

From Bike Rebalancing to Energy-Aware E-Bike Operations: A Review of Optimization Models and Solution Algorithms

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Abstract: Bike-sharing systems face persistent spatial imbalances caused by uneven travel demand, making vehicle rebalancing an important operational problem. With the development of shared electric bicycles, traditional rebalancing has evolved into a more complex problem involving both vehicle distribution and battery energy management. This paper reviews the development of rebalancing research from conventional bike-sharing systems to energy-aware e-bike operations. First, static and dynamic rebalancing problems and the main operator-based and user-based strategies are summarized. The additional operational challenges introduced by e-bikes are then discussed, with particular attention to battery states, charging, battery swapping, and integrated rebalancing and energy replenishment. Subsequently, major optimization modeling approaches and solution algorithms are reviewed, including mixed-integer programming, rolling-horizon methods, heuristics, and reinforcement-learning-based approaches. The literature indicates a gradual transition from spatial vehicle redistribution toward integrated spatial-energy coordination and more dynamic and intelligent operational management. Future research should further explore joint rebalancing and energy replenishment, real-time optimization, multi-resource coordination, and the integration of operations research with artificial intelligence.

Keywords: Bike-Sharing Rebalancing, E-Bike Sharing, Battery Swapping, Energy-Aware Operations, Optimization Models, Solution Algorithms

1. Introduction

Bike-sharing has become a widely used form of shared mobility for short-distance urban travel and first- and last-mile connections. However, because users can pick up and return bicycles at different locations and travel demand varies over space and time, bicycles are often unevenly distributed across the service area. Some locations may experience shortages while others accumulate excessive bicycles, reducing vehicle availability and system service performance. Rebalancing is therefore an important operational task in bike-sharing systems [1]. Existing studies have developed different approaches to redistribute bicycles from surplus locations to deficient locations. For example, Lahoorpoor et al. [2] investigated static rebalancing by clustering stations and optimizing redistribution routes, while Jin and Tong [3] examined the rebalancing problem in station-free systems and highlighted the additional spatial and computational challenges caused by the absence of fixed stations.

The development of shared electric bicycles further increases the complexity of system operation. In conventional bike-sharing systems, vehicle availability is mainly determined by the spatial distribution of bicycles. In e-bike-sharing systems, however, the remaining battery energy also affects whether an e-bike can continue to serve users. Consequently, operators need to consider not only where e-bikes are located but also their battery conditions and energy-replenishment requirements. Xu et al. [4] studied a dockless e-bike-sharing system in which mobile vans can perform both vehicle rebalancing and battery swapping. Zhou et al. [5] further considered e-bike inventories and battery power levels simultaneously when developing dynamic battery-swapping and rebalancing strategies. These studies show that electrification extends the traditional spatial rebalancing problem to a more complex operational problem involving both vehicle distribution and energy availability.

Existing review studies have summarized many important issues related to conventional bike-sharing rebalancing. Vallez et al. [1], for example, reviewed the major challenges and solution approaches for

dock-based bike-sharing rebalancing. Meanwhile, recent studies have increasingly considered dynamic and data-driven operations. Cipriano et al. [6] developed a data-driven dynamic rebalancing methodology that uses historical usage information to support redistribution decisions. With the expansion of e-bike sharing, however, additional issues such as battery states, charging, battery swapping, and the coordination between relocation and energy replenishment have become increasingly relevant. It is therefore useful to examine the rebalancing literature from the perspective of the transition from conventional bicycles to electric bicycles.

Accordingly, this review summarizes the evolution from conventional bike rebalancing to energy-aware e-bike operational optimization. It first reviews static and dynamic rebalancing and the main strategies used in conventional bike-sharing systems. It then discusses the new operational challenges introduced by battery states and energy replenishment in e-bike-sharing systems. The major optimization models and solution algorithms are subsequently summarized and compared. Finally, future research directions are discussed, particularly regarding spatial-energy coordination, integrated rebalancing and energy replenishment, real-time optimization, and intelligent decision-making methods.

2. Rebalancing in Conventional Bike-Sharing Systems

2.1. Static and Dynamic Rebalancing

Rebalancing in conventional bike-sharing systems can generally be divided into static and dynamic operations. Static rebalancing is usually performed when user activity is low or temporarily ignored. Before the next operating period, bicycles are moved from locations with excessive inventory to those with insufficient inventory so that the system can start from a more balanced state. Typical decisions include the routes of rebalancing vehicles and the numbers of bicycles picked up and delivered at different locations [1,3]. Such problems have been studied not only for station-based systems but also for free-floating systems, where the absence of fixed stations requires the operating area to be divided into suitable spatial units for evaluating bicycle shortages and surpluses [3].

