Modeling the Location and Deployment Problem of Battery Swapping Stations for an Electric Scooter Company

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***Abstract*— The increasing adoption of electric scooters in urban areas has prompted new challenges in energy management and infrastructure optimization. Efficient deployment of Battery Swapping Stations (BSS) is crucial to support this growing demand while maintaining sustainable and convenient services for users. This study addresses the problem of optimally locating BSS and allocating batteries to meet dynamic customer demands. The problem is a variant of the Facility Location Problem (FLP) but with additional complexities, such as battery availability constraints, station capacity limitations, and time-sensitive customer demand patterns. To tackle these challenges, we propose a Mixed-Integer Linear Programming (MILP) model to optimize station deployment and customer assignments, minimizing both station opening and assignment costs. Two experimental studies were conducted. The first analyzed the impact of station opening and customer distance costs on the number of open stations and the objective function value. The second study examined the influence of the number of batteries per station on operational efficiency. Results demonstrate valuable insights for companies, enabling more effective decision-making for station deployment and battery management.**

I. Introduction

Electric scooters are increasingly popular in many regions worldwide, particularly in parts of European, where their density is significantly increased. These scooters play a vital role in maintaining a green and sustainable environment by reducing emissions of toxic gases, especially in dense urban areas. However, their usage is hindered by limitations in range, which restrict their ability to support longer journeys without frequent battery recharges or replacements. While investing in large-scale charging stations may appear to be a solution, it is often economically inefficient in these regions. An alternative approach to overcoming these challenges is to establish strategically located battery swapping stations.

Figure 1. A battery swapping station

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These stations would allow customers to continue their journeys seamlessly without being constrained by battery range limitations, see Figure 1. Thus, identifying the optimal locations for battery swapping stations is critical to enhancing the feasibility and convenience of electric scooter use.

Several studies have addressed the problem of deploying charging infrastructure for other types of electric vehicles. Researchers have applied various mathematical models and optimization techniques to determine optimal locations and configurations for charging stations. For instance, equilibrium modeling frameworks [1], genetic algorithms ([2],[3]), queuing models [4], and cluster analysis [5] have been employed to address factors such as electricity pricing, user demand, and power consumption. These approaches demonstrate the effectiveness of combining advanced mathematical modeling with optimization techniques to design efficient charging networks. In [6], the genetic algorithm algorithm is applied to solve the proposed model for the optimal placement of electric vehicle charging stations (EVCS). The model incorporates two objective functions: minimizing the construction cost of EVCS and the access cost for users. In their paper [7], Luo and Qiu propose a model for optimally locating electric vehicle charging stations (EVCS) to enhance resource utilization in sustainable cities. The model incorporates reservation services, idle rates during off-peak periods, and waiting times during peak periods. A case study from Chengdu, China, demonstrates the model's effectiveness, revealing that introducing a reservation service positively impacts total cost reduction. This approach supports the development of sustainable cities and promotes healthier living environments.

Building on this foundation, this paper presents a mathematical model for locating Battery Swapping Stations (BSS) for electric scooters. The proposed model incorporates parameters such as battery availability, user demand, operational costs, and recharging durations to optimize station placement and to offer customers the nearest station based on their location and the station's capacity. This work contributes to the growing field of sustainable transportation by addressing the unique requirements of electric scooters in a city, offering a framework that can guide future infrastructure development in similar contexts. Most existing studies have primarily focused on planning the deployment of charging stations for electric vehicles, with significantly fewer addressing the unique challenges associated with electric scooters. For example, Yan et al, [8] addresses the placement of battery swapping stations for electric scooters, particularly in tourism-focused contexts, where unique operational characteristics are often overlooked. Using network flow and mathematical programming techniques, the problem is modeled as an integer network flow problem with side constraints, classified as NP-hard. To tackle large-scale instances effectively, the authors develop a solution algorithm. Real data from Taichung City, Taiwan, is used for validation, demonstrating that the model and algorithm can provide practical and efficient solutions for battery station location and deployment. Torkayesh and Deveci [9] introduces a robust decision-making tool, TRUST (mulTi-noRmalization mUlti-distance aSsessmenT), for selecting optimal locations for battery swapping stations (BSS) for electric scooters. Their approach integrates multiple normalization techniques and various distance measures (Euclidean, Manhattan, Lorentzian, Pearson) to calculate relative scores for location alternatives while addressing sustainability criteria. A real-life case study in Istanbul identifies Beyoğlu as the best location for a BSS. The proposed method minimizes subjectivity, ensures data reliability, and demonstrates feasibility for urban planning challenges. Lin et al [10] proposes the Stochastic Tri-objective Grid-based Scooter Battery Swap Station Allocation Model (STGSBSSAM) to optimize the location and sizing of BSSs for scooters. Using a grid-based approach, STGSBSSAM integrates traffic flow data detected through deep learning and assumes battery swapping demands correlate with hourly traffic patterns. The study shows that equal allocation rules outperform inverse distance rules for battery distribution. Results validate STGSBSSAM's effectiveness, highlighting its potential to promote environmentally sustainable urban mobility by optimizing BSS allocation across cities. For additional studies on the planning and deployment of charging stations for electric vehicles, readers are referred to references [11] and [12].

