Strategic Matching for Battery Swapping Service: Balancing Customer Satisfaction and Resource Utilization

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Abstract

As electric vehicles (EVs) thrive, battery swapping is increasingly recognized as a faster alternative to conventional plug-in charging services for such vehicles. However, the adoption of battery swapping poses distinct challenges. For instance, the owner of a new car might receive a degraded battery at a battery swap station, leading to customer dissatisfaction. In addition, assigning new batteries to older cars leads to under-utilization of battery resources and potential loss. In this paper, we explore a battery matching strategy aiming to better match batteries to vehicles. We develop a two-period game-theoretical model that takes into account the uncertainty of customer arrivals and the battery swapping service provider's evolving understanding of this market demand. We show that implementing a battery matching strategy can directly boost a service provider's profitability by enhancing the accuracy of battery allocation, although the service provider might not always adopt it. By updating the understanding of customers' arrival rate, the service provider might sometimes adopt a matching strategy and subsequently abandon it. The acquisition of new batteries tends to hinder the adoption of a battery matching strategy, whereas battery aging and service rate improvements tend to promote it. We further indicate that if battery matching is adopted, the service provider tends to reduce its investment in battery maintenance and cut back on new battery purchases. Interestingly, if the service provider initially invests in battery maintenance technologies, the adoption of battery matching in subsequent period might counterintuitively undermine the service provider's expected revenue. The findings provide battery swapping service providers with insights on balancing operational behavioral and market factors to optimize battery allocation decisions and enhance customer satisfaction and promote widespread adoption, contributing to social benefits.

Keywords: game theory, electric vehicle, battery swapping, matching strategy

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1. Introduction

As the world grapples with climate change and growing sustainability demands, Industry 5.0 is emerging as a new industrial paradigm that moves beyond automation and efficiency to emphasize collaboration between humans and intelligent systems, innovation for social good, and environmental responsibility. In this context, the electric vehicle (EV) sector plays a central role by enabling low-carbon transportation. A smooth transition to EVs requires more than only widespread infrastructure, additionally calling for intelligent, user-centered solutions that address key concerns such as cruise range, service accessibility, and charging speed (Zhang et al., 2018; Pi et al., 2024). These priorities resonate with the core principles of Industry 5.0, which emphasizes sustainable innovation and integrating advanced technology to enhance user experience and societal value. In this context, battery swapping is emerging as a promising and reviving charging solution, particularly as the continued deployment of swap stations enhances both service speed and user convenience (Hu et al., 2023).

Although battery swapping comprises a smaller market share compared to conventional EV charging services, the demand for battery swapping service is expected to surge in the coming years as EV uptake thrives. By 2025, the number of EVs equipped for battery swapping is anticipated to reach 1.24 million, requiring more than 12,370 battery swap stations.[1] NIO—a leading EV manufacturer and battery swapping service provider in China—plans to establish 5,000 battery swap stations by 2025 (Qi et al., 2023). Meanwhile, Alton—another market leader—announced that they had accumulated more than 82.52 million cycles of battery swapping by November 2023.[2] By replacing empty batteries with fully charged ones at battery swap stations, battery swapping services can serve as an alternative to conventional plug-in charging methods, ensuring faster regarding for EVs (Shi and Hu, 2022; Qi et al., 2023).

However, battery swapping services also present unique challenges. For instance, EV owners with a brand-new battery might be reluctant to swap their battery at a battery swap station due to the possibility of being swapped with an older, degraded battery (Zhou et al., 2024). Aging batteries have a negative impact on battery performance, particularly cruise range (Gu et al., 2021). Evidence from Nissan Leaf batteries suggests that on average a one-year-old battery could experience a 1.8% loss in cruise range, whereas a five-year-old battery could experience as much as a 21.8% loss.[3] Concerns about swapping empty new batteries with fully charged old ones have become the main barrier for many EV users in adopting battery swapping services, according to customer discussions on social media platforms.

To ensure the practical relevance of our research, we conducted several case and empirical studies,

[1] See https://epaper.chinadaily.com.cn/a/202101/04/WS5ff2575aa31099a234352f90.html, accessed February 12, 2024.
[2] See https://www.aulton.com/index.php/en/list-4.html, accessed February 12, 2024.
[3] See https://www.nimblefins.co.uk/study-real-life-nissan-leaf-battery-deterioration, accessed July 28, 2023.

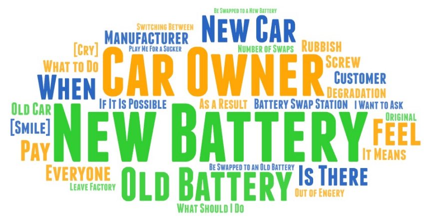
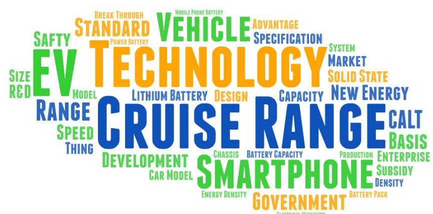
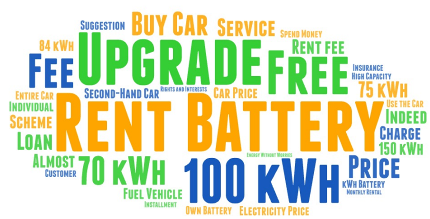
including interviews with NIO staff and a text analysis of a large volume of customer-generated content from social media platforms. Specifically, we conducted structured interviews with sales representatives at NIO with more than two years of experience directly engaging with customers throughout the purchasing and after-sales processes. These interviews confirmed that approximately 30% of new car buyers are concerned about the possibility of their new batteries being swapped for older, potentially degraded ones through the battery swapping service. This concern has emerged as a significant factor concerning whether customers choose to adopt the service (see the interview report in section EC.2.1 of the Appendix).

We also extract evidence from user-generated content on social networks, including: 1) *TikTok*, a popular social media platform; and 2) *Autohome.com*, a Chinese automotive-focused online platform with brand-specific forums. We extract 81,798 reviews from TikTok and 18,900 reviews from Autohome, associated with battery swapping services by NIO. After filtering, we obtain a total of 16,354 relevant reviews. We then employ the latent Dirichlet allocation (LDA) topic modeling approach to identify the most concerned topics among the social media platforms. Following the LDA methodology outlined in Huang et al. (2018) and Oh et al. (2023), we drive the most popular topics and their sentiment scores as described in Table 1. Further details about the modeling process are presented in Appendix EC.1. Table 1 shows that "new and old battery allocation" (Topic 2) represents a prevalent concern among customers, as the most frequent topic among all reviews (i.e., 23.9%). Sentiment regarding this topic is negative, with 53.2% of reviews being negative, 27.1% neutral, and only 19.7% positive. Therefore, allocating old batteries to new cars incurs significant consumer dissatisfaction, which makes battery allocation a critical issue for the battery swapping service provider.

The service provider could implement an advanced battery matching strategy to ease customer concerns and encourage new customers to opt for battery swapping services.[4] Specifically, when customers request battery swaps through digital platforms, in addition to pre-ordered battery capacities, advanced matching algorithms can be employed to evaluate and categorize batteries based on age and performance. For instance, new batteries could be designated for new cars (i.e., "new-battery-to-new-car" match), while older batteries could be assigned to older vehicles (i.e., "old-battery-to-old-car" match), aligning with the respective EV owners' expectations. However, implementing an advanced battery matching strategy certainly incurs extra costs, such as investments in matching algorithms, technology, and personnel (Liu et al., 2024b). Moreover, the success of the matching strategy also hinges on the frequency of customer arrivals. For example, if only one customer requests a slot and arrives at the station within a brief window where the next fully charged battery becomes available,

[4] NIO has provided an application (i.e., NIO APP) that enables users to request a battery swapping slot before arriving at the station. This feature provides necessary times for matching the batteries.

Table 1: Results of Topic Modeling and Sentiment Analysis

No.	Topic Label	Related Reviews	Word Cloud	Sentiment
1	Battery Performance	3074 (18.8%)		Average Score: 4.1 Negative Reviews: 59.8% Neutral Reviews: 19.7% Positive Reviews: 20.5%
2	New and Old Battery Allocation	3908 (23.9%)		Average Score: -0.8 Negative Reviews: 53.2% Neutral Reviews: 27.1% Positive Reviews: 19.7%
3	Technology Improvement	3371 (20.6%)		Average Score: 10.8 Negative Reviews: 43.0% Neutral Reviews: 23.3% Positive Reviews: 33.7%
4	Rent Battery	3568 (21.8%)		Average Score: 3.5 Negative Reviews: 45.5% Neutral Reviews: 24.3% Positive Reviews: 30.2%

Note: The average score for each topic is calculated as the mean of the sentiment scores for all reviews related to that topic. These scores range from -50 to +50, where 0 indicates a neutral sentiment.

the battery matching strategy would not demonstrate its advantage as the battery would naturally be assigned to that vehicle to ensure prompt service. However, with multiple service requests, the matching algorithm could optimize battery assignments to maximize customer satisfaction. Consequently, successfully implementing a battery matching strategy requires a thorough grasp of market demand. Customer charging behavior is subject to strong uncertainty, being influenced by factors such as public holidays, weather conditions, social events, and personal travel plans(Wang et al., 2015; Shi and Hu, 2022; Chen et al., 2023). Consequently, return on investment for the battery matching strategies is not guaranteed. On this basis, and motivated by real-world cases, this study investigates the following questions:

(1) Considering the uncertain market demand, should the service provider adopt an advanced match-

ing strategy for their battery swapping service?

(2) How do service rate improvement, battery maintenance, and battery replenishment affect the decision to implement a matching strategy?

To address these research questions, we develop a two-period model that incorporates uncertain market demand. The model captures the company's evolving understanding of customer arrival rates over time, as discussed by (Liu et al., 2024b). This structure is particularly suited for analyzing short-term operational decisions as it reflects how demand and battery availability evolve across periods, allowing the service provider to adapt strategies accordingly. Moreover, it provides insights into multi-period scenarios in a traceable manner. We begin by exploring a scenario in which the service provider initially operates in a non-matching manner, generating different revenue levels depending on the types of batteries available and the cars that arrive for service. In addition to the highest revenue generated by optimal matches, the service provider might receive a medium level of revenue, reflecting the opportunity cost of suboptimally utilizing the battery resources (i.e., assigning new batteries to old cars), or equally, it might receive a low level of revenue, reflecting customer dissatisfaction due to the allocation of old batteries to new cars. Based on this revenue generated in the initial period, the service provider updates their understanding of the customer arrival rate and decides whether to adopt a battery matching strategy in the subsequent period. We then explore the circumstances under which a service provider might directly adopt a battery matching strategy and analyze the dynamic evolution of this decision. The impacts of service rate improvement, battery maintenance, and battery replenishment on battery matching are also explored. Finally, we extend our analysis to analyze the cases of compatibility issues and market competition.

Our analysis reveals several noteworthy findings. Interestingly, while the matching technology can directly increase profitability, the service provider might choose not to adopt it because it also provides additional insights into market demand, in addition to its direct impact. For instance, the service provider might sometimes adopt a matching strategy but subsequently abandon it upon realizing a low revenue level and inferring a low market demand, even if they become more cost-efficient at matching. We also demonstrate that when the cost is moderate, battery matching only proves advantageous after the available fully charged batteries have been used up in providing a swapping service. Intuitively, the replenishment of new batteries hinders the adoption of battery matching, while the aging of batteries might incentivize it. We further show that the impact of battery degradation (i.e., an increase in the proportion of old batteries) on the battery matching strategy is amplified if the potential loss from assigning old batteries to new cars significantly outweighs the opportunity cost of assigning new batteries to old cars.

Furthermore, improvements in service rate can incentivize adopting the battery matching strategy.

We also show that if the service provider opts for battery matching, it might reduce investment in battery maintenance or new battery purchases. Counterintuitively, if a service provider invests in battery maintenance technology, compared to scenarios where no matching strategy is used, battery matching might unexpectedly reduce expected revenue in the subsequent period, even if it requires minimum costs. Finally, even if the current battery inventory is insufficient, service providers might forgo acquiring new batteries in the subsequent period, instead depending entirely on battery matching to mitigate customer dissatisfaction.

Our study contributes to the literature in several ways. First, our research is the first attempt to explore the unique challenge presented by the mismatch between batteries and EVs in battery swapping services, as an issue not encountered in conventional plug-in charging services. We extend the application of matching strategies to the field of battery swapping services in the EV sector, complementing the literature on matching strategies that has primarily explored the context of two-sided markets (Alaei et al., 2016; Shah et al., 2020; Liu et al., 2024b). Second, our research extends beyond simply focusing on a battery matching strategy to examining its interactions with service rate improvement, technological enhancement in battery maintenance, and the impact of battery inventory replenishment on the battery swapping service provider's financial performance. Finally, our research derives several important managerial insights. For example, we demonstrate the potential of the battery matching strategy as it shows stronger benefits as the proportion of old batteries increases in the market and/or the battery swapping service speed improves. The profitability of battery matching is further influenced by the extent of customer dissatisfaction caused by mismatch, as well as the opportunity cost from the suboptimal utilization of battery resources in strategic planning. Crucially, service providers should use demand information to dynamically adjust their strategies to achieve profit maximization.

