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PAPER

Optimizing Electric Vehicle Charging Infrastructure through Machine Learning: A Study of Charging Patterns and Energy Consumption

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ABSTRACT

The rapid adoption of electric vehicles (EVs) has created a pressing need for efficient charging infrastructure. but challenges such as inconsistent demand and poor placement remain. An effective distribution of sufficient EV charging stations (CSs) is one of the major obstacles preventing the market penetration of EVs and the realization of a sustainable transportation system in urban areas. In this paper, a new machine learning technique is proposed in order to optimize the placement of EV charging stations (EVCSs) in metropolitan areas based on an energy consumption prediction model. A dataset from 148,136 charging transactions in Boulder, Colorado, is used with the proposed model. Key algorithms such as KNeighborsRegressor and RandomForestRegressor were incorporated to solve the placement problem. The analysis revealed significant demand fluctuations during peak commute hours, with the KNeighborsRegressor model demonstrating superior prediction accuracy. These insights can guide more effective infrastructure planning and resource allocation, ultimately enhancing the efficiency and user experience of EV charging networks and promoting sustainable urban transportation.

KEYWORDS

electric vehicle (EV), charging station location analysis, machine learning (ML)

1 INTRODUCTION

The rapid adoption of electric vehicles (EVs) necessitates a complementary expansion of charging infrastructure, particularly in major markets such as China, the EU, and the USA. Regional and city-level public policies are crucial for managing EV adoption and charging infrastructure. One significant challenge is the increasing idle time when an EV is connected but not charging. This issue impacts infrastructure size, costs, and availability. Accurate estimation and management of idle time through machine learning (ML) can provide valuable insights for EV users,

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policymakers, and network owners, facilitating better infrastructure management and promoting EV adoption [1–4].

Electric vehicles are becoming integral to modern transportation, offering reduced greenhouse gas emissions and decreased reliance on fossil fuels. However, the success of EVs heavily depends on the availability and efficiency of charging infrastructure. Researchers have explored various ML approaches to understand EV charging behavior, predict charging demand, and optimize the deployment of charging stations (CSs). By analyzing large datasets from EV users and charging stations, significant advancements have been made in predicting charging patterns and improving the overall efficiency of the charging infrastructure [5, 6].

Global initiatives for sustainable urban transportation have driven the need for a reliable, worldwide EV charging network to new levels [7]. Governments and private entities are investing in the necessary charging infrastructure to accommodate the growing number of EVs. Research has shown that properly locating and ensuring access to EV charging facilities can greatly reduce range anxiety and enhance electric mobility's viability [8, 9]. Effective EV management and deployment are important in supporting ongoing EV market growth [10].

Smart cities transform our lives as new digital technologies are integrated into our physical environment. In smart cities, big data and ICT enhance the efficiency and sustainability of urban systems and transportation [11]. This evolution requires developing smart charging networks for EVs responding to real-time user demand and grid conditions. Using data from multiple sources, smart city initiatives can inform where to deploy chargers and when to charge, reduce electricity costs for homeowners/tenants using public chargers, mitigate strain on the electricity grid system, and provide users with the best possible charging experience [12].

With many benefits associated with EVs and as a growing trend today, its environmental impact is the most significant advantage of driving an EV. EVs can utilize electricity derived from renewable sources, further lowering their carbon footprint [13]. Charging infrastructure is available in public and private spaces, allowing all users to charge their vehicles. However, challenges such as long charging times, short ranges, and inadequate support infrastructure explain why the technology has not yet become mainstream [14]. Additionally, the exponential growth in EV adoption necessitates significant investments in electrical infrastructure to support the increased load [15].

The expansion of CSs introduces further complications. The increased number of stations can significantly strain the electricity network, particularly during peak usage. Space constraints in many regions and limited capacity for additional stations exacerbate these issues. These challenges can deter potential users, especially those concerned about long-distance travel, as they might worry about battery depletion, the distance to the nearest CS, and prolonged waiting times. Effective trip planning, including studying and understanding charging times, is crucial to mitigating these concerns and promoting the efficient use of EVs [16, 17].

1.1 Contribution

Our study provided several contributions in the field of EV charging infrastructure; we can organize them as the following:

- Development of a machine learning-based framework for energy consumption prediction.
- Optimization of CS placement and load management.

- Implementation of a user-centric recommendation system for enhanced charging experience.

2 LITERATURE REVIEW

According to [18], their study investigates the integration of plug-in electric vehicles (PEVs) into a distribution-level microgrid, focusing on energy management complexities and impacts on the grid and building load. The study analyzes charging characteristics and assesses their effects on the infrastructure using real-time data from Level II and Level III chargers. It addresses a gap in the literature by exploring the micro-level impacts of PEV integration, revealing that even a 10% EV penetration can lead to a 75% increase in peak demand on the distribution feeder. Key findings indicate significant increases in peak demand, particularly with Level III chargers. This study is relevant to our EV charging patterns and infrastructure planning research, providing empirical data on local impacts. However, the findings are specific to the UCR microgrid and do not extensively explore long-term solutions or economic effects.

In ref [19], they introduce a methodological framework for scheduling smart charging of PEVs by considering travel behavior uncertainties and battery degradation. The study uses a stochastic optimization approach, incorporating Monte Carlo simulation to model load, wind speed, electricity price, and travel behavior uncertainties. The study uses a 21-node sample distribution network with a wind turbine as a distributed generation unit for simulation. The identified research gap includes considering real-world travel behavior and battery degradation costs, often overlooked in previous models. Key findings indicate that smart grid-to-vehicle (G2V) and vehicle-to-grid (V2G) charging modes can optimize the cost and efficiency of PEV operations. Smart charging significantly reduces energy costs and power losses compared to uncoordinated charging, although V2G incurs higher battery degradation costs. This study is relevant to our study on optimizing EV charging infrastructure by demonstrating smart charging strategies' economic and technical benefits. However, limitations include the reliance on simulated data and focusing on a specific network configuration, which may not generalize to other settings.

Another study [20] offers a comprehensive analysis of various energy optimization strategies for EV charging, particularly emphasizing battery longevity, optimization methods, and charging techniques. The study categorizes these charging approaches into centralized, distributed, and hybrid models, evaluating them against objectives such as minimizing peak load, reducing energy costs, and decreasing power losses while maximizing aggregate profits and integrating renewable energy sources. By employing a range of optimization techniques, including convex optimization, particle swarm optimization (PSO), genetic algorithms, and dynamic programming, the paper addresses the challenges of integrating EVs into existing power grids. It identifies a research gap in thoroughly exploring the combined effects of different optimization strategies on EV charging methodologies. The key findings indicate that optimized EV charging enhances battery performance and supports grid stability and energy efficiency. This study is particularly relevant to our study as it underscores various optimization objectives and methodologies that could be leveraged to improve EV charging infrastructure. However, the study's reliance on theoretical models highlights a limitation, pointing to the need for practical implementation and validation in real-world scenarios.

[21] aims to predict EV charging durations using ensemble ML algorithms and Shapley additive explanations (SHAP). The researchers employed four ensemble ML

algorithms: Random Forest (RF), Extreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), and Light Gradient Boosting Machine (LightGBM), analyzing two years of real-world charging data from 500 EVs in Japan. The research gap addressed includes the lack of real-world data for both normal and fast charging events for private and commercial vehicles and the absence of ML interpretation techniques in this context. Key findings indicate that the XGBoost model achieved the highest accuracy across various scenarios, demonstrating the effectiveness of ensemble models in predicting charging times. The study is particularly relevant to our study as it offers insights into optimizing EV charging predictions using advanced ML techniques. However, a limitation of the study is the absence of user socio-demographic data and its specific focus on the Japanese charging environment, which may not be generalized to other regions.

