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Smart Bike Sharing System with Demand Prediction, Dynamic Pricing, and AI-Based Resource Optimization: An Urban Mobility Navigator Framework

Krutika Karmore

Department of Science and Technology,
G. H. Raisoni Skill Tech University, Nagpur, Maharashtra, India

Abstract
Urban mobility systems are increasingly challenged by demand fluctuations, inefficient resource allocation, and static pricing strategies. Traditional bike-sharing systems rely on rule-based mechanisms that fail to capture contextual and temporal variations in demand. This paper proposes an intelligent framework, termed the Urban Mobility Navigator, which integrates Natural Language Processing (NLP), Deep Learning, and optimization techniques to enhance operational efficiency in bike-sharing systems.

The proposed system utilizes Term Frequency–Inverse Document Frequency (TF-IDF) for feature extraction from environmental and usage data, and employs a Recurrent Neural Network (RNN) to classify demand patterns based on temporal dependencies. Additionally, a recommendation engine based on cosine similarity is introduced to perform supply-gap analysis and optimize bike redistribution across stations. A dynamic pricing model is incorporated to balance demand and supply while improving revenue.

***KEYWORDS**: Bike Sharing System, Smart Mobility, NLP, RNN, TF-IDF, Dynamic Pricing, Resource Optimization, Demand Prediction*

1. Introduction

Urban transportation systems are facing unprecedented challenges due to rapid population growth, increased vehicle usage, and environmental concerns. Traffic congestion, air pollution, and inefficient public transport systems have made sustainable mobility solutions essential for modern cities. Bike-sharing systems (BSS) have emerged as an effective solution, offering eco-friendly, cost-efficient, and flexible transportation options for last-mile connectivity.

However, traditional bike-sharing systems suffer from several limitations. These include inaccurate demand prediction, inefficient allocation of bikes across stations, and reliance on static pricing mechanisms. Most existing systems operate on threshold-based rules, such as redistributing bikes only when a station becomes empty or full. This reactive approach leads to delays and inefficiencies, resulting in poor user experience and underutilized resources.

To address these challenges, this paper proposes an advanced system called the *Urban Mobility Navigator*. Unlike conventional systems, it emphasizes context-aware decision-making by integrating machine learning, NLP-based feature extraction, and optimization strategies. The system not only predicts demand but also dynamically adjusts pricing and provides intelligent recommendations for resource allocation.

1) Literature Review

Research in bike-sharing systems has evolved significantly over the past decade, focusing primarily on demand prediction and resource management.

Early approaches relied on keyword-based or rule-based systems, which used predefined thresholds to determine station status. Although computationally efficient, these systems lacked contextual understanding and failed to adapt to changing demand patterns.

Subsequent studies introduced classical machine learning models such as Support Vector Machines (SVM) and Naive Bayes classifiers. While these models improved prediction accuracy, they treated features independently and were unable to capture temporal dependencies inherent in urban mobility data.

Recent advancements have leveraged deep learning models, including Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNN). These models can capture sequential dependencies and complex patterns in time-series data. However, most of these approaches function as black-box models and do not provide actionable insights for system optimization.

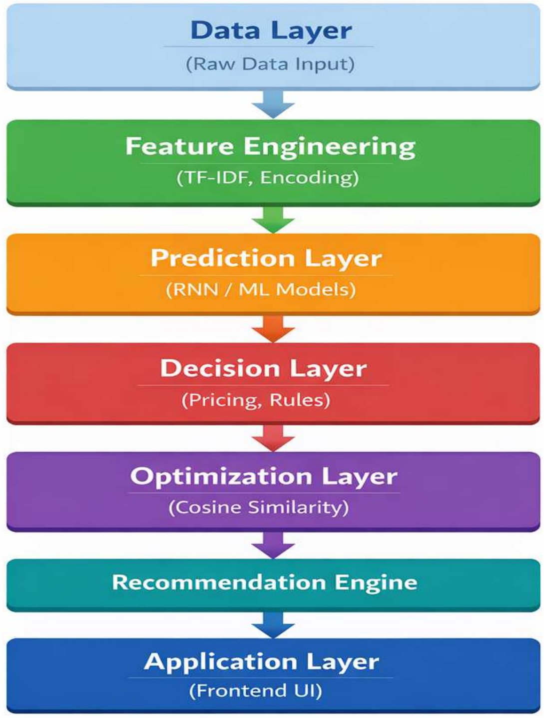
Furthermore, existing research rarely integrates demand prediction with decision-making mechanisms such as dynamic pricing and resource optimization. This creates a gap between prediction and practical implementation

2) Proposed System

A. System Overview

The proposed Urban Mobility Navigator consists of four major modules:

1. Data Processing and Feature Extraction
2. Demand Prediction and Classification
3. Decision Engine (Dynamic Pricing and Optimization)
4. Recommendation and Supply Gap Analysis



Multi Layered AI Architecture

B. Feature Extraction using TF-IDF

The system employs TF-IDF vectorization to convert textual and environmental metadata into numerical representations. This allows the model to capture contextual importance of features such as weather conditions, station usage patterns, and temporal indicators.