Following this introduction, we subsequently review the relevant literature, before introducing the assumptions and developing our model. We then analyze the base model of the second-period matching strategy and explore the strategic battery matching decisions for periods 1 and 2. We then analyze the impacts of service rate, battery maintenance, and battery inventory replenishment on the matching strategy. Next, we extend our analysis by exploring the non-fully compatible case and competition from battery charging, before highlighting the managerial implications derived from our findings. Finally, we conclude by summarizing the key insights and contributions of the research, and outline potential directions for future work.

2. Related Literature

Our work is related to and builds on the literature on EV adoption and matching strategies. A large body of literature has studied charging infrastructure (Zhang et al., 2016; Wu and Sioshansi, 2017; Markopoulos and Hosanagar, 2018; Kumar et al., 2021; Xiao et al., 2024), industry-level government policies (Cohen et al., 2016; Kök et al., 2020; Shi and Hu, 2022; Yu et al., 2022; Chen et al., 2025), and firm-level operational strategies (Lim et al., 2015; Schneider et al., 2018; Shi and Hu, 2022; Çatay and Sadati, 2023; Zhang et al., 2024).

The deployment of charging infrastructure influences consumers' decisions to switch to EVs. As a primary solution for public charging infrastructure, fast charging stations have received substantial attention. Kadri et al. (2020) develop a stochastic integer programming approach to determine the best locations for fast charging stations, aiming to meet fluctuating market demand while remaining within a predefined investment budget. With a stronger focus on uncertain demand, Zhang et al. (2017) also explore the location problem for fast charging infrastructure. By developing a multi-period heuristic method, they highlight the importance of considering demand dynamics in the planning of charging infrastructure for sustainable transportation. Wu and Sioshansi (2017) employ a stochastic flow-capturing model for the location problem and show that despite the majority of stations being situated within the urban core, strategically expanding the charging service network to establish stations on the city outskirts could be an optimal approach. Kınay et al. (2023) study the optimal location and capacity sizing of charging stations by incorporating users' routing and charging behaviors, demonstrating how service-level requirements and user cooperation influence infrastructure deployment. He et al. (2021) focus on EV sharing operations and integrate charging infrastructure planning with a queuing-location model that captures both customer behavior and operator charging strategies, showing the benefits of proactive charging and strategic charger placement for fleet profitability. Building on this line of research, other studies consider location and sizing decisions under different constraints. For instance, Mubarak et al. (2021) and Liu et al. (2024a) explore wireless and dynamic charging configurations, while Pourvaziri et al. (2024) incorporate queuing models and deep learning to enhance station-level operations. Further, Yang (2018) and Xie et al. (2018) highlight the trade-offs involved in fast-charging deployment under demand uncertainty and user choice behavior.

In terms of battery swapping services, Mak et al. (2013) develop optimization models to facilitate planning for battery swapping infrastructure deployment, examining the effects of battery standardization and technological advancements on the optimal deployment strategy. Qi et al. (2023) study a new battery swapping network where decentralized swap stations are supplied by centralized charging hubs. They show that while pooling charging demand offers limited benefits, the main advantage of this design lies in faster centralized charging, which helps to reduce the total number of batteries needed across the system. Zhang et al. (2025) examine the deployment strategy for successive generations of battery swap stations, considering customer waiting time, range anxiety, and technological advancements. Despite extensive work on infrastructure planning, the operational challenge of mismatched battery allocation in battery swapping services has received limited attention. Our work fills this gap by introducing a battery matching strategy that enhances both user satisfaction and operational efficiency.

Furthermore, governments have introduced policies to promote the uptake of EVs by offering subsidies for EV purchases (Cohen et al., 2016; Yu et al., 2022) and infrastructure deployment (Shi and Hu, 2022). Cohen et al. (2016) examine the influence of customer-side subsidies on green technology adoption, considering the response of the manufacturing industry. They show that an increase in demand uncertainty results in increased production volumes and reduced prices, which in turn reduces profits for the manufacturer. Recognizing that charging stations are often located in suburbs while customers prefer downtown locations, Zhang and Dou (2022) examine both firm- and customer-side subsidies and demonstrate their different effects on promoting EV adoption and alleviating the spatial mismatch. Shi and Hu (2022) and Yu et al. (2022) both also investigate the impacts of deployment targets and firm- and customer-side subsidies on EV adoption.

Our work closely relates to the firm-level operational strategies associated with battery swapping services, encompassing areas such as battery acquisition (Sun et al., 2019), battery leasing (Lim et al., 2015; Shi and Hu, 2022), and battery inventory management (Avci et al., 2015). Sun et al. (2019) propose a periodic fluid model to investigate the optimal balance between battery purchasing and recharging strategies, aiming to minimize the costs associated with battery investment, recharging, and customer waiting time. Lim et al. (2015) and Shi and Hu (2022) analyze battery leasing strategies, with the former exploring the influence of battery ownership (whether owning or leasing) on alleviating customer anxiety regarding cruise range and resale value, while the latter concentrates on the battery leasing model, categorizing batteries based on their capacity levels, and investigating the effectiveness of flexible battery upgrades. Employing inventory theory, Avci et al. (2015) determine the optimal service price and the inventory level of spare batteries. Their findings indicate that while battery swapping boosts the EV adoption rate, it also promotes more frequent driving compared to plug-in charging services. Zhang et al. (2024) compare a battery swapping service with a fast charging service regarding firms' strategic investment in charging infrastructure, considering charging speed, battery lifespan, and peak-valley electricity prices. While certain types of anxieties such as resale value and cruise range have been explored, the existing research largely overlooks customer dissatisfaction arising from the mismatch of batteries and vehicles, reflecting a distinct challenge in battery swapping services compared to plug-in charging services. In response, our work complements the literature by introducing and examining the effectiveness of a battery matching strategy. Furthermore, our research explores the interplay among various operational strategies, including the impacts of service rate improvement, battery maintenance, and inventory replenishment on the successful implementation of a battery matching strategy.

Matching strategies that entail assigning the most appropriate employers/resources/experts to employees/customers have been studied in the context of two-sided markets such as expert platforms (i.e., Quora and Stack Exchange), labor platforms (i.e., LinkedIn), and gig-economy platforms (i.e., Uber). For instance, Shah et al. (2020) develop a model for a task-expert matching system where the assignment of a task to an expert is based not only on the prior information about the task but also the insights gained from previous matches. The authors demonstrate that without internalizing an externality, a method driven by greed (i.e., assigning the most suitable task to each expert based on their abilities) is not always optimal. Liu et al. (2024b) reach similar conclusions when analyzing the effects of advancements in matching technology on a gig-economy platform's profitability. They show that despite assigning better-suited jobs to workers, an advanced matching technology could detrimentally affect a company's revenue. To the best of our knowledge, our research represents the first attempt to analyze the matching between batteries and vehicles as applied to battery swapping services in the EV sector, thus addressing unique concerns raised by many EV users. This is significant because in contrast to two-sided markets, the EV market exhibits unique characteristics related to battery degradation, improvements in service rates, advancements in maintenance technology, and battery replenishment, all of which influence the impact of the battery matching strategy on battery swapping service providers' profitability. We summarize the existing research and highlight our contributions in Table 2.

3. Model Setup

We consider a scenario in which battery swap-based EV users swap their depleted batteries for fully charged ones at a battery swap station. The total number of batteries at the station is n, with n_o of them considered to be old. We define new batteries as those with fewer than τ_n discharge cycles, implying that their cruise range remains high with minimal degradation.[5][6] The objective of optimally matching an available battery with a car is to *achieve higher customer satisfaction* or *minimize the opportunity cost* for the service provider.

For instance, if a new battery is assigned to a new car, it could achieve high customer satisfaction due to resulting in minimal reductions in cruise range. This scenario is referred to as a "new-battery-to-new-car" match. Similarly, an "old-battery-to-old-car" match represents an optimal use of resources and could minimize the service provider's opportunity cost. This is the case because owners of older cars are typically more willing to tolerate the potential range reduction associated with a degraded battery than owners of new cars. Considering external opportunities, owners of new cars have the alternative option of using plug-in charging methods instead of replacing their new battery with a

[5] Lithium-ion batteries typically last for 3,000 to 5,000 cycles, with noticeable degradation occurring after 2,000 to 3,000 cycles. See https://dragonflyenergy.com/battery-life-cycle/ and https://www.azocleantech.com/article.aspx?ArticleID=1598, accessed on June 27, 2023.

[6] To retain tractable analytical insights, we model the battery type as either old or new. Our main results remain robust when considering a continuous distribution of the battery state.

Table 2: Existing Literature and Gaps

Literature Stream	Focus of Existing Studies	Identified Gaps	Our Contribution
EV Charging Infrastructure	Charging station location, sizing, capacity under demand uncertainty and user behavior (Kadri et al., 2020; Wu and Sioshansi, 2017; Zhang et al., 2017; Kumar et al., 2021; Kınay et al., 2023; He et al., 2021; Çatay and Sadati, 2023)	Limited attention to battery swapping; Overlook battery–vehicle mismatch	Reframe battery swapping infrastructure and introduce a battery matching strategy.
Battery Swapping Infrastructure	Battery swap station deployment (Mak et al., 2013; Qi et al., 2023; Zhang et al., 2025; Xiao et al., 2024)	Overlook station-level mismatches and battery degradation	Shift focus from macro-level deployment to micro-level operational matching between batteries and vehicles.
EV Policy and Adoption	Government and firm-side policies for EV adoption (Cohen et al., 2016; Shi and Hu, 2022; Yu et al., 2022; Zhang and Dou, 2022; Chen et al., 2025)	Lack of integration between policy incentives and operational decision-making	Analyze how battery matching reduces user dissatisfaction and promotes adoption.
Battery Swapping Operations	Battery inventory, acquisition, and leasing strategies (Sun et al., 2019; Lim et al., 2015; Shi and Hu, 2022; Avci et al., 2015; Zhang et al., 2024)	Lack of integration between EV-specific factors and battery allocation	Propose a new battery matching strategy that integrates inventory, degradation, and service rate.
Two-Sided Matching Platforms	Matching in expert/gig platforms with externalities and strategic behavior (Shah et al., 2020; Liu et al., 2024b)	Matching models not extended to physical goods/services like EV sector	Pioneer the application of matching to battery swapping, with operational considerations (e.g., aging, maintenance) unique to the EV sector.

potentially older one. However, this alternative is not as relevant for owners of older cars because for them battery swapping is essentially a decision without opportunity costs. This assumption is further verified by our text analysis of social media data regarding battery swapping service, as shown in Appendix EC.1.2. We consider both “new-battery-to-new-car” and “old-battery-to-old-car” scenarios as “optimal” matches that could generate a high expected revenue of r_h. Allocating a new fully charged battery to an older car represents a suboptimal use of resources, creating an opportunity cost for the service provider because a new battery could have better served an owner of a new car. Therefore, a “new-battery-to-old-car” match is suboptimal because it generates an intermediate expected revenue of r_m. Finally, “old-battery-to-new-car” match provides the service provider with the lowest revenue due to the resulting customer dissatisfaction, denoted as r_l.

We examine a case in which the next fully charged battery becomes available at the station based on battery swapping requests through digital platforms, such as a smartphone app or official website. In such a scenario, the new- and old-car customers submit a request at the station with identical probability p, where a higher value of p indicates a higher market demand. The probability of a customer arriving at the station is independent of their type (i.e., new or old). The fluctuation in demand reflects the demand uncertainty for the EV charging service market. For example, customers might require a long cruise range and more frequent battery swaps during public holidays or social events, which implies a higher value for p. Four potential situations can occur: 1.) no service requests with probability $(1-p)^2$, 2.) a single request from a new car with probability $p(1-p)$, 3.) a single request from an old car with probability $p(1-p)$, or two requests from a new and old car with probability p^2. Following Stein (2002), we assume that if two cars make a battery-swapping request, arriving cars will always exhibit differences in their batteries, even if they are minor. This implies that whenever two cars request the service, one will invariably be newer and the other older.

