# REDUCING RANGE ANXIETY WITH AI: A CONTEXT-AWARE EV CHARGING RECOMMENDATION ENGINE

#### A MINI PROJECT REPORT

Submitted by

# ABHIJIT R (221801001) JAI SAARATHI R (221801019) MONISH RAJA RATHINAM M (221801033)

In partial fulfilment for the award of the degree of

# BACHELOR OF TECHNOLOGY IN ARTIFICIAL INTELLIGENCE AND DATA SCIENCE





# RAJALAKSHMI ENGINEERING COLLEGE ANNA UNIVERSITY, CHENNAI MAY, 2025

### ANNA UNIVERSITY, CHENNAI

#### **BONAFIDE CERTIFICATE**

Certified that this Report titled "REDUCING RANGE ANXIETY WITH AI: A CONTEXT-AWARE EV CHARGING RECOMMENDATION ENGINE" is the bonafide work of ABHIJIT R(221801001), JAI SAARATHI R (221801019), MONISH RAJA RATHINAM M (221801033) who carried out the work under my supervision. Certified further that to the best of my knowledgethe work reported herein does not form part of any other thesis or dissertationonthebasis of which a degree or award was conferred on an earlier occasion onthis or anyother candidate.

Dr. J.M. Gnanasekar M.E., Ph.D.,	Mr. Suresh Kumar S M.E., Ph.D.,		
Professor and Head	Professor		
Department of AI&DS	Department of AI&DS		
Rajalakshmi Engineering College	Rajalakshmi Engineering College		
Chennai – 602 105.	Chennai – 602 105.		
Submitted for the project viva-voce examination held on			

INTERNAL EXAMINER

**EXTERNAL EXAMINER** 

#### **ACKNOWLEDGEMENT**

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavor to put forth this report. Our sincere thanks to our Chairman Mr. S. MEGANATHAN, B.E, F.I.E., our respected Chairperson Dr. (Mrs.) THANGAM MEGANATHAN, Ph.D. and our Vice Chairman Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S., for providing us with the requisite infrastructure and sincere endeavoring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. J.M. GNANASEKAR., M.E., Ph.D.,** Head of the Department, Professor and Head of the Department of Artificial Intelligence and Data Science for his guidance and encouragement throughout the project work. We are glad to express our sincere thanks and regards to our coordinator **Mr. S. SURESH KUMAR M.E., Ph.D., Professor**, Department of Artificial Intelligence and Data Science, Rajalakshmi Engineering College for her valuable guidance throughout the course of the project.

Finally, we express our thanks for all teaching, non-teaching, faculty and our parents for helping us with the necessary guidance during the time of our project.

#### **ABSTRACT**

As the adoption of electric vehicles (EVs) continues to rise, efficient and reliable trip planning remains a critical challenge—primarily due to range anxiety, unpredictable charging availability, and lack of intelligent routing. This report presents a Real-Time Charging Station Recommendation Engine that leverages Artificial Intelligence (AI), the Internet of Things (IoT), and cloud-based technologies to provide personalized, context-aware charging solutions for EV users.

Unlike conventional navigation systems that offer static, proximity-based suggestions, the proposed system analyzes real-time data streams such as vehicle telemetry, traffic conditions, terrain elevation, charging station availability, grid load, and user-defined preferences. Through a sophisticated multi-factor evaluation algorithm, it ranks and recommends optimal charging stations based on criteria like charging speed, cost, queue status, and route impact.

The engine supports dynamic rerouting if a selected station becomes unavailable, enhancing trip continuity and reducing delays. It also adapts over time by learning from user behavior and preferences, enabling smarter and more efficient recommendations. Integration with vehicle dashboards and mobile navigation apps ensures a seamless user experience with real-time updates and notifications.

By addressing key limitations in existing EV navigation platforms, this system improves energy efficiency, minimizes wait times, and enhances the overall driving experience—paving the way for more intelligent and sustainable EV travel.

# TABLE OF CONTENT

S.NO	TITLE	PAGE NUMBER
	ABSTRACT	iv
	TABLE OF FIGURES	vii
1.	INTRODUCTION	1
1.1	GENERAL	1
1.2	NEED FOR THE STUDY	1
1.3	OVERVIEW OF THE PROJECT	2
1.4	OBJECTIVES OF THE STUDY	3
2.	REVIEW OF LITERATURE	5
2.1	INTRODUCTION	5
2.2	LITERATURE REVIEW	5
3.	SYSTEM OVERVIEW	8
3.1	EXISTING SYSTEM	8
3.2	PROPOSED SYSTEM	13
3.3	FEASIBILITY STUDY	17
4.	SYSTEM REQUIREMENTS	20
4.1	HARDWARE REQUIREMENTS	20
4.2	SOFTWARE REQUIREMENTS	21

5.	SYSTEM DESIGN	23
5.1	SYSTEM ARCHITECTURE	23
5.2	MODULE DESCRIPTION	25
6.	RESULTS AND DISCUSSION	28
7.	CONCLUSION AND FUTURE ENHANCEMENT	29
7.1	CONCLUSION	29
7.2	FUTURE ENHANCEMENT	30
	APPENDIX	32
<b>A1</b>	SAMPLE CODE	32
<b>A2</b>	OUTPUT SCREENSHOT	35
	REFERENCES	37

## **TABLE OF FIGURES**

S.NO	FIGURE	PAGE NUMBER
5.1	SYSTEM ARCHITECTURE	23
5.2.1	MODULE DESCRIPTION	24
A2.1	LANDING PAGE	35
A2.2	PERSONAL DETAILS	35
A2.3	SLOT BOOKING	36
A2.4	GRID RECOMMENDATION	36

#### CHAPTER 1

#### INTRODUCTION

#### 1.1. GENERAL

With the rapid adoption of electric vehicles (EVs), fueled by both increasing environmental awareness and advancements in clean energy technologies, the demand for a smart and scalable EV infrastructure has become more urgent than ever. One of the most significant obstacles hindering mainstream EV adoption is range anxiety — the persistent concern among drivers that their vehicle may run out of charge before reaching a suitable charging point. While traditional navigation systems are capable of plotting routes, they are often static and fail to consider real-time, dynamic factors critical to EVs. These include the vehicle's current State of Charge (SoC), charging station availability, charging speed, electricity pricing, queue length, grid load conditions, and predicted wait times. As a result, drivers can face unexpected delays, inefficient detours, or inaccessible stations, severely impacting the user experience and trust in EV mobility.

To address this problem, the project introduces an intelligent, real-time EV charging station recommendation system. The system uses a combination of live vehicle telemetry, route data, user preferences, and charging station status to recommend optimal charging stops along a journey. Unlike traditional GPS-based tools, this solution dynamically adapts to changes in vehicle state or charging network conditions and recalculates in real-time. It not only minimizes travel disruptions and detour times but also supports efficient energy usage, enabling a more reliable and user-friendly electric driving experience.

#### 1.2. NEED FOR THE STUDY

As the adoption of electric vehicles (EVs) accelerates globally, so does the complexity of managing their charging requirements. Despite improvements in EV infrastructure, the ecosystem still lacks an intelligent, context-aware guidance system

that operates in real time. This shortfall leads to various inefficiencies that hinder both individual driving experiences and system-wide energy optimization.