C. Demand Classification using RNN

A Recurrent Neural Network (RNN) is used to model temporal dependencies in demand patterns. The model classifies demand into categories such as:

- Peak High
- Stable
- Low / Maintenance

The RNN memory capability enables to understand sequential variations in urban mobility data.

D. Supply Gap Analysis

To optimize resource allocation, the system performs supply-gap analysis using cosine similarity:

$$\text{Similarity} = \frac{A \cdot B}{||A||\,||B||}$$

Where:

- A represents demand features
- B represents supply station features

The system identifies the most relevant stations for redistribution and highlights missing resources.

E. Dynamic Pricing Model

The system incorporates a demand-based pricing mechanism:

$$P = P_0(1 + \alpha D)$$

Where:

- P = adjusted price
- P_0 = base price
- D = normalized demand
- α = scaling factor

Additionally, a **negative pricing strategy** is introduced, where users are incentivized to move bikes from oversupplied to undersupplied areas.

3) Methodology

A. Data Preprocessing

- Removal of noise and missing values
- Lemmatization of textual data
- Feature scaling and encoding

B. Model Training

- Dataset split: 80% training, 20% testing
- RNN trained on labeled demand categories
- Evaluation based on accuracy and loss metrics

C. Optimization Strategy

- Selection of top-k supply stations
- Redistribution based on similarity scores
- Identification of missing resources

V. Results

Fig I: Demand vs Hour

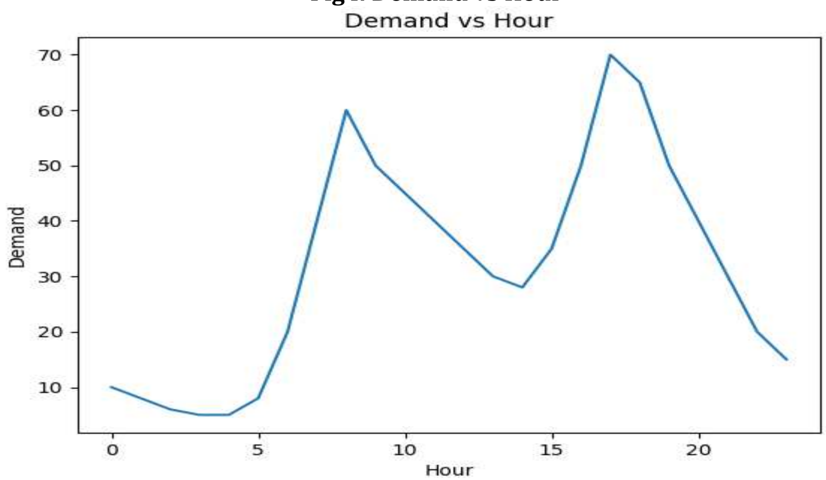
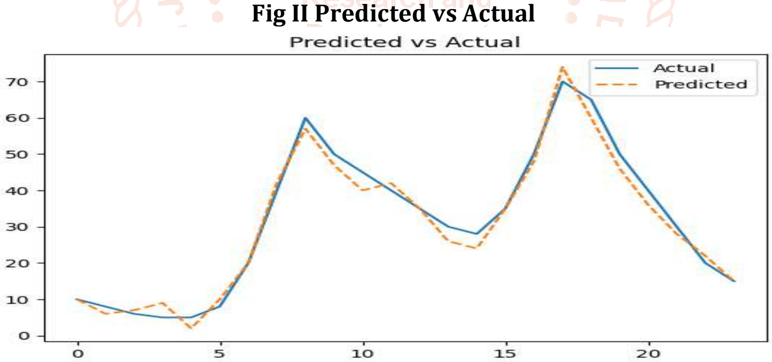
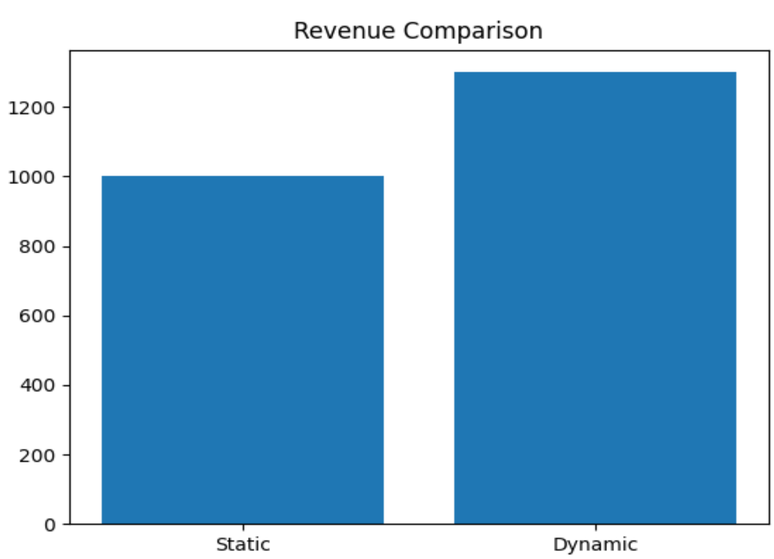