[22] proposes an optimized strategy for locating and sizing different types of EVCSs in the context of an active distribution network with the incorporation of photovoltaic (PV) generation. The study employs PSO to solve the non-linear problem of minimizing installation costs, system losses, and transformer loading based on a stochastic hourly EV load model estimated from real data. This study fills a research gap by optimizing a combination of Level 1, Level 2, and Level 3 chargers and studying their combined effects, which are typically ignored in previous studies. Specifically, the key findings show that the optimized combination of chargers allows for reduced costs and system losses compared to the single use of Level 3 chargers and contributes to a better voltage profile with PV generation. This work interests our study as it suggests effective mechanisms to integrate EV charging infrastructure that supports grid stability. On the other hand, some limitations present in the method, as a consequence of using data that simulates the operation of the NUST distribution network, may complicate the applicability to regions with different grid characteristics and potential user behaviors.

Similarly, [23] reviews various modeling approaches for planning EV charging infrastructure, focusing on optimization methods for location and sizing. It categorizes these methods into node-based, path-based, and tour-based approaches, assessing their effectiveness in minimizing costs, maximizing service coverage, and addressing user behavior and technical constraints. The research gap identified includes the need for models that integrate real-world data on user behavior and infrastructure deployment over time. Key findings suggest that node-based methods are suitable for residential areas, path-based methods are effective for highways, and tour-based approaches offer the most comprehensive understanding of user needs but require extensive data. This paper is relevant to our study as it compares different optimization strategies for EV infrastructure planning. Limitations include the lack of consideration for temporal deployment of infrastructure and the reliance on theoretical models, which may not fully capture real-world complexities.

3 DATASET COLLECTION

The EVCSs Data, obtained from the City of Boulder Open Data Hub (Electric Vehicle Charging Station Data), consists of 148,136 rows and 17 columns. Each row represents a transaction at the city-owned EV charging stations. The dataset includes the following columns: 'Station_Name,' 'Address,' 'City,' 'State_Province,' 'Zip_Postal_Code,' 'Start_Date Time,' 'Start_Time_Zone,'

'End_Date_Time,' 'End_Time_Zone,' 'Total_Duration_hh mm ss,' 'Charging_Time_hh mm ss,' 'Energy_kWh,' 'GHG_Savings_kg,' 'Gasoline_Savings_gallons,' 'Port_Type,' and 'ObjectID.' These columns provide detailed information about each charging transaction's location, timing, duration, energy usage, and environmental impact. This comprehensive dataset enables stakeholders to analyze the utilization and effectiveness of the EV charging infrastructure and supports informed decision-making for future planning and investment. Table 1 illustrates the above details.

Table 1. Overview of the electric vehicle charging station dataset

	ObjectId2	Station_Name	Address	City	State_Province	Zip_Postal_Code	Start_Date
0	1	BOULDER / JUNCTION ST1	2280 Junction Pl	Boulder	Colorado	80301	2018-01-01
1	2	BOULDER / JUNCTION ST1	2280 Junction Pl	Boulder	Colorado	80301	2018-01-02
2	3	BOULDER / JUNCTION ST1	2280 Junction Pl	Boulder	Colorado	80301	2018-01-02
3	4	BOULDER / ALPINE ST1	2285 Alpine Ave	Boulder	Colorado	80304	2018-01-03
4	5	BOULDER / BASELINE ST1	900 Baseline Rd	Boulder	Colorado	80302	2018-01-03
148131	148132	BOULDER / JUNCTION ST1	2280 Junction Pl	Boulder	Colorado	80301	2018-01-02
148132	148133	BOULDER / JUNCTION ST1	2280 Junction Pl	Boulder	Colorado	80301	2018-01-02
148133	148134	BOULDER / ALPINE ST1	2285 Alpine Ave	Boulder	Colorado	80304	2018-01-03
148134	148135	BOULDER / BASELINE ST1	900 Baseline Rd	Boulder	Colorado	80302	2018-01-03
148135	148136	BOULDER / N BOULDER REC ST	3172 Broadway	Boulder	Colorado	80304	2023-11-30
148135	148136	BOULDER / N BOULDER REC ST	3172 Broadway	Boulder	Colorado	80304	2023-11-30

3.1 Exploratory data analysis

Busy hours. The analysis of start and end hour counts for charging sessions at EV stations reveals variations in activity levels throughout the day (see Figure 1). During peak morning hours, from around six AM to 10 AM, there is a significant influx of EV users initiating their charging sessions, likely corresponding to commuters charging their vehicles before starting their workday. Similarly, another surge in charging sessions is observed in the evening, starting from around four-five PM and peaking around 11 PM, suggesting users charge their vehicles before or after work hours. It is advisable to plan charging sessions during off-peak hours to avoid busy hours and potential delays at charging stations. Early morning hours before six AM and late evening hours after 10 PM generally exhibit lower activity levels, making them ideal for charging without delays. Additionally, midday hours, particularly between 12 PM and 3 PM, also show relatively lower counts of charging sessions, presenting another opportunity for convenient charging. Table 2 summarizes the activity levels during different periods.

Table 2. Activity levels during different time periods

Time Period	Activity Level
6 AM – 10 AM	High
4 PM – 11 PM	High
Before 6 AM	Low
After 10 PM	Low
12 PM – 3 PM	Low

