MGSC 662 Final Project Report

Optimizing Electric Vehicle Charging Infrastructure in Washington State

Arial Huang, Maggie Huang, Maralmaa Batnasan, Thao Nguyen, Nehal Joshi

Contents

1 Introduction

The rapid adoption of electric vehicles (EVs) presents both opportunities and challenges for infrastructure planning. This project focuses on optimizing the placement and number of EV chargers across Washington State, with the primary objective of maximize total charging capacity per hour, secondary objective of minimizing environmental impact, and the tertiary objective of minimizing cost.

Project Goal

The key focus of the project is on determining the optimal locations for EV charging stations and the optimal number of each type of chargers by solving an optimization problem. This will serve as a benchmark to evaluate the efficiency of WA's current charging infrastructure.

Significance of the Problem

Washington holds the second-highest EV market share in the U.S., with EVs comprising 10% of all vehicle registrations[1]. The state is on track to meet ambitious zero-emission vehicle targets, requiring 68% of new cars to be pollution-free by 2030 and 100% by 2035[2]. Despite this progress, critical challenges mentioned below still remain[4].

- **Unknown efficiency in resource allocation**: It is unclear if the current distribution of chargers is effectively meeting demand or minimizing underutilization.
- **Potential inefficient location strategy**: Poorly located charging stations may not serve high-demand areas or key routes, leading to inefficiencies.
- **Environmental consideration**: Excessive deployment of hardware can increase carbon footprint and material waste.

The problem's complexity makes it a valuable study in balancing environmental, economic, and operational factors. Optimizing Washington's EV landscape offers practical solutions to inform infrastructure investment and policy decisions.

2 Mathematical Formulation

Sets and Indices

$\mathcal{I}$: The set of candidate locations where new charging stations can potentially be built. Index i refers to a specific candidate location.

$\mathcal{J}$: The set of demand locations (e.g., ZIP codes or postal codes where electric vehicles (EVs) are located). Index j refers to a specific demand location.

$\mathcal{K} = \{0, 1, 2, 3\}$: The set of possible electrical upgrade tiers, indicating the level of electrical infrastructure improvement needed at a station location. The index k selects a tier.

Explanation: In the given code, the sets $\mathcal{I}$ and $\mathcal{J}$ are the same (both drawn from the keys of the dictionary EV). Essentially, each location in $\mathcal{I}$ can also be a demand point in $\mathcal{J}$.

Symbol	Description
$C(i,j)$	1 if location i covers demand location j 0 otherwise
EV_j	Daily EV demand (in miles) at location j
H	Available charging hours per day
`public_charger_demand`	Fraction of total EV demand to be met by public chargers
`avg_percentage_charged`	Average percentage of EV battery capacity to be charged publicly
`demand_factor`	`public_charger_demand` $\times$ `avg_percentage_charged`
$\tilde{D}_j$	$EV_j \cdot \text{demand\_factor}$
s_2	15 miles/hour for Level 2 chargers
s_3	210 miles/hour for Level 3 chargers
e_2	0.000027405 (env. impact per mile for L2)
e_3	0.0002945 (env. impact per mile for L3)
f_2	\$8,250 (cost per Level 2 charger)
f_3	\$65,000 (cost per Level 3 charger)
f_{base}	\$50,000 (base station cost)
u_0	0 (upgrade cost for tier 0)
u_1	\$30,000 (upgrade cost for tier 1)
u_2	\$75,000 (upgrade cost for tier 2)
u_3	\$100,000 (upgrade cost for tier 3)
`panel_capacity`	500 amps
`usable_capacity`	0.8 $\times$ `panel_capacity`
`existing_load`	200 amps
R	`usable_capacity` $-$ `existing_load`
Load per charger type	L2: 40 amps L3: 150 amps
M	20 (max chargers per station)
D_{total}	$\sum_{j \in \mathcal{J}} EV_j \cdot \text{demand\_factor}$

Parameters

Explanation:
- The coverage matrix $C(i,j)$ indicates which demand points j can be served if a station is built at location i.
- EV_j quantifies how much charging (in miles) is needed at location j. Multiplying by demand_factor gives the fraction of that demand that must be met by the stations we decide to build.
- Speeds s_2 and s_3 indicate how many miles per hour of charge a given charger can provide.
- Costs f_2, f_3, and f_{base} define the economic trade-offs. The upgrade costs u_k show how expensive it is to increase electrical capacity.
- The electrical load parameters and R determine how many chargers can be installed before an upgrade is needed.

