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Optimal Charging Station Placement and Scheduling for Electric Vehicles in Smart Cities

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Abstract: Electric vehicles (EVs) have emerged as a transformative solution for reducing carbon emissions and promoting environmental sustainability in the automotive industry. However, the widespread adoption of EVs in the United States faces challenges, including high costs and unequal access to charging infrastructure. To overcome these barriers and ensure equitable EV usage, a comprehensive understanding of the intricate interplay among social, economic, and environmental factors influencing the placement of charging stations is crucial. This study investigates the key variables that contribute to demographic disparities in the accessibility of EV charging stations (EVCSs). We analyze the impact of various factors, including EV percentage, geographic area, population density, available electric vehicle supply equipment (EVSE) ports, electricity sources, energy costs, per capita and average family income, traffic patterns, and climate, on the placement of EVCSs in nine selected US states. Furthermore, we employ predictive modeling techniques, such as linear regression and support vector machine, to explore unique nuances in EVCS installation. By leveraging real-world data from these states and the identified variables, we forecast the future distribution of EVCSs using machine learning. The linear regression model demonstrates exceptional effectiveness, achieving 90% accuracy, 94% precision, 89% recall, and a 91% F1 score. Both graphical analysis and machine learning converge on a significant finding: Texas emerges as the most favorable state for optimal EVCS placement among the studied areas. This research enhances our understanding of the multifaceted dynamics that govern the accessibility of EVCSs, thereby informing the development of policies and strategies to accelerate EV adoption, reduce emissions, and promote social inclusivity.

Keywords: electric vehicles; environmental sustainability; optimized placement; machine learning; traffic pattern

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1. Introduction

Green developments have become an integral part of modern cities, as rapid urbanization has led to increased transportation usage, heightened pollution levels, and critical environmental issues [1]. To address these challenges, it is imperative to take proactive measures and implement strict management to control and minimize the emissions released by vehicles [2]. The research community is currently focused on developing powered cars with almost zero emissions, making electric vehicles (EVs) a promising solution. EVs, driven by clean energy sources, emit harmless byproducts instead of exhaust gases, thereby improving air quality in cities and promoting the health of their residents [3,4]. In addition to their positive environmental impact, EVs play a vital role in future smart grids by conserving energy, reducing carbon emissions, and promoting sustainability [5,6]. The adoption of EVs by consumers has been increasing steadily, with global sales surpassing 10 million in 2022. Furthermore, it is projected that by the end of 2023, approximately 14 million EVs will be sold, accounting for 18% of all vehicle sales throughout the year [7]. Notably, China, Europe, and the United States dominate the global EV market, with the United States experiencing a 55% increase in sales in 2022, aiming to achieve a 50% market share by 2023 through initiatives such as the Inflation Reduction Acts (IRA) and California's Advanced Clean Cars II rule [6].

The infrastructure that provides electrical power from a power outlet to an EV charger is known as EV supply equipment (EVSE), or more commonly, an electric charging station [8,9]. EVSE integrates utility electricity with wiring, connections, and interfaces to supply power to an EV battery. The power arrangement varies across different regions based on factors such as frequency, voltage, power grid connection, and transmission protocols [10,11]. Charging levels are categorized by the Electric Power Research Institute (EPRI) and the Society of Automotive Engineers (SAE) as AC level 1, AC level 2, and DC fast charging level 3, each with its corresponding functionalities and security systems [12,13]. As the number of EVs on the roads continues to rise, concerns regarding the availability and feasibility of charging stations for users become more prominent [14]. In the United States, only 12% of the required Level 2 charging stations are installed as of 2023 [15]. Furthermore, there is a lack of charging stations that support multiple brands, creating an inadequate charging network that fails to accommodate the changing demand patterns associated with population growth and the increased adoption of EVs in smart cities [16,17]. The limited accessibility to affordable electric vehicles is a significant issue for a large portion of the population, particularly those in low-income groups, people of color, and individuals with disabilities. The availability of EV charging stations is crucial for these individuals to access job opportunities and meet their basic needs [18,19].

In addition to the challenges related to accessibility, other factors such as high costs, regional demographics, traffic flow, and environmental conditions pose obstacles to the widespread deployment of charging stations [20,21]. The proper placement and sizing of EV charging stations are crucial to mitigating the negative effects associated with EV adoption. Numerous studies have addressed the optimal placement and configuration of charging stations, mainly focusing on economic and power-grid principles [22]. It has been found that it is essential to optimize the installation and scheduling of electric vehicles in order to encourage the use of electric vehicles (EVs) and to lower carbon emissions. For the purpose of facilitating EV owners' vehicle charging, charging stations should be positioned in easily accessible areas [23]. Similar to the accessibility of conventional fueling stations for petrol and diesel vehicles, this convenience will motivate more people to switch to electric vehicles. Better air quality and lower greenhouse gas emission are the outcomes of having more electric vehicles (EVs) on the road, as it is intrinsically more energy efficient than internal combustion engine vehicles. The strategic placement of EVs collectively promotes greener and more sustainable modes of transportation and propels the market for electric vehicles [24]. However, basing the placement and sizing solely on economic considerations is neither reasonable nor realistic [25]. Therefore, the primary objective is to determine an ideal position and sizing for EV charging stations by employing optimization techniques that minimize overall expenditure while ensuring power system security [26]. Recently, several heuristic optimization techniques have been employed to address the challenges associated with the location and design of charging stations [27]. These heuristic methods have the advantage of identifying optimal solutions even in complex problem scenarios [28,29]. However, further research is necessary to understand the precise causes of spatial disparities in the availability of charging stations across different cities. Additionally, maximizing the accessibility and efficiency of charging stations is essential to meet the growing demand for charging services effectively [30].

Thus, in order to fulfill the research gaps in the literature and to address the abovementioned problems, this manuscript aims to identify the crucial factors for optimal charging station placement and scheduling. Furthermore, machine learning approaches, including the regression model and support vector machine, are utilized to predict the placement of charging stations in the most densely populated areas with EVs, using historical data on the key factors. The novelty of the manuscript is that this study helps in determining the contribution and impact of various factors in the optimal placement and scheduling of EVCSs. The role of various factors in the optimal placement of electric vehicles is practically determined, and by utilizing these factors, a comparison between the different states has been carried out regarding the optimal electric vehicle charging station placement. This manuscript is the source of collective data, but by also utilizing these data, the charging station forecasting has been conducted in nine different states of the US. The optimality of charging stations has been identified in the comparison of nine states of the US, including California, Florida, Texas, Washington, New Jersey, New York, Georgia, Illinois, and Colorado. The most recent trends in EV adoption in nine different states of the US, including charging station placement, temperature impact, electricity generation, and cost and mean family income, are determined and utilized for forecasting the demand for charging stations. Moreover, the performance of machine learning models in predicting strategic placement is also compared, and it is found that the regression model performed well with 90% accuracy and 94% precision. Furthermore, graphical and mapping analysis, along with machine learning optimization, presents a clear picture of important factors and their role in placing EVCSs' existing stations and forecasting the need for future charging stations in the US states. This study will be beneficial for researchers and stakeholders to determine which state has the most demand for EVCSs. This will motivate researchers to further elucidate the optimal placement in these individual states according to the present demand.

In conclusion, this paper is organized as follows: Section 1 provides an introduction to the significance of electric vehicles and their usage worldwide, charging infrastructure, and the challenges associated with placement. Section 2 presents a review of the relevant literature on the optimal scheduling of EVs and charging station placement. Section 3 outlines the problem statement and objectives of this study. Section 4 describes the data collection process and the methodology employed to achieve the study's objectives. Section 5 presents a brief summary of the results, and the Discussion in Section 6 elaborates on the key findings and implications of the proposed strategy as well as the limitations of the study. Finally, Section 7 concludes the study and highlights future prospects.

2. Previous Approaches

A study was conducted in which the indicators were identified that play an important role in the sustainable placement of electric vehicles [31]. The long list of parameters was identified, and then a unified approach consisting of an algorithm and Monte Carlo simulation was applied to determine the weightage of key indicators in determining the sustainable placement of EVs. The high-weightage indicators for the optimal scheduling of EVs consisted of charging demand, economic factors, demographics, and behavioral and environmental factors. This study helped in selecting the greatest contributing key indicators of EVs' optimal placement for this manuscript. Moreover, numerous studies have investigated the optimal placement of charging stations (CSs) for electric vehicles (EVs) in various regions worldwide. These studies have utilized various optimization techniques, such as genetic algorithms, particle swarm optimization (PSO), machine learning algorithms, and linear programming to optimize EVCSs [22,32]. For instance, a Mixed Integer Linear Programming (MILP) model was developed to determine the best location and size of charging stations in cities. This model incorporated inputs such as land-use classifications, recharging descriptions, and traffic patterns to determine the optimal placement and number of charging stations [33]. Another study employed a genetic algorithm to determine the position and type of recharging outlets while considering budgetary constraints and optimizing the placement based on the number of travels ending at specific locations in the city [34]. Additionally, a quantum-based PSO algorithm was utilized as a multi-objective approach to optimize EVCS placement, considering factors such as grid stability, maximum coverage, customer demand, and cost reduction [35,36].