Dynamic rebalancing is conducted while users are continuously renting and returning bicycles. Since bicycle inventories change over time, operators need to update repositioning decisions according to the current and expected system states. Chiariotti et al. [7] proposed a dynamic rebalancing approach that uses historical data to predict station conditions and activates redistribution when necessary. Their results show that an adaptive strategy can better respond to fluctuations in bicycle demand than a fixed rebalancing schedule. Compared with static rebalancing, dynamic approaches can respond to imbalance more quickly, but they also require more frequent state updates and more efficient computational methods. Therefore, the evolution from static to dynamic rebalancing reflects the transition from periodic inventory restoration toward real-time operational management.

2.2. Main Rebalancing Strategies

Existing strategies can also be classified according to who performs the redistribution. The most direct approach is operator-based rebalancing, in which trucks or operational staff physically relocate bicycles between locations. This strategy allows operators to directly control bicycle inventories and is widely used in both station-based and free-floating systems [1,3]. However, frequent truck operations may lead to substantial routing and labor costs.

An alternative is user-based rebalancing, in which users are encouraged to participate in redistribution through incentives. Ban and Hyun [8] developed a simulation framework for a user-participation-based rebalancing service and examined how incentive levels, participation rates, and additional walking distances affect system imbalance and operating costs. Wu et al. [9] similarly considered a free-floating bike-sharing system in which users are financially incentivized to perform repositioning activities under limited information. These studies indicate that user participation can supplement operator-based redistribution and reduce the dependence on dedicated rebalancing vehicles.

In practice, operator- and user-based strategies can also be combined. Operators may use trucks to handle large or urgent imbalances while using incentives to guide smaller-scale bicycle movements through normal user trips. Therefore, conventional bike-sharing rebalancing has gradually developed from a single operator-controlled redistribution process toward more flexible strategies involving both operational resources and users.

3. From Bike Rebalancing to E-Bike Operational Optimization

3.1. New Operational Challenges of E-Bike Sharing

The introduction of electric bicycles adds a new operational dimension to bike-sharing systems. For conventional bicycles, service availability mainly depends on whether bicycles are located where users need them. For e-bikes, however, physical presence alone does not guarantee that a vehicle is available for service because the remaining battery energy must also be sufficient for subsequent trips. Therefore, e-bike-sharing systems need to manage both vehicle distribution and battery conditions.

This difference changes the information required for operational decision making. In addition to bicycle inventories at different locations, operators may need to monitor battery levels and identify e-bikes that require energy replenishment. Zhou et al. [5] explicitly represented both e-bike inventory and battery power levels when developing dynamic battery-swapping and rebalancing strategies. Xu et al. [4] also considered a dockless e-bike-sharing system with removable batteries, in which mobile vans can undertake both vehicle rebalancing and battery-swapping activities. These studies show that the operational state of an e-bike-sharing system is more complex than that of a conventional bike-sharing system because spatial availability and energy availability are interdependent.

Battery requirements also introduce additional infrastructure and resource decisions. Zhao et al. [10] studied the planning of battery-swapping and recharging facilities for e-bike-sharing systems and compared centralized and decentralized recharging arrangements. Their study shows that battery-swapping operations require decisions not only on battery replenishment but also on facility locations and service routes. Thus, energy management becomes an important part of the overall operation of e-bike-sharing systems.

3.2. Charging, Battery Swapping and Integrated Rebalancing

Two common approaches to restoring the energy of shared e-bikes are direct charging and battery swapping. Direct charging requires low-energy e-bikes or their batteries to remain connected to charging facilities for a certain period, which may temporarily reduce the number of serviceable vehicles. Battery swapping, by contrast, replaces a depleted battery with a charged battery and allows the e-bike to return to service more quickly. However, this operating mode requires operators to manage charged and depleted battery inventories and organize the movement of batteries among service locations [5,10].

Because vehicle location and battery status jointly determine whether an e-bike can satisfy demand, rebalancing and energy replenishment are naturally related. Xu et al. [4] considered mobile vans that can perform pure rebalancing, pure battery swapping, or both types of tasks during operation. Zhou et al. [5] further coordinated dynamic e-bike rebalancing and battery swapping according to predicted vehicle inventories and battery states. These studies represent a shift from treating rebalancing and battery management as separate tasks toward their joint consideration.

More recent studies have extended this integration to multiple rebalancing resources. Emami and Ramezani [11] proposed an integrated method for dockless shared e-micromobility in which platform-owned trucks relocate vehicles and replace batteries, while users can also receive incentives to return vehicles to designated locations. Their model simultaneously considers vehicle locations and charge levels and coordinates operator- and user-based actions. This suggests that the operation of electric shared micromobility is gradually moving toward the coordination of vehicle relocation, energy replenishment, and multiple operational resources.