Decision Variables

$$
\begin{aligned}
x2_i \in \mathbb{Z}_{\geq 0} &: \text{Number of Level 2 chargers at location } i \\
x3_i \in \mathbb{Z}_{\geq 0} &: \text{Number of Level 3 chargers at location } i \\
z_i \in \{0,1\} &: 1 \text{ if a station is built at location } i, 0 \text{ otherwise} \\
y_{i,k} \in \{0,1\} &: 1 \text{ if electrical upgrade tier } k \text{ is chosen at } i, 0 \text{ otherwise} \\
\text{DFL2} \geq 0 &: \text{Total demand (miles) fulfilled by Level 2 chargers} \\
\text{DFL3} \geq 0 &: \text{Total demand (miles) fulfilled by Level 3 chargers}
\end{aligned}
$$

Explanation:
- $x2_i$ and $x3_i$ represent how many chargers of each type are installed at location i.
- z_i indicates if we decide to open a station at location i. If $z_i = 0$, no station is built there. If $z_i = 1$, we pay the base cost and can install chargers.
- $y_{i,k}$ selects which electrical upgrade tier is implemented at location i. Exactly one tier must be chosen.
- DFL2 and DFL3 aggregate the total miles of EV charging demand met by Level 2 and Level 3 chargers, respectively, and help link environmental impact and cost calculations.

Objectives

The model has three objectives with different priorities:

Primary Objective (Maximize Total Charging Capacity/Hour):

$$\max \sum_{i \in \mathcal{I}} (x2_i s_2 + x3_i s_3)$$

Secondary Objective (Minimize Environmental Impact):

$$\min\ (e_2 \cdot \text{DFL2} + e_3 \cdot \text{DFL3})$$

Tertiary Objective (Minimize Total Cost):

$$\min \left(\sum_{i \in \mathcal{I}} (x2_i f_2 + x3_i f_3) + \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} u_k y_{i,k} + f_{\text{base}} \sum_{i \in \mathcal{I}} z_i \right)$$

Explanation:
- The primary objective is to maximize the configurations that provide greatest total charging capacity (more miles of range per hour), which helps serve EVs more efficiently.
- Then, we will minimize the total environmental impact, measured by emissions associated with the electricity supplied by these chargers.
- Finally, we will minimize the total cost of setting up the network of stations and chargers, including electrical upgrades.
- In practice, these are solved in a hierarchical manner (multi-objective optimization with priorities): first maximize charging capacity, then minimize environmental impact, finally minimize cost.

Constraints

Coverage Constraint:

$$\forall j \in \mathcal{J}: \quad \sum_{i \in \mathcal{I}} C(i,j) z_i \geq 1$$

Explanation: Every demand location j must be covered by at least one operational station. If $C(i,j) = 1$, then a station at i can serve j. We need at least one station covering each j.

Demand Coverage Constraint:

$$\forall j \in \mathcal{J}: \quad \sum_{i \in \mathcal{I}} C(i,j)(x2_i s_2 + x3_i s_3) H \geq \tilde{D}_j$$

Explanation: The installed chargers must provide enough charging capacity to meet the daily demand of each location j. The left-hand side represents the total miles of range per day provided to location j by all stations that cover it, accounting for the number and type of chargers and the hours available. This must be at least the effective demand $\tilde{D}_j$.

Tier Selection Constraint:

$$\forall i \in \mathcal{I}: \quad \sum_{k \in \mathcal{K}} y_{i,k} = 1$$

Explanation: At each location i, exactly one upgrade tier is chosen (no upgrade, minor upgrade, moderate, or major upgrade).

