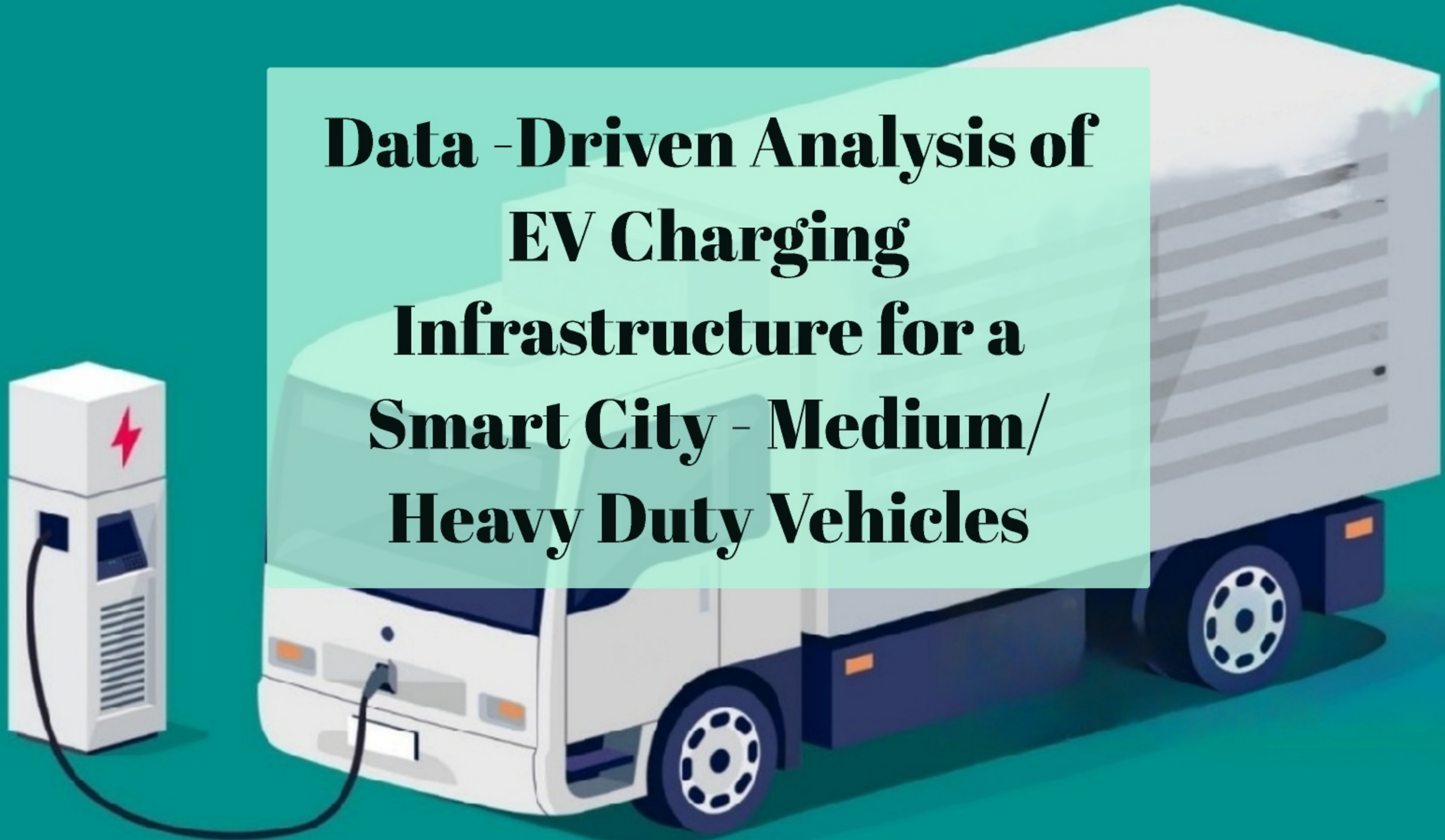
Data -Driven Analysis of EV Charging Infrastructure for a Smart City - Medium/ Heavy Duty Vehicles



MEET THE

Project Advisor :

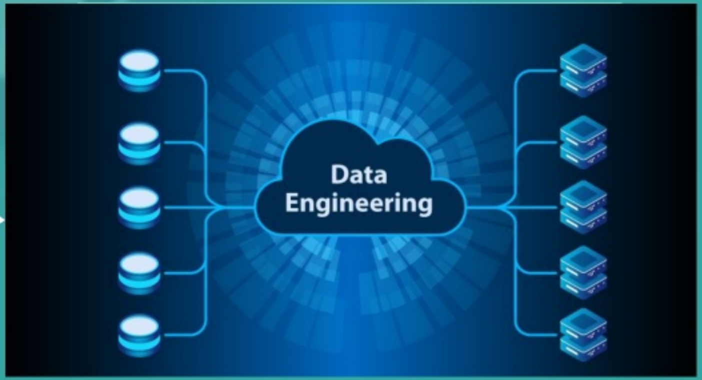
Dr. Zeyu Jerry Gao

TEAM 6 :

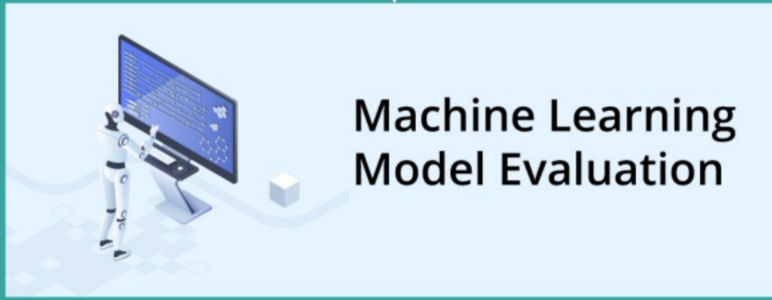
Lohitha Vanteru
Mahe Jabeen Abdul
Pranavi Sandrugu
Rohan Naga Venkata Mayukh Ungarala

AGENDA

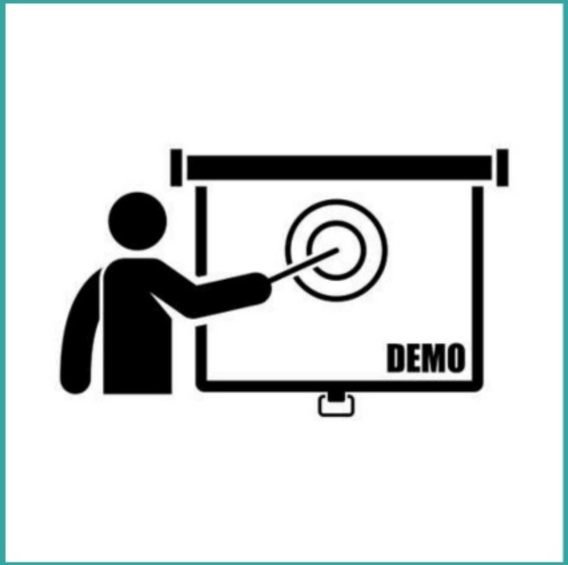

INTRODUCTION


Data
Engineering


Machine Learning
Models


Machine Learning
Model Evaluation


WEB PORTAL
DEVELOPMENT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Charging Ahead: Project Introduction

Introduction:

- The global shift towards sustainable transportation demands a focus on electric vehicles (EVs) for medium/heavy-duty applications.
- The project addresses the crucial need for efficient and scalable EV charging infrastructure tailored for larger vehicles.

Objectives:

- Evaluate the current state of EV charging infrastructure for medium/heavy-duty vehicles.
- Identify challenges and opportunities in the existing infrastructure.
- Propose data-driven solutions to enhance EV charging accessibility and efficiency.

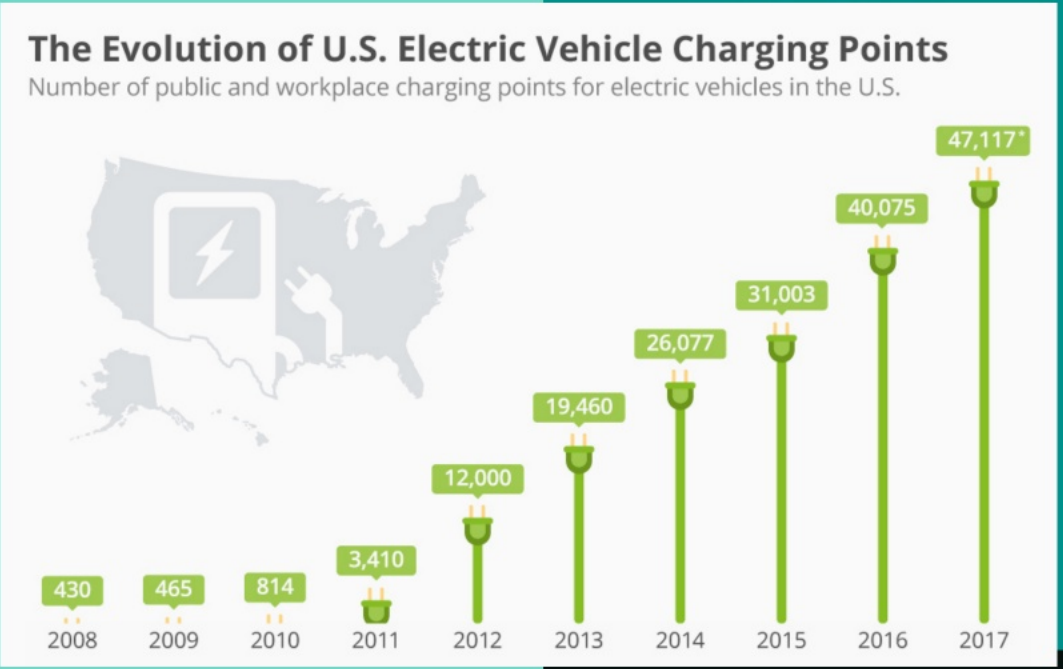
Navigating the Terrain: Project Background

Current Landscape:

- *Heavyweights in the Spotlight:* Despite their emission-reducing role, medium/heavy-duty EVs lack tailored charging infrastructure.
- *Light-Duty Dominance:* Existing infrastructure leans towards light-duty vehicles, prompting a need for a robust solution.

Smart City Context:

- *Green Urban Blueprint:* Aligning with smart city initiatives, our project contributes to sustainable transportation and energy-efficient urban development.
- *Beyond Charging:* It's not just about powering vehicles; it's about shaping a smarter and greener urban landscape.



Electrifying Ambitions: Project Motivation

Addressing Emission Challenges:

MD/HD vehicles in the U.S. contribute to nearly one-third of the country's on-road transportation greenhouse gas emissions, emphasizing the urgent need for sustainable alternatives.

Government Commitment:

The United States' Infrastructure Investment and Jobs Act (IIJA) allocates significant funding:

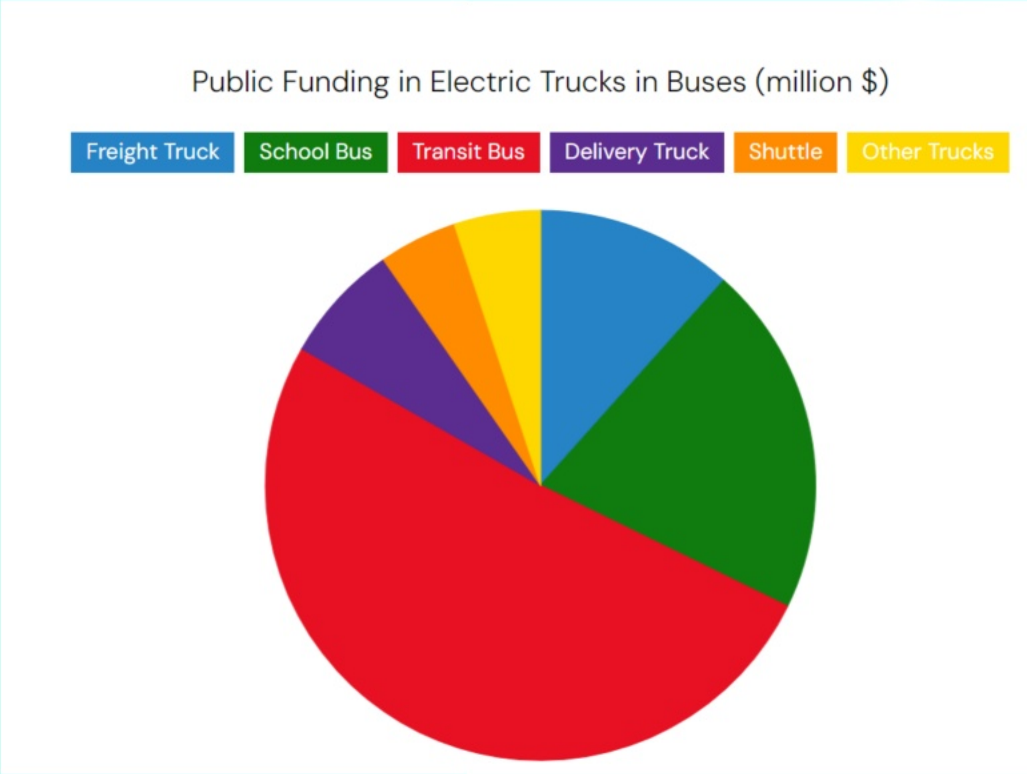
- $5 billion for highway charging.
- $2.5 billion for alternative fueling infrastructure.
- $5 billion for a Clean School Bus program.

Promoting Sustainability:

The IIJA funding demonstrates a commitment to advancing electric vehicle infrastructure and sustainability initiatives on a national scale.

Challenges Faced by MD/HD Vehicle Owners:

- *Limited Range:* Heavy-duty vehicle owners often experience range limitations due to on-premises charging necessities.
- Infrastructure Constraints: Charging at regular passenger car stations is impractical, highlighting the need for dedicated and optimized charging solutions.



Currents and Trends: EV Market Analysis

Pioneers of Electric Commercial Vehicles:

Forefront companies in the medium and heavy-duty electric vehicle market, such as Blue Bird, Lion Electric, BYD, and others, play a pivotal role in advancing sustainable transportation through the electrification of school buses, trucks, and various commercial vehicles.

Key Players of EV Charging Stations:

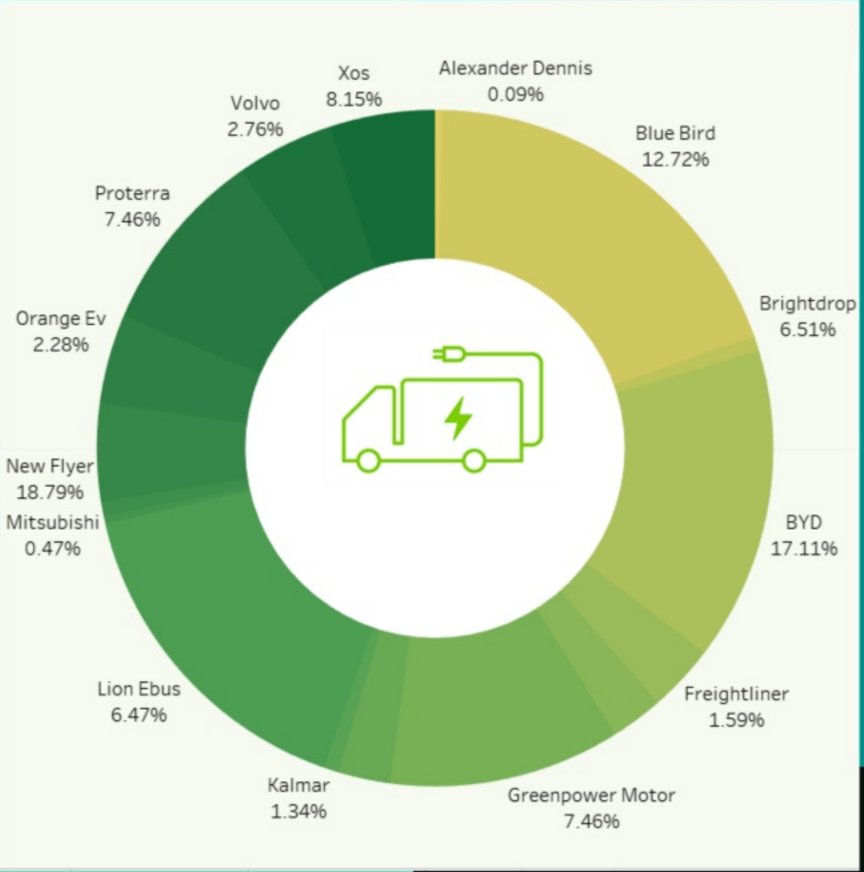
Major players in the EV charging infrastructure market include ChargePoint, Tesla, Electrify America, and others. These companies may provide both public and private charging solutions.

Technological Trends:

Fast-charging technologies, battery-swapping solutions, and smart grid integration have been among the notable trends in the EV charging infrastructure sector.

Consumer Adoption:

Fleet operators, logistics companies, and municipal services have shown increasing interest in electric medium and heavy-duty vehicles, driven by both environmental concerns and potential cost savings over time.



Dashboard Link

Charging Challenges: Targeted Problems

- ***Anticipating EV Market Growth***
  Forecasting the growing demand for EVs and the need for expanded charging infrastructure.

- ***Addressing Range Anxiety***
  Ensuring electric vehicle (EV) adoption by mitigating concerns related to limited driving range.

- ***Efficient Energy Resource Allocation***
  Optimizing energy resources by accurately forecasting short and long-term energy demand.

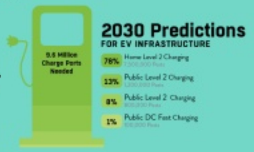
- ***Strategic Charging Infrastructure***
  Strategically placing charging stations to accommodate diverse vehicle types and urban mobility needs.

Data-Driven Roadmap: Project Deliverables

Planning of EV Infrastructure for heavy and medium motorized vehicles with an AI Powered model using Machine Learning Algorithms.

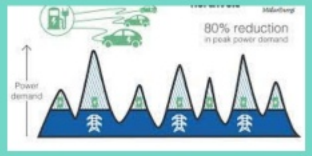
PROJECT GOALS

EV Vehicle and Charging Station Count Prediction



Heavy/ Medium Duty EV Vehicle Range Prediction

EV Charging Station Energy Demand Prediction



Optimal Location Prediction for New Charging Station

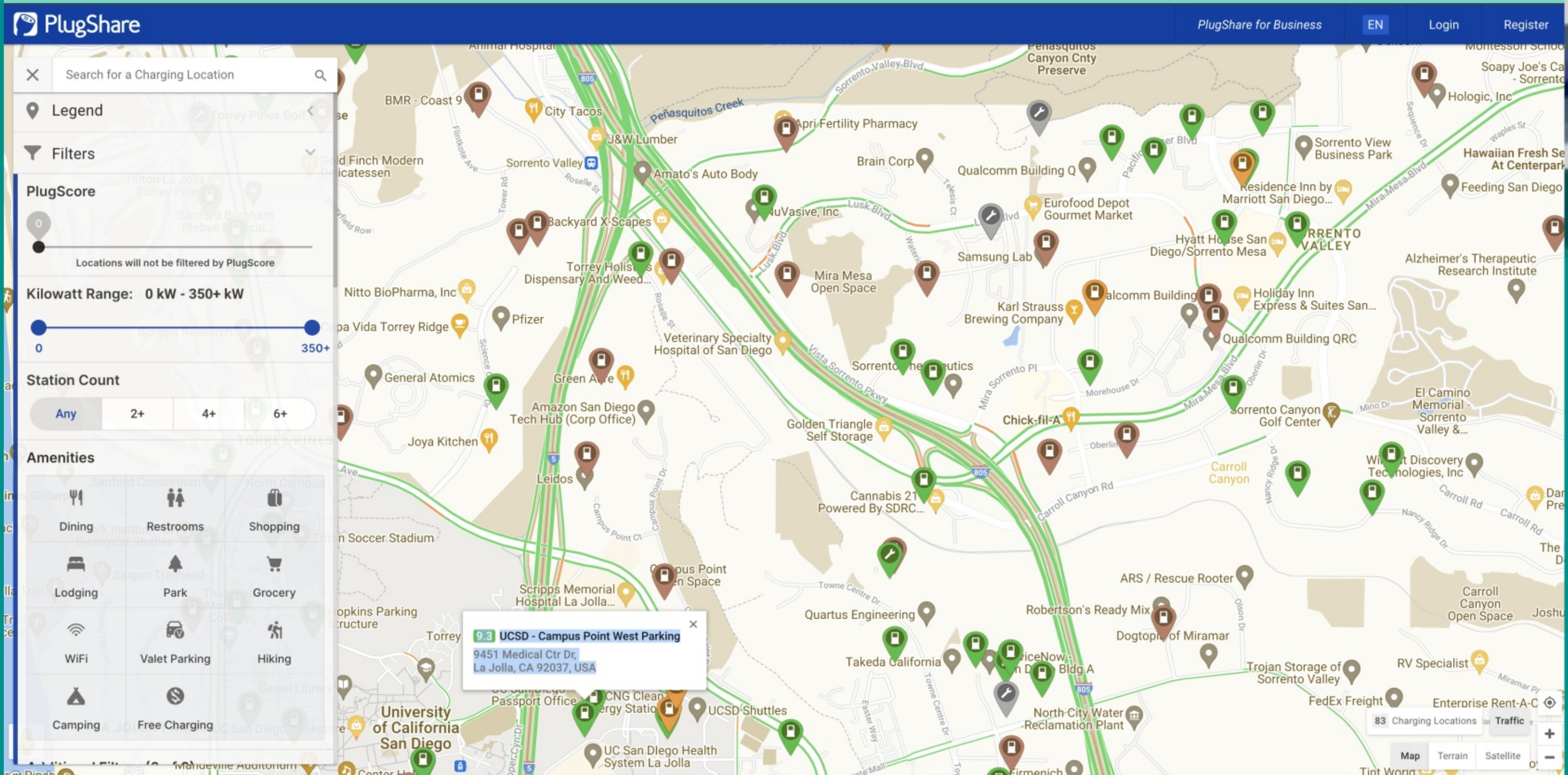
Website Implementation

Technology Survey

Objective	Methods	Description	Negatives
Planning Electric vehicle infrastructure for various types of vehicle	Heavy- and medium-duty vehicles	Uses Return-to-base model and the on-route charging model, summarizes the challenges of charging commercial electric vehicles (CEVs) at public locations.	Need for a balanced exploration of alternative charging strategies beyond the return-to-base model and V2G technology.
	Heavy duty trucks only	Joint routing and charging (JRC) scheduling approach for electric trucks, to minimize costs and delivery delays.	Computational complexity of the optimization problem, operational adaptability in environments.
	E-Trucks & Buses	Growth of electric truck and buses by industry engagement, facilitating the electrification of vehicles.	There is a need for adjustments in utility rates and a lack of adequate charging infrastructure.
Utilizing the Energy Demand of Electric vehicles (EVs)	SHapley Additive exPlanations (SHAP)	Examines (BEVs) to identify factors influencing BEV energy consumption and provide insights for enhancing energy efficiency and informing transport policies.	More detailed comparative analysis of urban and rural routes, validation of ML models against external datasets.
	Energy-efficient route planning	Estimating energy consumption in electric vehicles compared to conventional methods.	Can improve by providing more detailed results of statistical tests.
	Hybrid simulation model	Examine EVs through strategies addressing greenhouse emissions from electricity generation and EV adoption in passenger transportation.	Oversimplified alternative options, lack of a detailed transportation demand forecast, and unclear model validation.
Methods used for locating charging stations	Activity-based approach	Locate the (sub)optimal locations for charging stations using multiday travel activity constraints.	Lack of information on grid stability and electricity demand charging infrastructure utilization.
	Route-based analysis	Analyze the infrastructure development and EV efficiency in minimizing travel time and maximizing user comfort.	Uncertainty in optimal charging stop selection and waiting times was not included in the study.
	GIS-based approach	Identify the optimal locations for EVSE in terms of improved efficiency and lower emissions.	Lack of available specialists in electric mobility and incomplete vehicle registration data.

