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Artificial intelligence and machine learning-based decision support system for forecasting electric vehicles' power requirement

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ABSTRACT

Increasing pollution is causing adverse environmental effects, leading to increased interest in combating this issue. There has been a significant interest in minimizing the pollution caused by combustion engine vehicles, with high research and development investments in hybrid and electric vehicle (EV) batteries. The innovations in EVs have a high potential to contribute to an optimized transportation sector while also playing a crucial role in reducing greenhouse gas emissions. This study contributes to the EV industry by precisely predicting the power demand at a particular charging station and identifying the optimal charging station characteristics. We proposed a modified business process based on digital technologies to maximize customer engagement and operational efficiency. Our research has incorporated technologies like artificial intelligence (AI) and machine learning (ML). This study addresses the issues of EV infrastructure facilities, the issues raised by the lack of service features for EVs, and the optimal power requirement for charging stations. The proposed framework has managerial and technological implications, suggesting that the system must promptly receive, store, and analyze substantial volumes of data and demonstrate adaptability in response to environmental factors, such as the availability of EVs and the utilization of renewable energy sources. Despite the challenges, there is potential promise in developing decision assistance systems for electric vehicle power demands based on AI and ML.

1. Introduction

Digital transformation represents a paradigm shift across industries, cultures, and businesses, leveraging innovative digital technologies to drive profound change and adaptation (Issa et al., 2022; Truong and Papagiannidis, 2022). Accordingly, companies are redefining their processes to align with the demands of the digital age, ushering in an era of digital transformation (Zhang et al., 2022; Pereira et al., 2022). This phenomenon extends across various domains, encompassing sales and marketing strategies, delivering exceptional customer service, and migrating towards digital platforms to accommodate the integration of innovative products and their applications (Bakhsh et al., 2017; Muhammad, 2019). The cornerstone elements of digital transformation comprise the reengineering of processes, operations, and client engagements (Wu et al., 2020).

Artificial intelligence (AI) integration into business processes exemplifies digital transformation, as evidenced by various studies (Datta et al., 2023; Kashyap, 2021; Bag et al., 2021). This study explicitly employs AI as the cornerstone technology to drive digital transformation forward, particularly in predicting the demand requirements of charging stations. With the escalating consumption of vehicles, there has been a surge in global demand for fossil fuels (Van Steenbergen and Mes, 2020). Consequently, various sectors have intensified their focus on pollution reduction, driven by heightened concerns about combating the adverse impacts of environmental degradation (McCollum et al., 2017; Varga et al., 2019). One notable initiative in this regard is the development of efficient batteries for electric and hybrid vehicles. These innovative technologies have the potential to contribute to the optimization of the transportation sector and play a crucial role in climate change mitigation, given the reduction in greenhouse gas (GHG) emissions as well as

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air and noise pollution when compared to combustion engine vehicles (Wiriyasart et al., 2020; Reinhardt et al., 2019). Despite the increasing demand for efficient batteries for electric and hybrid vehicles, a significant challenge persists: the lack of comprehensive information on establishing optimized charging stations and accurately forecasting power requirements across different timeframes. Researchers have introduced performance metrics to address this issue and enhance our understanding of the design prerequisites for optimized charging stations (Baars et al., 2021; Groenewald et al., 2017).

The growing acceptance and production of electric vehicles (EVs) have positively impacted various aspects of building an EV ecosystem. Prior research has highlighted several improvements, including the expansion of public charging infrastructure, a notable rise in government initiatives supporting EV projects, decreased production and maintenance costs of EVs, and increased awareness regarding the consequences of global warming (Love et al., 2018; Karmaker et al., 2018; Adeyanju et al., 2018; Sankaran and Venkatesan, 2021). Car rental companies, such as Uber, Europcar, and Hertz, also contribute to EV market expansion by introducing zero-emission vehicles in their fleet (Khalfaoui et al., 2022). The transition from gasoline-powered vehicles to electric vehicles (EVs) has increased demand for EV batteries (Mohanty and Kotak, 2017; Singh et al., 2021). This rapid growth in the EV sector has spurred the development of a diverse range of customizable EV battery products tailored for various vehicles, including trucks, buses, loaders, and excavators. Consequently, this expansion contributes to the increased demand for products within the transportation and construction industries (Ghiassi-Farrokhfal et al., 2021; Zhdanov et al., 2022). Conventional energy sources, including wood, coal, charcoal, petroleum, gas, oil, and uranium, are employed to fulfill energy demands.

Amid concerns regarding finite energy resources, endeavors are underway to optimize energy utilization, leading to a progressive reduction in reliance on fossil fuels. Concurrently, there is a notable uptick in demand for renewable energy sources like hydro, solar, biomass, and geothermal (Bakhsh et al., 2017; Muhammad, 2019). The shift towards renewable energy resources has led to compatibility and new applications in the automotive industry, particularly in the EV segment. Li-ion batteries have emerged as the most suitable substitute for fossil fuel energy, and a similar trend has been observed in the adoption by industrialists, government bodies, and others (Gao et al., 2024; Yang et al., 2023a; Yang et al., 2023b; Sankaran and Venkatesan, 2021). In addition, government initiatives to familiarize the market with EVs contribute to increased product demand (Pal et al., 2021; Kumar et al., 2021; Vidhi and Shrivastava, 2018). Moreover, purchasing EVs supports the government's provision of various incentives and financial aid for the EV battery market.

This study is driven by the objective of developing an AI and machine learning (ML) model aimed at identifying critical influencers in charging stations. The study proposes optimized parameters for establishing charging stations by government policies to achieve this goal. In the initial phase, data collection for ML techniques is conducted, followed by the sequencing of parameters to prioritize the most influential factors in charging station setup. The subsequent phase involves forecasting the demand for these charging stations. The study presents an optimized model incorporating essential parameters for setting up optimal charging stations through these steps. These parameters encompass factors such as frequency, recency, and the division of total costs incurred during unplanned outages by the number of occurrences. Additionally, the study utilizes a numerical example from the EV market to illustrate the proposed method for selecting the necessary charging station features and determining their optimal periods.

After a thorough review of existing literature, it becomes evident that developing a decision-making model is crucial for configuring the features of EV charging stations and accurately estimating the required power, all while considering environmental concerns. To bridge this gap, this study proposes a pioneering decision-making model to select optimal EV charging station features and predict the power needed to cater to consumers. More specifically, an optimization model was employed within the framework of the Indian EV charging station industry. The primary objectives of this study were as follows:

- To propose a method that identifies the optimal features of EV charging stations while assigning customer segments using the RFM approach. This model integrates EV charging station features with customer preferences.
- To integrate the research findings and forecasting techniques for timely delivery, eco-friendly standards, cost reduction, and improved recharging station efficiency.
- To propose an innovative approach that accounts for multiple factors and obtain accurate predictive solutions by applying forecasting models.

The paper is organized into six sections after the introduction. Section 2 conducts a detailed literature review. Section 3 delineates the various challenges. Section 4 offers insights into model development and establishes the study's framework. The applications of the model and resulting insights are presented in Section 5. Lastly, Section 6 concludes the study, addressing its limitations and proposing avenues for future research.