These works often fail to capture key characteristics of electric scooter used by a specific French company. Unlike electric vehicles, where the location-routing problem has been the primary focus, the considerations in this study specific trip chain demands, battery swapping station placement, and battery allocation constitute a location-scheduling problem. This distinction emphasizes the need for specialized models tailored to the unique operational dynamics of electric scooters.

Additionally, the approach to battery management for electric scooters differs significantly from that of electric vehicles. While electric vehicle recharging often involves lengthy and variable charging times, battery swapping for electric scooters is a fast and standardized process, taking approximately one minute. These operational differences render traditional planning methods for electric vehicle charging infrastructure unsuitable for electric scooter battery management. Although battery swapping exists for electric vehicles and is governed by international standards such as IEC 62840, the operational context for electric scooters presents distinct characteristics. In scooter-sharing systems, battery swapping is typically managed by the service provider and is designed to be extremely fast, usually taking less than one minute without requiring user intervention. In contrast, battery swapping for electric cars often involves larger infrastructure, longer handling times, and user participation, making it less suited for high-frequency urban mobility. These operational differences justify the development of a dedicated model tailored to the specific constraints and dynamics of electric scooter networks.

To address these gaps, this study employs network flow and mathematical programming techniques to develop a model for the optimal placement of battery swapping stations and the assignment of stations to customers. The objective is to minimize two costs: the cost of opening stations and the cost of assigning customers to stations at a given time t. The model is formulated as a Mixed-Integer Linear Programming (MILP) model. MILP is particularly well-suited for generating baseline results and ensuring model accuracy for small to medium-sized instances. Although metaheuristics and AI-based algorithms are known for their scalability and responsiveness in real-time and large-scale environments, they do not guarantee optimality and often require extensive calibration. Given the strategic, planning-oriented scope of this work, MILP was deemed appropriate. Nonetheless, future research will consider heuristic or AI-based approaches to address larger instances and support real-time, adaptive decision-making.

The remainder of this paper is structured as follows. Section 2 presents the description of the problem. Section 3 introduces the mathematical model. Section 4 presents and discusses the experimental results. Finally, Section 5 presents the conclusion and provides some perspectives.

II. Problem Description

The planning of battery swapping station locations for electric scooters involves addressing multiple factors and balancing competing objectives. This problem is well-known in the field of operations research as the "Facility Location Problem" (FLP). In this study, we adapt the FLP to the specific case of a French company specializing in electric scooter and battery swapping solutions. The model aims to achieve two main objectives: (i) minimizing the costs of opening battery swapping stations and (ii) minimizing the costs associated with assigning customers at time t to one station, which are influenced by factors such as distance and station capacity. When a customer decides to swap their batteries at time t, he notifies the company through the application. The system then directs the customer to the nearest station with sufficient capacity to accommodate their request. This approach ensures that customers do not encounter stations with inadequate capacity while enabling the company to accurately predict and manage the battery inventory across its stations.

To achieve these objectives, the problem requires answers to two critical questions:

1. Should a station be opened at a particular location?
2. Which station should be assigned to a customer based on their location and the station's capacity at a given time?