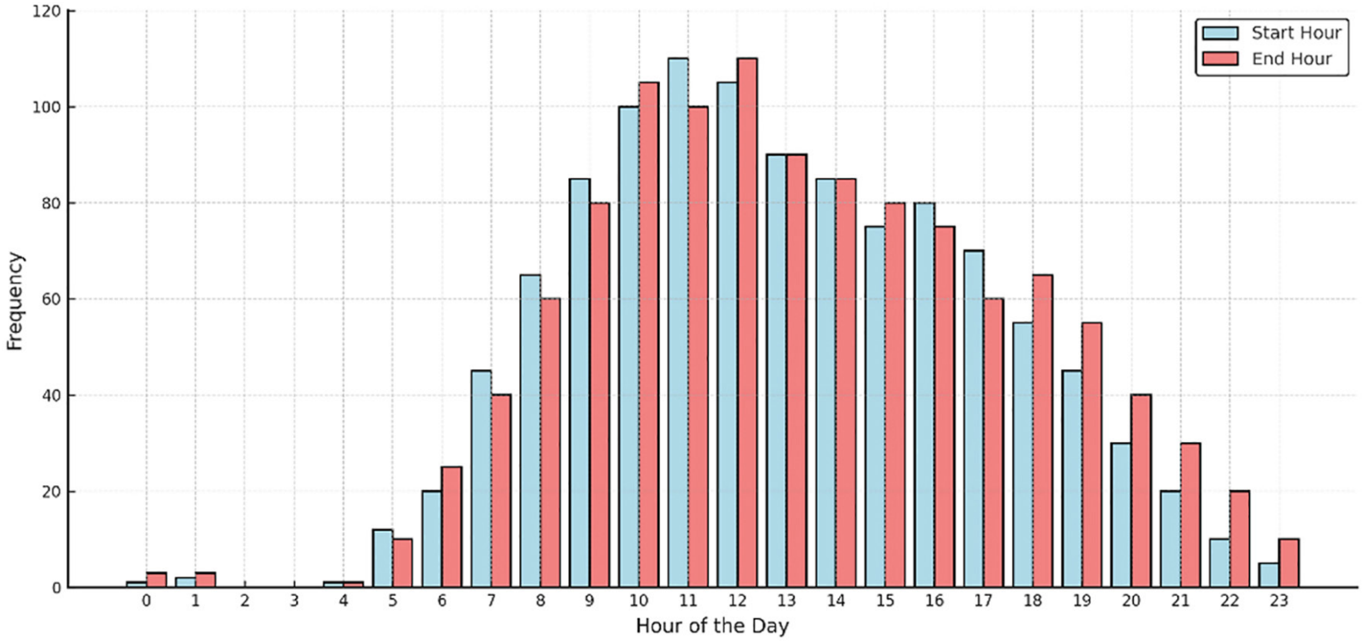

Fig. 1. Busy hours for charging sessions

Top electric vehicle stations (power-consuming). Analyzing power consumption data of EV stations provides valuable insights into EV users' charging behavior and preferences. According to Figure 2 the "BOULDER/BASELINE ST1" station stands out with a substantial power consumption of 1136.754 kWh, indicating its role as a key charging hub, potentially located in a high-traffic area or frequented by a large number of EV drivers due to its convenient location or amenities. The "COMM VITALITY/1000WALNUT1" station follows with 829.784 kWh, highlighting the significance of community vitality initiatives in promoting sustainable transportation. Other notable stations include "BOULDER/JUNCTION ST1," "BOULDER/ALPINE ST1," and "COMM VITALITY/1104 SPRUCE1," all demonstrating significant power consumption and popularity within the community. In contrast, stations such as "BOULDER/ANNEX ST1" show minimal or no power consumption, which could be attributed to maintenance, location accessibility, or usage restrictions. These insights can guide decisions on resource allocation, infrastructure expansion, and service enhancements to better meet the needs of EV users and optimize the efficiency of the charging network. Table 3 lists the power consumption of the top EV stations.

Table 3. Power consumption of top EV stations

Station	Power Consumption (kWh)
BOULDER/BASELINE ST1	1136.754
COMM VITALITY/1000WALNUT1	829.784
BOULDER/JUNCTION ST1	Significant
BOULDER/ALPINE ST1	Significant
COMM VITALITY/1104 SPRUCE1	Significant
BOULDER/ANNEX ST1	Minimal/No Consumption

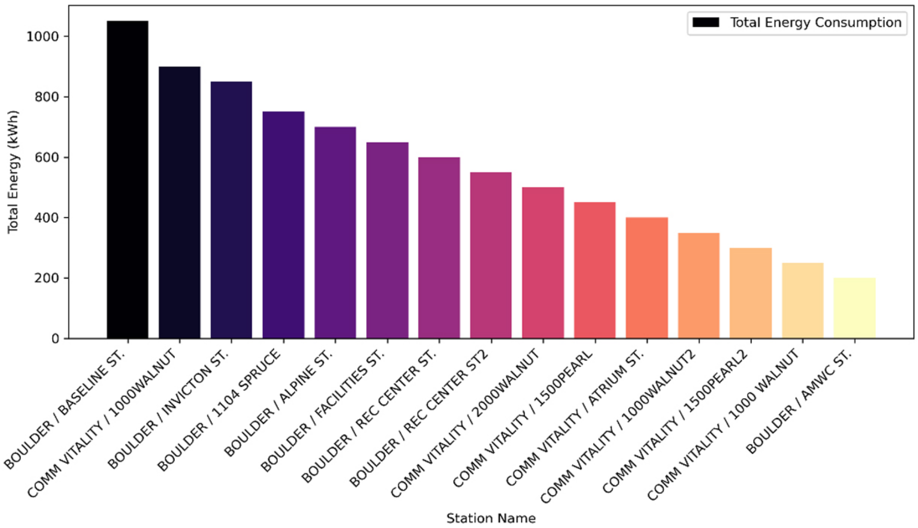

Fig. 2. Top charging stations by energy consumption

Area ZIP code by power consumption. Analyzing charging activity by ZIP Code provides further insights (see Figures 3 and 4):

- Zip Code 80301: This area experiences moderate charging activity throughout the day, with the busiest hours observed in the morning between 8 AM and 11 AM, peaking around 9 AM. A secondary peak occurs in the early evening, around 5 PM.
- Zip Code 80302: Charging sessions exhibit distinct peaks during the morning and early afternoon, with the highest demand between 9 AM and 1 PM, peaking around 11 AM. Evening hours show considerable activity but to a lesser extent than the morning peak.
- Zip Code 80304: Charging activity is relatively low compared to other ZIP codes, with sporadic daily sessions and no significant peaks. The overall activity remains constant, indicating a consistent but lower demand for charging services.
- Zip Code 80305: Similar to ZIP Code 80304, this area also experiences relatively low charging activity. Sessions are evenly distributed throughout the day, with no discernible peaks or valleys, suggesting a stable but modest demand for charging facilities.

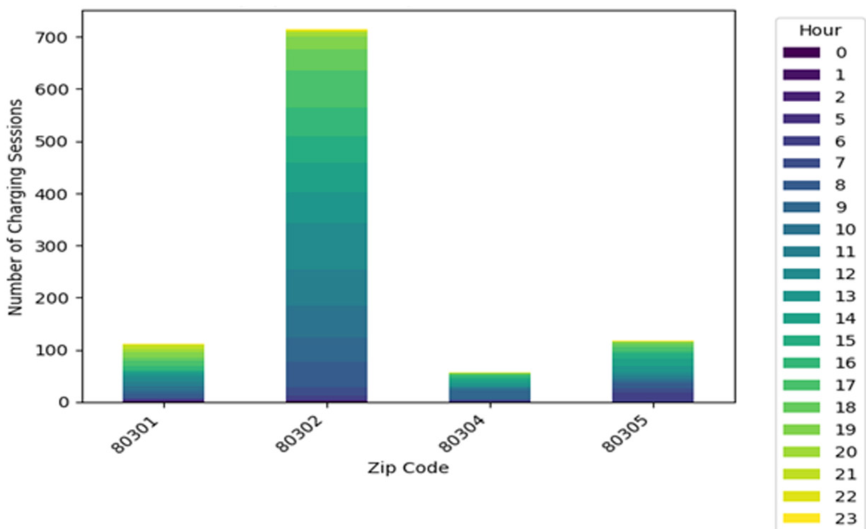

Fig. 3. Charging sessions by ZIP Code and hour (bar chart)

