A Framework for Solving Sequential Charging Facility Location Estimation Problem in Urban Setting

Ashraf Uz Zaman Patwary[1], Francesco Ciari[1,*], Arsham Bakhtiari[1], and Hamed Naseri[1]

[1]Polytechnique Montréal, Quebec, Canada,
[*]francesco.ciari@polymtl.ca

Extended Abstract

Electric vehicles (EVs), with zero runtime emissions and higher energy efficiency than gasoline vehicles, are increasingly adopted to reduce carbon emissions. Advances in battery technology, rising demand, emission goals, and regulations have prioritized electrification for the automotive industry (Zhao et al. 2024). Despite advancements, the unavailability of charging infrastructure remains a critical deterrent to EV adoption (Bailey et al. 2024). In urban settings, charging is linked to Individuals' daily activities governing charging start times and durations (Liu et al. 2022). However, very few literature applied activity-based charging logic in EV infrastructure planning.

Zhang et al. (2020) used an activity-based traffic model with K-means clustering to identify charger locations for a ridesharing fleet but focused only on spatial distances, neglecting queuing times, connection durations, and energy served. Csiszár et al. (2019) optimized charger placement using land-use data to identify activity hotspots but ignored temporal demand variations and activity durations. None explicitly address activity-governed charging and existing charging infrastructures.

For the location choice model, existing literature has broadly approached the problem using two primary design principles: demand-based charger allocation and flow-capturing charger allocation. Demand-based methods focus on satisfying the estimated charging demand from simulations or data-driven models (Zhang et al. 2020). On the other hand, flow-capturing methods prioritize strategically locating chargers to maximize accessibility and coverage (Csiszár et al. 2019). As both approaches address key aspects of EV users' behavior and charging dynamics, in this study, we combine these approaches into a multi-step framework.

Given the above literature landscape, this paper proposes a two-step, activity-driven, sequential charger allocation framework in the urban context, combining both demand-satisfying and flow-capturing approaches for the EV charger location choice problem.

1 Problem statement

This study aims to reduce charging queues within budgetary and power constraints. $i \in I$ is defined as candidate spots and $j \in J$ as current charger locations, with Q_i and V_i representing average queue and power draw per plug at i. Decision variables x_i and p_i denote charger type and plug count at i, while x_j and p_j represent the same for existing chargers j. Setup and operation costs are $C_{s,x}$ and $C_{o,x}$, bounded by budgets B_s and B_o. Zones are denoted by z and I_z and J_z are sets of candidate and current charger locations in z. With that, the problem can be formulated as follows. We use Micro Agent Traffic Simulation, i.e., MATSim for simulating electric vehicle charging in the proposed urban context.

$$
\begin{aligned}
&min_{x_i,p_i} \frac{1}{|I|+|J|}\left\{\sum_{i\in I} Q_i + \sum_{j\in J} Q_j\right\}; \forall i \in I;\ x_i, x_j \in X;\ p_i, p_j \in P \\
&s.t.\ \sum_{i\in I} p_i \times C_{o,x_i} + \sum_{j\in J} p_j \times C_{o,x_i} \le C_o;\ \sum_{i\in I} p_i \times C_{s,x_i} \le C_s;\ \sum_{i\in I_z} V_i + \sum_{j\in J_z} V_j \le V_z; \forall z \in Z
\end{aligned} \tag{1}
$$

2 Methodological Framework

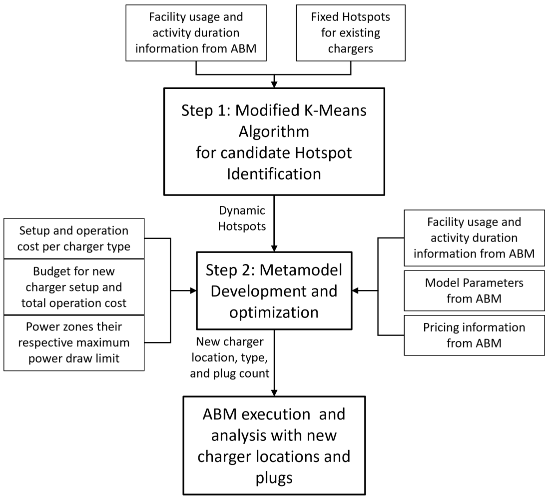


Figure 1: Schematics of the proposed charger location estimation algorithm.

We propose a two-step, sequential charger location estimation framework. The first step identifies candidate charger locations (I) using a modified K-means algorithm, which maximizes the capture of agent activity locations and durations while accounting for existing facilities. The second step involves a single-shot physical metamodel-based optimization to determine the optimal locations and plug counts for the new charger facilities satisfying the demand. Finally, the results are analyzed and evaluated within the original simulator, as illustrated in Figure 1.