Current static or semi-dynamic navigation tools often fail to incorporate key parameters such as real-time State of Charge (SoC), charger availability, wait times, or user-specific travel goals. As a result, EV users—especially first-time drivers—frequently encounter confusion and delays when planning longer trips or reacting to unforeseen battery depletion.

The absence of a real-time recommendation system contributes to:

- Suboptimal charging stops, often leading to unnecessary detours, longer travel times, and increased energy consumption.
- Poor user experience due to unexpected wait times, incompatible chargers, or missing price visibility at the station level.
- Imbalanced charger utilization, where some stations are overwhelmed while others remain underused—further straining the energy grid.
- A lack of personalized decision-making tools, which makes it difficult for drivers to factor in their cost preferences, desired Depth of Charge (DoC), or route constraints.

These challenges highlight the pressing need for a smarter solution—one that dynamically evaluates live data and provides intelligent, user-centric charging station recommendations for both everyday and long-distance EV travel.

#### 1.3. OVERVIEW OF THE PROJECT

The system introduces a Real-Time EV Charging Station Recommendation System designed to intelligently assist electric vehicle users in identifying the most efficient, cost-effective, and accessible charging points during their journey. Unlike conventional navigation tools that offer static charger listings, this system actively adapts to changes in vehicle status, travel context, and charging network conditions to

provide smarter, real-time guidance.

The system works by aggregating and analyzing multiple layers of live data to determine the best charging options along or near the driver's planned route. It takes into account the following core inputs:

- Vehicle telematics, including real-time State of Charge (SoC), battery capacity, and energy consumption rate, to estimate remaining range and forecast charging requirements based on current and upcoming travel conditions.
- Navigation context such as starting point, destination, selected route, traffic flow, and road topology to determine how far and where a charge is needed along the journey.
- Charging station analytics covering live availability, queue status, charger types (AC/DC), compatibility, predicted wait time, grid load at each location, and reliability based on historical usage patterns.
- Dynamic pricing models, including time-of-use electricity rates and congestion-based tariffs, to help users make cost-effective charging decisions without compromising convenience or safety.

The system evaluates all available options using a weighted scoring algorithm to recommend the top 1–3 stations that offer the best balance of speed, cost, and detour efficiency. It continuously monitors for changes and re-routes in real time if a chosen station becomes unavailable, enhancing driver confidence, reducing inefficiencies, and promoting smarter energy distribution across the EV infrastructure.

#### 1.4 OBJECTIVES OF THE STUDY

The system is intended to support EV drivers by minimizing range anxiety, optimizing charging routes, and ensuring energy-efficient travel. The specific goals of this project are as follows:

1. To develop an intelligent, real-time charging station recommendation engine

- that considers a vehicle's current State of Charge (SoC), planned route, and user-defined charging preferences (e.g., fastest, cheapest, minimal detour).
- 2. To integrate heterogeneous data sources such as vehicle telemetry (SoC, location, energy consumption), live navigation APIs (e.g., Google Maps or Mapbox), and real-time charging station feeds (availability, queue status, charger type, and pricing) to make dynamic, context-aware decisions.
- 3. To design a modular and extensible scoring system that evaluates and ranks charging stations based on multiple criteria including:
  - Charger type (AC/DC, kW rating)
  - Real-time station availability
  - o Estimated queue length and wait time
  - Dynamic pricing or tariff rates
  - Detour distance from the current route
  - Compatibility with the vehicle's charging port and preferred network providers.
- 4. To build an intuitive and user-centric interface (mobile or web) that visually recommends the best charging stations on a map. The interface will also support live updates, voice-based alerts, and rerouting in response to changes in charging station conditions (e.g., if a charger becomes occupied en route)
- 5. To simulate real-world travel scenarios (urban commutes, highway travel, and low-SoC emergencies) and evaluate the accuracy, responsiveness, and effectiveness of the system in making timely and beneficial recommendations.
- 6. To promote sustainable driving practices by optimizing for energy efficiency, reducing time spent searching for chargers, and preventing unnecessary queueing or detours—thereby lowering energy wastage and reducing driver stress.

#### **CHAPTER 2**

#### **REVIEW OF LITERATURE**

#### 2.1 INTRODUCTION

The electric vehicle (EV) market is expanding rapidly, supported by advances in battery technology, environmental awareness, and supportive government policies. However, EV users still face key challenges—such as limited range, charging delays, and uneven infrastructure, which affect their travel confidence and convenience. These issues highlight the growing need for smarter, real-time solutions that support EV trip planning and energy management.

Traditional route planning systems were built for internal combustion engine vehicles and often fail to consider EV-specific factors like current State of Charge (SoC), charger type, compatibility, real-time availability, queue length, and energy cost. As a result, EV drivers may experience inefficient routes, unexpected wait times, or charging uncertainty—commonly referred to as range anxiety.

To address these gaps, recent research has focused on integrating real-time data, artificial intelligence, and vehicle telemetry to provide intelligent, personalized charging recommendations. Such systems can improve decision-making by evaluating both user preferences and live infrastructure data, ultimately leading to more reliable, cost-effective, and efficient EV travel experiences.

#### 2.2 FRAMEWORK OF LITERATURE REVIEW

#### 1. Intelligent EV Routing Systems

A number of research studies have introduced intelligent routing algorithms tailored to electric vehicles, aimed at minimizing both travel time and energy consumption. These include energy-aware shortest path algorithms that factor in terrain elevation, regenerative braking potential, road type, and traffic conditions to calculate the most efficient path. However, while these systems are optimized from a mobility and

energy usage standpoint, they often operate on static or semi-dynamic datasets. As a result, they do not account for real-time charger availability, outages, or dynamic pricing, which are critical for making reliable and timely charging decisions.

#### 2. Charging Station Optimization and Grid Load Management

As electric mobility grows, researchers have explored how EV charging behavior impacts energy grids, especially during peak hours. Many solutions focus on load-balancing strategies, where smart charging platforms distribute charging demand across multiple stations to reduce stress on any single grid node. Although this contributes positively to grid stability, many of these grid-optimized systems are designed from a utility-centric perspective and overlook real-time user constraints, such as charger queue length, station detour distance, and preferred charging speed. This results in efficient energy distribution at the grid level, but often at the cost of poor user experience and longer charging times.

#### 3. Use of Real-Time Data in EV Applications

Modern EV routing systems like Google Maps EV mode and proprietary applications by manufacturers such as Tesla, Ather, and Hyundai incorporate real-time location and charger data. These platforms inform users about nearby charging stations, availability, and estimated time to charge. However, most of these applications are OEM-specific and tightly integrated with vehicle brand ecosystems. They are not extensible to other vehicle models or third-party infrastructure networks. Independent efforts using open platforms like Open Charge Map provide broader access, but typically lack personalization features and real-time scoring based on individual SoC, travel plans, or pricing sensitivity.

#### 4. Context-Aware Decision Support Systems

Context-aware computing has been successfully implemented in various domains such as healthcare, smart homes, and city traffic management. These systems use sensor and environment data to deliver adaptive, situational responses. Applying this concept to EV routing shows potential, especially when considering multiple

variables such as SoC, expected travel range, live charger conditions, and user preferences. By tailoring suggestions based on a combination of real-time conditions and personal context, EV recommendation engines can become far more effective in minimizing range anxiety and improving decision-making.