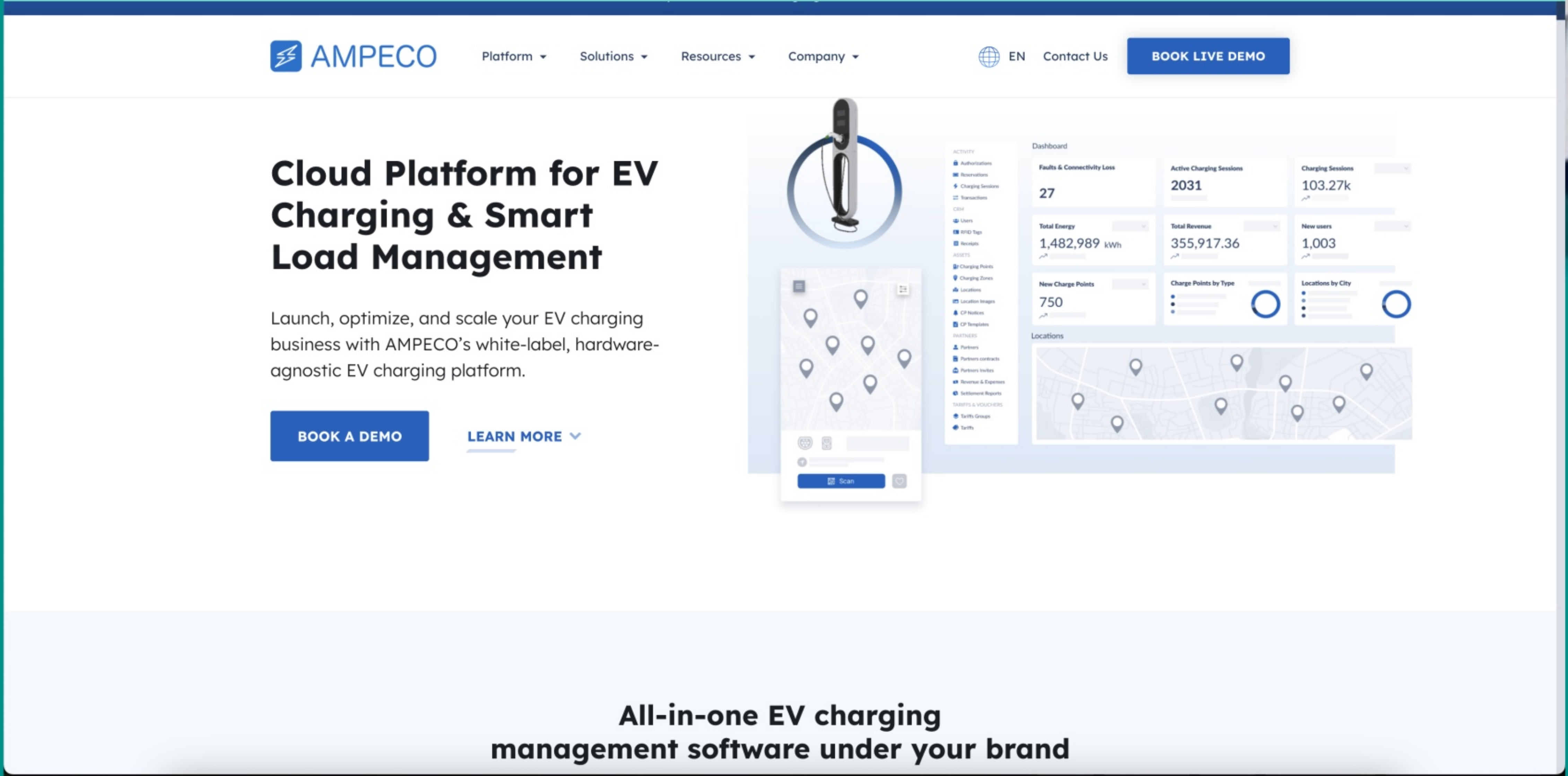
Current Charging Frontiers: Existing Live Technologies

PlugShare - provides information on the location and details of charging stations for electric automobiles utilizing the user's location or a provided address .It provides basic information on the station's specifications and fees and amenities nearby the station.



Current Charging Frontiers: Existing Live Technologies

AMPECO - a white-label EV charging management solution, that includes a backend platform, web portal, and mobile app for drivers that cover all business use cases – public, private, fleet, and residential charging.



Literature Survey

Objective	Region	Dataset	ML Models	DL Models	Other models	Eval Metrics
Forecasting medium-term public EV charging demand	Scotland, UK	Eleven charging stations	LinReg, RF, SVM, KNN	ANN	ARIMA	MAE, RMSE, SMAPE
Forecasting demand for EV charging post-session start	Morocco	Two Public charging stations	N	ANN, RNN, LSTM, GRU	N	MAPE, RMSE
EV charging demand predictions for short-term and long-term forecasting	Boulder, Colorado	Twenty-five Public charging stations	N	ANN, LSTM, Transformer	ARIMA, SARIMA	RMSE, MAE
Addresses the challenges of mass electric vehicle (EV) adoption on power systems	Shenzhen China	real-world EV charging station datasets	N	DNN, RNN, LSTM, GRU	N	NRMS, normalized mean absolute error (NMAE)
Smart EVC solution—an intelligent charging station management platform based on Blockchain and Artificial Intelligence	United Kingdom	real-time data on the energy consumption and charging demand.	N	N	Custom Reservation Algorithm Reservation	Charging time
Forecast electric vehicle charging demand	Atlanta, USA	EV charging dataset of Georgia Tech	N	Deep Learning-based LSTM, DLSTM	arithmetic optimization algorithm (AOA), empirical mode decomposition (EMD).	MAE, RMSE, Accuracy

Objective	Region	Dataset	ML Models	Deep Learning	Other models	Eval Metrics
Analyze the effects of different environmental parameters on energy consumption and driving range	Various regions of China	Real-world BEV	N	N	Micro-simulation model	Accuracy, Relative error, Absolute error.
Improve the driving range prediction accuracy	Beijing	Real-world data from Baic New Energy Automobile	Classification and Regression tree, MLR, GBDT	N	N	MAE, Accuracy Maximum, minimum error
Reduce driver's range anxiety by estimating the real-time energy consumption of EVs	United States	Nissan Leaf 2013, Argonne National Laboratory (ANL)	N	Deep Convolutional Neural Networks	N	RMSE, MAE, K-fold correlation
Predict the remaining driving range of EVs	Major cities in China	National Big Data Alliance of New Energy Vehicles	XGBT, Boosting Regression Tree, XGBoost	N	Blended Model	MAE, RMSE, MAPE
Accurately estimating the driving range of electric vehicles	China	National Monitoring and Management Platform for New Energy Vehicles	Gradient boosting decision tree (LGBM), SVM	N	N	MAE, MSE, RMSE, R2 (R-Square)
Impact of driving electric vehicles (EVs) at highway speeds, using auxiliary loads	Australia	Mitsubishi i-MiEV and Nissan Leaf test car data	N	N	Vehicle mathematical modeling	Mean unsigned error, Energy consumption

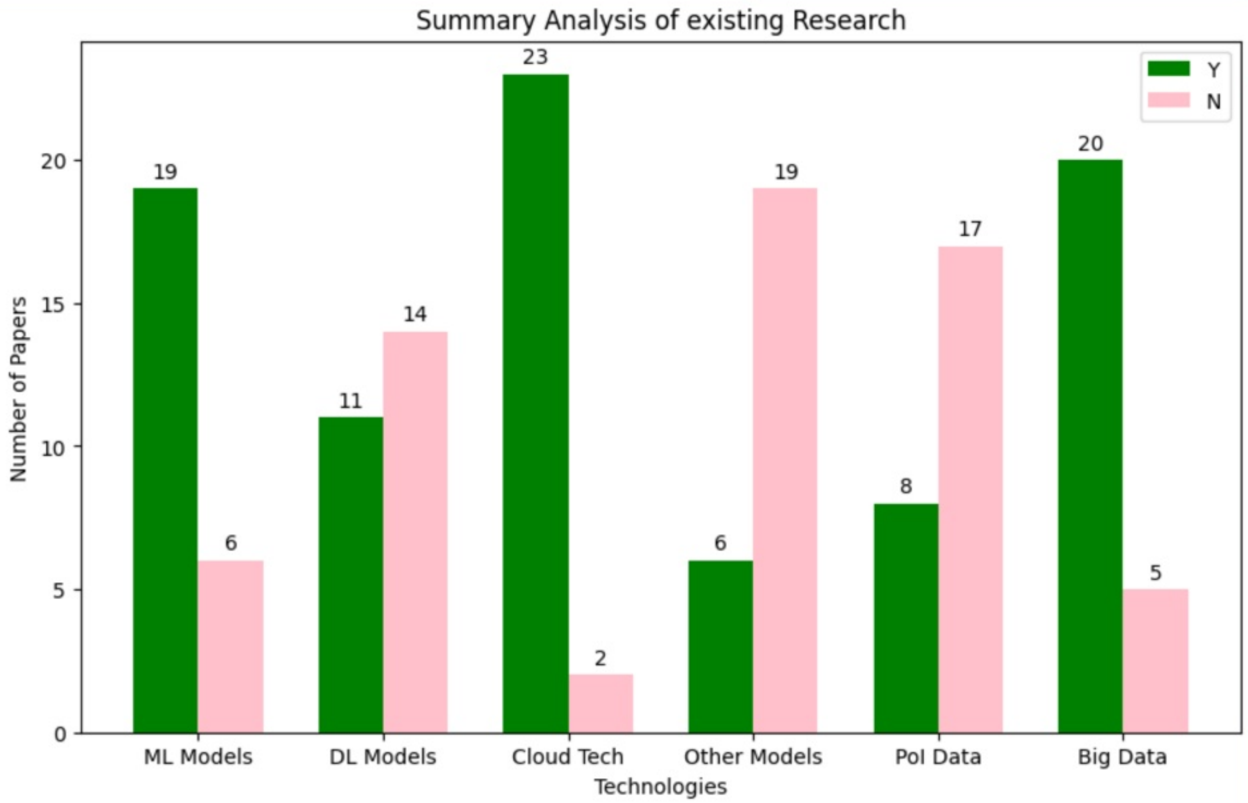
Literature Survey

Objective	Region	Dataset	ML Models	Other models	Eval Metrics
Predicting the energy usage during charging sessions for plug-in electric vehicles (PEVs)	Nebraska, USA	public charging stations	RF, SVM, Xgboost, LinReg	N	RMSE, MAE, R2
Predicting the energy demand for EVs	Dundee city, UK	Charging stations data(CS)	RF, DT, KNR, SVR, SGDR	Federated Energy Demand Learning (FEDL), Clustering based EDL,	RMSE
Predicting the energy consumption in electric vehicles (EVs)	Brussels	Controller Area Network (CAN) bus signals of a 2012 Nissan Leaf	Multiple linear regression	Macro and hybrid model	correlation coefficient (R2), Accuracy
China's road transport sector's energy consumption and greenhouse gas emissions at the provincial level up to 2050	Mainland China	National Bureau of Statistics of China, Annual statistic of population	N	CPREG model, GHG Emissions Analysis model	BAU scenario, LC scenario, GDP growth rate
Analyze future trends in China's road transport sector, evaluating direct and life cycle energy demand and greenhouse gas emissions	China	China Automotive Technology and Research Center (CATARC) data	N	Gompertz curve model, bottom-up model	BAU scenario, HEV application rate

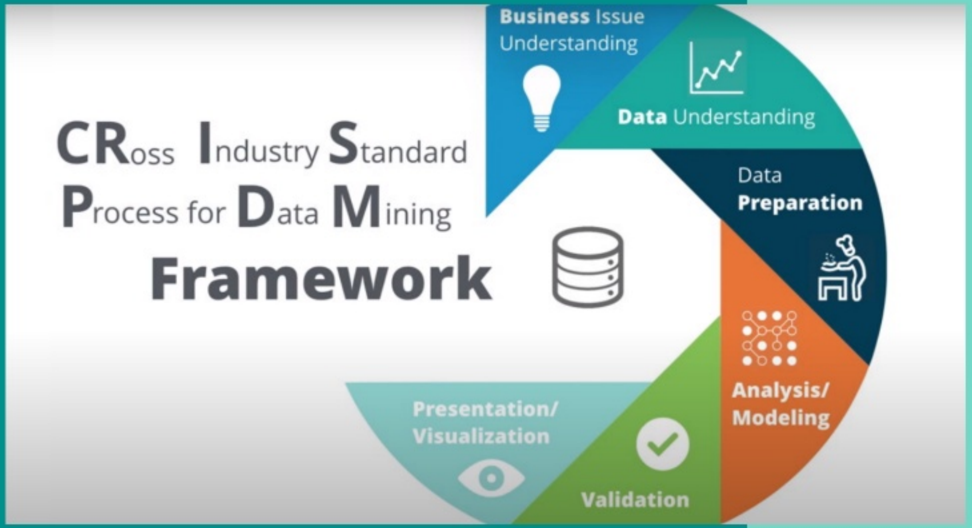
Objective	Region	Dataset	ML Models	Deep Learning	Other models	Eval Metrics
Optimizing the selection of EV charging station	Singapore USA, UK	Road network data, charging station data	N	N	Proximal Policy Optimization algorithm, RL	profit increase, travel time, charging time
Resolving EV charging infrastructure planning	Sydney, Australia	Traffic flow Distribution network data	N	CNN (GCN)	Cournot competition game model	Travel time, wait time, charging time
Determining the placement of charging stations	Germany	Charging Station data	LinReg	N	N	MAE, MAPE, RMSE
Optimization model using GIS data and grid partitioning to locate and size public charging stations for EVs.	Thailand	GIS data, Vehicle Population	N	N	Optimization and spatial analysis models	EV–CP ratio, Service time
Allocating charging stations in large-scale transportation networks for electric vehicles (EVs)	Southern Sweden	The Swedish National Road Database (NVDB)	N	N	Probabilistic rule, Integer programming for solving the optimization problem	Maximal route cost
Address the multi-stage placement of electric vehicle (EV) charging stations	San Pedro District of Los Angeles.	zip code tabulation area (ZCTA), Road network data	N	N	Nested logit model, Bayesian game analysis	Charging Demand, Total Profit, Overall Utility.

Existing Research Summary

Technology	Level 1	Level 2	DC Fast Charging	Wireless Charging
Power Output	1.4 kW	7.2 kW	50-350 kW	3.7-7.7 kW
Charge Time (0-100%)	8-12 hrs	4-8 hrs	20-60 min	3-4 hrs
Connector Types	NEMA 5-15	J1772	CCS1, CCS2, CHAdeMO, Tesla Supercharger	Qi, SAE J2954
Compatibility	Light Duty	All EVs	Medium and Heavy Duty	Limited
Cost	Low	Medium	High	Very High
Convenience	Low	High	Medium	High
Availability	High	High	Low-Medium	Low

