



PREDICTING BIKE USAGE AND OPTIMIZING OPERATIONS AT REPAIR SHOPS IN BIKE SHARING SYSTEMS

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Abstract

Big data analytics (BDA) and supply chain responsiveness have attracted a lot of attention from academics and industry professionals. BDA aids researchers in comprehending the huge amount, velocity, and variety of data, among other contemporary data management issues. Improving supply chain networks' responsiveness to bike-sharing systems (BSS), which display BDA features, is the focus of this study. We examine multi-factor BSS data (publicly available data from the Washington, D.C. BSS) that includes parameters like weather, registration, humidity, date, and time in order to estimate bike utilization and optimize repair shop operations accordingly. To forecast bike usage and repair, we employ machine learning techniques such ensemble random forest, K-nearest neighbor, neural networks, decision-tree-based regression, and support vectors. This piece challenges the outcomes and illustrates how well supply chain network design and machine learning work together. Bike repairs are modeled using supply

chain networks using capacity extensions, which involves a nonlinear problem. In this work, we solve a nonlinear supply chain network model using a gradient search. Bike repair shops in the BSS show a promising 50% decrease in lead repair time by enabling capacity extension. Additionally, a 25% boost in BSS throughput is attained overall. In the end, this study shows how crucial operational flexibility is to addressing big data concerns.

1. INTRODUCTION

1.1 Introduction

Fighting pollution and greenhouse gas emissions is a problem that cities around the world must deal with. The movement of people and products in the United States has been responsible for around one-third of carbon dioxide emissions, according to Barth and Boriboonsomsin [7]. In an effort to reduce the detrimental effects of automobile emissions on the environment, several cities around the world have constructed bike lanes and are working to incorporate more cutting-edge technologies to promote sustainable living [24]. As a result, bike sharing has become



more and more popular in recent years. Additionally, contemporary infrastructure—especially non-motorized infrastructure, which helps lessen traffic—is highly valued in smart cities. Typically, bike stations (also known as docking stations) are used for bike sharing, where customers can rent bikes for a fee. Environmental benefits are the primary advantage of bike sharing systems. [64]. On the other hand, dockless systems let users pick up bikes from the closest place and drop them off when they get there. It is still difficult to predict the demand for bikes in both systems. For instance, several cities face problems due to the overabundance of dockless bikes [54]. The upkeep and storage of bikes present another difficulty for bike-sharing programs. Bike wear and tear and failure are caused by frequent use and sporadic misuse. These issues are made worse in colder climates by corrosion brought on by the usage of salt to de-ice roadways. Bikes that are left unattended may also be more susceptible to theft and vandalism. A model that can sustain and forecast bike demand is necessary to meet all of these issues. Bike-sharing systems (BSS) need a supply chain for bike maintenance. network of suppliers of parts and repair companies. A McGill University study [52] found that repair shops have a significant role in both completing

bike maintenance and creating jobs in the community. While some bike-sharing systems incur maintenance costs, others may rely on warranties to outsource maintenance. Information on impending planned maintenance and needed repairs can be obtained from user data from various bike sharing systems. Thus, a wide range of data (maintenance schedule, usage, weather conditions, etc.) would be necessary for an effective maintenance system. The extensive use of data in supply chain management (SCM) has led to significant cost reductions and efficiency gains. Data are essential for lead-time evaluation, supply chain visibility, and demand information sharing amongst supply chain participants [51].

2. Literature Survey

"Short-Term Forecast of Bicycle Usage in Bike Sharing Systems" (2024)

- Description: Proposes a spatial-temporal memory network for accurate short-term bike usage predictions, enhancing operational planning.
- Advantages: Incorporates spatial and temporal dependencies for precision.
- Disadvantages: Computational complexity [15] .

"Bike Usage Forecasting for Optimal Rebalancing Operations" (2023)



- Description: Uses machine learning and constraint programming to optimize daily rebalancing tasks.
- Advantages: Improves resource allocation efficiency.
- Disadvantages: Requires high-quality input data.

"Citywide Bike Usage Prediction in a Bike-Sharing System" (2023)

- Description: Introduces a hierarchical consistency prediction model for citywide bike demand prediction.
- Advantages: Provides granular station-level insights.
- Disadvantages: Limited generalization to other cities.

"Predictive Modelling for Optimization of Field Operations in Bike Sharing Systems" (2022)

- Description: Focuses on forecasting bike availability and rebalancing operations using AI modules.
- Advantages: Facilitates operational optimization.
- Disadvantages: Resource-intensive modelling.

