eBASE: Real-Time Battery Swap Recommendation System for eBike Users

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Abstract. The intelligent battery swap recommendation (BSRec) system for e-bikes is a critical need in the development of smart urban transportation. However, challenges such as limited observable data and the complexity of cabinet-battery constraints have hindered model generalization across multiple tasks. In this paper, we propose eBASE, the first model for e-bike BSRec, which integrates a hybrid expert system with dual-tower joint optimization. Experimental results show that eBASE outperforms existing models in three real-world tasks: cabinet, battery, and cabinet-battery recommendations. Additionally, the BSRec system developed with eBASE has been deployed in over 10 cities, significantly improving the multi-dimensional satisfaction of millions of riders.

Keywords: Battery Swap Recommendation · Smart Urban Transportation · Real-Time System.

1 Introduction

In the context of smart urban mobility, personalized battery-swapping recommendations for e-bikes are crucial for improving user satisfaction and addressing key challenges, such as minimizing unnecessary energy consumption [3]. However, achieving precision in these recommendations is complex due to the variability in user preferences. There is a significant gap in research and applications for battery swap recommendations in e-bikes [2, 6]. Practical data highlights two main challenges: (1) achieving accurate recommendations for both cabinets and batteries at each step while accommodating diverse user needs, and (2) overcoming the limited generalization of models trained on sparse datasets when applied to large-scale real-world data.

In this paper, we propose eBASE, a novel optimization framework for joint "cabinet-battery" recommendations. eBASE combines a mixture- of-experts model with multi-task learning to enhance recommendation accuracy and better meet user needs. We also develop and deploy the first intelligent battery swap recommendation(BSRec) system, improving user satisfaction across over a million riders in 10+ cities. Our contributions are as follows: (1) We propose eBASE, an innovative approach to addressing complex constraints in battery-swapping recommendations. (2) We demonstrate eBASE's superior performance through large-scale comparative experiments. (3) We develop the first intelligent BSRec system for electric bicycles, significantly improving user satisfaction, battery scheduling, and energy efficiency.

2 Methodology

Task of BSRec. Given the user's current information and the spatial distribution of nearby cabinets and batteries, the user's battery swap behavior follows a sequential pattern: 'platform-recommended cabinet → engagement (cabinet selection) → battery swap'. Consequently, the e-bike BSRec task can be conceptualized as an agent-based process that evaluates the battery swap rate (BSR), defined as $pBSR = p(swap|engagement, recommendation)$. For each swap event $(u, c \to b)$, drawn from a distribution D over the domain $\mathcal{U} \times \mathcal{C} \times \mathcal{B}$, we define the observed dataset for the BSRec system as $\mathcal{S} = \{(u_i, c_i \to b_i)\}_{i=1}^{N}$. BSR modeling aims to estimate $pBSR = p(b = 1|c = 1, u)$, which involves two related probabilities: the post-view cabinet-selection rate (CSR), $pCSR = p(c = 1|u)$, and the post-view cabinet selection and battery swap rate (CSBSR), $pCSBSR = p(c = 1, b = 1|u)$. Given battery swap interaction u, the probabilities follow:

$$\underbrace{p(c = 1, b = 1|u)}_{pCSBSR} = \underbrace{p(c = 1|u)}_{pCSR} \times \underbrace{p(b = 1|c = 1, u)}_{pBSR}. \tag{1}$$

where $u \in \mathcal{U}$ represents the feature space encompassing the attributes of the user, cabinet, and battery. $c \in \mathcal{C}$ and $b \in \mathcal{B}$ denote binary label spaces indicating the occurrence of a cabinet selection event and a battery swap event, respectively. N represents the total number of recorded swap events in the dataset.

The Proposed eBASE. The proposed eBASE model, illustrated in Fig. 1(a), tackles the challenges associated with modeling BSRec tasks by effectively leveraging the interdependent constraints among CSR, BSR, and CSBSR within the battery swapping sequence pattern. Specifically, as defined in Eq. 1, eBASE incorporates CSR and CSBSR as evaluative components to infer BSR across the global battery swapping data domain.

In summary, eBASE forms the core framework of the BSRec system, consisting of three key modules: the shared bottom layer, the adaptive mixture-of-experts layer, and the deep joint optimization layer. The shared bottom layer employs three linear mappers to project the features of users, cabinets, and batteries into a unified semantic space. Drawing inspiration from the Mixture of

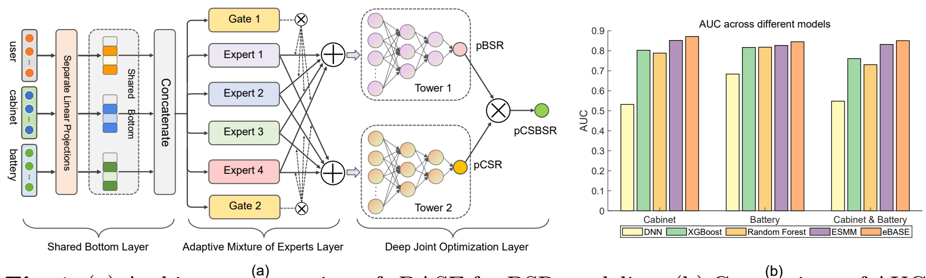

Fig. 1. (a) Architecture overview of eBASE for BSR modeling. (b) Comparison of AUC performance across different models.