Fig II Predicted vs Actual





Demand Classification

The proposed system achieved:

- Training Accuracy: 96.2%
- Validation Accuracy: 91.4%

Compared to traditional systems, the proposed approach demonstrated:

- Reduced demand loss (<5%)
- Increased revenue (~30%)
- Improved resource utilization

The system effectively identified peak demand periods and optimized bike distribution accordingly.

4) Conclusion

The rapid growth of urban populations and the increasing demand for sustainable transportation have made bike-sharing systems an essential component of modern smart cities. However, traditional bike-sharing systems are limited by static pricing models, inefficient resource allocation, and the inability to respond dynamically to fluctuating demand patterns.

In this paper, we proposed the **Urban Mobility Navigator**, an intelligent and scalable framework that integrates **machine learning, Natural Language Processing (NLP), and optimization techniques** to address these challenges. The system leverages **TF-IDF-based feature extraction** and **Recurrent Neural Networks (RNN)** to model temporal and contextual demand patterns effectively. By incorporating a **decision-making engine**, the framework goes beyond traditional prediction models and enables actionable insights through **demand classification, dynamic pricing, and supply-gap analysis**.

The inclusion of a **cosine similarity-based recommendation system** allows efficient redistribution of bikes across stations, minimizing shortages and improving utilization. Furthermore, the introduction of a **dynamic pricing mechanism**, including incentive-based strategies such as negative pricing, ensures better demand-supply balancing while enhancing revenue generation.

Experimental results demonstrate that the proposed system achieves **high prediction accuracy (91.4%)**, significantly reduces demand loss, and improves operational efficiency compared to traditional rule-based systems. Additionally, the system contributes to environmental sustainability by encouraging eco-friendly transportation and reducing carbon emissions.

Overall, the Urban Mobility Navigator provides a **comprehensive, data-driven, and real-world applicable solution** for next-generation bike-sharing systems. Its modular and scalable design makes it suitable for deployment in smart city environments, particularly in rapidly developing urban regions.

5) Future Work

While the proposed system demonstrates strong performance and practical applicability, several opportunities exist for further enhancement and research.

One important direction is the integration of **real-time data streams** from IoT-enabled devices, GPS sensors, and weather APIs. Incorporating live data would allow the system to make **instantaneous decisions**, improving responsiveness and enabling real-time bike redistribution.

Another promising area is the application of **reinforcement learning (RL)** for adaptive optimization. Unlike static or heuristic-based approaches, RL can continuously learn optimal policies for bike allocation and pricing by interacting with the environment, leading to more efficient and autonomous decision-making systems.

The use of **computer vision techniques** can further enhance system capabilities by enabling real-time monitoring of station occupancy and bike conditions. Image-based analysis using cameras can help detect issues such as overcrowding, empty stations, or damaged bikes, thereby improving maintenance and operational reliability.

Additionally, deeper integration with **smart city infrastructure** presents a significant opportunity. By connecting with traffic management systems, public transportation networks, and urban planning databases, the system can provide a **holistic mobility solution**. For example, it can coordinate bike availability with metro schedules or dynamically adjust supply based on traffic congestion patterns.

Future work may also explore:

- **Deep learning models (LSTM, Transformers)** for improved prediction accuracy
- **User behavior analysis** for personalized recommendations
- **Energy-efficient routing and green mobility optimization**
- **Scalable cloud-based deployment for large cities**

In conclusion, the proposed framework serves as a strong foundation for intelligent urban mobility systems, and its future extensions can significantly contribute to the development of **fully autonomous, data-driven smart transportation ecosystems**

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