Moreover, following Liu et al. (2024b), we consider a typical two-period model and assume a demand stickiness whereby p remains the same in both periods. Despite focusing on a short period that exhibits a relatively stable market demand, our main results remain qualitatively valid even if the probability of demand varies over time due to the strong correlation between two periods. We use $r_t, t \in \{1, 2\}$ to represent the revenue generated by the service provider over the two periods, respectively. Considering the service provider's lack of knowledge regarding the exact value of p during the initial period, it simply presumes that the probability of a car appearing in the market follows a uniform distribution between 0 and 1. This assumption is referred to as the prior of p, consistent with several other studies (Ghosh and Galbreth, 2013; Guan and Chen, 2017; Markopoulos and Hosanagar, 2018). We relax the uniform distribution assumption by considering a general prior distribution over p, and demonstrate the robustness of our results in the Appendix. Following the Kolmogorov axioms of probability and Jeffreys' theory of probability, we consider the Bayesian view of probability as a degree of belief that is constructed from partial information and updated when new information becomes available (Jeffreys, 1961; Guo and Zhao, 2009; Robert et al., 2009). During the initial period, the service provider operates in a non-matching manner, denoted by NM, based on possessing limited information about market demand p. However, in period 2, the service provider will infer the market demand based on its initial-period revenue (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$) and update the belief about p in a Bayesian manner. We assume that $c_1 > c_2$ reflects the expected cost reduction over time as the matching process becomes increasingly efficient. This cost dynamic accounts for early-stage inefficiencies such as manual operations, training, and unrefined matching algorithms in period 1, which are gradually reduced through procedure learning, process standardization, and algorithmic optimization in period 2. The updated demand belief and potential efficiency improvement in the matching process might then incentivize the service provider to adopt the battery matching strategy in period 2.

We now introduce the service provider's battery matching strategies. For this purpose, we consider two scenarios in the battery allocation procedure. In *(1) the non-matching strategy* (NM), the next fully charged battery is randomly assigned and swapped into an arriving car. This strategy—currently adopted by existing service providers—has lower operational costs due to the absence of advanced algorithms and the simplicity of the process. Specifically, on a first-come-first-served basis, the available battery—whether new (denoted as N) or old (denoted as O)—will be assigned to a car if it is the only one to request the service. This arrangement can generate revenue of either r_h, r_m, or r_l, depending on the type of battery and car. However, if two cars request the service within a short time window (the period until the next fully charged battery becomes available), each car has an equal probability of receiving the battery swapping service. If neither car requests the service, the battery is stored as a spare, and no revenue is generated.

(2) The battery matching strategy (denoted as M) employs advanced algorithms to effectively evaluate the condition of batteries and assign them to cars accordingly. If two cars request the service during the period, this matching strategy ensures an optimal match between the battery and car ("old-battery-to-old-car" and "new-battery-to-new-car" match), thereby generating possible higher revenue r_h.

The magnitude of the revenue differences between optimal match and mismatch will be further analyzed in later sections to examine their impact on battery matching strategies. However, if only one car requests the service, the available battery will be automatically assigned to that car to ensure prompt service. Finally, if no car appears, the battery will be stored as a spare, resulting in no revenue being generated. We use l and l' to represent the matching decisions in periods 1 and 2, respectively, where $l, l' \in \{NM, M\}$. Table 3 summarizes the notations.

We outline four scenarios, each represented as S_i, where $i \in \{1, 2, 3, 4\}$ (see Figure 1). Here, S_1 represents the optimal-match car scenario (i.e., an older car if the available battery is old or a newer car if the battery is new); S_2 the suboptimal (non-optimal) matched car scenario (i.e., an older car if the battery is new or a newer car if the battery is old); S_3 the scenario where two cars request a swapping service; and S_4 the scenario where no car requests the service. The likelihood of each scenario is as follows:

$$\begin{cases} \mathbb{P}(S_1|N) &= \mathbb{P}(S_1|O) = \mathbb{P}(S_1) = p(1-p), \\ \mathbb{P}(S_2|N) &= \mathbb{P}(S_2|O) = \mathbb{P}(S_2) = p(1-p), \\ \mathbb{P}(S_3|N) &= \mathbb{P}(S_3|O) = \mathbb{P}(S_3) = p^2, \\ \mathbb{P}(S_4|N) &= \mathbb{P}(S_4|O) = \mathbb{P}(S_4) = (1-p)^2. \end{cases} \tag{1}$$

Given the distribution of the prior $p \sim U(0, 1)$, the service provider updates its belief about p—

Table 3: Notations

Notation	Description
r_t	Revenue generated in periods 1 and 2, $t \in \{1, 2\}$
r_h	High revenue of "new-battery-to-new-car" or "old-battery-to-old-car" match
r_m	Medium revenue of "new-battery-to-old-car" match
r_l	Low revenue of "old-battery-to-new-car" match
p	Belief of customer appearance
$B \in \{N, O\}$	Type of battery: either new (N) or old (O)
$l \in \{M, NM\}$	Adoption of a matching (M) or non-matching (NM) strategy in period 1
$l' \in \{M, NM\}$	Adoption of a matching (M) or non-matching (NM) strategy in period 2
c_1	Initial-period matching cost per service
c_2	Second-period matching cost per service, $c_2 < c_1$
n	Total number of batteries
n_o	Total number of old batteries
s	Service rate (i.e., the average number of battery swaps that can be performed per time unit)
τ_n	Maximum discharge cycles under which battery degradation remains low
k	R&D costs for battery maintenance
b	Battery cost

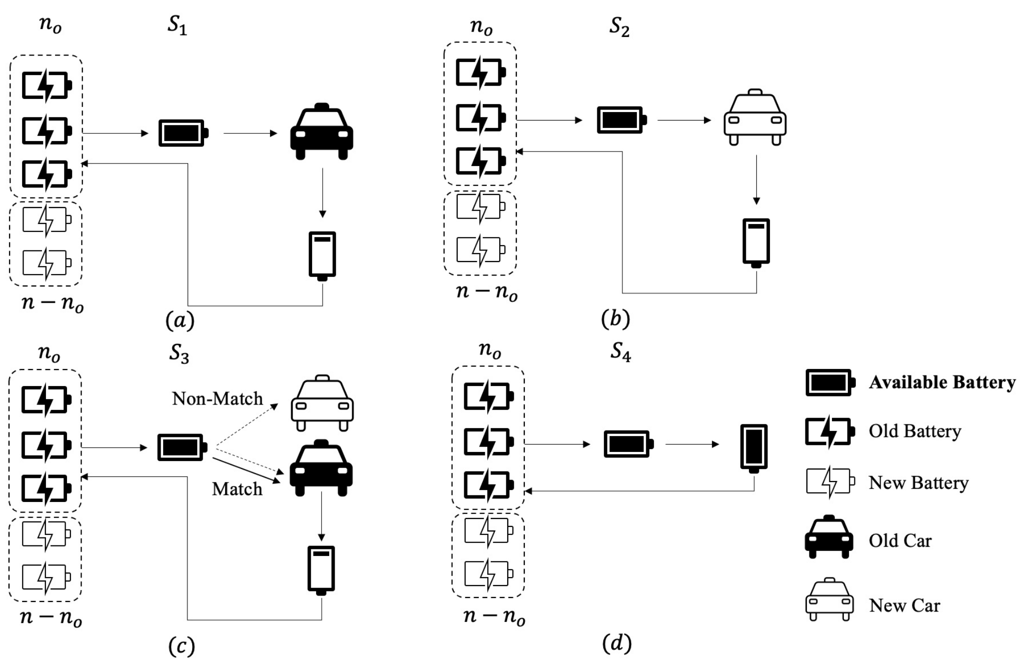


Figure 1: Examples of Battery Allocation (i.e., if Both the Fully Charged and Depleted Batteries are Old)

defined as the Bayesian posterior—based on its realized revenue obtained in period 1.[7]

$$f^l(p|r_1) = \frac{\mathbb{P}_1^l(r_1|p) f(p)}{\int_0^1 \mathbb{P}_1^l(r_1|p)\, dp}, \quad l \in \{M, NM\}. \tag{2}$$

[7]In Appendix EC.3, we prove that $f^l(p|r_1) = f^l(p|r_1, B)$, $l \in \{M, NM\}$ and $B \in \{N, O\}$. This implies that the service provider updates its belief about the arrival of each car in period 2 based entirely on the revenue gains in period 1, and this remains independent of the battery type.

Specifically, given that the service provider operates in a non-matching manner in period 1, it would update its belief about p, as represented by the probability density function of the posterior.

$$\begin{cases} f^{NM}(p|r_1 = r_h, r_m, r_l) & = \frac{3p(2-p)}{2}, \\ f^{NM}(p|r_1 = 0) & = 3(1-p)^2. \end{cases} \tag{3}$$

The derivation processes are shown in the Appendix. Equation (3) indicates that when the service provider does not adopt the battery matching strategy in period 1, the only important factor for the customer arrival frequency or market demand estimation in period 2 is whether there is customer demand in period 1, and the revenue level in period 1—-whether high, medium, or low—does not offer different insights into market demand.

4. Base Model for Battery Matching Strategy in Period 2

In the base model, we analyze the optimal battery matching strategy in period 2. The service provider can assess the potential of the matching strategy during period 1 by updating its understanding of the market demand. More specifically, we explore a scenario in which the service provider considers adopting a battery matching strategy in period 2, given a non-matching manner in period 1 (i.e., NM, l'). Figure 2 shows the decision sequence.

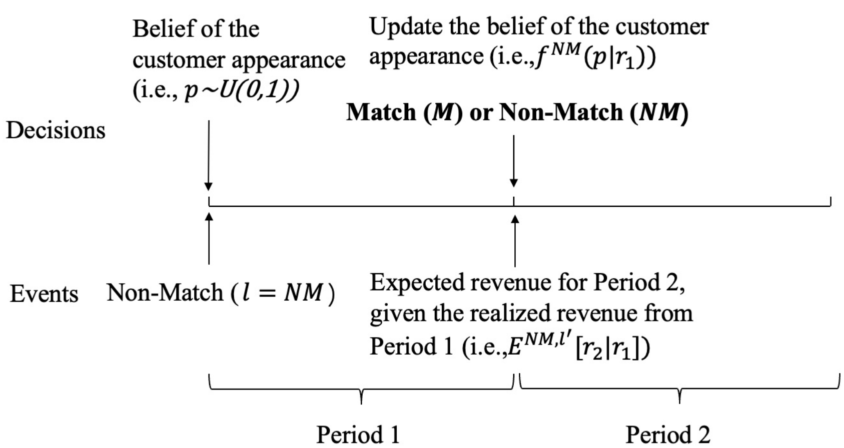


Figure 2: Decision Frame of Battery Matching Strategy in Period 2

The service provider decides whether to adopt a battery matching strategy or maintain the non-matching strategy in period 2 based on the expected revenue in this period, taking into account the obtained revenue from period 1 (i.e., $\mathbb{E}^{NM,l'}[r_2|r_1]$). Therefore, according to Bayesian inference,

$$\mathbb{E}^{l,l'}[r_2|r_1] = \int_0^1 \mathbb{E}^{l,l'}[r_2|p] f^l(p|r_1)\, dp. \tag{4}$$

With and without the battery matching strategy, the conditional expected revenues for period 2, depending on p, are

$$\begin{cases} \mathbb{E}^{l,M}[r_2|p] & = r_h\mathbb{P}_2^M(r_2 = r_h|p) + r_m\mathbb{P}_2^M(r_2 = r_m|p) + r_l\mathbb{P}_2^M(r_2 = r_l|p), \\ & = pr_h + \frac{p(1-p)}{n}[r_m(n - n_o) + r_l n_o], \\ \mathbb{E}^{l,NM}[r_2|p] & = r_h\mathbb{P}_2^{NM}(r_2 = r_h|p) + r_m\mathbb{P}_2^{NM}(r_2 = r_m|p) + r_l\mathbb{P}_2^{NM}(r_2 = r_l|p), \\ & = \frac{p(2-p)}{2n}[r_h n + r_m(n - n_o) + r_l n_o], l \in \{M, NM\}. \end{cases} \tag{5}$$

The service provider would adopt a matching strategy in period 2 if and only if $\mathbb{E}^{NM,M}[r_2|r_1] - \mathbb{E}^{NM,NM}[r_2|r_1] \geq c_2$. The result is summarized in Proposition 1. The proofs for all propositions and corollaries are detailed in the Appendix.

Proposition 1. *Given a non-matching strategy in period 1, the service provider's decision whether to adopt a battery matching strategy in period 2 depends on the matching cost c_2 and revenue in period 1 (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$),*

(i) if $c_2 \in [0, \bar{c}_2^b]$, the service provider always adopts a battery matching strategy in period 2;

(ii) if $c_2 \in (\bar{c}_2^b, \bar{\bar{c}}_2^b]$, the service provider only adopts a battery matching strategy in period 2 if $r_1 > 0$;

(iii) if $c_2 > \bar{\bar{c}}_2^b$, the service provider never adopts a battery matching strategy in Period 2;

where $\bar{c}_2^b = \frac{n(r_h - r_m) + n_o(r_m - r_l)}{20n}$ and $\bar{\bar{c}}_2^b = \frac{9n(r_h - r_m) + 9n_o(r_m - r_l)}{40n}$.