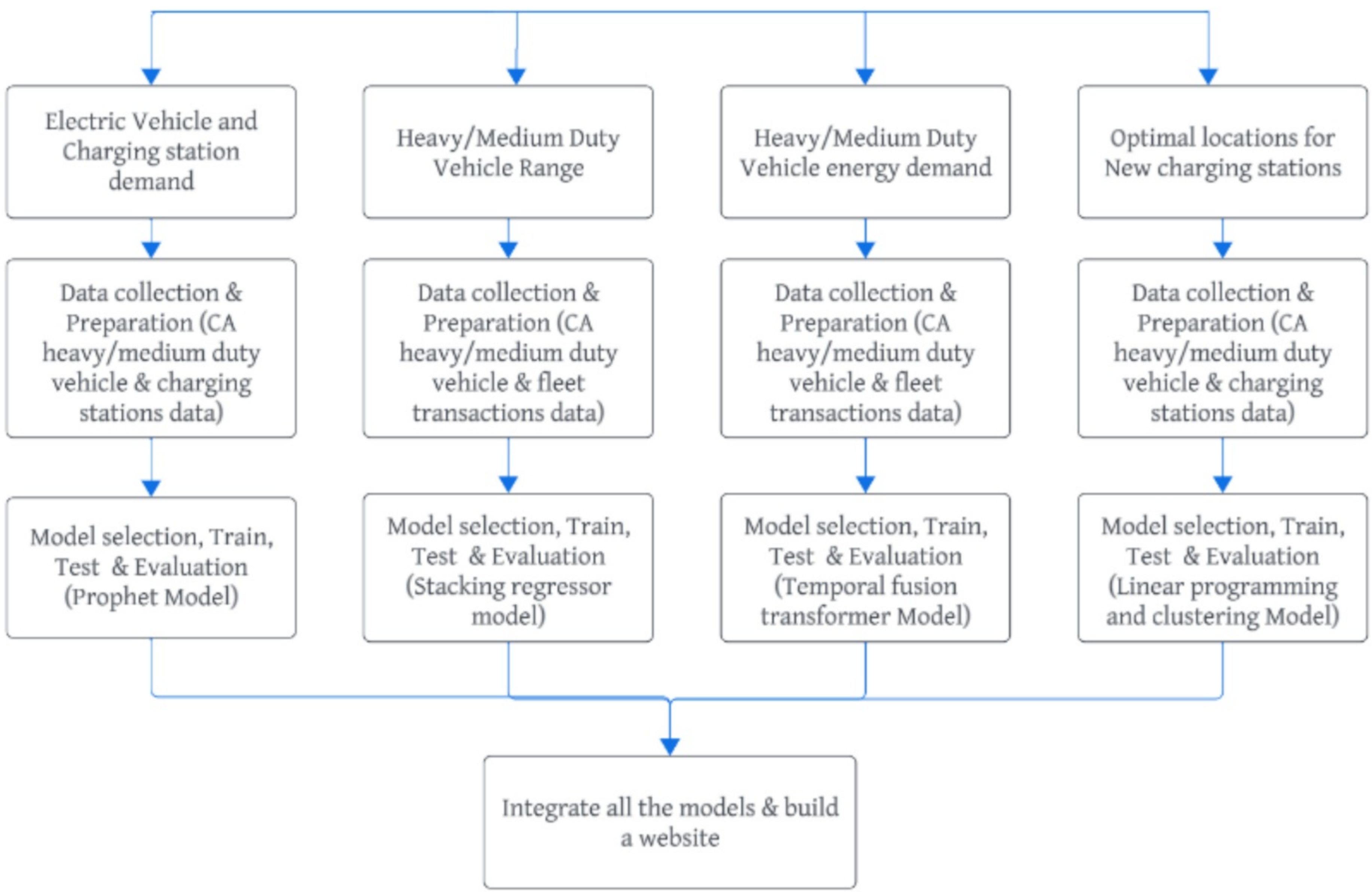


Project Management

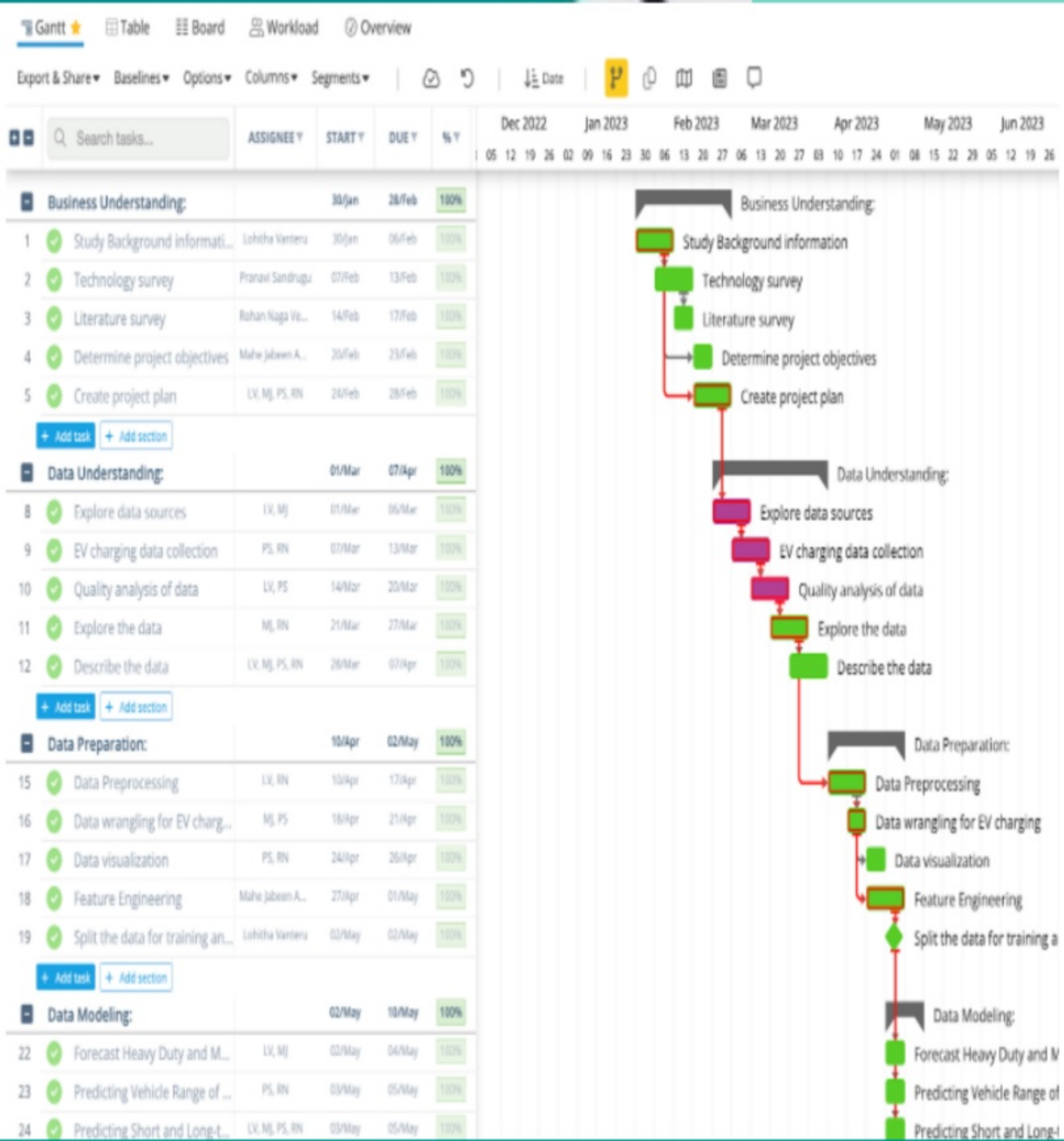


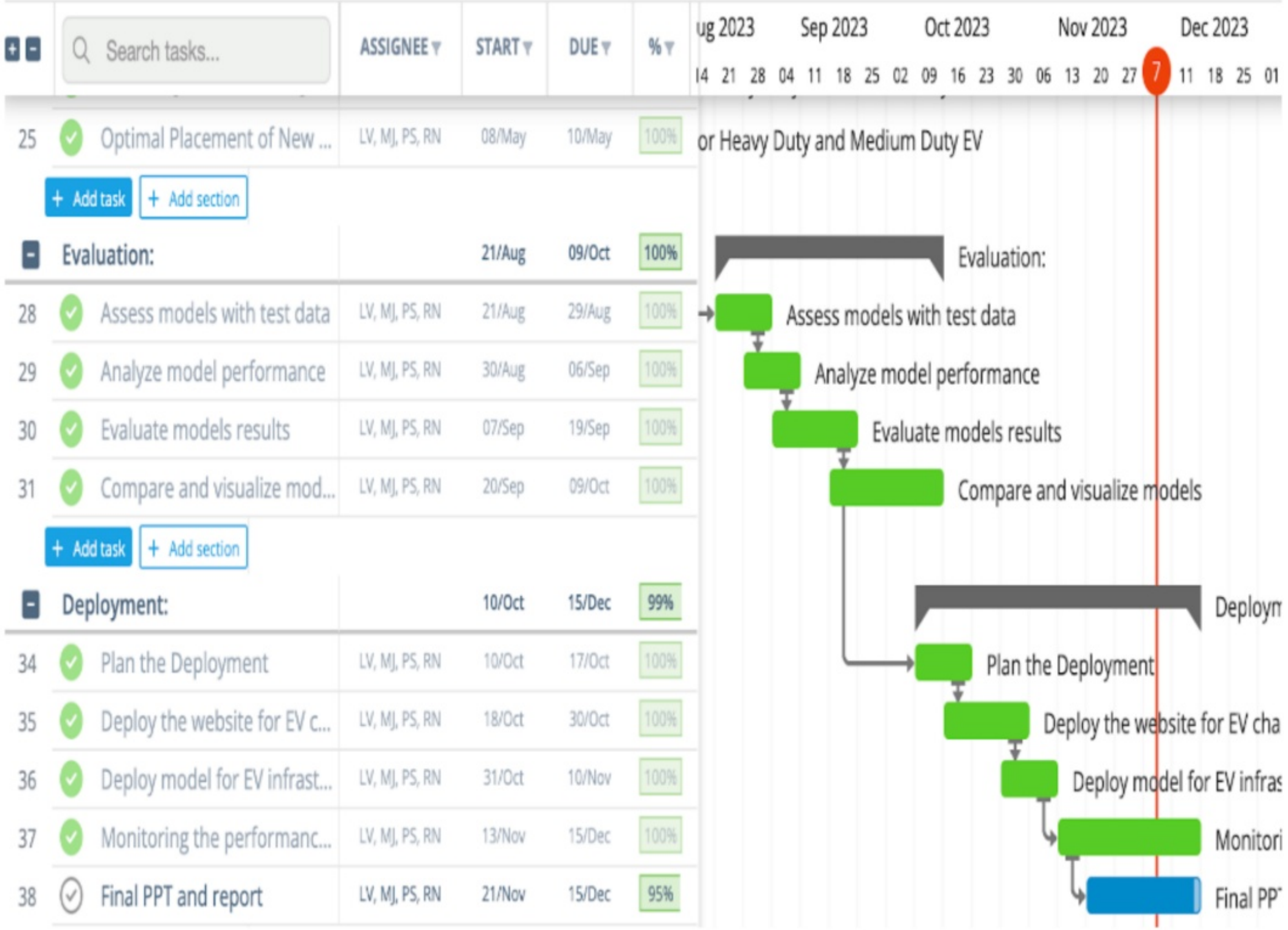
Task	Assigned
Data Extraction	Lohitha, Mahe, Pranavi
Data Cleaning	Pranavi, Rohan
Data Transformation	Pranavi, Lohitha
Feature Selection	Mahe, Lohitha, Rohan
Exploratory Data Analysis	All
Forecasting EV count and charging station demand of Medium and Heavy duty EVs based on electric vehicle registrations	Pranavi, Mahe
Predicting vehicle range of Medium and Heavy duty EVs based on Medium/Heavy duty transactions	Lohitha, Mahe
Predicting short and long-term energy demand of Medium and Heavy duty EVs based on Medium/Heavy duty transactions	Pranavi, Rohan
Optimal placement of new charging stations for each vehicle type such as school bus, transit bus and delivery truck	Lohitha, Rohan
Final Report and Presentation	All

Project Management



GANTT CHART


Gantt
Table
Board
Workload
Overview
Business Understanding:
Study Background information
Technology survey
Literature survey
Determine project objectives
Create project plan
Data Understanding:
Explore data sources
EV charging data collection
Quality analysis of data
Explore the data
Describe the data
Data Preparation:
Data Preprocessing
Data wrangling for EV charging
Data visualization
Feature Engineering
Data Modeling: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Aug 2023
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Dec 2023
25 Optimal Placement of New ... LV, MJ, PS, RN 08/May 10/May 100%
or Heavy Duty and Medium Duty EV
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Evaluation: 21/Aug 09/Oct 100%
28 Assess models with test data LV, MJ, PS, RN 21/Aug 29/Aug 100%
29 Analyze model performance LV, MJ, PS, RN 30/Aug 06/Sep 100%
30 Evaluate models results LV, MJ, PS, RN 07/Sep 19/Sep 100%
31 Compare and visualize mod... LV, MJ, PS, RN 20/Sep 09/Oct 100%
Compare and visualize models
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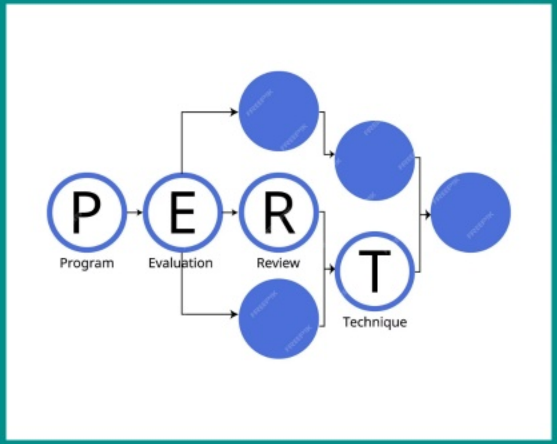
Deployment: 10/Oct 15/Dec 99%
34 Plan the Deployment LV, MJ, PS, RN 10/Oct 17/Oct 100%
35 Deploy the website for EV c... LV, MJ, PS, RN 18/Oct 30/Oct 100%
36 Deploy model for EV infrast... LV, MJ, PS, RN 31/Oct 10/Nov 100%
37 Monitoring the performanc... LV, MJ, PS, RN 13/Nov 15/Dec 100%
38 Final PPT and report LV, MJ, PS, RN 21/Nov 15/Dec 95%

PERT CHART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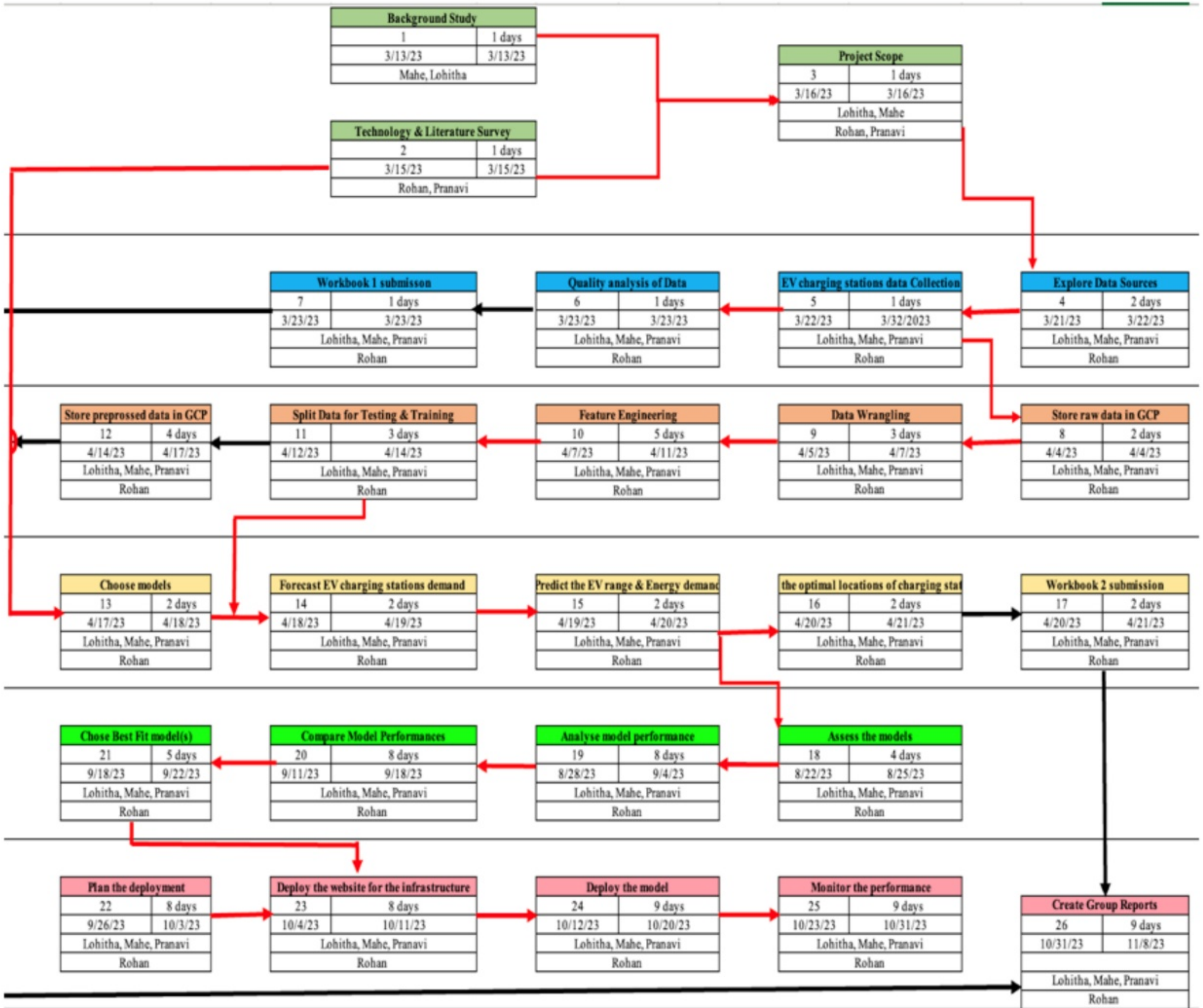
Background Study
1 1 days
3/13/23 3/13/23
Mahe, Lohitha
Technology & Literature Survey
2 1 days
3/15/23 3/15/23
Rohan, Pranavi
Project Scope
3 1 days
3/16/23 3/16/23
Lohitha, Mahe
Rohan, Pranavi
Explore Data Sources
4 2 days
3/21/23 3/22/23
Lohitha, Mahe, Pranavi
Rohan
EV charging stations data Collection
5 1 days
3/22/23 3/32/2023
Lohitha, Mahe, Pranavi
Rohan
Quality analysis of Data
6 1 days
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Lohitha, Mahe, Pranavi
Rohan
Workbook 1 submisson
7 1 days
3/23/23 3/23/23
Lohitha, Mahe, Pranavi
Rohan
Store raw data in GCP
8 2 days
4/4/23 4/4/23
Lohitha, Mahe, Pranavi
Rohan
Data Wrangling
9 3 days
4/5/23 4/7/23
Lohitha, Mahe, Pranavi
Rohan
Feature Engineering
10 5 days
4/7/23 4/11/23
Lohitha, Mahe, Pranavi
Rohan
Split Data for Testing & Training
11 3 days
4/12/23 4/14/23
Lohitha, Mahe, Pranavi
Rohan
Store preprossed data in GCP
12 4 days
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Lohitha, Mahe, Pranavi
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Choose models
13 2 days
4/17/23 4/18/23
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Forecast EV charging stations demand
14 2 days
4/18/23 4/19/23
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Predict the EV range & Energy demanc
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the optimal locations of charging stat
16 2 days
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Workbook 2 submission
17 2 days
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Lohitha, Mahe, Pranavi
Rohan
Assess the models
18 4 days
8/22/23 8/25/23
Lohitha, Mahe, Pranavi
Rohan
Analyse model performance
19 8 days
8/28/23 9/4/23
Lohitha, Mahe, Pranavi
Rohan
Compare Model Performances
20 8 days
9/11/23 9/18/23
Lohitha, Mahe, Pranavi
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Chose Best Fit model(s)
21 5 days
9/18/23 9/22/23
Lohitha, Mahe, Pranavi
Rohan
Plan the deployment
22 8 days
9/26/23 10/3/23
Lohitha, Mahe, Pranavi
Rohan
Deploy the website for the infrastructure
23 8 days
10/4/23 10/11/23
Lohitha, Mahe, Pranavi
Rohan
Deploy the model
24 9 days
10/12/23 10/20/23
Lohitha, Mahe, Pranavi
Rohan
Monitor the performance
25 9 days
10/23/23 10/31/23
Lohitha, Mahe, Pranavi
Rohan
Create Group Reports
26 9 days
10/31/23 11/8/23
Lohitha, Mahe, Pranavi
Rohan

Powering the EV Revolution :Data Engineering

Data Collection

Data Preprocessing

Data Preparation

Data Statistics

Gather datasets pertaining to electric vehicle (EV) charging stations

Prepare raw data for analysis through data processing

Preprocessed data is split into training, testing and validation sets

Analyzing a dataset to obtain descriptive statistical information

Charging Up Knowledge: Data Collection Sources

Open Source Datasets :

- **CA Vehicle Registration Data**
  Number of vehicles registered each year for every zipcode and county in CA.
- **CA EV Charging Stations Data**
  Real-time data of EV Charging stations for each zipcode in CA.
- **Transit Bus Stops Data**
  Data of public bus stations locations for transit bus in San Jose.
- **School Bus Terminals Data**
  Data of school bus terminal stations locations in San Jose.
- **Heavy/Medium Vehicle Fleet Transactions Data**
  Real-world data of commercial fleet vehicle operating data for each weight class .

Name	Vehicle Registration-Zip code	Charging Stations- Zip Code	Vehicle Fleet Transactions-Weight Class	Transit Bus Stations-City	School Bus Terminals-City
Source	California Department of Motor Vehicles	U.S. Alternate Fuel Data Center	National Renewable Energy Laboratory	CA Open Data Portal	CA Department of Education
Data Type	.xslx	.csv	.xslx	.geojson	.csv
Size	28.8 MB	16.7 MB	126.8 MB	1.6 MB	3.4 MB
Count	35,742	14,862	4,28,963	1289	3526
Yearly	Y	Y	Y	Y	Y
Weekly	N	N	Y	N	N
Monthly	N	N	Y	N	N
Duration	2010-2022	2010-2022	2018-2022	2022	2022

Refining the Charge: Data Preprocessing

Data cleaning:

- *Replacing spaces with underscores in column names makes them more suitable for data analysis and avoids potential naming issues.*
- *Assigning appropriate data types to columns.*

Converting 'Year' to Datetime:

The 'Year' column is converted to datetime format using pd.to_datetime.

Merging Data frames:

- *Used the merge method to combine two data frames, df and zc, based on a common column, which is 'Zip_Code'.*
- *Dropped the unnecessary columns, rearranges the columns in the resulting data frame to create a vehicle_data data frame.*

Data Aggregation:

Aggregated historical vehicle count data by grouping it based on the 'Year' column, summing the 'Vehicles' column for each year. This step organizes the data for analysis.

Handling missing values:

- *Removed rows from the Data Frame charging_data that contain missing (null) values.*
- *SimpleImputer is used to handle missing values in the resampled data. Missing values are filled with the mean value of the respective column using the fit_transform and transform methods for daily, weekly, and monthly forecasts, respectively.*

Data Transformation:

The new variables such as 'Charging_Duration,' 'Average_Power,' and 'Delta_SOC.' are created and added to the existing data to better represent and summarize aspects of the data.

Data Preparation:

- *Created fit_and_forecast function with the yearly_vehicle_count Data Frame and specified parameters for interval width.*
- *This prepares a Prophet model, fits it to the data, and forecasts EV vehicle counts until 2045.*
- *Feature engineering done calculating 'Delta_SOC' and 'Charging_Duration'), feature selection, and defining the target variable ('Range').*
- *The dataset is split into training and testing sets, preparing the data for subsequent machine learning modeling and evaluation.*

Snippets of Data Processing

```
Index(['Vehicle ID', 'Charger ID', 'Local Connect Time',
       'Local Disconnect Time', 'Local Charge Start Time',
       'Local Charge End Time', 'Average Power', 'Max Power',
       'Total Energy Delivered', 'Starting SOC', 'Ending SOC', 'Date',
       'Number of Charging Sessions', 'Connection Time', 'Charging Time',
       'SOC Charged', 'Starting SOC ', 'Local Charge E/Time'],
      dtype='object')
```

```
Index(['Vehicle_ID', 'Charger_ID', 'Local_Charge_Start_Time',
       'Local_Charge_End_Time', 'Average_Power', 'Max_Power',
       'Total_Energy_Delivered', 'Starting_SOC', 'Ending_SOC'],
      dtype='object')
```

```
Year              object
Fuel              object
Make              object
Duty              object
Vehicles           int64
Zip_Code          object
primary_city      object
state             object
county            object
dtype: object
```

```
Year          datetime64[ns]
Fuel                  object
Make                  object
Duty                  object
Vehicles               int64
Zip_Code              object
primary_city          object
state                 object
county                object
dtype: object
```

Local_Charge_Start_Time	Average_Power	Max_Power	Starting_SOC	Ending_SOC	Charging_Duration	Total_Energy_Delivered
2018-01-02	-0.730500	-0.700000	60.750000	60.500000	0.050000	0.012500
2018-01-03	10.968000	20.360000	60.750000	74.000000	0.250000	6.558000
2018-01-04	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-05	285.547308	356.476923	57.769231	96.346154	0.120513	28.323385
2018-01-06	263.824364	350.298182	60.500000	99.090909	0.124242	27.843273

