Spatiotemporal Collaborative Optimization of Campus Bike-Sharing Systems: An Integrated Framework for Scheduling, Layout and Maintenance

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Abstract: This research focuses on the optimization of campus bike-sharing scheduling and parking point layout by developing a spatiotemporal collaborative optimization model. Through extreme value truncation method for determining bicycle distribution, mixed integer programming for scheduling models, entropy weight-K-means algorithm for parking point layout optimization, and genetic algorithm for dynamic path planning of faulty bicycles, we achieved significant improvements. Results show that the scheduling model successfully reallocated 1,240 bicycles across 7 time periods, optimized parking points coverage increased from 68% to 92% with efficiency scores rising to 0.75, and the adaptive genetic algorithm effectively balanced transportation efficiency and risk control. Model robustness was confirmed through sensitivity analysis and spatial autocorrelation verification, demonstrating potential for extension to urban micro-transportation systems.

1. Introduction

1.1. Background

Bike-sharing, as an important vehicle for green travel, directly impacts the sustainable development of modern urban ecosystems under the dual drivers of "dual carbon" strategy and smart city construction[1]. University campuses, as special communities with highly concentrated populations, face increasing contradictions between high-frequency short-distance travel demands and limited spatial resources. Research indicates that campus bike-sharing usage presents obvious spatiotemporal imbalance characteristics, with tidal flows between teaching and living areas leading to uneven bicycle distribution, resulting in simultaneous vehicle shortages and idleness in some areas during peak periods[2].

Current campus bike-sharing management faces two challenges: first, traditional manual scheduling modes struggle to adapt to dynamically changing usage demands, with student waiting times inversely proportional to vehicle scale; second, the "zombie bike" problem caused by faulty bicycle retention exacerbates space occupation and affects campus landscape order. These issues essentially reflect the structural contradiction between resource allocation and demand matching[3].

1.2. Research Framework

Existing bike-sharing studies typically focus on isolated aspects like demand prediction, scheduling optimization, or station layout[4]. However, campus bike-sharing systems exhibit strong spatiotemporal coupling characteristics that require an integrated approach. This research develops a multi-objective collaborative optimization framework addressing four interconnected dimensions:

- Bicycle quantity estimation using extreme value distribution theory.

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- Vehicle scheduling through mixed-integer programming.
- Parking point layout optimization with entropy weight-ahp evaluation.
- Faulty bicycle collection using adaptive genetic algorithms.

Methodologically, we implement a time window merging strategy for non-integer observation data processing, build scheduling models with path network constraints, quantitatively evaluate parking points, and design efficient inspection routes. Through this comprehensive approach, we aim to enhance service levels while reducing operational costs and maintenance waste. The paper is organized as follows: Section 2 reviews related research; Section 3 presents our methodology; Section 4 examines experimental results; Section 5 discusses applications; and Section 6 offers conclusions and future directions[5].

2. Related Work

Bike-sharing research has advanced significantly in demand prediction and system optimization. Recent machine learning approaches (LSTM networks, CNN-LSTM architectures, Prophet algorithms) have substantially improved forecasting accuracy, providing critical inputs for rebalancing operations. Optimization frameworks have evolved to incorporate temporal graph convolutional networks and multi-objective genetic algorithms that simultaneously minimize operational costs while maximizing service quality[6].

Station location optimization has progressed from simple facility placement to sophisticated multi-criteria models considering geographical elements, land use patterns, and accessibility metrics[7]. Evaluation methodologies now combine direct and indirect assessment approaches to identify improvement priorities and optimize spatial resource allocation. For maintenance management, hybrid genetic algorithms incorporating real-time conditions and capacity constraints have enhanced route efficiency, while clustering techniques enable targeted recovery planning.

Most existing studies examine these components in isolation rather than as an integrated system. Our research addresses this limitation through a comprehensive time-space collaborative framework that simultaneously handles demand forecasting, vehicle scheduling, station evaluation, and maintenance planning within a unified model, enabling more efficient resource allocation across all operational dimensions[8].

