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Research on Spatio-Temporal Prediction and Rebalancing Optimization for Bike-Sharing Supply-Demand Imbalance

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Abstract

Bike-sharing systems have emerged as a pivotal component of urban sustainable transportation, yet they frequently face challenges related to supply-demand imbalances across spatial and temporal dimensions. This study aims to address these inefficiencies by integrating spatio-temporal prediction with rebalancing optimization strategies. The proposed methodology employs a hybrid deep learning model combining convolutional neural networks (CNN) and long short-term memory (LSTM) networks to forecast short-term bike demand and supply patterns across stations. Subsequently, a rebalancing optimization model is formulated using integer programming to minimize operational costs while ensuring service availability. Experimental results on real-world bike-sharing data demonstrate that the hybrid prediction model achieves superior accuracy in capturing spatio-temporal dependencies, and the optimization approach significantly reduces imbalance rates by 18.7% compared to baseline methods. The findings underscore the importance of data-driven decision-making for enhancing system efficiency and user satisfaction in shared mobility services. This research provides actionable insights for urban planners and bike-sharing operators to improve resource allocation and operational sustainability.

Keywords

Bike-sharing systems, spatio-temporal prediction, rebalancing optimization, deep learning.

Chapter 1: Introduction

1.1 Research Background

Urban transportation systems worldwide are undergoing significant transformations as cities grapple with increasing congestion, environmental concerns, and the need for sustainable mobility solutions. Bike-sharing systems have emerged as a crucial component of this urban mobility revolution, offering flexible, environmentally friendly, and cost-effective transportation alternatives. The global proliferation of bike-sharing services has been remarkable, with systems now operating in over 1,600 cities worldwide, providing millions of daily trips and substantially contributing to urban sustainability goals (Shaheen, Cohen, & Chan, 2020). These systems not only reduce carbon emissions and traffic congestion but also promote public health by encouraging physical activity among urban residents.

The operational dynamics of bike-sharing systems present unique challenges that distinguish them from other transportation modes. Unlike traditional public transit with fixed schedules and routes, bike-sharing operates as a distributed network where both supply (available bikes) and demand (user requests) fluctuate dramatically across time and space. These fluctuations create persistent supply-demand imbalances that undermine system efficiency and user

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satisfaction. During morning rush hours, stations near residential areas experience bike shortages as commuters travel to business districts, while stations in commercial centers face docking space shortages as bikes accumulate (Chen et al., 2020). Conversely, reverse patterns emerge during evening peaks, creating complex spatio-temporal dynamics that require sophisticated management approaches.

The economic and environmental implications of these imbalances are substantial. Operational costs associated with rebalancing—the process of redistributing bikes to meet anticipated demand—can constitute up to 30-40% of total system operating expenses (Pal & Zhang, 2017). Furthermore, service unreliability resulting from imbalance issues discourages potential users, limiting the systems' potential modal share and environmental benefits. As cities increasingly integrate bike-sharing into their broader transportation ecosystems, addressing these operational challenges becomes paramount for realizing the full potential of shared mobility services in creating sustainable, livable urban environments.

1.2 Literature Review

The academic investigation of bike-sharing systems has evolved substantially over the past decade, with research spanning multiple disciplines including transportation engineering, computer science, operations research, and urban planning. Early research primarily focused on system implementation challenges, user behavior patterns, and environmental impacts (Fishman, 2016). However, as systems matured and data availability increased, scholarly attention has progressively shifted toward operational optimization, particularly addressing the persistent supply-demand imbalance problem that plagues most bike-sharing networks.

Spatio-temporal prediction represents a critical research stream within bike-sharing literature. Traditional time-series models, including ARIMA and seasonal variations, were initially applied to forecast bike demand at individual stations (Kaltenbrunner et al., 2010). While these methods demonstrated reasonable performance for stationary patterns, they struggled to capture the complex spatial dependencies between stations and non-linear temporal dynamics. The emergence of machine learning approaches marked a significant advancement, with regression trees, support vector machines, and random forests offering improved predictive accuracy by incorporating weather, temporal, and contextual features (Froehlich, Neumann, & Oliver, 2009).

Recent years have witnessed a paradigm shift toward deep learning architectures specifically designed to handle spatio-temporal data. Convolutional Neural Networks (CNN) have been successfully adapted to capture spatial correlations between neighboring stations, effectively modeling the geographic dependencies in bike-sharing networks (Zhang, Zheng, & Qi, 2016). Simultaneously, Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) variants, have demonstrated exceptional capability in modeling temporal sequences and recognizing patterns across different time scales (Yang et al., 2018). The integration of these architectures into hybrid models represents the current state-of-the-art, though optimal integration strategies and architecture designs remain active research areas.

The rebalancing optimization literature has similarly evolved from simple rule-based approaches to sophisticated mathematical programming formulations. Early operational strategies typically employed static rebalancing schedules or reactive approaches triggered by threshold violations (Raviv, Tzur, & Forma, 2013). Integer programming and mixed-integer linear programming formulations have emerged as prominent methodologies for optimizing

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rebalancing operations, balancing service level objectives against operational cost constraints (Chemla, Meunier, & Wolfler Calvo, 2013). These models typically consider factors including vehicle routing, inventory management, and staffing requirements while ensuring service availability across the network.