In recent years, the introduction of machine learning (ML) has gained popularity in addressing challenges related to charging infrastructure management. Researchers have started employing ML-based algorithms to tackle issues such as CS location, charging demand prediction, and charging time management [37,38]. Machine learning approaches have proven beneficial in scheduling electric vehicles successfully [39,40]. Several studies have explored the predictive power of ML algorithms, including decision trees, supervised learning, and support vector machines, in assessing optimal charging station locations, demonstrating improved results with these models [41]. Regression trees, random forest (RF), and k-nearest neighbors (KNN) algorithms were utilized in one study to classify households for EV energy consumption [42]. The KNN algorithm was also applied to determine the energy consumption at charging stations in Los Angeles, California, providing insights into the charging needs of EVs in specific areas [43]. Logistic regression, RF, and XGBoost models were employed to determine charging infrastructure in urban areas, achieving accuracy values greater than 0.8 and an F-score of 0.68 [44]. A modified form of support vector machine (SVM) was used for CS placement in China, considering environmental input parameters and yielding better forecasting and evaluation matrices compared to conventional models [45]. Neural networks were employed in a study to forecast specific CS utilization data based on the station's actual placement within a network, providing immediate predictions of average utilization data for proposed architectures without the need for executing costly models. This approach assists developers in quickly testing multiple charging infrastructure placements to determine the best design according to their goals [46]. Another study compared three regression methods, RF, gradient boosting (GB), and XGBoost, using supervised ML on a dataset to determine the most influential variables affecting charging network management. XGBoost outperformed the other methods, achieving an R2 value of 60.32% and an MAE of 1.11 [47]. In a study on public charging stations in Nebraska, USA, the charging behavior was examined using three widely used models: XGBoost, SVM, and RF. The findings revealed that XGBoost regression outperformed the other models in forecasting demand, with an RSME of 6.68 kWh and an R2 of 51.9% [48]. Another study proposed a technique for projecting immediate electricity expenses to the 5 min level using an algorithm that incorporates eight artificial neural networks (ANNs). Each ANN consisted of a hidden layer with 20 neurons. The integrated ANN model accurately predicted the following day's power price or time-of-use (TOU) costing, providing valuable insights for EV planning [49].

All the above studies indicated the important optimization techniques, machine learning models, and other relevant approaches for EVCS placement and scheduling. The existing literature indicates that machine learning-based simulation models proved to be the most effective and suitable approaches for EVCS placement with greater accuracy and precision. Optimized charging station placement and scheduling for EVs is an evolving field, but the following existing research gaps in the literature will be addressed in this manuscript.

- There is a lack of studies that focus on research in multi-objective optimization, which takes into account cost, convenience, environmental impact, and other considerations at the same time and has the potential to provide more holistic solutions.
- Lack of development of models that consider the key variables to determine optimal placement of EVCSs in smart cities.
- Research is needed to develop data analytics and machine learning algorithms that can adapt to changing electricity demands and the availability of charging stations.

No study is present in the literature that collectively compares the major states of the US for the optimal placement and scheduling of EVCSs. Also, the literature has limitations in studying specific important areas like US states, real-time trends in EV adoption, EVCS placement, and other concerning factors. So, in continuation with the previous approaches, linear regression and support vector machine models are utilized for predicting the need for the optimal placement of CSs in various states of the US. This study aimed to determine the actual role of important indicators suggested by the above study in assessing the optimal placement in smart cities. The performance of both models in predicting the optimal placement of electric vehicle charging stations from these indicators is compared and analyzed.

3. Problem Formulation

The problem relates to the determination of important factors for the optimal placement of CS and scheduling of EVs in nine important states of the US, which is the third largest market for electric vehicles. The objectives of the study are given in the following sub-section.

Research Objectives

- Identify the key factors that significantly influence the optimal placement and scheduling of electric vehicle (EV) charging stations in urban areas. These factors include population density, area, EV ownership, environmental conditions (such as temperature and humidity), energy consumption patterns, and energy costs.
- Develop an optimization model that incorporates these key factors to determine the optimal placement and scheduling of EV charging stations in smart cities. This model will consider the aforementioned factors to ensure efficient and effective placement and scheduling strategies.
- This analysis will provide insights into the overall effectiveness and performance of the proposed ML model for charging infrastructure and compare the effectiveness of models in assessing the indicators for optimal placement.
- This evaluation will assess the model's ability to optimize charging infrastructure and contribute to the sustainability of the transportation sector.

It is important to note that while there have been various studies on EV charging station placement using machine learning techniques, to the best of the author's knowledge, no study has focused on utilizing and comparing the key factors for optimal placement. A study is present in the literature that only determines the key indicators for optimal placement, and no study actually utilized these factors for placement determination. Furthermore, despite the United States being the third largest market for electric vehicles, there is a lack of research that comparatively analyzes EV patterns across different states within the country. This study aims to address these gaps by determining the optimal placement of EV charging infrastructure based on key factors. To achieve this, machine learning algorithms, specifically linear regression and support vector machines, were employed to determine the optimal EV charging station placement based on the identified key factors. The study will provide valuable insights as to which states require EV charging stations the most based on current demand. The suggested model was evaluated using various performance metrics, including precision, accuracy, F1 score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), to ensure its effectiveness and reliability.

4. Research Methodology

The research methodology encompasses various components, including the study area, data collection, data analysis, machine learning model development, and evaluation of these models. The flowsheet diagram illustrating the research methodology is presented in Figure 1.

4.1. Study Area

To assess the impact of different factors on the charging infrastructure of electric vehicles (EVs) and determine the optimal placement of charging stations (CSs), the study area chosen was the United States. The United States is the third largest country globally, with a total land area of 9,147,420 km^2. It consists of 50 states and has a current population of 340,269,759, with a population density of 37 per km^2 and an urban population percentage of 82.9% (odometer, 2023; worlddata.info, 2023) [50].

Considering the United States' status as a developing country and its substantial share of the world's population (4.23%), it was deemed appropriate to focus on the 9 major states of the US. These states, namely California, Florida, Texas, Washington, New Jersey, New York, Illinois, Georgia, and Colorado, were selected based on their high electric vehicle percentages and were considered representative of the world's smart cities. The study aimed to analyze the impact of various factors within these states on the placement of CSs. Figure 2 highlights the selected states of the US.

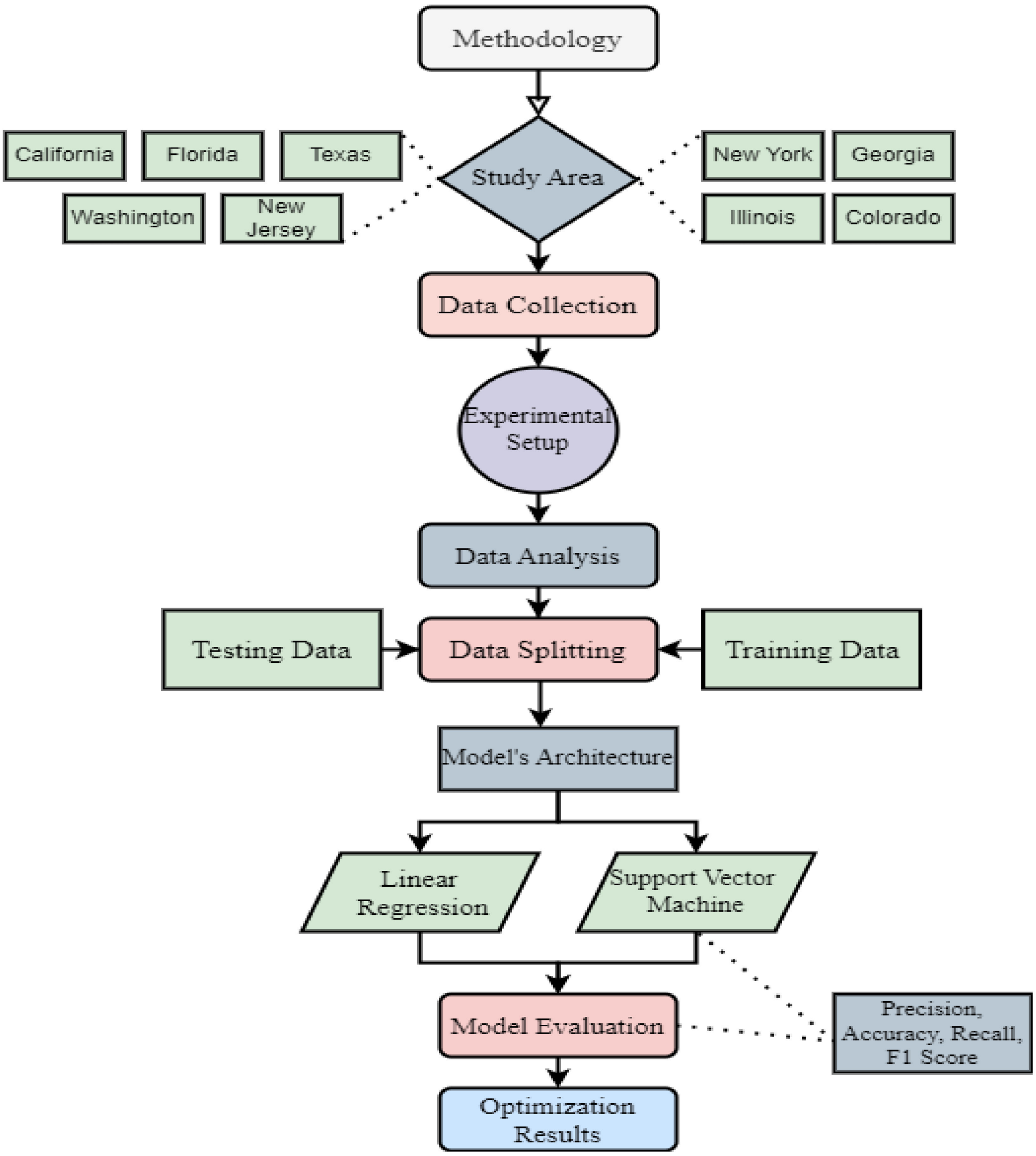

Figure 1. Flowsheet of methodology.