#### 5. Machine Learning and Predictive Modeling in EV Systems

Recent studies have explored the use of machine learning algorithms—including regression models, neural networks, and reinforcement learning—to forecast various EV-related outcomes such as queue lengths at chargers, expected charging costs, and charging behavior patterns. These models can be trained on historical data from charging networks to predict when and where congestion is likely to occur. They can also adapt to user-specific preferences over time. Integrating predictive modeling into EV routing can significantly enhance the responsiveness and reliability of recommendations, especially in high-density urban areas where demand for charging is volatile.

#### **6. Gaps in Existing Solutions**

Despite notable advancements, current EV routing and charging systems have key limitations. Most fail to incorporate a multi-variable real-time scoring model that balances distance, cost, availability, and queue time in a unified framework. Personalization based on SoC, DoC (Depth of Charge), and user charging preferences is rarely implemented. Furthermore, existing systems often lack the ability to adapt to real-time disruptions—such as a selected charger becoming unavailable or prices surging—leaving users without dynamic rerouting. Additionally, very few platforms integrate grid load information, dynamic pricing, and predictive wait times into a single intelligent engine, making current solutions fragmented and suboptimal for real-world travel.

#### **CHAPTER 3**

#### SYSTEM OVERVIEW

#### 3.1 EXISTING SYSTEM

In the current landscape of EV navigation, several platforms and applications aim to assist drivers in finding and utilizing charging stations during their trips. While systems like Google Maps EV mode, PlugShare, Tesla's Supercharger network, and others provide essential features such as charging station locations, estimated range, and route planning, they each have inherent limitations. These limitations often hinder their effectiveness in real-world driving scenarios, especially for long trips, during peak travel times, or when energy efficiency is crucial. The lack of real-time data integration, dynamic re-routing, and personalization means these platforms frequently fail to optimize charging stops for individual needs and vehicle-specific conditions.

#### 1. Google Maps EV Mode

#### **Description:**

Google Maps offers an "EV Mode" that helps users navigate to their destinations while considering available charging stations along the route. It shows the location of charging stations, suggests possible routes, and estimates the range based on the vehicle's battery status.

#### **Implementation:**

- Provides EV-specific routes with charging stations along the way.
- Shows charging station details, including type (AC or DC), location, and availability.
- Estimates travel time based on the current range and vehicle's battery state.

#### **Limitations:**

• Static Recommendations: Suggests charging stations primarily based on

proximity or route alignment, not considering current SoC or real-time energy consumption.

- Lack of Queue Intelligence: Does not provide real-time data about station queue times, leading to unanticipated delays at charging stations, especially during peak times.
- Limited Personalization: Users cannot specify preferences like charger type, charging speed, or cost sensitivity.
- **No Grid Integration:** Does not incorporate energy grid data to optimize charging recommendations for sustainability.

#### 2. PlugShare

#### **Description:**

PlugShare is an EV charging station locator app that offers a comprehensive map of charging stations across various networks. Users can search for stations, view real-time availability, and even check reviews and ratings for individual chargers.

#### **Implementation:**

- Provides detailed maps of charging stations worldwide, including user reviews and ratings.
- Allows users to filter results based on charging network, station type, and accessibility.
- Displays real-time availability and some live status updates for certain stations.

#### **Limitations:**

- **Basic Recommendations:** Primarily lists stations by proximity, without factoring in vehicle-specific details like SoC or user preferences.
- **Inconsistent Real-Time Data:** While some stations provide live updates, the app's real-time availability can be inaccurate for many stations, especially if the station doesn't have active reporting.

- Lack of Dynamic Re-routing: If a charging station is unavailable or unsuitable during a trip, users need to manually adjust their route without automated re-routing.
- Limited Personalization and Preferences: No customization for charger type, charging speed, or detour preferences.

#### 3. Tesla Supercharger Network

#### **Description:**

Tesla's navigation system integrates with the Tesla Supercharger network to guide drivers to the nearest available charging station, automatically factoring in range estimates and charging needs for Tesla vehicles.

#### **Implementation:**

- Uses real-time SoC and driving patterns to predict when and where a user will need a charge.
- The system automatically includes Supercharger stations along the most optimal route, minimizing charging stops.
- Provides estimated wait times for Superchargers and suggests nearby amenities.

#### Limitations:

- **Tesla-Specific:** Only applicable to Tesla vehicles, limiting its usefulness for other EV users.
- Limited Charging Network: Relies solely on Tesla Superchargers, which can result in limited station availability in areas with fewer Tesla chargers.
- Lack of Grid Load Data: Does not consider grid load or station congestion beyond Tesla's own data, which can lead to inefficient charging during peak demand times.
- Limited Personalization: Does not provide detailed customization options for

charger types, speeds, or detour preferences outside of Tesla's network.

#### 4. Hyundai Blue Link

#### **Description:**

Hyundai's Blue Link app offers navigation and remote control features for Hyundai EVs, including charging station locator, vehicle range estimation, and charging status monitoring.

#### **Implementation:**

- Displays the location of nearby charging stations, along with station availability and type.
- Allows remote control to check charging status and monitor energy consumption.
- Provides estimated remaining range based on current energy consumption and route ahead.

#### **Limitations:**

- Limited Coverage: Only available for Hyundai EV owners, which restricts its user base.
- **No Dynamic Re-routing:** Lacks the ability to automatically re-route if a charging station becomes unavailable mid-trip.
- **Basic Recommendations:** The app suggests stations based primarily on proximity without factoring in real-time driving conditions or user preferences like cost sensitivity or charging speed.
- No Grid Load Data: Does not integrate with the energy grid to suggest stations based on real-time power availability or sustainability concerns.

#### 5. Audi e-tron Navigation System

#### **Description:**

Audi's e-tron system helps drivers of Audi electric vehicles find and navigate to charging stations, providing information about charging station location, availability, and route planning.

#### **Implementation:**

- Integrates with the Audi MMI navigation system to find charging stations along the route.
- Displays details about each station, including type, compatibility, and charging speed.
- Provides estimated range and energy consumption predictions for the trip.

#### **Limitations:**

- **Vehicle-Specific:** Available only for Audi e-tron vehicles, limiting its reach to other EV users.
- Limited Charging Options: Only suggests Audi-compatible stations, limiting options if the user needs different types of chargers or network coverage.
- Static Recommendations: Primarily bases station suggestions on proximity and does not account for live traffic, energy usage, or user-specific preferences.
- **No Queue or Grid Load Data:** Does not offer real-time data on station queues or integration with the energy grid to optimize charging efficiency.

#### 6. ChargePoint

#### **Description:**

ChargePoint offers an EV charging network with a mobile app that helps drivers locate, navigate to, and pay for charging stations.

#### **Implementation:**

- Provides a comprehensive map of public charging stations, including availability, charging speed, and station type.
- Allows users to filter by charging speed, network, and station accessibility.
- Users can pay for charging directly through the app and check the status of their vehicle's charge remotely.