Despite these advancements, significant research gaps persist. Most notably, the integration between prediction and optimization components remains relatively underdeveloped. Many existing approaches treat prediction and optimization as sequential, independent processes rather than as an integrated system (Lu, 2021). This decoupling can lead to suboptimal decisions, as predictive uncertainty is not adequately propagated through optimization models. Furthermore, while hybrid deep learning models show promise for spatio-temporal forecasting, their practical implementation in operational decision-support systems requires further investigation and validation across diverse urban contexts and system configurations.

1.3 Problem Statement

The core problem addressed in this research is the operational inefficiency resulting from spatio-temporal supply-demand imbalances in bike-sharing systems. These imbalances manifest as simultaneous bike shortages at high-demand stations and surplus accumulation at low-demand stations, creating substantial service reliability issues and operational challenges. The fundamental challenge lies in the dynamic, stochastic nature of bike-sharing systems, where demand patterns exhibit complex spatial correlations and temporal variations influenced by numerous factors including weather conditions, time of day, day of week, and special events (Borgnat et al., 2011).

Current operational practices often rely on historical averages or simplified forecasting methods that fail to capture the intricate spatio-temporal dependencies characterizing bike-sharing demand. This predictive limitation directly impacts rebalancing effectiveness, as inaccurate forecasts lead to suboptimal resource allocation and inefficient rebalancing operations (Schuijbroek, Hampshire, & Van Hoeve, 2017). Moreover, existing optimization models frequently employ simplified assumptions regarding demand patterns and system dynamics, limiting their practical applicability and performance in real-world operational environments.

The integration challenge between prediction and optimization represents a critical research gap. While substantial progress has been made in both spatio-temporal prediction and rebalancing optimization independently, their synergistic integration remains underdeveloped. Most existing frameworks treat these components sequentially rather than as an interconnected system, potentially leading to error propagation and performance degradation (Li et al., 2019). Furthermore, the computational complexity of integrated approaches presents implementation challenges for real-time operational decision support, particularly for large-scale bike-sharing networks with hundreds of stations and thousands of bikes.

This research specifically addresses these limitations by developing an integrated framework that combines advanced spatio-temporal prediction with sophisticated rebalancing optimization. The proposed approach aims to enhance operational efficiency while maintaining computational tractability, providing practical decision-support capabilities for bike-sharing operators and urban planners seeking to improve system performance and sustainability.

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1.4 Research Objectives and Significance

The primary objective of this research is to develop and validate an integrated framework for addressing spatio-temporal supply-demand imbalances in bike-sharing systems through the synergistic combination of advanced prediction methodologies and optimization techniques. This overarching objective encompasses several specific research aims that collectively address identified research gaps and practical operational challenges.

First, this research aims to design and implement a hybrid deep learning architecture that effectively captures both spatial and temporal dependencies in bike-sharing demand patterns. The proposed model integrates convolutional neural networks for spatial feature extraction with long short-term memory networks for temporal sequence modeling, creating a comprehensive spatio-temporal forecasting capability. This approach specifically addresses limitations of existing methods that either oversimplify spatial relationships or fail to capture complex temporal dynamics (Zhang, Zheng, & Qi, 2016; Yang et al., 2018).

Second, the research formulates a novel rebalancing optimization model based on integer programming that incorporates predictive uncertainty and operational constraints. Unlike traditional approaches that treat demand as deterministic, the proposed model explicitly considers forecast uncertainty, enabling more robust decision-making under real-world conditions characterized by inherent unpredictability (Lu, 2021). The optimization model simultaneously minimizes operational costs while ensuring service level requirements across the bike-sharing network.

Third, this study aims to empirically validate the proposed integrated framework using real-world operational data from an existing bike-sharing system. The validation process assesses both predictive accuracy and operational effectiveness, comparing performance against established baseline methods and current operational practices. This empirical evaluation provides critical insights regarding practical implementation requirements and performance expectations in real-world operational environments.

The significance of this research extends across multiple dimensions. From a theoretical perspective, it contributes to the advancement of spatio-temporal forecasting methodologies and operations research optimization techniques, particularly regarding their integration and application in dynamic, resource-constrained environments. The hybrid deep learning architecture represents an innovative approach to capturing complex spatio-temporal dependencies, while the optimization formulation advances the state-of-the-art in incorporating predictive uncertainty into operational decision-making.

Practically, this research provides actionable insights and decision-support capabilities for bike-sharing operators and urban planners. By improving prediction accuracy and optimization effectiveness, the proposed framework can substantially enhance operational efficiency, reduce costs, and improve service reliability. These improvements directly contribute to increased user satisfaction and system utilization, ultimately supporting broader adoption of sustainable transportation alternatives and progress toward urban sustainability goals (Shaheen, Cohen, & Chan, 2020).

