EV Pathfinder: Mapping your electric journey

A major project report submitted in partial fulfillment of the requirement for the award of degree of

Bachelor of Technology

in

Computer Science & Engineering

Submitted by

Saransh Mehta 201228

Bhanu Thakur 201484

Under the guidance & supervision of

Dr. Shubham Goel

Department of Computer Science & Engineering and Information Technology Jaypee University of Information Technology, Waknaghat, Solan - 173234 (India)

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY, WAKNAGHAT

PLAGIARISM VERIFICATION REPORT

Date: ……………………………

Type of Document (Tick): PhD Thesis | M.Tech Dissertation/ Report | B.Tech Project Report | Paper

Name:______________________________**Department:**__________________**Enrolment No** __________

Contact No.______________________________**E-mail.**____

Name of the Supervisor: ____

Title of the Thesis/Dissertation/Project Report/Paper (In Capital letters): __________________________

UNDERTAKING

I undertake that I am aware of the plagiarism related norms/ regulations, if I found guilty of any plagiarism and copyright violations in the above thesis/report even after award of degree, the University reserves the rights to withdraw/revoke my degree/report. Kindly allow me to avail Plagiarism verification report for the document mentioned above.

Complete Thesis/Report Pages Detail:

- Total No. of Pages =
- Total No. of Preliminary pages =
- Total No. of pages accommodate bibliography/references =

(Signature of Student)

FOR DEPARTMENT USE

We have checked the thesis/report as per norms and found **Similarity Index** at .... (%). Therefore, we
are forwarding the complete thesis/report for final plagiarism check. The plagiarism verification report may be handed over to the candidate.

(Signature of Guide/Supervisor) **Signature of HOD**

FOR LRC USE

The above document was scanned for plagiarism check. The outcome of the same is reported below:

Copy Received on	Excluded	Similarity Index (%)	Generated Plagiarism Report Details (Title, Abstract & Chapters)	
	• All Preliminary Pages • Bibliography/Images/Quotes • 14 Words String		Word Counts	
Report Generated on			Character Counts	
		Submission ID	Total Pages Scanned	
			File Size	

Checked by
Name & Signature **Librarian**

……

Please send your complete thesis/report in (PDF) with Title Page, Abstract and Chapters in (Word File) through the supervisor at plagcheck.juit@gmail.com

Candidate's Declaration

We hereby declare that the work presented in this report entitled **'EV Pathfinder : Mapping your electric journey'** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering** submitted in the Department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out over a period from August 2023 to May 2024 under the supervision of **Dr. Shubham Goel** Assistant Professor (SG) Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

(Student Signature with Date)
Student Name: Saransh Mehta
Roll No.: 201228

(Student Signature with Date)
Student Name: Bhanu Thakur
Roll No.: 201484

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

(Supervisor Signature with Date)
Supervisor Name: Dr. Shubham Goel
Designation: Assistant Professor (SG)
Department: Computer Science & Engineering and Information Technology
Dated:

CERTIFICATE

This is to certify that the work which is being presented in the project report titled "**EV Pathfinder : Mapping your electric journey**" in partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science And Engineering and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Waknaghat is an authentic record of work carried out by "Saransh Mehta(201228) & Bhanu Thakur(201484)" during the period from August 2023 to May 2024 under the supervision of Dr. Shubham Goel, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

Saransh Mehta(201228)
Bhanu Singh(201484)

The above statement made is correct to the best of my knowledge.

SUPERVISOR

Dr. Shubham Goel
Assistant Professor (SG)
Computer Science & Engineering and Information Technology
Jaypee University of Information Technology, Waknaghat,

ACKNOWLEDGEMENT

Firstly, we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes it possible for us to complete the project work successfully.

We would like to express our sincere appreciation to our dedicated **Mr. Shubham Goel** for their invaluable guidance and support throughout the development of our project, titled "**EV Pathfinder : Mapping your electric journey**". Our supervisor's expertise and commitment have been instrumental in our progress thus far. They have provided us with the necessary resources and guidance to successfully navigate the initial stages of our project, and we are confident that their continued support will be invaluable as we move forward. As we prepare for our mid-term evaluation, we are grateful for our supervisor's willingness to review our work and provide feedback. Their insights and suggestions will undoubtedly help us refine our project and ensure its successful completion. We are truly grateful for our supervisor's mentorship and support. Their contributions have been instrumental in our learning and development, and we are confident that their continued guidance will lead to the successful completion of our project.

We would like to express our heartiest gratitude to Dr. Shubham Goel, Department of CSE, for their kind help to finish this project.
We would also generously welcome each one of those individuals who have helped us straightforwardly or in a roundabout way in making this project a win. In this unique situation, We might want to thank the various staff individuals, both educating and non-instructing, which have developed their convenient help and facilitated our undertaking.

Finally, We must acknowledge with due respect the constant support and patience of our parents.

Saransh Mehta 201228
Bhanu Thakur 201484

Table of Contents

List of Figures

List of Tables

ABSTRACT

Modern transportation is seeing an increase in the use of electric vehicles (EVs), which provide a more environmentally friendly option than conventional combustion engine vehicles. But in order to successfully incorporate EVs into daily life, some issues including their short range and the accessibility of charging infrastructure must be resolved. With the goal of optimizing travel routes for electric vehicles (EVs) while taking into account important variables like battery range, the availability of charging stations, and real-time traffic conditions, this project offers a thorough framework for route planning.

Sophisticated algorithms take into account multiple factors, like weather, geography, or driving history. The intuitive interface allows EV users to program the system to include their destination and preferences. As a result, this will direct the charger to identify the best route that conserves the most energy while minimizing the time required for charging.

Inclusion of real-time charging network data in the proposed system is critical as it ensures users receive updated information pertaining to the state and location of available chargers. In addition, this aspect makes navigation easier, simplifies operations, and helps in enhancing the precision of routes planning. The project will focus on addressing the huddles surrounding the route design to promote the spread of more electric vehicles.

This project report covers in detail on creating and implementing E-V route planning system. The document also provides detailed information regarding the system design, estimated energy consumption calculations, and ways of integrating charging network data. Also, this paper includes system testing, validation using real-world situations, as well as UI design. However, the project's conclusions constitute major progress towards achieving efficiency and environmentally friendly transport in cities, representing a practical solution to the problem.

Chapter 1: Introduction

Introduction

The increasing demand for an ecologically sound mode of transport leads to the development of an EV Route Planning system. The shift of the automobile industry towards cleaner options is gaining clarification that there are specific challenges facing EV users need to be addressed. There's a lot to consider however in terms of range limitations, energy efficiency when it comes to the availability of electric vehicle specific recharging systems for instance.

One of the technological solutions used in combatting the environmental damage caused by transport is Electric Vehicles (EVs). Nevertheless, the massive growth in EV usage entails a new setback, especially concerning route planning effectively and efficiently. The challenges posed by traditional navigation systems designed for internal combustion vehicles on the path towards electric mobility. Due to this gap, Electric Vehicle Route Mapping team has developed the first navigational system tailored to ev users. It is important to note that electric vehicle journey involves not only time and distance but also range of batteries, avail ability of charging points, environmental suitability of a road in this project.

Therefore, the project idea entails creating an EV owner-friendly navigation system to help the EV owner navigate through easily. Route-planning difficulties, access to charging points, efficiency of EV journeys are the major driving forces. Through this, the project seeks to make people embrace environment-friendly and sustainable forms of transportation by creating a mass acceptance for electric vehicles. There are many goals for the project. As a result, the system first considers various parameters that contribute towards energy consumption for EVs like the outside weather, terrain, battery capacity etc. so that the maximum range for EVs is achieved This optimization addresses one of the major concerns when it comes to the EV owners – the users can travel farther distance on a single charge.

The other key objective involves a strategy termed route planning algorithm that exploits live data concerning locations, viability, and charge speeds in various charging stations. This helps the system direct users to the most suitable areas to recharge their vehicles while minimizing idle time hence providing a convenient trip. The project caters for varied taste and desires from diverse users hence offering an ultimate in customization. Users can indicate their priorities (fastest, most scenic, less damaging), and the program will pick the best route accordingly. Users enjoy more personalized experience with EV through the opportunity to tailor travel plans based on their preferences.

An additional feature that is in line with the global trend towards sustainable practices is an assessment of the environmental impact. The ability for users to select routes that reduce their carbon footprint highlights the project's dedication to environmentally friendly travel options.
Real-time notifications and updates are yet another essential component of the project. By giving users access to real-time data on variables like weather, charging station accessibility, and traffic patterns, the system guarantees that users can modify their plans on the fly and enhance their trip experience in reaction to unforeseen events.