The selection of these states was based on their diverse geographical and environmental conditions. The indicators that were utilized for the optimal placement of electric vehicles are the key indicators of sustainable locations (KISLs) and were the highest contributing factors in this regard, as identified by Carra et al. [31]. By carefully considering factors such as electric vehicle ratio, ownership, existing charging infrastructure, environmental factors, electrical energy consumption, cost, and traffic flow, we ensured a comprehensive representation of different conditions to study their influence on optimal CS placement.

4.2. Data Collection

Data were collected regarding the total area, population density, total no. of EVs and percentage increase of electric vehicles in each selected state, number and type of charging stations and EVSE ports, temperature, humidity, electricity generation and electricity cost, EV incentives, traffic flow and average and mean income of families in each state. All these factors are important in optimizing electric vehicles in any state, as suggested by Carra et al. [51]. Data regarding these factors were collected from different as given below.

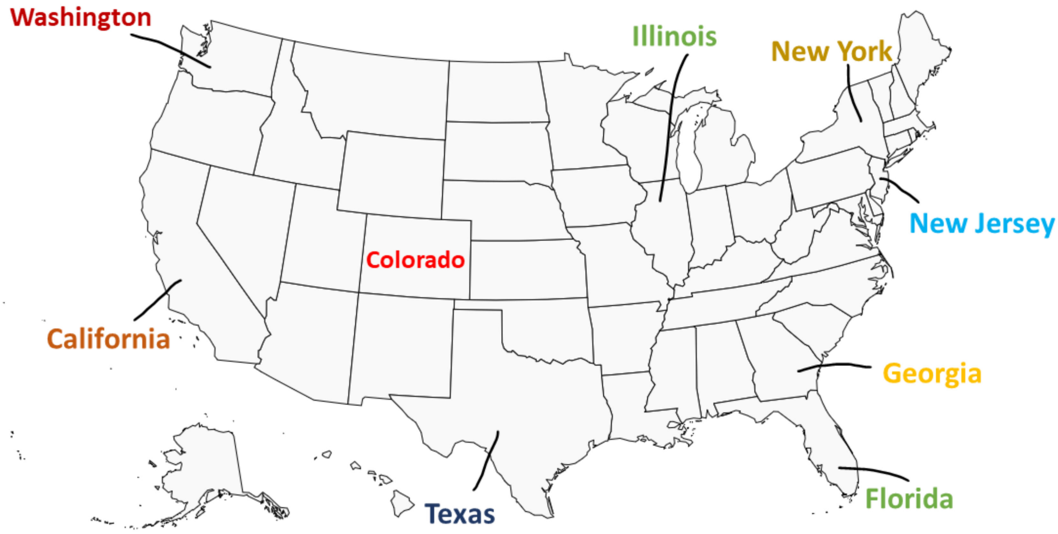

Figure 2. Selected states of the US as study area.

1. National Household Travel Survey (NHTS) (United States): This dataset provides information on travel behavior, vehicle ownership, and household demographics. It can be used to analyze the factors influencing EV adoption and charging demand in urban areas. Data access: [NHTS Data] (https://nhts.ornl.gov/) (accessed on 5 Septemeber 2023).
2. US Department of Energy (DOE)—Alternative Fuels Data Center (AFDC): This source provides comprehensive data on existing EV charging stations, including their locations, charging capabilities, and usage statistics. Data access: [AFDC Station Locator] (https://afdc.energy.gov/stations/#/analyze) (accessed on 10 Sepetmber 2023).
3. OpenStreetMap (OSM): This crowdsourced mapping platform can obtain geographical information on road networks, land use, and points of interest, which are essential for the placement analysis of charging stations. Data access: [OSM Data] (https://www.openstreetmap.org/) (accessed on 31 August 2023).
4. National Oceanic and Atmospheric Administration (NOAA)—Climate Data Online (CDO): This dataset contains historical weather data, which can be utilized to estimate renewable energy generation potential and influence the placement of charging stations. Data access: [NOAA CDO] (https://www.ncei.noaa.gov/access/search/data-search/global-summary-of-the-day) (accessed on 2 Sepetmber 2023).

4.3. Experimental Setup

The investigation was carried out using Python version 3.8, and Google Colab had access to 16 GB of RAM for the tests. Access to N.V.I.D.I.A. GPUs and CPUs is freely accessible through the Google Colab platform, and these resources may significantly boost the pace at which simulations are conducted and the ultimate efficiency of the experiments. Furthermore, Google Colab has an easy-to-use interface and integrates well with Python, making it a useful tool for investigating and processing code. The platform provides a large amount of RAM for the trials (16 gigabytes), allowing it to handle larger datasets and memory-intensive operations.

Graphical analysis methods, such as line graphs and Pi-charts, were employed to analyze the data and identify key factors influencing the optimal placement of CSs. These graphical representations facilitated an understanding of the impact and relationships among various factors, contributing to the optimization process.

Data splitting, a common approach in machine learning (ML), involves dividing the dataset into at least two subsets, usually training and testing sets. The purpose of data splitting was to evaluate the performance of ML models on unseen data. In this study, the dataset was split into two halves, with 80% of the data utilized for training the ML models and the remaining 20% used for model evaluation. In the process of developing and accessing machine learning models, such as support vector machine (SVM) and linear regression, splitting data into training and testing sets is essential. To make sure the model generalizes well, the performance of the model on untested data is evaluated. First, the dataset is prepared by cleaning, initial processing, and arranging it to make sure any missing value is handled and the data are in accurate format. The data are split on the basis of the size of dataset and the problem to be identified. This removes the uncertainty of input data. To make sure that the data effectively reflect the problem that we are trying to address and are appropriate for training a machine learning model, data validation is essential. In order to guarantee the consistency and quality of the dataset, data validation entails preparation and checking of data. The missing numbers, outliers, and inconsistent data are first eliminated or corrected in order to clean up the data. In order to evaluate the accuracy or completeness of data, any discrepancies or input data errors were searched. Then, data processing is carried out in validation process by scaling, normalizing, or transforming features and standardizing units that make the data appropriate for machine learning algorithms.

4.4. Model's Architecture

This section contains information regarding the machine learning models utilized to find the optimal placement of EVCSs by utilizing the collected input data regarding the states of the US. Two different models of different natures are utilized in this study, and the comparison of their effectiveness has been made in optimal placement and scheduling of EVCSs. These two models work independently irrespective of each other and are utilized to determine their effectiveness towards the quantitative linear data of indicators for assessing the optimal placement of charging stations in smart cities. The results have suggested which model is the best-suited model for this kind of data. The linear regression model is utilized in this study because of its simple interpretability nature. It enables us to comprehend the relationship between influencing factors and EVCS placement. This computationally simple model entails understanding which factor has the most significant impact. However, SVM is a flexible option for effectively placing charging stations in increasingly intricate urban environments due to its advantages in managing complex, non-linear interactions, versatility to high-dimensional data, and generalization to various scenarios. Where complicated spatial and geographical patterns may impact EVCS placement, SVM is better able to identify non-linear connections. SVM copes well with high-dimensional data when placement decisions are based on multiple considerations. By using alternative kernel functions (such as linear, polynomial, and radial basis functions) to adjust to diverse distributions of information and relationships, SVM offers versatility. As both models work independently, the effectiveness of both models for optimized EVCS placement and scheduling is compared and determined in this manuscript.

4.4.1. Linear Regression

Regression-based optimization is a strategy that integrates regression analysis with optimization techniques to determine the best values for particular parameters or variables [50]. It is frequently utilized when you have data points and wish to establish the link between the input parameters and an output variable, then use that correlation to optimize the output variable [52]. It is especially beneficial when an intricate relationship between factors cannot be stated using simple mathematical formulae. Regression analysis can be useful for determining the optimum location for electric vehicle (EV) charging stations. The purpose is to identify the best places for CS to increase utilization, access, and convenience [53].