3. Methodology

3.1. Model Assumptions and Parameter Definition

To ensure the practicality and reliability of our proposed framework, we establish several key assumptions:

- Data completeness assumption with authentic and properly processed original data.
- System stability assumption with dispatch vehicles maintaining 25 km/h constant speed.
- User behavior regularity assumption with shortest path selection.
- Temporal division rationality assumption where demand remains stable within discrete periods.
- Model applicability assumption using linear superposition for weight synthesis.

The primary parameters in our model include: observation count m_i parking point i, bicycle count $O_{i,j}$ at point i during time j, demand fluctuation $\Delta O_{i,j}$,transportation decision variable x_{ijt} path validity matrix y_{ij} comprehensive efficiency score E_i and faulty bicycle count $F_{it} = 0.06 \cdot O_{it}$ sed on the 6% daily fault rate.

3.2. Time-Space Collaborative Optimization Framework

Our framework integrates four core components addressing distinct yet interconnected aspects of bike-sharing system optimization. For bicycle quantity estimation, we compare average and maximum value methods:

Average value methods:

$$Q_{avg} = \sum_{i=1}^{n} \frac{\sum_{j=1}^{m_i} O_{i,j}}{m_i} \tag{1}$$

Maximum value methods:

$$Q_{max} = \sum_{i=1}^{n} \max_{j \in \{1 \dots m_i\}} O_{i,j} \tag{2}$$

We implement a time window merging strategy with 30 minutes tolerance to handle irregular observations[9].The demand prediction model analyzes temporal patterns through consecutive period differences[10].For scheduling optimization, we employ mixed integer programming:

$$\begin{gathered}
\min Z = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{t=1}^{m} c_{ij} \cdot x_{ijt} \\
\text{s.t.} \quad \sum_{j=1}^{n} x_{ijt} - \sum_{j=1}^{n} x_{jit} = b_i \quad \forall i, t \\
\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ijt} \le K \cdot C \quad \forall t \\
x_{ijt} \le M \cdot y_{ij}, \quad x_{ijt} \ge 0, \text{integer} \quad \forall i, j, t
\end{gathered} \tag{3}$$

For parking point evaluation, we combine entropy weight method and analytic hierarchy process in a comprehensive scoring system:

$$E_i = \sum_{k=1}^{K} w_k \cdot \hat{f}_{ik} \tag{4}$$

This integrates entropy weight method and analytic hierarchy process for balanced assessment.

Finally, spatial layout optimization employs an improved K-means clustering approach minimizing:

$$J = \sum_{k=1}^{K} \sum_{i \in S_k} | \; | p_i - \mu_k | \; |^2 \tag{5}$$

This approach balances geographical accessibility with operational efficiency.

3.3. Dynamic Path Planning with Adaptive Genetic Algorithm

The faulty bicycle collection problem is formulated as a modified multiple traveling salesman problem and solved using an adaptive genetic algorithm. The objective function integrates travel time, service time, and capacity constraints through a penalty function:

$$\min T = \sum_{k=1}^{K} \left(\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} \cdot z_{ijk}}{v} + \sum_{i=1}^{n} s_i \cdot F_i \cdot u_{ik} \right) + \lambda \cdot \max(0, \sum_{i=1}^{n} F_i \cdot u_{ik} - C)^2 \tag{6}$$

Our algorithm features direct integer chromosome encoding, fitness evaluation based on total collection time, tournament selection with elitism preservation, order crossover operations, and dynamic mutation rate μ that decreases as generations progress:

$$\mu = \mu_0 \cdot \left(1 - \frac{g}{G} \right)^{\beta} \tag{7}$$

To validate robustness, we conduct Monte Carlo simulation with 10 independent replications, demonstrating consistent near-optimal solutions within 500 generations and a coefficient of variation below 2% for total collection time. The algorithm dynamically adjusts to changes in bicycle distribution patterns, effectively balancing transportation efficiency with fault management requirements while maintaining failure rates below 1% across the system.