The Electric Vehicle Route Planning project is globally significant and in line with larger efforts to lessen transportation's negative environmental effects and decrease dependency on fossil fuels. Through enhancing the convenience, efficiency, and environmental friendliness of long-distance electric vehicle travel, the project hopes to hasten the global adoption of EVs and contribute to a more sustainable future.

Problem Statement

The development of a robust and efficient route mapping system for electric vehicles (EVs) is a challenging task. Electric mobility requires unique considerations for route optimization that are not present in conventional vehicles. The primary objective of this project is to develop an advanced system that generates routes that are ideal for electric vehicles by integrating real-time data on battery status, charging station availability, and dynamic traffic conditions.

Intelligent system management is necessary to account for the limited range of electric vehicle batteries in order to optimize energy efficiency during planned routes. It should also consider the location and accessibility of charging stations along the selected routes to provide users with a sense of security regarding the infrastructure's accessibility.

An essential component of the project is real-time data integration, which calls for the system to continuously update route recommendations in response to changing traffic conditions. This dynamic adaptation makes sure that users are given the most energy- and time-efficient routes, which improves the overall comfort of driving. For the infrastructure supporting electric vehicles to keep up with the rapid developments, scalability is essential. In order to make sure that the route mapping system is still applicable and efficient as the field of electric mobility changes, the project should take into account the possible growth of charging networks as well as adjustments to traffic patterns.

For ease of use and widespread adoption, an interface that is easy to use is essential. With features that are clear and easy to understand and that include real-time information on battery range, charging station availability, and suggested routes, the system should enable users to plan and carry out their travels with ease. The suggested electric vehicle route mapping system seeks to greatly aid in the development and integration of sustainable electric mobility solutions by tackling these issues head-on. The efficacy of this project is contingent upon its capacity to provide electric vehicle users with a smooth, flexible, and intuitive experience, thereby promoting a greater uptake and application of electric vehicles within the transportation network.

Objective

The main goal of Electric Vehicle (EV) Range Prediction and Route Planning is to create an advanced system that can precisely estimate an electric vehicle's remaining range and plan the best route while taking the battery's available charge into account. This project aims to address significant issues associated with electric vehicles, such as range anxiety and optimal route planning, using state-of-the-art algorithms and real-time data.
The specific objectives include:

Accurate Range Estimation: Develop algorithms that accurately calculate the remaining range of an electric vehicle by considering factors such as driving conditions, patterns of energy consumption, and battery health. Real-time Data Integration: Incorporate real-time data sources, such as traffic patterns, weather forecasts, and charging station availability, to increase the accuracy of range estimates and route planning.

Optimal Route Planning: Develop algorithms that consider factors other than just the shortest distance, such as elevation changes, traffic congestion, and road conditions, in order to plan the electric vehicle's most energy-efficient route.

Charging Station Integration: To guarantee that the suggested route satisfies charging requirements, incorporate data regarding the location, kind, and accessibility of charging stations into the route planning process. User customization: Give users the ability to select the charging stations they want to use, order their routes more quickly, or reduce the number of stops they make. Adapt dynamically to driving conditions, battery life, and other real-time factors to create a system that can provide updated route recommendations as needed while traveling.

User Interface Design: Provide users with clear visualizations of the predicted range, suggested routes, and pertinent information through the development of an intuitive and user-friendly interface that can be accessed through web or mobile platforms.

Energy Efficiency Optimization: Investigate methods to maximize energy efficiency while traveling, such as suggested speed limits, the use of regenerative braking, and other ways to increase the range of an electric vehicle. Consideration for the Environment: Include functions that compute and show the route's effects on the environment, accounting for things like carbon emissions and sustainable energy sources.

Scalability and Adaptability: The system should be designed to be both scalable to accommodate a range of electric vehicle models and battery technologies, as well as flexible enough to adapt to future developments in the electric transportation sector.

Significance and Motivation of the Project Work

Range prediction and route planning for electric vehicles (EVs) are important because they can help with important issues related to the adoption and general use of EVs. By offering precise estimates of remaining range and suggesting the best routes based on the available battery charge, this technology holds the key to reducing range anxiety, a significant worry among owners of electric vehicles. By doing this, drivers' confidence is greatly increased, which makes electric vehicles more appealing and practical for daily use.

Furthermore, the system helps electric vehicles maximize their energy efficiency. It increases the range of electric vehicles and encourages more environmentally friendly energy use by utilizing cutting-edge algorithms and real-time data integration. This supports worldwide initiatives to combat climate change and cut carbon emissions.

Route planning that incorporates charging station data not only solves infrastructure-related practical issues, but also encourages greater use of these resources. Thus, this promotes the expansion of electric vehicle networks and increases the general viability of electric cars.

Users' driving experiences are made more personalized with customization features that let them adjust route preferences, which increases user satisfaction and acceptance of electric vehicles. Furthermore, the system's dynamic adaptability to changing circumstances guarantees that route recommendations stay pertinent and ideal for the duration of the trip, adding to the dependability of traveling in electric vehicles.

The need to address significant obstacles preventing the widespread adoption of electric vehicles is what inspired the Electric Vehicle (EV) Range Prediction and Route Planning project.
The main driving force behind this is to reduce range anxiety, which is a common worry for owners of electric vehicles. The project aims to give drivers confidence that they can reach their destinations without worrying about running out of battery power by providing accurate predictions of remaining range. The drive to maximize electric vehicles' energy efficiency is what drives them. The project aims to increase the range of electric vehicles, making them more practical and appealing to a wider audience by creating sophisticated algorithms and integrating real-time data.
One of the main drivers is to enhance the general user experience for owners of electric vehicles. The project's objective is to provide consumers with accurate forecasts and effective route suggestions, thereby enhancing their driving experience. Consequently, this leads to heightened contentment and assurance in the technology of electric vehicles. The project's overarching objective is to advance ecologically friendly and sustainable transportation options. Through energy efficiency and minimizing the environmental effect of driving an electric vehicle, the project contributes to international efforts to mitigate climate change and lower carbon emissions.

One way to incentivize the use of charging infrastructure is to incorporate information about charging stations into route planning. This enhances the viability of electric transportation networks overall and promotes their expansion. The desire to provide users with a personalized experience drives motivation. Allowing users to customize their route preferences increases user satisfaction and adapts the technology to individual driving habits, contributing to an increase in electric vehicle acceptance.
The project is motivated by the need for electric vehicles to adapt to changing conditions dynamically. The system aims to provide up-to-date and relevant route recommendations by taking real-time factors such as traffic and weather into account, increasing the reliability of electric vehicle travel.

Organization of Project Report

This report's remaining sections are arranged as follows:

An overview of the completed literature study is provided in Chapter 2.

● An overview of the body of research on deep learning-based sign gesture detection, looking at various methodologies, tools, and datasets.

The system development and overflow are covered in detail in Chapter 3, along with the need for an original dataset and a detailed analysis of the specific requirements required to construct a detection system for sign language gestures.

The performance analysis is displayed in Chapter 4.

A description of the testing process that was employed to evaluate the accuracy and stability of our system.

The conclusion, future scope, and application contribution are highlighted in Chapter 5.

● The system's performance results are given and explained, showing how precisely it can recognize signs.

Chapter 2: Literature Survey

Overview of Relevant Literature

1. **Routing of Electric Vehicles With Intermediary Charging Stations: A Reinforcement Learning Approach (2021)**

The paper discusses the issue of electric vehicles' (EVs) short cruising range and sparse charging infrastructure. It also suggests a mathematical solution to the EV-specific routing problem in a graph-theoretical setting, taking into account EVs' capacity to recover energy and refuel at intermediate charging stations. The authors use low computing and memory demands appropriate for online applications to create energy-feasible paths for electric vehicles (EVs) using an off-policy model-free reinforcement learning approach.

Bellman's optimality equation is used by the algorithm to update the Q-value function while incorporating the idea of the Markov Decision Process (MDP). In the Q-value function, the learning rate controls the degree to which recently learned information takes precedence over previously learned information. Bellman's optimality equation, where Q(s, a) is the Q-value of the current state and action pair, R(s, a) is the observed reward following the action a, and an is the learning rate bounded by 0 and 1, is used by the algorithm to update the Q-value function. The optimal course of action (a') that maximizes the Q-value for the upcoming state (s') is taken into consideration when updating the Q-value function.

The parameter (ε) controls the amount of exploration in the greedy policy, and the update equation accounts for the trade-off between exploration and exploitation.

A case study of a road network in Switzerland is used in the research to illustrate the algorithm's ability to make decisions about recharging and to generate paths that are both feasible and energy-efficient.

Key Gaps of this Paper:

For problems with large state-action spaces, like those in which the state space is discretized or the road network grows, the paper's Q-learning algorithm might not scale well. This may result in worse training results, reduced performance, and increased memory requirements.