"Bicycle Demand Prediction to Optimize Rebalancing of Bike Sharing Systems" (2022)

- Description: Evaluates demand prediction for rebalancing operations using machine learning techniques.
- Advantages: Enhances system efficiency and reduces downtime.
- Disadvantages: May face accuracy challenges in dynamic environments

3. OVERVIEW OF THE SYSTEM

3.1 Existing System

Current bike-sharing systems rely on traditional statistical methods for predicting bike usage and managing repair operations. These include simple regression models and historical data analysis. While these systems provide basic insights, they fail to consider complex patterns in demand and maintenance schedules, leading to inefficiencies in resource allocation and station rebalancing. Limited integration of advanced algorithms results in suboptimal repair schedules and delayed services, negatively impacting user satisfaction.

3.1.1 Disadvantages of Existing System

- Inability to capture real-time demand fluctuations.
- Inefficiency in predicting station-level bike shortages.
- Lack of dynamic rebalancing mechanisms.
- High downtime for repairs and maintenance.
- Poor integration with operational data



streams.

- Overreliance on manual decision-making.
- Limited scalability to different urban contexts.
- Ineffectiveness in resource allocation.
- Delays in service response during peak hours.
- Increased operational costs due to inefficiencies.

3.2 Proposed System

- The proposed system addresses the identified gap in research by designing a supply chain network for BSS management that integrates demand prediction, repair shop capacities, and transportation costs.
- Multiple machine learning algorithms are employed to predict the demand for bike repairs, which serves as input for the supply chain network. The repair shops are designed to be flexible, capable of extending their capacities to meet demand fluctuations.
- The model considers transportation costs across the supply chain and aims to provide decision-makers, such as city planners, with operational characteristics for optimizing service levels and operational costs.

3.3 Methodology

Service Provider

In this module, the Service Provider has to

login by using valid user name and password.

After login successful he can do some operations such as Train & Test Bike Data Sets, View Trained and Tested Bike Datasets Accuracy in Bar Chart, View Trained and Tested Bike Datasets Accuracy Results, View Bike Usage and Repair Time Type, Find Bike Usage and Repair Time Type Ratio, Download Predicted Datasets, View Bike Usage and Repair Time Type Ratio Results, View All Remote Users

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorize the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT BIKE USAGE AND REPAIR TIME TYPE, VIEW YOUR PROFILE.

Dataset

we will take bike repair data set from online sources which has features as customer bike repair details and prediction labels

Preprocessing

Data is in text format to convert data to binary we use count vectorizer in preprocessing and

regular expression to convert data without unwanted data.

Model Training Module:

In this module data set is collected from online sources website and data is preprocessed and converted using count vectorizer, then testing training dataset is divided, algorithm is initialized and features are labels are fitted to algorithm and prediction with accuracy is performed then model is saved to system.

4 Architecture

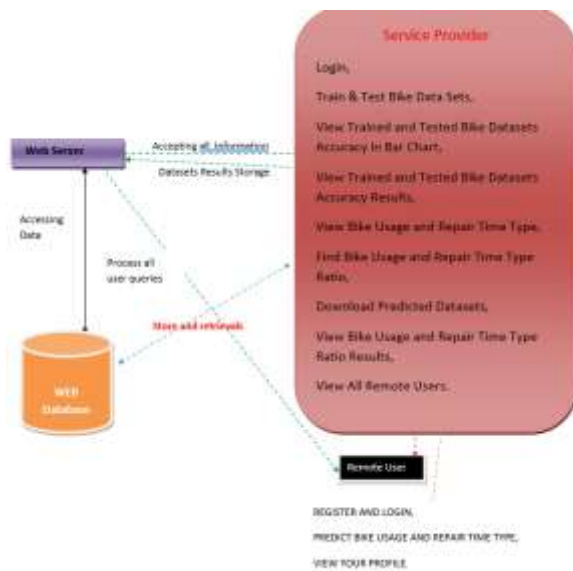


Fig 1: Frame work of proposed method

Figure 1 depicts our proposed model for the bike optimization operations identification method using random forest classifier.