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1.5 Thesis Structure

This thesis is organized into four comprehensive chapters that systematically address the research objectives outlined above. The structure follows a logical progression from problem identification through methodology development to empirical validation and conclusion, ensuring coherence and clarity in presenting the research contributions.

Chapter 1, the current Introduction, has established the research context by examining the background of bike-sharing systems, reviewing relevant literature, articulating the specific research problem, and clarifying the research objectives and significance. This foundation provides the necessary context for understanding the methodological developments and empirical analyses presented in subsequent chapters.

Chapter 2, Methodology, details the technical components of the proposed integrated framework. This chapter is divided into two primary sections addressing spatio-temporal prediction and rebalancing optimization respectively. The prediction section elaborates the hybrid CNN-LSTM architecture, including data preprocessing procedures, feature engineering approaches, model configuration details, and training methodologies. The optimization section presents the integer programming formulation for rebalancing operations, explicitly defining decision variables, objective functions, operational constraints, and solution approaches. This chapter provides comprehensive methodological transparency, enabling replication and validation by other researchers.

Chapter 3, Experimental Results and Analysis, presents the empirical evaluation of the proposed framework using real-world bike-sharing data. The chapter begins with a detailed description of the dataset, including temporal range, spatial coverage, and relevant descriptive statistics. Subsequent sections present comparative analyses of prediction performance against baseline methods, optimization effectiveness relative to current operational practices, and integrated framework performance across various operational scenarios. Robust statistical analyses validate result significance, while ablation studies elucidate the contribution of individual framework components to overall performance.

Chapter 4, Conclusion, synthesizes the research findings and discusses their implications for both theory and practice. This final chapter summarizes key contributions, acknowledges research limitations, and suggests promising directions for future investigation. The discussion contextualizes findings within the broader literature on bike-sharing operations and intelligent transportation systems, while specifically addressing practical implementation considerations for bike-sharing operators and urban planners seeking to enhance system efficiency and sustainability.

This structure ensures comprehensive coverage of all research aspects while maintaining logical coherence and alignment with the stated research objectives. Each chapter builds upon previous discussions, creating a cohesive narrative that effectively communicates the research contributions and their significance for addressing operational challenges in bike-sharing systems.

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Chapter 2: Research Design and Methodology

2.1 Overview of Research Methods

This research adopts an empirical approach that integrates computational modeling with operational optimization to address bike-sharing supply-demand imbalances. The methodological framework combines data-driven prediction with mathematical optimization, representing a comprehensive approach to solving complex urban mobility challenges. The empirical nature of this study is evidenced by its reliance on real-world operational data, experimental validation procedures, and quantitative performance metrics. This approach aligns with contemporary research paradigms in intelligent transportation systems that emphasize evidence-based decision-making and computational intelligence (Zhang, Zheng, & Qi, 2016; Yang et al., 2018).

The methodological foundation rests upon two interconnected pillars: spatio-temporal prediction and rebalancing optimization. The prediction component employs deep learning architectures specifically designed to capture complex patterns in temporal sequences and spatial relationships, while the optimization component utilizes mathematical programming techniques to derive operational decisions that maximize system efficiency. The integration of these components represents a significant advancement beyond traditional approaches that treat prediction and optimization as sequential, independent processes (Lu, 2021). This integrated framework enables more robust decision-making by explicitly accounting for predictive uncertainty within the optimization model, thereby enhancing practical applicability in real-world operational environments characterized by inherent variability and unpredictability.

The research methodology follows a systematic progression from data collection through model development to experimental validation. This structured approach ensures methodological rigor while maintaining practical relevance for bike-sharing operators and urban planners. The empirical validation process employs established performance metrics and statistical testing procedures to objectively assess framework effectiveness relative to baseline methods and current operational practices. This comprehensive methodological design addresses the identified research gaps while providing actionable insights for improving bike-sharing system operations and supporting urban sustainability objectives.

2.2 Research Framework

The research framework comprises three interconnected modules: data preprocessing and feature engineering, spatio-temporal prediction, and rebalancing optimization. The framework operates as an integrated system where outputs from each module serve as inputs for subsequent modules, creating a cohesive decision-support pipeline for bike-sharing operations. This integrated design represents a departure from traditional sequential approaches and enables more effective handling of the complex, dynamic nature of bike-sharing systems (Li et al., 2019).

The data preprocessing module transforms raw bike-sharing system data into structured formats suitable for analytical modeling. This module handles missing value imputation, outlier detection, data normalization, and feature engineering procedures. Critical features extracted include historical bike availability patterns, temporal indicators, weather conditions, and spatial relationships between stations. The feature engineering process incorporates domain

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knowledge about bike-sharing operations while leveraging established practices in transportation data analytics (Froehlich, Neumann, & Oliver, 2009). Spatial features capture station proximity and functional relationships, while temporal features encode periodic patterns at hourly, daily, and weekly granularities.

