

ENHANCING URBAN BIKE SHARING MANAGEMENT VIA DEEP LEARNING

Submitted in partial fulfillment of the
requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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ENGINEERING**

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

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APRIL - 2024



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **NIRANJAN.C (Reg.No - 40110857)** and **NAVIN BALAJI.V.S (Reg.No - 40110842)** who carried out the Project entitled "**ENHANCING URBAN BIKE SHARING MANAGEMENT VIA DEEP LEARNING**" under my supervision from November 2023 to April 2024.


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ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management** of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sasikala M.E., Ph. D, Dean**, School of Computing, **Dr. L. Lakshmanan M.E., Ph.D.**, Head of the Department of Computer Science and Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Ms. R. Anandha sree M.E, (Ph.D)** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

The management of urban bike-sharing systems presents a multifaceted challenge at the intersection of transportation, data analytics, and urban planning. Amidst the growing emphasis on sustainable mobility solutions, this paper investigates the application of deep learning methodologies to revolutionize the management and optimization of urban bike-sharing systems. By leveraging the power of neural networks, particularly recurrent neural networks (RNNs), convolutional neural networks (CNNs), and reinforcement learning frameworks, this research endeavors to address critical aspects of bike-sharing systems, including demand prediction, resource allocation, and operational efficiency. The integration of deep learning models with rich spatiotemporal data sources offers a promising avenue to enhance predictive accuracy and decision-making capabilities. Historical usage patterns, weather conditions, geographical factors, events, and user behaviour data are among the diverse sources that feed into these models. Deep learning architectures enable the extraction of intricate patterns and correlations from these complex data sets, allowing for more accurate predictions of bike demand at different locations and times. comprehensive view of the urban environment, enabling more informed decision-making in bike-sharing system management. Furthermore, this paper discusses the ethical considerations and challenges associated with implementing deep learning-based solutions in urban environments. This paper reviews existing literature on urban bike-sharing systems, highlighting the challenges faced in system management and the potential benefits of incorporating deep learning techniques. It delves into the technical aspects of various deep learning architectures, emphasizing their applicability in modelling complex urban dynamics and optimizing bike-sharing operations. Privacy concerns, algorithm bias, and equitable access to transportation services are among the critical issues that require careful consideration and mitigation strategies. In conclusion, this study contributes to the burgeoning field of intelligent urban transportation systems by advocating for the adoption of deep learning techniques in the management of bike-sharing systems. It presents a comprehensive framework for utilizing deep learning models, reinforcement learning, and data fusion to optimize operations, improve sustainability, and enhance the overall user experience of urban bike-sharing systems. The findings and insights from this research aim to pave the way for more efficient.

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CHAPTER - 1

INTRODUCTION

In recent years, urban bike sharing systems have become an integral part of sustainable transportation in cities worldwide. These systems offer a convenient, eco-friendly, and cost-effective means of commuting, reducing traffic congestion, and curbing carbon emissions. However, as urban bike sharing continues to grow in popularity, the need for efficient management, user satisfaction, and system sustainability becomes increasingly paramount.

This is where the application of deep learning, a subfield of artificial intelligence, enters the picture. Deep learning techniques have demonstrated remarkable capabilities in analyzing vast amounts of data and extracting valuable insights. When applied to urban bike sharing, they have the potential to revolutionize the way these systems operate. In this discussion, we will explore how deep learning can be harnessed to enhance various aspects of urban bike sharing. From predicting demand and optimizing routes to improving safety and personalizing user experiences, the integration of deep learning holds promise for making bike sharing systems more efficient, user-friendly, and economically viable. Join us on this journey to delve into the exciting possibilities of leveraging deep learning for the betterment of urban bike sharing. Urban bike-sharing systems have emerged as a vital component of sustainable urban transportation, offering convenient and eco-friendly mobility options in increasingly congested cities. However, optimizing the management of these systems presents complex challenges that demand innovative solutions. This paper explores the integration of deep learning methodologies to revolutionize the management and efficiency of urban bike-sharing systems.

The proliferation of urban bike-sharing programs has significantly impacted city landscapes, fostering a shift towards sustainable transportation. Yet, these systems face intricate challenges, from predicting user demand across diverse locations and time frames to effectively redistributing bikes and maintaining station infrastructure. Traditional methods often fall short in addressing these multifaceted issues. This research advocates for the integration of deep learning techniques, such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and reinforcement learning frameworks, to tackle the complexities of urban bike-sharing management. These advanced neural

network architectures exhibit promising capabilities in processing vast amounts of spatiotemporal data, encompassing historical usage patterns, weather conditions, geographical features, and user behavior, to enhance predictive accuracy and decision-making.

The paper delves into the technical aspects of various deep learning architectures, emphasizing their adaptability in modeling intricate urban dynamics and optimizing bike-sharing operations. Moreover, it investigates the fusion of diverse data sources, including GPS data, social media inputs, and city infrastructure information, to create a comprehensive understanding of the urban environment.