2. Literature review

The primary structure of this literature review is divided into four sections.

2.1. Eco-friendly power requirement

Over the years, traditional resources such as wood, coal, charcoal, petroleum, gas, oil, and uranium have been utilized to satisfy energy demands (Jauhar et al., 2022). Efforts have been made to optimize energy consumption to address concerns regarding insufficient energy resources and environmental degradation. As a result, over time, there has been a decline in the utilization of fossil fuels and an increase in demand for renewable energy sources, such as wind power, hydropower, solar power, biomass, and geothermal heat power (Bakhsh et al., 2017; Muhammad, 2019). This development has fostered resource compatibility and facilitated the application of these resources in the automotive industry, particularly in the EV segment. The Li-ion battery segment has emerged as a promising alternative for substituting fossil fuel energy, presenting opportunities for optimal resource utilization. Similar trends have been observed in other sectors, including the manufacturing and agriculture industries (Gao et al., 2024; Yang et al., 2023a; Yang et al., 2023b; Sankaran and Venkatesan, 2021).

Replacement strategies for using eco-friendly fuels have begun in various industries, including the automotive sector. Li-ion batteries are among the best discoveries in the EV-based automobile segment (Deng, 2015; Nitta et al., 2015). The current research studies have mainly focused on the adoption of EVs and the viability of recharge stations, not paying much attention to the characteristics of a battery charging station based on the needs of users (Van Steenbergen and Mes, 2020; Ghiassi-Farrokhfal et al., 2021).

Since the introduction of EVs in India was delayed relative to other countries, there was a lack of awareness about electric mobility technology, resulting in a customer preference for fuel-based vehicles (Murugesan et al., 2021; Jauhar et al., 2022). Moreover, in India, customers prefer cost-effective parameters, such as mileage, so the researchers here are conducting numerous studies to increase the single-charge range of EVs (Pereira et al., 2022).

Indian customers are becoming increasingly aware of the necessity to conserve energy and address climate change concerns. Consequently, Indian customers have begun to utilize green energy, reducing pollution levels (Jauhar et al., 2023; Pratap et al., 2022). Government agencies have started implementing various plans in this direction because electric transportation results in zero-emission vehicles (Zhang et al., 2022; Pereira et al., 2022). This study focuses on developing AI and ML models to identify critical factors for implementing charging stations. The model begins with creating a data mining model and ranking the influential parameters. The parameters are then used in time-series forecasting to predict the EV's power requirement.

2.2. EV adoption

Numerous scenario-based studies have examined consumer behavior regarding EV adoption. Jaiswal et al. (2021) studies consumer behavior in the Indian market using the 'Technology Acceptance Model' (TAM). Attitude, usefulness, usability, and risk were examined with financial incentive policy as a moderator. The findings showed that attitude partially mitigated the influence of usefulness and usability on adoption intention. Moreover, the customer's perspective is based on cost-effective parameters, such as fuel economy and cost-effectiveness, which is why Indian researchers are conducting numerous studies to increase the single-charge range of EVs (Wu et al., 2020; Ghiassi-Farrokhfal et al., 2021).

Studies by Wang et al. (2017), Zhang et al. (2018), and Dong et al. (2020) found that various factors such as vehicle number plates, government subsidies, environmentalism, and social innovator symbolism can affect customer intention for EV adoption. They found that, in the current scenario, most of these parameters positively impact the increased use of EVs, with long-term forecasts indicating positive outcomes.

Artificial intelligence and ML applications have proven effective in numerous fields. These techniques have been used to enhance and assess tasks in new applications (Van Steenbergen and Mes, 2020; Ghiassi-Farrokhfal et al., 2021). Numerous factors affect the performance of EV charging stations. The primary objective of this study was to apply AI and ML techniques in the context of customer development while considering environmental factors. Therefore, we focused on identifying the most influencing factors by employing AI and ML techniques, thereby determining the best practices for EV charging stations (Zhdanov et al., 2022; Zhang et al., 2022; Pereira et al., 2022).

Many frameworks have been established to study EV adoption. The most common framework is the Theory of Planned Behavior (TPB) (Ajzen, 1991). This social psychological theory explains how people form intentions to accomplish something and how those intentions become actual conduct. The Diffusion of Innovation (DOI) theory explains how people and organizations adopt new items and technologies (Rogers, 2003). Value-belief-norm (VBN) theory explains how values, beliefs, and norms affect behavior (Venkatesh et al., 2003).

TPB, DOI theory, VBN theory, and TAM are widely used to study EV adoption. The hypothesis based on these theories has a different focus and emphasizes different adoption aspects. The TPB proposes that attitude, subjective norms, and perceived behavioral control affect purchase intentions. A person's attitude towards the invention is either positive or negative. A subjective norm is an individual's view of what others think is essential. Perceived behavioral control is a person's confidence in accepting innovation. The DOI theory examines the adoption of social technologies. This approach divides adoption into five stages: knowledge, persuasion, decision, implementation, and confirmation. The knowledge step involves discovering an invention. The persuasive stage occurs when someone forms an opinion about the idea. Individuals decide whether to accept innovation at the choice stage. Individuals evaluate their acceptance of innovation through confirmation (Khalfaoui et al., 2022).

The VBN theory examines values, beliefs, and norms. According to this notion, values are terminal, instrumental, and beliefs. Terminal values represent an individual's ideal end-state. Individuals' opinions on how to achieve their goals are called instrumental values. A person's worldview reflects their beliefs. The TAM evaluates a person's attitude towards new technology and its perceived ease of use. Individuals' views on the technology's usefulness and ease of use determine their attitudes. Ease to use is the person's belief that they can easily use the technology.

2.3. Use of AI and ML to identify the influencing factors

The effective use of data provides diverse insights (Allal-Chérif, 2022). With the increased number of charging stations, research is being conducted to determine their significant influence on power distribution demand and improve its dependability (Yusuf et al., 2019; Jahangir et al., 2019). Numerous studies have analyzed private and public charging station data to investigate their effects on power distribution. Consequently, these studies have utilized GPS monitoring systems, surveys, and other methods to collect user information. (Wang et al., 2017; White and Sintov, 2017).

Based on their findings, the studies predicted that the total energy demand would rise in areas with rising demand, such as residential areas (Li et al., 2020; Trappey et al., 2021). In addition, demand is anticipated based on the unique characteristics of charging stations. This model comprises two modules: classification and forecasting. These modules were used to forecast the daily EV charging-demand profile based on geography and client variables. Similarly, to predict the power requirement and meet the increasing demand of customers, it is necessary to have a demand forecast so that the supply and demand cycle functions at the optimal rate throughout the period (Ghiassi-Farrokhfal et al., 2021; Zhang et al., 2022).