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 553 entries, 146 to 15198
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Fuel_Type_Code      553 non-null    object
 1   Station_Name        553 non-null    object
 2   Street_Address      553 non-null    object
 3   City                553 non-null    object
 4   State               553 non-null    object
 5   ZIP                 553 non-null    object
 6   EV_Level2_EVSE_Num  524 non-null    float64
 7   EV_DC_Fast_Count    37 non-null     float64
 8   Latitude            553 non-null    float64
 9   Longitude           553 non-null    float64
 10  ID                  553 non-null    object
 11  Facility_Type       29 non-null     object
 12  Charger_Type        553 non-null    category
dtypes: category(1), float64(4), object(8)
memory usage: 56.8+ KB
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 553 entries, 146 to 15198
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Fuel_Type_Code      553 non-null    object
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 2   Street_Address      553 non-null    object
 3   City                553 non-null    object
 4   State               553 non-null    object
 5   ZIP                 553 non-null    object
 6   EV_Level2_EVSE_Num  553 non-null    float64
 7   EV_DC_Fast_Count    553 non-null    float64
 8   Latitude            553 non-null    float64
 9   Longitude           553 non-null    float64
 10  ID                  553 non-null    object
 11  Facility_Type       553 non-null    object
 12  Charger_Type        553 non-null    category
dtypes: category(1), float64(4), object(8)
memory usage: 56.8+ KB
```

Local_Charge_Start_Time	Average_Power	Max_Power	Starting_SOC	Ending_SOC	Charging_Duration	Total_Energy_Delivere
2018-01-31	230.756000	298.048872	51.793233	91.488722	0.136341	29.02159
2018-02-28	234.649350	300.472000	50.879167	92.004167	0.169167	29.96994
2018-03-31	186.202639	237.322532	56.639241	91.857595	0.153270	25.12594
2018-04-30	215.297506	279.485517	59.387931	94.025862	0.143487	24.70412
2018-05-31	245.237020	308.616939	63.336735	96.576531	0.120238	23.59476
2018-06-30	252.317563	331.284423	58.002404	95.149038	0.136538	27.08023
2018-07-31	259.351796	337.040905	59.631222	97.217195	0.124434	27.50661
2018-08-31	257.955053	335.258133	57.500000	96.573333	0.122444	28.73204

DATA CLEANING

Remove Empty Columns

Purpose: Remove empty coloumns in the dataset

Before

- Total Coloumns: 65
- Empty Columns: 27

After

- Total Coloumns: 38
- Empty Columns: 0

Drop Irrelavant Columns

Purpose: Remove irrelavent coloumns not useful for the analysis and prediction

Before

- Total Columns:
- Irrelevant Columns: 13

After

- Total Columns:
- Irrelevant Columns: 0

Renaming the columns

Purpose: Have meaningful names for columns

Before

- Vehicle ID
- Charger ID
- Local Charge Start Time
- Local Charge End Time

After

- Vehicle_ID
- Charger_ID
- Local_Charge_Start Time
- Local_Charge_End_Time

Raw Data Statistics

Dataset	Vehicle Registration-Zip code	Charging Stations- Zip Code	Vehicle Fleet Transactions-Weight Class	Transit Bus Stations-City	School Bus Terminals-City
Data Type	.xslx	.csv	.xslx	.geojson	.csv
Size	28.8 MB	16.7 MB	126.8 MB	1.6 MB	3.4 MB
Count	35,742	14,862	4,28,963	1289	3526
Features	15	65	48	12	16
Duplicate Rows	0	0	96	0	0
Missing Values	29	27	258	0	0

Refined Data Statistics

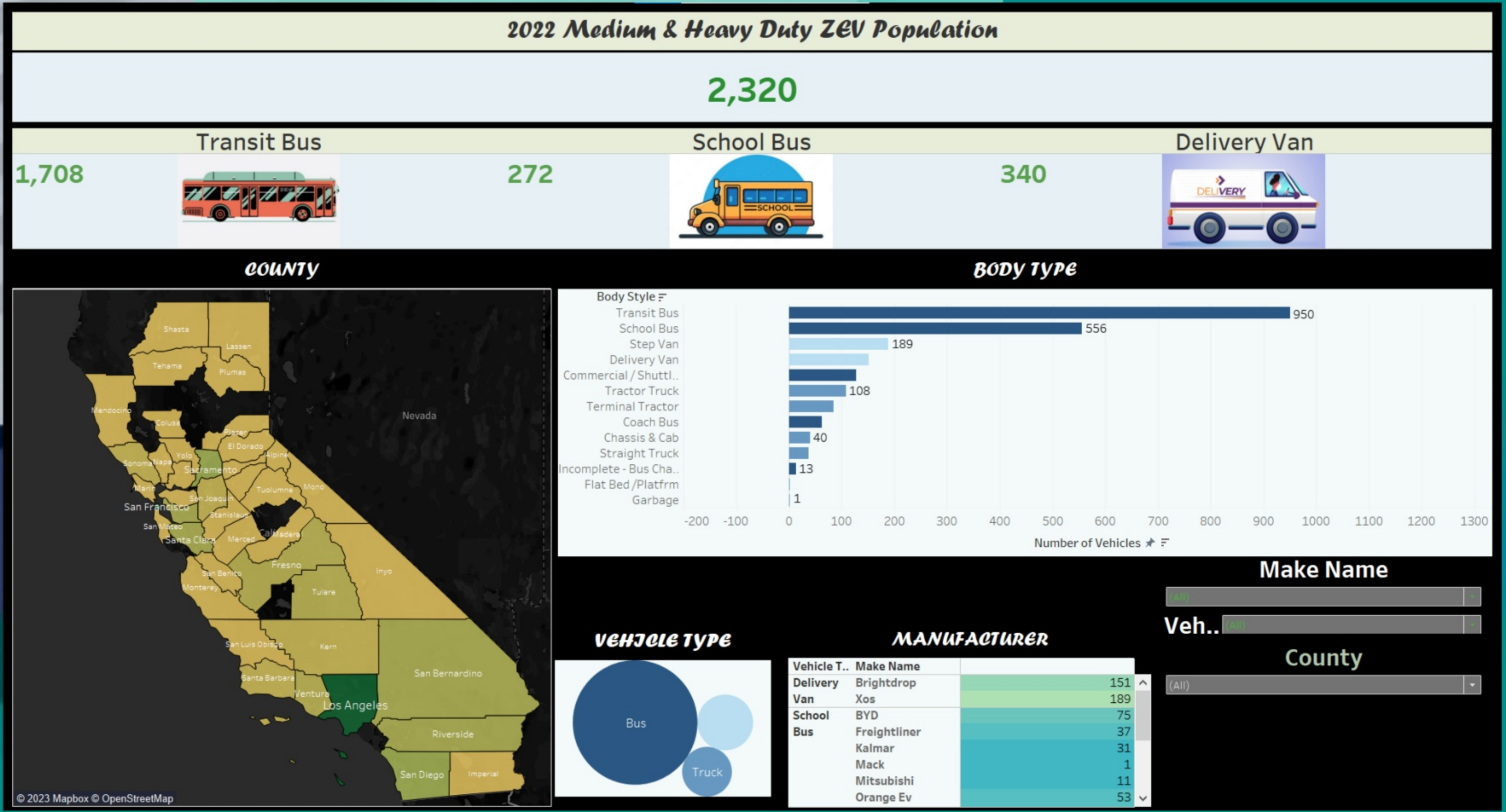