#### **Limitations:**

- Limited Real-Time Data: Some stations may not provide live updates on availability, leading to potential issues with finding a free station.
- **No Dynamic Re-routing:** Similar to other platforms, users need to manually adjust their route if a station becomes unavailable.
- Lack of Personalization: Does not support user-specific preferences for charger types or maximum detour distances.
- No Grid Load Integration: Does not incorporate grid load data to prioritize stations based on power availability, leading to inefficient routing during high-demand periods.

#### 3.2 PROPOSED SYSTEM

The Real-Time Charging Station Recommendation Engine is an advanced solution designed to optimize electric vehicle (EV) trip planning by offering personalized, data-driven charging suggestions. By integrating cutting-edge technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and cloud services, the system aims to enhance the EV driving experience by reducing range anxiety, improving route efficiency, and promoting energy sustainability. The system continuously analyzes real-time data to make informed decisions about the best charging stations along the route, ensuring the most efficient and cost-effective options for the user.

#### **Key Features:**

#### 1. Real-Time Data Integration:

- The system collects real-time data from multiple sources, including vehicle telemetry, traffic conditions, route progress, terrain elevation, and weather information. This data is used to predict energy needs, optimize charging decisions, and adapt to changes during the trip.
- Additionally, the system integrates live data from external APIs about station availability, charging speeds, charger types, and queue status, ensuring that charging stations are selected based on the most current information available.

#### 2. Personalized Recommendations:

- The system tailors recommendations based on **user preferences**, such as preferred charger type (e.g., fast chargers or specific networks), desired charging speed, cost sensitivity, and acceptable detour distances.
- Over time, the system learns from the user's past driving behavior, charging habits, and preferences to deliver increasingly accurate and relevant charging station suggestions for future trips.

#### 3. Multi-Factor Evaluation:

- Using a sophisticated scoring algorithm, the system evaluates multiple factors for each charging station, including vehicle-specific needs (SoC, energy consumption), station compatibility, proximity, user preferences, and real-time availability.
- Additionally, the system considers grid load data to ensure that charging demand is distributed evenly across the grid, promoting both sustainable energy usage and reduced congestion at popular stations.

#### 4. Dynamic Re-routing:

- The system continuously monitors the journey and provides **real-time rerouting** if a selected charging station becomes unavailable due to congestion, maintenance, or other factors. This ensures minimal disruption to the trip.
- If a more suitable charging station is detected during the trip (e.g., a faster charger with lower wait times), the system can proactively suggest an alternative route to the user, optimizing the overall charging experience.

#### **5. Seamless User Integration:**

- The recommendation engine integrates with **third-party navigation apps** (e.g., Google Maps, Apple Maps) and **in-vehicle displays**, providing **real-time notifications** and **route updates** directly to the driver.
- This integration ensures a seamless user experience, where users can follow the system's recommendations without needing to switch apps or manually input new destinations or charging stations.

#### **System Workflow:**

#### 1. Trip Initiation and Data Collection:

- The user inputs their destination and desired **Depth of Charge (DoC)** into the system. The system collects real-time data from the vehicle's **telemetry** (including **SoC**, energy consumption rate, battery health) and external sources such as **traffic data**, **terrain elevation**, and **weather conditions** along the route.
- The system also pulls **live data** on charging station availability, queue status, and charger types from external APIs to ensure up-to-date information.

#### 2. Evaluation and Ranking:

- The system's multi-factor algorithm evaluates available charging stations based on criteria such as the vehicle's current SoC, estimated energy consumption, charging station availability, user preferences (e.g., charger type, speed, cost sensitivity), and grid load to determine the most suitable charging stops.
- The algorithm ranks the top 1-3 charging stations based on these factors and presents them to the user with detailed information, including estimated routes, charging times, and costs.

#### 3. Real-Time Decision Making and Recommendations:

- The system continuously analyzes the data and provides the user with real-time updates and recommendations throughout the journey. If a selected station is unavailable, the system **automatically reroutes** the user to the next best alternative.
- The user is notified of **real-time changes** such as station availability, wait times, and route adjustments, ensuring that the trip proceeds smoothly without manual intervention.

#### 4. Continuous Monitoring and Updates:

• The system provides **continuous monitoring** of the user's **current SoC** and **station availability** throughout the journey. If the conditions change (e.g., new stations open, or selected stations become unavailable), the system will provide **instant updates** and suggest alternative charging options.

#### 5. Post-Trip Analytics:

- After the trip, the system provides a **post-trip summary** that includes detailed analytics on the total energy used, the cost of charging, detours taken, and charging station performance (e.g., wait times, station availability).
- This feedback can be used to refine the system's algorithms and provide better

recommendations for future trips, while also offering **personalized** suggestions for improving the charging experience.

#### **Benefits:**

#### 1. Reduced Wait Times and Improved Availability:

By providing real-time station availability and queue status, the system ensures
users avoid stations with long wait times or congestion, leading to faster, more
predictable charging stops.

#### 2. Enhanced Energy Efficiency:

 The system optimizes station usage based on grid load data and vehicle needs, helping to balance energy demand across multiple stations and contribute to grid stability, reducing the risk of overloading specific stations.

#### 3. Optimized User Experience:

Seamless integration with navigation apps and vehicle displays ensures that
users have access to real-time updates, automatic rerouting, and personalized
recommendations, improving the overall journey and reducing the stress of
managing charging stops.

#### 3.3 FEASIBILITY STUDY

A comprehensive feasibility study was conducted to evaluate the practicality of developing and deploying the Real-Time EV Charging Station Recommendation System. The study considers technical, economic, operational, legal, and schedule aspects to ensure the system can be successfully implemented and sustained.

#### **Technical Feasibility**

The proposed system is technically viable due to the availability and maturity of the technologies it depends on. It utilizes APIs such as Open Charge Map for charger data, Google Maps or Mapbox for navigation and route planning, and OEM telemetry interfaces for vehicle data like State of Charge (SoC). Backend frameworks such as Python (Flask or FastAPI) and Node.js are capable of handling real-time API requests and data processing with minimal latency. The integration of machine learning models for predicting queue times and pricing trends enhances the system's intelligence. Cloud platforms such as AWS, GCP, or Firebase provide the scalability needed for deployment, ensuring high availability and low response time (typically under one second). This confirms the project's strong technical foundation for real-time decision-making and dynamic user interaction.

#### **Economic Feasibility**

From an economic standpoint, the system is cost-effective in its early stages, as it can be developed using open-source libraries, public APIs, and cloud services within free-tier limits. As the system scales, expenses may include cloud hosting fees, API usage charges for map and traffic data, and frontend development costs for mobile or web interfaces. Despite these costs, the project holds promising revenue potential. Monetization options include offering subscription-based services to EV users, licensing the platform to automotive manufacturers or fleet managers, and providing analytics and data insights to charging station operators. These revenue channels can offset development and operational costs, making the project economically sustainable in the long term.

### **Operational Feasibility**

Operationally, the system is designed for ease of use and minimal user training. The user interface will resemble standard navigation apps, allowing users

to input their destination, view top charging recommendations, and receive real-time updates without needing technical expertise. The system is capable of learning user behavior over time, adjusting to preferences such as preferred networks, pricing sensitivity, or maximum acceptable detour. This personalization improves system utility and encourages continued use. The modular design also makes it easy to maintain and scale, allowing updates and feature enhancements to be deployed with minimal disruption to users.