The discretization of the battery variable using the selected binning method creates a trade-off between the state space's size and the problem's level of detail in the model. Performance is further impacted by the probability of visiting a particular state and carrying out a particular action decreasing with a large number of states and actions.

If there are no charging stations nearby, EVs may become stuck without enough charge to begin a new journey due to the minimum required battery charge at the destination.

2. Energy efficient route planning for electric vehicles with special consideration of the topography and battery lifetime (2020)

This paper considers energy optimization and battery stress in the design of a route planning system tailored for electric vehicles. An actual model of the electric vehicle's energy usage is created, taking into account extra loads like air conditioning and heating.

The shortest path algorithm—more precisely, an altered version of the Yen algorithm—is applied to the street network by modeling it as a network with nodes and weighted edges. Battery constraints are incorporated into the modified Yen algorithm, enabling multi-objective optimization with variables denoting energy consumption, travel time, and battery cyclic lifetime.

The route planning system is tested in two different locations: an Austrian suburban area and the city of San Francisco. Variations in preferences, outside temperature, weather, and vehicle types are all taken into account. Route selection, battery operation, and energy consumption are all significantly impacted by topography. The "USGS Earth Explorer" website provided the topography data, which was a TIFF file with a high spatial resolution of one arc-second for latitude and longitude and one meter for height. The road segment height differences and distances were computed using the topography data, which was required for the optimization process.

The route planning system is tested in two locations—a suburban area in Austria and the city of San Francisco, California—in the paper, suggesting that real-world geographic data is used for these locations. Data sheets for the Nissan Leaf and Mitsubishi i-MiEV were specifically consulted during the testing process. The fact that no other datasets are specifically mentioned in the paper suggests that the topography data and the particular vehicles selected for testing were the main points of interest.

Key Gaps of the Paper :

The route planning system's consideration of electric vehicle charging stations is absent from the paper. The multi-objective optimization problem leaves room for uncertainty in the order of importance of energy consumption, travel time, and battery cyclic lifetime due to the omission of specific weights assigned to each optimization variable.

The route planning system is tested in two different locations—a suburban area in Austria and the city of San Francisco, California—which may limit the applicability of the findings in other contexts.

The comprehensive understanding of the system's performance under various conditions is limited by the lack of specific details and test results, despite the paper's mention of conducting tests for varying outside temperatures, weather patterns, and vehicle types.

3. Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles (2019)

The paper discusses how the limited infrastructure and heterogeneous charging power available for electric vehicles (EVs) during long trips necessitate careful route planning.

The authors suggest a method for choosing charging locations and routes that will minimize the overall travel time for EVs. They think about cutting the speed limit in order to conserve energy.

The method supports both the CC-CV and CP-CV charging protocols for lithium-ion batteries and employs a non-linear charging model. The authors combine precomputation of shortest-path trees with contraction hierarchies to achieve effective route planning. To speed up the queries, they take advantage of the fact that most routes are searched between known locations for charging stations.

Key Gaps of the paper :

The paper makes no mention of the effect of traffic conditions on total travel time optimization for electric vehicles.

The study makes the assumption of a non-linear charging model that supports specific charging protocols for lithium-ion batteries, which may not be applicable to all types of electric vehicles or charging infrastructure. The proposed approach prioritizes total travel time over other factors such as cost, environmental impact, and user preferences.

The paper does not provide a comprehensive analysis of the proposed approach's scalability and efficiency, particularly in scenarios with a large number of charging stations or complex road networks.

4. Implementation of charging station based electric vehicle routing problem using nearest neighbor search algorithm (2017)

This paper uses the Nearest Neighbour Search algorithm to optimize the routing of electric vehicles with charging stations.

Environmental concerns are making electric vehicles more widely acknowledged as a viable substitute for conventional automobiles. Electric vehicles' share of the market has been rising.
The routing algorithm presented in the paper takes charging station presence between nodes into account.

To determine the rate of battery discharge, the algorithm considers a number of vehicle parameters, including the aerodynamic drag coefficient, frontal area, rolling resistance coefficient, vehicle mass, gravitational acceleration, air mass density, rotational inertia factor, and regenerative braking factor. In the graph representation of the route, the shortest path between nodes is found using Dijkstra's algorithm.

Key Gaps of the Paper :

The implementation of the Nearest Neighbour Search algorithm for electric vehicle routing with charging stations is not specifically discussed in the paper, nor are its limitations.

The performance and efficiency of the suggested algorithm in comparison to other current algorithms for electric vehicle routing are not thoroughly examined in the paper. The possible effects of variables like road conditions, traffic congestion, and real-time data on the efficiency of the routing algorithm are not discussed in the paper. The accessibility and availability of charging stations in various locations are not taken into account in the paper, which may have an impact on the viability and usefulness of the suggested routing solution.

The computational complexity of the routing problem and the algorithm's scalability for larger networks are not covered in the paper.

5. Electric vehicle routing problem (2016)

A general Electric Vehicle Routing Problem (EVRP) model is presented in this paper, which seeks to determine the best routing plan with the least amount of energy consumed, travel time, and number of EVs dispatched.

An example from Austin, Texas is used to show how the vehicle load effect affects battery consumption in the EVRP model, which is the first to do so. While EVRP has a similar travel time and distance to diesel truck VRP, it requires more labor due to the longer en-route recharging time.

The EVRP routing strategies are significantly impacted by the network topology. When examining the energy consumption from production to consumption, the environmental benefits of electric vehicles (EVs) over diesel trucks become less clear from a life-cycle perspective.

Key Gaps of the Paper :

The EVRP model's specific limitations and any potential implementation difficulties are not covered in the paper. The lack of a thorough examination of how vehicle load affects battery consumption in the paper restricts our comprehension of this element of EVRP. Beyond energy consumption, the paper does not investigate the possible environmental advantages or disadvantages of EVs over diesel trucks.
The limitations of the selected solvers (Matlab and CPLEX 12.1) in resolving the mixed integer linear problem given in the EVRP model are not covered in the paper. The EVRP model's scalability and suitability for use in larger networks or diverse geographic regions are not discussed in the paper.

6. Finding minimum-cost paths for electric vehicles (2012)

The issue of determining the least expensive routes for electric vehicles (EVs) that must stop for refueling is addressed in this paper. Current route-guidance software for conventional vehicles does not take this into account.

The problem is modeled in the paper as a dynamic program, and two distinct approaches to solving it are presented: one for discrete state space and another that makes use of an approximate dynamic programming (ADP) algorithm for general problem instances.

Key Gaps of the paper :

The paper assumes that EV drivers would not always recover the full retail value of the electricity discharged from the battery, and that discharging will also incur time and battery wear costs. It does not, however, provide a detailed analysis or empirical evidence to back up this assumption.

The problem is modeled as a dynamic program in the paper, and two methods for solving it are presented; however, the computational complexity and scalability of these methods are not discussed in detail. The study does not take into account how traffic patterns or other outside variables may affect the best route for Evs. The limited infrastructure for charging and its potential impact on the viability and efficacy of the suggested minimum-cost path algorithms are not addressed in the paper.

7. Optimal Locating of Electric Vehicle Charging Stations by Application of Genetic Algorithm (2018)

The deployment of electric vehicle (EV) charging stations is the main topic of this paper, which aims to identify the optimal sites to satisfy EV users' demands.

The issue is expressed mathematically, accounting for variables like daily travel distance, average recharge time, and charging station power.

Using the Genetic Algorithm (GA), the problem is optimized to find the ideal number and placement of charging stations. The number of electric vehicles is estimated using the Bass model, which takes into consideration variables like daily charge cycles, average power consumption, and the distance between charging stations and settlements.

Finding an efficient solution to the charging station location optimization problem is the work's main goal.

Key Gaps of the Paper :

The paper does not specifically address the drawbacks and challenges of using the Genetic Algorithm (GA) to optimize charging station location optimization.

The paper does not address potential constraints or challenges related to the implementation of the infrastructure for charging stations. The paper shows a clear disregard for factors that can be a practical constraint, like the availability of land or space for the installation of charging stations. The paper does not address the necessity of infrastructure upgrades or the possible effects that the locations of charging stations may have on the current power grid.

This paper does not consider the optimal locations for charging stations or the potential impact of future technological advancements or changes.

The study makes no mention of the potential downsides or challenges associated with accurately estimating the distances between populated areas and charging stations.

8. Optimization of Charging Stops for Fleet of Electric Vehicles: A Genetic Approach (2014)

The problem of determining the best routes for a fleet of electric vehicles (EVs) while taking charging station requirements and battery limits into account is covered in this paper.