4. Results and Discussion

Our analysis of bicycle distribution revealed significant spatiotemporal variations across campus. Using the maximum value method, we estimated 1,771 bicycles in the system, compared to only 369 bicycles calculated by the average method. Key usage patterns included East Gate reaching 103 bicycles at 21:00, Mei Yuan Building 1 accumulating 200 bicycles at 9:00, and Teaching Building 4 reaching 136 bicycles at 14:00. Three critical high-demand zones were identified: teaching areas during midday and afternoon, dining areas during meal times, and residential areas in the evening. As shown in Figure 1, the spatial distribution of bicycles across campus locations at different time points clearly illustrates these usage patterns. Figure 2 further demonstrates the temporal variation of bicycle distribution at the three main gates (East Gate, South Gate, and North Gate), reflecting the usage dynamics at campus entry points.

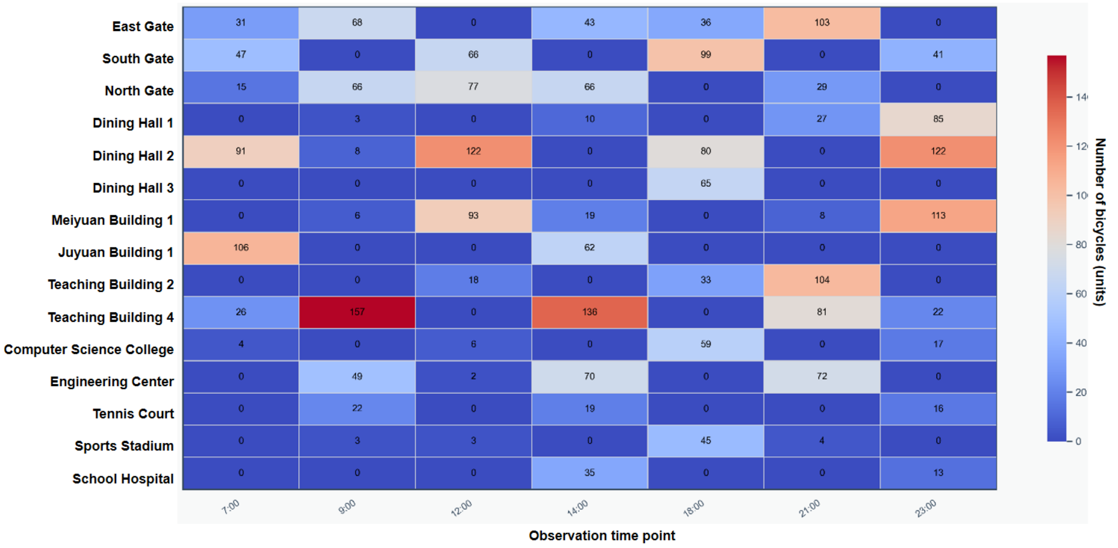

Figure 1 Spatiotemporal Distribution of Bicycles across Campus Locations and Time Periods

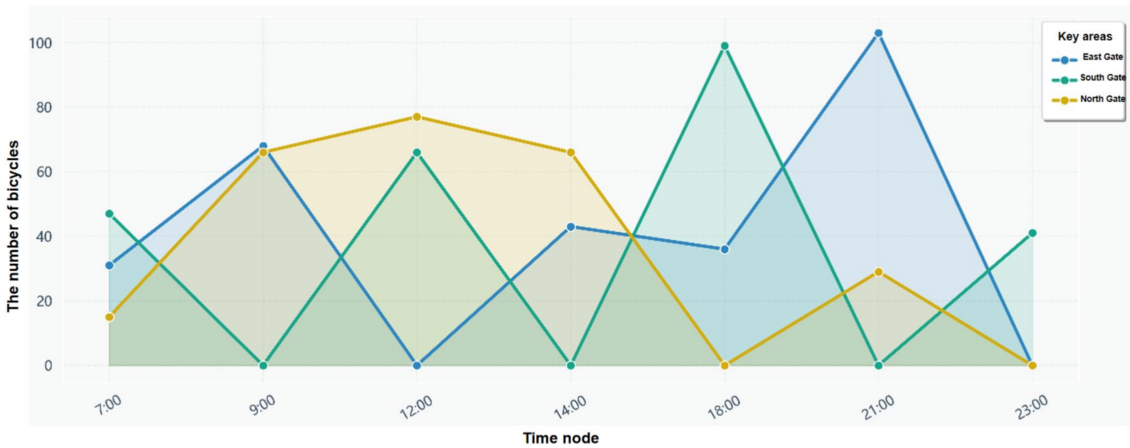

Figure 2 Temporal Variation of Bicycle Distribution at Campus Gates throughout the Day