#### **Legal and Ethical Feasibility**

Legally and ethically, the system adheres to all major data privacy regulations, including the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). It ensures transparency by requiring user consent before accessing vehicle or location data and by providing clear policies on data usage. All collected information is stored securely, anonymized when appropriate, and used solely to improve user experience and system accuracy. The system functions as a recommendation engine, not an autonomous controller, which means final decisions always rest with the user—preserving autonomy and ethical responsibility.

#### **Schedule Feasibility**

The project is feasible within a realistic development schedule, which is structured over three months for a minimum viable product (MVP). In the first month, foundational tasks such as SoC integration, route mapping, and interface design are completed. The second month focuses on integrating real-time data from charging station APIs and implementing the scoring and recommendation algorithm. The third month is dedicated to training predictive models, testing various user scenarios, and optimizing both the backend and frontend for responsiveness.

#### **CHAPTER 4**

#### **SYSTEM REQUIREMENTS**

#### 4.1 HARDWARE REQUIREMENTS

To develop and run the EV Charging Recommendation System efficiently, the following hardware specifications are recommended:

#### 1. Processor (CPU)

- Minimum: Intel Core i5 (2.5 GHz, quad-core) or AMD Ryzen 5
- **Recommended**: Intel Core i7 / AMD Ryzen 7 (3.0 GHz, hexa-core or better)
- **Justification**: Required for handling real-time data ingestion, route calculations, and ML-based scoring in a responsive manner.

#### 2. Memory (RAM)

- Minimum: 8 GB
- **Recommended**: 16 GB or more
- **Justification**: Ensures smooth multitasking during live API calls, model inference, and UI responsiveness.

#### 3. Storage

- Minimum: 128 GB SSD
- **Recommended**: 256 GB SSD or higher
- **Justification**: Faster read/write speeds are crucial for caching route data, session logs, and charger status updates.

#### 4. Graphics Processing Unit (GPU)

- Optional: NVIDIA GTX 1050 or higher (for ML model training)
- Justification: Not mandatory for deployment, but helpful during model

training for predictive analytics (e.g., queue/wait time estimation).

#### 5. Network Interface

- **Requirement**: Stable high-speed internet (10 Mbps or more)
- **Justification**: Ensures smooth access to real-time APIs for maps, charger status, and telematics.

#### 6. Input/Output Devices

• Display (HD or higher), keyboard, and optionally mobile device for on-road simulation and testing.

#### **4.2 SOFTWARE REQUIREMENTS**

#### 1. Operating System

- **Minimum**: Windows 10 / Ubuntu 18.04+ / macOS 10.14+
- **Recommended**: Ubuntu 22.04 LTS or Windows 11
- **Justification**: Stable environment for backend development, API integration, and cloud deployment.

#### 2. Programming Languages & Frameworks

- **Backend**: Python (Flask / FastAPI) or Node.js
- Frontend: ReactJS / Flutter (for mobile version)
- **Justification**: These frameworks are lightweight, scalable, and widely supported.

#### 3. APIs & Services

- Maps & Routing: Google Maps API / Mapbox
- Charging Station Data: Open Charge Map API / OEM-specific APIs
- Vehicle Telemetry: OBD-II data simulators or OEM integration (mocked

#### during prototype)

#### 4. AI & Data Processing Libraries

- Pandas, NumPy: Data manipulation and analysis
- Scikit-learn / XGBoost: For predictive scoring and wait-time estimation
- GeoPy / Haversine: For geospatial calculations
- **TensorFlow / PyTorch** (optional): For training custom ML models

#### 5. Database

- **Development**: SQLite (lightweight)
- **Production**: PostgreSQL / Firebase / MongoDB
- Justification: To store user sessions, charger logs, and scoring data efficiently.

#### 6. Authentication and Security

- User Authentication: JWT (JSON Web Tokens)
- Security: SSL/TLS for encrypted communication
- Compliance: GDPR, CCPA (for handling location and personal data)

#### 7. Development Tools

- **Version Control**: Git + GitHub / GitLab
- Code Editor: VS Code / PyCharm
- **Testing Tools**: Postman (API testing), Pytest (unit testing), Selenium (UI testing)
- CI/CD: GitHub Actions / Jenkins for continuous deployment

#### 8. Deployment Platform

- Containerization: Docker (for environment consistency)
- **Production**: AWS / GCP / Azure

#### **CHAPTER 5**

#### SYSTEM DESIGN

#### 5.1 SYSTEM ARCHITECTURE

#### EV Charging Recommendation System v.1-/025

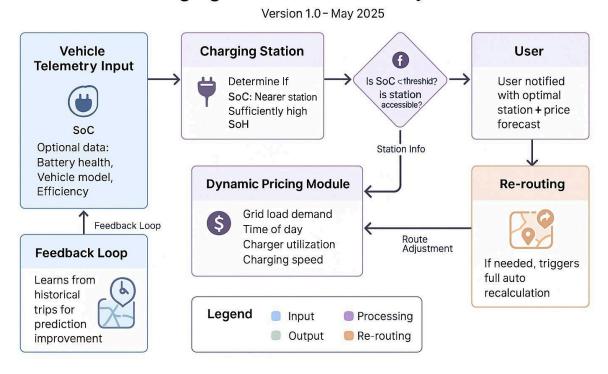


Fig 5.1 System Architecture

The system architecture is designed as a modular, scalable, and real-time recommendation engine that integrates multiple data sources and processes live information to generate personalized charging station suggestions for EV users. It is structured into six primary layers, each responsible for specific operations:

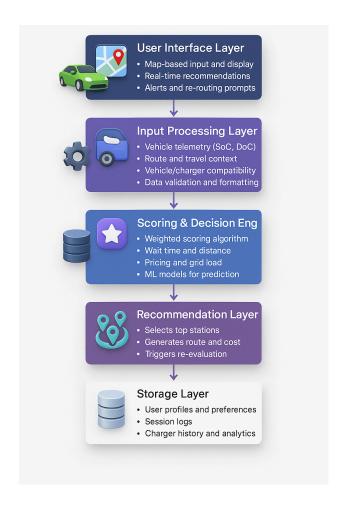


Fig 5.2 MODULE DESCRIPTION

#### 1. User Interface Layer:

- Allows users to input destination and preferred Depth of Charge (DoC).
- Displays real-time charger recommendations and route options.
- Supports visual and voice-based alerts for rerouting.
- Accessible via mobile or web applications.

#### 2. Input Processing Layer

- Processes real-time vehicle telemetry (e.g., SoC, battery capacity, consumption rate).
- Accepts trip data such as start point, route, and ETA.
- Checks vehicle compatibility with charging stations (connector type, power rating).

#### 3. Data Aggregation Layer

- Connects to APIs like Open Charge Map and Google Maps for station data and routing.
- Retrieves grid load or dynamic pricing data from utility services.
- Loads user preferences and vehicle specifications from internal storage.
- Caches frequent queries to reduce latency.