Linear regression is a quantitative technique for modeling the connection between one or more independent factors (features) and one or more dependent variables. With charging station placement, linear regression can be utilized to determine the link between numerous parameters influencing charging station utilization and the expected demand [54].

Consider a simple situation in which two variables are independent, such as electric vehicles (X1) and area of state (X2), with EVCS usage (Y) as the dependent variable, Bo is the intercept, B1 is the coefficient for variables that determine the variable influence on Y, and ϵ is the error term. The linear regression model can be represented as

$$Y = \beta o + \beta 1 \times X1 + \beta 2 \times X2 + \epsilon, \tag{1}$$

We used statistical software and computer libraries (such as Python's scikit-learn) to execute the calculations and fit the regression to our data. We expand this concept to several independent variables and more advanced regression methods.

4.4.2. Support Vector Machine

A supervised ML strategy called a support vector machine (SVM) is applied to classification or regression challenges. It works well when a sharp difference exists between various classes or data points [55]. Support vector machines (SVMs) could be used to position charging stations. SVM regression can assist in predicting projected charging station utilization based on various parameters when it comes to placement [56]. SVM regression is used to identify the function that matches the data the best while maintaining a specific margin between the data points. Finding the hyperplane with the largest margin around the data points will enable us to anticipate a continuous output variable (charging station usage).

We fit the data points as closely as possible to select the optimum hyperplane for the SVM regression while still permitting some error. The model was made in which Y is the dependent variable that belongs to charging stations, X is the independent variable indicating indicators (EVs, area, temperature, energy dissipation, cost), w is the weight factor, b is the bias term, and ϵ is the error term that allows deviation from the hyperplane. The SVM regression model is represented mathematically by the following formula:

$$Y = w \times X + b + \epsilon, \tag{2}$$

We utilized the machine learning model (scikit-learn in Python) to perform the calculations and fit the SVM model. SVM is utilized to deal with complex relations with variables.

4.5. Model's Validation

An important stage in the model development strategy is model evaluation. It enables you to assess the effectiveness of your model, pinpoint its weak points, and make wise judgments about whether to deploy or modify it. In this study, the performance of a model was assessed using the well-known machine learning assessment metrics accuracy, precision, Recall, F1-score, ROC-AUC, and Confusion matrix [57,58]. Accuracy estimates the proportion of properly predicted occurrences to all instances in problems involving categorization. Although it's a simple measure, it might not be appropriate in situations where there are class disparities. Precision calculates the ratio of accurate positive predictions to all positive predictions. It is employed to evaluate the model's capacity for producing precise positive predictions. Recall calculates the ratio of genuine positive predictions to real positive occurrences. It is helpful in determining whether a model can account for every positive example. F1 score integrates recall and precision into a single statistic. It is helpful when we need to optimize both precision and recall because it offers a balance between the two. The accuracy, precision, recall values and F1 score are calculated using the following equations. The confusion matrix plot is used to examine the model's efficiency. It gives a tabular display of the predictions that were falsely positive, falsely negative, and true positive & negative. For a thorough examination of the model's performance, it is helpful. Using helpful metrics and confusion matrices, we can evaluate the overall number of correctly and erroneously identified classes and precision, recall, accuracy, and F1 scores.

TPA being the True positive of Class A, TPB is the True positive of class B and TPC is the true positive of class C with true positive value TP, false positive value FP and false negative value FN, the accuracy, precision, recall and F1 score is determined by utilizing the following equations.

$$\text{Accuracy} = \text{TPA} + \text{TPB} + (\text{TPC}/\text{Total}), \tag{3}$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}), \tag{4}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}), \tag{5}$$

$$\text{F1 Score} = 2\,(\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}), \tag{6}$$

4.6. Mapping Analysis

Mapping analysis was carried out to elucidate the location of the CSs in the particular state. The maps were collected from the Department of Energy, US alternative fuel data centers. This analysis was done to gain more insight into the present charging stations and to forecast the optimal placement of EVCSs for the future. The analysis of already present and expected corridors to link the cities was also carried out and elaborated in this study.

5. Results

The results of the applied methodology are briefly described in this section. First, the data analysis was carried out with the help of graphs to determine the impact or contribution of various factors on the electric vehicles and the charging station infrastructure.

5.1. Data Analysis

Data analysis was carried out with the help of graphs and pie charts to determine the detailed impact of each factor on electric vehicle charging stations. Various key factors take part in the optimal placement of EVCSs.

Graphical Analysis

First, the overall percentage increase of electric vehicles in the US is elaborated with the help of a graph, as shown in Figure 3. The graph indicates that the percentage of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) has continuously increased over the years. The percentage of BEV is far greater than PHEV, and to 2050, the percentage will reach almost 12% compared to 2012. Therefore, there is an entire need for CSs for BVC shortly. So, the optimal placement of these charging stations is also an important concern that needs to be focused on to fulfill the present and future requirements.

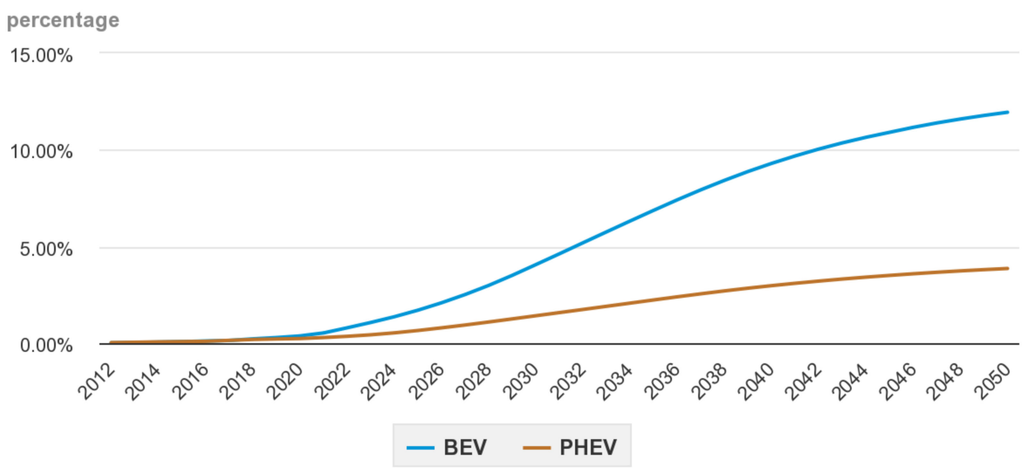

Figure 3. Percentage of EVs in the US.

To find the optimal placement from the selected states, it is very important to consider the total number of EV percentages in these states. Therefore, the Pi graphs have been plotted that compare the area, EVs, charging stations, electricity generation and electricity cost, and average income of families of each state, as shown in Figure 4. This analysis is carried out in order to compare with the linear regression model of machine learning that will also determine the relation between the factors and the charging station placement. By analyzing the relationship between the variables and charging stations, we can identify or predict the demand for optimal placement. Similarly, the machine learning model further elucidates this relation of factors with charging stations and gives the output in the form of state that demand for charging stations. This graphical analysis has its contribution in determining the model's performance. By considering these factors for the optimal charging station placement, policymakers can give priorities to areas with little charging coverages. The amount of EVs on the road today can help policymakers determine if more charging stations are necessary. In order to keep up with demand, strategies can give priority to expanding the infrastructure for EV charging. To maximise the effectiveness of their efforts, policymakers must also take into account the distinctive features of their respective regions. The graphs show California has the greatest number of electric vehicles (54% pi area) and charging stations (47% pi area). While comparing the other states, Florida and Texas have the second greatest number of electric vehicles and charging stations. Washington and New Jersey have an equal ratio of EVs and EVCSs, but New York has only 5% EVs, and stations are 11% compared to the other states. Similarly, Illinois, Georgia, and Colorado have fewer EVs and EVCSs. When the other factors of these states were compared to determine the optimal state for CS placement, it can be seen that Texas has the greatest area and electricity generation compared to all other states. At the same time, the electricity cost is also low in Texas, with a greater average family income. Low-priced power makes it easier to deploy EVs since it lowers the cost of charging for EV owners and may encourage a higher adoption rate. The ideal location for EVCS placement considers the regions with reasonable prices. Moreover, it's critical that the local energy infrastructure can accommodate the extra demand caused by EV charging. If not properly handled, high concentrations of EVs charging concurrently could put pressure on the grid. For optimal outcomes, locations with adequate grid capacity or plans to upgrade their infrastructure to support EV charging requirements should be chosen.

By considering the average ratio of EVs, present charging stations, area, electricity generation, and cost, we can infer that Texas would be the optimal state for charging station placement in the future. The percentages of all the key factors according to the pi-chart for comparison are also given in Table 1 below.

The impact of temperature was also investigated and found that temperature has a considerable impact on EV charging efficiency. High surrounding temperatures can aggravate thermal control concerns, while low temperatures might raise the battery's resistance and reduce the charging effectiveness. Charging time rises when the temperature drops, especially at low battery SOC. The ideal location should consider temperature control, favoring regions with temperate climates that increase EV efficiency and range. The temperature pattern of the selected states is shown in Figure 5.