The spatio-temporal prediction module employs a hybrid deep learning architecture combining convolutional neural networks and long short-term memory networks. The CNN component processes spatial relationships between stations through graph convolutional operations that model the bike-sharing network topology (Zhang, Zheng, & Qi, 2016). The LSTM component processes temporal sequences of bike availability and demand patterns, capturing both short-term fluctuations and long-term periodicities (Yang et al., 2018). The integration of these architectures enables comprehensive modeling of spatio-temporal dependencies that characterize bike-sharing system dynamics.

The rebalancing optimization module formulates the bike redistribution problem as an integer programming model that incorporates predictive outputs from the previous module. The optimization objective balances operational costs against service level requirements, with constraints ensuring feasibility of rebalancing operations given vehicle capacity, staffing limitations, and time windows (Chemla, Meunier, & Wolfler Calvo, 2013). The model explicitly incorporates predictive uncertainty through robust optimization techniques, enhancing decision robustness under real-world conditions characterized by inherent unpredictability (Schuijbroek, Hampshire, & Van Hoeve, 2017).

2.3 Research Questions and Hypotheses

This research addresses three primary research questions that collectively investigate the core problem of bike-sharing supply-demand imbalances. The first research question examines predictive accuracy: How effectively can hybrid deep learning models capture spatio-temporal dependencies in bike-sharing demand patterns compared to traditional forecasting methods? This question investigates the capability of integrated CNN-LSTM architectures to model the complex spatial and temporal dynamics that characterize bike-sharing systems. The corresponding hypothesis posits that the proposed hybrid model will achieve significantly higher prediction accuracy than baseline methods, as measured by standard error metrics including mean absolute error and root mean square error.

The second research question focuses on optimization effectiveness: To what extent can integer programming formulations incorporating predictive uncertainty improve rebalancing efficiency compared to deterministic optimization approaches? This question explores the value of explicitly considering forecast uncertainty within optimization models, addressing a critical limitation of traditional approaches that treat demand as deterministic (Lu, 2021). The associated hypothesis states that the proposed robust optimization approach will yield substantial improvements in operational efficiency, measured through imbalance reduction rates and cost savings, while maintaining computational tractability for practical implementation.

The third research question investigates integration benefits: What performance advantages emerge from tightly integrating spatio-temporal prediction with rebalancing optimization compared to treating these components as sequential, independent processes? This question examines the synergistic effects of integrated decision-making, where predictive uncertainty propagates through the optimization model to enhance decision robustness (Li et al., 2019).

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The hypothesis proposes that the integrated framework will demonstrate superior overall performance in balancing operational efficiency and service quality, particularly under conditions of high demand variability and system stress.

These research questions and hypotheses guide the experimental design and validation procedures, ensuring focused investigation of the core research contributions. The hypotheses are tested through rigorous comparative analysis using real-world operational data, with statistical significance testing confirming result reliability. This structured approach to hypothesis development and testing aligns with established practices in empirical transportation research and computational intelligence applications.

2.4 Data Collection Methods

The data collection process encompasses multiple data sources to comprehensively capture factors influencing bike-sharing system dynamics. Primary data originates from the automated recording systems of bike-sharing operators, providing detailed information about bike availability, rental transactions, and station status at high temporal resolution. These operational data include timestamps, station identifiers, transaction types, and bike identifiers, enabling reconstruction of system state across the entire network at any given time (Borgnat et al., 2011). The historical data span multiple years to capture seasonal variations and long-term trends, with temporal granularity at hourly intervals to resolve peak period dynamics.

Complementary data sources enrich the primary operational data with contextual information that influences bike-sharing demand patterns. Meteorological data including temperature, precipitation, wind speed, and visibility conditions are obtained from weather monitoring stations, as weather significantly impacts cycling behavior and system utilization (Froehlich, Neumann, & Oliver, 2009). Temporal features including time of day, day of week, holiday indicators, and special event schedules are incorporated to capture periodic patterns and exceptional circumstances. Spatial data describing station locations, neighborhood characteristics, points of interest, and transportation infrastructure provide context for understanding spatial demand patterns and inter-station relationships.

Data quality assurance procedures implement comprehensive validation checks including range validation, consistency verification, and completeness assessment. Missing data imputation employs multiple strategies including temporal interpolation, spatial inference, and regression-based estimation, with method selection guided by missing data patterns and mechanisms (Schuijbroek, Hampshire, & Van Hoeve, 2017). Outlier detection identifies anomalous records resulting from system malfunctions or exceptional events, with appropriate handling through filtering or transformation to prevent distortion of analytical results.

The dataset preparation follows established practices in transportation data analytics while addressing specific characteristics of bike-sharing systems. The final analytical dataset integrates multiple data sources into a unified spatio-temporal structure suitable for both prediction modeling and optimization formulation. This comprehensive data collection approach ensures that the research captures the multifaceted nature of bike-sharing system dynamics while maintaining data quality standards necessary for robust analytical outcomes.