#### 4. Scoring & Decision Engine

- Factors include route distance, charging speed, queue length, and dynamic pricing.
- Predictive ML models can estimate wait times and pricing trends.
- Scores are updated in real time as travel or station conditions change.

#### **5.** Recommendation Layer

- Selects top 1–3 optimal stations based on computed scores.
- Displays estimated time to station, charging duration, and cost.
- Recommends alternate stations if availability changes mid-journey.

#### 6. Storage Layer

- Stores session data such as trip logs, selected chargers, and outcomes.
- Maintains user profiles, charger usage history, and scoring statistics.
- Enables performance monitoring and long-term model refinement.

#### 5.2 MODULE DESCRIPTION

The system consists of nine distinct modules, each responsible for executing a key function within the real-time EV charging recommendation platform.

#### **MODULE 1: User Authentication**

This module handles secure access and identity management. Users can register or log in using an email address or mobile number. Authentication is implemented using JWT (JSON Web Tokens) to ensure secure, token-based session management. This mechanism prevents unauthorized access and allows each user to maintain a

personalized profile, including their trip history, charging preferences, and saved vehicles. Future versions can include multi-factor authentication (MFA) for enhanced security.

#### **MODULE 2: Trip & SoC Input**

In this module, the user begins by inputting their trip destination and optionally a desired Depth of Charge (DoC) target. The system simultaneously collects the real-time State of Charge (SoC) from the EV using onboard telemetry or simulated input for testing purposes. Based on the vehicle's current range and battery efficiency, this module estimates whether a charging stop is necessary and determines the optimal point along the route for recharging. It initiates the workflow for real-time charger discovery.

#### **MODULE 3: Station Data Aggregation**

This module integrates with multiple third-party APIs, such as Open Charge Map or OEM-provided networks, to retrieve up-to-date information on charging stations. Data includes charger type (AC/DC), power output, real-time availability, pricing per kWh, queue length, and maintenance status. To improve performance and minimize API calls, frequently accessed station data is cached temporarily and refreshed at defined intervals. It also checks charger compatibility with the vehicle model.

#### **MODULE 4: Real-Time Scoring Engine**

The scoring engine is the system's intelligence core. It evaluates all potential charging stations using a weighted scoring algorithm. Variables considered include proximity to the user's current route, estimated detour time, remaining SoC margin, current and predicted wait time, charging speed, and cost per unit of energy. User preferences, such as prioritizing cheaper stations or faster charging, are applied as weight factors. Additionally, real-time grid load and dynamic pricing trends can be factored in if utility data is available.

#### **MODULE 5: Recommendation Output**

This module ranks and displays the top 1–3 recommended charging stations based on the computed scores. For each option, users are shown detailed estimates such as time to arrival, charging duration, expected cost, and likelihood of waiting. The user interface presents this information through an interactive map with route overlays and icons, and optional voice guidance. If any selected station's conditions change (e.g., it becomes occupied), the recommendations are updated in real time without requiring user intervention.

#### **MODULE 6: Re-Routing Engine**

Designed to enhance reliability and prevent charging failures, this module monitors real-time station status during the journey. If a recommended charger becomes full, offline, or too congested before the EV arrives, the re-routing engine is triggered. It immediately recalculates alternatives using the same scoring engine logic and provides the user with a seamless navigation update.

#### **MODULE 7: Session Logging**

This module tracks and records all relevant trip data, including route taken, station recommendations shown, user selections, final charging outcomes (e.g., wait time, price), and system responses. These logs support backend analytics and feedback mechanisms for future scoring model improvements. Additionally, they help generate personalized suggestions based on historical behavior and enable system audits or diagnostics for development teams.

#### **MODULE 8: User Preferences & Profiles**

This module stores each user's configurable preferences, such as cost sensitivity (cheapest vs. fastest), preferred charging networks (e.g., Tata Power, Ather Grid), maximum allowable detour, and desired charging level. Preferences are applied automatically during scoring and ranking. Over time, the system can learn behavior patterns to suggest new default settings or adapt recommendations to suit the driver's habits, enabling a more personalized and efficient user experience.

#### **CHAPTER 6**

#### RESULT AND DISCUSSION

The Real-Time EV Charging Station Recommendation System is currently in the design and development phase. As such, no live deployment or field testing has been conducted. However, based on the system architecture, workflow, and module interactions, a theoretical evaluation has been conducted to anticipate its functionality, use cases, and expected performance in real-world scenarios.

The system is designed to fetch real-time vehicle telemetry and external data (e.g., charger status, pricing, queue time) with minimal latency. Using lightweight backend frameworks (such as Flask or FastAPI), and cloud deployment with API caching, the system is expected to support real-time recommendations during navigation. Responsiveness will be optimized by minimizing API call delays and using efficient routing and scoring algorithms.

The recommendation engine is built to consider multiple real-time parameters, including SoC, user preferences, route context, and live station conditions. The scoring model is structured to prioritize stations that align with the user's goals—such as minimizing detours, wait time, or cost. Once implemented, accuracy will be evaluated by comparing recommendations against manually optimized routes in simulated scenarios.

Predictive modeling using machine learning (e.g., regression-based models) is planned for future phases. These models will be trained using historical charging station usage data to estimate queue lengths and wait times. In early versions, basic rule-based approximations may be used, with upgrades to ML-driven forecasting once relevant data is collected. The system interface is intended to resemble familiar map-based navigation apps. Key features will include real-time charger recommendations, ETA displays, estimated charging times, and trip impact summaries. Visual elements such as color-coded station scores and route overlays are designed to improve user clarity and engagement.

#### **CHAPTER 7**

#### CONCLUSION AND FUTURE ENHANCEMENT

#### 7.1 CONCLUSION

The Real-Time EV Charging Station Recommendation System is designed to address a critical challenge in the evolving electric mobility landscape: the need for intelligent, context-aware charging decisions. By combining real-time vehicle telemetry, route planning data, live charging station information, dynamic pricing, and user-specific preferences, the system aims to reduce range anxiety, minimize charging delays, and improve the overall travel experience for electric vehicle users.

The system architecture supports high responsiveness, with the ability to process live inputs and provide timely, data-driven recommendations. The core scoring engine evaluates multiple variables simultaneously, ensuring that the suggested charging stations align with the user's current travel context and energy requirements. A user-friendly interface further enhances usability, presenting key details such as estimated travel time, charging cost, and station queue status in an accessible and interactive format.

While this project is currently in the conceptual or design stage, it demonstrates significant potential for scalability and integration into broader EV infrastructure. With further development, the system could support grid-aware load distribution, predictive maintenance, and fleet management—benefiting not only individual EV drivers but also charging network operators and utility providers.

Though not intended to replace existing OEM navigation or energy systems, this project highlights the viability of modular, AI-enhanced platforms that can function across multiple vehicle models and charging networks. It lays the groundwork for future innovations in smart transportation, particularly in the areas of sustainable urban mobility, data-driven grid optimization, and personalized energy services.

#### 7.2 FUTURE ENHANCEMENT

While the current system establishes a strong foundation for intelligent EV charging station recommendations, several enhancements can significantly increase its precision, adaptability, and overall impact. These future developments will improve system performance, expand its reach to diverse user groups, and enable integration with broader mobility and energy ecosystems.