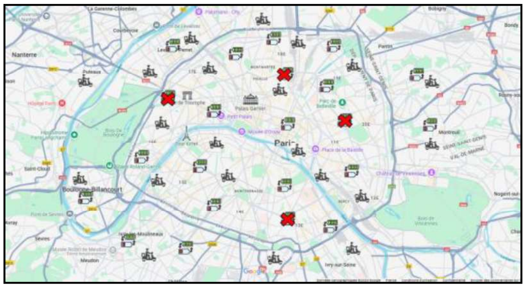

Figure 2. Example of selected stations opened on Paris city map

This study proposes a mathematical model formulated as a Mixed-Integer Linear Programming (MILP) problem to address these questions. It is designed to optimize station location and battery deployment strategies to ensure efficient operations while minimizing long-term costs. We consider a set of I stations, each comprising a set of B batteries. The indices i and b represent the station and battery, respectively. Over the planning horizon T, a set of J customers demand battery swaps. Let d_{jt} denote the demand of customer j at time t. When a customer uses battery b at time t, the battery becomes unavailable for a duration δ until it is fully recharged. The first objective is to determine which stations to open among the potential I stations, minimizing f_i, the cost of opening station i. The second objective is to assign customer j to station i at time t, minimizing C_{ijt}, which represents the cost associated with the distance between the customer's location and the station at time t. By controlling this assignment, the operator can balance demand across stations, prevent overload at specific locations, and ensure better resource allocation. This also enables the system to anticipate future demand based on planned assignments, leading to improved predictability, more efficient battery availability management, and overall system stability. In contrast to a decentralized model where customers independently choose stations potentially creating unbalanced demand our approach allows for optimized, proactive planning based on spatial and temporal factors.

III. MATHEMATICAL MODEL

This section presents the mathematical model based on MILP to solve the studied FLP problem. The model implementation is given below:

Parameter:

I : set of stations
J : set of customers
T : planning horizon
i : index of station i =1..I
B : number of batteries
j: index of customer j =1..J
b: index of battery b =1..B
t: index of period t =1..T
d_{jt}: demand of customer j at period t
C_{ijt}: cost applied if customer j use station i at period t
f_i : cost of opening station i
M : big value
δ: recharge time

Decision Variables:

$$y_i = \begin{cases} 1 \text{ if station } i \text{ is open} \\ 0 \quad \text{otherwise} \end{cases}$$

$$x_{bijt} = \begin{cases} 1 \text{ if customer } j \text{ use battery } b \text{ at station } i \text{ in period } t \\ 0 \quad \text{otherwise} \end{cases}$$

$$S_{bit} = \begin{cases} 1 \text{ if battery } b \text{ at station } i \text{ in period } t \text{ is available} \\ 0 \quad \text{otherwise} \end{cases}$$

$$K_{it} = \text{capacity of station } i \text{ at period } t$$

Objective Function:

$$minimize \sum_i^I y_i * f_i + \sum_t^T \sum_b^B \sum_j^J \sum_i^I C_{ijt} * x_{bijt}$$

Constraints:

$$\textstyle\sum_i^I x_{bijt} \le 1 \quad \forall b \forall j \forall t \tag{1}$$
$$\textstyle\sum_j^J x_{bijt} \le 1 \quad \forall b \forall i \forall t \tag{2}$$
$$x_{bijt} \le y_i \quad \forall b \forall i \forall j \forall t \tag{3}$$
$$\textstyle\sum_j^J \sum_b^B x_{bijt} \le K_{it} \quad \forall i \forall t \tag{4}$$
$$\textstyle\sum_b^B \sum_i^I x_{bijt} = d_{jt} \quad \forall j \forall t \tag{5}$$
$$\textstyle\sum_b^B S_{bit} = K_{it} \quad \forall i \forall t \tag{6}$$
$$\textstyle\sum_j^J x_{bijt} \le S_{bit} \quad \forall b \forall i \forall t \tag{7}$$
$$\textstyle\sum_{z=t+1}^{z=t+\delta} S_{biz} \le M(1 - \sum_j^J x_{bijt}) \quad \forall b \forall i \forall t = 1..T-\delta \tag{8}$$
$$\textstyle\sum_{b2}^B x_{b2ijt} \le d_{jt} + M(1 - x_{bijt}) \quad \forall b \forall i \forall j \forall t \tag{9}$$
$$\textstyle\sum_{b2}^B x_{b2ijt} \ge d_{jt} * x_{bijt} \quad \forall b \forall i \forall j \forall t \tag{10}$$
$$K_{it} \ge 0 \quad \forall i \forall t \tag{11}$$
$$x_{bijt}, y_i, S_{bit}, R_{bit} \in \{0,1\} \quad \forall b \forall i \forall j \forall t \tag{12}$$

Constraint (1) states that a customer can only use one station at a time. Constraint (2) ensures that customers cannot use the same battery simultaneously. Constraint (3) specifies that customers can only use stations that are open. Constraint (4) prevents a station from serving more than its capacity. Constraint (5) ensures that the station meets customer demand. Constraint (6) indicates that the capacity of a station at time t is the sum of the batteries available at that station. Constraint (7) ensures that when the battery is available, it can either remain unused or be used by at most one customer. Constraint (8) ensures that if a battery is used, it will remain unavailable for the entire recharge period δ. Constraints (9) and (10) indicate that customers must take all their required batteries from the same station. Constraints (11) and (12) define the domain of the decision variables.