Overall, electrification changes the traditional rebalancing problem from a primarily spatial redistribution problem into a spatial-energy coordination problem. The main operational question is no longer only how bicycles should be moved between surplus and deficient locations, but also how vehicles with different battery conditions should be managed and how energy-replenishment resources should be coordinated with relocation activities. These additional decisions also increase the complexity of optimization models and motivate the different modeling and solution approaches discussed in the following section.

4. Optimization Models and Solution Algorithms

4.1. Optimization Modeling Approaches

Optimization models for bike-sharing rebalancing generally describe the interaction between bicycle inventories and redistribution activities. A commonly used approach is mixed-integer programming (MIP or MILP), in which binary variables represent routing or visiting decisions, while continuous or integer variables describe bicycle pickup, delivery, and inventory levels. Lahoorpoor et al. [2] combined spatial clustering with an optimization model for static rebalancing, while Gao et al. [12] formulated a mixed-integer programming model for dynamic public-bicycle scheduling. In the latter study, station inventory changes were predicted from historical trip data, and vehicle routes were optimized to reduce total redistribution distance. For more complex operational settings, additional constraints can be introduced to represent heterogeneous vehicles, traffic restrictions, or multiple operational resources. For example, Jia et al. [13] formulated a mixed-integer programming model for a bike-sharing rebalancing problem involving a mixed fleet of electric and conventional repositioning vehicles.

Dynamic rebalancing requires models to represent changes in bicycle availability over time. One approach is to divide the operating horizon into successive decision periods and repeatedly update vehicle inventories and redistribution decisions. Rolling-horizon methods are commonly associated with this idea. Gao et al. [12], for example, compared their predictive scheduling method with a rolling-horizon scheduling approach in which the overall operating period is divided into consecutive stages. Data-driven models can further incorporate historical or real-time usage information to estimate future imbalances before determining redistribution actions [6,7].

For sequential decision problems, the system state can also be represented using Markov decision processes or related state-based models. In such formulations, the current distribution of bicycles or expected demand constitutes the system state, while rebalancing or incentive decisions are treated as actions. This modeling structure is particularly useful when future system conditions depend on both user demand and previous operational decisions. Wu et al. [9] used a reinforcement-learning framework for incentive-based rebalancing in a free-floating system, while Pan et al. [14] modeled the bike-sharing rebalancing problem using Markov decision process concepts and deep reinforcement learning. Similar state-based ideas become even more relevant in e-bike-sharing systems because battery conditions must be considered together with vehicle locations [4].

4.2. Solution Algorithms

The selection of solution algorithms largely depends on the scale and dynamic characteristics of the rebalancing problem. Mathematical programming models can directly generate optimized redistribution plans for relatively limited problem sizes, but the computational burden increases quickly when routing, loading and unloading, multiple vehicles, and time-dependent demand are considered simultaneously. Consequently, many studies combine mathematical programming with heuristic or metaheuristic procedures.

Heuristic and metaheuristic algorithms are widely used to obtain good solutions within acceptable computational times. Elhenawy et al. [15] proposed a heuristic method for a large-scale static bike-sharing rebalancing problem with multiple trucks and reported computational times suitable for practical rebalancing applications. Jia et al. [13] combined simulated annealing with variable neighborhood structures to solve their mixed-fleet rebalancing model. Such methods are particularly useful when the number of stations and feasible vehicle routes makes complete enumeration impractical.

Another development is the integration of prediction and optimization. In dynamic operations, historical trip data can first be used to estimate future station inventories or demand, after which redistribution decisions are generated according to the predicted system state [6,12]. This predict-then-optimize structure allows rebalancing decisions to be updated as system conditions change and is therefore more suitable for operating-period redistribution than a single static plan.

Machine-learning-based solution methods have also received increasing attention. Pan et al. [14] applied deep reinforcement learning to learn rebalancing decisions from the spatiotemporal state of a bike-sharing system, while the earlier incentive-based study of Wu et al. [9] also adopted a deep reinforcement learning approach. More recently, hybrid methods have combined traditional optimization with intelligent algorithms. Lim et al. [16], for example, proposed a hybrid genetic algorithm in which genetic search generates feasible vehicle routes and mixed-integer programming determines bicycle

rebalancing decisions. These studies suggest that solution methods are gradually developing from standalone mathematical optimization toward combinations of prediction, heuristic search, and learning-based decision making. Such hybrid approaches may provide greater flexibility for large-scale and dynamic bike- and e-bike-sharing operations.

5. Discussion and Future Research Directions

The reviewed literature shows a clear evolution in bike-sharing rebalancing research. Conventional studies mainly focus on correcting the spatial mismatch between bicycle supply and user demand, whereas e-bike-sharing systems introduce battery conditions and energy replenishment into operational decisions [4,5]. At the same time, dynamic data, prediction methods, and intelligent algorithms have increasingly been incorporated into rebalancing decisions [6,14]. Based on these developments, several research directions deserve further attention.

