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

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Abstract

The rapid growth of electric vehicles (EVs) necessitates efficient charging infrastructure planning, considering existing facilities. In urban contexts, EV charging times depend on activity durations rather than charging time itself. Considering both effects, this study proposes a sequential, two-step urban EV charger allocation framework. Step 1 uses a modified K-means algorithm to identify candidate locations, incorporating activity locations, participations, and durations. Step 2 employs metamodel-based optimization to allocate charger types and plug counts under setup, operational budget, and power constraints to the candidate locations. Applied to a 10% MATSim Montreal scenario with 74,542 EV users with only 1,392 public chargers, the framework reduced average peak-hour queues by 21% from the benchmark while respecting 60% increases in setup, operational, and power budgets. Results highlight a preference for deploying more slow chargers over fewer fast chargers in this high-demand scenario. Demand elasticity was observed, suggesting the need for improved behavioral modeling.

Keywords: EV, MATSim, K-Means, optimization, Location choice, Montreal

1 Introduction

Electric vehicles (EVs), with zero runtime emissions and higher energy efficiency than gasoline vehicles (1.5 km/mj vs. 0.28 km/mj) (Nie & Ghamami 2013), are increasingly adopted to reduce carbon emissions. In Canada, EV ownership grew sixfold from 2015 to 2018, driven by incentives like tax breaks, priority lanes, and free charging (Agency 2021), while Quebec aims for over 90% EV penetration by 2030 (Finance 2020). Advances in battery technology, rising demand, emission goals, and regulations have prioritized electrification for the automotive industry (Zhao et al. 2024, Csiszár et al. 2019, Li et al. 2021).

Despite advancements, the unavailability of charging infrastructure remains a critical deterrent to EV adoption (Bailey et al. 2024). Therefore, effective planning is essential for EV infrastructure. In urban settings, charging is linked to Individuals' daily activities governing charging start times and durations. This link of activities with charging patterns in urban settings is well recognized in EV simulation literature (Gharbaoui et al. 2013, 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 in EV infrastructure planning. Existing charging facilities were also not considered in most charger location choice literature, a crucial step for sequential charging network development. This study addresses these gaps with a sequential charger placement algorithm that explicitly considers existing infrastructure.

As 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 (Frade et al. 2011, Zhang et al. 2020). On the other hand, flow-capturing methods prioritize strategically locating chargers to maximize accessibility and coverage (Kuby & Lim 2005, 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 EV charger location choice problem.

2 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 below.

$$
\begin{aligned}
min_{x_i,p_i} \frac{1}{|I|+|J|} & \left\{ \sum_{i \in I} Q_i + \sum_{j \in J} Q_j \right\}; \forall i \in I \\
& x_i, x_j \in X \{Level\ 1,\ Level\ 2\ or\ Fast\} \\
& p_i, p_j \in P \{0, 1, 2, ..., p_{max}\} \\
s.t. & \\
& \sum_{i \in I} p_i \times C_{o,x_i} + \sum_{j \in J} p_j \times C_{o,x_i} \leq C_o \\
& \sum_{i \in I} p_i \times C_{s,x_i} \leq C_s \\
& \sum_{i \in I_z} V_i + \sum_{j \in J_z} V_j \leq V_z; \forall z \in Z
\end{aligned} \tag{1}
$$

We use Micro Agent Traffic Simulation, i.e., MATSim for simulating electric vehicle charging in the proposed urban context.

3 Methodological Framework

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.