IV. EXPERIMENTAL RESULTS

The MILP model was programmed using the IVE FICO Xpress solver. Simulations were conducted on a laptop equipped with a Core i7 processor clocked at 2.70 GHz and 8 GB of RAM. The model implementation follows the structure outlined in Section 3. In the following, we present an illustrative example using a reduced dataset.

A. Illustrative example

We conducted this test using the following data: I=2, J=2, T=5, B=2, δ=1, f_i= {30, 20}, d_{jt}={1, 1, 1, 1, 1, 1, 1, 1, 1, 1}. Table 1 presents the values of the parameter C_{ijt}. The data presented in Table I were synthetically generated for the purpose of model validation. In this initial example, identical values were assigned across certain columns (specifically columns 2 and 4, as well as columns 3 and 5) to simplify the input and focus on verifying the correctness and feasibility of the model.

TABLE I. THE VALUES OF C_{IJT}

t \ i,j	1,1	1,2	2,1	2,2
1	5	11	5	11
2	10	9	10	9
3	8	13	8	13
4	12	7	12	7
5	6	14	6	14

The execution results in an objective function value of 145. The model decided to open the two stations with the following assignments. The shaded boxes marked with a cross represent time periods when the battery is unavailable. The white boxes indicate that the battery is available but not utilized.

TABLE II. THE ASSIGNEMENT OF CUSTOMERS TO STATIONS FOR EXAMPLE 1

	t=1		t=2		t=3		t=4		t=5	
	b_1	b_2	b_1	b_2	b_1	b_2	b_1	b_2	b_1	b_2
Station 1	j_2	j_1			j_1	j_2			j_2	j_1
Station 2			j_1	j_2			j_2	j_1		

j_1 and j_2 represent customers 1 and 2, respectively. At time t=1, j_1 uses battery b_2 and j_2 uses battery b_1 from station 1. Once b_1 and b_2 are taken at t=1, they become unavailable at t=2. At t=2, the customers must switch to station 2 to meet their needs, and this process continues similarly for subsequent steps.

In a second example, we modified the demand values to d_{jt}={1,1,0,0,1,0,0,1,0,1}. The results indicate that the model chose not to open Station 1 due to its higher opening cost compared to Station 2. A single station is sufficient to satisfy the demand, resulting in the following assignments.

TABLE III. THE ASSIGNEMENT OF CUSTOMERS TO STATIONS FOR EXAMPLE 2

	t=1		t=2		t=3		t=4		t=5	
	b_1	b_2	b_1	b_2	b_1	b_2	b_1	b_2	b_1	b_2
Station 1										
Station 2	j_1			j_1	j_2				j_2	j_1

At time t=1, j_1 uses battery b_1 from station 2. Once b_1 is taken at t=1, it becomes unavailable at t=2. At t=2, only battery b_2 from station 2 is available, and it will be taken by j_1. At t=3, battery b_1 is recharged and will be taken by j_2, while b_2 remains unavailable. At t=4, there is no demand. At t=5, both batteries are available to meet both demands.

B. *The Impact of Costs on Station Openings*

In this section, we analyze the impact of the costs C_{ijt} and the station opening costs f_i on the obtained solutions. The experimental data used in this study were synthetically generated to conduct a controlled and reproducible analysis of the proposed MILP model. Specifically, the cost parameters C_{ijt} were generated using a discrete uniform distribution with three value ranges: U(1,3), U(1,6), and U(1,10), to reflect varying levels of customer travel cost between stations. The fixed opening costs of the stations f_i were assigned three values 10, 20, and 30 to observe their influence on the number of stations opened and the overall objective value. The demand values d_{jt} were also randomly generated and held constant across all experimental scenarios to ensure consistent comparisons. The demand values d_{jt} were randomly generated following a discrete distribution, where each value is either 0 or 2, representing the number of batteries requested by customer j at time t. At each time period, the value 2 is assigned with a probability of 50%, and the value 0 with a probability of 50%. This setting was chosen to simulate intermittent demand while ensuring that, when demand exists, it reflects a full battery exchange scenario (i.e., two batteries per request), which is common in dual-battery electric scooters. The instance parameters used were I=2 (number of stations), J=3 (number of customers), T=10 (planning periods), and B=4 (number of batteries per station). The results from these simulations are presented in Tables IV and V.