The data mining process generates the EV charging demand profile, which can then be used for various purposes, including predicting or forecasting the demand for power for a given period and working on the influencing factors. Forecasting demand is a method of estimating the range of demand that may occur in the future. Forecasting models have been used in different sectors to predict demand, such as a highly accurate deep learning method for AI-based tourism demand (Zhang et al., 2022), forecasting the monthly water demand based on previous consumption, and understanding passengers' travel demand to improve taxicab utilization and reduce costs (Zhang et al., 2018). Table 1 highlights the most significant studies and contextualizes this work within the context of prior research.

These studies have utilized historical and current data, sometimes complex, to estimate future demand and supply trends. Quantitative projective forecasting estimates future sales based on past data is the most common forecasting method (Gorji et al., 2021; Pillai et al., 2022; Baryannis et al., 2019). This method frequently employs moving average, exponential smoothing, auto-regressive integrated moving average, and the multiple aggregation prediction algorithm to obtain complex mathematical formulas (Díaz et al., 2018; Kohl and Gomes, 2018). In this study, we used exponential smoothing to forecast values using weighted averages of historical data. As we advance over time, the weights are adjusted. This implies that more significant considerations are given to recent observations.

2.4. Research contribution

The Indian EV market is divided into four segments: passenger vehicles, commercial vehicles, two-wheelers, and three-wheelers. The Indian government has launched several initiatives to promote the production and acceptance of EVs, to achieve reduced emissions following international treaties, and to develop e-mobility in the face of urbanization. The present study makes the following contributions.

1. Reviewing the relevant literature, this study determines the eco-friendly power requirements in India and the possibility of using renewable resources for charging station energy consumption.
2. Identify the current ideology behind EV adoption in India, observe trends that have impacted adoption, and determine the viability of various product variations within the R&D division.

Table 1
Previous research studies.

Author(s)	Methods	Type of Product	Multi-period
Srinivasulu et al. (2009)	DM	IT industry	–
Asmatulu et al. (2013)	Literature review	Aircraft Industry	–
Goli et al. (2022)	GAMS 22.9 software package	–	–
Kisomi et al. (2016)	Robust optimization	–	–
Amin et al. (2017)	MILP, decision tree	Tire	✔
Chen et al. (2022)	MILP	Solar energy	–
Shahriar et al. (2021)	ML	EV	–
Tosarkani and Amin (2018)	Fully fuzzy linear programming, fuzzy ANP	Battery	✔
Díaz et al. (2018)	Mechanical characterization	Cable industry	–
Kohl and Gomes (2018)	European Directive 2102/19/EU	Motherboards	–
Baryannis et al. (2019)	ML, Prediction	–	✔
Pillai et al. (2022)	Literature review	Automobile Industry	–
Zhang et al. (2022)	DF	Tourism Industry	–
Gorji et al. (2021)	Game-theory Approach	Automobile Industry	✔
Malinauskaite et al. (2021)	Literature review	Automobile Industry	–
Our Paper	DF, ML	EV	✔

Abbreviations: Mixed integer linear programming (MILP), Analytics network process (ANP), Demand Forecasting (DF), Data Mining (DM), Machine Learning (ML).

3. Using AI and ML techniques, we introduced a novel and effective method for determining the best features of EV charging stations and then allocating customer segments based on the RFM strategy. This new model configuration combines the features of EV charging stations with customer preferences.
4. With demand forecasting tools, we intend to pursue objectives such as on-time delivery rate, green model practices, cost reduction, and charging station efficiency optimization.

Advancements in the EV sector have resulted in many EV charging stations. The attributes required for charging stations are currently not addressed efficiently; therefore, this study focuses on these issues, predicts the demand based on the optimized characteristics, and provides insights by employing forecasting models such as Exponential Smoothing Models to obtain accurate predictive solutions.

3. Problem identification

According to a recent study, the automobile industry is a significant contributor to pollution, with this sector accounting for 27 %, crop burning for 17 %, and domestic cooking for 7 %, resulting in the deaths of over 2 million Indians due to air pollution (Zhang et al., 2022). In India, traffic congestion is a severe issue in Tier 1 cities and towns because of the large number of commercial vehicles on roads.

India's plan to reduce air pollution in the coming years includes using more electric buses and modernizing fossil fuel engines to meet the minimum requirements for a pollution-free environment. By 2023, EVs are projected to account for 25 % of Indian households and renewable energy is expected to be a primary power source. Vehicles older than 15 years or without BS6 emission regulations are prohibited on city streets. Based on data from Huang et al. (2018), and Habib et al. (2015), we derive Fig. 1, depicting the primary factors driving the upward trend and growth of EVs. Consequently, an increase in the viability of each parameter leads to an increase in the number of EVs on the road.

The adoption of EVs is rapidly increasing as governments and businesses worldwide attempt to lessen their reliance on fossil fuels. The worldwide EV fleet surpassed 10 million in 2020 and is expected to reach 145 million by 2030. More EVs are putting pressure on power systems (Liu et al., 2022). EVs require considerable power to charge their batteries. EV power requirements must be accurately predicted to minimize their impact on the power system. AI and machine-learning-based decision support systems make this possible. AI and ML decision support systems can forecast EV power requirements using historical and real-time data. These data can be used to optimize the electrical grid and ensure that the demand is satisfied (Ding et al., 2022).

Several recent studies have focused on AI and ML decision support systems (DSS) for EV power forecasting. Wang et al. (2022) created a deep learning-based DSS for estimating EV power demand. The DSS predicted the demand for EV power to be within 5 %. Zhang et al. (2022) published a data-driven DSS for EV power usage forecasts to be within 3

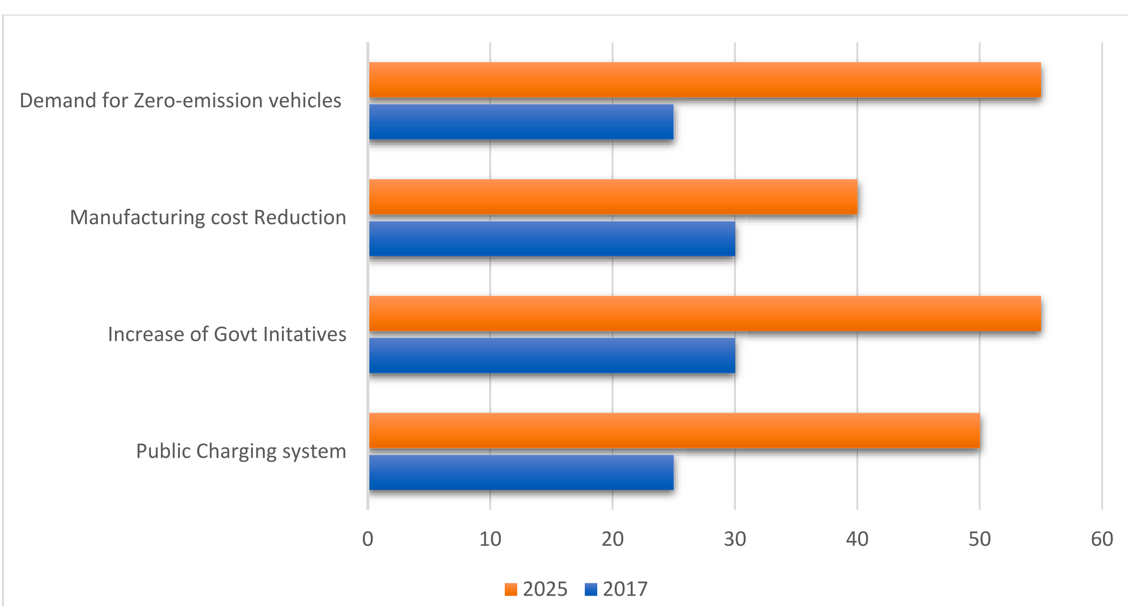

Fig. 1. Factors for customer adoption of EV.