As the graph indicates, Texas has a temperature in the normal range, making it an optimized state for EVCS placement. Moreover, Florida has high temperatures that affect electric vehicles' charging efficiency. Moreover, Washington has a low temperature that causes an increase in charging time for EVs. The results indicate that, these indicators play an important role in determining the optimal charging station placement as suggested by the previous study [57]. The graphical analysis of the statical data indicated the optimal placement of the EVCSs in Texas, and this optimization was also confirmed by machine learning, as given below.

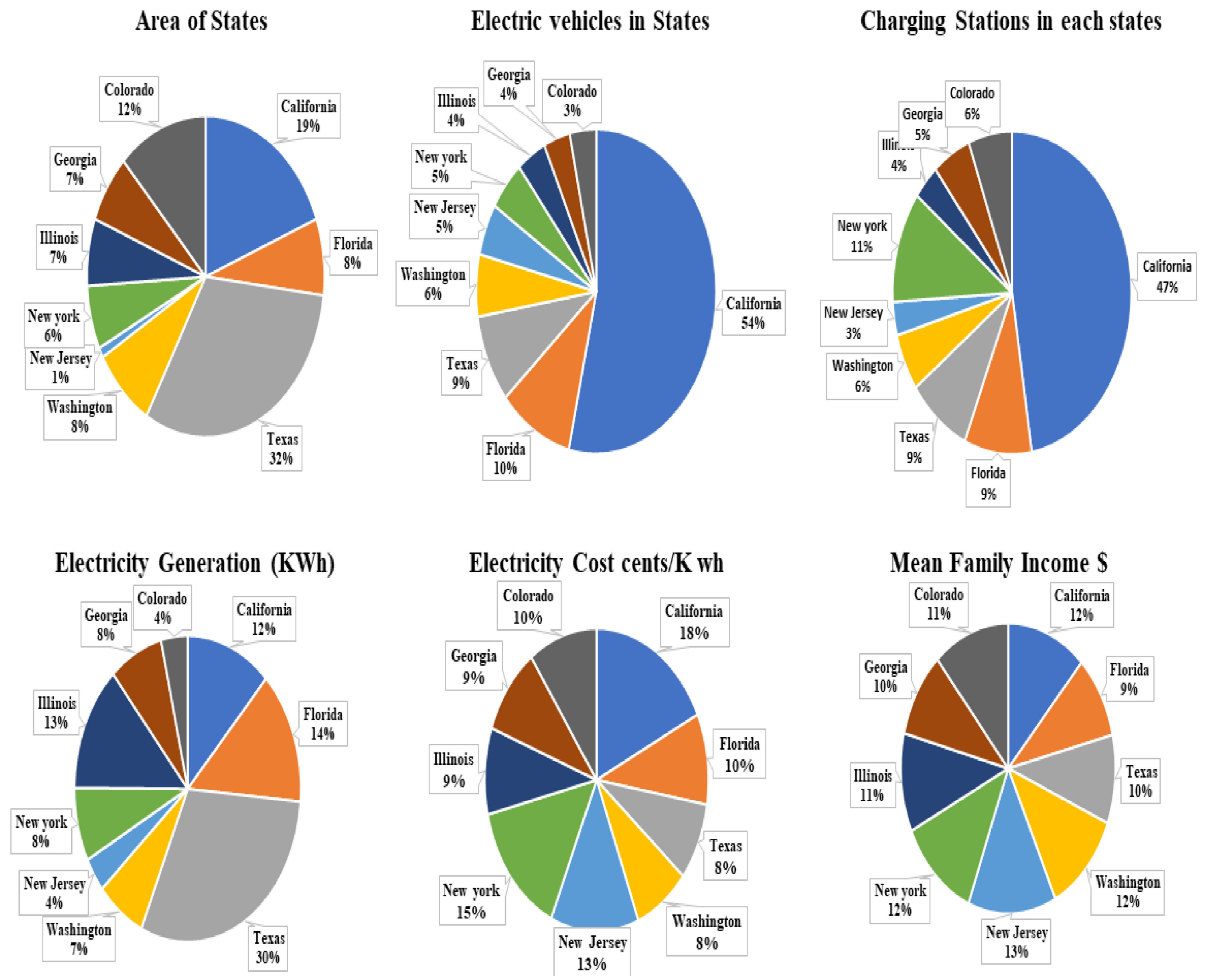

Figure 4. Key factors analysis in selected states.

Table 1. Percentage of variables from pie charts.

States	% of Area	% of EVs	% of EVCSs	% of Energy Generation	% of Energy Cost	Mean Family Income
California	19	54	47	12	18	12
Florida	8	10	9	14	10	9
Texas	32	9	9	30	8	10
Washington	8	6	6	7	8	12
New Jersey	1	5	3	4	13	13
New York	6	5	11	8	15	12
Illinois	7	4	4	13	9	11
Georgia	7	4	5	8	9	10
Colorado	12	3	6	4	10	11

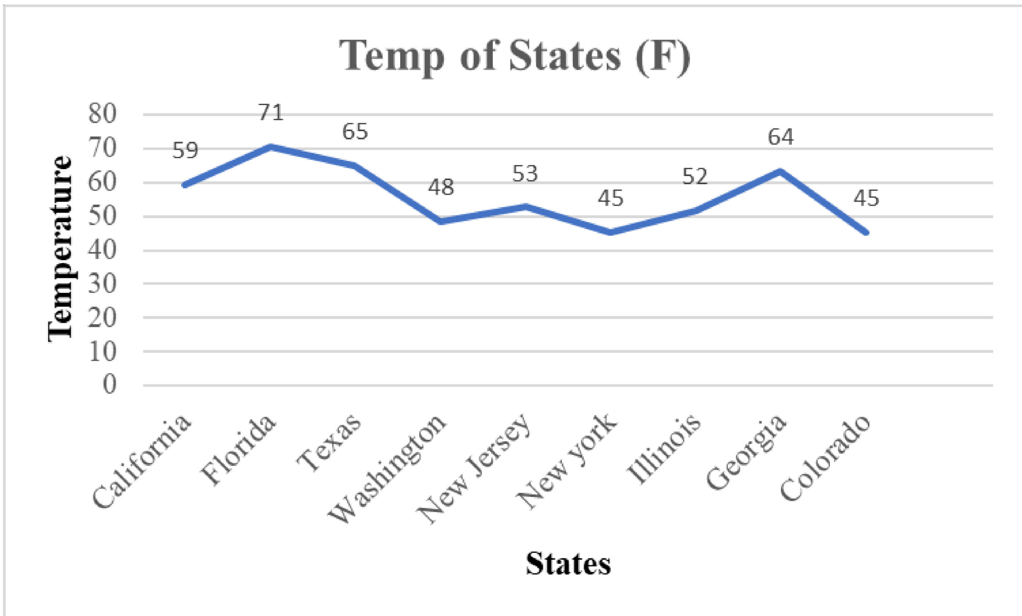

Figure 5. Temperature (f) in selected states.

5.2. Machine Learning Analysis

This study used two optimization algorithms, linear regression and support vector machine, to find the optimal placement and scheduling of EVCSs. The model evaluation utilized the precision, accuracy, F1 score, and AUC-ROC curve. The following results by various models indicated the optimal placement of charging stations in states.

5.2.1. Linear Regression Model

When the linear regression was applied to the input variables described in the methodology, the outcomes resulted in the graph, as shown in Figure 6 below. Given that regression is linear, both positive and negative consequences were anticipated and shown to exist. All estimates can be compared because they were all produced using the same approach and methodology. The results are given in the form of a bar graph. The graph generated after applying the optimization algorithm for the EVCSs placement in the selected states indicated that Texas would be the most optimized state for further placement of charging stations from all the given states by considering the input key factors. These results follow the analysis results, which depict the model's certainty and performance.

Texas indicated the highest results for optimized placement depending on the above-mentioned parameters. Then Washington would be the second most optimized state, followed by New Jersey and New York when analyzed by utilizing data of total electric vehicles, already present stations, EVSE ports, area, average power generation and cost, temperature, and the average income of families in each state. The confusion matrix of the applied regression is shown in Figure 7.

With the help of this confusion matrix, the precision, accuracy, recall, and F1 scores were calculated. The linear regression model indicated 90% accuracy, 94% precision, 89% recall, and 91% F1-score when evaluated from the confusion matrix.

5.2.2. SVM Model

The SVM model was utilized to identify the most important key factors in determining the optimized placement of charging stations. The key features for the optimization are shown in Figure 8 below. The figure indicated that the number of already present charging stations in the various states, temperature, and area or population of the states proved to be beneficial factors in evaluating the optimal placement of the charging stations.