TABLE IV. THE IMPACT OF COSTS ON OBTAINED SOLUTIONS

		y_1	y_2	$\sum y_i$	*Objective function*
f_1=f_2=10	C_{ijt}~U(1,3)	0	1	1	38
	C_{ijt}~U(1,6)	1	1	2	51
	C_{ijt}~U(1,10)	1	1	2	69
f_1=f_2=15	C_{ijt}~U(1,3)	0	1	1	43
	C_{ijt}~U(1,6)	0	1	1	59
	C_{ijt}~U(1,10)	1	1	2	79
f_1=f_2=20	C_{ijt}~U(1,3)	0	1	1	48
	C_{ijt}~U(1,6)	0	1	1	64
	C_{ijt}~U(1,10)	1	0	1	86

Table IV provides insights into how variations in station opening costs (f_i) and customer distance costs (C_{ijt}) influence the number of opened stations and the objective function values.

As the station opening costs increase from 10 to 20, the number of stations open generally decreases. When the opening cost is low (f_i=10), both stations are frequently opened (especially for larger C_{ijt} ranges), as the cost of keeping them operational is less impactful on the objective function. As the opening cost increases to f_i=15 or f_i=20, the model tends to select fewer stations, favoring solutions with just one operational station to minimize overall costs.

When customer distance costs are low (C_{ijt}~U(1,3)), the model often opens only one station, as the distance cost penalty for assigning customers to a single station is small. As distance costs increase to C_{ijt}~U(1,6) and C_{ijt}~U(1,10), the number of stations opened tends to increase. This shift occurs because it is becoming more economical to open an additional station to reduce the assignment costs for distant customers.

The results align with practical operational strategies: when the infrastructure cost is low, deploying more stations can improve service coverage. However, as operational costs rise, it becomes necessary to limit station openings and optimize customer assignments to maintain cost efficiency. Similarly, higher customer distance costs (e.g., in larger or more dispersed urban areas) justify the need for additional stations to reduce travel times and associated expenses. These findings highlight the importance of balancing fixed infrastructure costs with dynamic customer demand and travel cost considerations when planning battery swapping station networks.

To generalize this effect, we conducted the same study on 10 different instances by regenerating the values of C_{ijt}. The average of $\sum y_i$ and the objective function values are presented in Table V.

TABLE V. THE IMPACT OF COSTS ON THE AVERAGE SOLUTIONS

		Average $\sum y_i$	*Average Objective function*
f_1=f_2=10	C_{ijt}~U(1,3)	1	39.2
	C_{ijt}~U(1,6)	2	53.4
	C_{ijt}~U(1,10)	2	72.1
f_1=f_2=15	C_{ijt}~U(1,3)	1	45.0
	C_{ijt}~U(1,6)	1	61.3
	C_{ijt}~U(1,10)	2	82.7
f_1=f_2=20	C_{ijt}~U(1,3)	1	50.2
	C_{ijt}~U(1,6)	1	67.0
	C_{ijt}~U(1,10)	1	88.9

As f_i increases from 10 to 20, the number of open stations tends to decrease. This behavior is expected, as higher fixed costs discourage the opening of multiple stations, pushing the model to rely on fewer stations to minimize overall costs. On the other hand, as the distance costs C_{ijt} increase, the model increasingly opens a second station to minimize assignment costs. This trend demonstrates the trade-off between reducing travel-related costs and optimizing station operations. Figure 3 depicts this behavior.

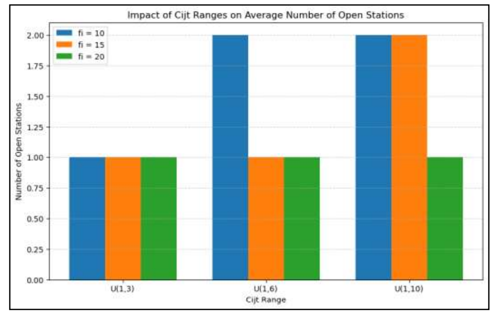

Figure 3. Impact of C_{ijt} Ranges on Average Number of Open Stations

These results highlight the importance of balancing infrastructure investments with customer service efficiency. In contexts where station costs are high, companies may prefer centralized operations, whereas in scenarios with high customer travel costs, decentralized station deployments become more advantageous.