%. Liu et al. (2022) developed a deep learning-based DSS for EV charging schedules. According to the study, DSS lowered the peak power grid load by 10 %. Chen et al. (2022) developed a model to forecast the hybrid EV power consumption utilizing deep learning and the grey wolf optimizer. According to the study, this approach increased the EV power demand estimations by 10 %.

Forecasting EV power consumption using AI and ML DSSs remains difficult despite recent advances. Among the difficulties is data availability; accurate forecasting necessitates a large amount of data on EV charging activity. Such data is difficult to obtain because it is rarely captured or stored centrally. The problem's complication: Forecasting is challenging due to the large number of EVs on the road, the time of day, and the weather. AI and ML DSSs require real-time data like power grid conditions and weather forecasts. This information is difficult to obtain and process in real-time.

AI and ML DSS research on EV power forecasting is promising. Addressing the challenges above can assist researchers in developing more accurate and efficient forecasting models to reduce the power grid impact of EVs.

The present study focuses on developing a model that incorporates the influence of entities on the behavior of service/charging stations and forecasting demand based on the same entities of the predictive model. This study uses AI and ML models to characterize charging stations. The model commences with the development of AI and ML models, followed by the application of parameter ranking. The parameters are then utilized in time-series forecasting to predict the optimization model for maximizing profit and implementing practices and technology for on-time delivery while minimizing cost factors and defective products.

4. Research methodology

Fig. 2 illustrates the methodology employed in this study, which introduces a novel and effective method for determining the most desirable characteristics of EV charging stations and then allocating customer segments based on the RFM strategy. This new model configuration combines the EV charging station characteristics with customer preferences. In the second phase, we combine the research findings with forecasting methodologies to achieve objectives such as on-time delivery rates, green model practices, cost reduction, and maximum charging station efficiency. This novel strategy considers several significant factors simultaneously. The outcome is used to generate insights by employing forecasting models such as Exponential Smoothing Models to produce predictive solutions.

4.1. Problem identified

Considering the government's desire to preserve the environment, EVs must be widely adopted throughout India. Consequently, various measures for establishing charging stations have been implemented following different international practices. Typically, stations are erected without maintaining the necessary features, resulting in various issues, such as the provision of delayed services and the maintenance of sufficient power across locations. Consequently, this study focused on the problems faced by customers.

4.2. Data parameters

Table 2 presents the data parameters extracted from the dataset. Based on the dataset parameters, we generated several graphs to comprehend the value distribution of the dataset. Fig. 3 demonstrates that weekdays require significantly more energy than weekends. Consequently, most EVs are used for transportation to and from offices, colleges, and other official activities.

Fig. 4 shows that non-festival months have the highest power demand compared to Festival months. As a result, most EV usage occurs during the working months, while people tend to travel less during the holiday season. Fig. 5 demonstrates that evening hours have the highest power demand compared with morning hours. Consequently, most EV usage occurs during work hours.

Fig. 6 illustrates the power demand distribution based on weather conditions. Service centers, workplaces, and hotels have the highest energy demands compared to other locations, as shown in Fig. 7. As a result, most EV usage is for day-to-day activities such as commuting to and from the office, college, and other official activities.

Fig. 8 depicts the annual distribution of electrical demand. The distribution of electrical demand for EVs has rapidly increased in recent years. The share of electric cars in total sales has significantly increased,

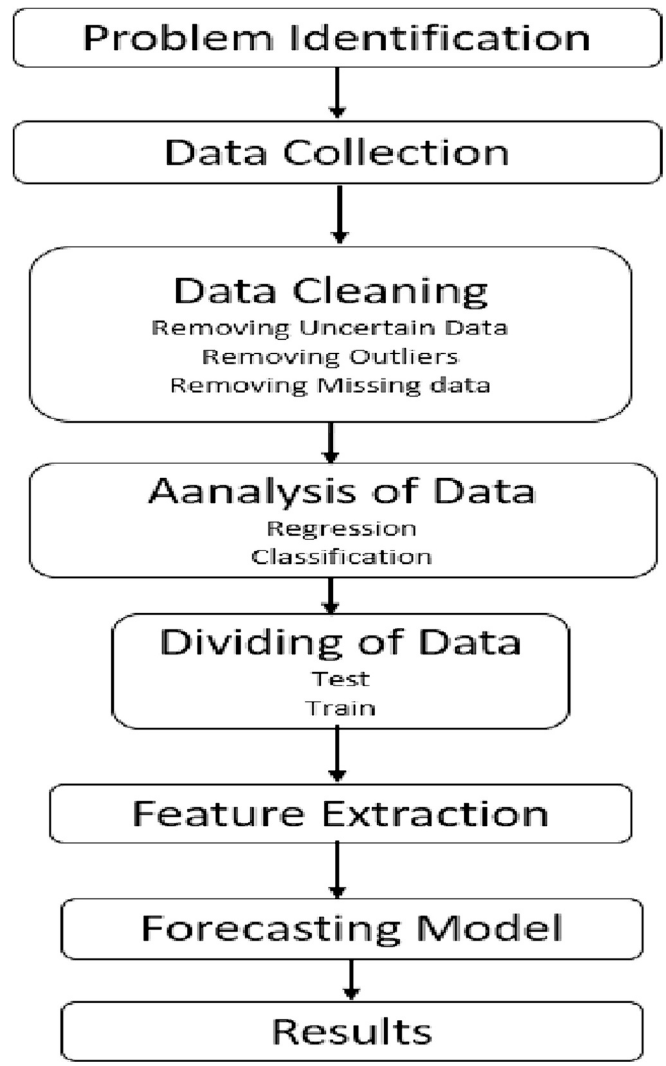

Fig. 2. The proposed framework of the research.

Table 2
Parameters of the dataset obtained for the study.