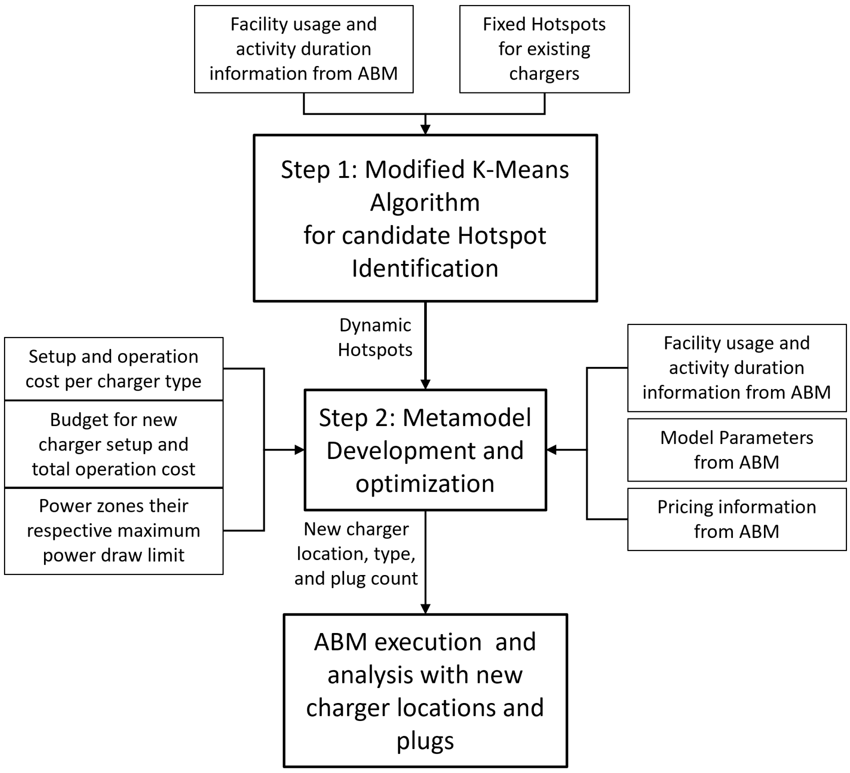


Figure 1: Schematics of the proposed charger location estimation algorithm.

3.1 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). During training, only the dynamic centroids are updated snapping to the nearest activity facility location. 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.

3.2 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 is because the urbanEV module of MATSim (Bakhtiari et al. 2024) that we employ to simulate EV charging, usage, and discharging in urban settings has a high computational cost. Directly optimizing 1, a combinatorial optimization problem with high-dimensional mixed-integer variables and nonlinear constraints with MATSim in the objective is infeasible. We use a single-shot, problem-specific metamodel that approximates

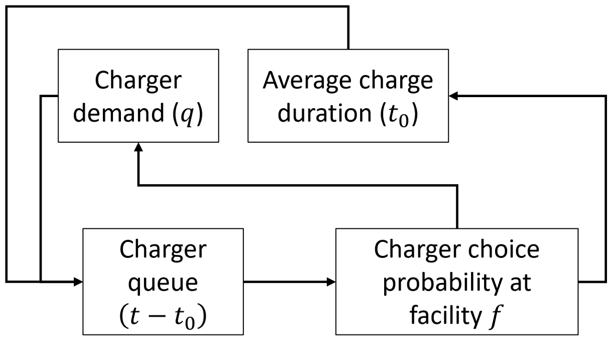


Figure 2: Wardrop's Equilibrium in the Demand Allocation Model

MATSim's outputs during optimization. This metamodel simplifies problem dynamics while preserving MATSim's behavioral parameters for consistency. Further manual parameter tuning can be performed to ensure alignment with the original simulator.

3.3 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 as shown in figure 2. 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.

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

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 5.

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

$$t_{0,i,h} = \frac{\sum_{f \in F} \rho\, \omega_{f,i}\, q_f\, \delta_{f,h}\, t_{0,f}}{\sum_{f \in F} \rho\, \omega_{f,i}\, q_f\, \delta_{f,h}} \tag{5}$$

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 6.

$$\begin{aligned} q_i &= max_{h \in H}\ q_{i,h} \\ t_{0,i} &= t_{0,i,h^*}; h^* = argmax_{h \in H}(q_{i,h}) \end{aligned} \tag{6}$$

The cyclic dependencies among the system of equations 2-6 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 7.

$$\begin{aligned} V_{i,h} &= max(b, t_{0,i,h} * v_{x_i} * q_{i,h}) \\ V_{z,h} &= \sum_{i \in I_z \cup J_z} V_{i,h} \end{aligned} \tag{7}$$

3.4 Metamodel Optimization

With the above formulations, the objective in equation 1 can be reformulated as below.

$$\begin{aligned} & min_{x_i,p_i} \frac{1}{|I| + |J|} \left\{ \sum_{i \in I} (t_i - t_{0,i}) + \sum_{j \in J} (t_j - t_{0,j}) \right\}; \forall i \in I \\ & \qquad x_i, x_j \in X \{Level\ 1,\ Level\ 2\ or\ Fast\} \\ & \qquad p_i, p_j \in P \{0, 1, 2, ..., p_{max}\} \\ & s.t. \\ & \qquad \sum_{i \in I \cup J} p_i \times C_{o,x_i} \leq B_o \\ & \qquad \sum_{i \in I} p_i \times C_{s,x_i} \leq B_s \\ & \qquad max_{h \in H}(V_{z,h}) \leq V_z; \forall z \in Z \end{aligned} \tag{8}$$

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 below.

$$
\begin{aligned}
& min_{x_i,p_i} \frac{1}{|I|+|J|} \left\{ \sum_{i \in I}(t_i - t_{0,i}) + \sum_{j \in J}(t_j - t_{0,j}) \right\} + \\
& \lambda \times min \left\{ max_{h \in H}(V_{z,h}) - V_z, 0 \right\}; \forall i \in I \\
& x_i, x_j \in X \{Level\ 1,\ Level\ 2\ or\ Fast\} \\
& p_i, p_j \in P \{0, 1, 2, ..., p_{max}\}
\end{aligned} \tag{9}
$$

λ here denotes the weight to prioritize constraints satisfaction vs objective minimization. In our experiments, we choose $\lambda = 1$. With a vast solution space most of which violates the budget and power limit constraints, we found that it is beneficial both in terms of convergence rate and objective quality to put the budget constraint in the random solution generation process rather than in the objective.

