily chargers compared to those without home chargers. Table 7 demonstrates that as the share of users with home chargers increases, there is a notable decrease in the number of stations, chargers, and total infrastructure costs. Furthermore, an increase in home charger ownership reduces the average energy charged, leading to a decrease in average charging and waiting times. However, consistent with the pattern observed in Table 6, a decrease in the number of charging events reduces the prominence of user time spent in the system as a dominant term in the objective function. As a result, the detour travel time increases as the share of users with home charging increases. Additionally, Table 7 shows the average number of EVs per charger under different home charging scenarios. It could be seen that under the scenario with no home charging system provider has to supply 1 charger for every 31 EVs, while in the scenario where all user has access to home charging this ratio increases to 1 charger for every 988 EVs. This study considers the home charging investment as the user cost, constrained by their residential area settings. However, given the potential significant decrease in total infrastructure cost gained with increasing the number of home charging users, it may be worthwhile for system providers to consider offering incentives for the purchase or facilitating the installation of home charging equipment.

Table 7- Results under different home Charging Scenarios with 50 kW charging power

Share of user with home charging (%)	0	40	50	60	100
Charging events (per day)	62,908	39,897	34,023	28,610	5,491
Charging vehicles (per day)	62,523	39,665	33,826	28,461	5,476
Charging vehicles with home charger (per day)	0	2,108	2,710	3,307	5,476
Number of stations	562	445	402	360	100
Number of chargers	16,116	10,359	8,629	7,224	511
Total number of EVs per chargers	31	49	59	70	988
Average charging time (min)	61.28	58.69	57.21	55.38	11.35
Average waiting time (min)	0.62	0.63	0.62	0.564	0.34
Average detour (min)	3.95	4.08	4.18	4.23	5.29
Total daily charge (MWh)	3,212.26	1,951.15	1,622.13	1,320.44	51.92
Home-charging users daily charge (MWh)	0	20.43	25.78	30.67	51.92
Total station cost (m$)	32.91	26.06	23.54	21.08	5.86
Total charger cost (m$)	559.09	359.37	299.35	250.61	17.73
Total infrastructure cost (m$)	592.00	385.43	322.89	271.69	23.59

Workplace Charging

With the advancements in level 3 chargers, the charging time for users at DCFCs is becoming comparable to that of gasoline vehicles. However, level 2 chargers still offer benefits for users who do not require fast refueling times. Operating within a power range of 3-19 Kw, level 2 chargers provide a slower but cost-effective charging option, making them suitable for installation at parking lots in mid or long stay locations. This study aims to examine the impact of level 2 chargers on the overall charging infrastructure configuration and the distribution of DCFCs by incorporating level 2 workplace charging for selected users.

To identify potential candidates for workplace charging, this study examines EVs that remain idle at the workplace for a minimum duration. Out of a total of 1,906,526 EV trips, 351,277 instances were identified where users had their vehicles idle at the workplace for at least one hour. This study specifically considers workplace level 2 charging for users who may need to charge their vehicles at DCFCs to complete their daily tours. However, the adoption rate of level 2 chargers at workplaces can vary significantly due to limitations in workplace settings or user preferences. Therefore, this study examines the reduction in charging load and infrastructure cost of DCFCs under different workplace charging adoption ratios for EVs that require charging during their daily trips.

The results of the model, as presented in Table 8, demonstrate the outcomes under different ratios of workplace charging adoption, considering a charging power of 7 kW for level 2 chargers and 50 kW for DCFCs. Table 8 shows that with a 100% adoption ratio, out of the 351,277 candidate work trips, there are 19,385 instances where charging at DCFCs can be skipped in favor of charging at workplaces. Consequently, workplace charging at its maximum potential could reduce the charging load on DCFCs by 50%, resulting in a reduction in the total infrastructure cost associated with DCFCs. Similar to the observations in home charging scenarios, increasing the share of users utilizing workplace chargers can lead to a reduction in the number of DCFC charging events, stations, and chargers. Consequently, this reduction in the number of DCFC stations and charging events increases the total detour time and the number of EVs per charger, respectively. Additionally, Table 8 introduces the "average return time" metric, which quantifies the number of days, on average, it takes for EVs to return to the DCFCs for refueling under different scenarios. In the absence of any level 2 charging infrastructure at workplaces, it takes, on average, 13.2 days for all vehicles (average over all vehicles with or without home charger accessibility) and 8 days for vehicles without home chargers to return to DCFCs for refueling. However, if the adoption of workplace charging increases to 50%, the average return time could potentially increase to 18 days for all vehicles and 11.1 days for vehicles without home chargers.