ID	minutes available
Connectedweekday	User Management
ConnectionDate	Billing Speed
Weather	Certification Level
kWhDelivered	Services
stationID	Workforce level
Location	Costing
userID	App Usage
WhPerMile	Plugin
kWhRequested	Charging Speed
milesRequested	Location rating

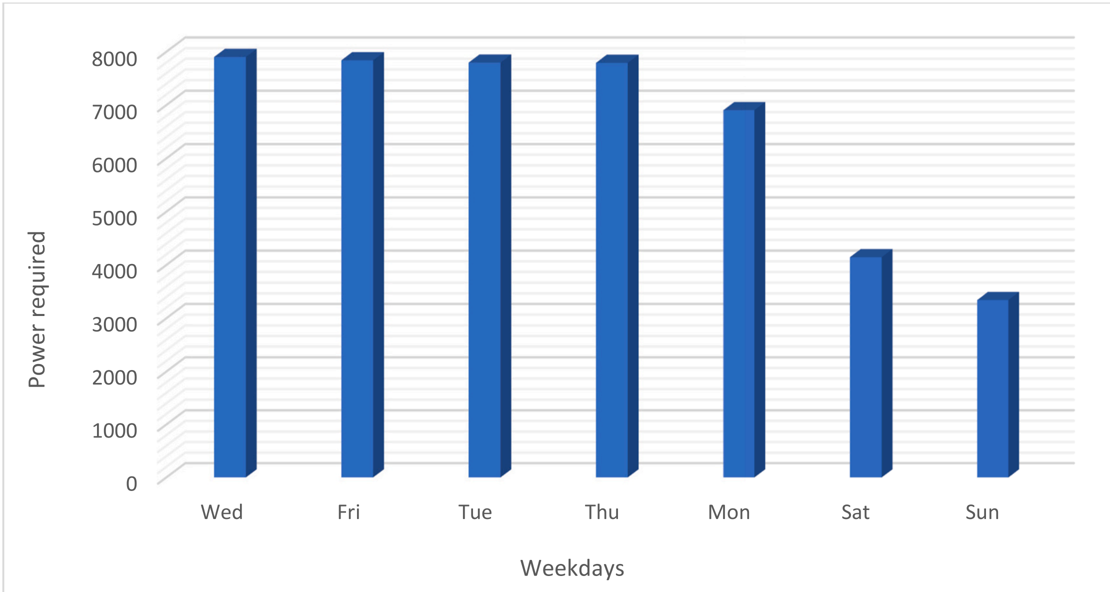

Fig. 3. Distribution of power demand according to weekdays.

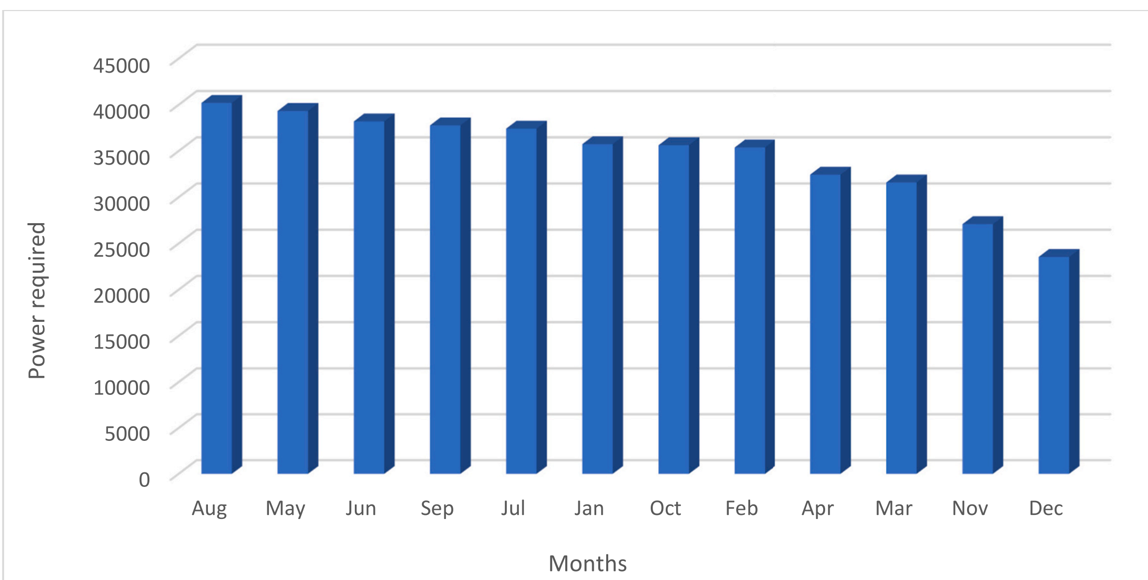

Fig. 4. Distribution of electrical demand by month.

reaching around 14 % in 2022 to approximately 4 % in 2020. Global sales of electric cars have been rising significantly, with 2 million sold in the first quarter of 2022, indicating a growth of 75 % compared to the same period in 2021.

4.3. Data collection and cleaning

The data used in this analysis were obtained from the ACN-Data source and Kaggle, which are publicly available data sources. The dataset contained 45,729 values from 2017 to 2021. The data cleansing process began by removing any uncertain data, such as negative charging times and booking dates, that were later than the arrival date. Additionally, any charging times less than 10 min and missing data values were eliminated as outliers.

The meticulous accumulation and data purification is indispensable for constructing an accurate and efficient decision support system that predicts the power requirements of EVs using AI and ML. These actions are essential to guarantee the trustworthiness and exactness of the proposed model. The research involved a stringent and methodical strategy for collecting data, in which pertinent observations and measurements were systematically gathered from various sources. Historical data on the power consumption of EVs and information on weather conditions, charging practices, and other relevant factors influencing power requirements were collected. The combination of qualitative and quantitative data was the foundation for this study's analysis.

A thorough data-cleaning procedure was implemented to improve the integrity of our dataset. The process encompasses six essential stages: Erroneous Data Removal refers to identifying and eliminating flaws and inconsistencies within a dataset, aiming to ensure the integrity and reliability of the results obtained from data analysis. By identifying and removing erroneous data, researchers can minimize the potential for skewed or biased outcomes arising from unreliable information.

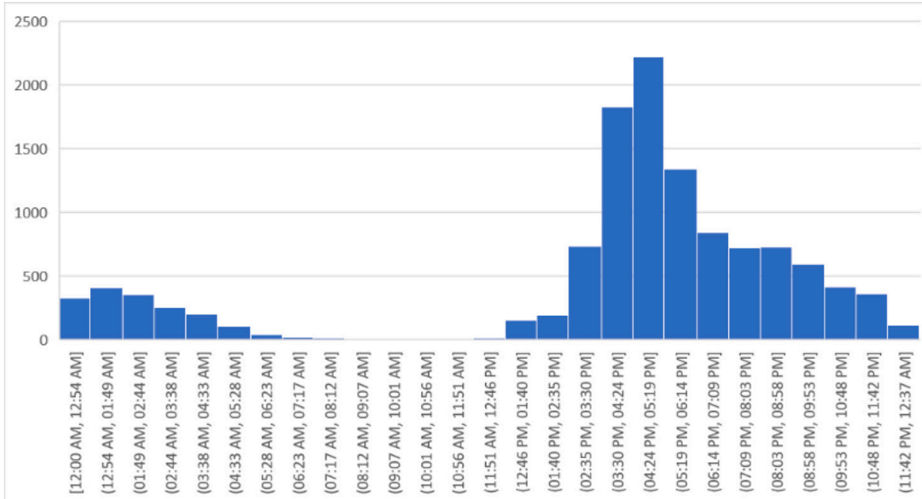

Fig. 5. Distribution of energy demand considering the time.