Proposition 1 indicates that while the matching technology can directly increase profitability by enhancing the accuracy of battery allocation, resulting in higher revenue, the service provider might not always implement it. Specifically, regardless of the revenue obtained in period 1, the service provider will implement a battery matching strategy in period 2 if the matching cost is sufficiently low or maintain the non-matching strategy if the cost is sufficiently high. However, when the cost of implementing a battery matching strategy in period 2 is intermediate, it only proves advantageous if the service provider gained positive revenue in period 1, indicating the presence of customer arrivals and that the available charged battery was not left idle during that period (i.e., $r_1 > 0$) (see Figure 1 (a) to (c)).

The trade-off between the cost of battery matching and the potential revenue gains from optimal matches is nuanced. While battery matching is generally advantageous in high-demand markets because it increases the probability of optimal matches, with a non-matching strategy in period 1, high (low) revenue does not necessarily indicate high (low) demand. This is the case because high (low) revenue can arise from two distinct scenarios: either a random battery allocation when two cars request services, or a first-come-first-served allocation when only one car places a request. In either case, the revenue level in period 1—whether high, medium, or low—does not offer different insights into customer arrival frequency or market demand. Therefore, as long as revenue in period 1 is positive, suggesting full battery utilization (i.e., *the available charged battery has not been left idle*), the service provider would retain the same inference about market demand and only opt for battery matching in period 2 if the associated costs are not excessive (i.e., $c_2 \leq \bar{\bar{c}}_2^b$). However, if no revenue is generated in period 1 (see Figure 1 (d)), indicating underutilized batteries, this could signal low market demand and deter the service provider from adopting battery matching, especially if the matching costs are significant.

In summary, when considering the adoption of a battery matching strategy in period 2, the service provider relies on revenue obtained from period 1 to access the uncertain market demand. However, any non-zero revenue does not necessarily indicate different insight into demand due to the random battery allocation. Therefore, the service provide can only infer a low market demand if the available charged battery remains idle, suggesting that no customer arrival within that brief period. This inference of low market demand consequently hinders adopting the battery matching strategy as it can only yield higher profits when market demand is high.

Next, we examine the impacts of different revenue levels (i.e., r_h, r_m, and r_l), the total number of batteries (i.e., n), and the number of old batteries (i.e., n_o) on the threshold for the matching cost. The results are given by the following corollary.

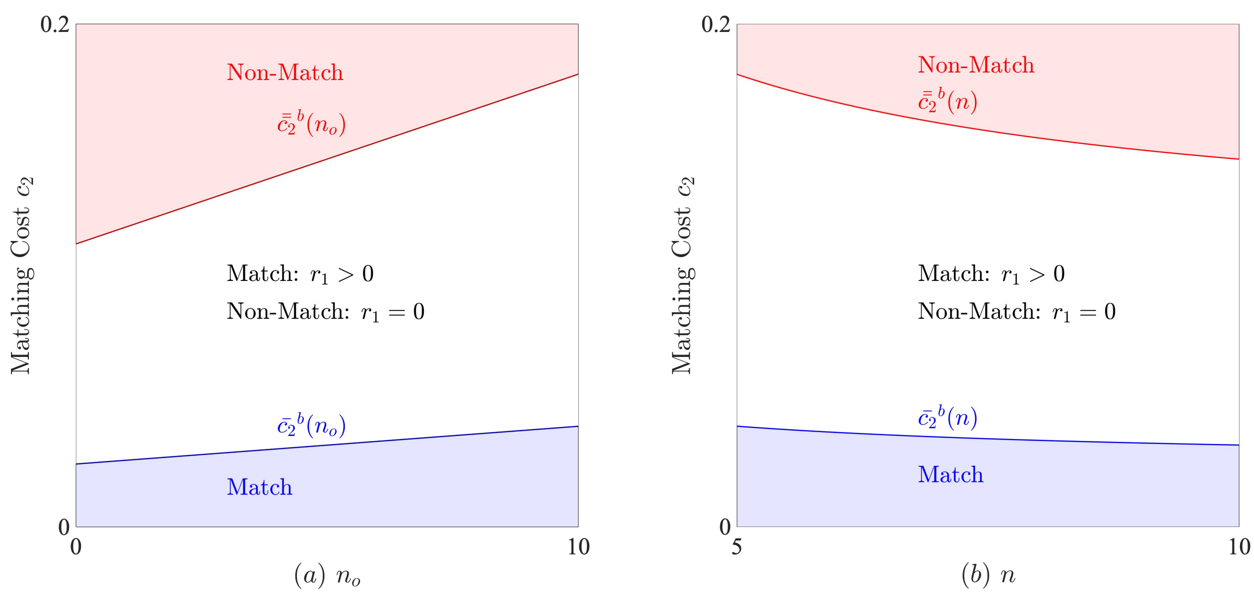
Corollary 1. *Both $\bar{c}_2^b$ and $\bar{\bar{c}}_2^b$ increase with r_h and n_o but decrease with r_m, r_l, and n. Additionally, $\frac{d\bar{c}_2^b}{dn_o} > \frac{d\bar{\bar{c}}_2^b}{dn_o}$ and $\frac{d\bar{c}_2^b}{dn} < \frac{d\bar{\bar{c}}_2^b}{dn}$.*

Proposition 1 introduces two thresholds for the matching cost in period 2, denoted by $\bar{c}_2^b$ and $\bar{\bar{c}}_2^b$, both of which are influenced by the values of high, medium, and low revenue as well as the proportion of old batteries. Intuitively, the decision region for adopting a battery matching (non-matching) strategy expands (shrinks) if the revenue from optimal matches (i.e., "old-battery-to-old-car" or "new-battery-to-new-car") increases or the revenue from suboptimal matches (i.e., "old-battery-to-new-car") or mismatches (i.e., "new-battery-to-old-car") decreases. Interestingly, if the revenue difference between suboptimal matches and mismatches is substantial, the service provider is more likely to adopt a battery matching strategy in period 2, especially when the proportion of old batteries (i.e., $\frac{n_o}{n}$) is high. This implies that as batteries age, a battery matching strategy could be more beneficial if the potential revenue loss resulting from customer dissatisfaction with a reduced cruise range *considerably outweighs* the opportunity cost associated with suboptimal utilization of battery resources.

The intuition is that as batteries age over time—indicated by an increasing proportion of old batteries (i.e., $\frac{n_o}{n}$ increases)—the likelihood of "new-battery-to-old-car" matches decreases, whereas "old-battery-to-new-car" matches become more probable, which holds true under both the battery matching and non-matching strategies. As a result, the service provider incurs a greater revenue loss due to battery aging, especially when the difference in these revenues (i.e., $r_m - r_l$) is substantial.

However, in the absence of battery matching, "new-battery-to-old-car" and "old-battery-to-new-car" scenarios are more likely to occur due to the random allocation of batteries. Specifically, they might occur under two specific circumstances, namely when one or two cars request the swapping service during the brief period when the next fully charged battery becomes available. By contrast, battery matching ensures optimal battery allocation when two cars request the service simultaneously, resulting in suboptimal match occurring when only one car requests the service. Therefore, a higher revenue difference between "new-battery-to-old-car" and "old-battery-to-new-car" leads to greater revenue loss in the case of non-matching, which makes the battery matching strategy more necessary.

Given that battery matching becomes more necessary as the proportion of old batteries $\frac{n_o}{n}$ increases, Figure 3 further illustrates that if the service provider acquires additional batteries to fulfill the market demand (i.e., n increases), the necessity of a battery matching strategy diminishes (see blue regions in Figure 3 (b)). Conversely, the continuous aging of batteries (n_o increases) makes the battery matching strategy more profitable (see blue regions in Figure 3 (a)). We also demonstrate that the effects of n and n_o on $\bar{\bar{c}}_2^b$ are more significant than those on $\bar{c}_2^b$. This indicates that the decision region where the service provider relies on the revenue from period 1 to make battery matching decisions for period 2 expands with the proportion of old batteries. This implies that even if the matching cost is substantial, as batteries age (i.e., $\frac{n_o}{n}$ increases), the battery matching strategy may still be preferable if the service provider generates positive revenue in period 1.



Note: (a) $r_h = 1, r_m = 0.5, r_l = 0.2, n = 10$; (b) $r_h = 1, r_m = 0.5, r_l = 0.2, n_o = 5$.

Figure 3: Impact of n and n_o on the Battery Matching Strategy

5. Battery Matching Strategy in Period 1

Next, we explore a scenario in which the service provider might directly opt for battery matching in period 1. For this purpose, we analyze the optimal matching decision for period 1, in which the service provider considers both the initial- and second-period matching costs, c_1 and c_2, as well as the expected revenue accumulated over the two periods. Figure 4 illustrates the decision-making sequence.

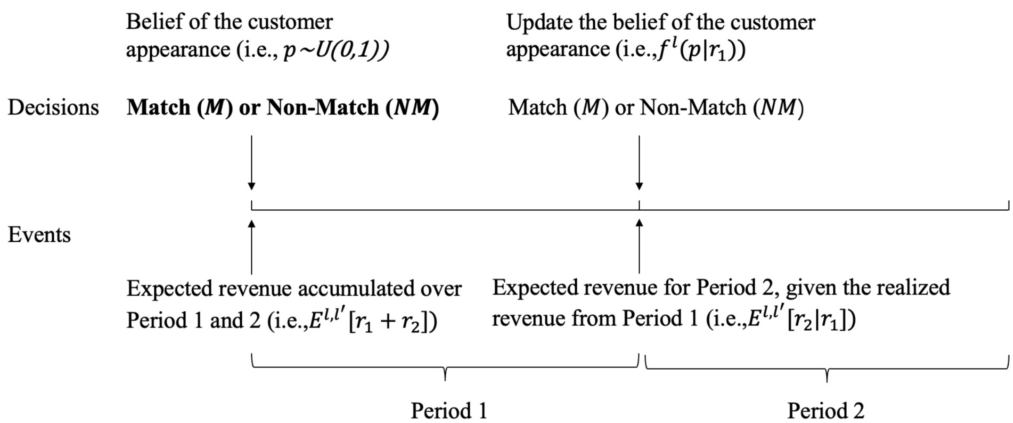


Figure 4: Decision Frame of Battery Matching Strategy in Period 1

The service provider will directly opt for a battery matching strategy in period 1 (i.e., $l = M$), provided they have the option (whether to forgo it in the subsequent period or not (i.e., $l' \in \{M, NM\}$)) to secure a greater profit compared to not implementing the strategy at all (i.e., $l = NM$). More specifically, the service provider evaluates the expected total profits over two periods and only opts to adopt a battery matching strategy in period 1 if the following condition is met:

$$\max\{\mathbb{E}^{M,NM}[r_1+r_2]-c_1, \mathbb{E}^{M,M}[r_1+r_2]-c_1-c_2\} > \max\{\mathbb{E}^{NM,NM}[r_1+r_2], \mathbb{E}^{NM,M}[r_1+r_2]-c_2\}. \tag{6}$$

Given the condition that the service provider improves their operational efficiency over time, denoted as $c_2 < c_1$, we further demonstrate that $\mathbb{E}^{M,NM}[r_1+r_2]-c_1 < \mathbb{E}^{NM,M}[r_1+r_2]-c_2$. Therefore, Equation (6) can be reduced to

$$\mathbb{E}^{M,M}[r_1+r_2]-c_1-c_2 > \max\{\mathbb{E}^{NM,NM}[r_1+r_2], \mathbb{E}^{NM,M}[r_1+r_2]-c_2\}. \tag{7}$$

This leads to the following proposition:

Proposition 2. *The service provider only will adopt a battery matching strategy in period 1 if* $c_1 \leq \bar{\bar{c}}_1^b$, *where* $\bar{\bar{c}}_1^b = \frac{n(r_h-r_m)+n_o(r_h-r_m)}{6n}$.

Considering that the service provider continues to improve its matching technology by enhancing efficiency (i.e., $c_1 > c_2$), we show that it will only directly adopt a battery matching strategy in period 1 if the initial-period matching cost is *absolutely* low (which is independent of the second-period matching cost). The intuition is that during period 1, the service provider possesses limited information regarding market demand and therefore makes battery matching decisions based on both the *absolute* and *relative* conditions. Specifically, there exists a relative threshold for c_1 (i.e., $c_1 \leq \bar{c}_1^b(c_2) \triangleq \frac{n(r_h-r_m)+n_o(r_h-r_m)}{3n} - c_2$), under which a "match-match" strategy is expected to outperform the "non-match-non-match" strategy. Meanwhile, the absolute threshold (i.e., $c_1 \leq \bar{\bar{c}}_1^b$) indicates a value beyond which the service provider expects to increase its total revenue by transitioning from a non-matching strategy in period 1 to a matching strategy in period 2. In other words, "match-match" outperforms the "non-match-match" strategy. However, the absolute condition supersedes the relative condition (i.e., if $c_1 \leq \bar{\bar{c}}_1^b$, then $c_1 \leq \bar{c}_1^b(c_2)$ always holds). Recall that in deciding on the adoption of battery matching for period 1, where the service provider only has access to limited information on market demand, the "non-match-match" is expected to always outperform the "match-non-match" strategy.[8] We can then conclude that when considering the adoption of the battery matching strategy in period 1, the service provider only needs to ensure that implementing the strategy across two periods can accumulate higher profits than delaying its implementation in anticipation of operational improvements in period 2 (i.e., "match-match" outperforms "non-match-match"), namely the initial-period matching cost is absolutely low.