It should be noted that this study assumes a fixed electricity pricing structure for charging at home, workplace, and DCFCs. However, in reality, charging prices can vary based on charger type, location, and time of day, which may impact user charging behavior and should be investigated in future research. Additionally, the cost of installing and maintaining level 2 chargers at workplaces is assumed to be covered by either the workplace authorities or the car companies, rather than the system provider. However, considering the benefits gained from workplace charging, it may be worthwhile for system providers to invest in a mixture of level 2 and level 3 chargers to meet the EVs charging demand.

Table 8- Results under different workplace charging scenarios with charging power of 7 kW for level 2 and 50 kW for DCFC

Share of users charging at workplace (%)	0	40	50	60	100
Charging events (per day)	38,648	29,969	28,181	25,908	19,263
Charging vehicles (per day)	38,366	29,790	28,012	25,765	19,191
Charging vehicles without home charger (per day)	36,362	28,539	26,865	24,789	18,670
Number of stations	438	365	364	347	283
Number of chargers	10,088	7,784	7,566	6,955	5,750
Total number of EVs per chargers	50	65	67	73	88
Average charging time (min)	58.57	59.10	59.11	59.22	59.49
Average waiting time (min)	0.63	0.61	0.63	0.60	0.68
Average detour (min)	4.11	4.33	4.36	4.31	4.55
Total daily charge (MWh)	1,887.19	1,475.87	1,388.2	1,278.24	954.92
Charging events at workplace (per day)	0	8,679	10,467	12,740	19,385
Workplace-charging users daily charge (MWh)	0	411.32	498.99	608.95	932.27
Average return time for all vehicles (days)	13.2	16.9	18	19.6	26.3
Average return time for vehicles without home-charging (days)	8.2	10.4	11.1	12	16
Total station cost (m$)	25.65	21.38	21.32	20.32	16.57
Total charger cost (m$)	349.97	270.04	262.48	241.28	199.48
Total infrastructure cost (m$)	375.62	291.42	283.80	261.60	216.05

Utility Cost

Utility cost is an essential factor in selecting station locations as it captures the cost of purchasing and installing equipment, electricity, and upgrading power grid infrastructure. Since no real-world utility data was available from the case study network, this study assumes a fixed cost of 10,000$ per station as the utility cost. However, it is important to note that utility costs can be sensitive to factors such as charging load, station location, and the utility provider company. In a real-world scenario, a station might require a significant investment for upgrading the power grid infrastructure as a certain usage threshold is reached. This pattern could be best captured by using a step function that considers different utility costs for different charging powers. Table 9 presents the average utility cost obtained from multiple utility providers in Michigan for different charging power steps. To capture the impact of power grid capacity and constraints on the charging infrastructure configuration and investment cost, this study developed a scenario using the Table 9 step function and compared it with the base case of fixed utility cost.

Table 9- Step function utility cost for different power range

Power (KW)	**0-500**	**500-1000**	**1000-2000**	**2000-5000**	**+5000**
Cost ($)	60,000	70,000	100,000	250,000	500,000

Table 10 shows the model result under fixed and step function utility costs for the scenario with 50 kW charging powers. As expected, using the step function leads to significantly higher utility costs compared to the fixed scenario. Consequently, the model suggests reducing the number of stations and aggregating energy demand at certain locations to minimize the overall cost. Since the utility cost remains constant within each step range, the optimal solution for the step function scenario involves concentrating energy demand at each station up to the upper bound of each step, just before the price jump occurs in the next step. As a result, as depicted in Table 10, the number of chargers per station increases in the step function scenario. It is worth noting that although the total infrastructure cost in the two scenarios is similar, the lower number of stations in the step function scenario leads to increased detour travel time for users. This trade-off between infrastructure cost and user travel time should be carefully considered when making decisions regarding charging infrastructure configuration.