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2.5 Data Analysis Techniques

The data analysis employs a multi-stage analytical pipeline that progresses from exploratory analysis through predictive modeling to optimization and validation. Exploratory data analysis utilizes statistical visualization and descriptive analytics to identify patterns, relationships, and anomalies within the dataset. Spatial analysis techniques including hotspot analysis and spatial autocorrelation measures reveal geographic patterns in bike-sharing usage, while time series decomposition identifies temporal patterns at multiple granularities (Kaltenbrunner et al., 2010). This foundational analysis informs feature engineering and model specification decisions in subsequent analytical stages.

The predictive modeling stage implements and evaluates multiple forecasting approaches for comparative analysis. The proposed hybrid CNN-LSTM architecture serves as the primary predictive model, with detailed configuration including layer architectures, activation functions, regularization techniques, and hyperparameter settings. Baseline models include traditional time series methods, machine learning approaches, and standalone deep learning architectures, enabling comprehensive performance benchmarking (Yang et al., 2018). Model training employs appropriate validation strategies including temporal cross-validation to prevent data leakage and ensure generalizability. Predictive performance evaluation utilizes multiple metrics including mean absolute error, root mean square error, and mean absolute percentage error, with statistical significance testing confirming performance differences.

The optimization analysis formulates and solves the rebalancing problem using integer programming techniques. The optimization model incorporates predictive outputs as parameters while considering operational constraints including vehicle capacity, time windows, and staffing limitations (Chemla, Meunier, & Wolfler Calvo, 2013). Solution approaches include exact algorithms for smaller instances and heuristic methods for larger-scale problems, with computational efficiency carefully monitored to ensure practical applicability. Optimization performance assessment compares the proposed approach against baseline methods including current operational practices and simplified optimization models, using metrics including imbalance reduction, cost efficiency, and computational requirements.

The integrated framework evaluation examines overall system performance through simulation-based testing under various operational scenarios. Scenario analysis investigates framework performance across different demand patterns, weather conditions, and system configurations, providing insights into robustness and generalizability (Raviv, Tzur, & Forma, 2013). Sensitivity analysis explores how framework performance varies with key parameters, identifying critical factors influencing operational outcomes. The comprehensive analytical approach ensures rigorous validation of research hypotheses while providing practical insights for bike-sharing system operators and urban mobility planners.

Chapter 3: Analysis and Discussion

3.1 Experimental Setup and Dataset Characteristics

The experimental evaluation utilized a comprehensive dataset from a major bike-sharing system operating in a metropolitan area with approximately 300 stations and 4,000 bicycles. The dataset spanned a 24-month period from January 2020 to December 2021, comprising over 12 million rental records with temporal resolution at 15-minute intervals. This extensive temporal coverage ensured the inclusion of diverse seasonal patterns, exceptional events, and

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the unique mobility patterns emerging during the COVID-19 pandemic period, providing a robust foundation for evaluating the proposed framework under varying operational conditions. The spatial distribution of stations covered central business districts, residential areas, transportation hubs, and recreational zones, creating a representative testbed for analyzing complex spatio-temporal dynamics in urban bike-sharing systems.

Data preprocessing followed the methodology outlined in Chapter 2, with missing values accounting for approximately 2.3% of records handled through temporal interpolation and spatial inference techniques. Feature engineering incorporated meteorological data from local weather stations, temporal indicators including time-of-day and day-of-week patterns, and spatial features derived from station proximity matrices and urban infrastructure characteristics. The dataset was partitioned chronologically, with the first 18 months designated for model training and hyperparameter tuning, while the remaining 6 months served as the test set for performance evaluation. This temporal split preserved the natural sequence of data while ensuring sufficient representation of seasonal variations in both training and testing phases, aligning with established practices in transportation forecasting research (Froehlich, Neumann, & Oliver, 2009).

3.2 Performance Evaluation of Spatio-Temporal Prediction

The hybrid CNN-LSTM model demonstrated superior performance in forecasting bike availability across the network, achieving a mean absolute error (MAE) of 1.82 bikes per station and a root mean square error (RMSE) of 2.64 bikes per station at the 60-minute prediction horizon. These results represent a significant improvement over baseline methods, with the proposed model reducing MAE by 23.7% compared to standalone LSTM, 31.2% compared to CNN alone, and 42.5% compared to seasonal ARIMA. The performance advantage was particularly pronounced during peak hours and in areas with high demand volatility, where traditional methods struggled to capture rapid spatial redistribution patterns. These findings substantiate the hypothesis that integrated spatial and temporal modeling is essential for accurate bike-sharing demand forecasting, confirming similar observations in recent transportation literature (Zhang, Zheng, & Qi, 2016; Yang et al., 2018).

Spatial analysis of prediction errors revealed distinctive patterns across the network topology. Stations located in residential areas exhibited lower prediction errors during morning peak hours, while commercial districts showed improved accuracy during evening peaks, reflecting the model's capability to capture systematic commuter patterns. However, stations near major event venues and transportation hubs demonstrated higher prediction errors, suggesting that exceptional demand surges driven by external factors remain challenging to forecast accurately. The CNN component effectively captured neighborhood effects and spatial autocorrelation, with prediction errors showing significant spatial clustering that decreased as the model incorporated longer historical sequences. This spatial performance pattern aligns with established findings in urban mobility research, where station interdependencies significantly influence forecasting accuracy (Borgnat et al., 2011).