Proposition 3. *Given a matching strategy in period 1, the service provider's decision to continue implementing or abandon the battery matching strategy in period 2 depends on the matching cost c_2 and the revenue in period 1 (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$),*

(i) if $c_2 \in [0, \bar{c}_2^b]$, the service provider continues implementing the battery matching strategy in period 2;

(ii) if $\in (\bar{c}_2^b, \bar{c}_2^d]$, the service provider only continues implementing the battery matching strategy in period 2 if $r_1 > 0$;

(iii) if $c_2 \in (\bar{c}_2^d, \bar{\bar{c}}_1^b]$, the service provider only continues implementing the battery matching strategy in period 2 if $r_1 = r_h$;

where $\bar{c}_2^b = \frac{n(r_h-r_m)+n_o(r_m-r_l)}{20n}$, $\bar{c}_2^d = \frac{3n(r_h-r_m)+3n_o(r_m-r_l)}{20n}$ and $\bar{\bar{c}}_1^b = \frac{n(r_h-r_m)+n_o(r_h-r_m)}{6n}$.

There are two points that warrant attention here. First, even with continuous improvement in the matching technology (i.e., $c_2 < c_1$), a service provider might initially adopt a battery matching strategy in period 1 (provided that their initial matching cost is low, i.e., $c_1 \leq \bar{\bar{c}}_1^b$) but subsequently choose to

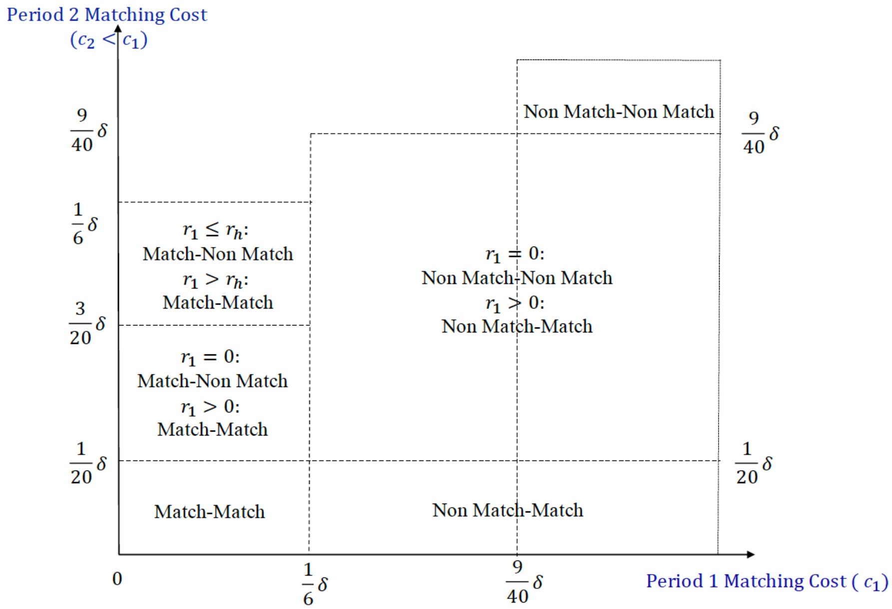
[8] Note that this might not hold true when the service provider updates its beliefs in period 2.

abandon it later. This is more likely to occur if the revenue obtained in period 1 is not sufficiently high. This implies that instead of a static rule, battery matching should be implemented as a strategic tool that can be dynamically adjusted based on realized revenue and real-time demand signals. As such, battery matching requires flexible deployment depending on early-period revenue tracking and cost-benefit trade-offs. The intuition is that the decision to implement battery matching in period 1 is based on limited market demand information, whereby the service provider might sometimes overestimate the actual demand, leading to the adoption of the strategy in period 1, which is less efficient. However, if they realize a low revenue, it then signals a low market demand, prompting them to subsequently abandon the battery matching strategy. The negative effect of information updates outweighs the promoting effect of matching technology improvement on the adoption of battery matching, leading to our counterintuitive finding that the service provider might initially adopt and subsequently abandon the battery matching strategy, even if their matching efficiency is improved.

Second, when the service provider does not implement a battery matching strategy in period 1, its decision in the subsequent period is not influenced by the magnitude of revenue obtained, regardless of whether it is low, medium, or high. However, this might not always be the case if the service provider initially adopts a matching strategy in period 1. A high revenue value from period 1 (i.e., $r_1 = r_h$) encourages the service provider to continue implementing the battery matching strategy in period 2 because it is unable to accurately grasp the market demand based on the revenue obtained (i.e., high, medium or low) in the absence of battery matching due to the randomness of battery allocation. Therefore, only a zero revenue can signal low market demand (as detailed in Proposition 1). However, with battery matching implemented in period 1, a medium or low revenue level can signal relatively low market demand because the service provider can guarantee an optimal match if more than one user requests the service within a time period when the next battery is available for use.

Drawing from the findings from Propositions 1, 2 and 3, we can then provide strategic guidance on the optimal battery matching strategy for both periods. As illustrated in Figure 5, first, if battery matching is not cost-efficient initially (i.e., $c_1 > \frac{1}{6}\delta$), the service provider would only transition to battery matching in period 2 if it can either significantly improve the cost efficiency of the matching process (i.e., $c_2 < \frac{1}{20}\delta$) or reduce the matching cost to a manageable level, given that the available battery has been utilized in period 1 (i.e., $c_2 < \frac{9}{40}\delta$ and $r_1 > 0$). Second, even if the service provider initially believes that battery matching is profitable in period 1 (i.e., $c_1 \leq \frac{1}{6}\delta$), it might reconsider and decide to forgo it in period 2 upon updating its understanding of the market demand. This dynamic framework is further validated through case-informed validation, which confirms its relevance to real-world decision-making (see Appendix EC.2.2).

Our findings on multi-period cost thresholds complement city-scale swapping and charging operations in the existing EV literature that model investment cost constraints, uncertain arrivals and



Note: $\delta = \frac{n(r_h - r_m) + n_o(r_h - r_m)}{n}$, and the battery matching decisions for the two periods are represented as "Period 1 Strategy – Period 2 Strategy".

Figure 5: Strategic Guidance on the Battery Matching Strategy Over Two Periods

heterogeneous consumer behavior (Zhang et al., 2017; Sun et al., 2019; He et al., 2021; Qi et al., 2023). The role of Period 1 revenue as a trigger for Period 2 adoption is consistent with models where observed utilization informs subsequent operational choices under uncertain arrivals (Liu et al., 2024a). At the station level, prior work on swap-station control and degradation-aware operations supports our micro-operational matching strategy that accounts for battery aging (Widrick et al., 2018; Zhang et al., 2024).

6. Impacts of Service Rate, Battery Maintenance, and Battery Replenishment

In this section, we derive further insights into adopting a battery matching strategy by considering the impacts of (i) service rate, (ii) battery maintenance, and (iii) battery replenishment on battery matching decisions.

6.1. Impact of Service Rate

Practical evidence shows that the frequency of EV use increases with the charging speed and cruise range, whereby the former is the more significant factor (Abouee-Mehrizi et al., 2021). Building on the base model in which the service provider believes that each car's probability of appearing on the swapping service market in period 1 (i.e., the service provider's belief of customer appearance) follows a uniform distribution, denoted by $p \sim U(0, 1)$, we extend our analysis to capture the impact of battery swap speed on the expected market demand. Following the approach of Shi and Hu (2022), we assume that the prior belief about demand increases with s, i.e., $p \sim U(0,s)$, where s denotes the service rate (i.e., the average number of battery swaps that can be performed per time unit).[9] This implies that the expected value of p, represented by $E(p) = \frac{s}{2}$, rises as the service rate s increases. We use a subscript S to represent this scenario.

Referring to Equation (2), we reframe Equation (3) to derive the update regarding the service provider's belief about p, which is represented by the probability density function of the posterior.

$$\begin{cases} f^{(S)NM}(p|r_1 = r_h) & = \frac{3p(2-p)}{s^2(3-s)}, \\ f^{(S)NM}(p|r_1 = r_m) & = \frac{3p(2-p)}{s^2(3-s)}, \\ f^{(S)NM}(p|r_1 = r_l) & = \frac{3p(2-p)}{s^2(3-s)}, \\ f^{(S)NM}(p|r_1 = 0) & = \frac{3(1-p)^2}{s(s^2-3s+3)}. \end{cases} \tag{8}$$

To ensure that the maximum value of p does not exceed 1, we assume that $s \in (0,1]$ throughout the paper. Now, we focus on analyzing the optimal battery matching decision for period 2, given a non-matching strategy in period 1. The service provider would adopt a battery matching strategy in period 2 if and only if $\mathbb{E}^{(S)NM,M}[r_2|r_1] - \mathbb{E}^{(S)NM,NM}[r_2|r_1] \geq c_2$. We summarize the results in Proposition 4.

Proposition 4. *Given the service rate $s \in (0,1)$, the service provider's decision to adopt a battery matching strategy in period 2 depends on the second-period matching cost c_2 and the revenue gained in period 1 (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$),*

(i) if $c_2 \in [0, \bar{c}_2^s]$, the service provider always adopts a battery matching strategy in period 2;

(ii) if $c_2 \in (\bar{c}_2^s, \bar{\bar{c}}_2^s]$, the service provider only adopts a battery matching strategy in period 2 if $r_1 > 0$;

(iii) if $c_2 > \bar{\bar{c}}_2^s$, the service provider never adopts a battery matching strategy in period 2;

where $\bar{c}_2^s = \frac{s^2(6s^2-15s+10)[n(r_h-r_m)+n_o(r_m-r_l)]}{20n(s^2-3s+3)}$ and $\bar{\bar{c}}_2^s = \frac{3s^2(5-2s)[n(r_h-r_m)+n_o(r_m-r_l)]}{20n(3-2s)}$. Furthermore, we have $\mathbb{E}^{(S)NM}[p|r_1 > 0] > \mathbb{E}^{(S)NM}[p|r_1 = 0]$, and $\frac{\partial \mathbb{E}^{(S)NM}[p|r_1>0]}{\partial s} > \frac{\partial \mathbb{E}^{(S)NM}[p|r_1=0]}{\partial s} > 0$.

Proposition 4 suggests that our key findings regarding the battery matching strategy in period 2 remain robust when considering the service rate. Specifically, if c_2 is intermediate, the service provider would only adopt a battery matching strategy in period 2 if they obtain positive revenue during period 1. Moreover, if the available charged battery has not been utilized and stored as a spare in period 1,

[9] The service provider anticipates increased market demand (i.e., a high value of $E(p)$) when the speed of battery swap increases. The reasoning behind this is that owners of battery-swapping EVs have the alternative option of using plug-in charging services. If the convenience of battery swapping increases (i.e., if the service rate increases), it is likely to increase the probability of these users participating in the market.

the service provider would update its belief about low market demand. In turn, this would hinder the adoption of the battery matching strategy.