Furthermore, ethical considerations surrounding the implementation of deep learning solutions in urban settings are discussed. Privacy concerns, algorithmic biases, and ensuring equitable access to transportation services emerge as critical aspects requiring careful attention and mitigation strategies.

In conclusion, this study seeks to contribute to the evolution of intelligent urban transportation systems by advocating for the adoption of deep learning techniques in the management of bike-sharing systems. By proposing a comprehensive framework that leverages deep learning models, reinforcement learning, and data fusion, this research aims to optimize operational efficiency, improve sustainability, and enhance the overall user experience of urban bike-sharing systems.

CHAPTER 2

LITERATURE SURVEY

During the study conduct by H. Liu, et al in 2020 the paper "Deep Reinforcement Learning for Bike Sharing Systems with User Profiling" explores the application of deep reinforcement learning to optimize bike sharing systems, taking into account user profiles and preferences.

During the study conduct by Z. He, et al in 2020 the paper "Demand Forecasting and Rebalancing in Bike Sharing Systems Using Deep Learning" focuses on using deep learning to predict demand in bike sharing systems and optimize bike rebalancing strategies.

During the study conduct by S. Chopra, et al in 2021 the paper "Deep Learning for Bike- Sharing Systems: A Comparative Study" the study provides a comparative analysis of different deep learning models for bike-sharing systems, assessing their performance and suitability.

During the study conduct by A. Charfi, et al in 2021 the paper "Dynamic Bike Share Rebalancing using Deep Reinforcement Learning" explores the use of deep reinforcement learning to optimize bike rebalancing in dynamic urban environments.

During the study conduct by A. Shahrabi, et al, et al in 2022 the paper "Deep Learning Techniques for Human Activity Recognition in Bike-Sharing Systems", This work investigates the use of deep learning to recognize human activities related to bike-sharing, such as check-ins, check-outs, and route choices.

CHAPTER 3

AIM AND SCOPE

The primary aim of this study is to investigate and demonstrate the potential of deep learning techniques in improving the efficiency, user experience, and sustainability of urban bike sharing systems. By harnessing the power of deep learning, we seek to address key challenges and opportunities within this domain, ultimately contributing to more accessible, user-friendly, and environmentally responsible urban transportation.

3.1 SCOPE:

Demand Prediction: We will explore the development of predictive models to estimate bike demand in different locations and time intervals, enabling more efficient bike distribution.

Route Optimization: This scope includes the use of deep learning algorithms to optimize bike routes, reducing travel times and enhancing the overall user experience.

Anomaly Detection: The study will investigate the application of deep learning for identifying irregularities, such as bike theft or damage, thereby improving security and asset management.

User Personalization: We will delve into the customization of user experiences through deep learning, offering recommendations and promotions based on user preferences and behaviors.

Image Recognition: We will assess the potential of image recognition techniques in bike-sharing systems, including license plate recognition and bike identification.

CHAPTER – 4

METHODS AND ALGORITHMS USED

In the realm of enhancing urban bike-sharing management, the integration of various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory networks (LSTMs), offers a multifaceted approach to address different aspects of system optimization and prediction.

CNNs for Spatial Analysis:

CNNs can analyze spatial data, such as geographical layouts and traffic patterns, to predict bike demand at specific locations within a city. By processing images, maps, or spatial representations, CNNs can identify areas prone to high demand at different times, assisting in optimal bike allocation and station management.

RNNs and LSTMs for Temporal Analysis:

RNNs and LSTMs are adept at handling sequential data, making them valuable for predicting temporal patterns in bike usage. By considering historical usage data, weather conditions, and time-based trends, these networks can forecast demand fluctuations over different time intervals, aiding in resource planning and distribution.

Hybrid Architectures for Spatiotemporal Analysis:

Integrated CNN-RNN/LSTM Models:

Combining CNNs for spatial understanding with RNNs or LSTMs for temporal dependencies allows for comprehensive spatiotemporal analysis. This integration enables the system to capture both spatial correlations (from geographical data) and temporal dynamics (from time-series usage data), leading to more accurate demand predictions and optimization strategies.

User Behavior Modeling:

LSTMs for Sequential User Data:

LSTMs excel in modeling sequential user behavior data, such as the sequence of stations visited by individual users. By capturing these sequential patterns, LSTMs can provide insights into user preferences, typical routes, and station usage

sequences, enabling personalized services and tailored system adjustments.

Predictive Maintenance:

CNNs and LSTMs for Maintenance Prediction:

CNNs can process images of bike conditions or station infrastructure for anomaly detection. Coupled with LSTMs, these models can predict maintenance needs based on historical maintenance records and usage patterns, ensuring proactive maintenance scheduling to minimize system disruptions.