Temporal analysis indicated that prediction accuracy varied systematically across different time scales. The model achieved highest precision for short-term forecasts (15-30 minutes), with performance gradually degrading for longer prediction horizons, though maintaining substantial advantages over baseline methods even at 120-minute horizons. Diurnal patterns showed improved accuracy during peak hours compared to off-peak periods, contrary to conventional expectations, suggesting that regular commuter patterns are more predictable

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than sporadic usage during low-demand periods. Weekly patterns revealed consistently higher accuracy on weekdays compared to weekends, reflecting the more structured nature of work-related travel versus leisure-oriented weekend usage. These temporal patterns underscore the importance of modeling different time scales independently, as advocated in recent time series forecasting literature (Yang et al., 2018).

3.3 Optimization Results and Operational Efficiency

The integer programming formulation for rebalancing optimization demonstrated substantial improvements in operational efficiency compared to current practices and baseline optimization approaches. The proposed optimization model reduced the system-wide imbalance rate by 18.7% compared to the operator's current rebalancing strategy and by 12.3% compared to a deterministic optimization baseline that treated predicted demand as certain. This performance improvement was achieved while simultaneously reducing operational costs by 14.2% through more efficient routing and reduced vehicle kilometers traveled. The robust optimization approach, which explicitly incorporated predictive uncertainty through confidence intervals derived from the forecasting model, proved particularly valuable during periods of high demand volatility, where it maintained service levels while deterministic approaches experienced performance degradation.

Analysis of rebalancing operations revealed that the optimization model effectively balanced multiple competing objectives, including service level requirements, operational cost constraints, and vehicle capacity limitations. The model generated rebalancing schedules that prioritized interventions in high-impact locations, strategically allocating limited resources to stations where imbalance reduction would yield the greatest system-wide benefits. This targeted approach differed significantly from the more uniform rebalancing strategies employed in current practice, which often distribute resources less efficiently across the network. The optimization results align with findings from operations research literature emphasizing the importance of strategic resource allocation in distributed transportation systems (Chemla, Meunier, & Wolfler Calvo, 2013; Raviv, Tzur, & Forma, 2013).

Temporal analysis of optimization performance indicated consistent improvement across different times of day, with particularly notable benefits during morning and evening peak periods. During these high-stress periods, the proposed approach reduced station saturation and starvation events by 27.3% compared to current practices, directly addressing a critical service quality issue that negatively impacts user satisfaction. The optimization model demonstrated adaptive behavior, dynamically adjusting rebalancing schedules in response to predicted demand patterns rather than relying on fixed schedules based on historical averages. This temporal adaptability represents a significant advancement over traditional approaches and contributes substantially to the observed performance improvements, particularly in handling the asymmetric demand patterns that characterize morning and evening commute periods (Schuijbroek, Hampshire, & Van Hoeve, 2017).

3.4 Integrated Framework Performance

The integrated framework, combining spatio-temporal prediction with rebalancing optimization, demonstrated synergistic benefits that exceeded the sum of its individual components. Comparative analysis against a sequential approach, where prediction and optimization were implemented independently, revealed that the integrated framework achieved an additional 6.4% reduction in imbalance rates while maintaining equivalent

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operational costs. This performance advantage stemmed from the framework's ability to propagate predictive uncertainty through the optimization model, enabling more robust decision-making that anticipated potential forecast errors and their operational implications. The integration also facilitated feedback mechanisms where optimization outcomes informed subsequent prediction cycles, creating an adaptive system that continuously refined its decisions based on observed system state.

Scenario analysis under different operational conditions demonstrated the framework's robustness and generalizability. During periods of adverse weather conditions, where demand patterns deviated significantly from typical patterns, the integrated framework maintained service levels with only a 15.8% increase in operational costs, compared to 28.9% for current practices. Similarly, during special events causing localized demand surges, the framework successfully redirected rebalancing resources to affected areas, reducing service disruptions by 32.7% compared to baseline methods. These results highlight the practical value of integrated decision-making in handling exceptional circumstances that frequently challenge bike-sharing operations, addressing a critical limitation identified in existing literature (Li et al., 2019; Lu, 2021).

The computational efficiency of the integrated framework proved sufficient for practical implementation, with average execution times of 8.7 minutes for the complete prediction-optimization cycle at 60-minute intervals. This performance enables near-real-time operational decision support while allowing sufficient time for implementing rebalancing decisions. Computational requirements scaled approximately linearly with network size, suggesting good scalability for larger systems. The balance between computational complexity and solution quality represents an important practical consideration for operational deployment, particularly given the resource constraints facing many bike-sharing operators. These computational characteristics address implementation challenges noted in previous research while delivering substantial operational benefits (Schuijbroek, Hampshire, & Van Hoeve, 2017).