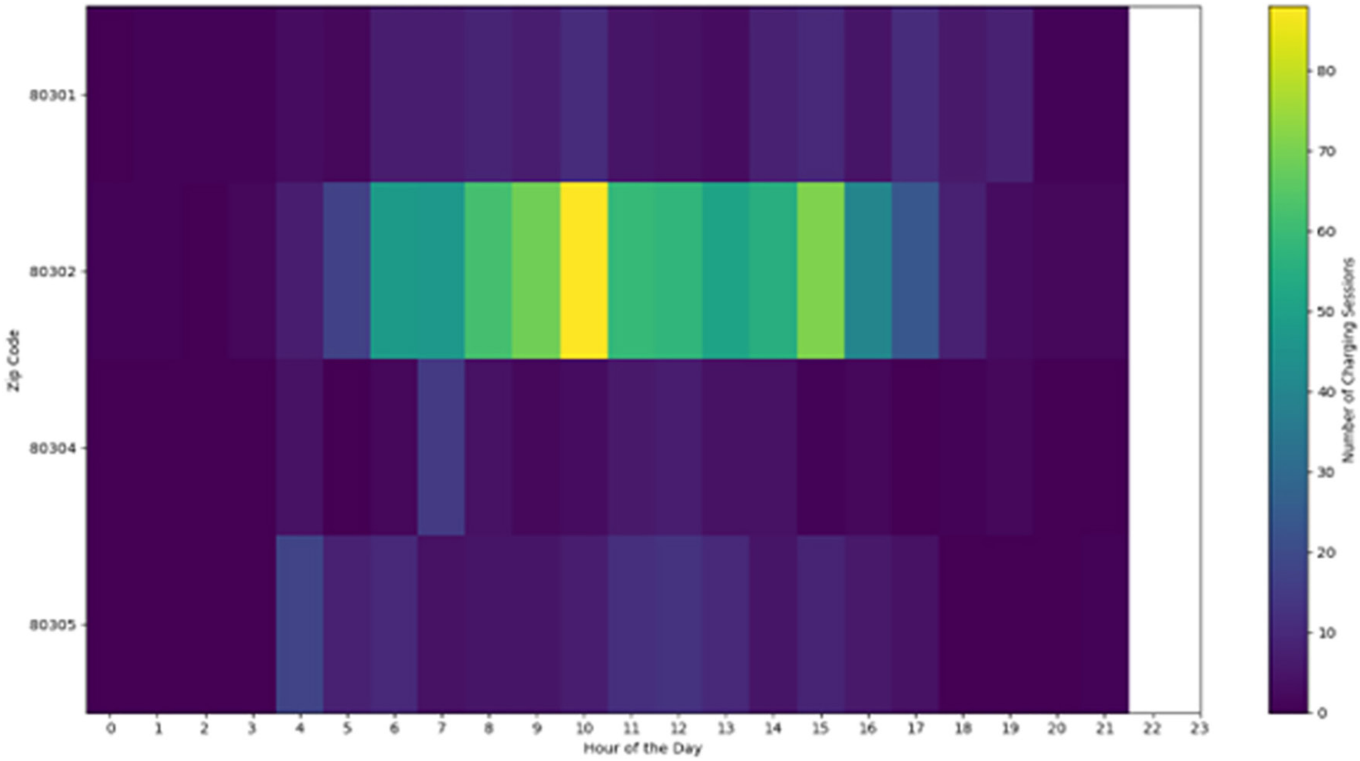

Fig. 4. Charging sessions by ZIP Code and hour (heatmap)

Table 4. Summarizes the charging activity by ZIP Code

ZIP Code	Activity Level	Peak Hours
80301	Moderate	Morning (8 AM – 11 AM), Evening (5 PM)
80302	High	Morning (9 AM – 1 PM), Evening
80304	Low	No significant peaks
80305	Low	No significant peaks

Figures 1–4 visually represent the busy hours, power consumption at top EV stations, and charging activity by ZIP code, respectively. These detailed analyses help in understanding the utilization patterns of EV CSs and can aid in optimizing the charging infrastructure to meet user demand efficiently. Table 4 summarizes the charging activity by ZIP code.

4 METHODOLOGY

The methodology of this study involves multiple steps to analyze and predict energy consumption at EV CSs based on geographic coordinates. The process encompasses data collection, geocoding, visualization, and ML techniques to provide accurate and actionable insights. The flowchart in Figure 5 illustrates the entire methodology, from reading the CSV file to the recommendation of CSs based on energy left. Figure 5 begins with reading the CSV file containing the addresses of EV charging stations. The unique addresses are then identified and geocoded to obtain geographic coordinates. These coordinates are mapped back to the original dataset to enrich it with spatial information. Next, the available stations are visualized on an interactive map using geographic visualization libraries. The data is then preprocessed to handle missing values, convert data types, and scale features, preparing it for ML algorithms. The models are selected and trained to predict energy consumption at specific locations. Finally, recommendations for CSs are made, considering both scenarios with and without energy left, to enhance the user experience and provide practical solutions for energy management and urban planning.

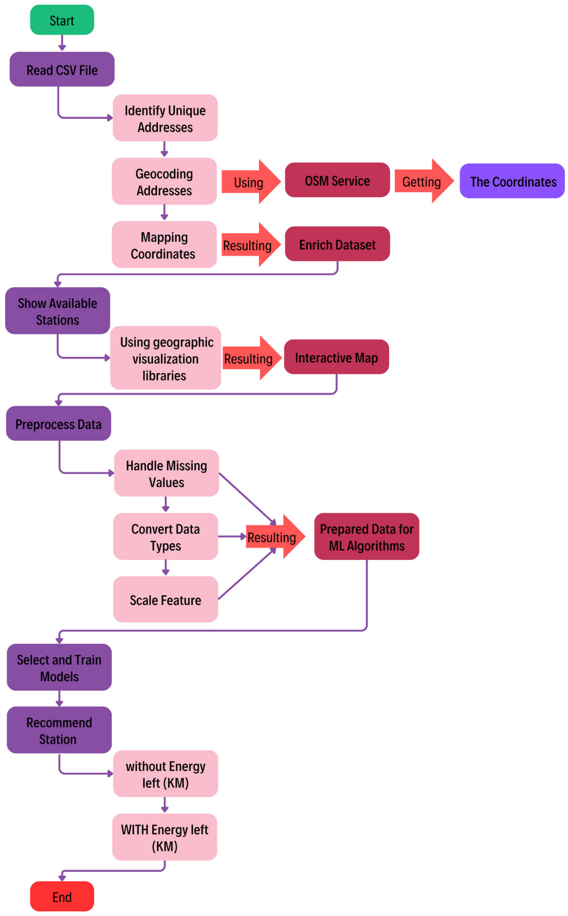

Fig. 5. Proposed methodology

4.1 GPS locations

This step aims to better geocode EV charging station addresses to enable precise location identification and spatial elaboration on a map. Everything starts with reading the CSV file with the data we need: charging station addresses. This methodology improves the geocoding efficiency by three significant steps:

1. **Identifying unique addresses:** The code first extracts unique addresses from the dataset. This step ensures each address is processed only once, eliminating redundancy and saving computational resources. By selecting unique addresses, the subsequent geocoding process is streamlined, preventing unnecessary repetition.
2. **Output results in a list of unique addresses,** and the code goes on to geocode each. Geocoding is converting addresses into geographic coordinates, typically latitude and longitude values. It is because such transformation is really important

to identify locations exactly or precisely so that we can map or perform spatial analysis. It uses the OSM (OpenStreetMap) service, which allows searching for accurate coordinates by its extensive geographic database.

3. **Mapping Coordinates:** Once the unique addresses are geocoded and their corresponding coordinates obtained, these coordinates are mapped back to the original dataset. This mapping links the geocoded coordinates to their respective addresses in the original dataset. By doing so, the dataset is enriched with spatial information, containing the original addresses and their precise geographic coordinates. This augmented dataset facilitates various analytical tasks, such as spatial visualization, proximity analysis, and route optimization.

This approach systematizes the geocoding of EV charging station addresses. The code improves spatial data handling workflow by extracting unique addresses, geocoding the addresses, and mapping the resulting coordinates back to the initial dataset. This allows for greater insight and better decision-making regarding EV infrastructure. Also, Figure 6 presents the Python code, which is used to extract addresses, geocode them, and map the coordinates back to the original dataset.

```
In [49]: import pandas as pd
         import geocoder

         def geocode_address(address):
             location = geocoder.osm(address)
             if location.ok:
                 return location.latlng
             else:
                 return [None, None]

         csv_file_path = 'ev.csv'
         df = pd.read_csv(csv_file_path)

         # Extract unique addresses
         unique_addresses = df[['Address', 'City', 'State_Province', 'Zip_Postal_Code']].drop_duplicates()

         # Geocode unique addresses
         unique_addresses['Full_Address'] = unique_addresses.apply(lambda row: f"{row['Address']}, {row['City']]
         unique_addresses[['Latitude', 'Longitude']] = unique_addresses['Full_Address'].apply(lambda x: pd.Serie

         # Merge coordinates back to original DataFrame based on multiple columns
         df = df.merge(unique_addresses[['Address', 'City', 'State_Province', 'Zip_Postal_Code', 'Latitude', 'Lo

         print(df[['Address', 'City', 'State_Province', 'Zip_Postal_Code', 'Latitude', 'Longitude']])
```

```
                 Address     City State_Province Zip_Postal_Code   Latitude  \
0        2280 Junction Pl  Boulder       Colorado           80301  40.024205
1        2280 Junction Pl  Boulder       Colorado           80301  40.024205
2        2280 Junction Pl  Boulder       Colorado           80301  40.024205
3         1275 Alpine Ave  Boulder       Colorado           80304  40.025998
4         900 Baseline Rd  Boulder       Colorado           80302  39.997527
...                   ...      ...            ...             ...        ...
148131      3172 Broadway  Boulder       Colorado           80304  40.032553
148132       1505 30th St  Boulder       Colorado           80303  40.011587
148133       1505 30th St  Boulder       Colorado           80303  40.011587
148134  1360 Gillaspie Dr  Boulder       Colorado           80305  39.974677
148135    1745 14th street Boulder       Colorado           80302  40.014976

         Longitude
0      -105.251808
1      -105.251808
2      -105.251808
3      -105.280780
4      -105.280990
...            ...
148131 -105.281964
148132 -105.253633
148133 -105.253633
148134 -105.248600
148135 -105.276309

[148136 rows x 6 columns]
```