When considering the impact of service rate, it is intuitive that a high service rate would increase the expected market demand (i.e., $\frac{\partial \mathbb{E}^{(S)NM}[p|r_1]}{\partial s} > 0$) in period 2. This is the case because as the speed of battery swapping service improves, EV users are more inclined to choose to use this service, meaning that likelihood of them arriving at the battery swap station increases. However, the service rate imposes different degrees of impact on the expected market demand depending on the revenue level received in period 1:

$$\mathbb{E}^{(S)NM}[p|r_1 > 0] = \int_0^s p f^{(S)NM}(p|r_1 \in \{r_h, r_m, r_l\})\, dp = \frac{s(8-3s)}{4(3-s)} \textit{ and} \tag{9a}$$

$$\mathbb{E}^{(S)NM}[p|r_1 = 0] = \int_0^s p f^{(S)NM}(p|r_1 = 0)\, dp = \frac{s(3s^2-8s+6)}{4(s^2-3s+3)}. \tag{9b}$$

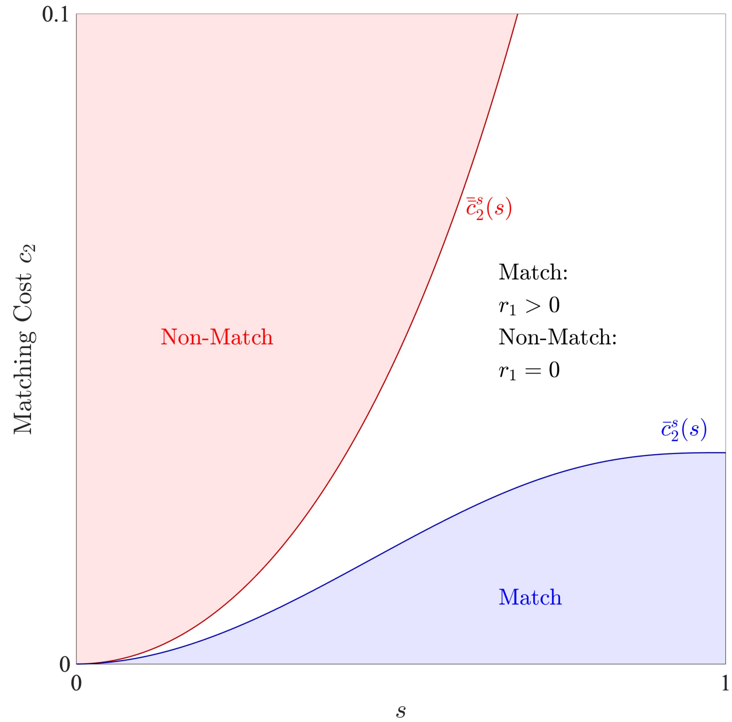
For any level of service rate, earning a positive revenue during period 1 would more strongly reinforce the service provider's confidence in customer acquisition than in situations where the available charged battery has not been utilized (i.e., $\mathbb{E}^{(S)NM}[p|r_1 > 0] > \mathbb{E}^{(S)NM}[p|r_1 = 0]$). This confidence is then further amplified by the service rate. This finding suggests that if the available charged battery was used for the battery swapping service in period 1 (i.e., the service provider accumulates a positive revenue), a higher service rate will further enhance a service provider's confidence in high market demand. Consequently, this will incentivize service providers to adopt the battery matching strategy.

Specifically, from a managerial perspective, service providers can consider their current service rate level when deciding whether to implement battery matching. A faster swap service can strengthen the service provider's confidence in sustained demand, thereby making battery matching more attractive. Moreover, a faster service rate expands the range of operational conditions under which battery matching is profitable. These insights suggest that technological upgrades aimed at improving swap efficiency can also create favorable conditions for service providers implementing battery matching.

We then assess the impacts of revenue values (i.e., r_h, r_m, and r_l), the total number of (old) batteries (i.e., n and n_o), and service rate (i.e., s) on the threshold for the matching cost. The results are shown in Corollary 2.

Corollary 2. *Both $\bar{c}_2^s$ and $\bar{\bar{c}}_2^s$ increase with r_h, n_o, and s but decrease with r_m, r_l, and n. Furthermore, we have $\frac{d\bar{c}_2^s}{ds} < \frac{d\bar{\bar{c}}_2^s}{ds}$.*

First, our primary finding remains consistent, namely that in period 2, increasing the number of batteries hinders the adoption of a battery matching strategy, whereas battery degeneration incentivizes such adoption. This could occur in a "steeper" decision region, where the positive effect of battery aging (i.e., the increasing proportion of old batteries) on the adoption of a battery matching strategy is further



Note: $r_h = 1, r_m = 0.5, r_l = 0.2, n = 10, n_o = 5.$

Figure 6: Impact of Service Rate on the Battery Matching Strategy

amplified by the service rate.

Second, our results indicate that the thresholds for the second-period matching cost increase with the service rate, implying that enhancements in service rate incentivize the service provider to adopt a battery matching strategy in period 2. As Proposition 4 outlines, the intuition is twofold: first, an improved service rate enhances the service provider's confidence in attracting customers, implying that the expected market demand rises with the service rate; and second, we have shown that battery matching is *only* more advantageous if more than one customer requests the service during the period when the next battery is fully charged for use. Therefore, the battery matching strategy is expected to be more profitable if market demand is high. As a result, a higher service rate—which increases the expected market demand—further encourages adopting the battery matching strategy.

Given that $\frac{d\bar{c}_2^s}{ds} < \frac{d\bar{\bar{c}}_2^s}{ds}$, we show that the decision region where the initial-period revenue influences the battery matching decisions for period 2 expands with the service rate (see the white region in Figure 6). This implies that even if the second-period matching cost is high, a high service rate would incentivize adopting battery matching strategy, provided the available battery was utilized in period 1.

6.2. Impact of Battery Maintenance

Service providers are increasingly investing in battery technology to reduce battery degradation to maintain high performance even with increasing discharge cycles. For instance, NIO plans to transition from lithium-ion batteries—which typically last between 2,000 and 3,000 cycles—to solid-state batteries, which can approach 10,000 cycles.[10] Similarly, Alton—a Chinese battery swapping service provider—maintains its batteries using real-time health monitoring, lifecycle management, and centralized recharging at lower voltages.[11] In this section, we assess the optimal investments (i.e., $\tau^{l,l'}$) in battery maintenance for each battery matching decision. For this purpose, we focus on a scenario in which service providers strategize their technological investments prior to period 1, which subsequently influences the battery matching strategy in period 2. It is worth noting that R&D in battery technology is a long-term commitment, necessitating advance planning and investments ahead of business operations. In addition, battery degradation typically occurs over a long-time duration, while a service provider's decisions regarding battery matching are oriented towards a relatively shorter timeframe. This suggests that the battery degradation between periods 1 and 2 is negligible. We use a subscript T to denote the scenario of battery maintenance. Figure 7 shows the corresponding decision sequence.

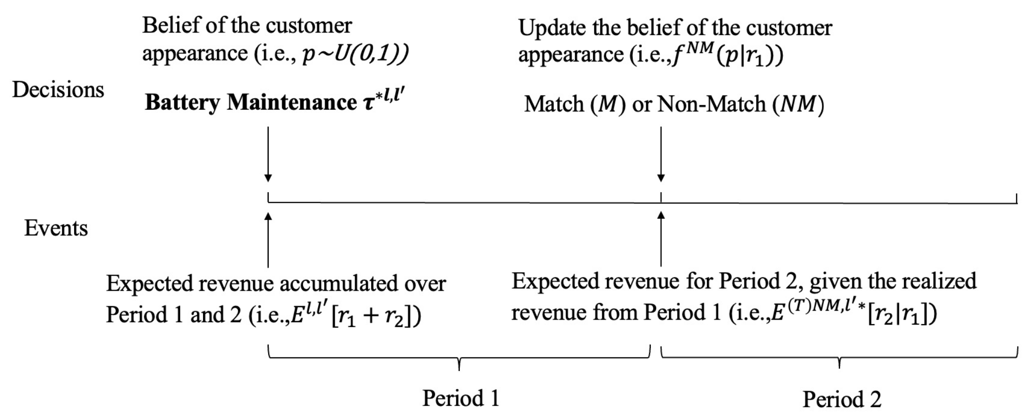


Figure 7: Decision Frame of Battery Maintenance

Building on the base model, we assume that the discharge cycles of the batteries in the battery swap station follow a uniform distribution from $[0, \tau_r]$. Here, τ_r denotes the maximum discharge cycles before a battery requires recycling. Given $\tau_n(\tau_n < \tau_r)$ as the maximum discharge cycles before substantial battery degradation occurs, a fraction $\frac{\tau_n}{\tau_r}$—denoted by a new parameter τ—of the batteries are categorized as new, with the remainder $(1 - \tau)$ classified as old. The R&D costs rise at an accelerating rate in line with τ, whereby a high value of τ typically correlates with increased R&D

[10]See https://insideevs.com/news/667011/nio-may-offer-evs-solid-state-batteries-this-year/ and https://www.azocleantech.com/article.aspx?ArticleID=1598, accessed on July 13, 2023.
[11]See https://www.aulton.com/index.php/list-20.html, accessed on July 13, 2023.

costs (Kim and Chhajed, 2002). Following prior studies (Xie et al., 2011; Zhao et al., 2022), we define a technological improvement cost $C(\tau)$, where k represents the marginal R&D cost in battery maintenance as $C(\tau) = k\tau^2$. With limited market demand information (i.e., $p \sim U(0,1)$) prior to period 1, the service provider determines optimal $\tau^{l,l'}$ by maximizing the overall ex ante expected profits for each matching strategy across two periods, where $\max_{\tau^{l,l'}} \left[\mathbb{E}^{l,l'}[r_1 + r_2] - C(\tau)\right]$.

By comparing $\mathbb{E}^{(T)NM,M^*}[r_2|r_1]$ with $\mathbb{E}^{(T)NM,NM^*}[r_2|r_1]$, the following proposition summarizes the optimal technological investment level and the impact of the battery maintenance on the battery matching strategy in period 2:

Proposition 5. *Given that* $\tau^{NM,M^*} = \frac{r_m - r_l}{4k}$ *and* $\tau^{NM,NM^*} = \frac{r_m - r_l}{3k}$*,*

(i) if $k < \frac{43r_m^2}{108r_h}$ *and* $r_l \in (0, \bar{r}_l)$*, the service provider never adopts a battery matching strategy;*

(ii) if $k < \frac{43r_m^2}{108r_h}$ *and* $r_l \in [\bar{r}_l, \bar{\bar{r}}_l)$*, the service provider only adopts a battery matching strategy in period 2 if* $r_1 > 0$ *and* $c_2 \leq \bar{\bar{c}}_2^T$*;*

(iii) if $k \in \left[\frac{43r_m^2}{108r_h}, \frac{7r_m^2}{12r_h}\right)$ *and* $r_l < \bar{\bar{r}}_l$*, the service provider only adopts a battery matching strategy in period 2 if* $r_1 > 0$ *and* $c_2 \leq \bar{\bar{c}}_2^T$*;*

(iv) if $k \geq \frac{7r_m^2}{12r_h}$ *or* $r_l \geq \bar{\bar{r}}_l$*, the service provider only adopts a battery matching strategy in period 2 if* $c_2 \leq \bar{c}_2^T$*, or* $r_1 > 0$ *and* $c_2 \in (\bar{c}_2^T, \bar{\bar{c}}_2^T]$*;*

where $\bar{r}_l = r_m - \frac{54}{43}k - \frac{6}{43}\sqrt{3k(27k + 43r_h - 43r_m)}$, $\bar{\bar{r}}_l = r_m - \frac{6}{7}k - \frac{2}{7}\sqrt{3k(3k + 7r_h - 7r_m)}$, $\bar{c}_2^T = \frac{-7r_l^2 + (-12k + 14r_m)r_l + 12kr_h - 7r_m^2}{240k}$ *and* $\bar{\bar{c}}_2^T = \frac{-43r_l^2 + (-108k + 86r_m)r_l + 108kr_h - 43r_m^2}{480k}$.

First, adopting a battery matching strategy would reduce a service provider's investment level in battery maintenance (i.e., $\tau^{NM,M^*} < \tau^{NM,NM^*}$). In addition to the R&D cost coefficient (i.e., k), the optimal investment level in battery maintenance increases with the revenue difference between "new-battery-to-old-car" and "old-battery-to-new-car" matches. However, it remains independent of the magnitude of r_h because as batteries age—measured by an increasing proportion of old batteries—the likelihood of "old-battery-to-new-car" matches rises, while "new-battery-to-old-car" matches decline. Even if the service provider always incurs higher revenue losses as $r_m - r_l$ increases, this revenue difference has a more detrimental impact in the case of non-matching due to random battery allocation making suboptimal matches more likely to occur (see Corollary 1). As a result, without battery matching, the service provider invests more in battery maintenance to minimize this impact by retaining a high proportion of new batteries, and this investment level escalates as $r_m - r_l$ increases.

Second, under certain circumstances, if the service provider initially invests in battery maintenance, implementing a battery matching strategy in the subsequent period might *reduce* the service provider's expected revenue (i.e., $\mathbb{E}^{(T)NM,M^*}[r_2|r_1] < \mathbb{E}^{(T)NM,NM^*}[r_2|r_1]$), even if the associated matching costs are considered negligible (i.e., $c_2 \approx 0$). This could occur if the R&D costs for battery maintenance are low and the potential loss from customer dissatisfaction is high (as illustrated in Proposition 5 (i)), or if either of these two factors is intermediate and the available battery has not been utilized in period 1 (i.e., $r_1 = 0$; as illustrated in Proposition 5 (ii) and (iii)).

Overall, investing in battery maintenance could make battery matching less profitable under certain circumstances, even without considering any cost associated with the matching process. The primary reason is that R&D in battery maintenance requires advanced planning. This means the service provider should first determine their optimal investment levels in battery maintenance for both matching and non-matching scenarios, while only having access to limited market demand information. This limited information might result in overestimating the market demand, leading to the case in which the adoption of the battery matching strategy—which hinders the service provider's initial battery maintenance efforts—might in turn reduce profitability in period 2.