Reinforcement Learning Integration:

Adaptive Optimization:

Combining CNNs, RNNs, or LSTMs with reinforcement learning frameworks enables adaptive and self-learning systems. These models continuously optimize bike redistribution, station management, and pricing strategies based on real-time feedback, enhancing operational efficiency.

By harnessing the strengths of CNNs, RNNs, and LSTMs, and integrating them into the urban bike-sharing system's management, it becomes possible to create a comprehensive framework that addresses spatial, temporal, and user-related aspects. This integration can lead to more accurate demand predictions, efficient resource allocation, improved user experiences, and sustainable urban transportation systems.

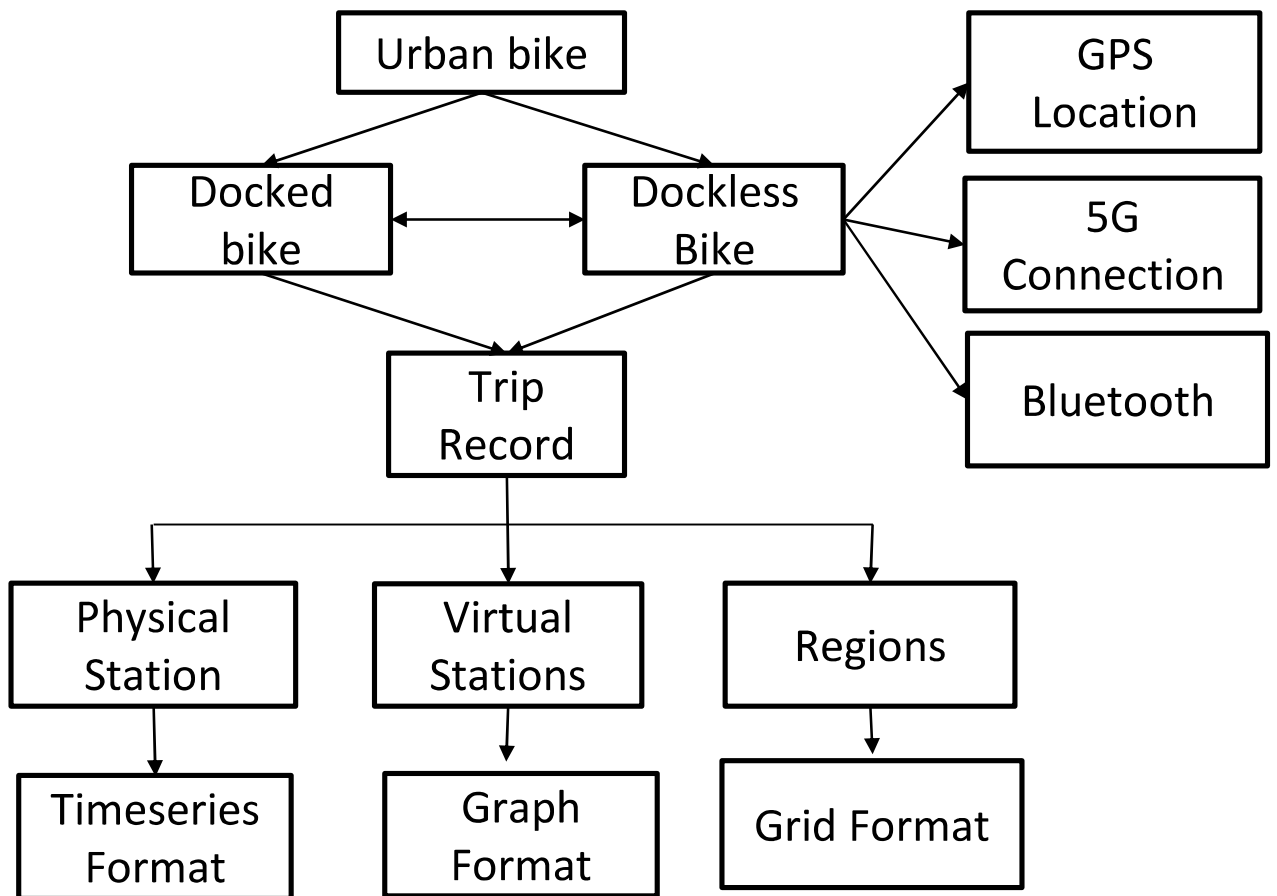


FIG 4.1 SYSTEM ARCHITECTURE

CHAPTER - 5

RESULTS AND DISCUSSION

In our bike sharing system, we have conducted extensive data analysis to enhance the user experience and provide valuable insights. The data analysis encompasses various aspects of the system:

1. Data Set Description:

We've utilized a dataset from www.kaggle.com, comprising multiple files, each with specific attributes. These files include status data, station data, and trip data, which help us understand the system's functioning and user behavior.