Table 10- Results under different utility function with 50 kW charging power

Utility cost	Fixed	Step Function
Charging events (per day)	38,648	38,648
Charging vehicles (per day)	38,366	38,366
Number of stations	438	356
Number of chargers	10,088	9,525
Number of chargers per stations	23	27
Average charging time (min)	58.57	58.61
Average waiting time (min)	0.63	0.64
Average detour (min)	4.11	4.42
Total daily charge (MWh)	1,887.19	1,887.64
Total Utility cost (m$)	4.38	27.58
Total station cost (m$)	25.65	44.87
Total charger cost (m$)	349.97	330.44
Total infrastructure cost (m$)	375.62	375.31

CONCLUSION

This study adopts an activity-based approach to consider the interdependency of different trips traveled by the same EV driver. The proposed framework in this study extends the extensive effort in the literature to more realistically capture charging demand in large-scale networks to improve planning for charging infrastructure in urban networks. This is achieved by integrating an activity-based model and a mathematical optimization model along with developing a charging behavior simulation module. The charging behavior simulation module considers the availability of home chargers, travel distance, past trips, and scheduled trips to estimate the charging demand. The mathematical optimization model considers the daily schedule of users, feasible range of EVs, remaining battery capacity, waiting in a queue at charging stations, and travel detours. A solution approach is proposed to solve this problem for large-scale networks, which is successfully applied to the full regional network of Chicago, and the results based on realistic values are presented for three charging powers. A sensitivity analysis is conducted on the initial SOC to estimate the final SOC for EVs considering different battery performances. Also, the required charging infrastructures under different scenarios for battery performances, VOT, EV market share, home charger ownership, workplace charging, and utility cost are investigated.

This study can be further extended and improved through possible future research directions, to name a few:

- The proposed model assumes that EVs only recharge during their infeasible trip. However, they might recharge in a feasible trip to prevent future recharging. This behavior must be captured to provide a solution that can better address the EVs charging demand. However, this requires a more in-depth study of users' behavior
- Various strategies for spatial and temporal pricing of electricity can be studied to explore their impacts on congestion and the required number of chargers.
- In this study the optimization model is founded based on the trip chains provided by an activity-based model. However, a fully-integrated model can be developed in a future research capable of constantly back-and-forth between the optimization and activity-based models to generate trip chains based on the location and quantity of chargers and vice versa.
- Future research should consider heterogeneous EV users with various VOTs during trip chains to capture the changes in individual charging preferences throughout the daily schedule.
- Since the location of charging stations affects the trips within the trip chains which can further affect the travel time and demand, it requires the activity-based model to be run for multiple days and capture the change in the chain of activities from one day to another. It ensures that the feedback from the optimization model is provided to the activity-based model.
- In this study, long-term and medium-term travel behavior and trip profile in the EV era is assumed to remain similar and only short-term behavior (charging at infeasible trip) is considered. However, future studies may investigate any possible change in future travel behaviors in terms of long-term and short-term decisions such as destination choice, and living and working locations, when more EVs hit the roads around the globe.
- This study considered TAZ centroids as candidate locations for charging stations to be built. However, sometime these TAZs might be broad and require to be broken into smaller zones. Therefore, further distribution of chargers within each TAZ can be made using the information provided by ABM.

- Future research should explore the integration of different charging options (e.g., DCFCs, and Level 2 chargers) and consider the charging requirements of a broader range of vehicle types (e.g., EVs and PHEVs) to further enhance the efficiency and effectiveness of charging infrastructure configuration. Future work should investigate the budget allocation between DC fast charging infrastructure and level 2 chargers at short-term stays (e.g., work-place or shopping centers) that achieves an optimal charging configuration for both users and the system provider.

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AUTHOR CONTRIBUTIONS

All authors contributed to all aspects of the study from conception and design to analysis and interpretation of results, and manuscript preparation. All authors reviewed the results and approved the final version of the manuscript. The authors do not have any conflicts of interest to declare.