Electrical Capacity Constraints: Define $L_i = 40x2_i + 150x3_i$ as the electrical load from chargers at station i. Given a chosen tier, the load must fit within the corresponding capacity range. Using a large number M (big-M method) to enable conditional constraints, we have:
For no upgrade (tier 0):

$$L_i \leq R + M(1 - y_{i,0})$$

For tier 1 upgrade:

$$L_i \geq R + 1 - M(1 - y_{i,1}), \quad L_i \leq R + 300 + M(1 - y_{i,1})$$

For tier 2 upgrade:

$$L_i \geq R + 301 - M(1 - y_{i,2}), \quad L_i \leq R + 750 + M(1 - y_{i,2})$$

For tier 3 upgrade:

$$L_i \geq R + 751 - M(1 - y_{i,3})$$

Explanation: These constraints ensure that if a certain tier is chosen (i.e., $y_{i,k} = 1$), the electrical load L_i fits within the range associated with that tier. If $y_{i,k} = 0$, the constraint is relaxed by the large M term. This structure ensures a consistent choice of upgrade tier depending on the load required by installed chargers.

Demand Fulfillment Variables:

$$\text{DFL2} = s_2 H \sum_{i \in \mathcal{I}} (z_i x2_i), \quad \text{DFL3} = s_3 H \sum_{i \in \mathcal{I}} (z_i x3_i)$$

Explanation: DFL2 and DFL3 compute how many miles of demand are fulfilled by Level 2 and Level

3 chargers, respectively, across all stations.

Station-Charger Linking Constraints:

$$\forall i \in \mathcal{I}: \quad x2_i + x3_i \leq M z_i, \quad x2_i + x3_i \geq z_i$$

Explanation: - If $z_i = 0$ (no station at i), the first constraint forces $x2_i + x3_i \leq 0$, so no chargers can be installed. - If $z_i = 1$ (station built), then $x2_i + x3_i \leq M$ ensures we do not exceed the maximum allowed chargers, and $x2_i + x3_i \geq z_i$ ensures at least one charger is installed at an operational station.

Number of Chargers Bounds:

$$\sum_{i \in \mathcal{I}} x2_i \leq 4546, \quad \sum_{i \in \mathcal{I}} x3_i \leq 1295$$

Explanation: These are the current numbers of Type 2 and Type 3 chargers in Washington. We used these as upper limits in our model, as the focus of our optimization is to create a benchmark to evaluate the efficiency of WA's **current** charging infrastructure.

Upper Bound on Total Fulfilled Demand:

$$\text{DFL2} + \text{DFL3} \leq 1.2 \cdot D_{\text{total}}$$

Explanation: This ensures that we do not grossly exceed the total needed demand by more than 20%. It prevents the model from over-building excessive capacity.

3 Numerical Implementation and Results

Data Source

The dataset we used has the number of registrations for 2024 for Electric Vehicles for the State of Washington in the United States of America. The source of the data is the Washington State Department of Licenses (DOL).

Implementation Logic

Our code implements an optimization model using Gurobi for Python to design an EV or Electric Vehicle charging infrastructure. The model tries to strike a balance between the objectives of cost efficiency, environmental impact and effectively covering the demand.

We leverage EV population data for different postal codes in the State of Washington, the average electric range of vehicles, and the distances between different postal codes derived using the Google Distance Matrix API to determine the most optimal locations for building charging stations and the number of level 2 and level 3 chargers needed at each location.

We started by preprocessing the data for the model. We explored what columns can be used to model the problem. We decided that the following columns will be used in our model or are relevant to the problem:

- Postal Code: Each different part of the state has a separate postal code. We used postal code in our calculations to group the demand from each postcode, this provided us the granularity we needed as County and State are too broad for our problem's context.

- Electric Vehicle Type: The dataset is split between Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). PHEVs usually use electric range as an addition to an additional power source like a gasoline-based engine. On the other hand, BEVs are completely reliant on their electric battery packs for power.
- Electric Range: This column gives us the all-electric range in Miles for each EV in the dataset. Again, there is a huge discrepancy between the ranges for BEVs and PHEVs. How we handled this discrepancy is discussed later in the report.

We analyzed the distance data between postal codes to establish coverage, identifying if a charging station in one location can serve the EVs in another location based on their ranges.
Optimization is achieved by setting up the decision variables and objective functions that we discussed earlier in the report. The objective functions focus on the primary objectives of maximizing the total charging capacity, minimizing the environmental impact which is measured by emissions associated with charger operation, and the tertiary objective of minimizing total costs, which includes installation and upgrade expenses while ensuring that the infrastructure meets the demand of EV charging across all locations.