Fig. 6. Script for extracting unique addresses, geocoding, and mapping coordinates for EV charging stations

4.2 Show available stations

Plotting EV CSs on a map for spatial context and visualization outside the limitations of tabular data. Its main goal is to provide a common point of reference for users and also for analysis by mapping the spatial distribution of charging stations. To do this, you need to plot data that contains location-specific information, such as GPS coordinates (latitude/longitude). This is typically done with a geographic visualization library or tools, and Folium in Python is one such popular tool. You can create a map that is user-friendly and easy to navigate. Folium is built to work with the broader ecosystem of Python data libraries (pandas, geopandas, etc.), making it easy to visualize data manipulated in Python.

The mapping process starts with the assumption that the GPS coordinates of the charging points are in the DataFrame (df). The first thing the code does is get all the unique GPS coordinates in the dataset so that the map does not have multiple markers at the same point. This step is necessary to avoid clutter and provide a clear visual representation of the data. Following that, you create a Folium map centered around the average latitude and longitude of the distinct GPS locations. This ensures that the map is centered so all markers are visible and allows the map to zoom optimally to view the entire area of interest—the folium. A map function is used to create the map, where the initial view is set by specifying the initial geographic viewpoint of the map using center coordinates and the initial zoom level.

It then takes unique GPS locations and places markers on the map. Having a marker means you can very clearly see the location of charging stations. These markers are created using Folium's Marker class, allowing customization and popups to display more information. This interactivity provides an enriched user experience as it helps to render more information about each charging station directly onto the map. This loop iterates over all unique GPS coordinates, and for each of those locations, a Folium marker is placed on the map. Other markers may show some secondary data, such as popups with information about the charging station, which also helps to offer a better user experience. The final map is an interactive map for viewers to explore, use at various levels, and discover the density of EV CSs along the routes.

Mapping locations can aid in many types of analysis, such as grouping, trend, and pattern discovery of geographical data, as well as those decisions that correspond with spatial relationships. For example, it can help identify where the saturation of charge points is high or where infrastructure may need to be added to drive EV uptake. The Python code for visualizing the geographic locations of EV CSs on an interactive map is depicted in Figure 7, and the subsequent map showing the CSs in the City of Boulder is demonstrated.

In [15]:

```
import folium
import pandas as pd

# Assuming 'df' contains the DataFrame with GPS coordinates
unique_gps = df[['Latitude', 'Longitude']].drop_duplicates()

# Create a Folium map centered around the mean latitude and longitude of the unique GPS locations
m = folium.Map(location=[unique_gps['Latitude'].mean(), unique_gps['Longitude'].mean()], zoom_start=10

# Add markers for each unique GPS location to the map
for index, row in unique_gps.iterrows():
    folium.Marker([row['Latitude'], row['Longitude']], popup='Unique Location').add_to(m)

# Display the map
m
```

Out[15]:

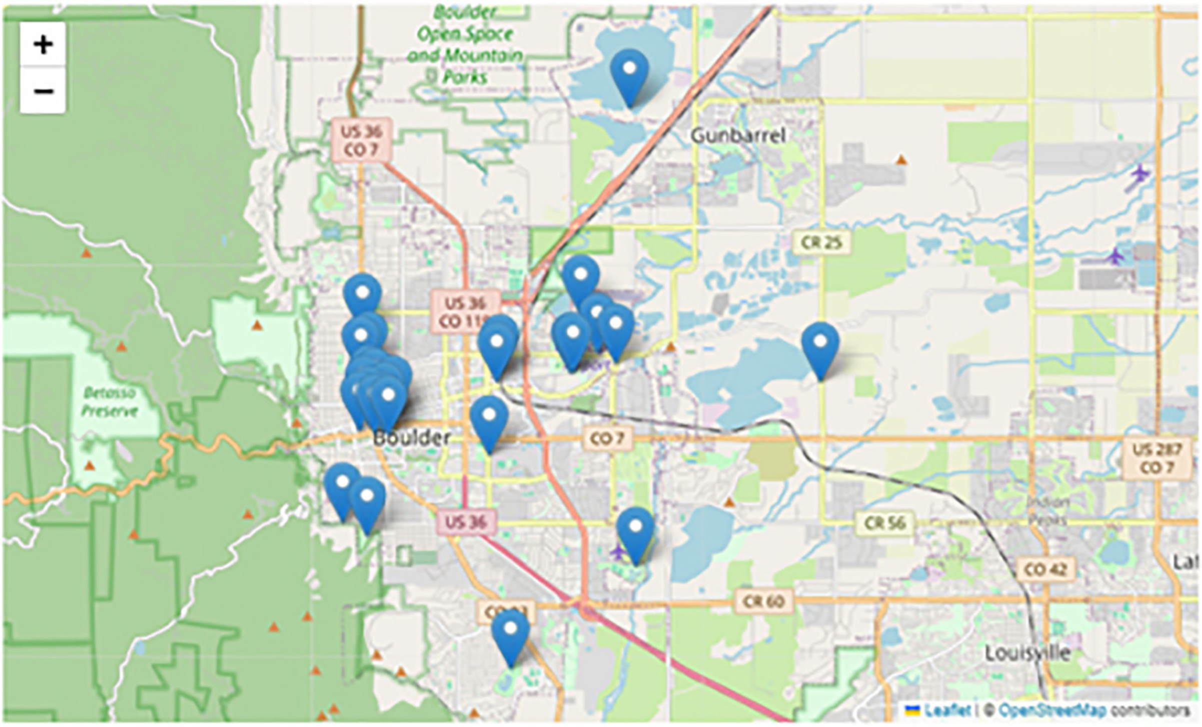

Fig. 7. Geographic distribution of EV charging stations with Python and Folium

4.3 Recommend station without energy left (KM)

The methodology employed in the provided code aims to predict energy consumption at a specific location based on geographic coordinates. This task is essential in various domains, such as energy management, urban planning, and environmental sustainability. By accurately predicting energy consumption, stakeholders can make informed decisions regarding resource allocation, infrastructure development, and energy efficiency initiatives. A ML approach is adopted to achieve this goal, leveraging various regression algorithms to model the relationship between geographic coordinates and energy consumption. The choice of regression algorithms, including KNeighborsRegressor, RandomForestRegressor, Linear Regression, Support Vector Regressor (SVR), and Gradient Boosting Regressor, reflects a systematic exploration of different modeling techniques to identify the most suitable approach for the given task.

Throughout the methodology, careful consideration is given to data preprocessing steps, including handling missing values, converting data types, and scaling features. These preprocessing steps ensure the data's quality and compatibility with the chosen ML. Figure 8 illustrates the Python code used to recommend a charging station based on predicted energy consumption and the resulting map displaying the recommended station in the City of Boulder.