4 Experimental Setup and Results

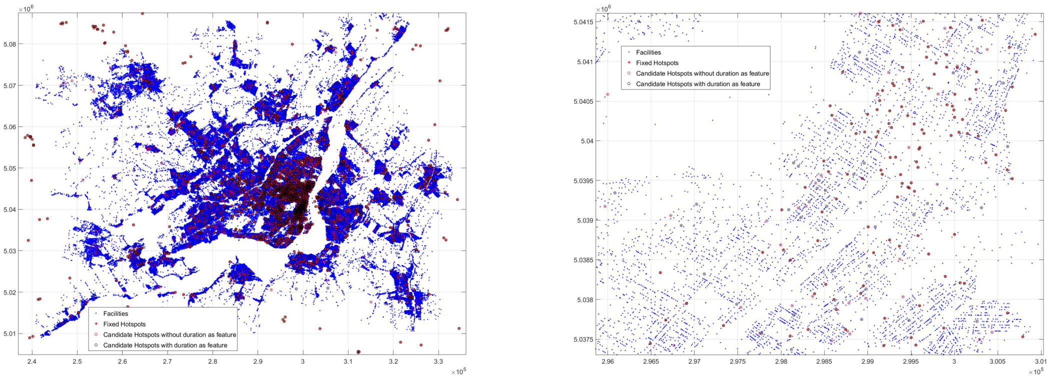
4.1 Scenario Description

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. The EV penetration rate of 25% aligns with Quebec's rapid adoption trend, despite exceeding Canada's 2023 national EV rate of 1.3%. 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 constraints limit setup costs to 60% and operation costs to 160% of current facility expenses. The network is divided into six zones, each with a power draw limit of 1.6 times the current draw. Step 1 evaluated 2,500 potential hotspots, including 1,392 fixed charger locations, resulting in 2,216 decision variables.

4.2 Step 1: Modified K-mean Algorithm Results

Figure 3 illustrates the outcomes of Step 1 for two different feature configurations. In the first case, the k-means algorithm used only location and facility usage data as input features. In the second case, the modified k-means algorithm incorporated location, facility usage, and the average activity duration of EV users into the feature set. Facility usage intuitively guides cluster centroids toward high-demand facilities and activity duration tends to guide centroids in long-duration activities, typically home.

To further evaluate the impact of the feature vector configurations, we assigned fast chargers with 10 plugs to all candidate charger locations generated by both configurations and ran the MATSim urban EV scenario to observe the outcomes. Figure 4 presents the total number of vehicles plugged in and queued throughout the day for both feature configurations, providing insights into their performance under identical resource allocation. The results indicate that, for similar resource allocation, the peak hour vehicle plug-in count was slightly higher and the number of queued vehicles was slightly lower when activity duration was included in the feature vector compared to when it was excluded. The number of agents unable to find chargers near their vicinity was 350 versus 650 out of 25,000 requests likely due to more balanced charger distribution between residential and non-residential areas when duration is excluded vs included.



(a) (b)

Figure 3: Existing and potential charger facilities among activity facilities for different feature vector configuration (a) Montreal network and (b) Zoomed-in portion of Montreal network

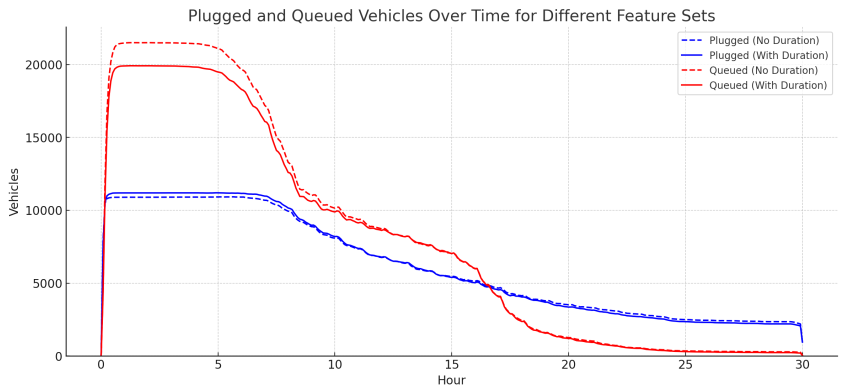


Figure 4: Vehicle plugged and queued in MATSim urban EV scenario for different feature configuration