5 RESULTS SCREEN SHOTS

DATASET:



Home Page:



Input Form:



Prediction Result:



Comparison Graph:



6. CONCLUSION

- ✓ The proposed system revolutionizes bike-sharing operations by integrating machine learning to predict usage patterns, optimize repair shop schedules, and enhance resource allocation. By addressing the limitations of existing systems, it ensures efficient station rebalancing, reduces downtime, and improves user satisfaction. Proactive maintenance scheduling and real-time decision-making make the system robust and scalable. Its data-driven approach significantly reduces operational costs, paving the way for smarter and more efficient urban mobility solutions..

7. Future Enhancement

Predicting bike usage and optimizing operations at repair shops within bike-sharing systems has a promising future scope, especially with advancements in data analytics, machine learning, and IoT (Internet of Things) technologies. Here are some key aspects of its future scope: Improved Predictive Models: As more data becomes available from bike-sharing systems, predictive models can become more accurate and sophisticated. These models can forecast bike demand at different locations and times, enabling operators to optimize bike distribution and maintenance schedules. IoT Integration: IoT devices can be used to gather real-time data on bike usage and condition. For instance, sensors on bikes can provide information on location, usage patterns, and mechanical health. This data can be leveraged to predict maintenance needs and reduce downtime. Maintenance Automation: Predictive analytics can aid in automating maintenance workflows. By predicting when bikes require servicing or repairs, operators can proactively schedule maintenance tasks, reducing operational costs and improving service reliability.

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8. References

- [2] R. Alvarez-Valdes, J. M. Belenguer, E. Benavent, J. D. Bermudez, F. Muñoz, E. Vercher, and F. Verdejo, “Optimizing the level of service quality of a bike-sharing system,” *Omega*, vol. 62, pp. 163–175, Jul. 2016.
- [3] C. Alzaman, Z.-H. Zhang, and A. Diabat, “Supply chain network design with direct and indirect production costs: Hybrid gradient and local search based heuristics,” *Int. J. Prod. Econ.*, vol. 203, pp. 203–215, Sep. 2018.
- [4] O. C. Arqué. (Jul. 7, 2020). Demand Forecast Model For A Bicycle Sharing Service. [Online]. Available: https://upcommons.upc.edu/bitstream/handle/2117/78121/Tesi_na.pdf?sequence=1&isAllowed=y
- [5] H. I. Ashqar, M. Elhenawy, M. H. Almannaa, A. Ghanem, H. A. Rakha, and L. House, “Modeling bike availability in a bike-sharing system using machine learning,” in *Proc. 5th IEEE Int. Conf. Models Technol. for Intell. Transp. Syst. (MT-ITS)*, Jun. 2017, pp. 374–378.
- [6] H. I. Ashqar, M. Elhenawy, H. A. Rakha, M. Almannaa, and L. House, “Network and station-level bike-sharing system prediction: A san Francisco bay area case study,” *J. Intell. Transp. Syst.*, vol. 26, no. 5, pp. 602–612, Sep. 2022.
- [7] M. Barth and K. Boriboonsomsin, “Traffic congestion and greenhouse gases,” Univ. California Transp. Center, Berkeley, CA, USA, Tech. Rep., 2011. [Online]. Available: http://www.uctc.net/access/35/access35_Traffic_Congestion_and_Grenhouse_Gases.shtml
- [8] L. Breiman, “Bagging predictors,” *Mach. Learn.*, vol. 24, no. 2, pp. 123–140, 1996.
- [9] X. Bustamante, R. Federo, and X. Fernández-i-Marin, “Riding the wave: Predicting the use of the bike-sharing system in Barcelona before and during COVID-19,” *Sustain. Cities Soc.*, vol. 83, Aug. 2022, Art. no. 103929.
- [10] A. Chatzikontidou, P. Longinidis, P. Tsiakis, and M. C. Georgiadis, “Flexible supply chain network design under uncertainty,” *Chem. Eng. Res. Design*, vol. 128, pp. 290–305, Dec. 2017.
- [11] H. Chen, R. H. L. Chiang, and V. C. Storey, “Business intelligence and analytics: From big data to big impact,” *MIS Quart.*, vol. 36, no. 4, pp. 1165–1188, Dec. 2012.
- [12] Y. L. Chong, B. Li, E. W. Ngai, E. Ch’ng, and F. Lee, “Predicting online product sales via online reviews, sentiments, and promotion strategies,” *Int. J. Oper. Prod. Manage.*, vol. 36, no. 3, pp. 366–386, 2016.
- [13] E. Collini, P. Nesi, and G. Pantaleo, “Deep learning for short-ter.