#### 1. Advanced Queue Prediction Models

To enhance the accuracy of estimated wait times at charging stations, the system can incorporate time-series forecasting techniques such as Long Short-Term Memory (LSTM) neural networks. By analyzing historical station usage patterns along with real-time traffic density and time-of-day variations, the system can deliver more precise queue forecasts. This will help drivers avoid unexpected delays and better plan their charging stops.

#### 2. Vehicle Integration APIs

A major improvement would be direct integration with electric vehicle OEM platforms through standardized APIs. Accessing real-time data such as battery health, charge curves, SoC, and efficiency metrics allows the system to make even more precise energy predictions. This direct connectivity ensures recommendations are fine-tuned to the unique characteristics of each EV model.

#### 3. Offline and Edge Deployment

To support users in areas with low or no internet connectivity, the system can be adapted for offline functionality. By pre-caching map data, charger information, and predictive routing instructions, the platform can offer essential services during travel disruptions. Edge inference capabilities would allow the scoring engine to function locally on the device, ensuring uninterrupted operation.

#### 4. Dynamic Pricing Optimization

The system can be extended to factor in dynamic electricity pricing and grid conditions. By identifying and suggesting off-peak hours or underutilized stations with lower tariffs, the system can help users save money and reduce grid strain during peak demand periods. This feature will be particularly valuable for cost-conscious users and for contributing to grid stability.

#### 5. EV Fleet Management Module

Another opportunity lies in scaling the system for commercial applications such as delivery fleets, ride-hailing services, or public transport operators. A dedicated module can be developed to optimize routing and charging for multiple EVs simultaneously, balancing factors like charger availability, route priority, and downtime reduction.

#### 6. Multi-language Support & Accessibility Enhancements

Expanding support for regional languages, voice-based navigation, and accessibility features will ensure the system is inclusive and user-friendly for a diverse audience. These enhancements will benefit users with visual impairments, elderly drivers, and those less familiar with digital interfaces.

#### 7. Carbon Footprint Estimation

To promote environmental awareness, a module can be added to track and display estimated emissions savings from using the system's optimized charging recommendations. This feature could be particularly impactful for eco-conscious users and can also support corporate sustainability reporting for fleet operators.

#### **APPENDIX**

#### A1. SAMPLE CODE

```
Script 1: Classifier (charge_decision_model.py)
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model selection import train test split
from sklearn.metrics import classification report
import joblib
np.random.seed(42)
data = pd.DataFrame({
  "state of charge": np.random.randint(10, 100, 1000),
  "distance to next station": np.random.randint(1, 50, 1000),
  "traffic_density": np.random.rand(1000),
  "energy consumption rate": np.random.rand(1000) * 2,
  "grid load": np.random.rand(1000),
  "charge now": np.random.choice([0, 1], 1000)
})
X = data.drop("charge now", axis=1)
y = data["charge now"]
X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
clf = RandomForestClassifier(n estimators=100, random state=42)
clf.fit(X train, y train)
joblib.dump(clf, "charge decision model.pkl")
print(classification report(y test, clf.predict(X test)))
```

# Script 2: ML Assistant (recommendation\_assistant.py) import joblib import pandas as pd clf = joblib.load("charge decision model.pkl") def get vehicle data(): return { "state of charge": 30, "distance to next station": 15, "traffic density": 0.5, "energy\_consumption\_rate": 1.2, "grid load": 0.4 charging\_stations = [ {"id": "ST1", "distance": 12, "queue": 2, "price": 5.5, "charging speed": 50, "grid load": 0.3}, {"id": "ST2", "distance": 18, "queue": 1, "price": 6.2, "charging\_speed": 100, "grid\_load": 0.6}, {"id": "ST3", "distance": 10, "queue": 0, "price": 5.0, "charging speed": 75, "grid load": 0.2} 1 def score station(station): return ( -0.3 \* station["distance"] + -0.2 \* station["queue"] +

-0.2 \* station["price"] +

-0.1 \* station["grid load"]

vehicle data = get vehicle data()

def recommend stations():

)

+0.2 \* station["charging speed"] +

```
input_df = pd.DataFrame([vehicle_data])
decision = clf.predict(input_df)[0]
if decision == 1:
    ranked = sorted(charging_stations, key=lambda x: score_station(x), reverse=True)
    return {"charge_now": True, "recommended_stations": ranked}
else:
    return {"charge_now": False, "recommended_stations": []}
if __name__ == "__main__":
    result = recommend_stations()
    if result["charge_now"]:
        print("Charging is recommended_ Top stations:")
        for station in result["recommended_stations"]:
            print(f"Station ID: {station['id']}, Score based on metrics.")
else:
        print("Charging not needed at this time.")
```