Dataset	Vehicle Registration-Zip code	Charging Stations- Zip Code	Vehicle Fleet Transactions-Weight Class	Transit Bus Stations-City	School Bus Terminals-City
Data Type	.csv	.csv	.csv	.csv	.csv
Size	14.2 MB	8.9 MB	87.1 MB	89 KB	1.4 MB
Count	35,713	14,835	4,28,609	1289	3526
Features	7	15	14	5	4
Duplicate Rows	0	0	0	0	0
Missing Values	0	0	0	0	0

Powering Up Analytics: Data Preparation

Dataset/Task	Raw	Preprocessed		Prepared		
			Total Rows	Train Rows	Test Rows	Validation Rows
CA Vehicle Registration Data	35,742	35713	35713	28571	3571	3571
CA EV Charging Station Data	14862	14835	14835	11869	1483	1483
Vehicle Fleet Transactions Data	4,28,963	4,28,609	4,28,609	3,42,887	42861	42861

All the Datasets are split into 80:10:10 ratio

Empowering Insights: Data Statistics

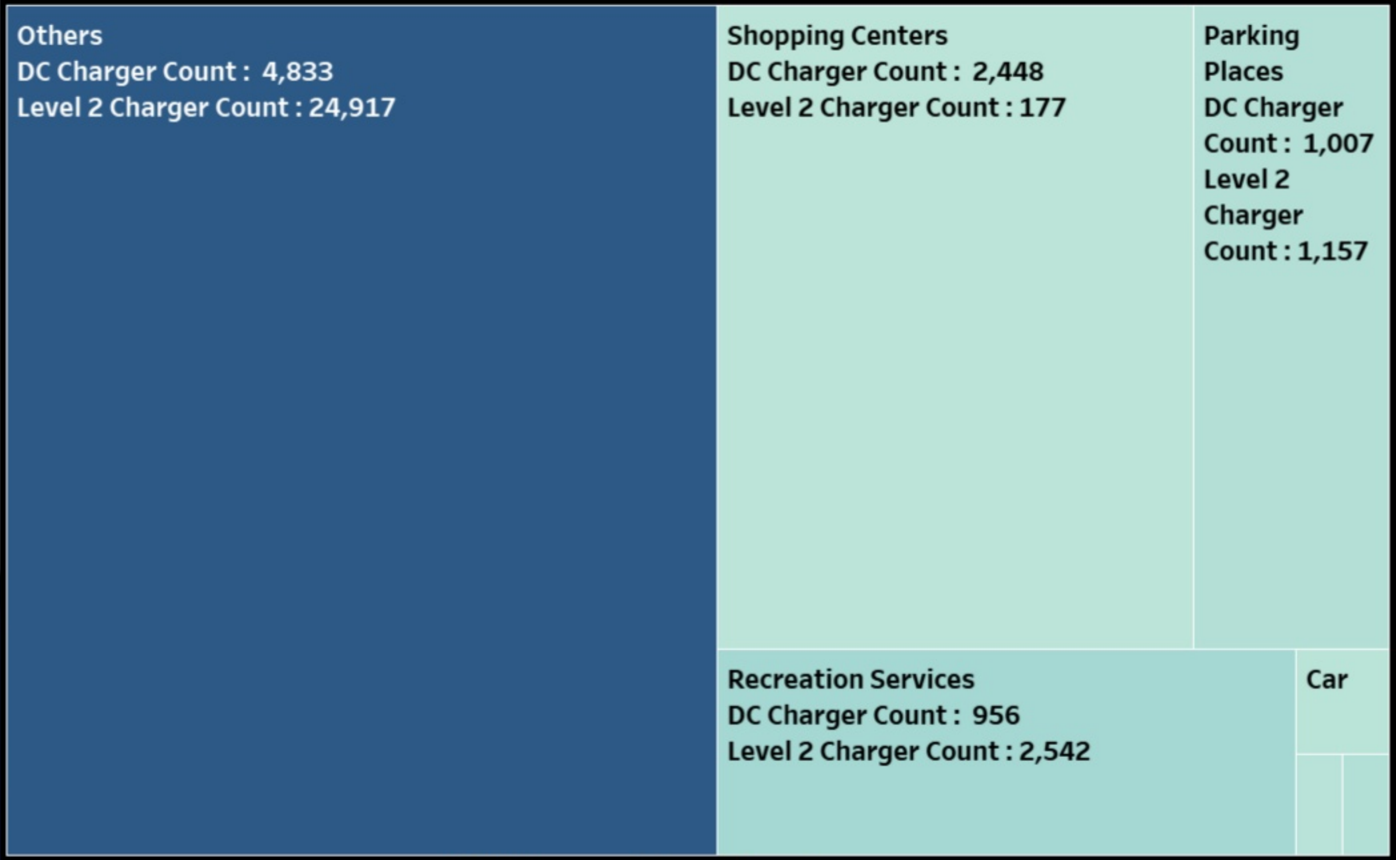


Whare are the Charging Stations ?

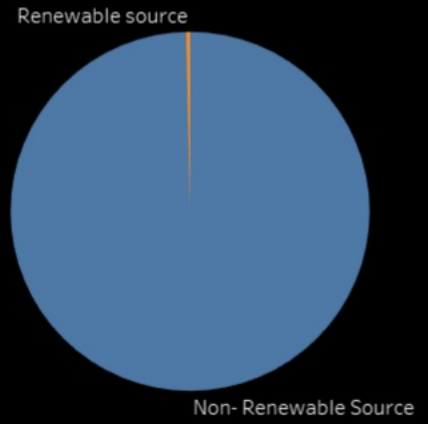
Facility Type

(All)

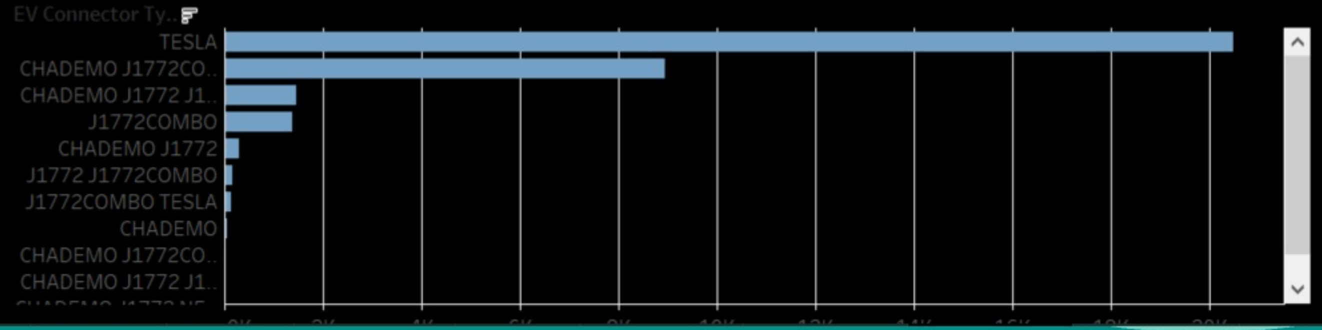
Facility Wise EV Charging Stations Count



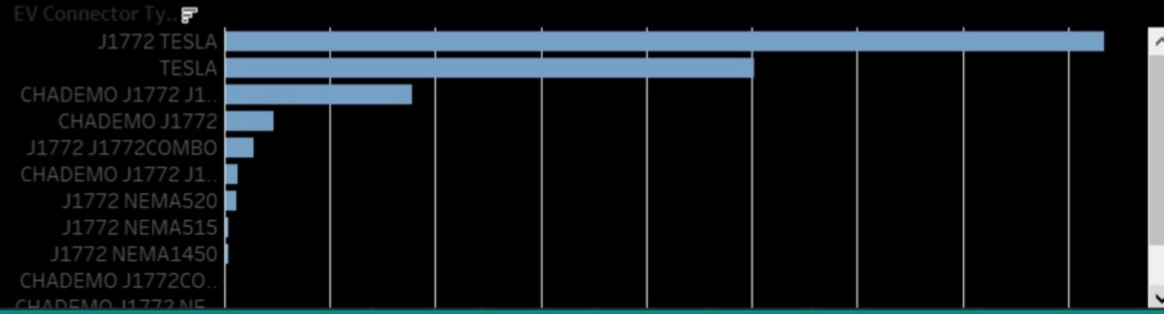
Energy Sources of Charging Stations



DC Charger Connector Types



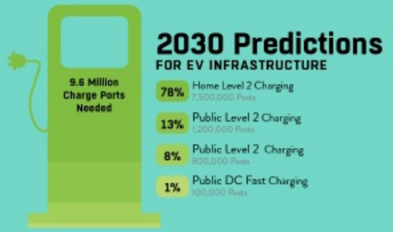
Level 2 Charger Connector Types



Predictive Power: Proposed Machine Learning Models

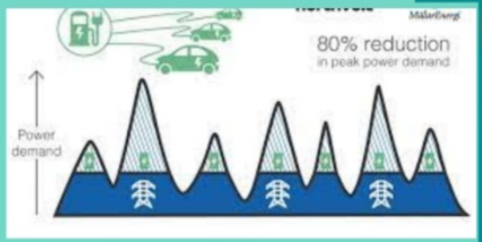
Machine Learning

EV Vehicle and Charging Station Count Prediction



Heavy/ Medium Duty EV Vehicle Range Prediction

EV Charging Station Energy Demand Prediction

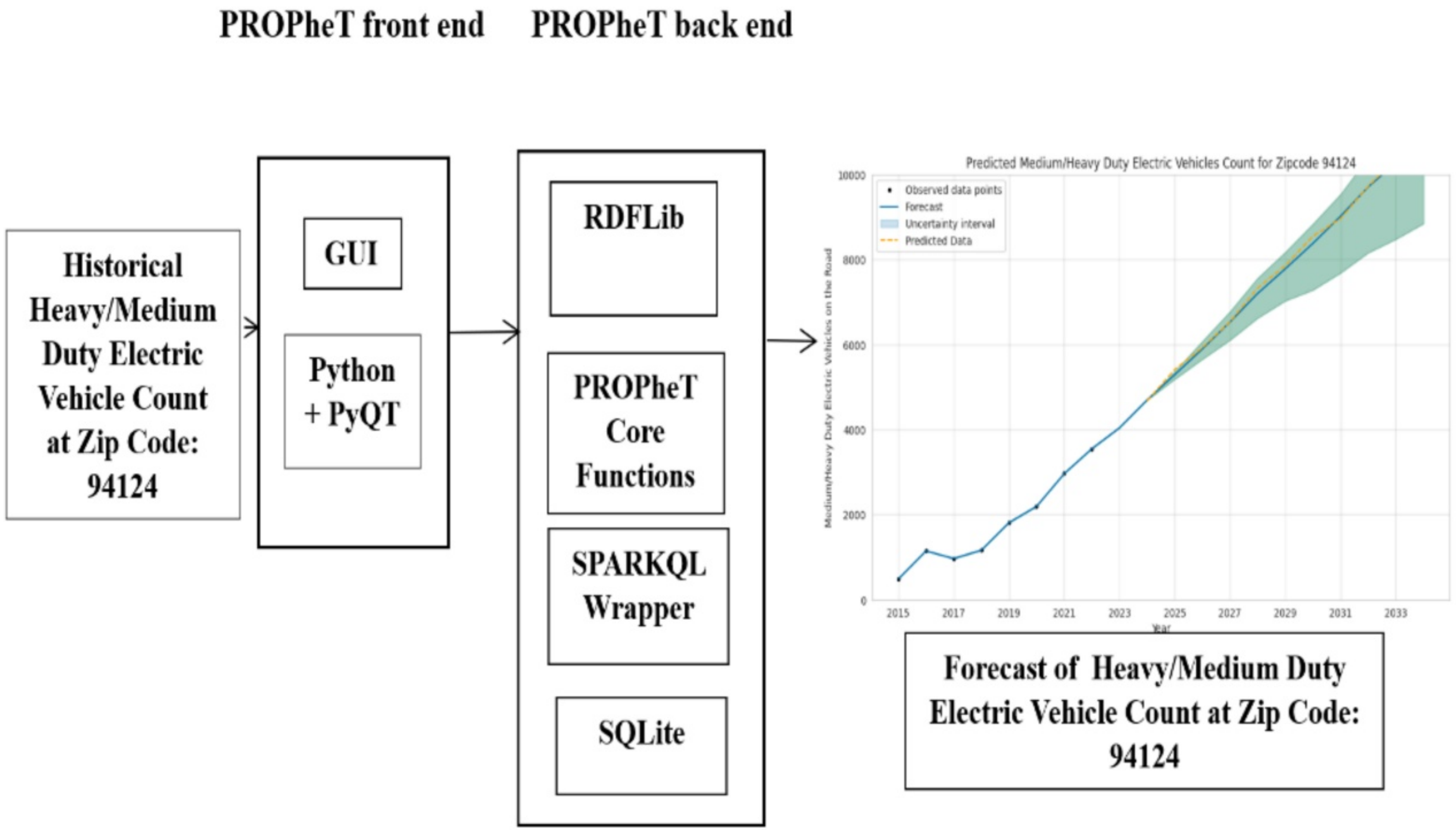


Optimal Location Prediction for New Charging Station

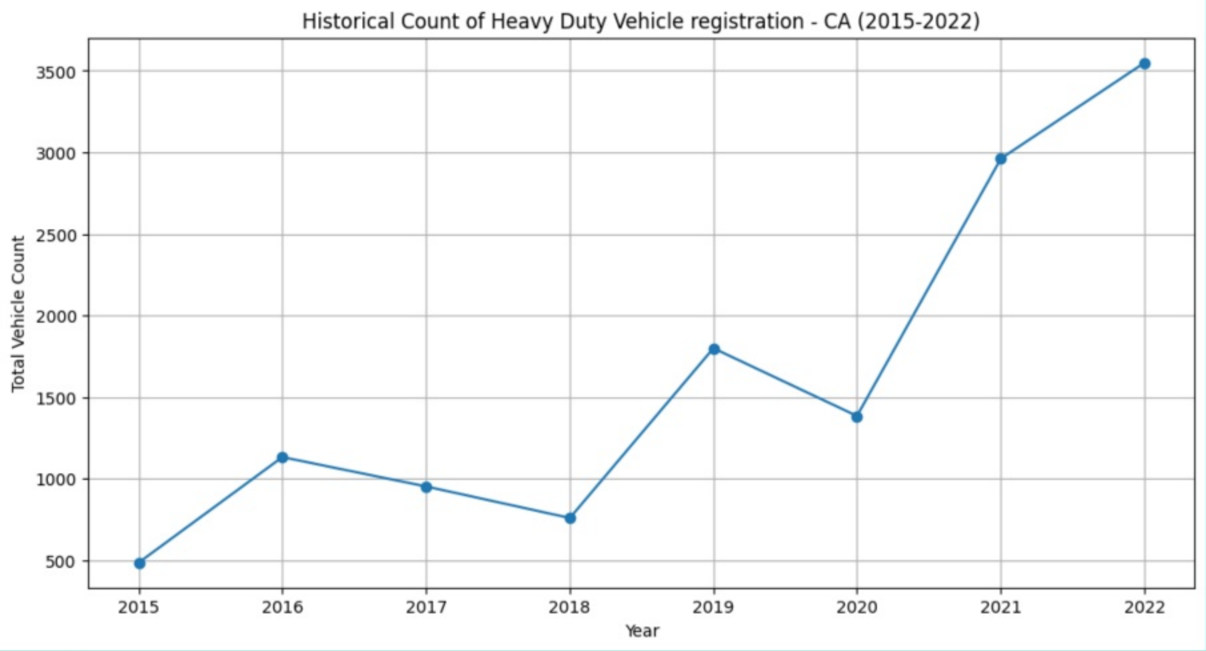
Forecasting Heavy And Medium Duty EV Count

PROPHET Model Architecture: Improvements

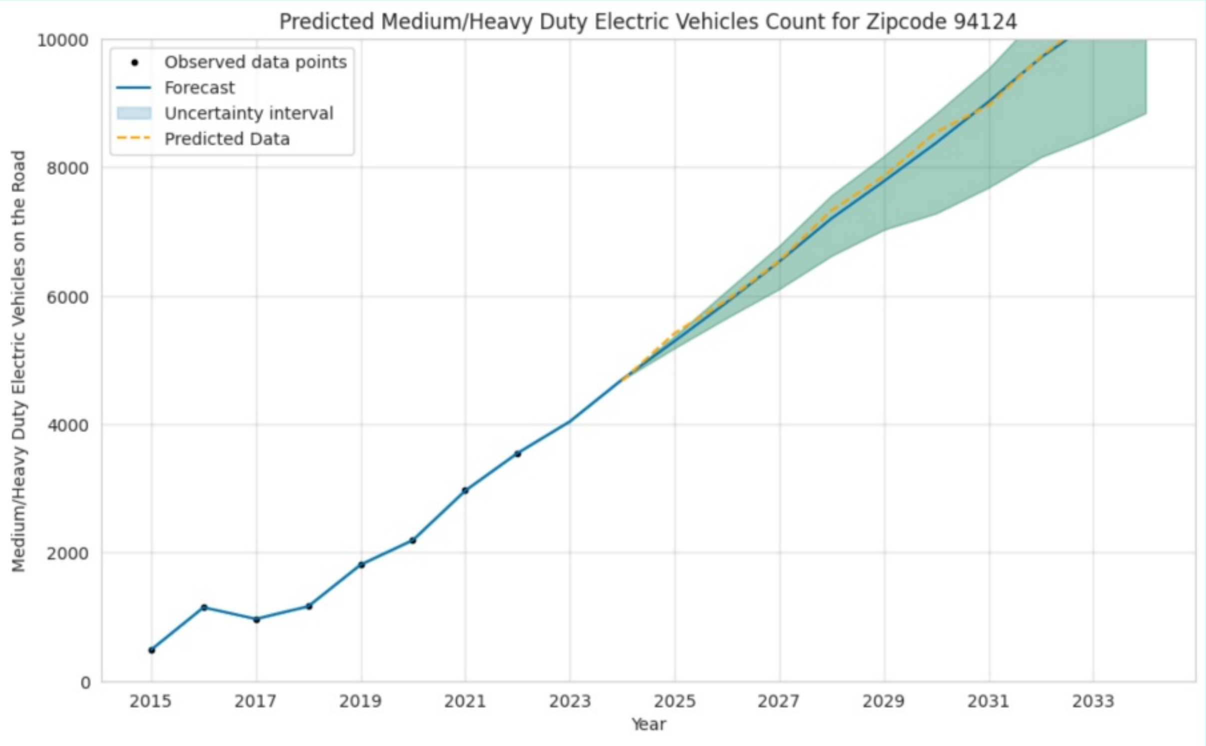
To Predict and forecast the future count of Heavy Duty and Medium Duty Vehicles and the required EV charging stations to cater the demand.



1. *Fine-tuned through hyperparameter optimization.*
2. *Adjusting critical parameters like changepoint_prior_scale and seasonality_prior_scale*
3. *Integrated additional regressors, consequently improving its predictive accuracy.*

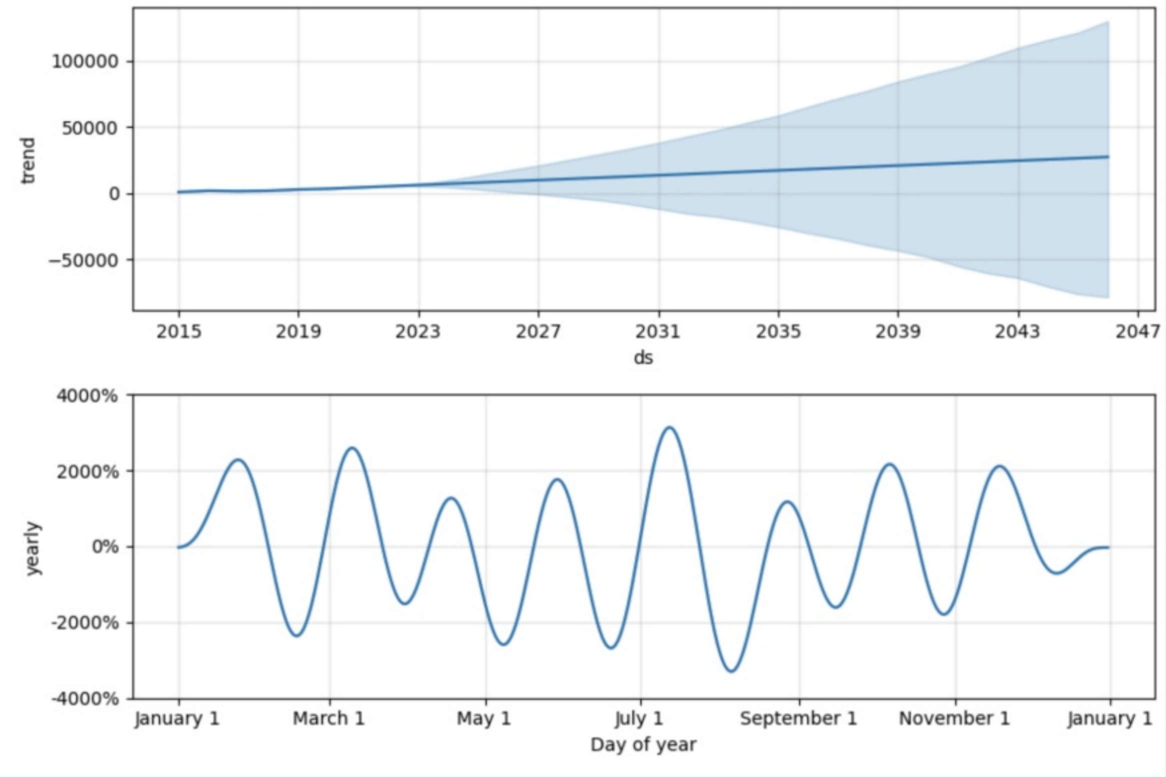


Historical Vehicle Count



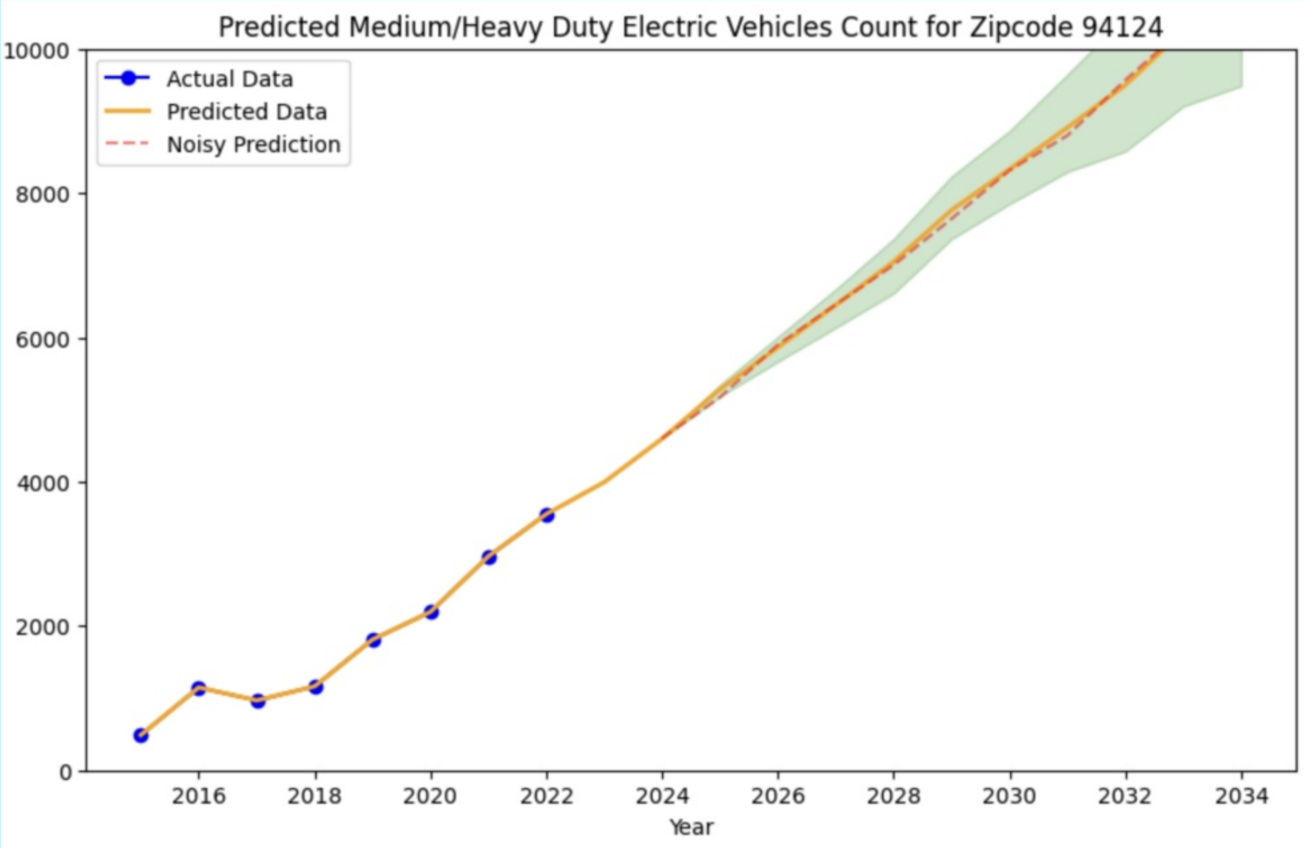
Forecasting Results for each Zip Code

Improved



Yearly Trend

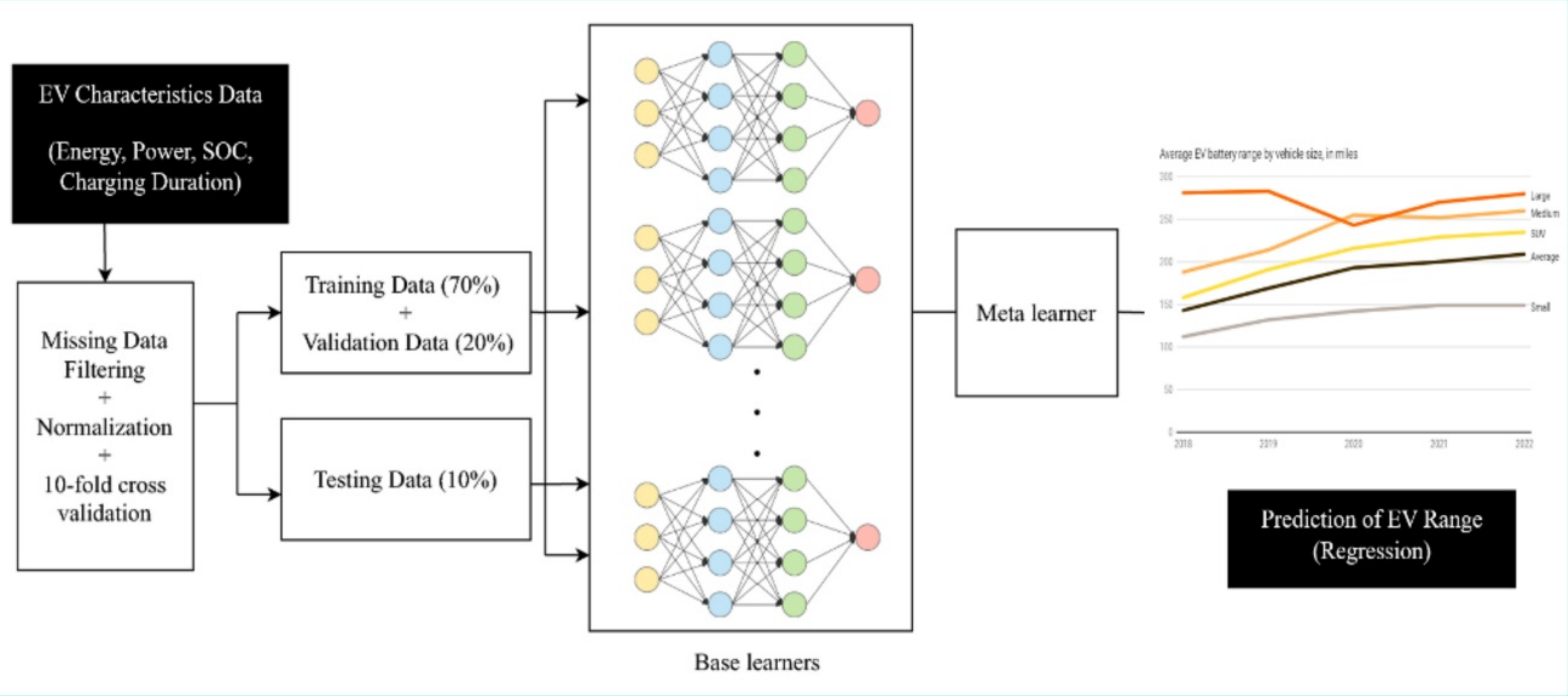
Forecasting Results for each Zip Code



Predicting Vehicle Range Of Heavy Duty And Medium Duty EV

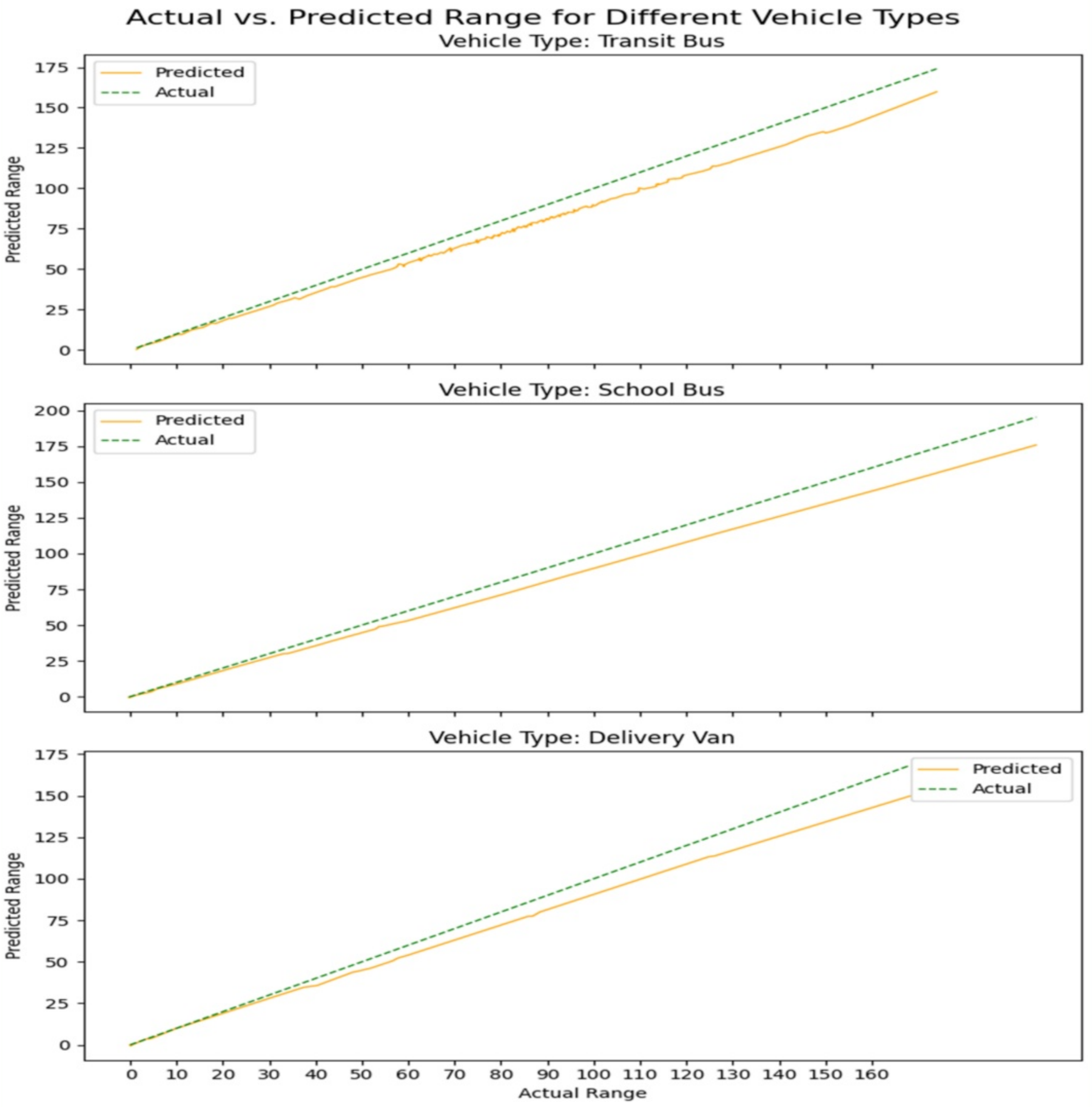
Stacking Regressor Model Architecture- Weighted Fusion Voting : Improvements

To forecast range of heavy and medium duty vehicles of each weight class using the charcteristics like charging duration, state of charge to the battery.



1. *Applied Min-Max scaling to ensure consistent impact of each feature on the model*
2. *Utilized a Gradient Boosting regressor with 100 estimators for improved ensemble learning*
3. *Incorporated L1 regularization with strength (alpha) of 0.005 to mitigate overfitting*
4. *Utilized two hidden layers (100 nodes each) and a Rectified Linear Unit (ReLU) activation function in MLP to explicitly capture complex non-linear dependencies in charging duration, state of charge*

Improved

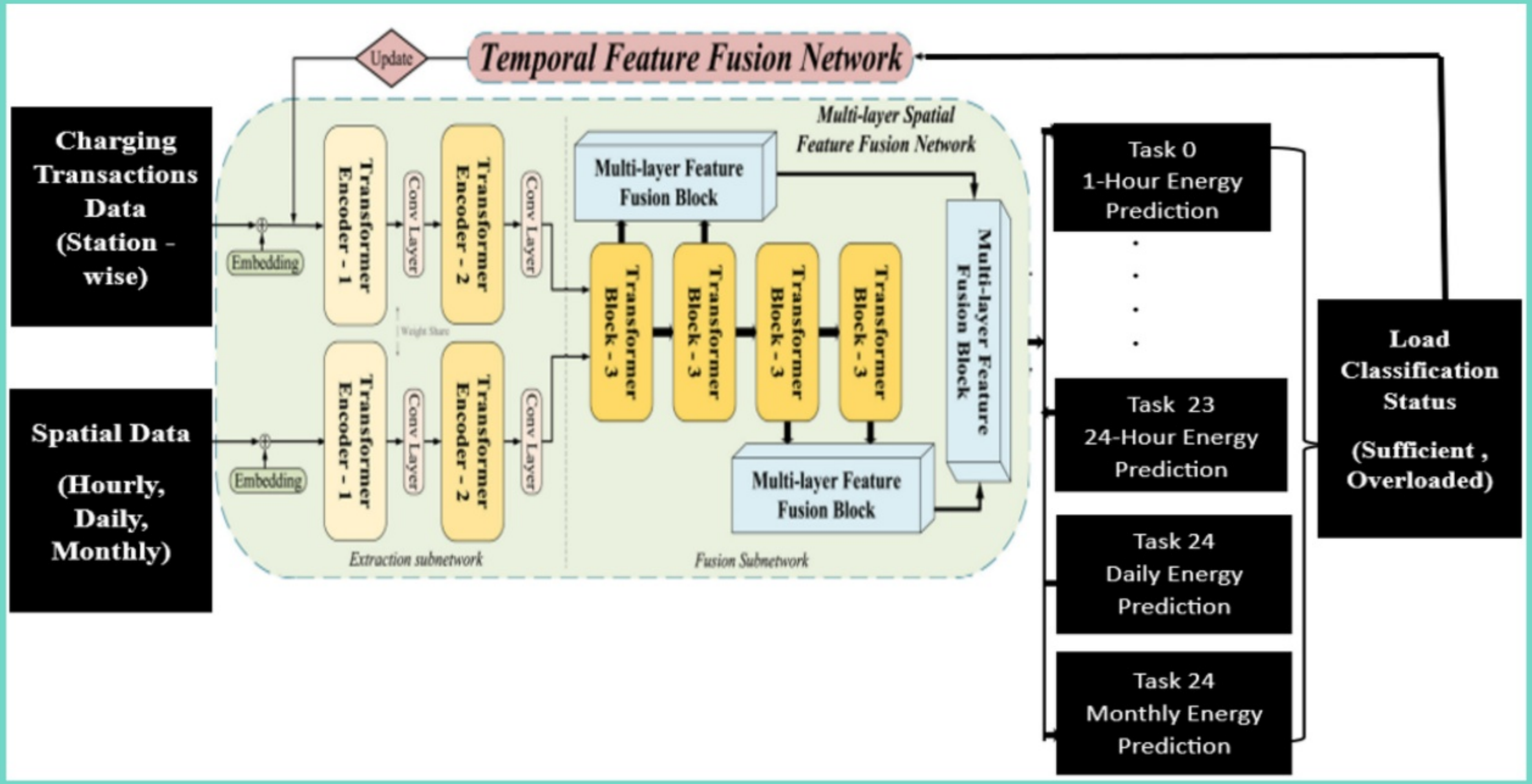


Actual vs. Predicted Range for Different Vehicle Types
Vehicle Type: Transit Bus
Predicted
Actual
Predicted Range
175
150
125
100
75
50
25
0
Vehicle Type: School Bus
Predicted
Actual
Predicted Range
200
175
150
125
100
75
50
25
0
Vehicle Type: Delivery Van
Predicted
Actual