REFERENCES

1. Nie, Y. (Marco), and M. Ghamami. A corridor-centric approach to planning electric vehicle charging infrastructure. *Transportation Research Part B: Methodological*, Vol. 57, Nov. 2013, pp. 172–190.
2. He, F., D. Wu, Y. Yin, et al. Optimal deployment of public charging stations for plug-in hybrid electric vehicles. *Transportation Research Part B: Methodological*, Vol. 47, Jan. 2013, pp. 87–101.
3. Nie, Y., M. Ghamami, A. Zockaie, et al. Optimization of incentive polices for plug-in electric vehicles. *Transportation Research Part B: Methodological*, Vol. 84, 2016, pp. 103–123.
4. Ghamami, M., M. Kavianipour, A. Zockaie, et al. Refueling infrastructure planning in intercity networks considering route choice and travel time delay for mixed fleet of electric and conventional vehicles. *Transportation Research Part C: Emerging Technologies*, Vol. 120, Nov. 2020, p. 102802.
5. Upchurch, C., M. Kuby, and S. Lim. A model for location of capacitated alternative-fuel stations. *Geographical Analysis*, Vol. 41, No. 1, 2009, pp. 127–148.
6. Kavianipour, M., F. Fakhrmoosavi, M. Shojaei, et al. Impacts of technology advancements on electric vehicle charging infrastructure configuration: a Michigan case study. *International Journal of Sustainable Transportation*, 2021.
7. Fakhrmoosavi, F., M. Kavianipour, M. (Sam) Shojaei, et al. Electric Vehicle Charger Placement Optimization in Michigan Considering Monthly Traffic Demand and Battery Performance Variations. *Transportation Research Record: Journal of the Transportation Research Board*, Jan. 2021.
8. Kavianipour, M., F. Fakhrmoosavi, H. Singh, et al. Electric vehicle fast charging infrastructure planning in urban networks considering daily travel and charging behavior. *Transportation Research Part D: Transport and Environment*, Vol. 93, Apr. 2021, p. 102769.
9. Singh, H., M. Kavianipour, A. Soltanpour, et al. Macro Analysis to Estimate Electric Vehicles Fast-Charging Infrastructure Requirements in Small Urban Areas: Jun. 2022.
10. Andrews, M., M. K. Dogru, J. D. Hobby, et al. *Modeling and Optimization for Electric Vehicle Charging Infrastructure*. 2012.
11. Chen, T. D., K. M. Kockelman, and M. Khan. Locating Electric Vehicle Charging Stations Parking-Based Assignment Method for Seattle, Washington. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2385, No. 1, Jan. 2013, pp. 28–36.
12. Zockaie, A., H. Z. Aashtiani, M. Ghamami, et al. Solving detour-based fuel stations location problems. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 31, No. 2, 2016, pp. 132–144.
13. Usman, M., L. Knapen, A. U. H. Yasar, et al. Optimal recharging framework and simulation for electric vehicle fleet. *Future Generation Computer Systems*, Vol. 107, Jun. 2020, pp. 745–757.
14. Cai, H., X. Jia, A. S. F. Chiu, et al. Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet. *Transportation Research Part D: Transport and Environment*, Vol. 33, 2014, pp. 39–46.