The model incorporates constraints to make the problem more realistic and practical. These include having a charging station that is within serviceable distance from each postal code, and having realistic limits on the number of chargers at each station, while still meeting the projected demand at each location. We also included tiered costs for electrical upgrades, allowing us to dynamically select the most suitable upgrade level based on projected loads.

Our Gurobi model then optimizes the model while staying within these constraints and provides us with an EV infrastructure that is economically viable, environmentally sustainable, and modular enough to allow for easy adaptation to changes in legislation around EVs and growing demand.

Total Demand in Miles Calculations

To calculate the total demand in miles, we first extrapolated and grouped the number of all Electric Vehicles registered in the State of Washington by the postal code.

As we discussed earlier, there is a big difference between the electric ranges of BEVs and PHEVs. To tackle this problem, we wanted a number that would allow us to meet demands on both ends of the spectrum. Taking the average of the electric ranges of vehicles for each postal code allows us to avoid both over-serving and under-serving the demand.

$$\begin{aligned}
\mathrm{EV}_j &: \text{Total EV demand at location } j \in I, \\
\text{Avg. } \mathrm{R}_j &: \text{Average electric range of a vehicle at location } j, \\
\mathrm{N}_j &: \text{Number of vehicles at location } j, \\
\mathrm{EV}_j &= \text{Avg. } \mathrm{R}_j \cdot \mathrm{N}_j.
\end{aligned}$$

Environmental Factor Calculations

To calculate a relevant Environmental Factor, we researched a measure that we could use with the units that we have, i.e., Miles and kW. After some research, we found a scientific article[9] that had a factor that we could use to set up the problem. However, the factor we found required us to make certain assumptions:

- Level 2 chargers get their electricity from a solar energy-based source with a power backup that uses diesel.
- Level 3 chargers are using electricity from a fossil-based source.

After setting up these assumptions we have the environmental factor calculated as below:

$$
\begin{aligned}
&\textbf{For Level 2:}\\
\text{Power Output} &: 7 - 19\,\text{kW},\\
\text{Average Power Output} &: 13\,\text{kW},\\
\text{Range in Miles Charged per Hour} &: 10 - 20\,\text{miles/hr},\\
\text{Average Range in Miles Charged per Hour} &: 15\,\text{miles/hr},\\
\text{kWh per Mile} &: \frac{13\,\text{kW}}{15\,\text{miles/hr}} = 0.87\,\text{kWh/mile},\\
\text{Environmental Factor}^9 &: 3.15 \times 10^{-5}\,\text{gha/kWh},\\
\text{Calculated Environmental Factor} &: 0.87\,\text{kWh/mile} \times 3.15 \times 10^{-5}\,\text{gha/kWh} = 0.0000274\,\text{gha/mile},\\
\text{Total Environmental Impact} &: e_2 = 0.0000274\,\text{gha/mile} \times DFL_2\,\text{miles}.
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{For Level 3:}\\
\text{Power Output} &: 50 - 350\,\text{kW},\\
\text{Average Power Output} &: 200\,\text{kW},\\
\text{Range in Miles Charged per Hour} &: 180 - 240\,\text{miles/hr},\\
\text{Average Range in Miles Charged per Hour} &: 210\,\text{miles/hr},\\
\text{kWh per Mile} &: \frac{200\,\text{kW}}{210\,\text{miles/hr}} = 0.95\,\text{kWh/mile},\\
\text{Environmental Factor}^9 &: 3.10 \times 10^{-4}\,\text{gha/kWh},\\
\text{Calculated Environmental Factor} &: 0.95\,\text{kWh/mile} \times 3.10 \times 10^{-4}\,\text{gha/kWh} = 0.0002945\,\text{gha/mile},\\
\text{Total Environmental Impact} &: e_3 = 0.0002945\,\text{gha/mile} \times DFL_3\,\text{miles}.
\end{aligned}
$$

Google Distance Matrix API

We used the Google Distance Matrix API to calculate the distances between different postal codes. This allowed us to figure out the exact demand covered by each charging location.