6.3. Impact of Battery Replenishment in Period 2

In addition to service rate improvement and battery maintenance, service providers might also purchase new batteries to maintain a sufficient supply of new batteries. In this section, we focus on a scenario in which after the initial period of operation, the service provider decides to acquire additional new batteries, denoted by n_2 for the subsequent period. This decision is based on the current proportion of old batteries (i.e., $\frac{n_o}{n}$) and the revenue generated during period 1 (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$). By maximizing the expected revenue for period 2, the service provider determines the number of batteries to acquire, denoted as $n_2^{NM,l'}|_{r_1}$, as well as the optimal battery matching decision for the subsequent period $l' \in \{NM, M\}$. We use a subscript A to represent this scenario:

$$n_2^{NM,l'*}|_{r_1} = \arg\max_{n_2} \left[\mathbb{E}^{(A)NM,l'}[r_2|r_1] - A_q(n_2)\right], \tag{10}$$

where $A_q(n_2)$ denotes the total acquisition cost of the batteries. We define $A_q(n_2) := bn_2$, where b represents the unit battery cost. Figure EC.3.1 in the Appendix shows the decision framework.

We begin by analyzing the optimal number of batteries, leading to the following corollary:

Corollary 3. *Given that $n_2^{NM,l'*}|_{r_1}$ can either be 0 or greater than 0, $n_2^{NM,M^*}|_{r1=0} \leq n_2^{NM,M^*}|_{r1>0} \leq n_2^{NM,NM^*}|_{r1=0} \leq n_2^{NM,NM^*}|_{r1>0}$,*

(i) if $n \geq \sqrt{\frac{2n_o(r_m-r_l)}{5b}}$, the service provider would never acquire additional batteries in period 2;

(ii) if $n \in [\sqrt{\frac{n_o(r_m-r_l)}{5b}}, \sqrt{\frac{2n_o(r_m-r_l)}{5b}})$, the service provider would only acquire additional batteries in period 2 if $r_1 > 0$ and the battery matching strategy is not adopted;

(iii) if $n \in [\sqrt{\frac{7n_o(r_m-r_l)}{40b}}, \sqrt{\frac{n_o(r_m-r_l)}{5b}})$, the service provider would only acquire additional batteries in period 2 if the battery matching strategy is not adopted;

(iv) if $n \in [\sqrt{\frac{3n_o(r_m-r_l)}{20b}}, \sqrt{\frac{7n_o(r_m-r_l)}{40b}})$, the service provider would acquire additional batteries in period 2 if $r_1 > 0$ or the battery matching strategy is not adopted;

(v) if $n < \sqrt{\frac{3n_o(r_m-r_l)}{20b}}$, the service provider would always acquire additional batteries in period 2.

First, the need for additional batteries predominantly depends on the service provider's current battery inventory (i.e., n). Intuitively, Corollary 3 (i) suggests that even without battery matching, if the current inventory is adequate, purchasing new batteries is not economically viable. However, even with an insufficient inventory level (as referred to in Corollary 3 (ii) to (iv)), the service provider might still forgo the acquisition of new batteries, instead depending entirely on battery matching to maximize its profit (i.e., $n_2^{NM,l'*}|_{r_1} = 0$). This is more likely to occur if the available battery was not utilized during period 1 (i.e., $r_1 = 0$), indicating a low customer arrival frequency and low market demand. Second, service providers planning on battery matching in period 2 usually cut back on new purchases (i.e., $n_2^{NM,M^*} \leq n_2^{NM,NM^*}$). Note that even with unused batteries from period 1 (i.e., $r_1 = 0$), if the service provider decides not to employ a battery matching strategy in period 2, it might still purchase more batteries than in a scenario where the service provider adopts a matching strategy in period 2 and all available batteries were fully utilized in period 1 (i.e., $n_2^{NM,M^*}|_{r_1>0} \leq n_2^{NM,NM^*}|_{r_1=0}$). Finally, if $n_2^{0,l^*}|_{r_1} > 0$, $n_2^{0,l^*}|_{r_1}$ increases in $r_m - r_l$, indicating that the service provider would acquire more batteries in period 2 if the revenue difference between "new-battery-to-old-car" and "old-battery-to-new-car" matches increases.

Recall that we have demonstrated that the service provider might opt not to purchase new batteries in period 2 given that it can efficiently match batteries with vehicles and the current battery inventory level is not too low. Now, we explore the scenario in which $n_2^{0,l^*}|_{r_1} > 0$, and examine how a battery replenishment strategy influences the service provider's decisions on battery matching.

Proposition 6. *Given that battery inventory is significantly insufficient (i.e., $n < \sqrt{\frac{3n_o(r_m-r_l)}{20b}}$), the service provider would acquire additional batteries for period 2 (i.e., $n_2^{NM,l'^*}|_{r_1} > 0$) and decide whether to adopt a battery matching strategy depending on the second-period matching cost c_2 and the revenue gained in period 1 (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$),*

(i) if $c_2 \in [0, \bar{c}_2^a]$, the service provider always adopts a battery matching strategy in period 2;

(ii) if $c_2 \in (\bar{c}_2^a, \bar{\bar{c}}_2^a]$, the service provider only adopts a battery matching strategy in period 2 if $r_1 > 0$;

(iii) if $c_2 > \bar{\bar{c}}_2^a$, the service provider never adopts a battery matching strategy in period 2,

where $\bar{c}_2^a = \frac{(r_h-r_m)}{20} + \frac{\sqrt{5}(2-\sqrt{3})\sqrt{bn_o(r_m-r_l)}}{5}$ and $\bar{\bar{c}}_2^a = \frac{9(r_h-r_m)}{40} + \frac{\sqrt{10}(4-\sqrt{7})\sqrt{bn_o(r_m-r_l)}}{10}$. Furthermore, $\bar{c}_2^b > \bar{c}_2^a$, $\bar{\bar{c}}_2^b > \bar{\bar{c}}_2^a$ and the threshold difference increases with n_o and $(r_m - r_l)$.

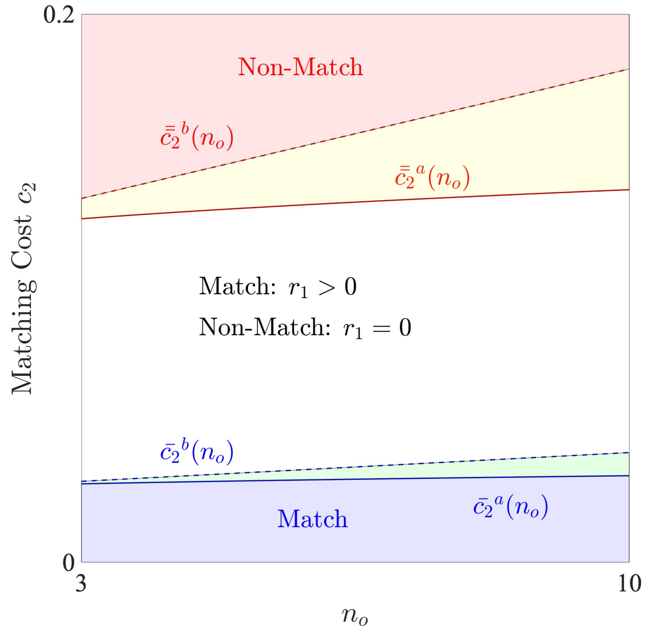


Figure 8: Impact of Battery Replenishment on the Battery Matching Strategy

Our main finding still holds true, namely the service provider would opt for a battery matching strategy when the available battery was used in period 1 (i.e., $r_1 > 0$), provided the matching cost is at a moderate level. Note that this occurs under stricter boundary conditions (i.e., $\bar{c}_2^b > \bar{c}_2^a$ and $\bar{\bar{c}}_2^b > \bar{\bar{c}}_2^a$), as battery replenishment in period 2 lowers the thresholds for the second-period matching cost. Specifically, as depicted in Figure 8, with battery replenishment, the decision region for non-matching expands (as shown by the yellow region), while for matching it shrinks (indicated by the green region). The decision region where the revenue from period 1 influences the matching decision in period 2 also decreases when additional batteries are acquired (given that the yellow region is larger than the green region). This implies that if the matching cost is intermediate, acquiring new batteries might discourage adopting a matching strategy in period 2, even if the fully charged battery was used in period 1 (as shown by the yellow region).

7. Extensions

7.1. Non-Fully Compatible Case

In this extension, we analyze a market in which EVs come from different brands, leading to compatibility issues. Specifically, we consider a scenario where there are different EV brands using different batteries. As a result, a car owner can use the battery swapping service if and only if their vehicle is compatible with the service provider's battery swapping system. A real-world example of this scenario is NIO, a battery swapping service provider that offers services to specific brands——such as its own and selected others (e.g., Geely and Changan)—but is incompatible with certain other brands (e.g., CATL's "Chocolate" battery swapping system). We assume that a car is compatible with the service with probability q. We use a superscript Q (or q) to denote this scenario.

In our framework, we distinguish between two distinct sources of uncertainty. First, the compatibility probability q is treated as a fixed parameter, representing the proportion of EVs in the market that are technically compatible with the service provider's battery swapping infrastructure. This information is generally accessible to the firm through market-level data and manufacturer specifications. For instance, NIO publicly lists compatible brands such as Geely, Changan, and JAC, making q effectively observable. By contrast, the service-request probability p is treated as a prior distribution; specifically, $p \sim \text{Uniform}(0, 1)$ reflecting the firm's *ex ante* uncertainty about a customer's arrival likelihood. The firm updates this belief over time based on revenue outcomes, capturing learning or adaptive behavior under uncertainty. Recall that considering the case where the next available battery is either new (N) or old (O), there are four scenarios, where $S = \{S_1, S_2, S_3, S_4\}$:

$$\begin{aligned}
&S_1 : \text{one compatible car reserves the service, an optimal-matched car;}\\
&S_2 : \text{one compatible car reserves the service, a sub-(non-) optimal-matched car;}\\
&S_3 : \text{two compatible cars reserve the service;}\\
&S_4 : \text{no compatible car reserves the service.}
\end{aligned} \tag{11}$$

Therefore, the conditional and unconditional probabilities for each scenario are

$$\begin{aligned}
\mathbb{P}_1^l(S_1 \mid N) = \mathbb{P}_1^l(S_1 \mid O) = \mathbb{P}_1^l(S_1) &= qpq(1-p) + qp(1-q)p + qp(1-q)(1-p),\\
&= qp(1-qp).
\end{aligned} \tag{12}$$

where $qpq(1-p)$ indicates that while both cars are compatible, only the optimally matched one (i.e., "old-battery-to-old-car" or "new-battery-to-new-car") requests the service; $qp(1-q)p$ indicates that while both cars request the service, only the optimally matched one is compatible; and $qp(1-q)(1-p)$ indicates that only the optimally matched car is compatible and requests the service. Similarly, we have

$$\begin{cases}
\mathbb{P}_1^l(S_2 \mid N) & = \mathbb{P}_1^l(S_2 \mid O) = \mathbb{P}_1^l(S_2) = qp(1-qp),\\
\mathbb{P}_1^l(S_3 \mid N) & = \mathbb{P}_1^l(S_3 \mid O) = \mathbb{P}_1^l(S_3) = q^2p^2,\\
\mathbb{P}_1^l(S_4 \mid N) & = \mathbb{P}_1^l(S_4 \mid O) = \mathbb{P}_1^l(S_4) = (1-qp)^2.
\end{cases} \tag{13}$$

We further define a new random variable $\zeta := qp \sim \text{Uniform}(0, q)$, where $q \in (0, 1)$. ζ represents the probability that a compatible car requests the battery swapping service. Given the adoption of the matching strategy in period 1, the service provider updates its belief regarding the probability that a car arrives in period 2.

$$\begin{cases} f^{(Q)M}(\zeta|r_1 = r_h) & = \frac{2\zeta}{q^2}, \\ f^{(Q)M}(\zeta|r_1 = r_m, r_l) & = \frac{6\zeta(1-\zeta)}{q^2(3-2q)}, \\ f^{(Q)M}(\zeta|r_1 = 0) & = \frac{3(1-\zeta)^2}{q(q^2-3q+3)}. \end{cases} \tag{14}$$

Given the adoption of the non-matching strategy in period 1, the service provider updates its belief regarding the probability that a car arrives in period 2.

$$\begin{cases} f^{(Q)NM}(\zeta|r_1 = r_h, r_m, r_l) & = \frac{3\zeta(2-\zeta)}{q^2(3-q)}, \\ f^{(Q)NM}(\zeta|r_1 = 0) & = \frac{3(1-\zeta)^2}{q(q^2-3q+3)}. \end{cases} \tag{15}$$

Proposition 7. *Given the compatible rate $q \in (0, 1)$, the service provider's decision on adopting a battery matching strategy in period 2 depends on the second-period matching cost c_2 and the revenue gained in period 1 (i.e., $r_1 \in \{r_h, r_m, r_l, 0\}$),*

(i) if $c_2 \in [0, \bar{c}_2^q]$, the service provider always adopts a battery matching strategy in period 2;

(ii) if $c_2 \in (\bar{c}_2^q, \bar{\bar{c}}_2^q]$, the service provider only adopts a battery matching strategy in period 2 if $r_1 > 0$;

(iii) if $c_2 > \bar{\bar{c}}_2^q$, the service provider never adopts a battery matching strategy in period 2;

where $\bar{c}_2^q = \frac{q^2(6q^2-15q+10)[n(r_h-r_m)+n_o(r_m-r_l)]}{20n(q^2-3q+3)}$ and $\bar{\bar{c}}_2^q = \frac{3q^2(5-2q)[n(r_h-r_m)+n_o(r_m-r_l)]}{20n(3-2q)}$. Furthermore, both $\bar{c}_2^q$ and $\bar{\bar{c}}_2^q$ increase with q.