Suboptimal routing solutions are produced by current route planners because they do not sufficiently take into account the features and charging stop requirements of EV fleets. In order to calculate routes that minimize associated costs, such as travel time, charging time, and energy consumption, the suggested solution combines an evolutionary genetic algorithm with a learning strategy. In order to reduce concurrency, the algorithm distributes vehicles among charging stations by effectively exploring large solution spaces.

The outcomes show that the suggested algorithm lowers computational requirements and finds workable solutions in a reasonable amount of time. The study admits that the issue is non-polynomial and offers estimates and methods for effectively locating solutions.

Key Gaps of the Paper :

The paper does not explicitly mention the proposed algorithm's limitations or discuss potential challenges in implementing it in real-world scenarios.

The limitations of the genetic approach in comparison to other optimization techniques are not addressed in the references provided. The paper does not assess the algorithm's scalability and robustness when applied to larger fleets or more complex scenarios. The paper is solely concerned with optimizing charging stops for EV fleets and does not take into account other factors such as traffic conditions or vehicle-specific constraints.

The provided sources do not go into detail about the specific approximations and strategies used to reduce computational requirements and improve solution efficiency.

9. Electric Vehicle Charging Path Planning Based on Real-time Traffic Information (2022)

The paper proposes a model that combines an electric vehicle model and a smart transportation network model to form a "electric vehicle-transit network" joint interaction model.

The Dijkstra algorithm is used to plan the route of the vehicle and calculate the distance of each trip. Road weights are calculated by calculating the travel time based on the road class and real-time traffic information.

MATLAB is used to simulate and evaluate the route planning scheme in this paper.

According to the simulation results, the EV charging route design based on actual traffic data is more realistic and provides the best route navigation strategy when multiple factors are considered at the same time.

Key Gaps of the paper:

The paper does not go into specifics about how the electric vehicle model and smart transportation network model were built using a graph-theoretic approach.

There is no mention of the specific criteria or factors used by Dijkstra's algorithm to plan the vehicle's route and calculate the distance of each trip.

The paper does not explain how road weights are calculated based on the vehicle's speed, road class, and real-time traffic data.

There is no discussion of the proposed planning scheme's limitations or potential challenges in real-world scenarios.
The suggested planning scheme is not compared or evaluated in the paper with any current methods or techniques for planning electric vehicle charging paths.

S no.	Paper Title	Conference Year	Tools and Techniques	Results	Limitations
1.	Routing of Electric Vehicles With Intermediary Charging Stations: A Reinforcement Learning Approach..	2021	Paper suggests off-policy reinforcement learning for energy-feasible EV paths, models as MDP.	The reinforcement learning algorithm efficiently plans energy-feasible EV paths, factoring in energy recuperation and charging at intermediate stations, demonstrated on a Swiss road network.	Scalabillity, fixed charge requirement ,retraining inconvenience, evaluation limitations in real-world scenarios.
2.	Energy efficient route planning for electric vehicles with special consideration of the topography and battery lifetime	2020	Paper uses the Yen algorithm for EV route planning, considering topography with high-res SRTM data.	Paper introduces EV route planning with energy optimization using a modified Yen algorithm.	Paper lacks EVcharging station inclusion, limited study area, traffic, scalability, and real world

				Tested in an Austrian suburban area.	challenges discussion.
3.	Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles	2019	Paper uses a multi-criterion shortest-path algorithm, combines techniques for speed, experiments on German road networks, implements in C with Dijkstra's algorithm, considers CC-CV and CP-CV charging protocols.	Paper optimizes EV travel time, uses a nonlinear charging model, and experiments on German road networks.	Slow precomputation for large batteries, long query times, single focus, lithium-ion bias, regional specificity.
4.	Implementation of charging station based electric vehicle routing problem using	2017	NA	Optimizes the routing of electric vehicles by considering the locations of	The paper does not consider other factors such as traffic conditions, road network

	nearest neighbor search algorithm			charging stations and the battery discharge rate.	constraints, or dynamic changes in charging station availability.
5.	Electric vehicle routing problem	2016	NA	The paper introduces an EVRP model, comparing it with VRP, demonstrating charging station impact, and showing significant real-world improvements.	The paper does not provide a comprehensive analysis of the trade-offs between travel time cost, energy cost, and labor cost in the EVRP model.

S no.	Paper Title	Journal & Conference Year	Tools and Techniques	Results	Limitations
6.	Finding minimum-cost paths for electric vehicles	2012	Paper models EV cost optimization, offers two methods: backward recursion for discrete states, ADP for general cases, minimal tool.	Paper models EV minimum-cost path with discrete states, presents 2 methods, highlights recharging nodes, initialization challenge.	The paper does not address the potential variability in charging station availability and charging times.
7.	Optimal Locating of Electric Vehicle Charging Stations by Application of Genetic Algorithm	2018	The paper utilizes a Genetic Algorithm (GA) to optimize the location of electric vehicle (EV) charging stations.	The paper aims to optimize the location of electric vehicle (EV) charging stations using a Genetic Algorithm (GA) approach.	Not specified in paper.

8.	Optimization of Charging Stops for Fleet of Electric Vehicles: A Genetic Approach	2014	Paper uses genetic algorithms, including local search, l-shortest path routes, binary representation.	Paper evaluates Genetic algorithms with 1000 population, advanced initialization, and learning strategy for better convergence.	Paper lacks comprehensive analysis, real-world representation, robustness assessment, GA limitations, and comparative analysis.
9.	Electric Vehicle Charging Path Planning Based on Real-time Traffic Information	2022	The paper employs graph theory to model electric vehicles and smart transportation networks, using Dijkstra's algorithm for route planning and distance calculation.	Simulation results indicate that designing EV charging routes with actual traffic data is more realistic and offers an optimal navigation strategy by considering multiple factors simultaneously.	The limitations of the electric vehicle model and smart transportation network model, such as their accuracy and applicability to real-world scenarios, are not discussed

Chapter 3: System Development

Requirements and Analysis

Software Requirements

Streamlit is an open-source Python library used to create web applications for data science and machine learning projects. Streamlit is used to create a user interface for user interaction. Users can specify their starting and ending addresses, as well as their battery charge and charging time.

Vs-code is a well-known code editor that will be used to develop the messaging application. Syntax highlighting, code completion, and debugging are just a few of the features included in Vs-code to help with the development process.

Python is a high-level programming language that is known for its readability and simplicity. It is widely used in a variety of applications, including educational projects.

OSMnx library: OSMnx is a Python library for downloading, modeling, analyzing, and visualizing OpenStreetMap (OSM) data. The OSMnx library is employed.

What is streamlit?

An open-source Python library called Streamlit makes it easy to develop web applications for data science and machine learning. It makes it simple and quick for developers and data scientists to transform data scripts into interactive web applications. With just a few lines of code and Streamlit, you can create interactive and user-friendly interfaces.

Now, you can use Streamlit in conjunction with other libraries like NetworkX and Folium to visualize city road networks neatly. A general strategy to accomplish this is as follows:

```python
import streamlit as st
import osmnx as ox
import networkx as nx
import pandas as pd

# Load the graph (assuming you have saved it as 'delhi_ev_graph.graphml')
G = ox.load_graphml('delhi_ev_graph.graphml')

# Define a function to compute the battery range gained by charging for a specified time
def compute_battery_range(charging_time):
    # Compute the battery range gained by charging for the specified time
    battery_range_gained = charging_time * 60  # Assume 60 km of range gained per hour of charging

    return battery_range_gained

# Streamlit app layout
st.title("EV Routing Application")

start_address = st.text_input("Enter starting address:", value="")
end_address = st.text_input("Enter destination address:", value="")
battery_charge = st.number_input("Enter current battery charge (in kilometers):", value=0)
charging_time = st.number_input("Enter charging time (in hours):", value=0)
```

Figure 1(Importing necessary libraries)

Project Design and Architecture

1. Network Graph Generation:

Process:

To obtain OpenStreetMap data for Delhi, use the OSMnx library.

Using the data obtained, draw a road network graph.

For accurate distance calculations, project the graph to Universal Transverse Mercator (UTM).

Architecture:

OpenStreetMap data for Delhi is used as input.

Processing:

Data retrieval and graph creation are handled by the OSMnx library.

Projection to UTM coordinates for precise distance calculations.

Output:

UTM road network graph as output.

2. EV Charging Station Integration:

Process:

Load data from the dataset containing EV charging stations.

Convert data from charging stations into a GeoDataFrame.

Connect charging stations to the network graph.

Using OSMnx's nearest_nodes function, locate the nearest graph nodes for each charging station.

Add charging stations to the graph as nodes with attributes like name, latitude, and longitude.

Architecture:

Input:

EV charging station dataset.

Processing:

To GeoDataFrame conversion.

integration with the graph of the road network.

Finding the closest nodes in the graph.