4.3 Step 2: Metamodel Optimization Results

In the optimization phase, the study evaluated a base scenario with 1,391 public chargers serving 75,000 EV users, revealing a severe supply-demand mismatch with an average peak-hour queue of 36.2 hours in the metamodel's volume delay function. 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 5 illustrates the convergence process over successive iterations. Figure 6 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 7 shows the spatial distribution of optimized chargers, with dot size indicating plug count. The solution favors Level 1 chargers in less congested areas and fast chargers in high-demand zones like business districts, with minimal use of Level 2 chargers. Overall, the optimization process did capture the spatial demand and activity type variability over the Montreal network.

The optimal solution simulated in MATSim showed a significant reduction in the average queue per plug, reflecting better resource distribution. However, the higher number of Level 1 chargers led to lower average plug utilization due to their lower throughput. The peak total queue rose, indicating demand elasticity. Future work will integrate demand elasticity into the metamodel for enhanced metamodel dynamics. Figure 8 shows the number of vehicles plugged in and queued per plug when running MATSim Montreal with the optimal charger configuration.

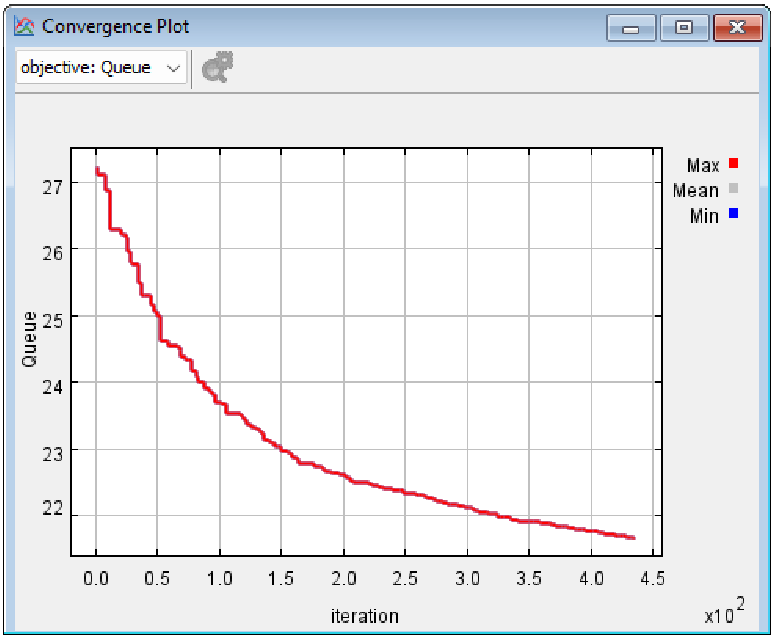


Figure 5: Convergence of Step 2: Metamodel Optimization

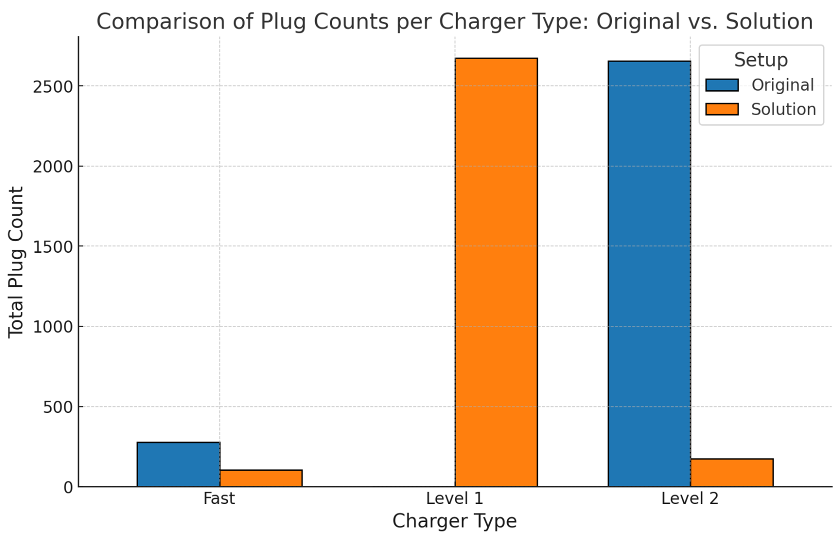


Figure 6: Charger type composition in original vs optimized new chargers

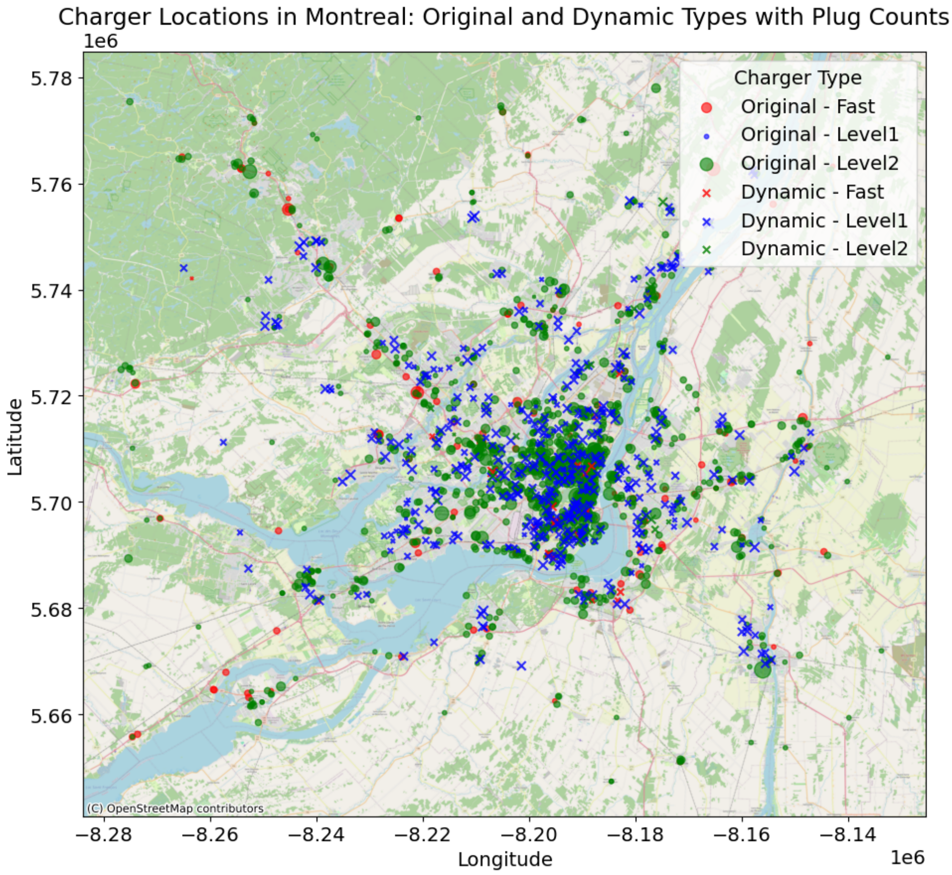


Figure 7: Spatial distribution of chargers in the optimization result

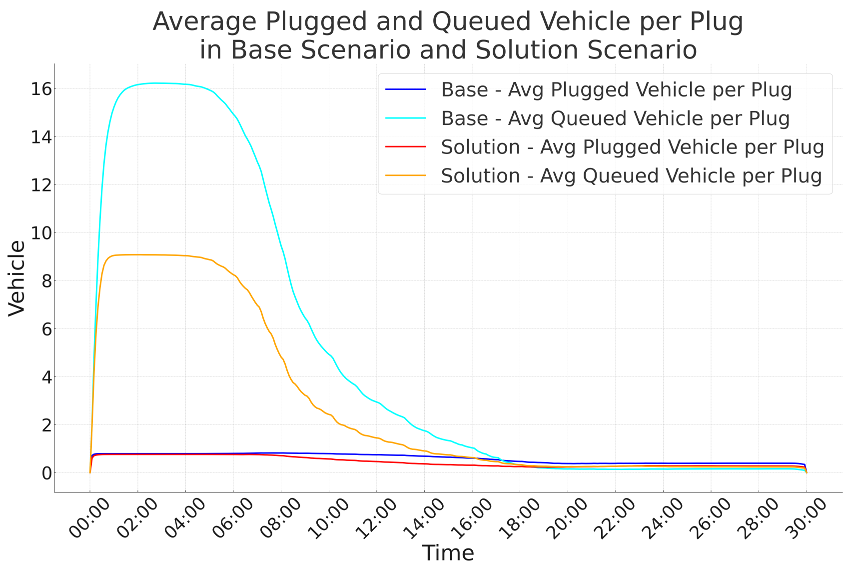


Figure 8: Normalized vehicle plugged in and queued per plug in the optimized urbanEV scenario

5 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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