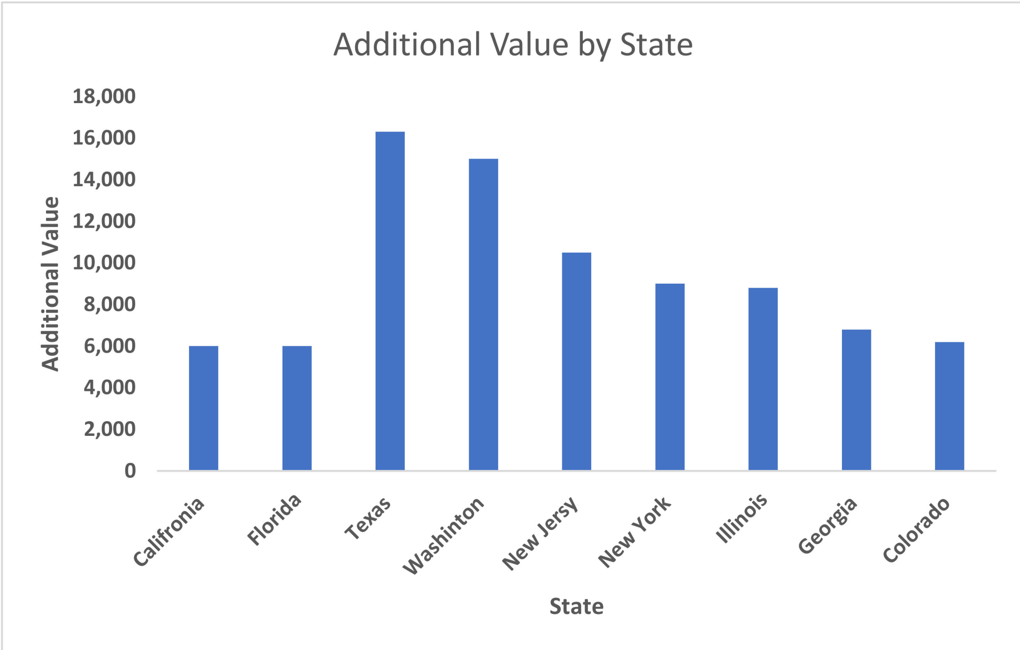

Figure 6. Linear regression optimization.

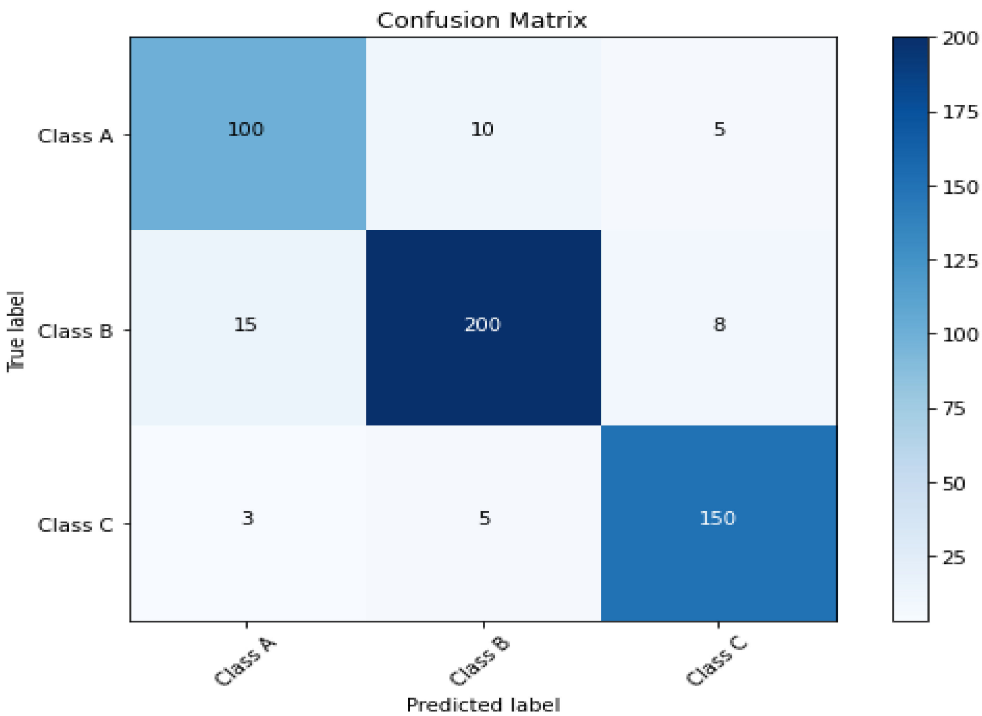

Figure 7. Confusion matrix of linear regression.

Optimized placement of charging stations was also evaluated with the help of a support vector machine by considering these key factors as input variables. The output was obtained in the form of the following Figure 9.

Feature 1 indicates the population, and Feature 2 represents the area of the states. We can see that there is no clear hyperplane between the data, indicating that the data are high-dimensional. The high-dimensional non-linear or kernel parameters were applied to map the data to the higher dimensional space where the separation would be possible. The results were obtained as shown in Figure 10.

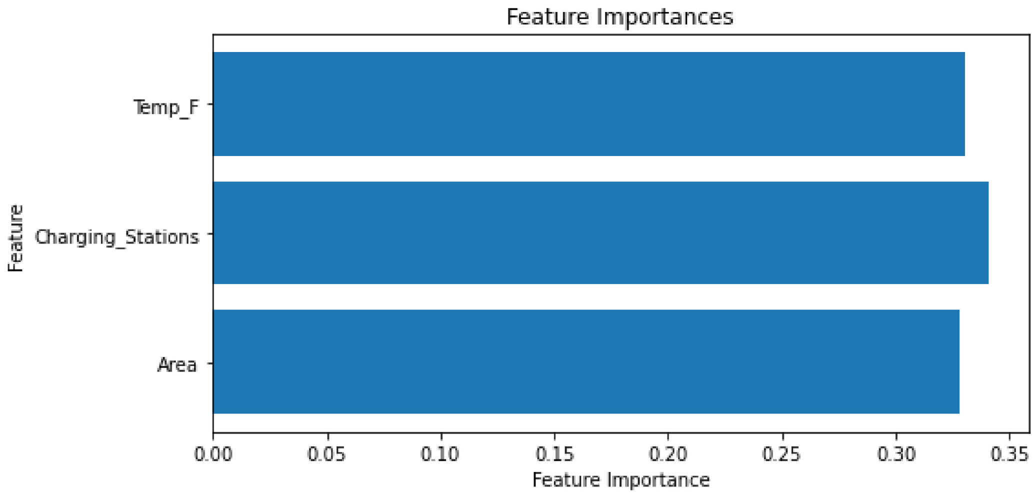

Figure 8. Important features.

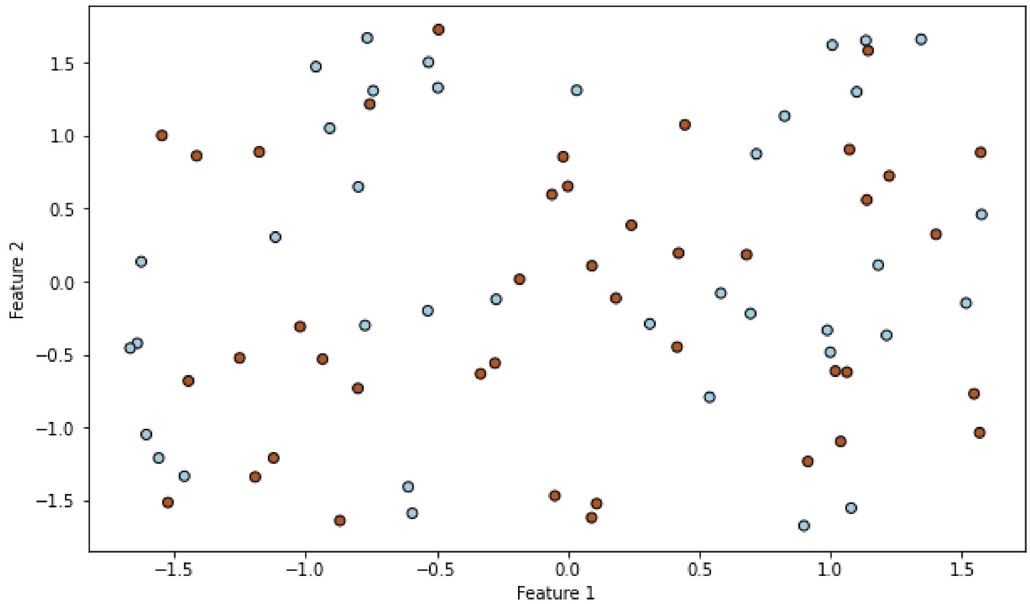

Figure 9. Optimization through SVM (low-dimensional).

The results indicated fewer charging stations in the more populated states with greater areas. The results suggested the more optimized charging stations in the states with greater electric vehicles, area, and population. The confusion matrix of the model is shown in Figure 11 below.

When the support vector machine model was evaluated with the help of evaluation matrices, the results demonstrated that this model showed less optimal results than the linear regression with only 35% accuracy, 27% precision, 38 recall matrix, 32% F1 score, and 35% ROC-AUC curve.