Predicted Range
175
150
125
100
75
50
25
0
0 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160
Actual Range

Predicting Short And Long - Term Energy Demand

Temporal Fusion Transformer Model (TFT) Architecture : Improvements

To Predict short term energy demand like hourly and long term enegry demand like weekly, monthly for each charging station.



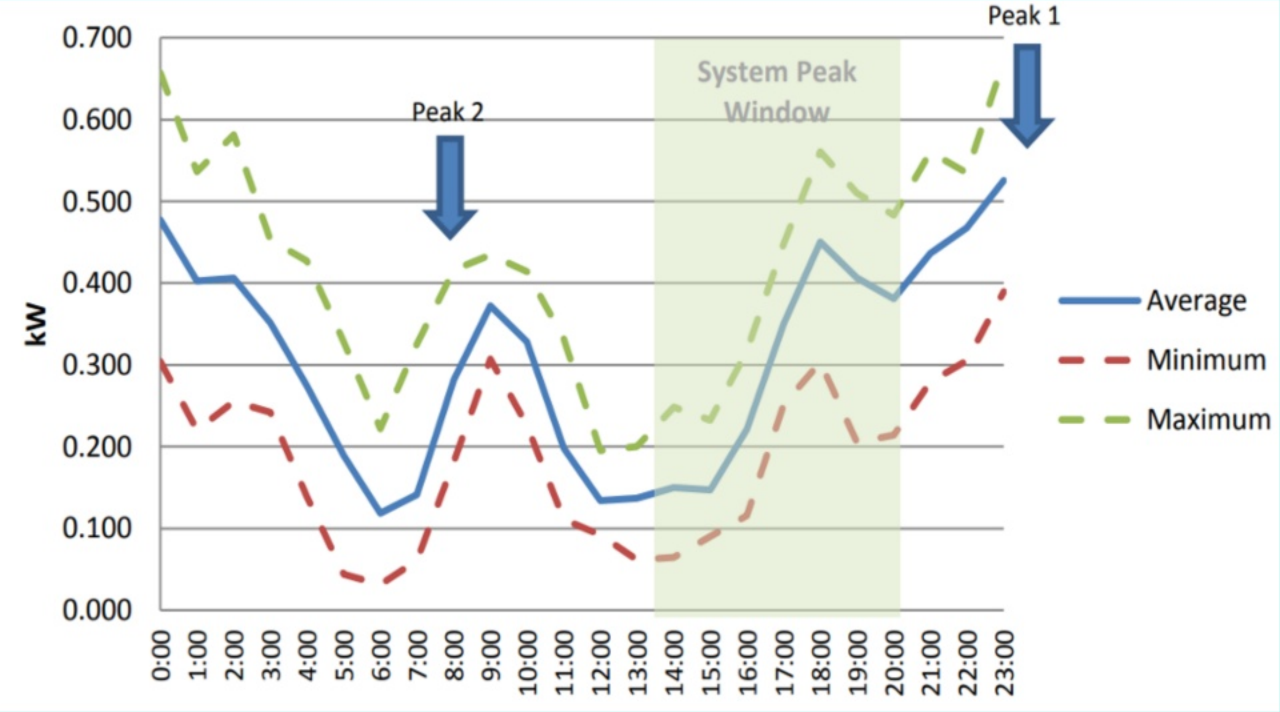
1 *Fine-tuned the HistGradientBoosting Regressor model, for optimal performance*

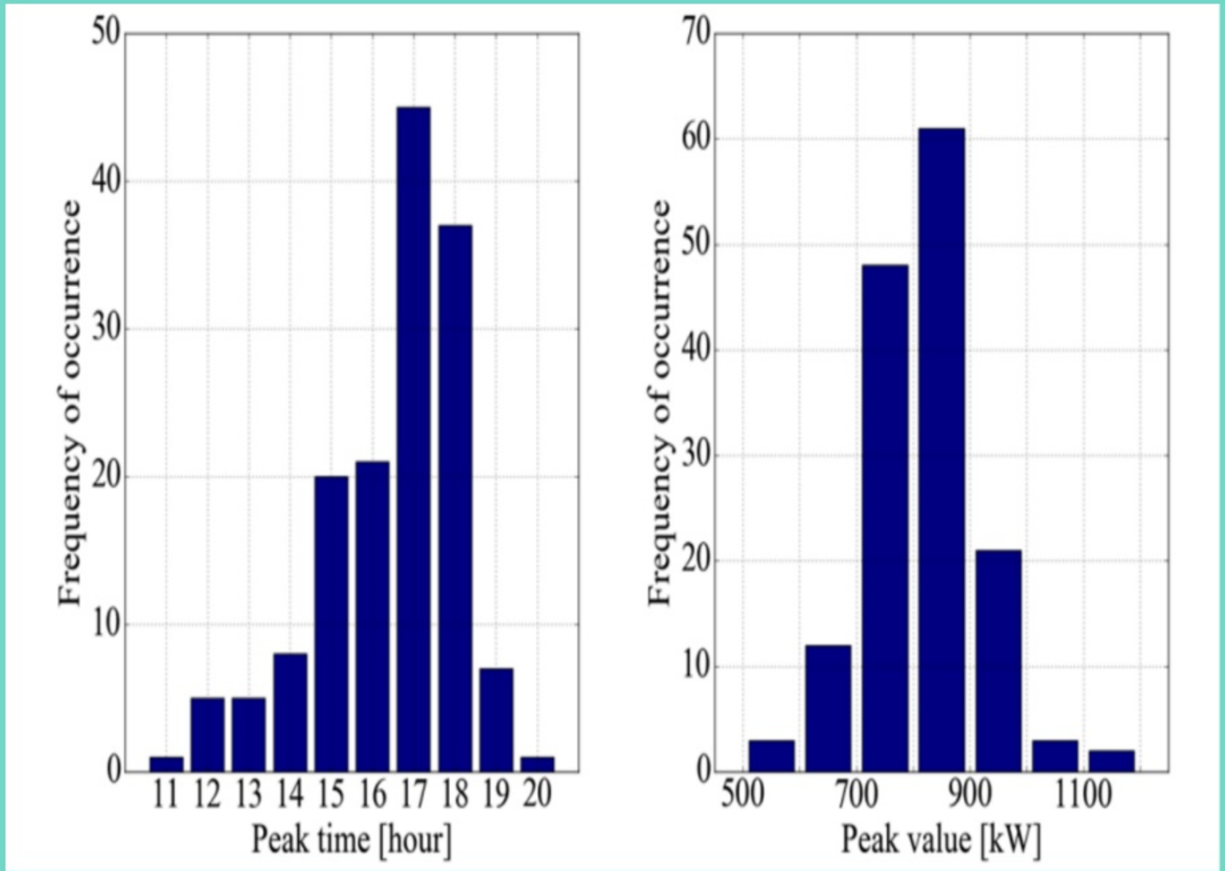
2 *Robust imputation strategy using the median instead of mean imputation.*

3 *Identified and utilized key features such as 'Average_Power', 'Max_Power', 'Starting_SOC', and 'Charging_Duration' for forecasting to enhance model accuracy.*

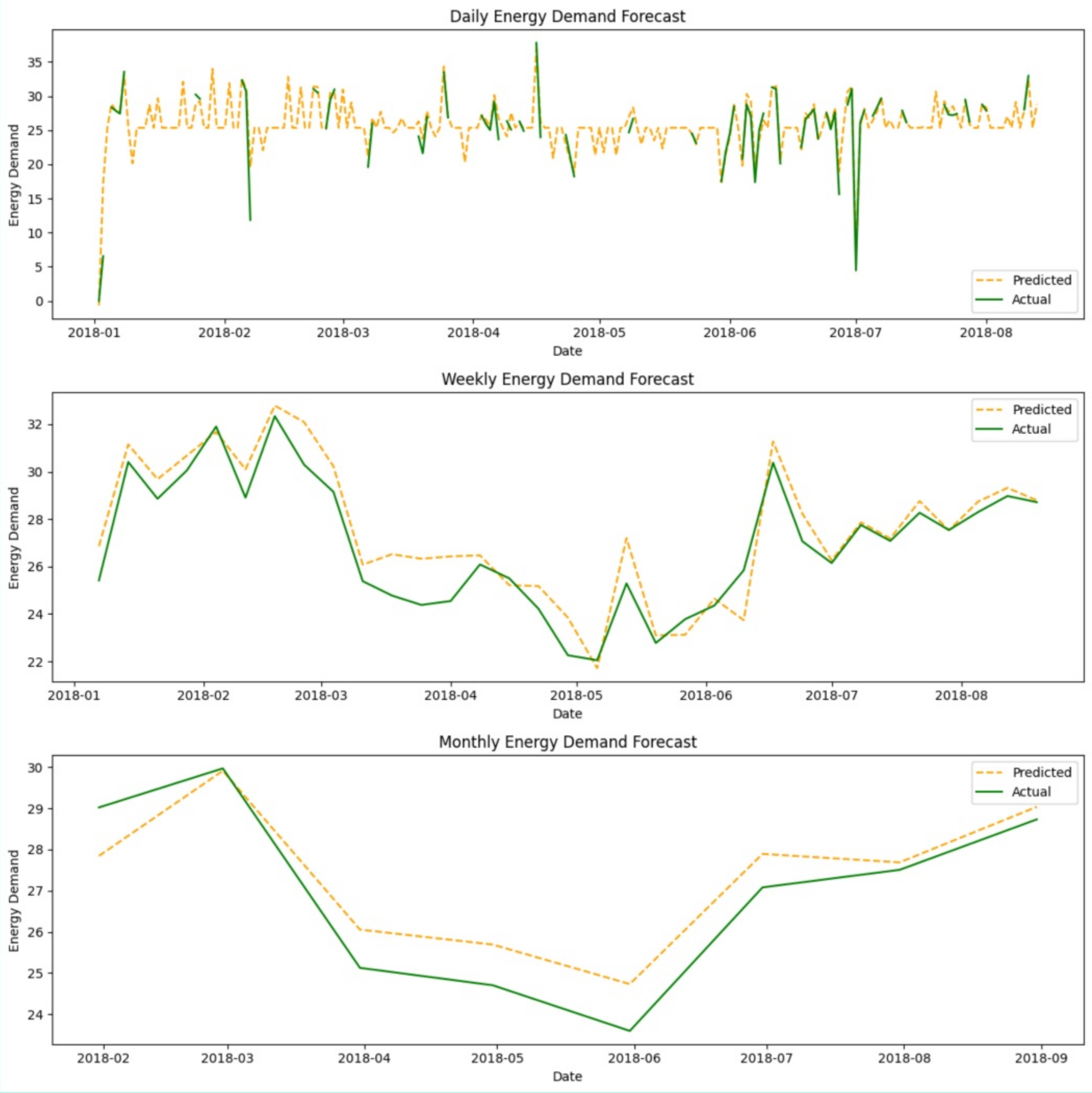
Energy Demand Prediction for a Charging Station

Improved





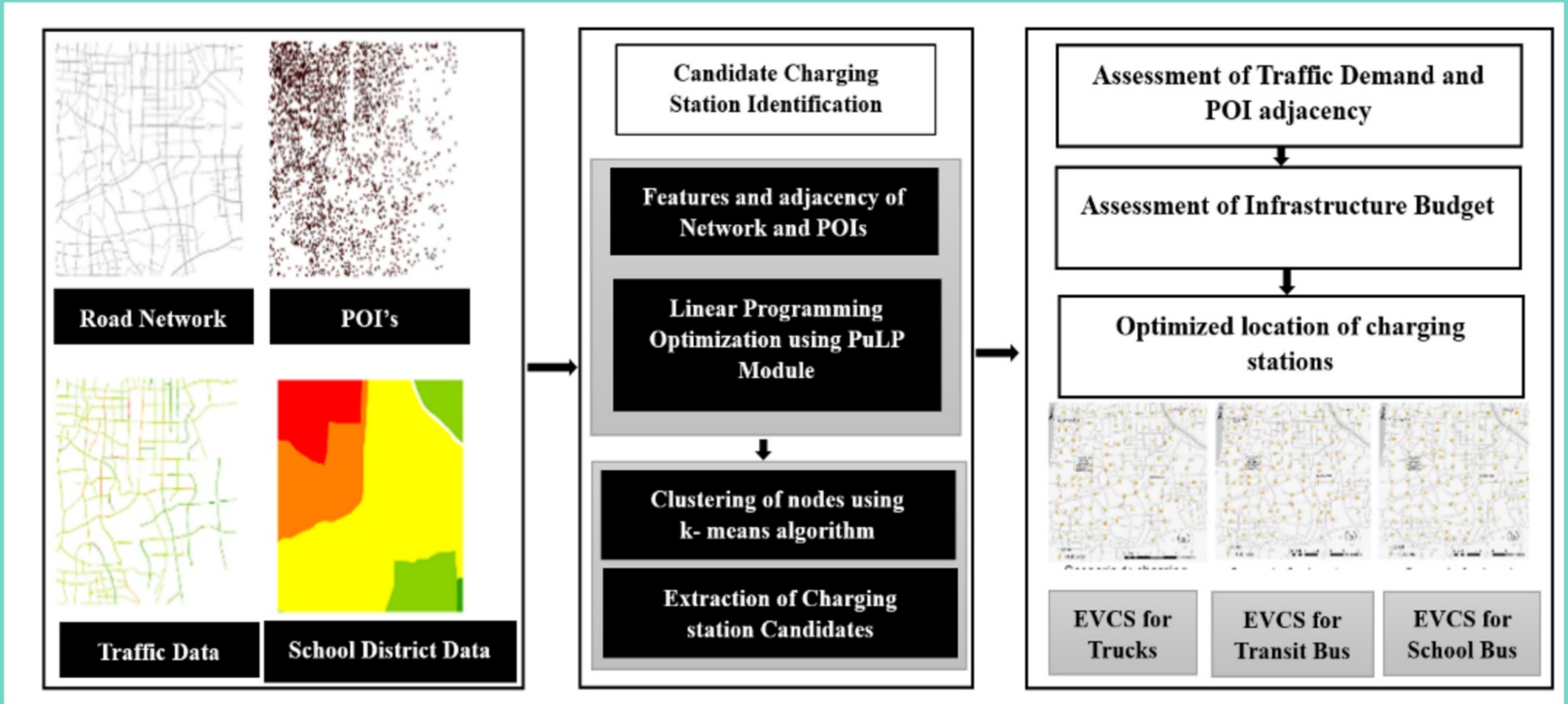
Energy Demand Prediction for a Charging Station



Optimal Placement Of New Charging Stations For Each Vehicle Type

Linear Programming and Clustering Model Architecture

To identify optimal locations for placing new charging stations for each type of vehicle using the point of interest related to them utilizing PulP library linear programming and K-Means Clustering model.



Optimal Locations for New EV Charging Stations- San Jose

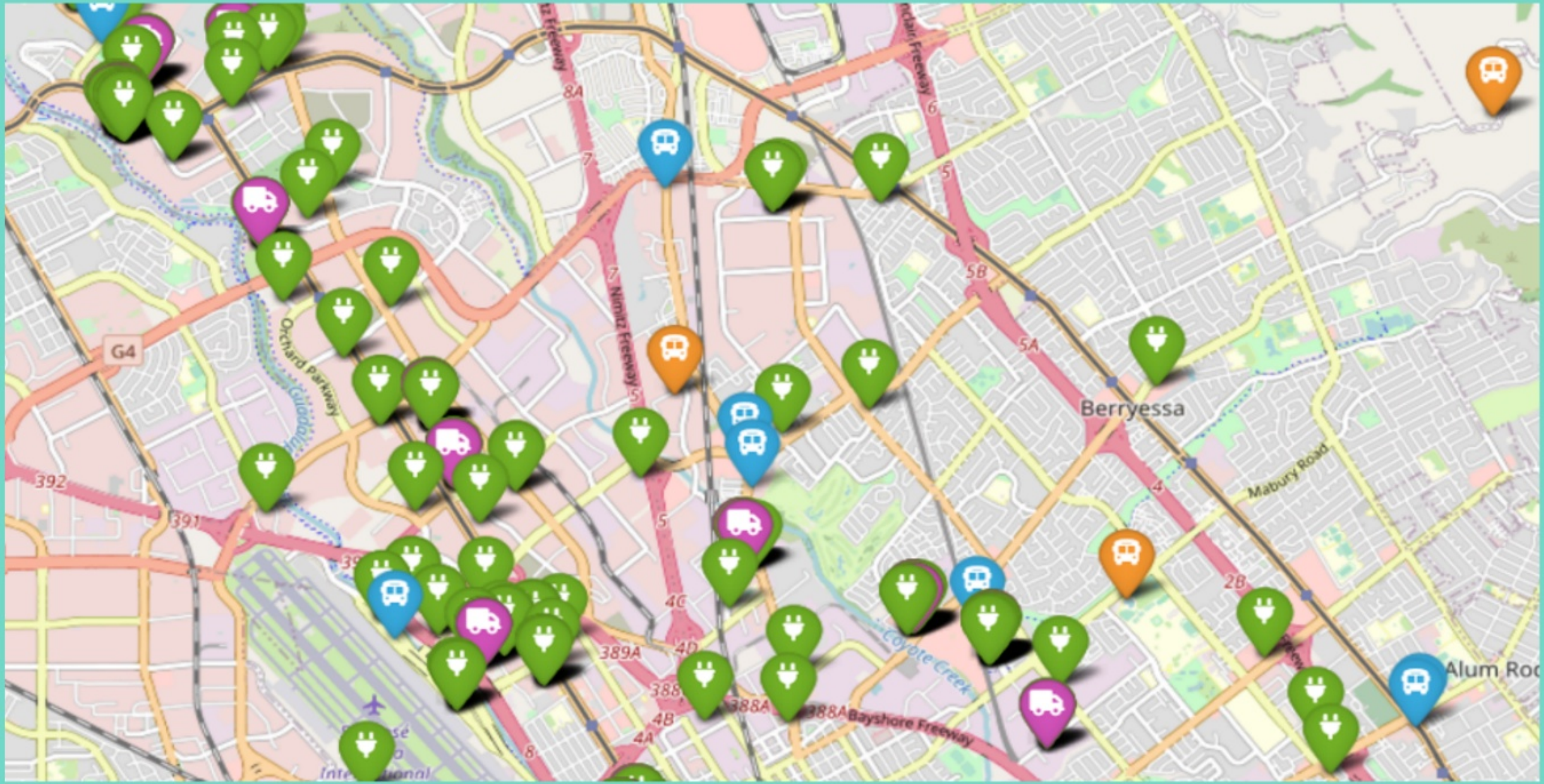
Improved

Green- Existing EV charging Stations

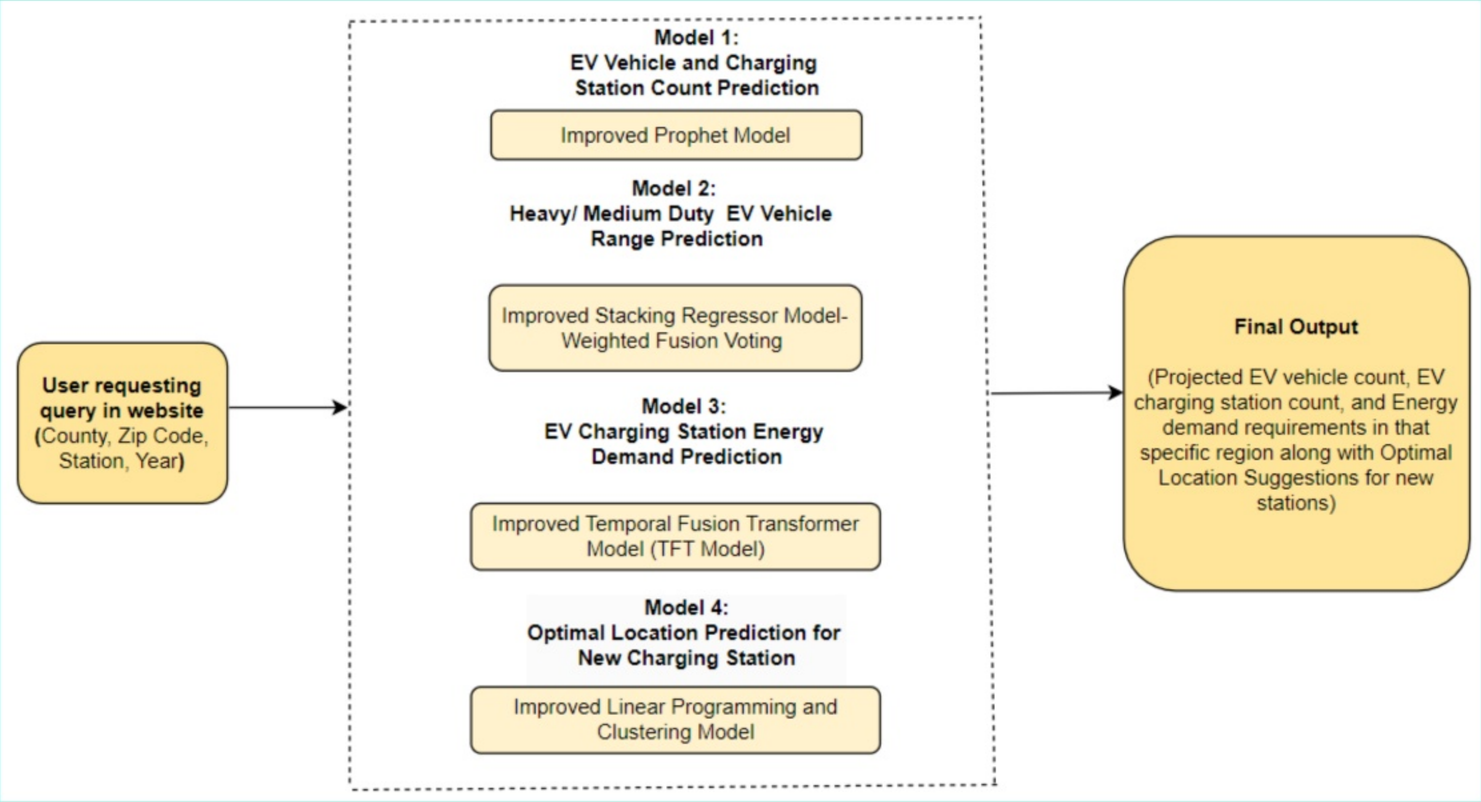
Blue- Suggested Charging Station Location for Transit Bus

Orange- Suggested Charging Station Location for School Bus

Purple- Suggested Charging Station Location for Delivery Truck



Machine Learning Modeling : Innovation



- Prophet dynamically adjusts to irregularities, ensuring accurate predictions even in the presence of outliers
- The use of precision-weighted fusion in the Stacking Ensemble Regressor model optimally combines predictions from individual models, assigning higher weights to more accurate models.
- The Temporal Fusion Transformer (TFT) Model's innovation lies in its ability to effectively handle temporal dependencies in EV charging station energy demand prediction which captures intricate temporal patterns
- The integration of PuLP linear programming optimization in the Optimal Location Prediction model, coupled with K-means clustering, ensures that the placement of new charging stations is not only data-driven but also optimized for cost-effectiveness and resource utilization.

Machine Learning Modeling : Comparision

Model Suitability and Dependencies:

The choice of the best model depends on the nature of the problem:

- Prophet excels in capturing seasonality patterns in time series data.
- Stacking Ensemble Regressor leverages the synergy of diverse models for high accuracy.
- Temporal Fusion Transformer handles temporal dependencies in time series.
- PuLP Linear Programming focuses on spatial optimization through linear programming and clustering.

Trade-offs in Speed and Accuracy:

- The models vary in training speed, with Prophet and PuLP Linear Programming being faster, while Stacking Ensemble Regressor and Temporal Fusion Transformer may require moderate to long training times.
- The accuracy is generally high across all models, but it is crucial to consider the trade-offs between training time and model performance

Characteristic	**Prophet**	**Stacking Ensemble Regressor**	**Temporal Fusion Transformer**	**PuLP Linear Programming with K-means Clustering**