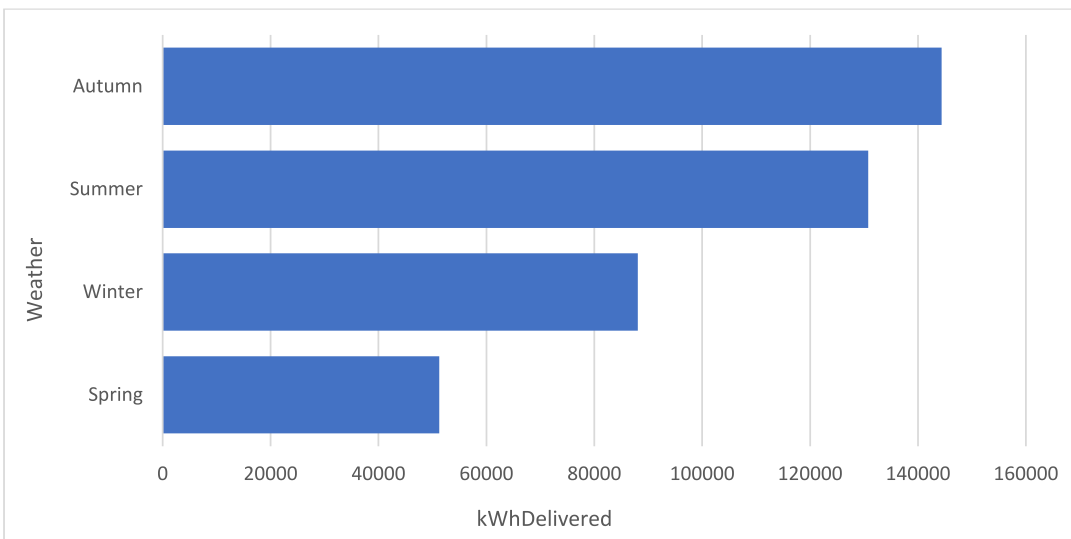

Fig. 6. Distribution of required power according to weather conditions.

Addressing Missing Values: Implementing strategies to handle missing data points while maintaining the integrity of the dataset. A consistency check refers to the process of ensuring uniformity in data presentation and the use of standardized units of measurement. Duplicate Removal: The process of identifying and eliminating duplicate records to mitigate data redundancy and outlier handling involves the application of several strategies aimed at mitigating the impact of outliers, which have the potential to introduce distortions in the study; normalization refers to the process of converting data onto a standardized scale to enable equitable comparison and analysis.

The meticulous data cleansing procedure was crucial in preparing our dataset for analysis, enhancing predictive accuracy and reliable insights. Through rigorous adherence to these procedures, we successfully generated a superior quality dataset, which formed the fundamental basis for our decision support system utilizing AI and ML techniques. Including references obtained from the search results, specifically those about data collection and cleaning, significantly enhanced our approach and comprehension, facilitating the successful execution of these pivotal stages.

4.4. Machine learning methods

Fig. 9 depicts how the model's first phase establishes the correlation between several distinctive traits examined for feature selection. We uncovered a substantial relationship between all variables, but the most significant association was between the certification level and charging station parameters, such as charging speed and workforce. The correlation quantifies the linear relationship between variables and aids in identifying the importance of the characteristics. The Pearson correlation coefficient and heatmap visualization are two popular methods.

Correlation-based feature-selection algorithms discover important traits by combining correlation measures with search heuristics. Advanced techniques use filter-based procedures to assess underlying data qualities, such as feature correlation. Feature selection requires selecting a subset of the most relevant features while removing redundant or noisy features. Making correlation plots, for example, aids in determining the links between features. Finally, these approaches guide the selection of informative features in machine-learning applications to increase model performance and interpretability. Fig. 10 depicts how we used density plots to examine the distribution of a variable in a dataset and observed that the data points followed a continuous pattern.

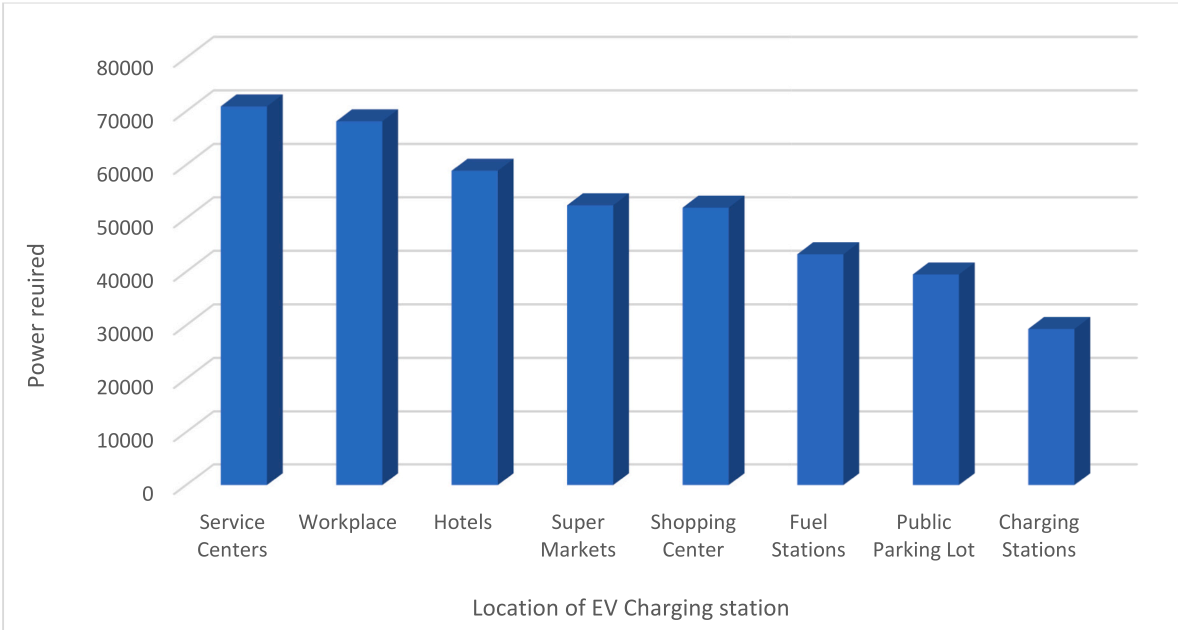

Fig. 7. Location-dependent distribution of power demand.