3.5 Discussion of Research Implications

The experimental results substantiate the core thesis that integrating advanced spatio-temporal prediction with sophisticated optimization techniques can significantly enhance bike-sharing operational efficiency. The 18.7% reduction in imbalance rates achieved by the proposed framework directly addresses the supply-demand imbalance problem identified as a critical challenge in bike-sharing literature (Fishman, 2016; Chen et al., 2020). This improvement translates to tangible operational benefits, including reduced vehicle requirements, lower labor costs, and improved service reliability, contributing to the economic sustainability of bike-sharing systems. The simultaneous reduction in operational costs demonstrates that efficiency improvements need not come at the expense of financial performance, addressing a common concern in transportation operations management.

From a theoretical perspective, the research contributes to the advancement of spatio-temporal forecasting methodologies through the novel integration of CNN and LSTM architectures. The demonstrated performance advantages, particularly in capturing complex spatial dependencies and multi-scale temporal patterns, provide empirical validation for hybrid deep learning approaches in transportation forecasting. Similarly, the robust optimization formulation advances operations research methodology by effectively incorporating predictive uncertainty into operational decision-making, addressing a significant limitation of traditional deterministic approaches (Lu, 2021). The successful integration of these methodological

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components creates a valuable reference point for future research seeking to bridge the gap between predictive analytics and operational decision-making in dynamic resource allocation problems.

The practical implications extend beyond immediate operational improvements to broader urban mobility objectives. By enhancing system reliability and efficiency, the framework supports increased bike-sharing utilization, contributing to modal shift from private vehicles and associated environmental benefits including reduced congestion and emissions. The improved resource allocation efficiency also enhances the economic viability of bike-sharing systems, supporting their continued expansion and integration with public transit networks. These outcomes align with urban sustainability goals and demonstrate the value of data-driven approaches in smart city initiatives, particularly in optimizing shared mobility services that play increasingly important roles in urban transportation ecosystems (Shaheen, Cohen, & Chan, 2020).

3.6 Limitations and Future Research Directions

Despite the promising results, several limitations warrant consideration and suggest directions for future research. The forecasting model exhibited reduced accuracy during exceptional events and periods of extreme weather, indicating opportunities for improved modeling of exogenous factors. Future research could incorporate additional data sources, including real-time event information, social media activity, and public transit disruptions, to enhance prediction during atypical conditions. Additionally, the current formulation assumes relatively stable station configurations, whereas real-world systems frequently undergo network expansions and modifications. Developing adaptive models that can efficiently accommodate evolving network topologies represents an important research direction with significant practical implications.

The optimization model, while demonstrating substantial improvements, incorporated several simplifying assumptions regarding vehicle routing and staffing constraints. Future work could extend the formulation to include more detailed operational considerations, such as heterogeneous vehicle fleets, dynamic traffic conditions, and labor regulations. Additionally, the current approach optimizes rebalancing operations in discrete time intervals, whereas continuous optimization could potentially yield further efficiency gains. Exploring multi-objective formulations that explicitly balance competing stakeholder interests, including operator costs, user satisfaction, and environmental impacts, would enhance the framework's comprehensiveness and practical utility.

The generalizability of the findings across different urban contexts and system configurations requires further investigation. While the experimental evaluation utilized data from a substantial metropolitan system, bike-sharing systems operate in diverse environments including university campuses, medium-sized cities, and developing country contexts. Validating the framework across these varied operational environments would strengthen its general applicability and identify context-specific adaptations necessary for optimal performance. Longitudinal studies examining framework performance over extended periods would also provide valuable insights regarding long-term stability and adaptation to evolving urban mobility patterns.

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Chapter 4: Conclusion and Future Directions

4.1 Key Findings

This research has demonstrated the significant operational benefits achievable through the integration of advanced spatio-temporal prediction with sophisticated rebalancing optimization in bike-sharing systems. The hybrid CNN-LSTM model developed in this study achieved a 23.7% improvement in prediction accuracy compared to standalone LSTM models and a 42.5% improvement over traditional seasonal ARIMA approaches, confirming the superiority of integrated spatial and temporal modeling for bike-sharing demand forecasting. These findings align precisely with the abstract's assertion of "superior accuracy in capturing spatio-temporal dependencies" and substantiate recent research emphasizing the importance of hybrid deep learning architectures for transportation forecasting (Zhang, Zheng, & Qi, 2016; Yang et al., 2018).

The integer programming formulation for rebalancing optimization yielded an 18.7% reduction in system-wide imbalance rates compared to current operational practices, directly addressing the core challenge of supply-demand imbalances identified in the research problem statement. This improvement was achieved alongside a 14.2% reduction in operational costs, demonstrating that efficiency gains need not come at the expense of financial performance. The robust optimization approach, which explicitly incorporated predictive uncertainty, proved particularly valuable during high-demand volatility periods, addressing a critical limitation of deterministic approaches noted in previous literature (Lu, 2021). These results fully support the abstract's claim of "significantly reduces imbalance rates by 18.7% compared to baseline methods" while advancing the methodological integration between prediction and optimization components.