Targeted Problems	EV Vehicle and Charging Station Count Prediction	Heavy/ Medium Duty EV Vehicle Range Prediction	EV Charging Station Energy Demand Prediction	Optimal Location Prediction for New Charging Station
Input	Electric Vehicle Registrations	Medium/Heavy Duty EV Transactions	Medium/Heavy Duty EV Transactions	EV Charging Station ,Traffic Data, Point of Interests, School and Transit Bus Network
Output	Projected Count of EV in each Zip Code	Predicted Range of EV	Short and Long term demand prediction of Energy	Optimal Location Suggestions for EV Charging station
Data Type	Discrete	Continuous	Continuous and Categorical	Continuous
Approaches	Time Series Decomposition	Ensemble Learning	Sequence-to-Sequence Model	Linear Programming + Clustering
Computational Complexity	Low	Moderate	High	Moderate to High
Strengths	Seasonality Patterns	Ensemble Synergy	Temporal Dependencies	Spatial Optimization

Powering Precision: EV Model Evaluation Metrics

Model Improvement Comparison

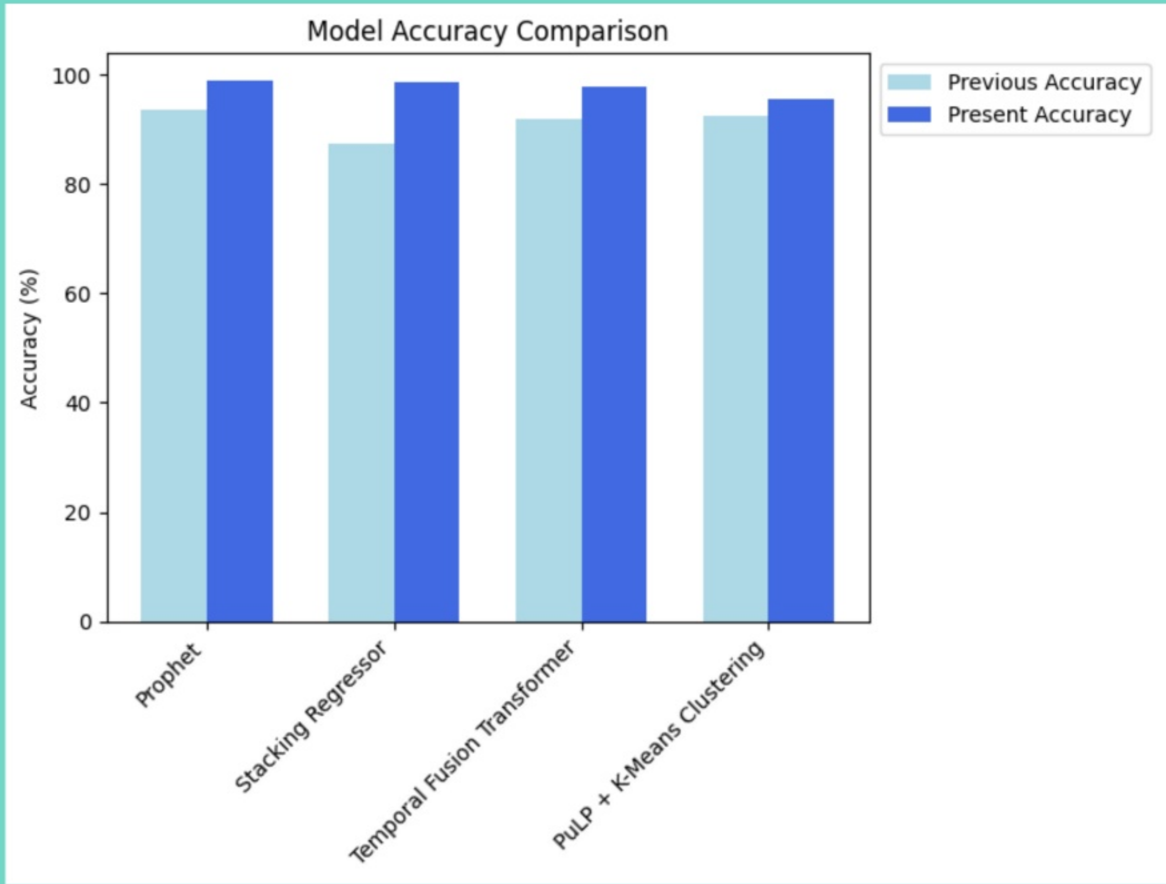
Feature	Vehicle Type	Model	Time Frame	Previous results				Current results			
				MSE	MAE	RMSE	R^2	MSE	MAE	RMSE	R^2
EV Demand Forecast	Heavy/ Medium Duty Vehicles	Prophet	Yearly	12.75	11.69	26.87	0.87	10.55	9.85	25.93	0.89
EV Range Prediction	Transit Bus	Weighted Fusion Meta Regressor Model	On Demand	9.063	9.874	88.113	0.75	8.076	8.50	88.007	0.75
	School Bus			8.947	9.113	87.248	0.76	8.57	9.037	86.23	0.77
	Delivery Truck			11.345	12.278	83.903	0.82	10.23	11.67	81.45	0.84
EV Energy Demand prediction	Transit Bus	Temporal Fusion Transformer	Daily	0.828	0.957	4.36	0.93	0.798	0.916	4.25	0.93
			Weekly	1.794	1.897	9.36	0.91	1.689	1.862	9.043	0.91
			Monthly	0.984	0.932	7.64	0.91	0.761	0.873	7.54	0.91
	School Bus		Daily	0.865	0.847	5.96	0.92	0.757	0.82	5.02	0.93
			Weekly	0.897	0.828	4.98	0.92	0.763	0.811	4.96	0.93
			Monthly	1.895	1.952	9.68	0.90	1.883	1.94	9.05	0.91
	Delivery Truck		Daily	2.969	2.643	12.36	0.88	2.619	2.531	10.67	0.89
			Weekly	2.453	2.387	11.97	0.89	2.35	2.053	11.99	0.89
			Monthly	2.874	2.775	13.01	0.88	2.853	2.766	12.93	0.88

Powering Precision: EV Model Evaluation Metrics

Metric	Station - Wise	Site - Wise	Zip Code - Wise
Mean Squared Error (MSE)	2.453	1.895	1.348
Mean Absolute Error (MAE)	2.387	1.952	1.652
Root Mean Square Error (RMSE)	11.97	9.68	6.942
R-squared (R2)	0.89	0.91	0.93
Clustering Accuracy	87%	92%	95%
Precision	0.85	0.89	0.94
Recall	0.88	0.92	0.96
F1-score	0.86	0.90	0.95

Improvement Summary for all Models

Run Time performance Comparision		
Feature	**Device Specifications**	**Average Run Time (Seconds)**
Forecasting future Medium/ Heavy Duty EV count on road	HP Pavilion Laptop Processor: 10th Generation Intel® Core™ i5 Memory: 16GB DDR4-2666 SDRAM	0.359
Predicting EV Range		0.056
Long and Short Term Energy Demand Prediction		0.981
Optimal Location Suggestion for new EV charging station		1.482
Integrated System		0.862



System Architecture

- ***Unified Workflow for Diverse Needs:***

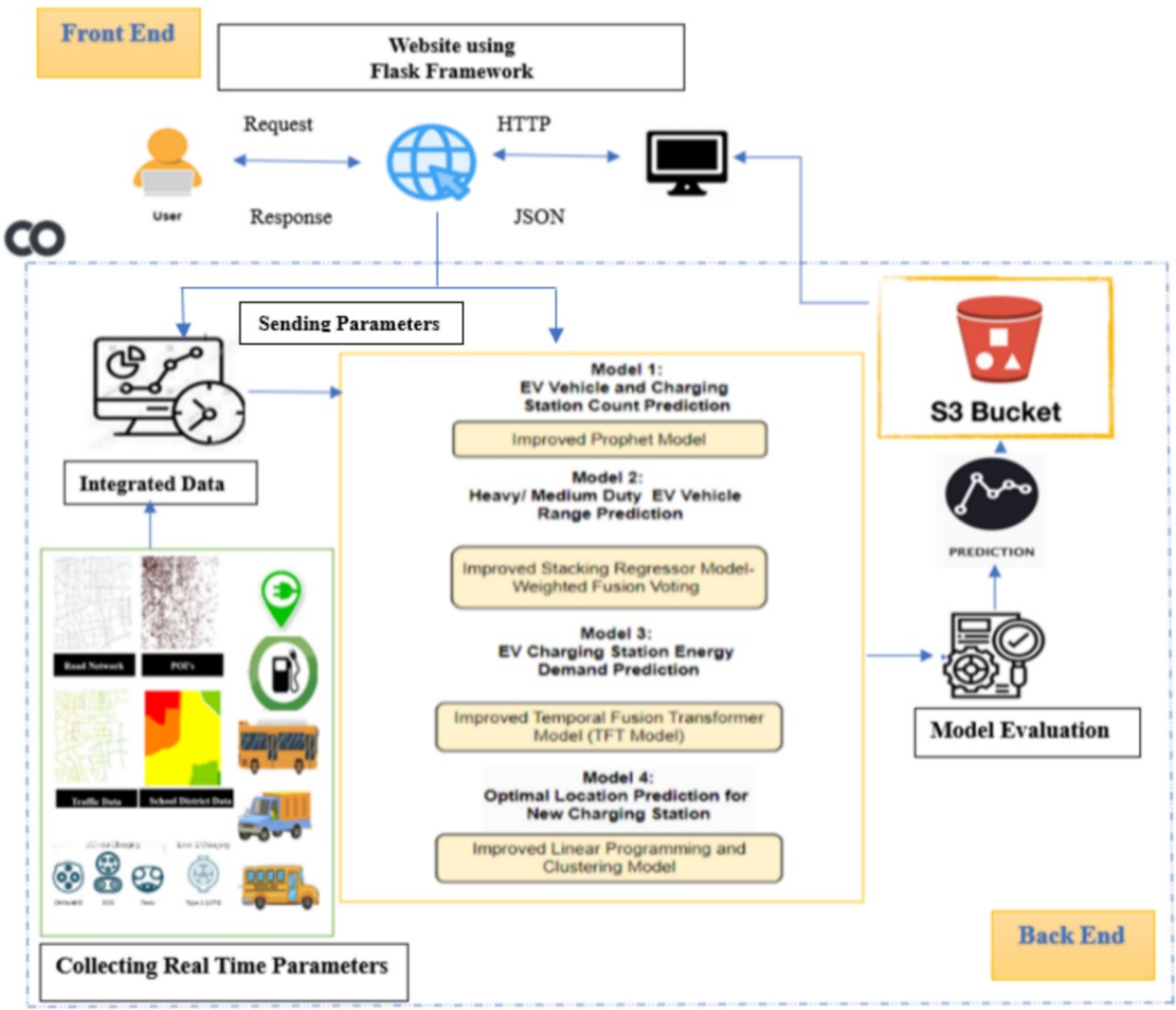
  Our system is designed to execute multiple use cases within a unified workflow, catering to the diverse needs of EV charging stations.

- ***User-Friendly Website on Flask Architecture:***

  Users initiate the process through a user-friendly website built on Flask Architecture, ensuring a seamless and intuitive interaction.

- ***AWS S3-Powered Backend with Machine Learning Integration:***