#### **A2. OUTPUT SCREENSHOTS**

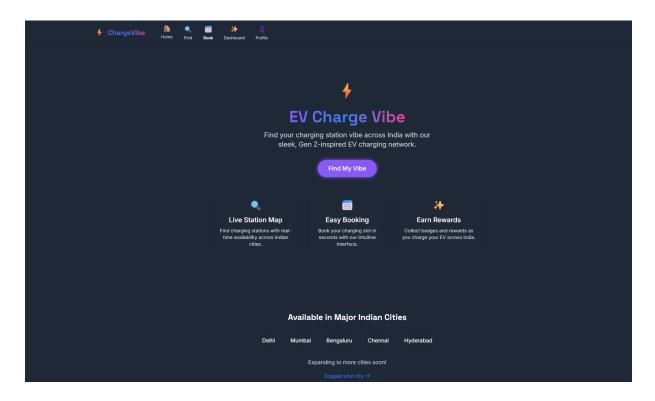


Fig A2.1 Landing Page

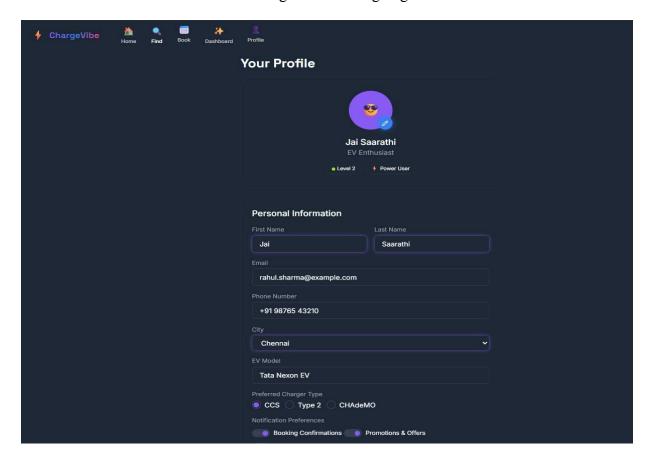


Fig A2.2 Personal Details

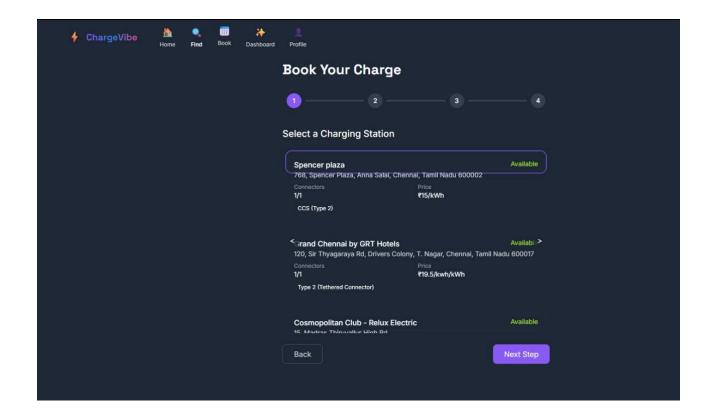


Fig A2.3 Slot Booking

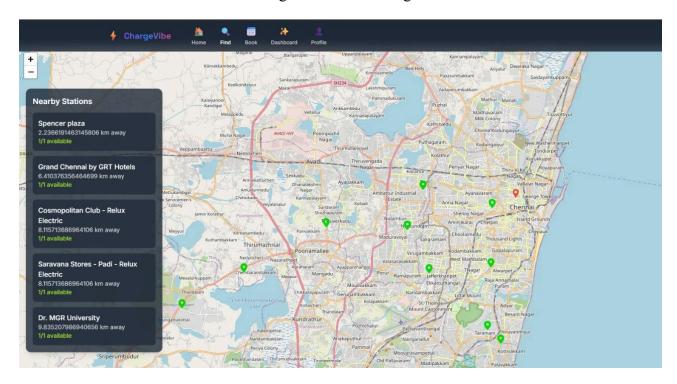


Fig A2.4 Grid Recommendation

#### REFERENCES

- 1. Z. Tian, T. Jung, Y. Wang, F. Zhang, L. Tu, C. Xu, C. Tian, and X.-Y. Li, "Real-Time Charging Station Recommendation System for Electric-Vehicle Taxis," IEEE Trans. Intell. Transp. Syst., vol. 17, no. 11, pp. 3258–3269, Nov. 2016, doi: 10.1109/TITS.2016.2539201.
- 2. P. Xu et al., "Real-time fast charging station recommendation for electric vehicles in coupled power-transportation networks: A graph reinforcement learning method," Eng. Appl. Artif. Intell., vol. 111, Jan. 2022, Art. no. 104856, doi: 10.1016/j.engappai.2022.104856.
- 3. S. Wang, X. Wang, and Y. Zhang, "A recommendation system for electric vehicles users based on restricted Boltzmann machine and waterwheel plant algorithms," IEEE Access, vol. 11, pp. 145111–145136, 2023, doi: 10.1109/ACCESS.2023.3308445.
- 4. S. Liu, X. Wang, X. Li, and Y. Li, "A Multi-Objective Optimization Model for Electric Vehicle Charging Station Location and Pricing," IEEE Access, vol. 8, pp. 172536–172547, 2020, doi: 10.1109/ACCESS.2020.3025042.
- 5. Y. Li, Y. Zhang, and J. Wang, "Optimal Dynamic Pricing for Electric Vehicle Charging Considering Renewable Energy and Energy Storage," IEEE Trans. Ind. Informat., vol. 14, no. 9, pp. 3917–3926, Sep. 2018, doi: 10.1109/TII.2018.2799219.
- 6. S. S. R. K. S. K. S. S. et al., "Dynamic Pricing Strategy for Electric Vehicle Charging Stations to Alleviate Congestion," Int. J. Electr. Power Energy Syst., vol. 161, 2024, Art. no. 108251, doi: 10.1016/j.ijepes.2024.108251.
- 7. S. K. Mishra, S. Mishra, and S. K. Panda, "Dynamic Pricing for Electric Vehicle Charging-A Literature Review," Energies, vol. 12, no. 18, p. 3574, Sep. 2019, doi: 10.3390/en12183574.

- 8. A. Mrkos, "Online Dynamic Pricing for Electric Vehicle Charging Stations with Reservations," arXiv preprint arXiv:2410.05538, 2024.
- 9. J. Wang, Q. Wu, and X. Guan, "Dynamic Pricing for Electric Vehicle Charging Based on Markov Decision Process," in Proc. IEEE PES General Meeting, 2018, pp. 1–5, doi: 10.1109/PESGM.2018.8586016.
- 10. K. Zhang, Y. Li, and Y. Wang, "Personalized dynamic pricing policy for electric vehicles," Transp. Res. Part C Emerg. Technol., vol. 164, 2024, Art. no. 103040, doi: 10.1016/j.trc.2024.103040.
- 11. R. K. Singh, R. K. Tripathi, and N. Kumar, "A Review of Electric Vehicle Charging Station Location and Pricing," IEEE Access, vol. 8, pp. 214234–214251, 2020, doi: 10.1109/ACCESS.2020.3039561.
- 12. H. Qin and W. Zhang, "Charging Scheduling With Minimal Waiting in a Network of Electric Vehicles and Charging Stations," in Proc. ACM Int. Conf. Autom. Sci. Eng., 2011, pp. 24–29, doi: 10.1109/CASE.2011.6042426.
- 13. Y. He, B. Venkatesh, and L. Guan, "Optimal Scheduling for Charging and Discharging of Electric Vehicles," IEEE Trans. Smart Grid, vol. 3, no. 3, pp. 1095–1105, Sep. 2012, doi: 10.1109/TSG.2012.2193847.
- 14. M. Yilmaz and P. T. Krein, "Review of the Impact of Vehicle-to-Grid Technologies on Distribution Systems and Utility Interfaces," IEEE Trans. Power Electron., vol. 28, no. 12, pp. 5673–5689, Dec. 2013, doi: 10.1109/TPEL.2013.2247393.
- 15. Y. Wang, S. Wang, and J. Li, "A Real-Time Recommendation System for Electric Vehicle Charging Stations," IEEE Access, vol. 8, pp. 12023–12034, 2020, doi: 10.1109/ACCESS.2020.2965982.
- 16. M. A. Razzaq, M. Nadarajah, and C. Ekanayake, "Demand Side Management

- of Electric Vehicles in Smart Grid: A Review of Smart Charging Approaches," IEEE Access, vol. 7, pp. 10823–10836, 2019, doi: 10.1109/ACCESS.2019.2891504.
- 17. J. Wang, C. Jin, P. Yi, and J. Wang, "Dynamic Pricing for Electric Vehicle Charging Using Multi-Agent Reinforcement Learning," IEEE Trans. Smart Grid, vol. 12, no. 5, pp. 4107–4118, Sep. 2021, doi: 10.1109/TSG.2021.3071448.
- 18. H. Wu, Y. Zhang, H. Li, and B. Zhang, "A Survey of Charging Infrastructure Planning for Electric Vehicles," IEEE Access, vol. 7, pp. 112760–112771, 2019, doi: 10.1109/ACCESS.2019.2934739.
- 19. S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid Integration of Electric Vehicles and Demand Response With Customer Choice," IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 543–550, Mar. 2012, doi: 10.1109/TSG.2011.2168437.
- 20. S. K. Mishra, S. Mishra, and S. K. Panda, "Dynamic Pricing for Electric Vehicle Charging-A Literature Review," Energies, vol. 12, no. 18, p. 3574, Sep. 2019, doi: 10.3390/en12183574.