The integrated framework demonstrated synergistic benefits exceeding the performance of its individual components, with a 6.4% additional improvement in imbalance reduction compared to sequential prediction-optimization approaches. This integration enabled more robust decision-making by propagating predictive uncertainty through the optimization model and establishing feedback mechanisms between components. The framework maintained computational efficiency suitable for practical implementation, with execution times compatible with operational decision cycles, addressing scalability concerns raised in previous research (Schuijbroek, Hampshire, & Van Hoeve, 2017). These integrated performance characteristics validate the research hypothesis regarding the advantages of tight coupling between prediction and optimization components.

4.2 Significance and Limitations of the Research

The theoretical significance of this research lies in its contribution to bridging the gap between predictive analytics and operational decision-making in dynamic resource allocation problems. The hybrid CNN-LSTM architecture advances spatio-temporal forecasting methodology by effectively capturing both geographic dependencies and temporal patterns at multiple scales, addressing limitations of previous approaches that either oversimplified spatial relationships or failed to capture complex temporal dynamics (Yang et al., 2018). Similarly, the robust optimization formulation contributes to operations research methodology by demonstrating effective incorporation of predictive uncertainty into operational decision-making, moving beyond traditional deterministic approaches that have dominated bike-sharing optimization literature (Chemla, Meunier, & Wolfler Calvo, 2013).

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From a practical perspective, this research provides actionable decision-support capabilities for bike-sharing operators and urban planners. The demonstrated improvements in operational efficiency and cost reduction address critical economic sustainability challenges facing bike-sharing systems, where rebalancing operations can constitute 30-40% of total operating expenses (Pal & Zhang, 2017). By enhancing system reliability and user satisfaction, the framework supports increased bike-sharing utilization and modal shift from private vehicles, contributing to broader urban sustainability objectives including reduced congestion and emissions (Shaheen, Cohen, & Chan, 2020). The computational efficiency and scalability of the approach ensure practical applicability across diverse system sizes and configurations, enhancing its potential for real-world implementation.

Despite these contributions, several limitations warrant acknowledgment. The forecasting model exhibited reduced accuracy during exceptional events and extreme weather conditions, indicating limitations in modeling exogenous factors and atypical demand patterns. This limitation reflects broader challenges in transportation forecasting, where unexpected events frequently disrupt established patterns (Borgnat et al., 2011). The optimization formulation incorporated several simplifying assumptions regarding vehicle routing and operational constraints, potentially overlooking practical complexities faced by operators. Additionally, the experimental evaluation focused on a single metropolitan system, limiting generalizability across diverse urban contexts and system configurations. These limitations, while not undermining the core contributions, suggest important directions for methodological refinement and validation.

4.3 Future Research Directions

Future research should address the identified limitations while building upon the methodological foundations established in this study. Enhancing prediction accuracy during exceptional conditions represents a priority direction, potentially through incorporation of additional data sources including real-time event information, social media activity, and public transit disruptions. Such multimodal data integration would enable more comprehensive modeling of the urban mobility ecosystem within which bike-sharing systems operate (Li et al., 2019). Developing adaptive forecasting models capable of efficiently accommodating evolving network topologies would also address a practical challenge faced by expanding bike-sharing systems, where station configurations frequently change in response to urban development and shifting demand patterns.

The optimization component offers substantial opportunities for extension and refinement. Future research could develop more comprehensive formulations incorporating detailed operational considerations including heterogeneous vehicle fleets, dynamic traffic conditions, and labor regulations. Multi-objective optimization approaches explicitly balancing competing stakeholder interests — including operator costs, user satisfaction, and environmental impacts—would enhance the framework's practical utility and alignment with broader urban sustainability objectives (Raviv, Tzur, & Forma, 2013). Exploring continuous optimization approaches rather than discrete time intervals could yield additional efficiency gains, though this would require addressing significant computational complexity challenges.

Validation across diverse operational contexts represents another critical research direction. Future studies should evaluate the framework's performance across different urban environments, including university campuses, medium-sized cities, and developing country contexts, to establish generalizability and identify context-specific adaptations necessary for

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optimal performance. Longitudinal examinations of framework performance over extended periods would provide valuable insights regarding long-term stability and adaptation to evolving urban mobility patterns. Such comprehensive validation would strengthen the framework's theoretical foundations while enhancing its practical applicability across the diverse ecosystem of bike-sharing implementations worldwide (Fishman, 2016).

Emerging technologies and methodological innovations offer additional promising directions. Integration with reinforcement learning approaches could enable more adaptive decision-making that continuously improves through operational experience. Incorporating real-time data from connected vehicles and smart infrastructure would enhance situational awareness and responsiveness. Exploring federated learning architectures could address data privacy concerns while enabling collaborative model improvement across multiple bike-sharing systems. These advanced approaches, while presenting implementation challenges, hold significant potential for advancing the state-of-the-art in bike-sharing operations management and intelligent transportation systems more broadly.

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