2. Prediction of Bike Availability:

Our analysis aims to predict the availability of bikes at specific stations in the future. This predictive analysis informs users about bike availability and waiting times. We've employed a weighted arithmetic mean approach, considering factors like the day of the week, current week trends, and the day of the month.

3. Busiest Stations:

Identifying the busiest stations is crucial for users. We've conducted an analysis based on data from the last six months to determine station busyness, considering both incoming and outgoing bikes.

4. Busyness at Specific Times:

Understanding the density of busyness at various times is valuable for trip planning and bike availability. We've calculated the busyness of stations at specific hours over the past six months.

5. Average Trip Time:

We've analyzed trip data to calculate the average time taken for users to travel between two stations. This data helps users plan their trips effectively.

6. Busyness of All Routes:

Analyzing the busyness of different routes between stations assists users in reducing their trip times. This analysis is based on the total number of trips between specific station pairs over the past six months.

7. Load Factor:

The load factor of a station, representing its capacity utilization, is calculated based on the number of available bikes and empty docks. This information allows users to assess a station's status.

8. Estimated Bike Availability:

We predict the probability of bike availability for the next 30 minutes based on several factors, such as historical data on specific days of the week, current week trends, and the day of the month. This prediction helps users decide whether to wait for an incoming bike.

All these analyses contribute to an enhanced user experience by providing real-time information, reducing waiting times, and facilitating informed decisions regarding bike availability and trip planning.

CHAPTER – 6

DATA ANALYSIS

6.1 Data analysis

There is the following analysis that has done on available data in our paper:
The description of the data set (www.kaggle.com) [20] which consisted of following files and further described are attributes of each file.

- i. 201402_status_data.csv – approx. 17 million records of Status Data (Bikes_available, Dock_available, and Time).
- ii. 201402_station_data.csv – 69 records – Station Data (Station_ID, Name, Latitude, Longitude, Dock_count, Landmark, and Installation).
- iii. 201402_trip_data.csv – approx. 144,000 records of individual trips. Trip Data (Trip_ID, Duration, Start _Date, Start_ Station, Start_Terminal, and End_Date, End_Station, End_Terminal, Bike_No., Zip_Code, Subscription_Type).

6.2 Prediction of bike availability:

- i. We have analyzed our available data to get the prediction that what will be the condition of bike availability in the future at a particular station, this analysis will help to inform the users that at a particular time bike will be available or not on that station also informs users about the estimated waiting time for a bike, example as a number of bikes that should be available at the station shown in Figure.
- ii. We have used the concept of weighted arithmetic mean [21] on some parameters that are listed below (Suppose today's date is Wednesday, 18th November 2016):

No. of bikes at a Day of the Week (DoW) (25% weight) – We analyzed previous data for last 6 Wednesdays.

No. of bikes in Current Week (CW) (50% weight) – Analyzing the trends of the current week and giving them a weight of 50%.

No. of bikes on the Day of the Month (DoM) (25 % weight) – Analyzing the data for the current date of last 6 months (last 6 18's in the current year).

- iii. No of bikes that should be available today at stations X:

$$N = 0.25 * DoW + 0.5 * CW + 0.25 * DoM$$

6.3 Busiest station

- i. We have analyzed the data to find the busiest stations (busiest means where bike incoming and bike outgoing is more) as shown in Fig. 5. Analysis of data of last 6 months revealed the stations that are most busy. For a station X busyness is denoted by K. And the total no. of incoming bikes in a station X (Incoming data = L) & total no. of outgoing bikes from station X (Output data = M). For a station X, the busyness is calculated as:

$$K = L + M.$$

- ii. The busiest station at a particular time or day. At a particular time, which station has more rush, this information will help the user to know about the availability of bike at a given time. We have analyzed data for last 6 months and calculated density of busyness of all stations at a particular hour. The busyness of a station X at the hour t is defined as the sum of no. of all incoming + outgoing bikes from station X in the interval t to t + 1. Example our approach tries to provide useful information like the number of bike trips from each station and the density of busyness of stations at a particular time as shown in Fig. 6 and Fig. 7 respectively. Also, we can calculate which station has a maximum number of incoming bikes at a particular time.

4. The Average time took between two stations:

The average time is taken by the user from a station to reach other stations. We analyzed trip data and took the arithmetic mean of all the trip times for trips between X to Y (xy1, xy2, xy3...xyn) and Y to X (yx1, yx2, yx3...yxm) in the past 6 months, which gave us an average trip time between two stations. For calculating trip times between stations X and Y: $((xy1, xy2, xy3...xyn) + (yx1, yx2, yx3...yxm))/N+M$

5. The Busyness of all routes:

To analyze the busyness of all routes, we analyzed trip data between two stations. This information helps the user to reduce their trip time. The busyness of a route between two stations is defined as the total number of trips between those two stations over the past 6 months.