Experts (MoE) model [4], the adaptive layer uses a dual-gating mechanism to dynamically select the most relevant experts for CSR and BSR decisions. The joint optimization layer, based on a dual-tower multilayer perceptron (MLP), extracts high-order features tailored for CSR and BSR modeling and prediction tasks. To enforce the tri-constraint relationship, the final CSBSR prediction is derived through an element-wise product operation, ensuring robust recommendation performance and strong generalization. To comprehensively assess the effectiveness of eBASE, we conduct experiments on a large-scale, real-world BSRec dataset, using the Area Under the ROC Curve (AUC) as the performance metric, as illustrated in Fig. 1(b). The experimental results indicate that eBASE consistently outperforms baseline models, including ESMM [5], XGBoost [1], DNN, and Random Forest, across three critical tasks: battery recommendation, cabinet recommendation, and cabinet-battery recommendation.

3 Demostraion

Leveraging the eBASE model's robust dual-constraint recommendation capabilities for both batteries and cabinets, we develop and deploy the first intelligent BSRec system for e-bikes[6]. This system integrates data from three key domains—user, cabinet, and battery—to optimize recommendations. Statistical analysis shows that the system currently serves over 1 million riders across more than 10 cities. It has also reduced unnecessary search distances by over 200,000 kilometers and increased the average riding range by more than 2 million kilometers. Riders may experience three distinct scenarios, labeled as (a), (b), (c), and (d) in Fig. 2:

(a) During off-peak periods, when demand is low, users are typically able to select an appropriate battery swap station and receive a satisfactory battery in a single recommendation cycle. (b) During off-peak or peak periods, due to users' proximity preferences or high demand for battery swaps, the selected station may not have batteries with sufficient charge, necessitating a secondary recommendation for a battery swap. (c) During peak periods, the availability of high-capacity batteries at the chosen swap station may be limited, increasing the likelihood of user dissatisfaction with the available selection. (d) During

[6] Video demonstration: `https://github.com/Anirudh-Siweizhou/eBASE_Demo`

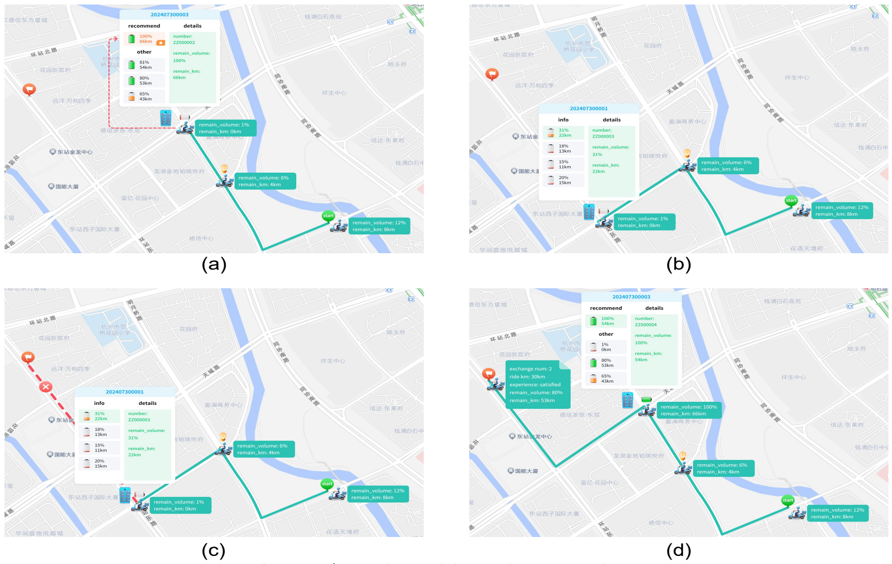

Fig. 2. A real-world application demo.

peak periods, the limited availability of batteries may lead to incorrect choices, requiring users to visit multiple stations before obtaining a high-capacity battery that meets their needs.

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References

1. Chen, T., Guestrin, C.: Xgboost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. p. 785–794 (2016)
2. Cui, D., Wang, Z., Liu, P., Wang, S., Dorrell, D.G., Li, X., Zhan, W.: Operation optimization approaches of electric vehicle battery swapping and charging station: A literature review. Energy **263**, 126095 (2023)
3. Li, Z., Ren, G., Gu, Y., Zhou, S., Liu, X., Huang, J., Li, M.: Real-time e-bike route planning with battery range prediction. In: Proceedings of the 17th ACM International Conference on Web Search and Data Mining. p. 1070–1073 (2024)
4. Ma, J., Zhao, Z., Yi, X., Chen, J., Hong, L., Chi, E.H.: Modeling task relationships in multi-task learning with multi-gate mixture-of-experts. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. p. 1930–1939. KDD '18 (2018)
5. Ma, X., Zhao, L., Huang, G., Wang, Z., Hu, Z., Zhu, X., Gai, K.: Entire space multi-task model: An effective approach for estimating post-click conversion rate. In: Proceedings of the 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. p. 1137–1140 (2018)
6. Revankar, S.R., Kalkhambkar, V.N.: Grid integration of battery swapping station: A review. Journal of Energy Storage **41**, 102937 (2021)