Results

The final results obtained from our base model were pretty surprising. We wanted to see how close the real-world numbers would be to our optimal solution so we set up the real-world numbers of each type of charger as a constraint. This was done as we want to utilize as many of the existing chargers and just ensure that they are placed optimally.

$$\begin{aligned}
\text{Total Charging Capacity per Hour} &: 225270\,\text{kWh}, \\
\text{Total Environmental Impact} &: 481.2880695\,\text{gha}, \\
\text{Total Cost} &: 119,899,500\,\text{USD}, \\
\text{Total Demand Fulfilled by Level 2 Chargers (miles)} &: 681,900\,\text{miles}, \\
\text{Total Demand Fulfilled by Level 3 Chargers (miles)} &: 1,570,800\,\text{miles}, \\
\text{Total Number of Level 2 Chargers} &: 4546, \\
\text{Total Number of Level 3 Chargers} &: 748
\end{aligned}$$

Table 1 has a few handpicked locations and the optimal number of each type of charger as picked by our base model.

4 Problem Extensions

Extension 1.1: Parameter Sensitivity - Varying the Coverage Threshold

In this extension, we explored the effect of varying the coverage threshold (θ) from 0.1 to 0.5 to analyze its impact on station coverage and network density. The purpose of this sensitivity analysis was to determine the balance between expanding the service area of each station and maintaining an efficient and cost-effective network.

Results

The summary of results is presented in Table 2:

Key Observations

While most metrics, such as total charging capacity, environmental impact, and the number of chargers, remain consistent across all thresholds, the number of stations deployed shows slight variations with changes in θ. This suggests that the network design is sensitive to coverage threshold adjustments when determining station deployment. As θ changes, the coverage radius affects the number of stations required. Larger coverage thresholds may reduce the need for stations, while stricter thresholds slightly increase the number of stations to maintain the required coverage and demand fulfillment.

Extension 1.2: Varying the Average Percentage Charged

Here, we discuss possible extensions to the base model by varying the **average percentage charged** (previously assumed to be fixed at 60%) and examine its numerical impact on the solution. This analysis sheds light on the robustness of the charging infrastructure under different usage scenarios and offers insights into the trade-offs involved in system design and operations.

Results

Table 3 summarizes the changes in key metrics as the average percentage charged is scaled using five demand scaling factors. This extension to the base model demonstrates how the solution adapts to different charging patterns and highlights its implications for operational, environmental, and cost-related dimensions.

Key Observations

This extension to the base model highlights the critical trade-offs and challenges in designing a charging infrastructure that adapts to varying usage scenarios. As the average percentage charged increases, the total cost escalates due to the need for additional chargers and infrastructure upgrades. The environmental impact increases significantly with the rising number of Type 3 chargers, which have a higher per-unit environmental footprint compared to Type 2 chargers. This highlights the trade-off between faster charging infrastructure and sustainability.

Extension 2: Weighted Multi-Objective Function

In this extension, we implemented a **weighted multi-objective function** to balance critical trade-offs between objectives. Weights were assigned to each objective to reflect their relative importance, prioritizing total range first, followed by environmental impact, and finally total costs. This approach allows a more holistic optimization compared to the hierarchical method. To counterbalance differences in scales between the objectives (miles/hour, gha, dollars), the following weights were assigned:

- **Maximize Total Range per Hour:** $150,000$
- **Minimize Environmental Impact:** $10,000$
- **Minimize Total Costs:** 0.000001

Results

Table 4 compares the results of the **Weighted** and **Hierarchical** approaches:

Key Observations

In the weighted approach, there are multiple potential solutions to achieve the optimal objective of our problem, and the solution presented is one of the possible outcomes. The weighted approach favored a slightly higher number of Type 3 chargers due to their higher charging capacity. However, it reduced the number of Type 2 chargers to balance environmental and cost considerations.