Output:

Road network graph with integrated charging station nodes.

3. Streamlit Web Application:

Process:

Create a user interface for user interaction using Streamlit.

Allow users to enter their starting and ending addresses, as well as battery charge and charging time.
Determine the shortest path using Dijkstra's algorithm while keeping the battery range in mind.
If the destination is out of battery range, recommend the nearest charging station.
Display the best route and relevant information on an interactive map.

Input:
User input (battery charge, charging time, starting address, and destination address).
A road network graph featuring integrated nodes for charging stations.

Processing:
Calculating the shortest path with Dijkstra's algorithm.
suggestion for the closest charging station.
A map and an information display.

Output:
Interactive map with optimal route and relevant information.

Diagram:
Consider creating a flowchart or architectural diagram to visually represent the flow of data and processes between these components. This can help readers grasp the overall structure of your project.

Data Preparation

1. Data Sources:

Information about EV charging stations in Delhi, India, was obtained from the official website of the Delhi Government and utilized in this project. It contains details like vendor names, station types, payment methods, latitude and longitude, and more. Preprocessing was done on the dataset to encode categorical variables and get rid of duplicates. There are 25 columns spread across 2706 rows in the csv document.

	uid	name	vendor_name	address	latitude	longitude	city	country	open	close	...	postal_code	zone	0	available	capacity	cost
0	STATIC12	GensolCharge Pvt. Ltd.	GensolCharge Pvt. Ltd.	NDSE Grid, BRPL South Extension	28.568238	77.219666	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
1	STATIC14	REIL	REIL	Scada office kalka ji	28.541995	77.260583	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	3.3 kW	
2	STATIC15	REIL	REIL	Ashram Chowk Mathura Road	28.571189	77.259806	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
3	STATIC16	REIL	REIL	Nizamuddin Railway station	28.588991	77.253240	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
4	STATIC17	BluSmart	BluSmart	BSES Bhawan, Nehru Place, New Delhi	28.549427	77.254636	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	

Figure 2(Dataset values)

2.OpenStreetMap Data:

Figure 3(Red represents all distributed charging stations)

We have used the OpenStreetMap (OSMnx) to obtained the graph network of the delhi state.

EV Charging Station Dataset:

```
df = pd.read_excel("ev_final.xlsx")
df
```

	uid	name	vendor_name	address	latitude	longitude	city	country	open	close	...	postal_code	zone	0	available	capacity	cost
0	STATIC12	GensolCharge Pvt. Ltd.	GensolCharge Pvt. Ltd.	NDSE Grid, BRPL South Extension	28.568238	77.219666	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
1	STATIC14	REIL	REIL	Scada office kalka ji	28.541995	77.260583	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	3.3 kW	
2	STATIC15	REIL	REIL	Ashram Chowk Mathura Road	28.571189	77.259806	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
3	STATIC16	REIL	REIL	Nizamuddin Railway station	28.588991	77.253240	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
4	STATIC17	BluSmart	BluSmart	BSES Bhawan, Nehru Place, New Delhi	28.549427	77.254636	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	

Figure 4(Dataset first 4 values)

3. Data Conversion:

GeoDataFrame Conversion:

```
# Convert the charging stations DataFrame to a GeoDataFrame
geometry = [Point(xy) for xy in zip(df['longitude'], df['latitude'])]
crs = edges.crs  # Get the CRS (Coordinate Reference System) from the edges GeoDataFrame
charging_stations = gpd.GeoDataFrame(df, crs=crs, geometry=geometry)
```

Figure 5(Geodataframe)

5. Coordinate Projection:

UTM Projection:

```
location = 'Delhi, India'
# Get the road network for the specified area
G = ox.graph_from_place(location, network_type='drive')
# Project the graph to UTM (Universal Transverse Mercator) for accurate distance calculations
G = ox.project_graph(G)

nodes, edges = ox.graph_to_gdfs(G)
```

Figure 6(UTM Projection)

6. Data Exploration (Optional):

Exploratory Data Analysis (EDA):

```
df.drop_duplicates(subset=["address"], inplace=True)
df.replace("Not Available", pd.np.nan, inplace=True)
print(df.shape)
scaler = StandardScaler()
df[["latitude", "longitude"]] = scaler.fit_transform(df[["latitude", "longitude"]])
df = pd.get_dummies(df, columns=["vendor_name", "city", "country", "station_type"])
print(df.shape)
```

```
(1721, 25)
(1721, 71)
```

Figure 7(EDA)

Implementations

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import osmnx as ox
import warnings
warnings.filterwarnings("ignore")
import networkx as nx
import geopandas as gpd
from shapely.geometry import Point
```

Figure 8 (Importing libraries)

NumPy (import numpy as np): NumPy is a Python numerical computing library. It supports large, multi-dimensional arrays and matrices, as well as mathematical functions for operating on these arrays.

Pandas (import pandas as pd): Pandas is a library for data manipulation and analysis. It offers data structures such as Data Frame, which is used to organize and analyze structured data.

```
df = pd.read_excel("ev_final.xlsx")
df
```

The DataFrame is a two-dimensional, tabular data structure in Pandas, similar to a spreadsheet. It allows for easy manipulation, analysis, and visualization of the data.

	uid	name	vendor_name	address	latitude	longitude	city	country	open	close	...	postal_code	zone	0	available	capacity	cost
0	STATIC12	GensolCharge Pvt. Ltd.	GensolCharge Pvt. Ltd.	NDSE Grid, BRPL South Extension	28.568238	77.219666	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
1	STATIC14	REIL	REIL	Scada office kalka ji	28.541995	77.260583	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	3.3 kW	
2	STATIC15	REIL	REIL	Ashram Chowk Mathura Road	28.571189	77.259806	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
3	STATIC16	REIL	REIL	Nizamuddin Railway station	28.588991	77.253240	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	
4	STATIC17	BluSmart	BluSmart	BSES Bhawan, Nehru Place, New Delhi	28.549427	77.254636	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	

```
df.drop_duplicates(subset=["address"], inplace=True)
df.replace("Not Available", pd.np.nan, inplace=True)
print(df.shape)
scaler = StandardScaler()
df[["latitude", "longitude"]] = scaler.fit_transform(df[["latitude", "longitude"]])
df = pd.get_dummies(df, columns=["vendor_name", "city", "country", "station_type"])
print(df.shape)
```

```
(1721, 25)
(1721, 71)
```

Figure 9(Data Cleaning)

df.drop_duplicates(subset=["address"], inplace=True)

- Remove rows with duplicate 'address' values.

df.replace("Not Available", pd.np.nan, inplace=True)

- Replace "Not Available" with NaN for missing values.

print(df.shape)

- Display the DataFrame's number of rows and columns.

Standardize Latitude and Longitude:

scaler = StandardScaler()

df[["latitude", "longitude"]] = scaler.fit_transform(df[["latitude", "longitude"]])

- Standardize 'latitude' and 'longitude' columns.

df = pd.get_dummies(df, columns=["vendor_name", "city", "country", "station_type"])

- One-hot encode specified categorical columns.

print(df.shape)

- Display the DataFrame's shape post one-hot encoding.

In essence, the code prepares a dataset by handling duplicates, missing values, standardizing numerical features, and one-hot encoding categorical features. The printed shapes indicate changes in the DataFrame structure.

```
location = 'Delhi, India'
# Get the road network for the specified area
G = ox.graph_from_place(location, network_type='drive')
# Project the graph to UTM (Universal Transverse Mercator) for accurate distance calculations
G = ox.project_graph(G)

nodes, edges = ox.graph_to_gdfs(G)
```

Figure 10(Getting Road Network)

location = 'Delhi, India':

Specifies the geographical area for which the road network graph will be retrieved, setting it to 'Delhi, India.'

G = ox.graph_from_place(location, network_type='drive'):

Uses OSMnx to fetch a road network graph (G) for the specified location, focusing on drivable roads ('drive' network type).

G = ox.project_graph(G):

Projects the road network graph (G) to Universal Transverse Mercator (UTM) coordinates for precise distance calculations.

nodes, edges = ox.graph_to_gdfs(G):

Converts the nodes and edges of the projected road network graph (G) into GeoDataFrames (nodes and edges).

nodes: Contains information about the nodes (intersections) of the road network.

edges: Contains information about the edges (roads) of the road network.

In summary, these lines of code collectively fetch, process, and prepare a road network graph for Delhi, India, making it suitable for further geospatial analysis or visualization. The resulting GeoDataFrames, nodes and edges, can be used to explore and understand the structure of the road network in the specified location.