6. Load Factor:

The load factor of a particular station as shown in Fig. 8. The calculated load factor (P) of a station represents the load a station is bearing. Load factor is calculated by the sum of a number of available bikes and a number of empty docks. Whereas, number of available bikes and number of empty docks are denoted by Q and R respectively. load factor increases are directly proportional to load increases on a station. The load factor for a station is calculated as:

$$P = Q + R$$

7. Estimated time of availability of a bike:

We try to calculate the probability of availability of a bike for each of the next 30 minutes as shown in Fig. 9. The data set (status_data describe attributes Bikes_available, Dock_available, and Time). The attribute time is used to calculate the probability of availability of bike. The attribute time is actually timestamp of the form (YYYY-MM-DD HH: MM: SS).

Let $Max_bikes(U)$ denote the maximum number of bikes that can be present at a station X for which the probability is to be calculated. Suppose today's date is 1st June, 2016 (Wednesday) and the time at which a user arrives at a station and finds zero bikes available is 15:45:00. In our bike sharing system, we attempt to predict and recommend to the user whether he/she should wait for an incoming bike or not. The prediction is based on calculating the probability for an availability of a bike for the next 30 minutes. To calculate the probability for an availability of a bike for the next 30 minutes we account three factors of the current timestamp (at which user finds zero bikes available).

No. of bikes on the day of a week (Wednesday) at the current time (t) (for the last 6 Wednesdays) denoted by $V1$.

No. of bikes in the current week at the current time (t) - this includes all the days of the current week denoted by $V2$.

No. of bikes on the day of a month (1st of every month) for the last 6 months at the current time (t) denoted by $V3$.

Let t denote the time at which the probability is to be calculated, t ranges from (time of user arrival) to (time of user arrival + 30 minutes). Let $w1$, $w2$ and $w3$ denote the weights assigned to the factors ($V1$, $V2$, and $V3$) experimentally. Therefore, probability of availability of a bike at t 'th minute (T) can be calculated by:

$$T = (w1 * V1 + w2 * V2 + w3 * V3) / U$$

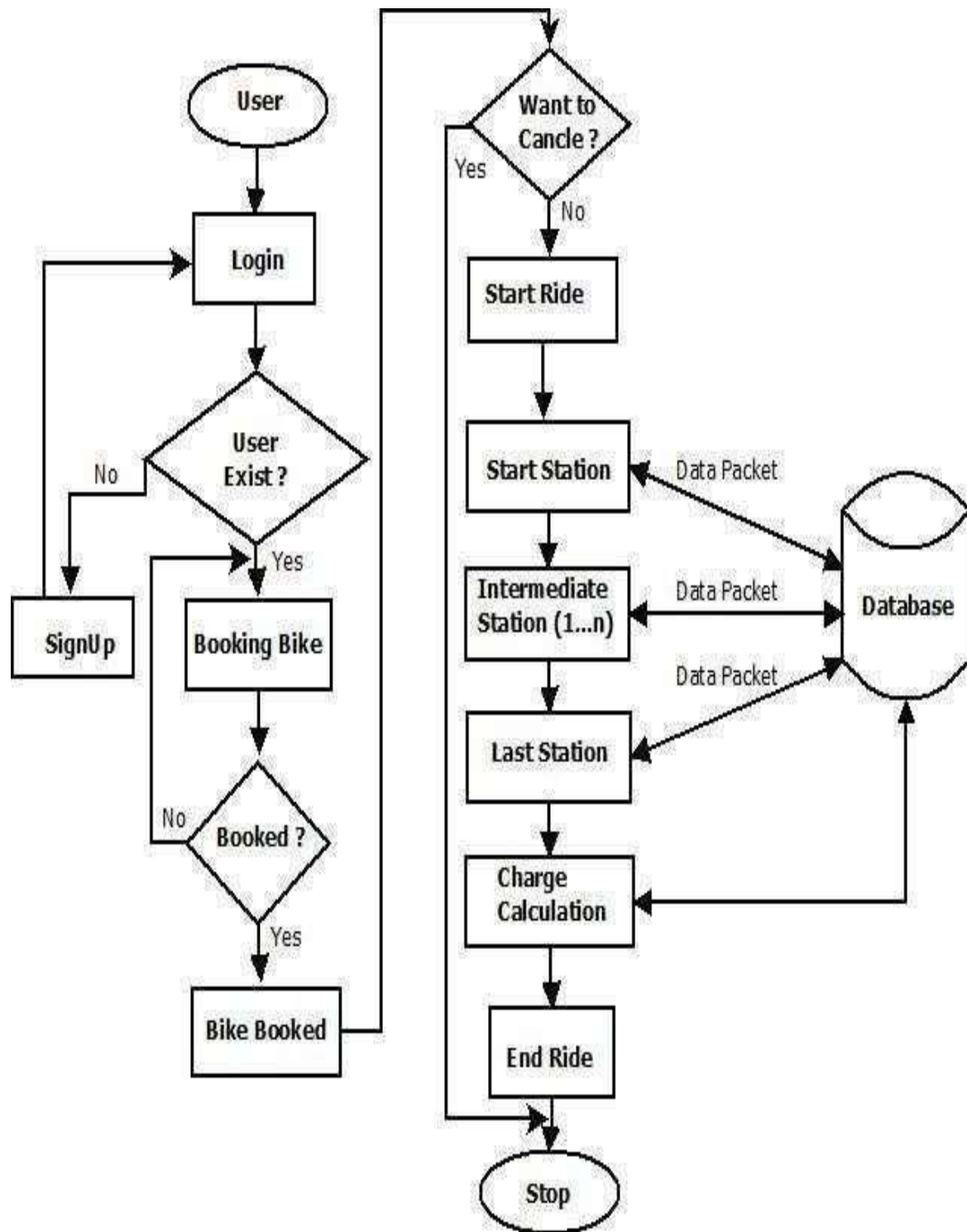


Fig. 5.1. Workflow of smart bike sharing system

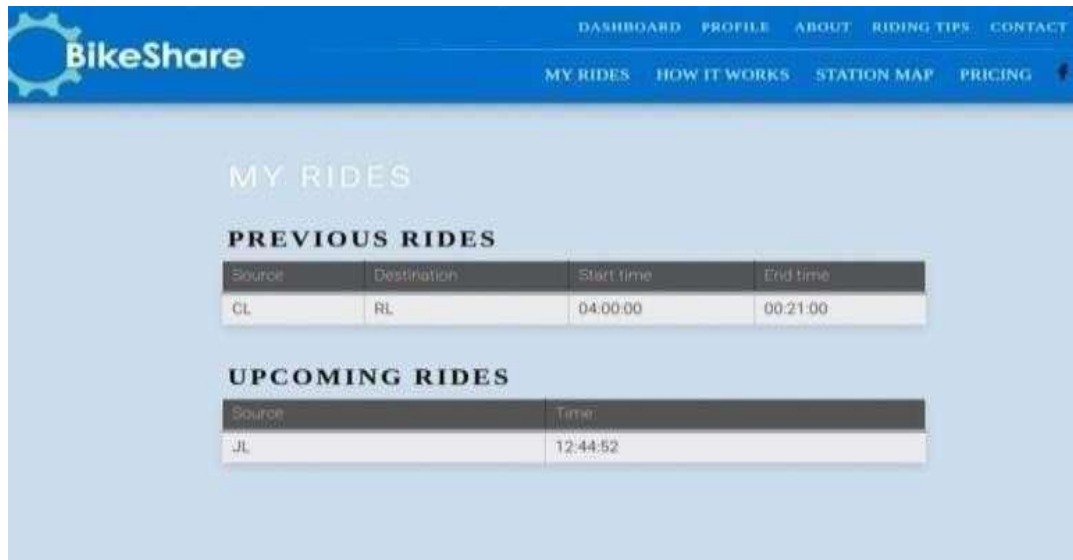


Fig. 5.2. User's previous and upcoming rides

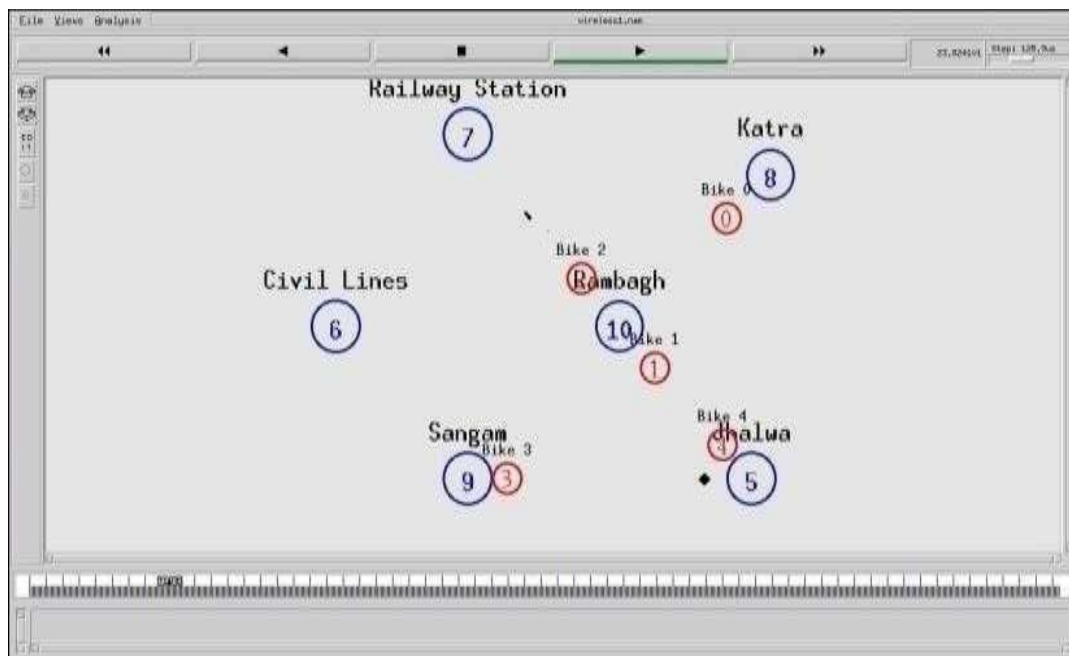


Fig. 5.3. NS2 Simulating the smart bike share system

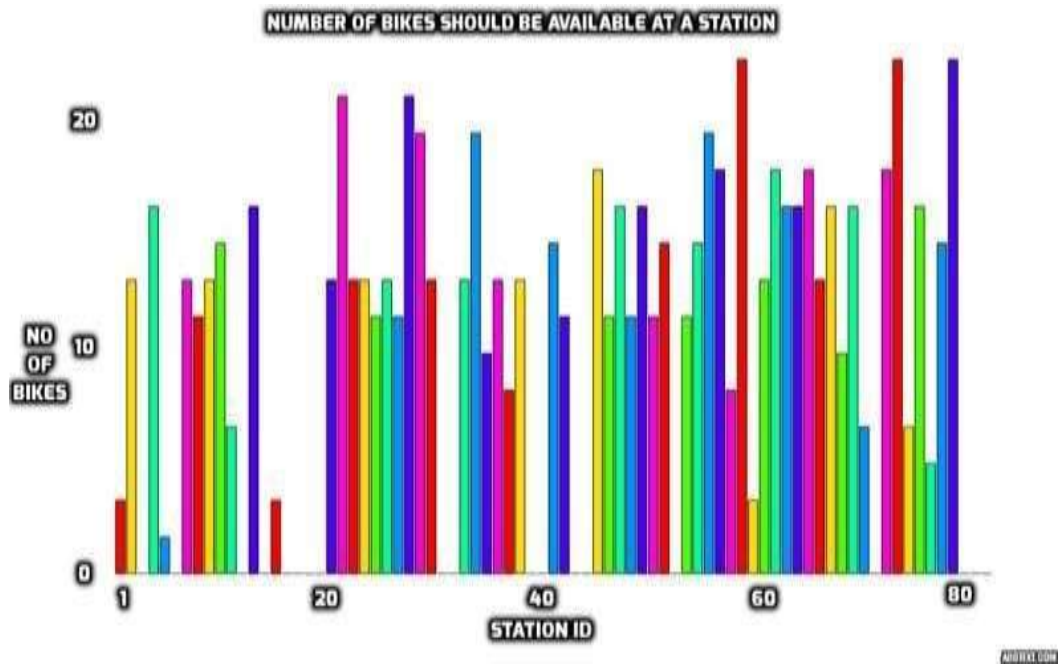


Fig.5.4. Number of bikes that should be available at the station tomorrow

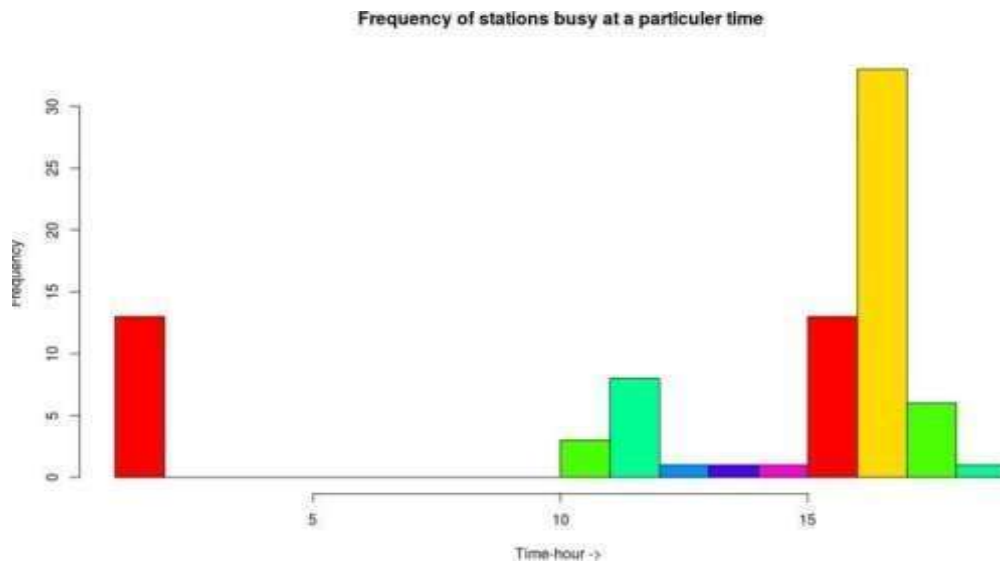


Fig. 5.5. Number of stations that are busy at a particular time

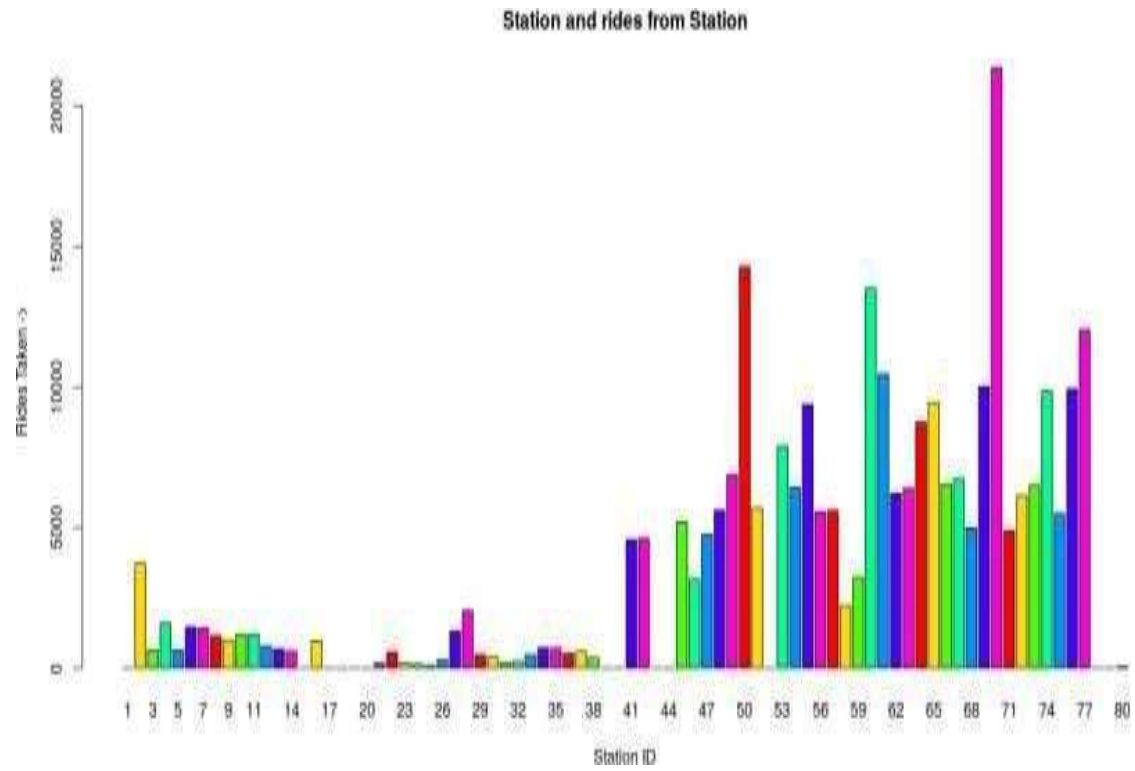


Fig.5.6. Number of bike trips from each station

CHAPTER - 7

CONCLUSION

In this paper, we present a comprehensive design, implementation plan, and evaluation of a smart bike sharing system that incorporates sensor networking techniques. Our system offers a unique mobile sensing experience for cyclists, facilitating data collection and community-based