Extension 3: Charger Breakdowns

In real-world scenarios, chargers are not operational 100% of the time. To incorporate this reality into the model, we introduce a **charger reliability factor**, which reflects the percentage of time each charger type is operational. This extension modifies the charging speeds of Level 2 and Level 3 chargers to account for their respective reliabilities:

- **Level 2 Charger Reliability:** 95%
- **Level 3 Charger Reliability:** 90%

These factors adjust the effective charging speeds, making the optimization model more realistic and robust. The adjusted charging speeds are calculated as:

$$\text{Effective Charging Speed (Level i)} = \text{Charging Speed (Level i)} \times \text{Reliability Factor (Level i)}$$

For Level 2 chargers: $15\,\text{miles/hour} \times 0.95 = 14.25\,\text{miles/hour}$.
For Level 3 chargers: $210\,\text{miles/hour} \times 0.90 = 189\,\text{miles/hour}$.

Results

Table 5 compares the performance of the **Breakdown** model with the original **Base** model:

Key Observations

Breakdown model achieved a similar total charging capacity to the Base model (225,288 vs. 225,270 miles/hour), indicating that charger reliability factors had minimal impact on total range but influenced charger and station allocation. Breakdown model deployed more Level 3 chargers (850 vs. 748) due to their effective charging speed, while Level 2 chargers remained relatively stable (4,536 vs. 4,546). The total environmental impact increased slightly (490.8 gha vs. 481.3 gha) due to the additional chargers and stations required to maintain reliability, with the number of stations increasing marginally from 265 to 271. These adjustments demonstrate the model's ability to balance coverage and reliability under real-world constraints.

Extension 4: Traveling Maintenance Man

Optimizing the Maintenance Route for 10 Stations

A maintenance man is tasked with servicing 10 charging stations. This extension analyzes the optimal route to minimize the total distance traveled between the stations, given their geographical locations (Table 6).

Key Observations

- **Optimized Route**: The optimized route minimizes the maintenance man's total travel distance while visiting all 10 stations, starting and ending in Seattle. The solution ensures efficiency in covering all required locations while reducing redundant travel.
- **Distance Efficiency**: By prioritizing shorter connections between stations, the total travel distance is minimized, directly reducing the time and resources required for maintenance tasks.
- **Scalability**: This method can be extended to incorporate additional stations or constraints, such as time windows or station priorities, without significant modifications

5 Conclusion and Recommendations

In undertaking this project, we confirmed that EV charging infrastructure planning is a complex problem requiring a balance of economic, environmental, and operational priorities. We learned the importance of carefully prioritizing each objective and critically assessing their relative significance. Additionally, conducting thorough research on realistic constraints was essential to develop practical solutions that align with Washington's long-term policy goals.

If given the opportunity to start over, we would adopt a more incremental modeling approach. The complexity of the task initially left our team feeling daunted and unsure where to begin, leading us to dive into a complex model too quickly. Instead, we could begin with a simplified version and gradually add complexity, such as incorporating finer geographic granularity, cost uncertainties, and policy constraints. This approach would have helped us build confidence and initial motivation, as well as ensured greater traceability and interpretability of our results.

In the future extensions of our project, we could incorporate more granular, location-specific data to refine station placement and charger allocation. For example, we could incorporate a geospatial layer of major highways, rest stops, and travel hubs into the model. This would involve mapping out high-traffic corridors and strategically positioning chargers at key intersections, near popular rest areas, and within significant travel hubs such as airports, train stations, and bus terminals. This approach helps in ensuring coverage where it's most needed and reducing range anxiety for EV drivers.

Another example is the consideration of local amenities and points of interest. Charging downtime can be more appealing if drivers have access to nearby amenities, such as shopping centers, parks, or recreational facilities. Charging stations can, in turn, boost spending at nearby businesses [8]. By integrating databases of local points of interest into the optimization model and applying preference weights, the model can select sites where users are likely to combine charging with other activities. Over time, usage patterns and customer feedback could further refine these preferences. This integration creates a positive feedback loop: increased foot traffic and spending at nearby businesses enhance the attractiveness of charging stations, leading to higher usage rates. In turn, the elevated usage further stimulates local economic activity, reinforcing the desirability and viability of additional charging infrastructure.

Last but not least, our current model focuses solely on Washington's existing EV charging supply and demand. To build a more future-proof solution, we aim to extend this project to include forecasts of future demand, informed by local EV adoption trajectories. Incorporating socio-economic data, state policy analyses, and historical EV growth trends will help us more accurately project future adoption rates. We can then apply scenario-based modeling—considering best- and worst-case outcomes—to develop a more robust, adaptive charging station network.