  Leveraging AWS S3 for data storage, our backend assembles relevant datasets, dynamically feeding user-submitted requests into machine learning models.



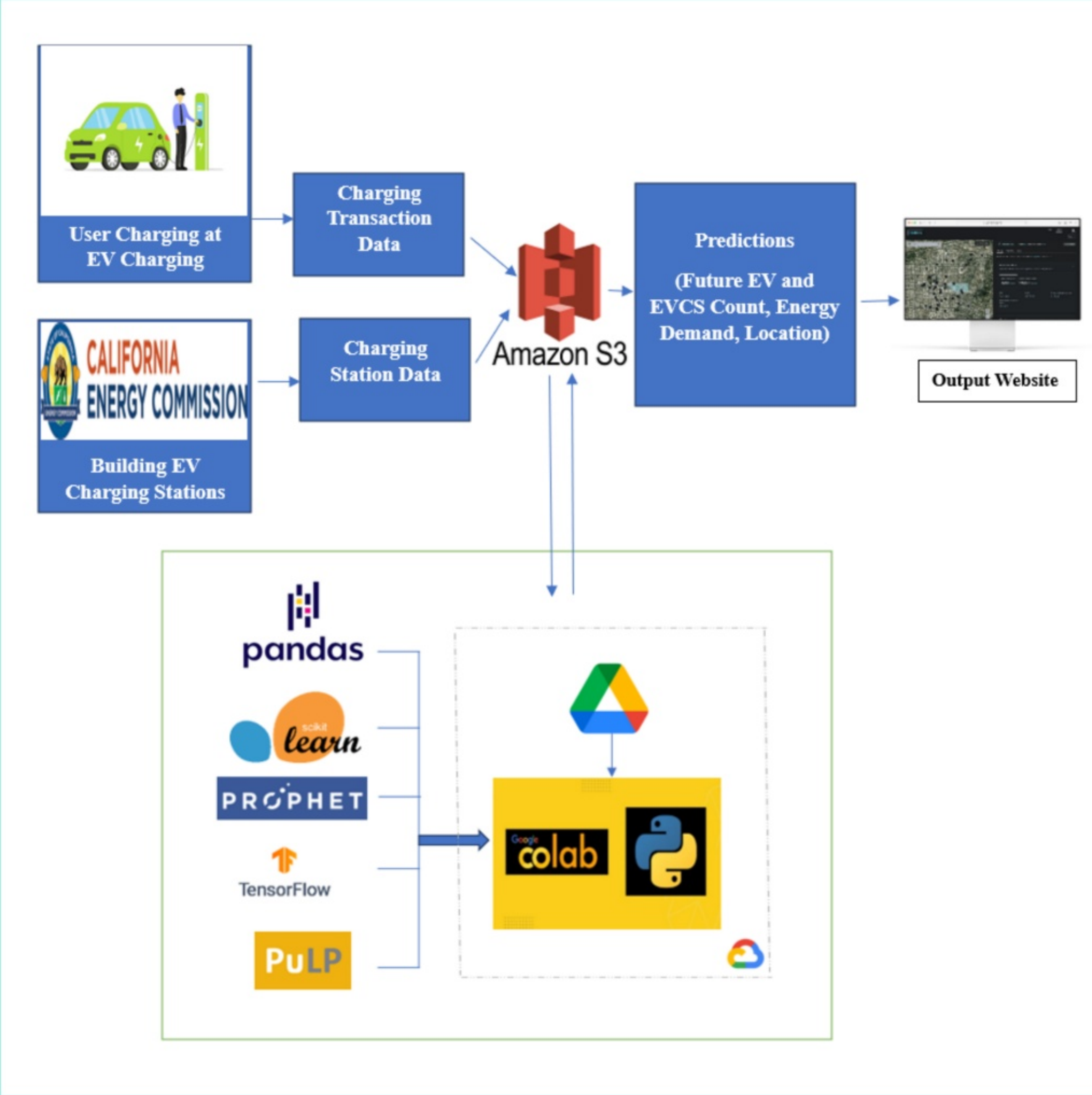
Intelligent Solution Development

Database Management

For Storing EV Charging related data and the generated predictions : AWS S3

Supporting Platforms and Cloud Environments

Model Development : pandas,scikit-learn, TensorFlow,Prophet, PuLP, Google Colab, GCP



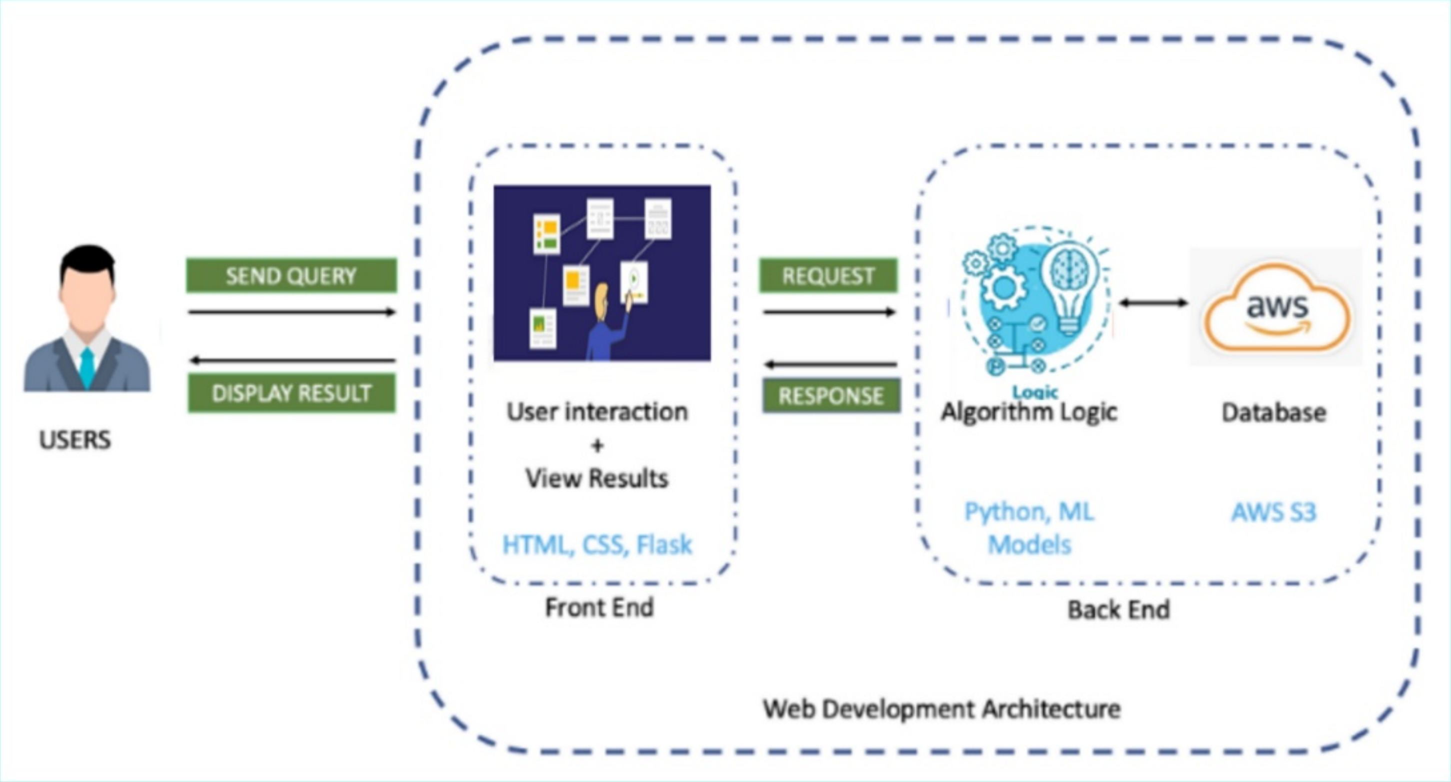
Web Development Infrastructure

Front End

- *GUI : web page displaying real-time EV details with HTML, CSS and JavaScript*
- *Response : AWS S3 HTTP response*
- *Web Framework: All modules are integrated using Flask*

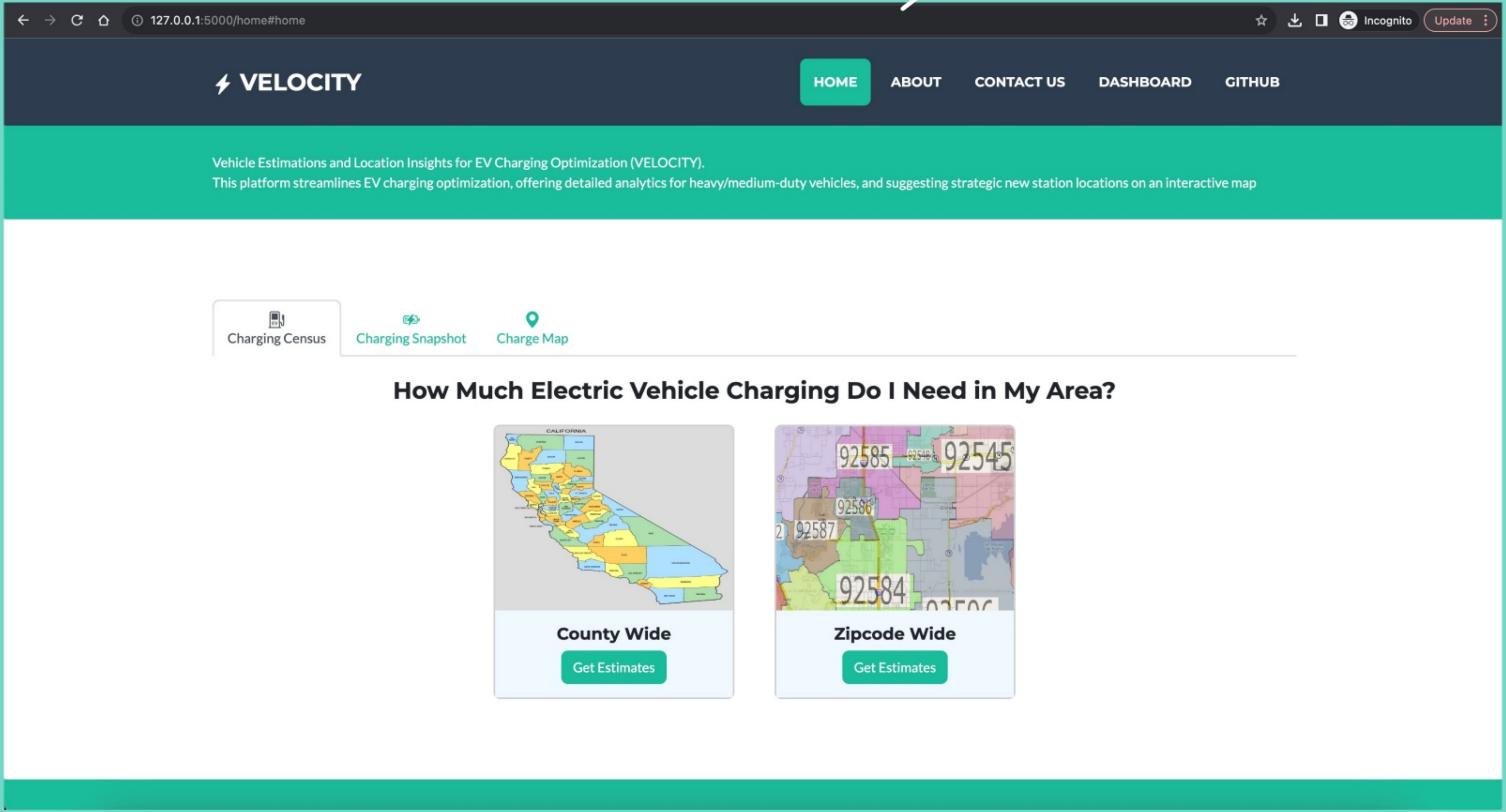
Back End

- *Database : AWS S3*
- *Algorithm : Python ML libraries and packages*

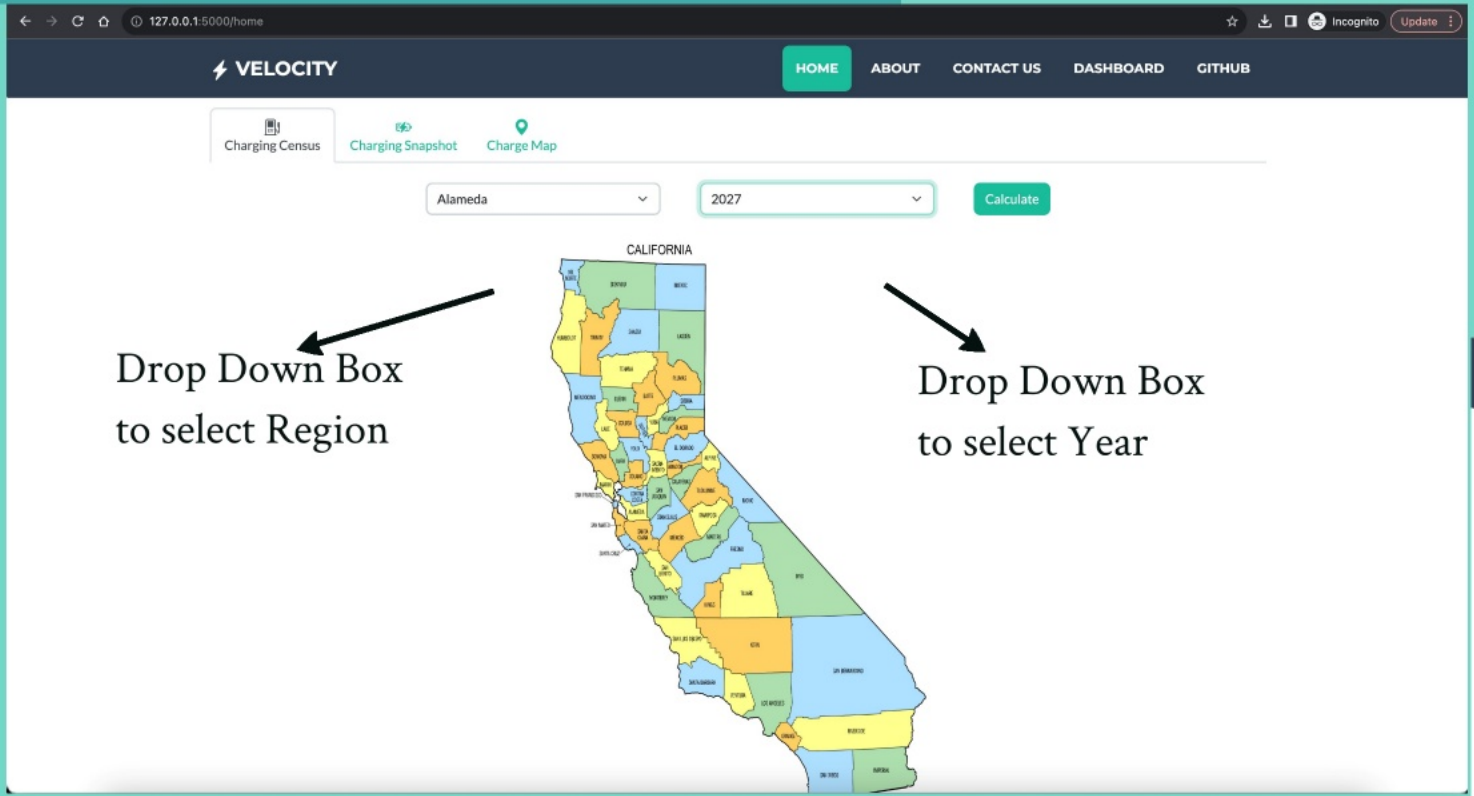


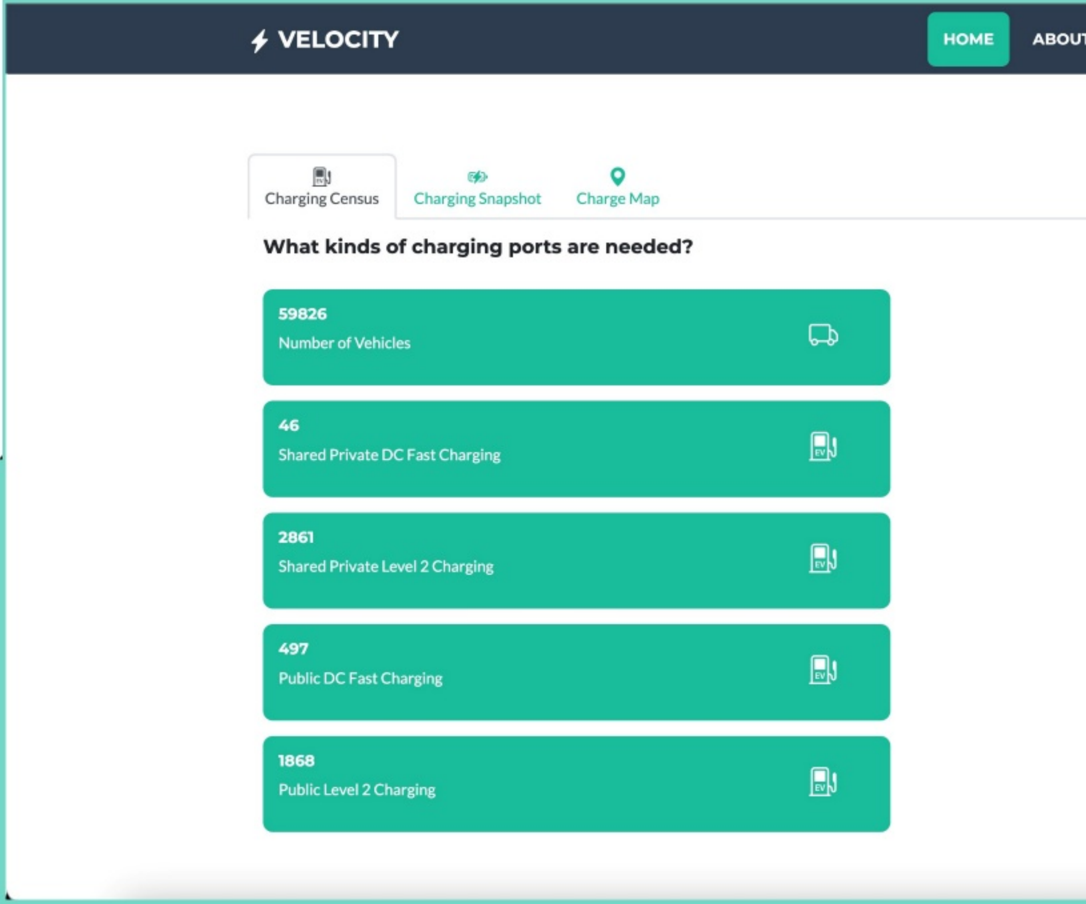
System Implementation

Navigation Bar(GitHub,
Dashboard etc.,)



System Implementation

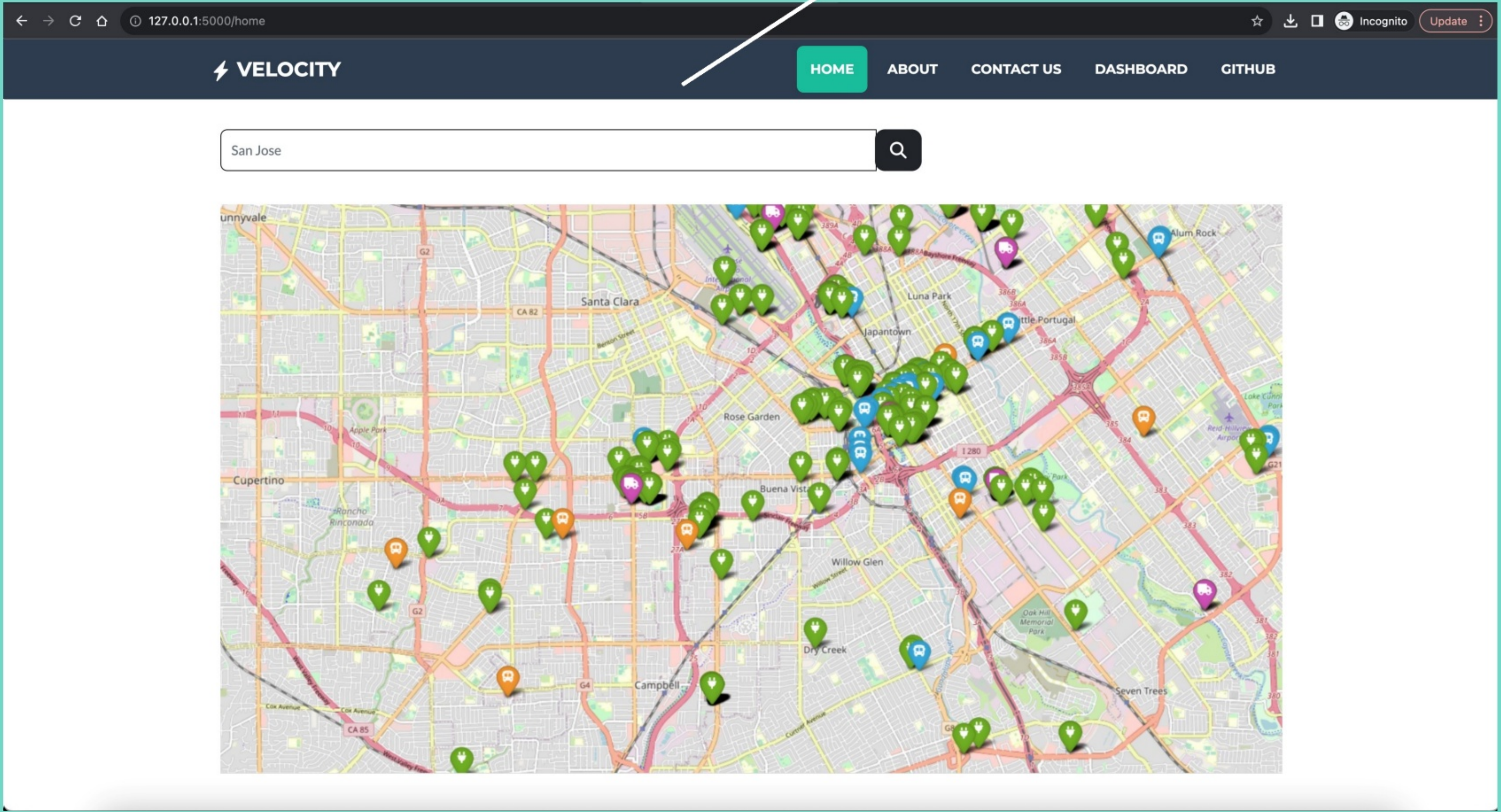




System Implementation

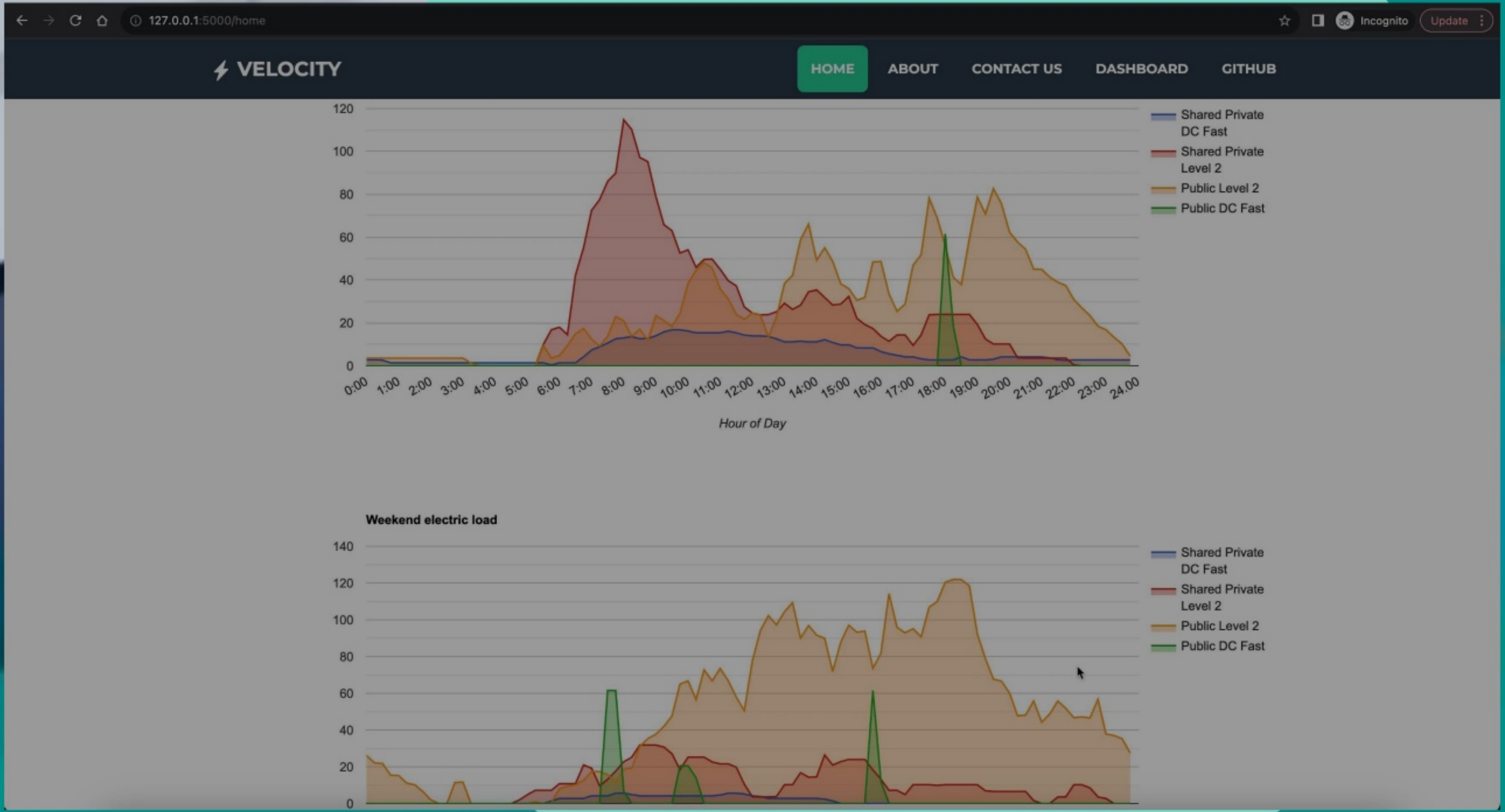
Search Box

Map displaying existing EV charging stations and newly proposed locations for San Jose



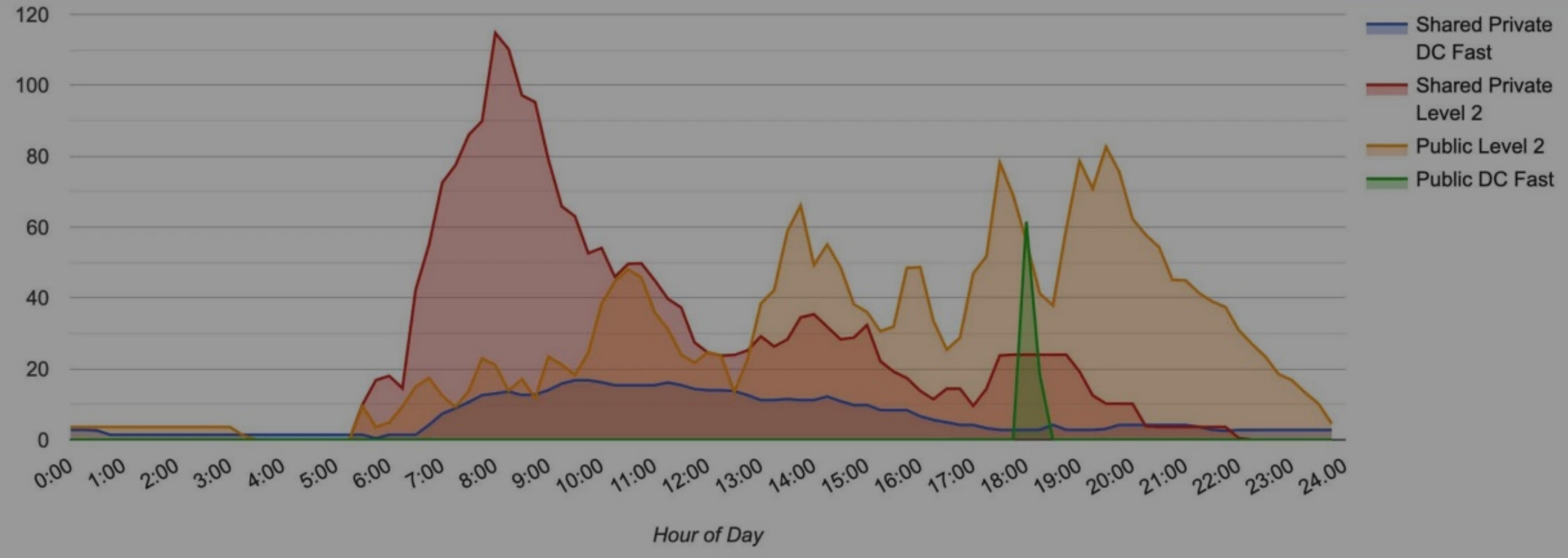
SYSTEM DEMO

Link to website: https://velocity-app-5b2dc0abb830.herokuapp.com/

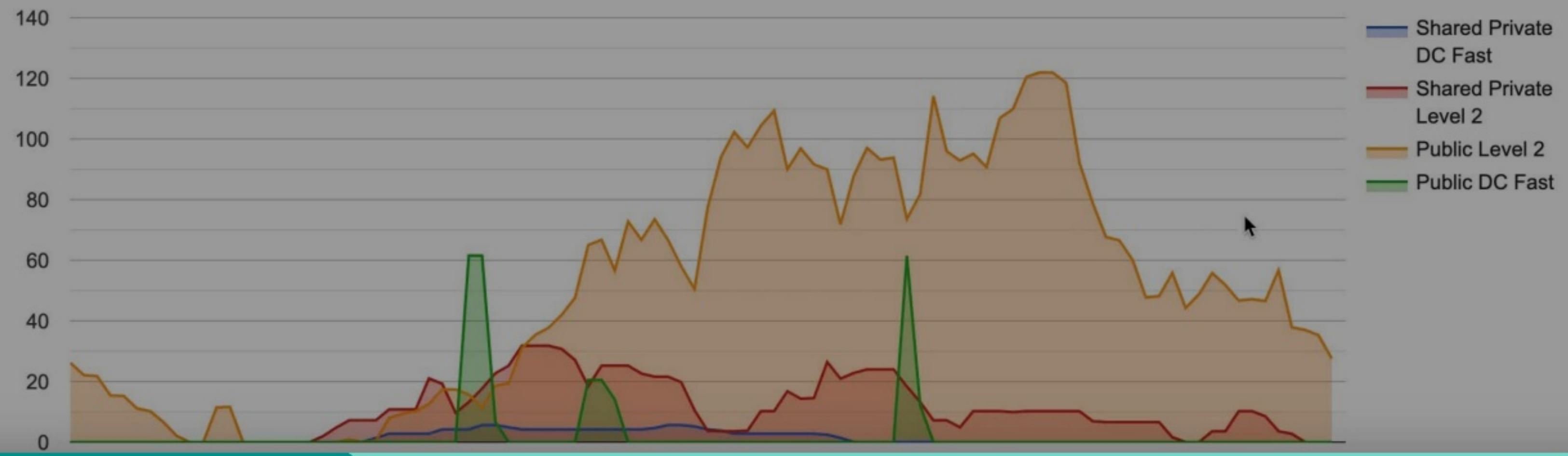


Scenarios Tested:

- Region Specific Future Charging Station Demand
- Region Specific Energy Demand snapshot
- Newly propose charging station locations for Transit Bus, School Bus and Delievry Truck in San Jose



Weekend electric load



Electrifying Tomorrow: Future Scope

Mercedes' Long-Haul Electric Semi Is Here

The EV truck sphere is growing, but is the infrastructure in any country ready for long-haul trucking?

BY JAY RAMEY PUBLISHED: OCT 11, 2023

DAIMLER TRUCK GLOBAL COMMUNICATIONS

Last-Mile vs. Long-Haul Focus:

Recognizing challenges in long-haul transportation, companies like Mercedes-Benz are introducing electric Class 8 semi trucks, signaling a broader industry focus on sustainable extended-route solutions.

High Energy Demand:

Long-haul electric trucks face substantial energy challenges due to their low efficiency, covering extensive distances, and the presence of large batteries.

Need for Innovative Solutions:

This includes advancements in battery technology, charging infrastructure, and energy management strategies to improve efficiency and make long-haul electric transportation more sustainable.

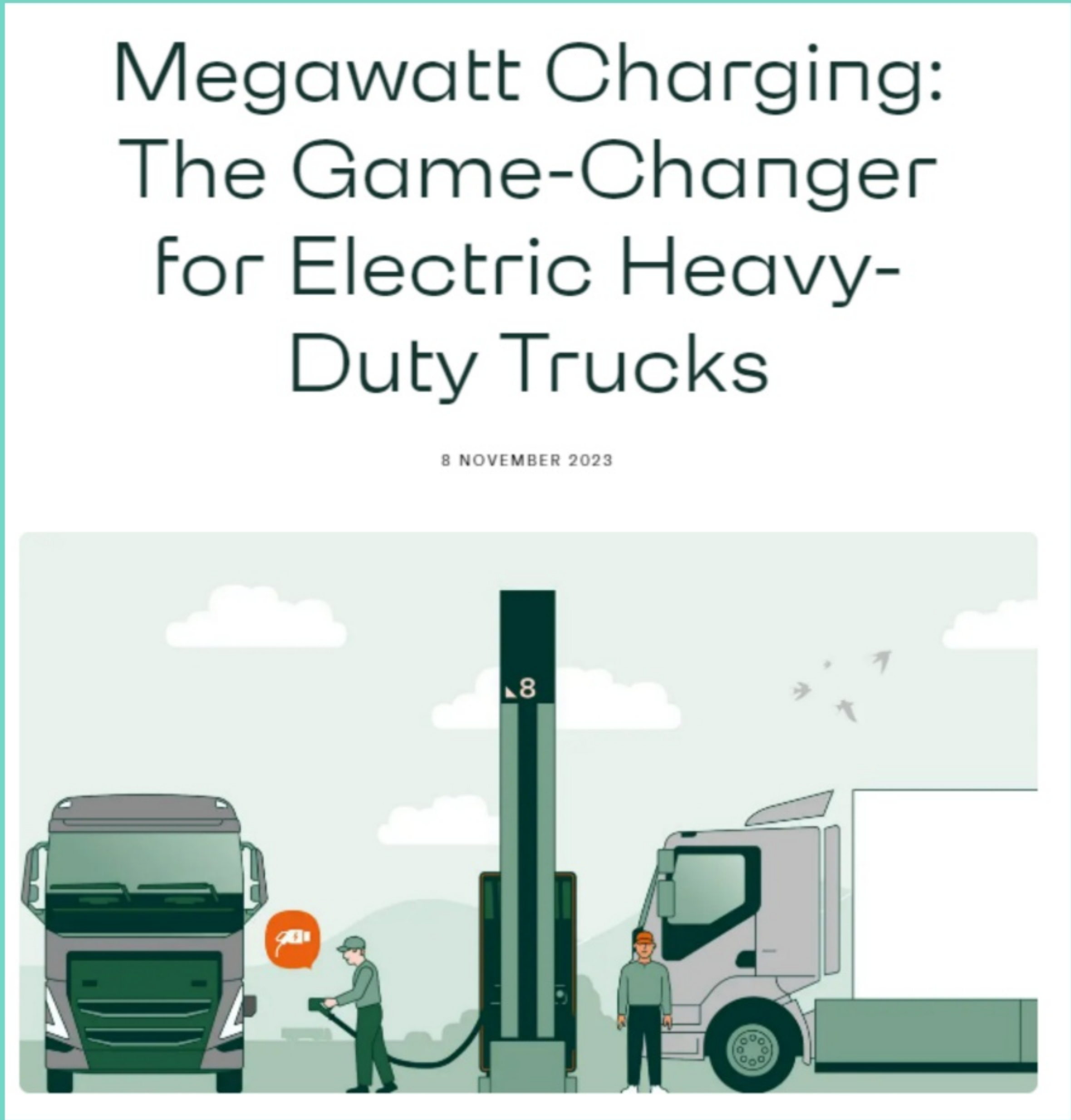
Electrifying Tomorrow: Future Scope

Megawatt Charging Revolutionizes Road Freight Electrification:

- IDTechEx forecasts a shift towards road freight electrification with the adoption of the Megawatt Charging System (MCS) for electric trucks.
- MCS, seven times faster than current super-fast chargers, delivers up to ~3.5 MW, drastically reducing charging times for heavy-duty trucks.

Efficiency and Safety of Megawatt Charging:

- MCS is designed for efficiency, ensuring maximum energy transfer to the vehicle's battery with minimal losses.
- Equipped with advanced cooling systems, MCS prioritizes safety during rapid energy transfer.



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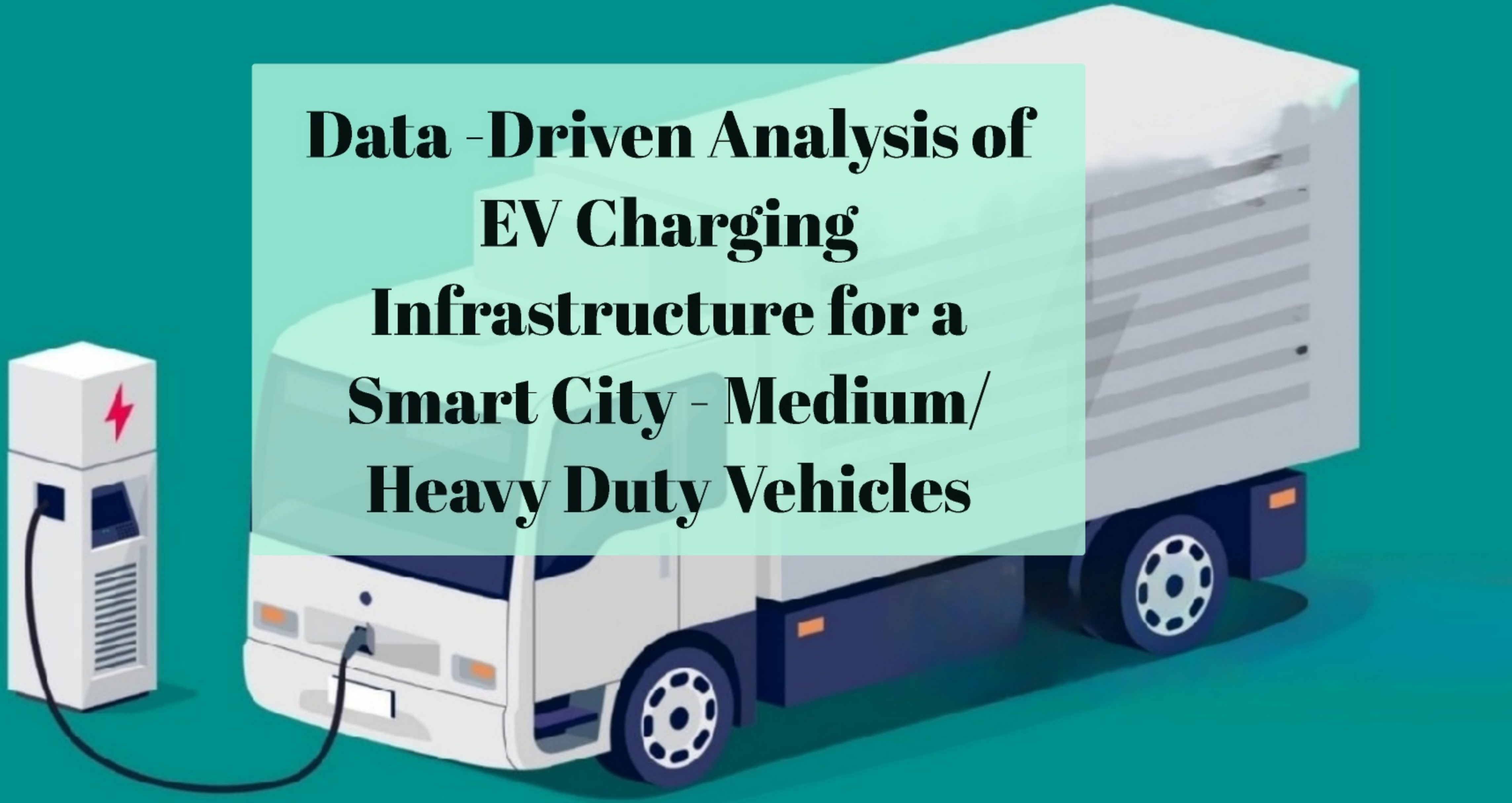
THANK YOU


Data -Driven Analysis of
EV Charging
Infrastructure for a
Smart City - Medium/
Heavy Duty Vehicles