environmental sampling. It operates in two modes, accommodating both delay-tolerant and real-time sensing. The collected data can be presented to individual cyclists and shared with others through backend services, fostering a social and interconnected network among cyclists.

Our smart bike sharing system is user-friendly, allowing users to book bikes effortlessly via the website without requiring human intervention. Users are provided with a smart card upon signup, which they can use to unlock bikes at stations and start their rides. Upon completing their trips, they can return the bikes to the nearest station.

The system relies on sensors for bike tracking and real-time data updates. These sensors transmit information to the nearest stations, which are connected to the website, ensuring that users can access up-to-date bike availability information through the app.

The data sent by the bikes includes valuable information such as traffic data, air quality data, and road conditions data. This data not only aids in solving the redistribution problem but also benefits system users, saving on operational costs and time. In a future where conventional energy sources may become scarce, bike sharing systems like ours can offer an efficient and eco-friendly means of urban transportation. It can even be made mandatory to promote cycling within the city.

Looking ahead, our smart bike sharing system has the potential for further improvement. We can explore the use of collaborative software agents to manage user and station details stored in ontologies. Ontologies provide a secure and expandable environment, offering machine-readable data for efficient agent interactions. Software agents can monitor data packets at diverse stations, providing real-time information for enhanced user experiences and operational efficiency.

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