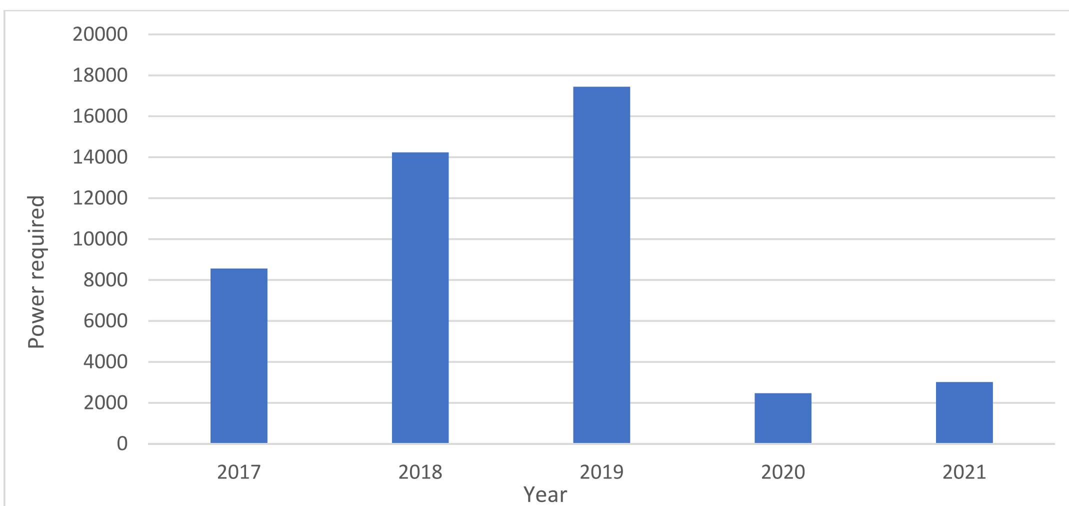

Fig. 8. Distribution of electrical demand by the year.

In supervised ML, classification is a common strategy for categorizing data points. It enables the organization of various datasets, including complex and massive datasets and small and fundamental datasets. The primary objective of an early classification strategy is to classify incomplete time series as quickly and precisely as possible. Numerous techniques for classifying early time series have been developed in recent years. Due to the diversity of approaches to the early classification problem, a comprehensive examination of the existing solutions is necessary to determine the field's status. Several potential applications of early categorization utilizing Univariate Time Series (UTS) or Multivariate Time Series (MTS) have been outlined in the literature (MTS). An MTS consists of numerous correlated time series collected for a particular event over a specific time. Several crucial application scenarios are listed below.

- Early classification identifies ongoing activity before completion. This early classification enhances user experience by accelerating the system's response time. The researchers used the MTS to characterize various human activities, such as walking, jogging, sitting, ascending stairs, and eating.
- An electrocardiogram (ECG) is a time-lapse sequence of cardiac electrical impulses. Multiple electrodes were frequently placed on the patient's chest to record an electrocardiogram time series. Early electrocardiographic classification (Ebrahimi et al., 2020) facilitated early detection of irregular heartbeats and lowered the risk of heart failure.
- Modern vehicles are equipped with various sensors. Therefore, it is possible to monitor the driver's demeanor, road surface condition, interior-exterior environment, and other parameters using sensory data. Shajalal et al. (2023) describe an early classification system that classifies the type of road surface using accelerometers, light, and temperature sensors. If the road surface could be of better quality, such as being bumpy or rough, a quick inspection can help choose an alternate route.

This response aims to provide specific instances of the application of

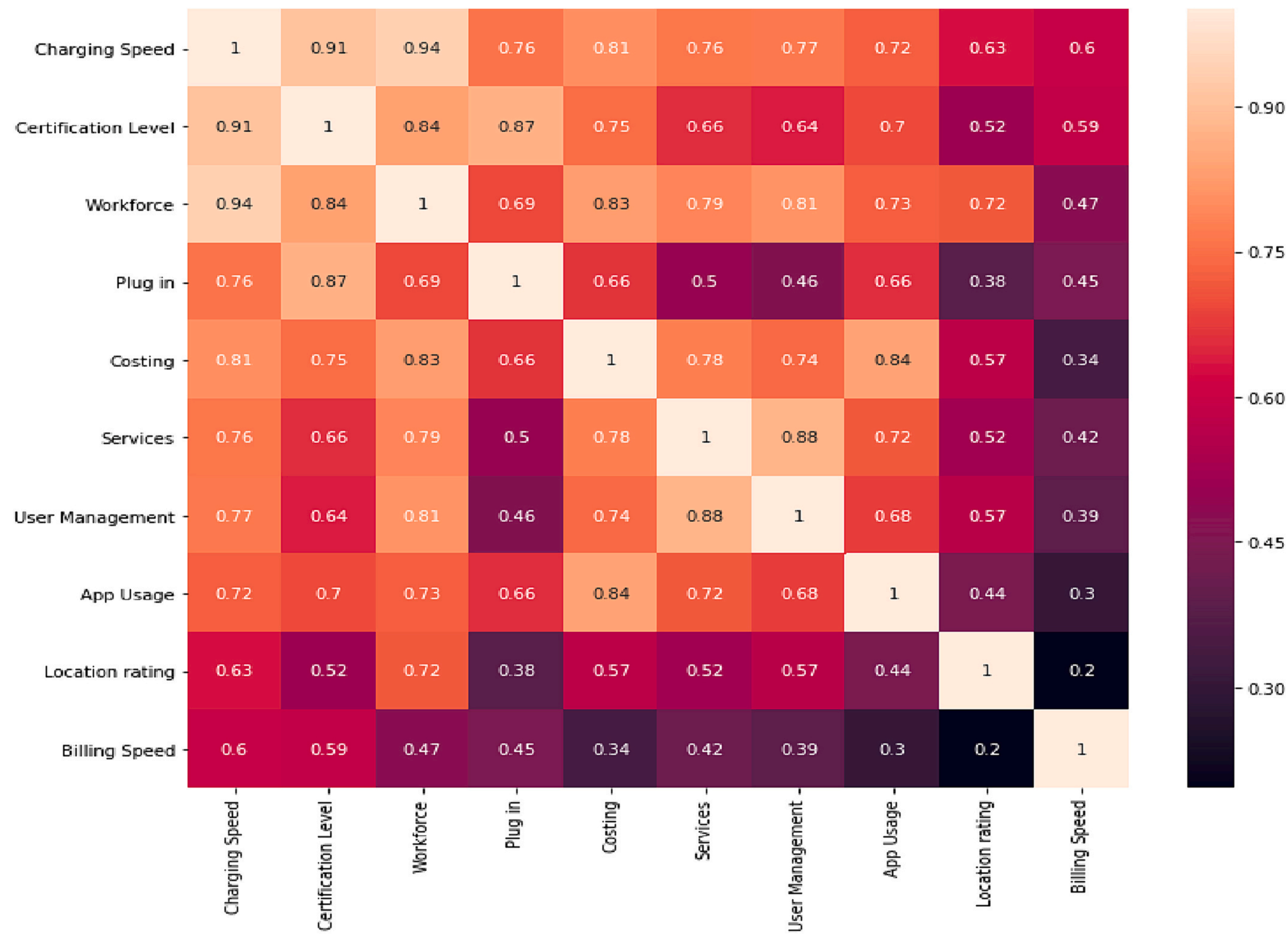

Fig. 9. Correlation between various charging station parameters.