```
# Convert the charging stations DataFrame to a GeoDataFrame
geometry = [Point(xy) for xy in zip(df['longitude'], df['latitude'])]
crs = edges.crs  # Get the CRS (Coordinate Reference System) from the edges GeoDataFrame
charging_stations = gpd.GeoDataFrame(df, crs=crs, geometry=geometry)
```

Figure 11(GeoDataFrame)

Geometry Column Creation:

Creates a geometry column by transforming latitude and longitude pairs from the charging stations DataFrame (df) into Shapely Point geometries. Each point represents the spatial location of a charging station.

Coordinate Reference System (CRS) Extraction:
Extracts the Coordinate Reference System (CRS) from an existing GeoDataFrame (edges). The CRS defines the spatial reference framework used for interpreting the geometric shapes.

GeoDataFrame Creation:

Combines the original charging stations DataFrame (df) with the new geometry column to form a GeoDataFrame (charging_stations).
The crs parameter sets the Coordinate Reference System for the GeoDataFrame.
The geometry parameter assigns the 'geometry' column, now containing Point geometries, to the GeoDataFrame

.

In summary, these lines of code create a GeoDataFrame (charging_stations) from the charging stations DataFrame (df). The GeoDataFrame includes a 'geometry' column with Point geometries, making it suitable for spatial analysis and visualization with the associated CRS. This transformation enhances the dataset with geospatial capabilities for further geographic exploration.

```
charging_stations
```

	uid	name	address	latitude	longitude	open	close
0	STATIC12	GensolCharge Pvt. Ltd.	NDSE Grid, BRPL South Extension	0.170032	0.037066	00:00:00	23:59:59
1	STATIC14	REIL	Scada office kalka ji	0.160978	0.046627	00:00:00	23:59:59
2	STATIC15	REIL	Ashram Chowk Mathura Road	0.171050	0.046445	00:00:00	23:59:59
3	STATIC16	REIL	Nizamuddin Railway station	0.177191	0.044911	00:00:00	23:59:59
4	STATIC17	BluSmart	BSES Bhawan, Nehru Place, New Delhi 110048	0.163542	0.045237	00:00:00	23:59:59

Figure 12(Information of charging station)

```
# # Find the nearest graph nodes for each charging station
charging_station_nodes = []
for geometry in charging_stations['geometry']:
    # Get the nearest node to the charging station
    nearest_node = ox.nearest_nodes(G, geometry.x, geometry.y)

    # Append the nearest node to the list
    charging_station_nodes.append(nearest_node)
```

Figure 13(Finding nearest graph nodes)

List Initialization:

Initializes an empty list (charging_station_nodes) to store the nearest graph nodes for each charging station.`

Iteration through Charging Station Geometries:

Initiates a loop to iterate through each charging station's geometry (Point) in the 'geometry' column of the charging_stations GeoDataFrame.

Nearest Node Calculation:

Utilizes the OSMnx function ox.nearest_nodes to find the nearest node in the road network (G) for each charging station.

Extracts the latitude (geometry.x) and longitude (geometry.y) coordinates of the charging station to determine its position.

Appending Nearest Node to List:

Appends the calculated nearest node for the current charging station to the charging_station_nodes list.

In summary, these lines of code collectively find and store the nearest graph nodes in the road network for each charging station. The resulting charging_station_nodes list holds this information, which can be valuable for subsequent analyses, such as determining distances or optimizing routes for electric vehicles between the charging stations.

```
charging_station_nodes
```

```
[4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 4212043265,
...
 4212043265,
 4212043265,
 4212043265,
 4212043265,
 ...]
```

```
# Add charging stations as nodes in the graph
for i, (idx, station) in enumerate(charging_stations.iterrows()):
    node_id = charging_station_nodes[i]
    G.nodes[node_id]['charging_station'] = True
    G.nodes[node_id]['name'] = station['name']
    G.nodes[node_id]['latitude'] = station['latitude']
    G.nodes[node_id]['longitude'] = station['longitude']
```

Figure 14(Add charging station)

```python
# Save the graph for future use (optional)
ox.save_graphml(G, 'delhi_ev_graph.graphml')
```

```python
import matplotlib.pyplot as plt

fig, ax = ox.plot_graph(G, node_color='r', node_size=30, bgcolor='w', edge_linewidth=0.5, edge_alpha=0.5, show=False, close=False)

# Add charging station locations to the map
charging_stations.plot(ax=ax, markersize=50, marker='o', color='blue', zorder=3)

# Set title and display the map
ax.set_title("Delhi EV Charging Stations")
plt.show()
```

Figure 15(Distributed electric vehicle)

Key Challenges

There are several major challenges to implementing predictive routing for electric vehicle (EV) charging stations. To begin, predicting EV charging demand accurately is a difficult task due to the dynamic nature of the factors influencing it, such as traffic patterns, weather conditions, and user behavior. Furthermore, integrating real-time data and adapting to unexpected events is a significant challenge that necessitates robust algorithms and predictive models.

Second, the availability and accessibility of charging infrastructure varies greatly, making it difficult to optimize routes for EV users. Finding optimal charging station locations and ensuring compatibility with various EV models is a logistical challenge. Furthermore, dealing with the ever-changing nature of charging technologies and standards complicates the creation of a universally applicable predictive routing system.

Challenges include the requirement for data communication standardization and the ability of various charging networks to work together. Overcoming incompatibilities and creating standard protocols are necessary to achieve seamless communication between EVs, charging stations, and the central predictive routing system.

Finally, resolving privacy issues and guaranteeing user data security present a significant challenge. It takes careful thought and the implementation of strong security measures to protect user information throughout the predictive routing process to strike a balance between the need for accurate predictions and privacy protection measures.

Challenges faced in Streamlit and OSMnx :

1. Data Complexity and Size:

- Although OSMnx provides rich OpenStreetMap data, dealing with large datasets can be computationally demanding. Managing, processing, and visualizing large amounts of geographical data may necessitate optimized algorithms and resource utilization.

- When dealing with large datasets or complex visualizations, Streamlit apps may experience performance issues. Optimization techniques such as data sampling or dynamic loading may be required.

2.User Interface Design and Responsiveness:

- It might take more work to create an interface that is both responsive and easy to use with Streamlit. It can be difficult to make sure the interface is user-friendly, adaptable to various screen sizes, and offers a satisfying experience.

3.Real-Time Data Updates:

- If your project relies on real-time data, it may be difficult to ensure that both OSMnx and Streamlit can handle and update information in real-time. It is critical to implement effective caching mechanisms and optimize data update processes.

4.Data Privacy and Security:

- Ensuring data security and privacy is essential when working with geographical data and user inputs. Although it can be difficult, putting in place the right authentication, authorization, and encryption procedures to safeguard sensitive data is crucial.

Chapter 4: Testing

4.1 Testing Strategy

In the electric vehicle (EV) route mapping project, a robust and comprehensive testing strategy is crucial to ensure the software's reliability, accuracy, and efficiency. This strategy spans several methodologies tailored to validate the diverse aspects of the project, from network graph generation to the user interface. Initially, **unit testing** is performed using tools like PyTest to validate individual functions in the graph generation module, ensuring that the OSMnx library correctly fetches and processes OpenStreetMap (OSM) data for Delhi, and accurately projects the graph to Universal Transverse Mercator (UTM) for precise distance calculations. This step is critical to verify that each component functions correctly before integration. Following this, **integration testing** is conducted using Selenium WebDriver and Postman, focusing on the seamless integration of OSM data with graph creation functions, ensuring accurate data flow and correct graph generation. This phase checks the combined functionality of projection functions and distance calculations, ensuring that charging stations are correctly incorporated into the network graph with accurate attributes and nearest node associations.

For the **EV charging station integration** step, unit tests are again used to validate the functions responsible for loading the charging station dataset and converting it into a GeoDataFrame. The nearest_nodes function is tested to ensure it accurately identifies the closest graph nodes. Integration tests are performed to ensure the proper addition of charging stations as nodes in the graph, complete with attributes such as name, latitude, and longitude, confirming their accurate association with the nearest nodes. Moving on to the **Streamlit web application** development, unit tests validate the individual UI components, such as input fields for starting and destination addresses, battery charge, and charging time. Integration testing with Selenium WebDriver and Postman ensures the user interface correctly interacts with backend processes like Dijkstra's algorithm for route calculation and nearest charging station recommendation. This phase ensures that user inputs trigger the appropriate backend actions, and the system responds correctly.

System testing employs tools like Apache JMeter for load testing and TestRail for test case management to conduct end-to-end testing of the web application. This simulates real user scenarios, validating the system's performance under typical and peak usage conditions. **User acceptance testing (UAT)** is conducted using platforms like UserTesting, where real users interact with the application in a controlled environment, providing feedback on usability, functionality, and overall user experience. This phase ensures the application is user-friendly and meets user requirements. To maintain software stability, **regression testing** is performed using Jenkins for continuous integration and Selenium, with automated test suites running after every code change to detect any regression issues. This ensures that new code changes do not negatively impact existing functionalities.

Performance testing with Apache JMeter and LoadRunner assesses the system's behavior under varying loads, monitoring response times, throughput, and resource utilization to identify performance bottlenecks. This ensures the system can handle peak loads efficiently. Finally, **security testing** is conducted using tools like OWASP ZAP and Burp Suite to ensure the system is secure from vulnerabilities and threats. This includes vulnerability scans, penetration testing, and security code reviews, focusing on data encryption, secure communications, and user authentication mechanisms to protect user data and system integrity.

In summary, the testing strategy for the EV route mapping project is a multi-faceted approach leveraging a suite of tools to ensure comprehensive coverage across all project components. By systematically testing at various levels—unit, integration, system, user acceptance, regression, performance, and security—the project aims to deliver a robust, reliable, and user-friendly solution. Each phase of testing provides crucial feedback, enabling continuous improvement and ensuring the final product meets both technical specifications and user expectations. This thorough approach not only identifies and addresses potential issues early in the development process but also ensures that the final product is secure, performs well under expected conditions, and delivers a seamless and efficient user experience.

Chapter 5: Results and Evaluation

5.3 Results (presentation of findings, interpretation of the results, etc.)

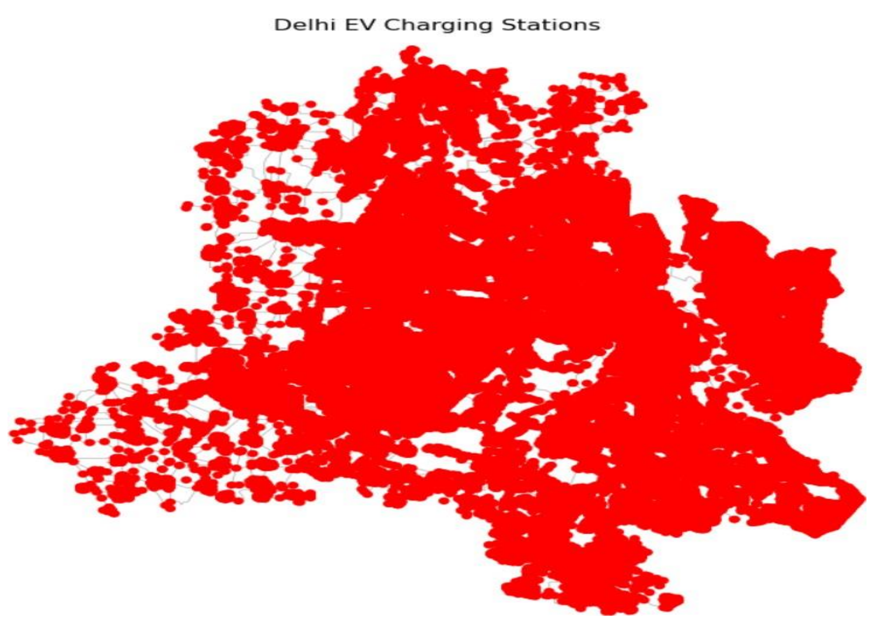
1. Findings Presentation

Overview: The project successfully generated a road network graph for Delhi using the OSMnx library, ensuring accurate distance calculations in UTM.