B. Optimal number of batteries per station

In this section, we varied the number of batteries B to assess its impact on the number of open stations and the objective function value. The same data as in the previous study were used, with the matrix C_{ijt} fixed to values generated from ~U(1,10).

TABLE VI. OBJECTIVES AS A FUNCTION OF THE NUMBER OF BATTERIES PER STATION

	B	*Average* $\sum y_i$	*Average Objective function*
f_1=f_2=10	1	No solution	No solution
	2	2	70
	3	2	69
	4	2	69
	5	2	69
f_1=f_2=15	1	No solution	No solution
	2	2	80
	3	2	79
	4	2	79
	5	2	79
f_1=f_2=20	1	No solution	No solution
	2	2	90
	3	2	89
	4	1	86
	5	1	86

When B=1, no solution is found for any scenario, regardless of the station opening costs (f_1=f_2). This indicates that one battery per station is insufficient to meet customer demands, making the system infeasible. When $B \geq 2$, the model consistently finds solutions, with all scenarios maintaining an average of two stations being open for lower station opening costs (f_1=f_2=10 and f_1=f_2=15).

As the number of batteries increases beyond 2, the objective function values stabilize. For example, when f_1=f_2=10, the objective remains constant at 69 for B=3,4,5. This suggests that increasing the battery count beyond a certain threshold does not significantly improve the solution or reduce costs. For f_1=f_2=20, the objective function slightly decreases when B=4 and remains constant at 86 for B=5. This implies a marginal benefit from having a fourth battery but no additional gains with a fifth battery.

As the number of batteries increases, the objective function value decreases until it reaches a certain threshold, beyond which the value remains stable. Therefore, in this case, increasing the number of batteries per station is not recommended.

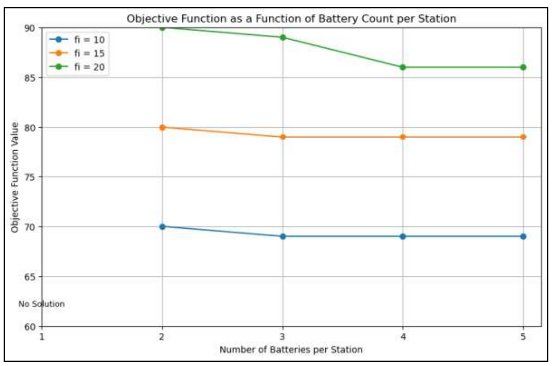

Figure 4. Objective function as a function of Battery count station

V. CONCLUSION

This paper addresses the problem of optimally locating Battery Swapping Stations (BSS) for electric scooters and allocating batteries to meet dynamic customer demands. The objective is to minimize both station opening costs and customer assignment costs while ensuring efficient service delivery. The problem can be seen as a variant of the Facility Location Problem (FLP), but with additional complexities such as battery availability constraints, station capacity limitations, and customer-specific demand patterns over time. These factors make it a more complex and dynamic location-scheduling problem compared to traditional location-routing models. To tackle this problem, a Mixed-Integer Linear Programming (MILP) model was proposed and validated through a series of numerical experiments. The study demonstrated key findings:

- Impact of Station and Customer Costs: Higher station opening costs reduce the number of open stations, while higher customer distance costs justify the need for additional stations.
- Optimal Battery Allocation: Increasing the battery count offers diminishing returns in cost efficiency until it reaches a point where the station's capacity fully satisfies customer demand without resource shortages or excessive idle batteries.

This study provides valuable insights for companies, enabling more effective decision-making for station deployment and battery management. In future research, we propose developing a model that considers partial battery recharge levels. When a battery reaches a certain recharge threshold, it can become available even if it is not fully charged. Additionally, we aim to extend this study by testing real-world instances. While the proposed MILP model demonstrates promising results on small instances, its scalability to larger, real-world scenarios remains a challenge; future work will explore heuristic or metaheuristic approaches such as genetic algorithms or decomposition methods to efficiently solve larger-scale instances within practical computational times

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