Optimizing Battery Swapping Operations in Shared E-Bike Systems

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1 Introduction

The rise of shared electric bikes (e-bikes) has significantly transformed urban transportation, enabling more flexible and sustainable mobility solutions. The increasing adoption of e-bikes, particularly in dockless shared micromobility systems, has introduced new operational challenges, especially in battery management. According to the latest report by National Association of City Transportation Officials (2024), shared micromobility usage across the U.S. and Canada reached a record-breaking 157 million trips in 2023, marking a 20% increase compared to 2022. E-bikes played a pivotal role in this growth, with station-based e-bike trips in the U.S. increasing by 40% and dockless e-bike trips growing by 50%.

One of the primary challenges in shared e-bike systems is maintaining optimal battery levels to ensure high fleet availability and user satisfaction. Riders tend to prefer e-bikes with higher charge levels, as depleted batteries limit their usability and range. If most e-bikes in a system have low charge levels, it results in decreased ridership, user dissatisfaction, and reduced operational efficiency. Unlike station-based e-bikes, which rely on dedicated charging docks, dockless systems require decentralized battery management strategies. The most common approaches include **charging stations, where e-bikes must be brought to fixed infrastructure for recharging; battery swapping, which allows depleted batteries to be replaced with fully charged ones without removing the bike from circulation; and relocating e-bikes to centralized charging depots, where they are charged before being redistributed**.

Among these methods, battery swapping has emerged as the most effective solution, as it decouples charging from e-bike availability, ensuring continuous service with minimal downtime. However, this approach presents substantial logistical and operational complexities. Prior studies, such as those by Zhu (2021) and Yang et al. (2021), have examined fleet optimization and battery-swapping logistics, proposing strategies to enhance efficiency. Similarly, He et al. (2021) explored charging strategies in shared mobility, focusing on infrastructure placement and operational costs. While these studies provide valuable insights, they primarily address station-based systems, where structured fleet movements and designated charging points simplify energy management. Dockless e-bike-sharing networks introduce new challenges, requiring adaptive solutions for decentralized energy management, real-time demand fluctuations, and dynamic fleet balancing.

This study addresses these challenges by proposing an optimization-driven framework specifically designed for dockless e-bike-sharing systems. Our approach integrates dynamic clustering with a multi-objective vehicle routing problem (VRP) model, ensuring cost-effective battery swaps and efficient fleet utilization. The proposed model optimizes logistics by clustering e-bikes based on state of charge (SOC) levels, geographic proximity, and van capacity constraints, significantly reducing travel distances and operational expenses. By leveraging real-world data from the Bay Wheels bike-sharing system, this study provides a scalable and data-driven solution for enhancing battery-swapping efficiency in shared e-bike networks.

2 Methodology

This study develops an optimization-driven framework to enhance battery-swapping efficiency in dockless e-bike-sharing systems. The approach integrates a mixed-integer optimization model for battery swap decisions and van routing with a dynamic clustering technique to efficiently group e-bikes. The objective is to minimize operational costs while ensuring high fleet availability by optimizing swap selection, routing, and demand balancing.

2.1 Optimization Model

The optimization model is formulated as a mixed-integer linear programming problem that determines which e-bikes require battery swaps and plans the optimal routing of a service van. The decision variables include a binary variable indicating whether the battery of an e-bike is swapped, another binary variable representing whether the van travels directly from one e-bike to another, and a continuous variable ensuring a feasible route sequence while eliminating subtours.

The objective function balances profitability from battery swaps against travel costs:

$$Z = \sum_{i=1}^{N} \sum_{j=1}^{N} \left(R_i^F - R_i^C \right) \times x_i + R_i^C - \lambda \left(d_{ij} \times y_{ij} \right), \tag{1}$$

where the expected revenue from swapping a battery and continuing operations without swapping are represented by R_i^F and R_i^C, respectively. The parameter λ is a cost factor that controls the trade-off between profitability and travel distance. The model includes constraints that regulate battery levels, ensuring that swaps occur only when necessary, and route continuity, guaranteeing that the van visits every e-bike requiring a swap. Additional constraints enforce van capacity limits and prevent subtours in the optimization model.

2.2 Dynamic Clustering

To improve computational efficiency and reduce unnecessary travel, e-bikes are grouped before optimization using a two-stage clustering approach. The first stage clusters e-bikes based on their state of charge, prioritizing those with the lowest charge while ensuring that the total swaps within each cluster do not exceed the van's capacity. This process reduces the solution space by filtering out e-bikes that do not require immediate swaps, improving computational performance.

The second stage refines the initial clusters by incorporating geographic proximity to minimize the total travel distance. If two clusters are located near each other, bikes are reassigned between them when doing so leads to lower operational costs. A cost function evaluates both travel distance and state of charge distribution to ensure that clusters remain compact and operationally feasible. This modular approach simplifies a complex multi-objective problem into manageable steps, making the routing and swapping process more efficient.