5.1. Integrated Spatial and Energy Rebalancing

In conventional bike-sharing systems, rebalancing is primarily concerned with moving bicycles between surplus and deficient locations. For e-bike-sharing systems, however, vehicle quantity alone cannot fully represent service capacity because e-bikes with insufficient battery energy may not be able to satisfy subsequent demand. Existing studies have therefore begun to incorporate both vehicle inventory and battery states into operational decisions [4,5].

Future research could further integrate these two dimensions by considering the spatial distribution of both e-bikes and usable energy within a unified framework. Such models should determine not only how many e-bikes are required at each location but also whether their battery conditions are sufficient for expected trips. The dynamic allocation of charged batteries between swapping locations is another related issue. Zou et al. [17], for example, developed a dynamic scheduling model for redistributing fully charged batteries among battery-swapping stations under spatially heterogeneous demand. These developments suggest that future e-bike operations should move from simple vehicle balancing toward coordinated management of vehicle supply and energy supply.

5.2. Joint Rebalancing and Energy Replenishment

Vehicle rebalancing and battery replenishment are closely related because both activities affect the number of serviceable e-bikes available to users. Nevertheless, these activities can require different operational resources and may compete for vehicle capacity, labor, and operating time. Xu et al. [4] considered vans that can undertake rebalancing, battery swapping, or a combination of the two, while Zhou et al. [5] jointly optimized dynamic battery swapping and e-bike rebalancing. Emami and Ramezani [11] further coordinated truck-based battery replacement and vehicle relocation with user-assisted rebalancing. These studies demonstrate the potential benefits of considering multiple operational tasks together.

Future models could further investigate how limited truck capacity, battery inventories, workers, and other operational resources should be shared among relocation and energy-replenishment activities. This issue becomes particularly important in systems containing multiple vehicle types, such as conventional bicycles and e-bikes, where different vehicles have different operational requirements but may share the same rebalancing resources.

5.3. Dynamic and Real-Time Optimization

Static rebalancing is useful for restoring system inventories before an operating period, but actual bike-sharing demand continuously changes throughout the day. Existing dynamic approaches have used historical data, short-term prediction, and rolling decision processes to respond to these changes [6,7,12]. For e-bike-sharing systems, real-time operation becomes more difficult because both vehicle inventories and battery conditions change over time.

Future research should therefore place greater emphasis on adaptive and real-time optimization. One possible direction is to combine short-term demand prediction with rolling-horizon optimization, so that future demand, current bicycle inventories, battery conditions, and operational resources can be updated continuously. Such approaches may provide a practical compromise between long-horizon optimization and the computational requirements of real-time operations.

5.4. Integration of Operations Research and Artificial Intelligence

The increasing availability of bike-sharing operational data creates opportunities for combining traditional operations research methods with machine-learning techniques. Previous research has already applied machine learning to demand prediction, usage analysis, and other bike-sharing problems. Albuquerque et al. [18] reviewed machine-learning applications in bike-sharing systems and identified prediction and classification as major application categories. Deep reinforcement learning has also been directly applied to rebalancing decisions [9,14].

Future research could further combine the strengths of data-driven and optimization-based methods. Machine learning can be used to predict demand, vehicle returns, or future system states, while mathematical optimization can generate operationally feasible rebalancing and energy-replenishment plans. Reinforcement learning may also be combined with mathematical programming, with learning-based methods providing high-level or real-time decisions and optimization models ensuring feasibility under routing, capacity, and energy constraints. Such hybrid approaches could improve the adaptability and computational efficiency of large-scale dynamic bike- and e-bike-sharing operations.

6. Conclusions

This paper reviews the development of rebalancing research from conventional bike-sharing systems to energy-aware e-bike-sharing operations. Conventional bike-sharing studies mainly address spatial supply-demand imbalance through static or dynamic redistribution and employ operator-based, user-based, or combined strategies. With the introduction of e-bikes, battery conditions become an additional determinant of vehicle availability, extending the traditional rebalancing problem to include charging, battery swapping, and energy-resource allocation.

Correspondingly, optimization approaches have developed from conventional routing and mixed-integer programming models toward dynamic, state-based, and data-driven formulations, while solution methods increasingly combine exact optimization, heuristics, rolling-horizon methods, and intelligent algorithms. Overall, the literature indicates a transition from spatial vehicle redistribution toward integrated spatial-energy coordination. Future research should further investigate joint rebalancing and energy replenishment, dynamic resource coordination, real-time optimization, and the integration of operations research with artificial intelligence to support efficient operation of increasingly complex bike- and e-bike-sharing systems.

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