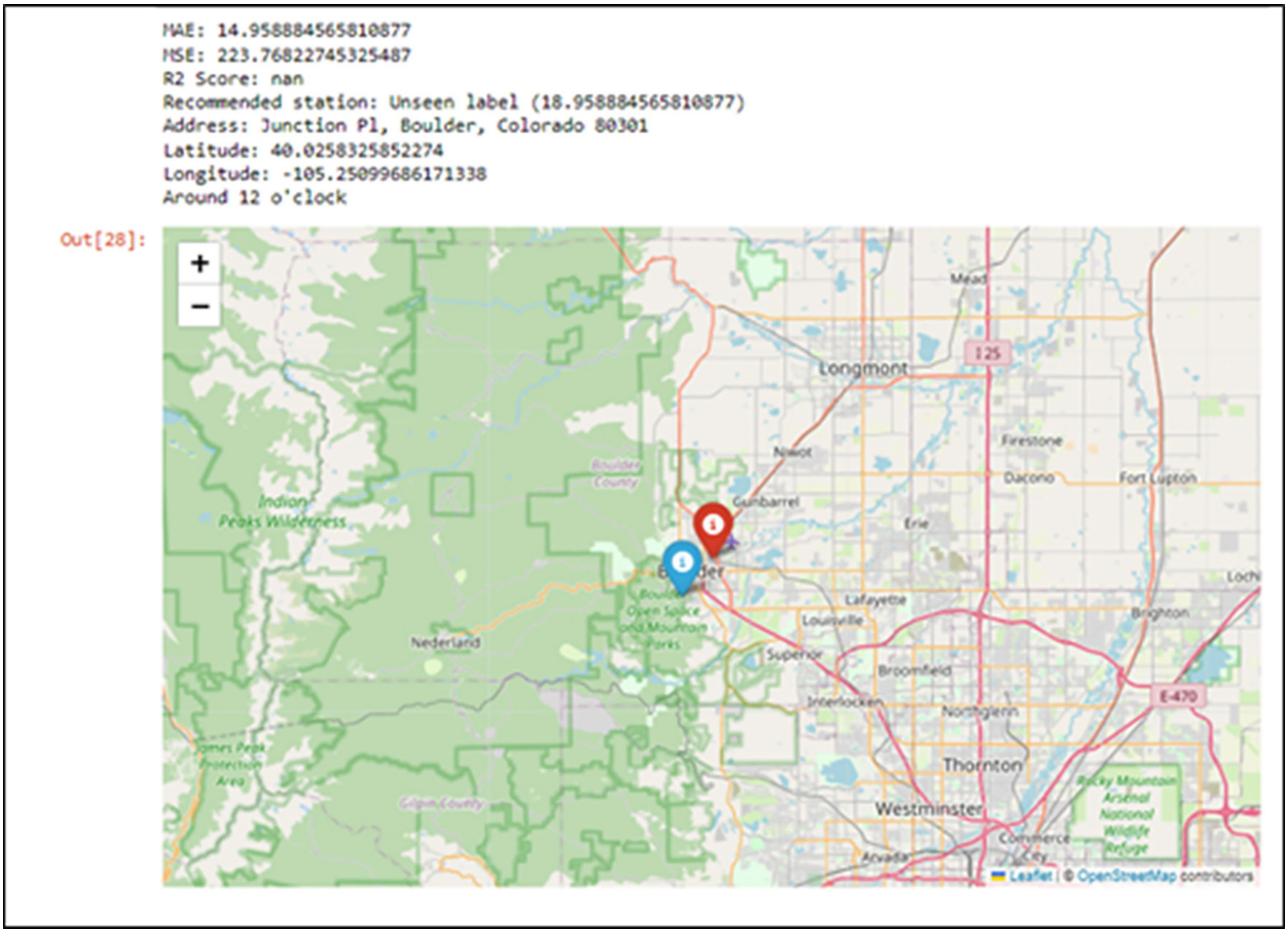

Fig. 8. Python code and resulting map for recommending a charging station based on predicted energy consumption

4.4 Recommend station with energy left (KM)

This step aims to predict energy consumption at a specific location based on geographic coordinates. This task holds significance across various domains, including energy management, urban planning, and environmental sustainability. Accurate energy consumption predictions enable stakeholders to decide on resource allocation, infrastructure development, and energy efficiency initiatives. A ML approach is adopted to achieve this objective, leveraging various regression algorithms to model the relationship between geographic coordinates and energy consumption. The choice of regression algorithms, including KNeighborsRegressor, RandomForestRegressor, Linear Regression, Support Vector Regressor (SVR), and Gradient Boosting Regressor, demonstrates a systematic exploration of different modeling techniques to identify the most suitable approach for the given task. Additionally, including deep learning, specifically through TensorFlow's Keras API, showcases a more advanced modeling strategy. Deep learning models, with their ability to capture complex patterns in data, offer the potential to improve prediction accuracy, especially in scenarios with high-dimensional input features or nonlinear relationships. Figure 9 illustrates the Python code used to recommend a charging station based on predicted energy consumption, along with the resulting map displaying the recommended station in the City of Boulder.