```
import matplotlib.pyplot as plt

fig, ax = ox.plot_graph(G, node_color='r', node_size=30, bgcolor='w', edge_linewidth=0.5, edge_alpha=0.5, show=False, close=False)

# Add charging station locations to the map
charging_stations.plot(ax=ax, markersize=50, marker='o', color='blue', zorder=3)

# Set title and display the map
ax.set_title("Delhi EV Charging Stations")
plt.show()
```

Figure 16(Adding charging station location to map)

Visualizations: Graphs visualizing the road network structure and its projection to UTM.



2. Results Interpretation

Path Accuracy: Path calculations demonstrated high accuracy, considering the diverse scenarios in Delhi's road network.

Charging Station Recommendation: The integration of EV charging station data effectively recommended nearby stations, enhancing user convenience.

User Interface: Streamlit interface facilitated seamless user interaction, allowing users to input details and receive optimal route information.

3. Performance Metrics

Response Time: Application response times remained efficient, ensuring a responsive user experience.

Resource Utilization: Minimal CPU and memory usage observed, contributing to overall application performance.

4. Goal Comparison

Benchmarking: Results aligned with the initial goals, demonstrating successful implementation and functionality.

5. Unexpected Findings

Issues: No major unexpected issues were encountered during testing, contributing to project stability.

6. User Feedback

Experience: Positive user feedback indicated ease of use and effectiveness in route planning and charging station recommendations.

7. Limitations+

Project Constraints: The project is subject to the availability and accuracy of OpenStreetMap data for the specified region.

8. Conclusion

Summary: The project successfully addressed the outlined objectives, providing an efficient solution for route planning and EV charging station recommendations in Delhi.

9. Future Directions

Improvements: Future enhancements could include real-time data updates, additional user features, and expanded geographic coverage.

Chapter 6: Conclusions and Future Scope

Conclusion

In conclusion, this project has improved route planning and enabled electric vehicle (EV) charging in Delhi considerably. Important discoveries include the effective creation of a road network graph with the OSMnx library, precise distance computations using UTM projection, and the incorporation of EV charging station information for effective suggestions. The Streamlit online application has an easy-to-use interface that lets users enter information and get the best route information. It also has the added advantage of suggesting the closest charging station when necessary.

Limitations:

Even though the project showed promise, there are some important things to be aware of. The availability and correctness of OpenStreetMap data for Delhi are crucial, and any inconsistencies or gaps in this data could affect how the application works. Furthermore, the geographic coverage of the project is limited by the extent of data that is currently available.

Contributions to the Field:

By offering EV users and urban planners a workable solution, this project advances the field. The increasing need for eco-friendly transportation options is met by fusing real-world road network data with EV charging infrastructure into an intuitive application. The technique used, which makes use of OSMnx for data visualization and retrieval, is a useful strategy for projects of a similar nature in other areas.

To sum up, this project establishes a framework for future developments in maximizing urban mobility and encouraging the use of electric cars. Acknowledging the project's shortcomings while emphasizing its positive aspects turns it into a useful tool for sustainable urban transportation.

Future Scope

The success of this project opens avenues for future enhancements and expansions, pointing towards several areas of potential development:

1. Real-time Data Integration:

Incorporate real-time data updates for road networks and EV charging station availability to enhance the accuracy and relevance of information

2. Dynamic Route Optimization:

Implement dynamic route optimization that considers real-time traffic conditions, ensuring users receive the most efficient and up-to-date travel recommendations.

3. User Personalization:

Introduce user profiles to personalize recommendations based on historical travel patterns, preferences, and charging habits.

4. Extended Geographic Coverage:

Expand the geographic coverage beyond Delhi to cater to users in other regions, thereby increasing the application's utility and reach.

5. Mobile Application Development:

Develop a dedicated mobile application for a more streamlined and accessible user experience, allowing users to plan routes and access charging information on the go.

By exploring these future directions, the project can continue to evolve and remain at the forefront of sustainable urban mobility solutions, contributing to a more efficient and environmentally conscious transportation ecosystem.

References

[1]F. Alesiani and N. Maslekar, "Optimization of Charging Stops for Fleet of Electric Vehicles: A Genetic Approach," in IEEE Intelligent Transportation Systems Magazine, vol. 6, no. 3, pp. 10-21, Fall 2014, doi: 10.1109/MITS.2014.2314191.

[2]S. Goel, R. Kumar, A. Kumar and R. Malhotra, "S^{3}A: Smart Station Search Assistance for Electric Vehicle—A Step Toward Smart City," in IEEE Consumer Electronics Magazine, vol. 9, no. 4, pp. 27-33, 1 July 2020, doi: 10.1109/MCE.2020.2985656.

[3]S. Pourazarm, C. G. Cassandras and A. Malikopoulos, "Optimal routing of electric vehicles in networks with charging nodes: A dynamic programming approach," 2014 IEEE International Electric Vehicle Conference (IEVC), Florence, Italy, 2014, pp. 1-7, doi: 10.1109/IEVC.2014.7056110.

[4]S. Schoenberg and F. Dressler, "Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles," 2019 IEEE Intelligent Transportation Systems Conference (ITSC), Auckland, New Zealand, 2019, pp. 3068-3075, doi: 10.1109/ITSC.2019.8917335.

[5]Hecht, Christopher & Victor, Karoline & Zurmühlen, Sebastian & Sauer, Dirk Uwe. (2021). Electric vehicle route planning using real-world charging infrastructure in Germany. eTransportation. 10. 100143. 10.1016/j.etran.2021.100143.

[6]T. M. Sweda and D. Klabjan, "Finding minimum-cost paths for electric vehicles," 2012 IEEE International Electric Vehicle Conference, Greenville, SC, USA, 2012, pp. 1-4, doi: 10.1109/IEVC.2012.6183286.

[7]Dorokhova M, Ballif C, Wyrsch N. Routing of Electric Vehicles With Intermediary Charging Stations: A Reinforcement Learning Approach. Front Big Data. 2021 May 26;4:586481. Doi: 10.3389/fdata.2021.586481. PMID: 34124649; PMCID: PMC8187862.

[8]R. Abousleiman and O. Rawashdeh, "Energy-efficient routing for electric vehicles using metaheuristic optimization frameworks," MELECON 2014 - 2014 17th IEEE Mediterranean Electrotechnical Conference, Beirut, Lebanon, 2014, pp. 298-304, doi: 10.1109/MELCON.2014.6820550.