Proposition 7 shows that our key insights regarding the battery matching strategy in period 2 remain valid when accounting for the compatibility issue among brands. Specifically, when the value of c_2 lies within an intermediate range, the service provider adopts the battery matching strategy in period 2 if and only if positive revenue was obtained in period 1. Moreover, if the next available battery remains unused and is carried over as a spare from period 1, the service provider updates its belief towards lower market demand because either arriving vehicles are more likely to be incompatible or the arrival rate of EVs is low. Consequently, this updated belief discourages the adoption of the battery matching strategy.

It is intuitive that a higher compatibility rate increases the service provider's expected market demand in Period 2. As compatibility improves, EV users are more likely to use the service due to fewer mismatch issues. Consequently, the probability of requesting and utilizing the service rises. However, the effect of the compatibility rate on expected market demand varies depending on the revenue outcome in period 1. Specifically, for any given compatibility level, earning positive revenue in period 1 strengthens the service provider's confidence in customer acquisition more significantly than when the charged battery remains unused. This pattern aligns with the findings presented in Proposition 4.

Our results further reveal that the thresholds for adopting the battery matching strategy in period 2 rise with the compatibility rate. This implies that enhancing compatibility across EV brands encourages the service provider to implement the matching strategy more readily. Since battery matching becomes more profitable under high market demand, increasing the compatibility across brands and EV models—by raising expected demand—further incentivizes the service provider to adopt the matching strategy.

7.2. Competition from Battery Charging

In this section, we extend our main analysis to explore competition from battery charging services. For EV owners who use battery swapping, charging remains a viable alternative (e.g., all vehicles designed for swapping can also be charged), thus introducing competition between the two service modes (denoted by C). To model this, we consider two key characteristics through which competition influences both customer behavior and the operations of the battery swapping service provider.

First, a higher level of competition alleviates customers' charging anxiety, thereby reducing the likelihood that they choose battery swapping. This is driven by improvements in charging service rates, the broader accessibility of charging infrastructure, and other related factors. Second, competition exerts downward pressure on the battery swapping service fee as providers must remain price-competitive. To capture these effects, we introduce a competition factor $\xi > 1$, which reduces the customer arrival rate from $p \sim \text{Uniform}(0, 1)$ to $p \sim \text{Uniform}(0, \frac{1}{\xi})$, and discounts the revenue from r_t to $\frac{r_t}{\xi}, t \in \{1, 2\}$. We then examine how market competition influences the service provider's decisions on battery matching.

Proposition 8. *Given the competition intensity $\xi > 1$, the service provider's decision to adopt a battery matching strategy in period 2 depends on the second-period matching cost c_2 and the revenue gained in period 1 (i.e., $r_1 \in \{\frac{r_h}{\xi}, \frac{r_m}{\xi}, \frac{r_l}{\xi}, 0\}$),*

(i) if $c_2 \in [0, \bar{c}_2^c]$, the service provider always adopts a battery matching strategy in period 2;

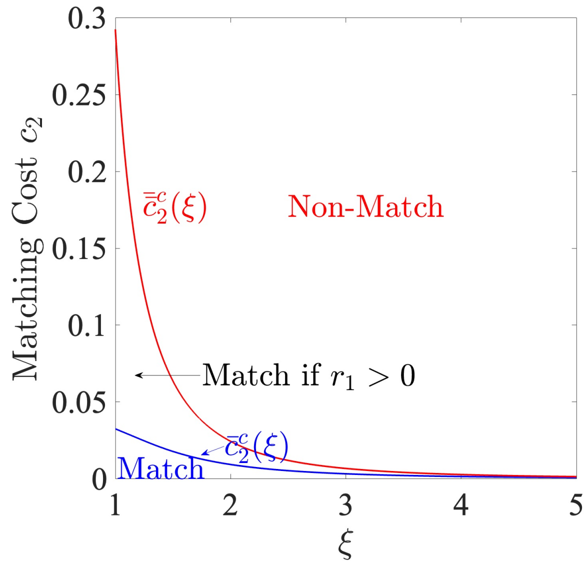
(ii) if $c_2 \in (\bar{c}_2^c, \bar{\bar{c}}_2^c]$, the service provider only adopts a battery matching strategy in period 2 if $r_1 > 0$;

(iii) if $c_2 > \bar{\bar{c}}_2^c$, the service provider never adopts a battery matching strategy in period 2;

where $\bar{c}_2^c = \frac{(6-15\xi+10\xi^2)[n(r_h-r_m)+n_o(r_m-r_l)]}{20n\xi^3(1-3\xi+3\xi^2)}$ and $\bar{\bar{c}}_2^c = \frac{3(5\xi-2)[n(r_h-r_m)+n_o(r_m-r_l)]}{20n\xi^3(3\xi-2)}$. Furthermore, both $\bar{c}_2^c$ and $\bar{\bar{c}}_2^c$ decrease with ξ.

Proposition 8 confirms that our main insights on battery matching hold under competitive conditions. When c_2 falls within an intermediate range, the provider adopts the matching strategy in period 2 if and only if positive revenue was realized in period 1. Conversely, if the available battery remains unused, the provider infers weaker demand, which deters adopting the strategy.

Figure 9 further illustrates that the cost thresholds under which the matching strategy remains profitable decline as competition intensity increases. As battery charging services improve, the battery swapping service provider's confidence in attracting customers weakens, leading to lower expected



Note: $r_h = 1, r_m = 0.5, r_l = 0.2, n = 10, n_o = 5.$

Figure 9: Impact of Competition Intensity on the Battery Matching Strategy

market demand. In addition, competition further pressures the service provider to lower the battery swapping price, directly reducing the expected revenue. This twofold reduction discourages the adoption of the matching strategy, highlighting the substitution effect of battery charging. As shown in Figure 9, when ξ becomes sufficiently large, a predetermined low c_2 results in a shift from unconditional matching to conditional matching (only if revenue is realized in period 1), and eventually to no matching.

8. Implications

8.1. Managerial Implications

Our results offer several managerial insights. First, service providers should not treat battery matching as a static rule but rather a strategic tool that can be dynamically adjusted based on real-time demand signals and battery inventory composition. To maximize effectiveness, operational policies should allow for flexible deployment of matching depending on observed utilization patterns.

Second, institutionalizing demand forecasting and early-period revenue tracking as part of the decision-making process can improve the timing and effectiveness of battery matching. Since early revenue outcomes influence the perceived value of future matching, these signals can serve as more informative inputs than fixed cost-benefit thresholds alone.

Third, investments in battery inventory and maintenance can be jointly considered alongside the adoption of matching. While matching might reduce the reliance on new battery purchases or intensive maintenance, its effectiveness diminishes when such investments have already been made. A coordinated approach helps to mitigate potential conflicts between overlapping strategies. The above implications are further supported by our interview findings, where NIO professionals acknowledged the practical feasibility of implementing battery matching, particularly when historical operational data indicate consistent customer activity, such as sustained revenue generation or high battery utilization.

Fourth, developing mechanisms to assess customer dissatisfaction—particularly when old batteries are assigned to new vehicles—can support more informed matching decisions. The industry professionals interviewed in our study highlighted that the growing proportion of aged batteries further strengthens the case for adopting battery matching by helping to mitigate customer dissatisfaction stemming from perceived performance degradation. Aspects such as perceived fairness and service personalization—central to Industry 5.0's human-centric design—are likely to influence customer retention and the long-term adoption of battery swapping services. The advanced battery matching strategy can serve as a mechanism enabling the intelligent allocation of battery resources, supporting the broader goals of Industry 5.0 by simultaneously enhancing customer satisfaction and resource efficiency, both of which are critical to sustainable and socially responsive infrastructure systems.

8.2. Contributions to the Literature

We then summarize our contributions and clarify how this study advances the existing literature. First, we foreground the station-level battery–vehicle mismatch unique to battery swapping, absent from the conventional plug-in charging literature, and study a matching strategy that pairs new (old) batteries with new (old) cars. In doing so, we complement city- or network-level deployment and capacity-planning work by shifting the lens to micro-operational design where battery inventory, degradation, service rate, and maintenance/compatibility constraints jointly shape the performance of battery swapping (Mak et al., 2013; Qi et al., 2023).

Second, we extend matching strategies beyond two-sided digital platforms to a physical service system with EV-specific frictions (battery aging, maintenance technology, and service rate). We show that matching adoption is dynamic and signal-driven: with moderate costs, matching in Period 2 is optimal only following positive realized revenue in Period 1, whereas low (high) costs imply unconditional adoption (non-adoption). This pattern is fundamentally consistent with Liu et al. (2024b), which shows advanced matching technologies might unintentionally hinder participation due to abandonment risks. However, we complement it by highlighting an operational difference: in two-sided platforms, providers (e.g., drivers) can exit after low initial revenue, whereas in battery swapping markets, the battery stock and its state-of-health composition carry over from Period 1 to Period 2. Consequently, the adoption rule is governed by the interaction between matching cost and the magnitude of realized revenue, rather than participation exit alone. Our findings provide a bridge from platform-matching insights to EV operations.

Third, we identify how EV-specific primitives reshape the region in which matching is attractive: matching becomes more valuable with aging-induced heterogeneity and less necessary with abundant new-battery inventory; faster service rates expand the adoption region by strengthening demand realization and lowering opportunity costs. These results add an operational layer to work on inventory and resource management in battery swapping (Avci et al., 2015; Lim et al., 2015; Sun et al., 2019; Shi and Hu, 2022; Zhang et al., 2024). Finally, we articulate an operational channel to EV adoption: by mitigating dissatisfaction from receiving an older battery in a new car, battery matching can complement policy- and market-design approaches to EV adoption (Shi and Hu, 2022; Yu et al., 2022; Zhang and Dou, 2022).

9. Concluding Remarks

This paper develops a two-period analytical model to characterize the optimal adoption of battery matching at battery swap stations. Our finding indicates that battery matching can improve allocation accuracy and raise profitability, but adoption is state- and cost-contingent rather than universal. With *moderate* matching costs, implementing battery matching in Period 2 is optimal only when Period 1 realized revenue is positive—i.e., when the service provider receives a strong demand signal. If the available battery remains idle, the inferred arrival rate is low and subsequent matching is abandoned. With *low* costs, adoption is optimal regardless of the Period 1 outcome; while with *high* costs, matching should not be adopted. The belief-updating mechanism also rationalizes dynamic patterns: a provider may adopt early and subsequently abandon matching even if matching costs decline. This signal-driven logic is consistent with evidence that realized revenue can shape matching decisions (Liu et al., 2024b). We also show that EV-specific factors shift the matching decision in different ways. Specifically, battery aging increases the value of matching, while abundant inventories of new batteries make matching less attractive. Faster service rates expand the domain in which matching is profitable by strengthening demand realization. In addition, battery matching should interact with battery maintenance and replenishment choices: it can substitute for battery maintenance or new purchases in some states (e.g., when matching effectively mitigates dissatisfaction). Yet maintenance can erode the incremental benefit of matching; consequently, adopting matching after investing in maintenance may be *less* profitable, even when the marginal matching cost is negligible. Overall, matching should be treated as a dynamic, signal-driven policy rather than a one-off choice, with clear managerial triggers tied to costs, realized demand, inventory mix, service rate, and battery aging.

It is worth mentioning that we do not consider non-sensitive customers who do not exhibit a preference for old or new batteries. Even owners of new cars—who generally require a low cruise range in their normal usage—might not be concerned about the diminished range associated with older batteries. Thus, differentiating customers according to their sensitivity to battery cruise range could be an interesting direction for future research. In addition, our research primarily focuses on uncovering the underlying mechanisms and strategical decision on battery matching. We acknowledge that the implementation of battery matching is a dynamic problem, necessitating the use of other dynamic optimization methodologies (Chen et al., 2015; Jafarian et al., 2025). Although it is beyond the scope of our current research objectives, this could represent a promising avenue for future research. We also acknowledge some other limitations: to maintain analytical tractability and focus on the core mechanisms, we abstract from broader market factors such as competition, policy incentives and technological disruptions. Additionally, while our study focuses on battery matching strategies, we do not model other critical operational challenges, including infrastructure costs, regulatory constraints, and battery standardization or compatibility issues. We identify these omissions as important directions for future research.

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