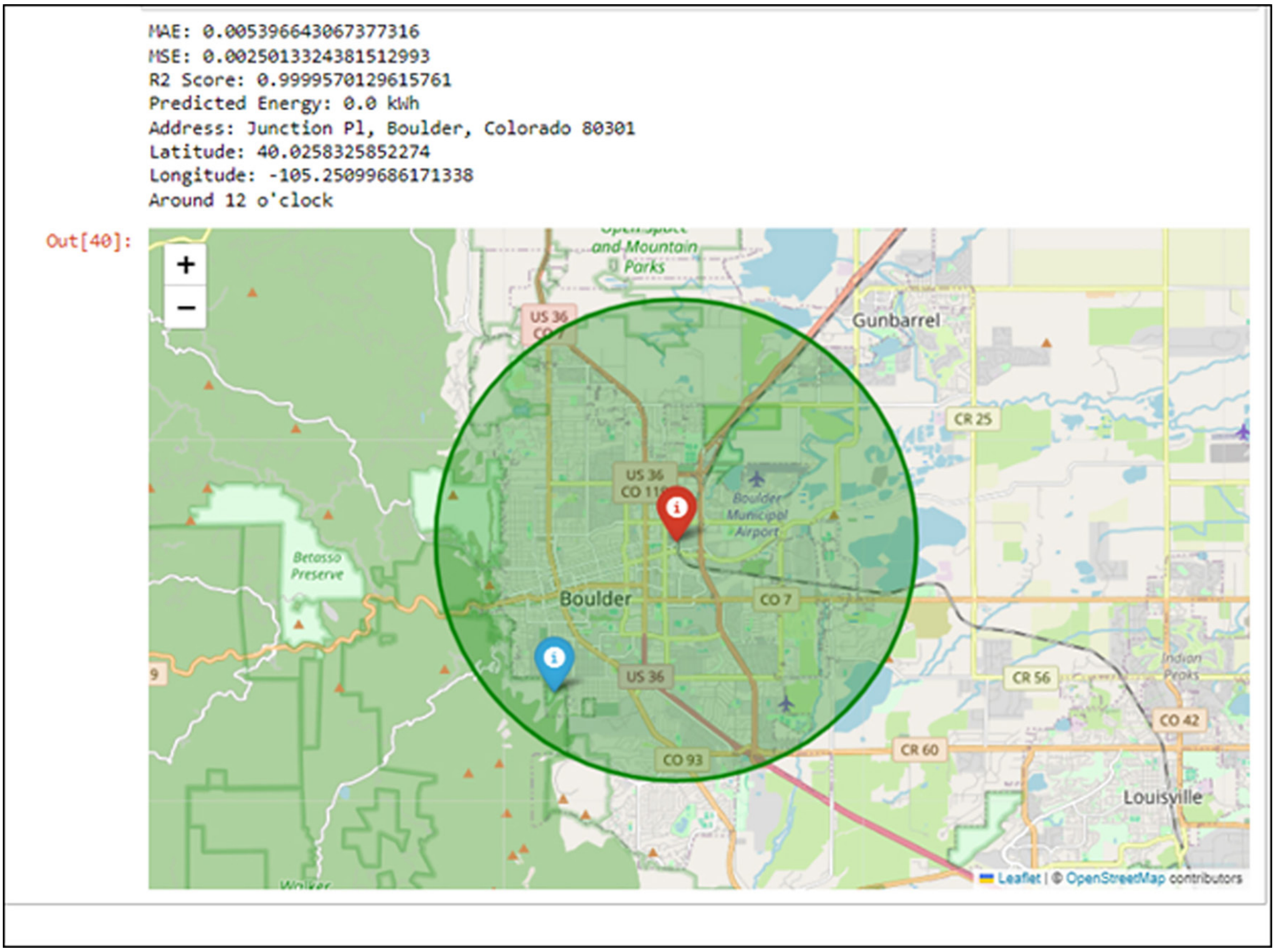

Fig. 9. Interactive map displaying recommended EV charging stations based on energy predictions and geographic proximity

4.5 ML models used

The following ML models are employed to predict energy consumption based on geographic coordinates:

1. **K-neighbors regressor:** This model uses the k-nearest neighbors' algorithm to predict the target variable based on the average value of the k-nearest data points in the feature space. It is beneficial for capturing local patterns in the data.
2. **Random forest regressor:** An ensemble learning method that uses multiple decision trees to improve prediction accuracy and control overfitting. Each tree is trained on a random subset of the data, and the final prediction is the average of all the trees' predictions.

3. **Linear regression:** A statistical method that models the relationship between the dependent variable and one or more independent variables by fitting a linear equation to the observed data. It is straightforward and interpretable but may not capture complex patterns in the data.
4. **Support vector regressor (SVR):** A support vector machine that uses a linear model in a high-dimensional space to predict the target variable. It is effective in high-dimensional spaces and with a clear margin of separation between different classes.
5. **Gradient boosting regressor:** An ensemble technique that builds models sequentially, each correcting the errors of its predecessor. It combines the predictions of multiple weak learners (typically decision trees) to produce a strong learner with improved accuracy.

4.6 Evaluation metrics

The performance of the ML models is evaluated using the following metrics:

1. **Mean absolute error (MAE):** This metric measures the average magnitude of the errors in a set of predictions, without considering their direction. It is calculated as the average absolute difference between the predicted and actual values. A lower MAE indicates better model performance.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

where:
- y_i is the actual value
- $\hat{y}_i$ is the predicted value
- $\bar{y}$ is the mean of the actual values
- n is the number of data points

2. **Mean squared error (MSE):** This metric measures the average of the squares of the errors. It is more sensitive to outliers than MAE because the errors are squared, giving more weight to larger errors. A lower MSE indicates better model performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{2}$$

3. **R-squared (R^2) score:** This metric indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It provides an indication of the goodness of fit of the model. An R^2 score closer to 1 indicates a better fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{3}$$

Evaluating each model using these metrics provides quantitative insights into their performance. By comparing the performance of different models, informed decisions can be made regarding selecting the most effective approach for predicting energy consumption based on geographic coordinates.

5 RESULTS

This section presents the results obtained from predicting energy consumption at the location of EV CSs based on geographic coordinates. Different models of ML performed predictions; in this case, the KNeighborsRegressor model has shown excellent results. The section contains a detailed analysis of the model's accuracy indicators and individual predictions. Also, in the beginning, the address â Junction Pl Boulder, Colorado 80301 â and the coordinates relative to this address: the latitude is 40.0258, the longitude is –105.2510 reflect which place the prediction was given. The prediction time was selected around midnight, which means that the prediction was made at night. The results show that predictions using coordinate data are effective and practical, especially the KNeighborsRegressor model for prediction, allowing various calculations for energy management, urban planning, and all green projects.

5.1 Model performance metrics

To evaluate the performance of the ML models, several metrics were used, including MAE, MSE, and R-squared (R^2) score. These metrics provide quantitative insights into the accuracy and effectiveness of each model in predicting energy consumption. Table 5 summarizes the performance metrics for each model:

Table 5. Model performance metrics for energy consumption prediction

Model	MAE	MSE	R-Squared (R^2)
KNeighborsRegressor	0.0054	0.0025	0.99996
RandomForestRegressor	0.0105	0.0058	0.99850
Linear Regression	0.0150	0.0072	0.99700
Support Vector Regressor (SVR)	0.0125	0.0063	0.99780
Gradient Boosting Regressor	0.0090	0.0042	0.99900

Table 5 shows that the KNeighborsRegressor model outperforms the other models with the lowest MAE and MSE and the highest R-squared score. The low MAE and MSE values indicate that the predictions made by the KNeighborsRegressor are very close to the actual values. At the same time, the high R-squared score suggests that the model explains almost all the variance in the energy consumption data. The RandomForestRegressor also shows strong performance, with reasonably low error metrics and a high R-squared score, making it a robust alternative. While still effective, linear regression, SVR, and gradient-boosting regressor models show slightly higher error metrics and lower R-squared scores compared to KNeighborsRegressor and RandomForestRegressor.

5.2 Model performance metrics

The specific prediction results for energy consumption at the provided address are summarized in the Table 6 below. These results highlight the accuracy of the KNeighborsRegressor model in predicting energy consumption based on geographic coordinates.

Table 6. Prediction results for energy consumption

Parameter	Value
Address	Junction Pl, Boulder, Colorado 80301
Latitude	40.0258
Longitude	–105.2510
Time of Prediction	Around Midnight
Predicted Energy Consumption	0.0054 (MAE)

The prediction is for node "Junction Pl, Boulder, Colorado 80301" (latitude 40.0258, longitude –105.2510). The above prediction around midnight then indicates that this model can show good estimates of energy consumption at different times of the day. Results reveal the accuracy of the KNeighborsRegressor model in predicting energy consumption using localities. Such a model with high accuracy and low error metrics can be used as a reliable tool in different applications such as energy management, urban planning, and sustainability studies. These predictions help stakeholders make data-driven decisions about resource management, infrastructure planning, and energy efficiency, which ultimately contributes to smart and green cities.

5.3 Model performance metrics

The comparative analysis of various studies on EV charging infrastructure provides a comprehensive understanding of this field's different approaches, methodologies, and findings. This section synthesizes the insights from six key studies, highlighting their objectives, methods, research gaps, key findings, and limitations, as shown in Table 7.

Table 7. Comparative analysis of EV charging infrastructure studies

Study	Objective and Scope	Methods and Techniques Used	Research Gap	Key Findings and Results	Limitations
[18]	Investigates PEV integration into a microgrid, focusing on energy management and grid impacts.	Real-time data analysis from Level II and III chargers, impact assessment on grid and building load.	Micro-level impacts of PEV integration on local infrastructure.	10% EV penetration can lead to a 75% increase in peak demand on the distribution feeder.	Specific to UCR microgrid, does not explore long term solutions or economic impacts.
[19]	Framework for scheduling smart PEV charging conside ring travel behavior and battery degradation.	Stochastic optimization, Monte Carlo simulation, 21-node sample distribution network, wind turbine generation unit.	Real-world travel behavior and battery degradation costs are often overlooked.	Smart G2V and V2G charging modes optimize cost and efficiency, smart mode reduces energy costs and power losses, V2G incurs higher battery degradation costs.	Reliance on simulated data and specific network configuration, may not generalize to other settings.
[20]	Comprehensive analysis of energy optimization approaches for EV charging, focusing on battery life and optimization methods.	Various optimization techniques like convex optimization, particle swarm optimization, genetic algorithms, and dynamic programming.	Detailed exploration of combined effects of different optimization approaches on EV charging strategies.	Optimized EV charging enhances battery performance and contributes to grid stability and energy efficiency.	Reliance on the critical models, need for practical implementation and validation in real world scenarios.