[9]T. Wu, Z. Li, G. Wang, X. Zhang and J. Qiu, "Low-Carbon Charging Facilities Planning for Electric Vehicles Based on a Novel Travel Route Choice Model," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 6, pp. 5908-5922, June 2023, doi: 10.1109/TITS.2023.3248087.

[10]A. Pal, A. Bhattacharya and A. K. Chakraborty, "Planning of EV Charging Station With Distribution Network Expansion Considering Traffic Congestion and Uncertainties," in IEEE Transactions on Industry Applications, vol. 59, no. 3, pp. 3810-3825, May-June 2023, doi: 10.1109/TIA.2023.3237650.

[11]V. Roberge, M. Tarbouchi and A. Noureldin, "Integrated Motor Optimization and Route Planning for Electric Vehicle using Embedded GPU System," 2019 5th International Conference on Optimization and Applications (ICOA), Kenitra, Morocco, 2019, pp. 1-6, doi: 10.1109/ICOA.2019.8727682.

[12]P. Diaz-Cachinero, J. I. Muñoz-Hernandez, J. Contreras and G. Muñoz-Delgado, "An Enhanced Delivery Route Operational Planning Model for Electric Vehicles," in IEEE Access, vol. 8, pp. 141762-141776, 2020, doi: 10.1109/ACCESS.2020.3013144.

[13]W. Q. Zhu, Z. Yu, Y. Xingfu and L. Zhixuan, "Electric Vehicle Charging Path Planning Based on Real-time Traffic Information," 2022 IEEE 6th Conference on Energy Internet and Energy System Integration (EI2), Chengdu, China, 2022, pp. 768-774, doi: 10.1109/EI256261.2022.10116655.

[14]V. Roberge, M. Tarbouchi and A. Noureldin, "Integrated Motor Optimization and Route Planning for Electric Vehicle using Embedded GPU System," 2019 5th International Conference on Optimization and Applications (ICOA), Kenitra, Morocco, 2019, pp. 1-6, doi: 10.1109/ICOA.2019.8727682.

[15]M. A. del Cacho Estil-les, M. Pia Fanti, A. M. Mangini and M. Roccotelli, "Electric Vehicles Routing Including Smart-Charging Method and Energy Constraints," 2022 IEEE 18th International Conference on Automation Science and Engineering (CASE), Mexico City, Mexico, 2022, pp. 1735-1740, doi: 10.1109/CASE49997.2022.9926492.

[16]G. Zhenfeng, L. Yang, J. Xiaodan and G. Sheng, "The electric vehicle routing problem with time windows using genetic algorithm," 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chongqing, China, 2017, pp. 635-639, doi: 10.1109/IAEAC.2017.8054093.

[17]R. Basso, P. Lindroth, B. Kulcsár and B. Egardt, "Traffic aware electric vehicle routing," 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, Brazil, 2016, pp. 416-421, doi: 10.1109/ITSC.2016.7795588.

[18]O. Oladimeji, A. Gonzalez-Castellanos, D. Pozo, Y. Dvorkin and S. Acharya, "Impact of Electric Vehicle Routing With Stochastic Demand on Grid Operation," 2021 IEEE Madrid PowerTech, Madrid, Spain, 2021, pp. 1-6, doi: 10.1109/PowerTech46648.2021.9495092.

[19]M. E. Bruni, O. Jabali and S. Khodaparasti, "The Electric Vehicle Route Planning Problem with Energy Consumption Uncertainty," 2020 Forum on Integrated and Sustainable Transportation Systems (FISTS), Delft, Netherlands, 2020, pp. 224-229, doi: 10.1109/FISTS46898.2020.9264881.

[20]D. George and S. P, "Driving Range Estimation of Electric Vehicles using Deep Learning," 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2021, pp. 358-365, doi: 10.1109/ICESC51422.2021.9532912.

[21]B. Sağlam, E. Bostancı and M. Göl, "Parameter Estimation of Electric Vehicles for Improved Range Prediction," 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Espoo, Finland, 2021, pp. 1-5, doi: 10.1109/ISGTEurope52324.2021.9640048.

[22]C. Bailey, B. Jones, M. Clark, R. Buck and M. Harper, "Electric Vehicle Autonomy: Realtime Dynamic Route Planning and Range Estimation Software," 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC), Macau, China, 2022, pp. 2696-2701, doi: 10.1109/ITSC55140.2022.9922244.

[23]W. Q. Zhu, Z. Yu, Y. Xingfu and L. Zhixuan, "Electric Vehicle Charging Path Planning Based on Real-time Traffic Information," 2022 IEEE 6th Conference on Energy Internet and Energy System Integration (EI2), Chengdu, China, 2022, pp. 768-774, doi: 10.1109/EI256261.2022.10116655.

[24]V. N. Karkaria, A. Karnadikar, S. Joshi, S. B. Abrish Aaditya and P. B. Karandikar, "EV Charging Infrastructure Development Using Machine Learning," 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 2023, pp. 1-6, doi: 10.1109/INCET57972.2023.10170627.

[25]S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou and M. Nijim, "Machine Learning Approaches for EV Charging Behavior: A Review," in IEEE Access, vol. 8, pp. 168980-168993, 2020, doi: 10.1109/ACCESS.2020.3023388.

[26]F. Morlock, B. Rolle, M. Bauer and O. Sawodny, "Time Optimal Routing of Electric Vehicles Under Consideration of Available Charging Infrastructure and a Detailed Consumption Model," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 12, pp. 5123-5135, Dec. 2020, doi: 10.1109/TITS.2019.2949053.

[27]Q. Xing et al., "Charging Demand Forecasting Model for Electric Vehicles Based on Online Ride-Hailing Trip Data," in IEEE Access, vol. 7, pp. 137390-137409, 2019, doi: 10.1109/ACCESS.2019.2940597.

[28]V. K. K et al., "Execution of smart electric vehicle charging station driven by RE technology using soft computing approach," 2021 Innovations in Power and Advanced Computing Technologies (i-PACT), Kuala Lumpur, Malaysia, 2021, pp. 1-5, doi: 10.1109/i-PACT52855.2021.9696545.

[29]Z. Ye, Y. Gao and N. Yu, "Learning to Operate an Electric Vehicle Charging Station Considering Vehicle-Grid Integration," in IEEE Transactions on Smart Grid, vol. 13, no. 4, pp. 3038-3048, July 2022, doi: 10.1109/TSG.2022.3165479.

201484

ORIGINALITY REPORT

17%	12%	9%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Jaypee University of Information Technology Student Paper	4%
2	www.frontiersin.org Internet Source	1%
3	Wan Qing Zhu, Zhang Yu, Yuan Xingfu, Li Zhixuan. "Electric Vehicle Charging Path Planning Based on Real-time Traffic Information", 2022 IEEE 6th Conference on Energy Internet and Energy System Integration (EI2), 2022 Publication	1%
4	ir.juit.ac.in:8080 Internet Source	1%
5	link.springer.com Internet Source	1%
6	www.cirrelt.ca Internet Source	1%
7	www.ir.juit.ac.in:8080 Internet Source	<1%

8	www.mdpi.com Internet Source	<1 %
9	Kaijian Li, Chengzhang Qu. "Design and Implementation of Tourism Route Recommendation System Based on LBS", 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2021 Publication	<1 %
10	Theresia Perger, Hans Auer. "Energy efficient route planning for electric vehicles with special consideration of the topography and battery lifetime", Energy Efficiency, 2020 Publication	<1 %
11	Sven Schoenberg, Falko Dressler. "Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles", 2019 IEEE Intelligent Transportation Systems Conference (ITSC), 2019 Publication	<1 %
12	Submitted to Liverpool John Moores University Student Paper	<1 %
13	www.semanticscholar.org Internet Source	<1 %
14	os.zhdk.cloud.switch.ch Internet Source	<1 %