6 References

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7 Appendices

Zip Code	Level 2 Chargers	Level 3 Chargers
98188	19	1
98125	0	20
98177	19	1
98683	0	20
98043	11	9
98239	18	1
98284	19	1
98257	19	1
98848	0	20
98340	0	20
99122	19	1
99218	14	1
99006	19	1
98512	19	1
98362	19	1
98221	19	1
98315	19	1
98617	0	20
98862	19	1
99115	0	20

Table 1: Sample Charger Distribution by Zip Code

θ	Total Charging Capacity per Hour (miles/hour)	Total Environmental Impact (gha)	Total Cost ($)	Demand Fulfilled by Type 2 Chargers (miles)	Demand Fulfilled by Type 3 Chargers (miles)	Total Type 2 Chargers	Total Type 3 Chargers	Total Number of Stations
0.1	225,270	481.3	$119,939,500	681,900	1,570,800	4,546	748	267
0.2	225,270	481.3	$119,899,500	681,900	1,570,800	4,546	748	265
0.3	225,270	481.3	$119,949,500	681,900	1,570,800	4,546	748	269
0.4	225,270	481.3	$119,889,500	681,900	1,570,800	4,546	748	266
0.5	225,270	481.3	$119,904,500	681,900	1,570,800	4,546	748	266
0.6	225,270	481.3	$119,899,500	681,900	1,570,800	4,546	748	265

Table 2: Detailed summary of charging capacity, environmental impact, and infrastructure requirements.

Scaling Factor	Avg % Charged	Total Charging Capacity (miles/hour)	Total Environmental Impact (gha)	Total Cost ($)	Demand Fulfilled by Type 2 Chargers (miles)	Demand Fulfilled by Type 3 Chargers (miles)	Total number of Type 2 Chargers	Total Type 3 Chargers
0.5	30%	112,635	149.8	$80,993,250	681,150	445,200	4,541	212
0.8	48%	180,225	348.9	$104,271,750	680,850	1,121,400	4,539	534
1.0	60%	225,270	481.3	$119,899,500	681,900	1,570,800	4,546	748
1.2	72%	270,330	614.8	$135,254,500	678,900	2,024,400	4,526	964
1.5	90%	337,920	813.9	$158,623,000	678,600	2,700,600	4,524	1,286

Table 3: Impact of varying average percentage charged on key metrics.

Metric	Weighted	Hierarchical
Total Charging Capacity (miles/hour)	225,495	225,270
Total Environmental Impact (gha)	486.4	481.3
Total Cost ($)	$123.3M	$119.9M
Total Number of Stations	392	265
Total Range Fulfilled by Type 2 Chargers (miles)	665,250	681,900
Total Range Fulfilled by Type 3 Chargers (miles)	1,589,700	1,570,800
Total Number of Type 2 Chargers	4,435	4,546
Total Number of Type 3 Chargers	757	748

Table 4: Comparison of Weighted and Hierarchical Multi-Objective Approaches

Metric	Breakdown	Base
Total Charging Capacity per Hour (miles/hour)	225,288	225,270
Total Environmental Impact (gha)	490.8	481.3
Total Cost ($)	$127.1M	$119.9M
Total Number of Stations	271	265
Total Range Fulfilled by Type 2 Chargers (miles)	646,380	681,900
Total Range Fulfilled by Type 3 Chargers (miles)	1,606,500	1,570,800
Total Number of Type 2 Chargers	4,536	4,546
Total Number of Type 3 Chargers	850	748

Table 5: Comparison of Breakdown and Base Models

Order	ZIP Code	City/Town	Optimal Distance (miles)
1. Start	98122	Seattle	
2	98012	Bothell	23
3	98027	Issaquah	20
4	98903	Yakima	149
5	98597	Yelm	73
6	98001	Auburn	47
7	98366	Port Orchard	32
8	98110	Bainbridge Island	12
9	98109	Seattle	3
10. End	98144	Seattle	2

Table 6: Optimized route and distances for the maintenance man.