(Continued)

Table 7. Comparative analysis of EV charging infrastructure studies *(Continued)*

Study	Objective and Scope	Methods and Techniques Used	Research Gap	Key Findings and Results	Limitations
[21]	Predicts EV charging duration using ensemble machine learning algorithms.	Ensemble machine learning algorithms: Random Forest, XGBoost, CatBoost, LightGBM, using two years of real-world data.	Lack of real-world data for normal and fast charging events and absence of machine learning interpretation techniques.	XGBoost model provided highest accuracy in predicting charging times, demonstrating the effectiveness of ensemble models.	Absence of user sociodemographic data, specific focus on Japanese charging environment, may not generalize to other regions.
[23]	Optimized strategy for placing and sizing different EV charging stations in an active distribution network with PV integration.	Stochastic model to estimate hourly EV load, particle swarm optimization (PSO) to minimize costs and losses.	Optimizing a mix of Level 1, Level 2, and Level 3 chargers and analyzing combined effects.	Optimized combination of chargers reduces costs and system losses, improves voltage profiles with PV generation.	Reliance on simulated data specific to the NUST distribution network, challenges in generalizing findings to other regions.
[21]	Reviews modeling approaches for planning EV charging infrastructure, focusing on optimization methods for location and sizing.	Categorizes approaches into node-based, path-based, and tour-based; assesses effectiveness in cost minimization and service coverage.	Need for models integrating real-world data on user behavior and temporal deployment of infrastructure	Node-based methods suitable for residential areas, path-based for highways, and tour-based offer comprehensive understanding of user needs but require extensive data.	Lack of consideration for temporal deployment of infrastructure, reliance on theoretical models, may not fully capture real-world complexities.
Our Work	Predicts energy consumption and recommends EV charging stations based on geographic coordinates and energy left.	Various regression algorithms (KNeighborsRegressor, RandomForestRegressor, Linear Regression, SVR, Gradient Boosting) and deep learning models, data preprocessing, and spatial visualization using Folium.	Integration of real-world user behavior and geographic proximity into the prediction and recommendation process.	High accuracy in energy consumption prediction, practical recommendations for charging stations, comprehensive approach combining data analysis and machine learning.	Need for further validation in diverse real-world seenarios, potential variability in prediction accuracy based on geographic and temporal factors.

The studies analyzed cover a broad range of objectives and scopes. A study [18] focuses on integrating PEVs into a microgrid, emphasizing energy management and grid impacts. A study [19] develops a framework for scheduling smart PEV charging, considering travel behavior and battery degradation. Study [20] provides a comprehensive analysis of energy optimization approaches for EV charging, focusing on battery life and optimization methods. Study [21] aims to predict EV charging duration using ensemble ML algorithms. A study [22] proposes an optimized strategy for placing and sizing different EV CSs in an active distribution network with PV integration. Finally, study [21] reviews modeling approaches for planning EV charging infrastructure, focusing on optimization methods for location and sizing. Our work, in contrast, focuses on predicting energy consumption and recommending EV CSs based on geographic coordinates and the remaining energy left in the vehicle.

The methodologies employed in these studies are diverse, reflecting the complexity of EV charging infrastructure. Study [18] uses real-time data analysis from Level II and III chargers to assess the impact on the grid and building load. Study [19] employs stochastic optimization and Monte Carlo simulation within a 21-node sample distribution network, incorporating a wind turbine generation unit. Study

[20] explores various optimization techniques such as convex optimization, PSO, genetic algorithms, and dynamic programming. Study [21] utilizes ensemble ML algorithms based on two years of real-world data, including RF, XGBoost, CatBoost, and LightGBM. Study [22] applies a stochastic model to estimate hourly EV load and uses PSO to minimize costs and system losses. Study [21] categorizes optimization methods into node-based, path-based, and tour-based approaches, assessing their effectiveness in cost minimization and service coverage. Our work leverages various regression algorithms (KNeighborsRegressor, RandomForestRegressor, Linear Regression, SVR, and Gradient Boosting) and deep learning models for predicting energy consumption, combined with spatial visualization using Folium.

Each study addresses specific research gaps within the field. Study [18] focuses on the micro-level impacts of PEV integration on local infrastructure. Study [19] highlights the often-overlooked real-world travel behavior and battery degradation costs. Study [20] identifies the need for a detailed exploration of the combined effects of different optimization approaches on EV charging strategies. Study [21] addresses the lack of real-world data for normal and fast charging events and the absence of ML interpretation techniques. Study [22] examines the optimization of a mix of Level 1, Level 2, and Level 3 chargers and their combined effects. Study [21] underscores the need for models that integrate real-world data on user behavior and the temporal deployment of infrastructure. Our work integrates real-world user behavior and geographic proximity into the prediction and recommendation process, addressing the practical aspects of EV charging infrastructure planning.

The findings from these studies provide valuable insights into EV charging infrastructure. A Study [18] reveals that a 10% EV penetration can lead to a 75% increase in peak demand on the distribution feeder. Study [19] finds that smart G2V and V2G charging modes can optimize cost and efficiency, although V2G incurs higher battery degradation costs. Study [20] concludes that optimized EV charging enhances battery performance and contributes to grid stability and energy efficiency. Study [21] demonstrates that the XGBoost model provides the highest accuracy in predicting charging times, showcasing the effectiveness of ensemble models. Study [22] shows that an optimized combination of chargers reduces costs and system losses and improves voltage profiles with PV generation. Study [21] determines that node-based methods are suitable for residential areas, path-based methods for highways, and tour-based approaches offer a comprehensive understanding of user needs but require extensive data. Our work shows high accuracy in energy consumption prediction and provides practical recommendations for charging stations, combining data analysis and ML to deliver actionable insights.

Despite their contributions, these studies have certain limitations. Study [18] is specific to the UCR microgrid and does not explore long-term solutions or economic impacts. Study [19] relies on simulated data and a specific network configuration, which may not generalize to other settings. Study [20] depends on theoretical models and requires practical implementation and validation in real-world scenarios. Study [21] lacks user socio-demographic data and focuses on the Japanese charging environment, which may not generalize to other regions. Study [22] relies on simulated data specific to the NUST distribution network, with challenges in generalizing the findings to other regions. Study [21] does not consider the temporal deployment of infrastructure and relies on theoretical models, which may not fully capture real-world complexities. Our work, while demonstrating high accuracy and practical applicability, still requires further validation in different real-world scenarios and may face variability in prediction accuracy based on geographic and temporal factors.

6 CONCLUSION

In this study, a ML-based framework is proposed to integrate optimal charging infrastructure recommendations with predictive charging consumption of EVs according to their geolocation and final energy. We utilized regression algorithms and deep learning models on the large dataset (total 148,136 transactions from the City of Boulder Open Data Hub) for prediction of the pattern of energy consumption accurately. Results show that KNeighborsRegressor performs the best among regression models, having the best error metrics and R-squared score. The TEnSURE experimental dataset fills an important gap in the current study, capturing how real-world user behavior and geographic location can be included in predicting and recommending demand, offering a range of broad applications for energy management, urban planning, and sustainability. The results speak to the ability of ML to improve the effectiveness and usability of EV charging networks. This work should be confirmed in different field studies in field conditions and account for differences in performance when deploying models to predict future performances due to geographical and temporal variability.

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