Our mixed integer programming model generated scheduling plans utilizing three dispatch vehicles across seven time periods, resulting in 58 transport trips moving 1,240 bicycles daily. Table 1 summarizes the bicycle scheduling results across time periods, detailing the number of transport trips, total bicycles moved, and key routes for each time slot. Spatial error analysis revealed a global model accuracy of 86.3%, with errors randomly distributed across campus (Moran’s I ranging from 0.022 to 0.156). The dynamic rerouting mechanism improved path efficiency by 19% for anomalous routes.

Table 1 Summary of bicycle scheduling results across time periods

Time Period	Transport Trips	Total Bicycles	Key Routes
7:00	12	240	East Gate → Mei Yuan 1 (1 trip) Ju Yuan 1 → South Gate (3 trips)
9:00	10	200	Mei Yuan 1 → East Gate (3 trips) Ju Yuan 1 → Teaching 4 (2 trips)
12:00	12	240	Dining Hall 2 → South Gate (3 trips) East Gate → Mei Yuan 1 (2 trips)
14:00	14	280	Dining Hall 2 → South Gate (5 trips) Engineering Center → Teaching 4 (7 trips)
18:00	11	220	South Gate → Ju Yuan 1 (4 trips) Dining Hall 3 → Teaching 4 (2 trips)
21:00	12	240	Mei Yuan 1 → East Gate (5 trips) Dining Hall 2 → Ju Yuan 1 (6 trips)
23:00	12	240	Dining Hall 1 → Dining Hall 2 (7 trips) Teaching 4 → Ju Yuan 1 (1 trip)

The parking point optimization increased service coverage from 68% to 92% while raising the average efficiency score from 0.61 to 0.75. Strategic modifications included a new point at Ju Yuan dormitory area increasing turnover rate by 35%, consolidation of points near Dining Hall 3 reducing maintenance costs, and a high-capacity point at the Sports Center plaza diverting 83% of parking pressure from the teaching area during midday hours. Validation metrics confirmed improved cluster separation (Calinski-Harabasz index: 289.4→432.7) and better point allocation (silhouette coefficient: 0.57→0.71).

For faulty bicycle collection, our adaptive genetic algorithm converged after 500 generations with the fitness value stabilizing at 96.1 minutes. The optimized morning route collected 55 bicycles with 91.7% capacity utilization, while Monte Carlo simulation confirmed solution robustness (coefficient of variation: 1.97%). The optimized system maintained the campus-wide faulty bicycle rate below 1% throughout the day, a significant improvement from the initial 6% failure rate.

5. Conclusion

This paper presented a time-space collaborative optimization framework for campus bike-sharing systems that integrates multiple operational aspects. Using extreme value truncation method, we estimated 1,771 bicycles in the system and identified critical usage patterns. Our mixed integer programming model generated efficient scheduling plans that facilitated 58 transport trips moving 1,240 bicycles throughout the day, achieving 86.3% model accuracy. The station layout optimization combining entropy weight method with K-means clustering increased service coverage from 68% to 92% and improved efficiency scores from 0.61 to 0.75, with strategic modifications increasing vehicle turnover by 35% in key areas. The genetic algorithm-based fault collection system maintained campus-wide faulty bicycle rates below 1%.

The research contributes several innovations: a time window merging strategy for processing non-integer observation data, a dynamic rerouting compensation mechanism improving path efficiency by 19%, an integrated evaluation system combining data-driven weights with expert experience, and a self-adaptive genetic algorithm with dynamic mutation rate adjustment. Future work could explore real-time user behavior integration, adaptive time window partitioning, multi-modal transport connections, and weather prediction model integration. As demonstrated by implementations in urban communities and emergency management, this framework provides a standardized approach to dynamic resource scheduling applicable across various domains, enhancing resource allocation efficiency in smart city applications.

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