5.3. Mapping Analysis

The total number of charging stations in Texas was also analyzed using mapping analysis, as shown in Figure 12. The green dots in the figure below represent Texas's electric vehicle charging stations. It can be seen that the present stations are mostly situated on the north side of Texas, and very few are present on the other side. This means there is a need to optimize the placement of CS and the scheduling of EVs inside Texas to satisfy the needs of the people. Areas with significant traffic volumes, such as crowded metropolitan centers, business districts, shopping malls, and office buildings, should be selected strategically for charging stations. High-traffic locations ensure that many potential EV customers may quickly reach charging stations while making their daily commutes or going about their usual business.

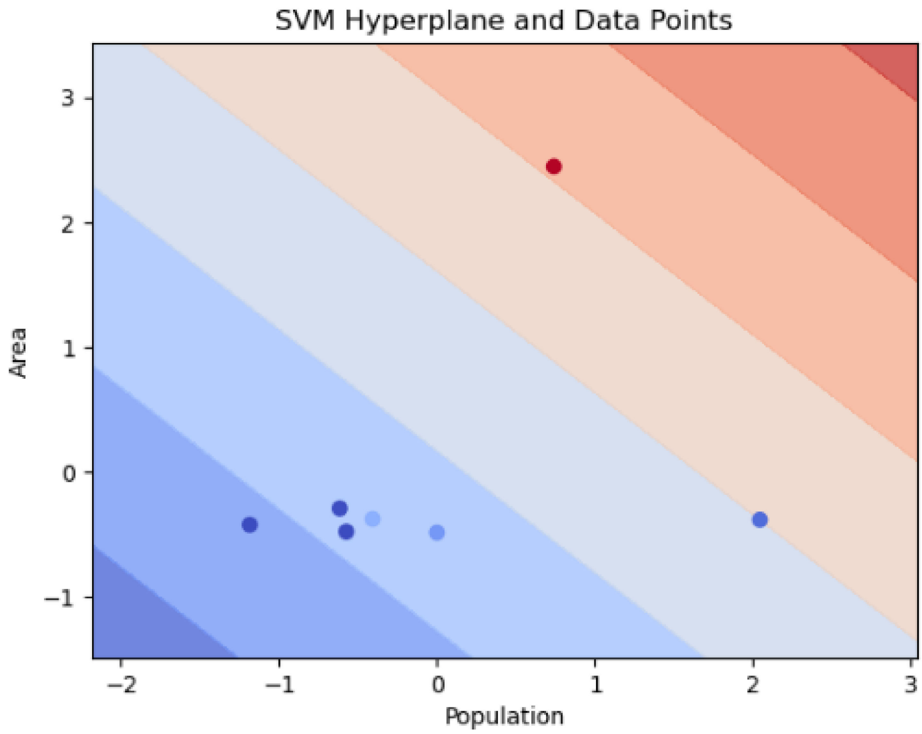

Figure 10. High-dimensional optimization through SVM.

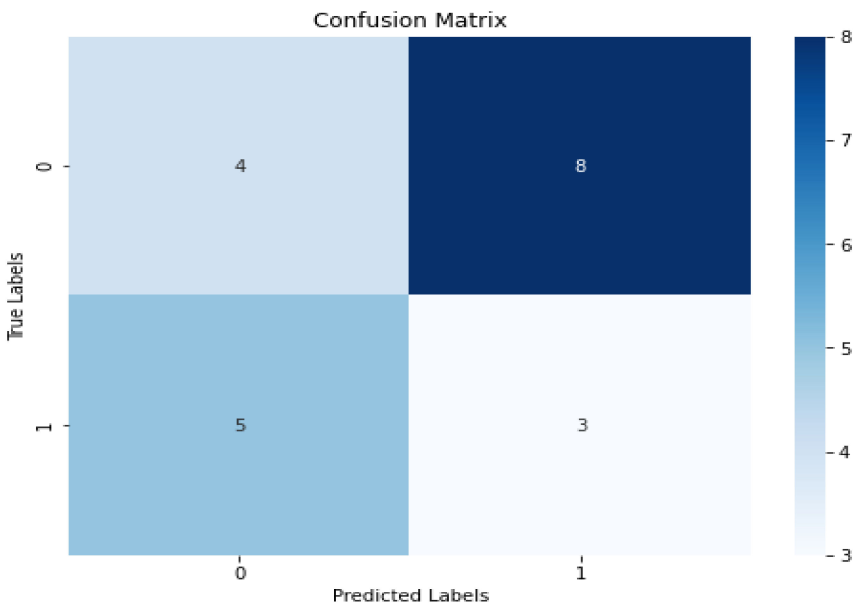

Figure 11. Confusion matrix of SVM.

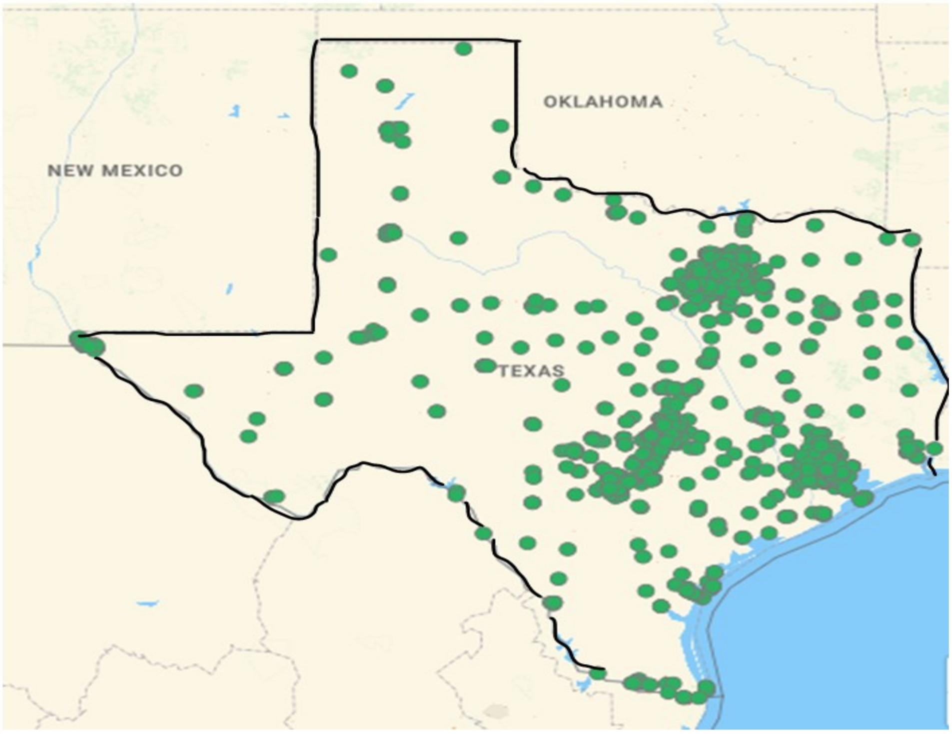

Figure 12. Mapping analysis of EVCSs in Texas.

The already present corridors that link one city of Texas with another are also mentioned on the map with dark green lines. The suggested corridors are also evaluated by light green lines in Figure 13. These corridors will allow people in both cities to share the stations. This also suggests the optimal placement of electric vehicle charging stations.

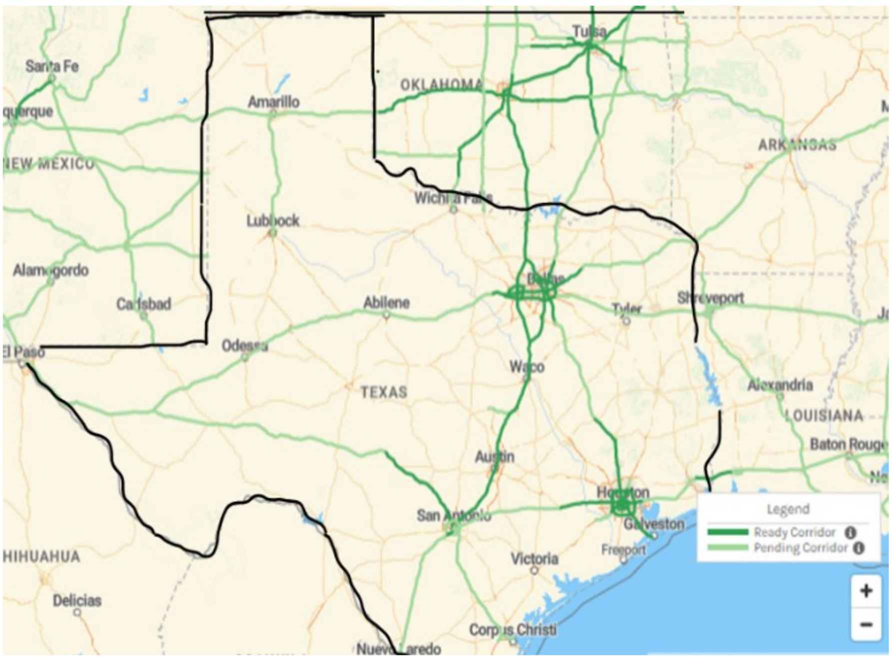

Figure 13. Mapping analysis of present and expected corridor (AFDC) in Texas.