2.1 Step 1: Modified K-Means Algorithm

The modified K-mean algorithm reduces the solution space by identifying candidate charger locations (hotspots). The algorithm processes two types of clusters: dynamic (candidate locations) and static (preexisting chargers). Only the dynamic centroids are updated snapping to the nearest activity facility location during training. Feature vectors include location coordinates, user counts, and optionally activity durations, favoring high-activity areas. The number of candidate locations and hence the dimensions of the step 2 problem are configured in this step.

2.2 Step 2: Metamodel development and optimization

step 2 solves the optimization problem presented in equation 1 except the queue and power draw for chargers at locations $i \in I$ and $j \in J$ are approximated using a problem-specific Demand Allocation metamodel. This metamodel simplifies problem dynamics while preserving MATSim's behavioral parameters for consistency.

2.3 Demand Allocation Metamodel Formulation

For each location in a given solution $[X, P]$, the metamodel approximates three outcomes for charger demand allocation: demand per charger (q_i,q_j), average intended charging duration ($t_{0,i}, t_{0,j}$), and average charging time t_i, t_j. The intended duration $t_{0,i}$ reflects users' desired charging time, while the actual duration t_i includes delays, analogous to free flow vs. actual travel time in static traffic models. These terms are interdependent: demand (q) affects queue time (t), which influences charger choice probabilities, in turn shaping intended durations (t_0) and peak hour demands. This cyclic dependency creates a Wardrops equilibrium.

For facility f, this choice set is defined by $I_f : d_{i,f} \leq d_{max}$. Then, the probability of choosing charger i from facility f, $\omega_{f,i}$ is calculated using the logit model and can be written as follows. Here the utility includes queue time $(t_i - t_{i,0})$, distance $d_{f,i}$, charging cost c_i if any, and the obtained charge to battery capacity ratio $\frac{t_{0,i}\ v_{x_i}}{b}$ for determining the attractiveness of a charger.

$$\omega_{f,i} = \frac{e^{\eta U_{f,i}}}{\sum_{i' \in I_f} e^{\eta U_{f,i'}}};\ U_{f,i} = \beta_t \times (t_i - t_{0,i}) + \beta_d \times d_{f,i} + \beta_m \times c_i + \beta_r \times min(\frac{t_{0,i}\ v_{x_i}}{b}, 1) \tag{2}$$

Queuing effects are captured while calculating t_i from $t_{0,i}$ using the volume delay function as below. Here, α and γ controls the smoothness of the curve. In our experiments, $\alpha = 0.15$ and $\gamma = 1$.

$$t_i = t_{0,i}\left\{1+\alpha\times\left(\frac{q_i\times min(t_{0,i},3600)}{3600\times p_i}\right)^{\gamma}\right\} \tag{3}$$

After calculating the utility and charger choice probability, we can get hourly demand for a charger from surrounding facilities using equation 4. Here, facility demand is multiplied by the facility to charger probability and ρ, the peak hour factor taken as 0.12. Weighted average durations from these facilities according to their hourly demand give the hourly intended charging duration as shown in equation 4.

$$q_{i,h} = \sum_{f\in F} \rho\,\omega_{f,i}\,q_f\,\delta_{f,h};\;\; t_{0,i,h} = \frac{\sum_{f\in F}\rho\,\omega_{f,i}\,q_f\,\delta_{f,h}\,t_{0,f}}{\sum_{f\in F}\rho\,\omega_{f,i}\,q_f\,\delta_{f,h}} \tag{4}$$

Finally, the maximum of these hourly demands ($q_{i,h}$) is chosen as the design charger demand q_i and the corresponding average intended charging duration is chosen as the intended charging duration for that charger and for that demand. The process is expressed in mathematical form as shown in equation 5.

$$q_i = max_{h\in H}\;q_{i,h};\;\; t_{0,i} = t_{0,i,h^*}; h^* = argmax_{h\in H}(q_{i,h}) \tag{5}$$

The cyclic dependencies among the system of equations 2-5 create a stochastic user equilibrium. We solve this system of equations using the accelerated method of successive average (AMSA) proposed by Liu et al. (2009). Once the equilibrium is solved, the hourly energy draw per zone ($V_{z,h}$) can be calculated by summing up the hourly charger power draws $V_{i,h}$ for chargers in that zone. The maximum value among the hourly power draw is the maximum energy draw per zone V_z. This value will be used to calculate the zonal power constraints. The process is explained mathematically in equation 6.

$$V_{i,h} = max(b, t_{0,i,h} * v_{x_i} * q_{i,h});\;\; V_{z,h} = \sum_{i\in I_z\cup J_z} V_{i,h} \tag{6}$$

2.4 Metamodel Optimization

We used OPT4J a library in JAVA specialized for meta heuristics optimization for solving our problem. The evolutionary algorithm in OPT4J supports nonlinear large-dimension problems, however, with an 11s runtime of the metamodel, we had to keep the maximum budget of 10,000 evaluations. GA does not support constrained optimization directly. Hence, the nonlinear i.e., the zonal power constraint was moved to the objective as penalties for violating constraints.