3 Results and Discussion

To evaluate the effectiveness of the proposed optimization framework, we conduct a computational study demonstrating how the model prioritizes battery swaps and optimizes van routing in a dockless e-bike-sharing system. The analysis consists of two parts: a computational example for a single cluster of 50 e-bikes and a large-scale clustering experiment applied to e-bikes in San Francisco.

In the first scenario, the model optimizes battery swaps for a cluster of 50 e-bikes and a service van. The optimization framework determines which e-bikes should be prioritized for swapping based on their state of charge (SOC) and overall profitability. The objective is to maximize operational efficiency while minimizing travel distance. Figure 1 illustrates the optimized route for battery swapping within this cluster with two different capacities of 20 and 30 battery swaps. The depot, where the service van starts and ends its route, is marked in red, while the e-bikes requiring battery swaps are shown in blue. The dashed lines represent the optimized route taken by the van. The model successfully identifies the most critical swaps while ensuring that the vehicle does not exceed its battery-carrying capacity. The difference between the two plots shows how the model adapts to the van's capacity constraint and how it can prioritize the e-bikes that need a battery swap.

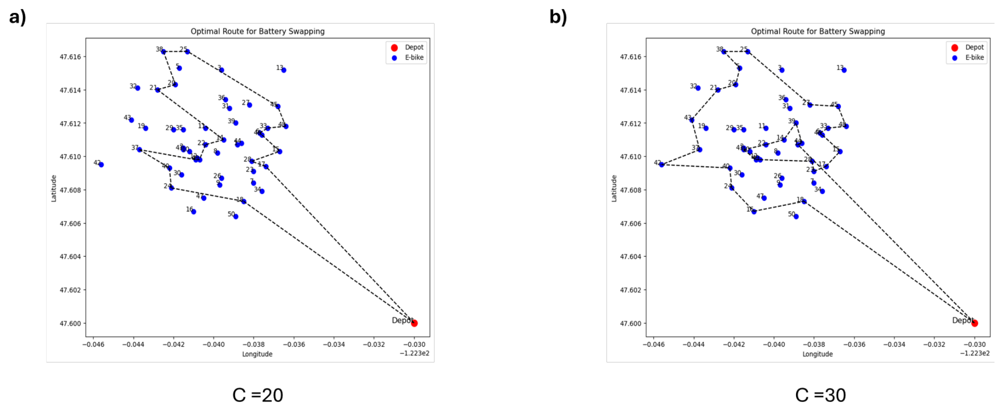

Figure 1: Optimized route for battery swapping within a single cluster containing 50 e-bikes with a) service van capacity of 20 batter swaps and b) service van capacity of 30 batter swaps

To further evaluate the model's scalability, we applied the optimization framework to a larger dataset of dockless e-bikes in San Francisco. The e-bikes were clustered into 10 groups based on SOC and spatial distribution, ensuring that each service van operates within a manageable region while optimizing travel efficiency. Figure 2 presents the optimized routes for all clusters, with each color representing a distinct cluster assigned to a specific van. The clustering approach effectively reduces the complexity of the routing problem by partitioning e-bikes into smaller, more manageable subsets. This hierarchical optimization improves battery-swapping efficiency by minimizing inter-cluster travel distances while ensuring balanced service coverage across the network.

The results indicate that the proposed model effectively optimizes battery-swapping decisions in localized and large-scale scenarios. The single-cluster experiment highlights the framework's ability to prioritize battery swaps based on SOC and route efficiency, ensuring that the service van operates within its battery-carrying limits. The system-wide clustering experiment further validates the approach's scalability, demonstrating that clustering significantly reduces routing complexity and operational costs.

Compared to traditional static battery-swapping strategies, the proposed approach introduces a data-driven optimization strategy that dynamically adjusts to real-time SOC variations and spatial distributions. The ability to integrate profitability considerations and van routing constraints ensures that battery swaps are executed cost-effectively, improving overall fleet availability. These findings suggest that optimizing swap assignments and vehicle routing can significantly enhance operational efficiency in dockless e-bike-sharing systems.

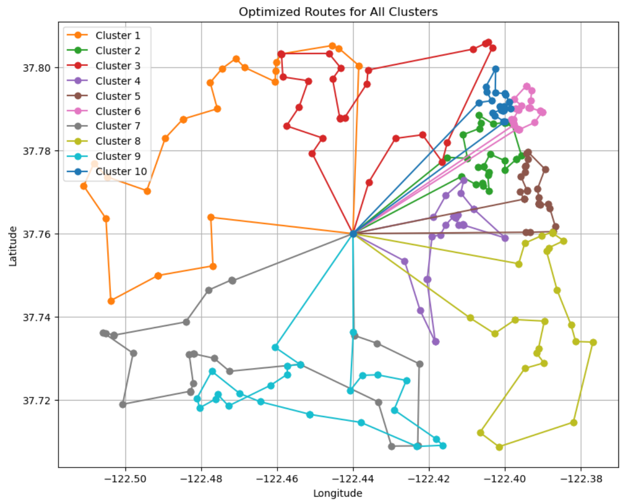

Figure 2: Optimized routing for all clusters in the San Francisco dockless e-bike-sharing network. Each route color represents the service van assigned to a specific cluster.

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