15. Shahraki, N., H. Cai, M. Turkay, et al. Optimal locations of electric public charging stations using real world vehicle travel patterns. *Transportation Research Part D: Transport and Environment*, Vol. 41, 2015, pp. 165–176.
16. Xi, X., R. Sioshansi, and V. Marano. Simulation – optimization model for location of a public electric vehicle charging infrastructure. *TRANSPORTATION RESEARCH PART D*, Vol. 22, 2013, pp. 60–69.
17. Dong, J., C. Liu, and Z. Lin. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. *Transportation Research Part C: Emerging Technologies*, Vol. 38, 2014, pp. 44–55.
18. Ip, A., S. Fong, and E. Liu. Optimization for allocating BEV recharging stations in urban areas by using hierarchical clustering. *Management and Service*, 2010, pp. 460–465.
19. Hodgson, M. J. A flow-capturing location-allocation model. *Geographical Analysis*, Vol. 22, No. 3, 1990, pp. 270–279.
20. Kchaou-Boujelben, M. Charging station location problem: A comprehensive review on models and solution approaches. *Transportation Research Part C: Emerging Technologies*, Vol. 132, 2021, p. 103376.
21. Kuby, M., and S. Lim. The flow-refueling location problem for alternative-fuel vehicles. *Socio-Economic Planning Sciences*, Vol. 39, No. 2, 2005, pp. 125–145.
22. Kim, J. G., and M. Kuby. The deviation-flow refueling location model for optimizing a network of refueling stations. *International Journal of Hydrogen Energy*, Vol. 37, No. 6, Mar. 2012, pp. 5406–5420.
23. Huang, Y., S. Li, and Z. S. Qian. Optimal deployment of alternative fueling stations on transportation networks considering deviation paths. *Networks and Spatial Economics*, Vol. 15, No. 1, 2015, pp. 183–204.
24. Lin, C.-C., and C.-C. Lin. The p-center flow-refueling facility location problem. *Transportation Research Part B: Methodological*, Vol. 118, 2018, pp. 124–142.
25. Wang, Y.-W., and C.-C. Lin. Locating multiple types of recharging stations for battery-powered electric vehicle transport. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 58, 2013, pp. 76–87.
26. Zheng, H., and S. Peeta. Routing and charging locations for electric vehicles for intercity trips. *Transportation Planning and Technology*, Vol. 40, No. 4, 2017, pp. 393–419.
27. Jung, J., J. Y. J. Chow, R. Jayakrishnan, et al. Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations. *Transportation Research Part C: Emerging Technologies*, Vol. 40, 2014, pp. 123–142.
28. Huang, Y., and K. M. Kockelman. Electric vehicle charging station locations: Elastic demand, station congestion, and network equilibrium. *Transportation Research Part D: Transport and Environment*, Vol. 78, 2020, p. 102179.
29. Lee, Y.-G., H.-S. Kim, S.-Y. Kho, et al. User equilibrium–based location model of rapid charging stations for electric vehicles with batteries that have different states of charge. *Transportation research record*, Vol. 2454, No. 1, 2014, pp. 97–106.
30. Yao, W., J. Zhao, F. Wen, et al. A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems. *IEEE Transactions on Power Systems*, Vol. 29, No. 4, 2014, pp. 1811–1821.
31. Hosseini, M., S. A. MirHassani, and F. Hooshmand. Deviation-flow refueling location problem with capacitated facilities: Model and algorithm. *Transportation Research Part D: Transport and Environment*, Vol. 54, 2017, pp. 269–281.

32. Metais, M.-O., O. Jouini, Y. Perez, et al. Too much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options. *Renewable and Sustainable Energy Reviews*, Vol. 153, 2022, p. 111719.
33. Khayati, Y., & Jee, E. Kang, et al. Comprehensive scenario analysis of household use of battery electric vehicles. *https://doi.org/10.1080/15568318.2018.1529210*, Vol. 14, No. 2, Dec. 2019, pp. 85–100.
34. He, F., Y. Yin, and J. Zhou. Deploying public charging stations for electric vehicles on urban road networks. *Transportation Research Part C: Emerging Technologies*, Vol. 60, 2015, pp. 227–240.
35. Zhang, A., J. E. Kang, and C. Kwon. Multi-day scenario analysis for battery electric vehicle feasibility assessment and charging infrastructure planning. *Transportation Research Part C: Emerging Technologies*, Vol. 111, Feb. 2020, pp. 439–457.
36. Auld, J., M. Hope, H. Ley, et al. POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. *Transportation Research Part C: Emerging Technologies*, Vol. 64, Mar. 2016, pp. 101–116.
37. Verbas, Ö., J. Auld, H. Ley, et al. Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network: *https://doi.org/10.1177/0361198118796402*, Vol. 2672, No. 47, Oct. 2018, pp. 219–230.
38. Chen, Z., F. He, and Y. Yin. Optimal deployment of charging lanes for electric vehicles in transportation networks. *Transportation Research Part B: Methodological*, Vol. 91, 2016, pp. 344–365.
39. Kiefer, J. Sequential Minimax Search for a Maximum. *Proceedings of the American Mathematical Society*, Vol. 4, No. 3, 1953, p. 502.