6. Discussion

The key findings and limitations of this study are discussed in this section. This section elaborates on the results and the implications of the findings for policymakers, stakeholders, and the general public. The comparison of the findings of this manuscript with the previous methods is also made in this section to indicate the capability of the proposed model. Moreover, the limitations or drawbacks of the proposed model are also discussed, along with the future directions for research.

6.1. Key Findings and Implications

This study aimed to determine the optimal placement of electric vehicle charging stations (EVCSs) in smart cities by considering various factors in nine selected US states. The investigation focused on factors such as EV percentage, area, population density, EVCS ports, energy demand and production, energy cost, and temperature. The graphical analysis involved generating line graphs and pie charts to compare variables and key factors among the selected states and their influence on EV placement and scheduling. The findings revealed that California had the highest number of EVs and charging stations in the US, while Florida and Texas showed the highest increase in EV adoption after California. Texas exhibited the highest optimization potential for future EV placement when considering factors like area, energy demand and production, average income, and temperature. The analysis also highlighted that moderate-temperature areas are more suitable for charging stations and EVs compared to regions with high or low temperatures. This indicates the significant contribution of various factors in determining the optimal spatial distribution for electric vehicles. In order to ascertain the relationship between the factors and the position of the charging station, this analysis is performed in comparison with the machine learning linear regression model. We are able to determine or forecast the need for ideal placement by examining the correlation between the factors and charging stations.

The statical data of the key factors are utilized as input data in both machine learning models, including linear regression and support vector machine. The efficiency of both models is compared for these data. In linear regression, by taking into account the input important factors, the graph produced by using the optimization method to locate EVCSs in the chosen states showed that Texas would be the most optimal state for the subsequent placement of charging stations out of all the states provided. These findings show the performance and certainty of the model, and they come after the analysis results. When compared to the graphical analysis, the findings of the linear regression model are also supported by its findings. This demonstrates the feasibility and efficiency of the proposed model for strategic placement. SVM showed that while determining the optimal location for the charging stations, the number of charging stations that are currently in place in each state, the temperature, and the area or population of each state proved to be useful considerations. The high-dimensional non-linear or kernel parameters were used in SVM to map the high-dimensional data to the higher dimensional space where separation would be feasible. For this type of data, the linear regression model proved to be more efficient than SVM with higher accuracy and precision. The evaluation matrices for both models are given in Table 2 below.

Table 2. Evaluation matrices for machine learning.

Model	Accuracy	Precision	Recall	F1-Score
Linear Regression	90%	94%	89%	91%
SVM	35%	27%	38%	32%

Linear regression exhibited the advantage of high accuracy and precision as compared to the various models of the literature in the optimal placement of EVCSs, as indicated in Table 3 below.

Table 3. Comparison of model with previous studies.

Author	Model	Findings	Reference
Verma et al., 2015	KNN, RFA	79.28% and 84.95% accuracy indicated by KNN and RFA for forecasting household plug-in vehicles.	[42]
Majidpour et al., 2014	KNN	KNN showed better prediction of energy consumption by EVs with 1 h granularity and 24 h horizon of prediction.	[43]
Straka et al., 2020	Logistic regression, GB, RF	All models showed more than 80% accuracy in prediction of CSs.	[44]
Zhang et al., 2018	Fuzzy clustering (FC), LSSVM, Wolf pack algorithm (WPA)	FC-WPA-LSSVM indicated higher forecasting ability of e-bus charging stations load with 2.07–2.29 RMSE	[45]
Ramachandran et al., 2018	Neural networks	0.2–0.3% error in predicting power statistics for individual EVSEs	[46]
Lucas et al., 2019	RF, GB, XGBoost	XGBoost outperformed for estimating idle time on CSs with 1.11 mean absolute error.	[47]
Almaghrebi et al., 2020	XGB, SVM, RF	XGB had greater efficiency in predicting charging demand with RMSE of 6.68 kW/h.	[48]
This study	Linear regression, SVM	Linear regression outperformed in optimized placement of EVCSs with 90% accuracy and 94% precision. This study elaborates on the factors influencing CS demand.	

As Texas is considered the most demanding state for the optimal placement and scheduling of EVCSs, the mapping analysis is carried out to demonstrate the presence of already present stations, and the expected corridors have also been identified where the utilization of the stations will be maximum. Machine learning models, specifically linear regression (LR) and support vector machine (SVM), were utilized to address the challenges of determining the geographical convenience for EVCS placement. The findings suggested the need for fair distribution by installing stations in the underrepresented areas of Texas. Additionally, the analysis considered the present and upcoming corridors in Texas that connect different cities.

This study and its findings can become the basis for stakeholders and petitioners who are willing to develop charging stations to promote the usage of electric vehicles. The study can be further proceeded to identify the optimal placement of EVCSs within all the desired states. This study will open the doors for many other further studies on optimal charging station placement.

6.2. Limitations of Study

The proposed methodology has limitations as well. This strategy did not take into account other important factors like traffic flow and consumer behavior in optimal charging station placement. This strategy indicated the recent general demand for EVCS placement in various smart states of the US. The proposed models have not been utilized to determine the optimal placement in an individual state, but this can be implemented in future studies. Only two machine learning models are used in this study for optimization. Other models can also be implemented for this purpose, and their effectiveness in optimal placement determination can be identified.

6.3. Future Prospects

The proposed models can be implemented in real-world studies due to the advantages they offer. The real-world usage of linear regression in smart cities with vast networks of possible charging station placements is possible due to its ability to be scaled up for larger regions and more data without demanding substantial computational resources. SVM may produce precise predictions for data points that have not yet been seen because it often possesses strong generalization properties. This is crucial when modeling the locations of charging stations across various regions or addressing upcoming modifications to urban infrastructure. This study provides insights into the demand for charging stations in each state and can serve as a foundation for future studies on EV forecasting. Researchers, policymakers, and analysts can utilize the findings for optimized charging station placement in individual states. Furthermore, other machine learning models like KNN, XGBoost, and ANN will be employed to further enhance EV optimal placement and scheduling. By leveraging the power of machine learning, we anticipate building charging networks that are responsive to the evolving demands of both the energy grid and electric vehicle customers, thus improving decision-making and accommodating changing conditions.

7. Conclusions

This study aimed to determine the optimal placement of electric vehicle charging stations (EVCSs) in smart cities by considering various factors in nine selected US states. The investigation focused on factors such as EV percentage, area, population density, EVCS ports, energy demand and production, energy cost, and temperature. Two approaches, including machine learning and graphical analysis, were employed for forecasting and analysis. In order to assess variables and important criteria among the chosen states and their impact on EV placement and scheduling, a graphical analysis was performed. According to the findings, California has the greatest number of EVs and charging stations in the US, while Florida and Texas witnessed the largest increase in EV adoption after California. Based on acreage, energy output and consumption, average income, and temperature, Texas showed the best optimization potential for future EV placement. This graphical analysis will help the petitioners, policymakers, and government officials to consider the trend of EV adoption in different states. By considering these factors for optimal charging station placement, policymakers can give priority to areas with little charging coverage. Strategies can be made to prioritize extending the infrastructure for EV charging in order to meet demand. Machine learning models, specifically linear regression (LR) and support vector machine (SVM), were utilized to address the challenges of determining the geographical convenience for EVCS placement. The LR model demonstrated high accuracy and efficiency in predicting optimal placement and outperformed the SVM model with 90% accuracy and 94% precision. The SVM model helped identify the most crucial factors for optimization, emphasizing the multidimensional nature of the data and the role of each factor in forecasting optimal charging station placement. These models will also support future studies on the optimal placement of charging stations in other regions, contributing to sustainable transportation and low carbon emissions.

This study will help in enabling more sophisticated models for optimal charging station placement and scheduling in future studies. These models can also incorporate real-time data on traffic patterns, electricity demand, and user behavior to optimize the location. Future smart city charging station placement and scheduling will be dynamic, influenced by changing urban planning, increased sustainability consciousness, and technology breakthroughs. The role of EVs and charging infrastructure will become more and more crucial as cities continue to deal with the issues of urbanization and environmental impact, with new possibilities and rising difficulties.

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Abbreviations

Description of all variables.

Variables	Description
EV	Electric Vehicle
EVCSs	Electric Vehicles Charging Stations
EVSE	Electric vehicle supply equipment
EPRI	Electric Power Research Institute
SAE	Society of Automotive Engineers
MILP	Mixed Integer Linear Programming
PSO	Particle Swarm Optimization
ML	Machine Learning
RF	Random Forest
KNN	K-Nearest Neighbor
GB	Gradient Boost
SVM	Support Vector Machine
ANN	Artificial Neural Networks
MAE	Mean Absolute Error
RSME	Root Mean Square Error
TOU	Time of user
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
NHTS	National Household Travel Survey
DOE	Department of Energy
AFDC	Alternative Fuels Data Center
OSM	OpenStreetMap
NOAA	National Oceanic and Atmospheric Administration
TPA	True positive of Class A
TPB	True positive of Class B
TPC	True positive of Class C
TP	True positive
FP	False positive
FN	False Negative
BEV	Battery electric vehicles
PHEV	Plug-in hybrid electric vehicles

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