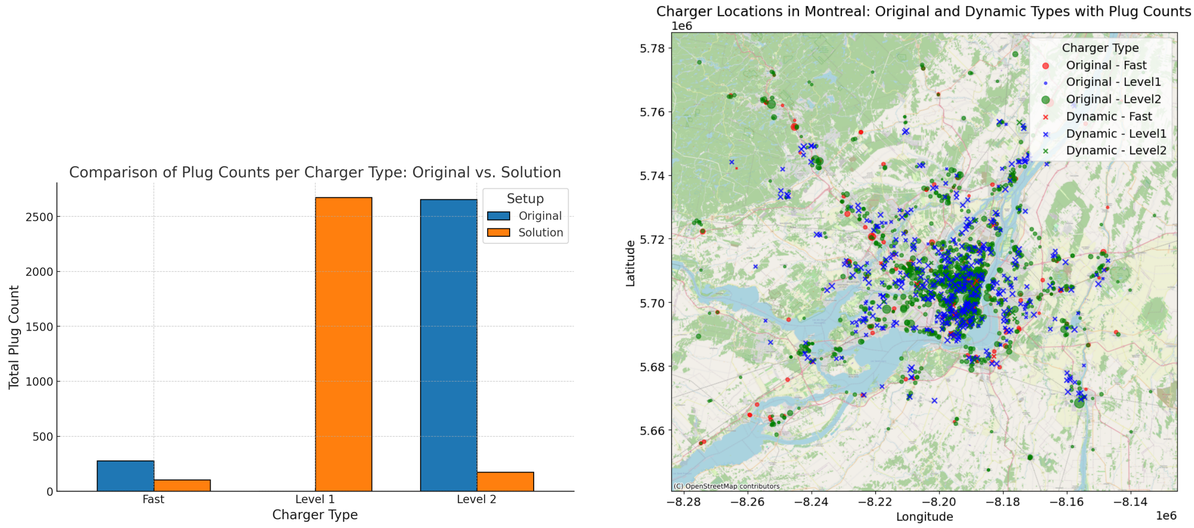
3 Experimental Setup and Results

3.1 Scenario Description

The experimental setup uses a 10% Montreal scenario (Bakhtiari et al. 2024) with 297,128 individuals, 25% of them EV owners, 1,392 existing public chargers, and no home chargers, creating a high-demand context to rigorously test the framework. Charger setup costs are \$5k, \$10k, and \$20k per plug for Level 1, 2, and Fast chargers, with operation costs at \$200, \$400, and \$800 per plug, respectively. Budget and power draw constraints were set to 60% more than the current scenario. Step 1 evaluated 2,500 potential hotspots, including 1,392 fixed charger locations, resulting in 2,216 decision variables.

3.2 Optimization Results

Multiple random assignments of plugs and charger types were tested across 25 scenarios, utilizing the full budget. The average peak-hour queue for the 25 random scenarios utilizing the full budget dropped to 27.3 hours, establishing a benchmark for the optimization algorithm. Finally, the proposed optimization framework achieved a 21% improvement over the benchmark, reducing the average peak-hour queue to 21.47 hours after 500 generations of the genetic algorithm. Figure 2a illustrates the optimized solution, which deployed more plugs than the original scenario while using only 60% of the budget. The algorithm prioritized plug quantity over higher-power chargers, aligning with the activity-driven charging behavior model. Figure 2b shows the spatial distribution of optimized chargers, with dot size indicating plug count.



(a) (b)

Figure 2: Comparison of charger type composition (a) and spatial distribution of optimized chargers(b).

4 Conclusion

This study introduced a two-step, activity-driven, sequential charger allocation framework for optimizing electric vehicle (EV) charging infrastructure in urban contexts. In Step 1, a modified K-means clustering algorithm identified candidate charger locations using activity-based features, and in Step 2 minimization of the charger queues within budget and power constraints was performed by utilizing a problem-specific metamodel to approximate charger demand allocation, queue, and charging time. The genetic algorithm achieved a 21% improvement over the random allocation benchmark, reducing the average peak-hour queue from 27.3 hours to 21.47 hours while adhering to budgetary and zonal power constraints. The optimized solution prioritized slow Level 1 chargers in low-congestion areas and fast chargers in high-demand zones, deploying 40% more plugs than the original scenario while utilizing only 60% of the setup budget. Demand elasticity was observed when simulating the optimal solution necessitating further development in the metamodel in future research.

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