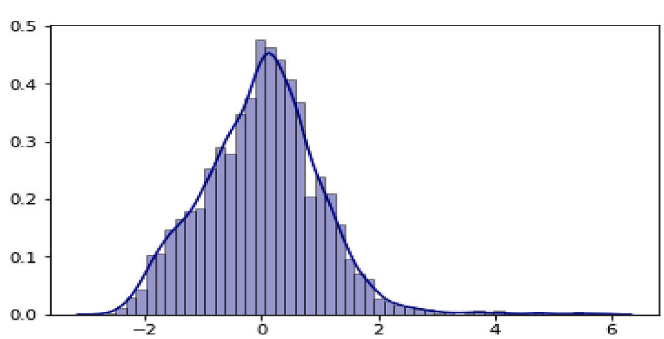

Fig. 10. The variable distribution of EV charging stations.

univariate time series (UTS) and multivariate time series (MTS) in the academic literature concerning the EV charging station dataset. These studies primarily focused on using AI -and ML-based decision support systems to forecast EVs' power requirements.

In a study conducted by Dong et al. (2020), the power demand of an EV charging station was forecasted using a univariate ARIMA model. The model's training involves utilizing past data about the power demand exhibited by the charging station. The model successfully generated power demand forecasts, achieving accuracy with an error rate of less than 5 %. This study aimed to investigate the impact of social media on mental health.

In a recent investigation conducted by Zhang et al. (2022), a multivariate long short-term memory (LSTM) model was employed to predict the power demand of an EV charging station. The model training utilized past data on the power requirement of the charging station, weather conditions, and the number of EVs present in the vicinity. The model successfully predicted the power demand with an accuracy rate of less than 3 %. Liu et al. (2022) employed a hybrid approach integrating a univariate autoregressive integrated moving average (ARIMA) model with a multivariate long short-term memory (LSTM) model to predict the power demand of an EV charging station. The predictive algorithm successfully projected the power demand with an accuracy rate of less than 2 %.

The instances above illustrate the utilization of Univariate Time Series (UTS) and Multivariate Time Series (MTS) methodologies in the scholarly literature about the dataset of electric car charging stations. These studies aimed to investigate the efficacy of AI -and ML-based decision support systems in accurately predicting the power demands of EVs. Appropriate methodologies are selected based on the dataset's characteristics and research inquiry.

In addition to the studies above, several other investigations have employed Universal Time Series (UTS) and Multivariate Time Series (MTS) methodologies to predict the power demand of EV charging stations. These investigations have employed various methodologies, encompassing ARIMA, LSTM, SVM, and random forests. The findings of these investigations indicate that the UTS and MTS have the potential to yield accurate predictions regarding the power consumption requirements of EV charging stations. However, the optimal approach depends on the dataset under consideration and the unique research inquiry.

In ML, many classifiers, such as logistic regression, allow a model to predict the likelihood of a specific event or class. Logistic regression was used when the predicted variable was binary, all predictors were independent, and there were no missing data values. Linear regression is a regression approach that employs supervised learning. Independent variables were used to model the prediction value. Its primary purpose is to establish the relationship between forecasting and variables. In data mining, a decision tree is the most reliable categorization tool. This is a flowchart of the tree shape. Each internal node in this diagram represents a conditional test, and each branch indicates the result of the conditional test (true or false). The leaf nodes of the decision tree were labeled with appropriate classes. Using a decision tree, we divided the data into multiple groups. The random forest classifier adapts decision trees to different subsamples from various datasets. The average was used to increase the forecast accuracy while avoiding overfitting.

Using multiple regression, we determine the significant variables to be 'Weather _Summer,' 'kWhRequested,' 'Services,' 'Location Hotels,' 'userID,' 'Costing,' 'WhPerMile," minutes Available,' and 'spaceID.' However, because regression focuses on weather and location, we employ a different technique, such as classification. Because the location is the most critical parameter, we explored the location parameters to determine the other crucial parameters for establishing an EV charging station. In addition, we categorized the parameters according to three segments.

parking = ["Workplace," "Shopping Center," "Super Markets," "Hotels"].

specific = ["Charging Stations," "Fuel Stations," "Public Parking Lot"].

repairs = ["Service Centers"].

The classification distribution was plotted to determine whether it followed a normal distribution. As a result, we plotted graphs like Figs. 11, 12, and 13 for the various location-based classifications. The classification distribution is a graphical representation of the probability density function of a dataset. This tool facilitates the visualization of data distribution and enables the identification of trends or outliers.

The normal distribution, or Gaussian distribution, is a symmetrical probability distribution frequently employed to represent the data distribution. A bell-shaped curve characterizes it. These two parameters were determined based on the mean and standard deviation. The mean represents the arithmetic average of the dataset, whereas the standard deviation serves as a metric for quantifying the dispersion or variability of the data. To visualize the distribution of the classification, it is necessary to compute the mean and standard deviation of the dataset. The distributions presented in this study were developed using the Python statistical software.

After obtaining the values of the mean and standard deviation, it becomes possible to generate a graphical representation of the probability density function associated with the dataset. The probability density function (PDF) is a mathematical function that quantifies the likelihood of a specific value occurring within a given probability distribution. A Gaussian function is a mathematical function representing a normal distribution graphically. The Gaussian function, the normal distribution, is a symmetrical probability density function characterized by its bell-shaped curve. It is mathematically described by the mean and standard deviation, which determine the central tendency and spread of the data, respectively.

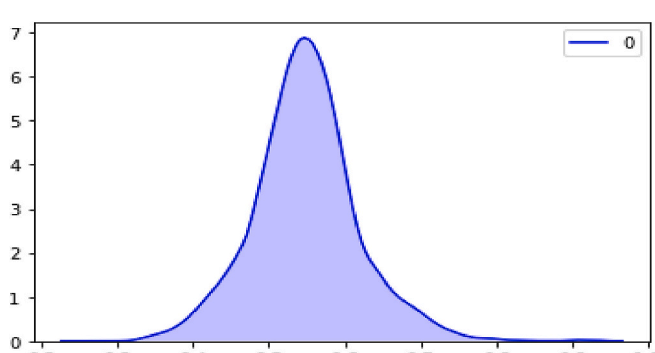

Fig. 11. Parking parameter distribution of EV charging stations.

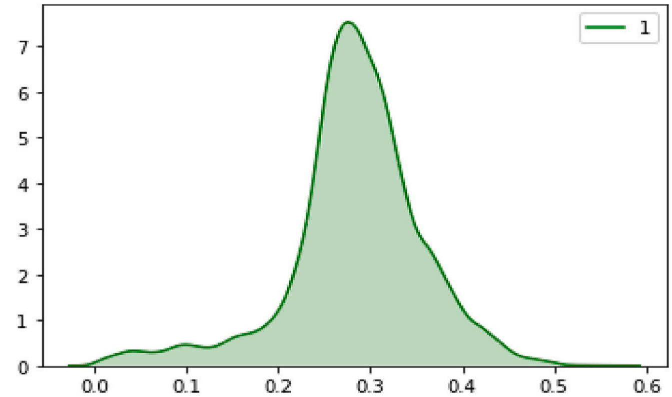

Fig. 12. Distribution of specific charging station parameter.

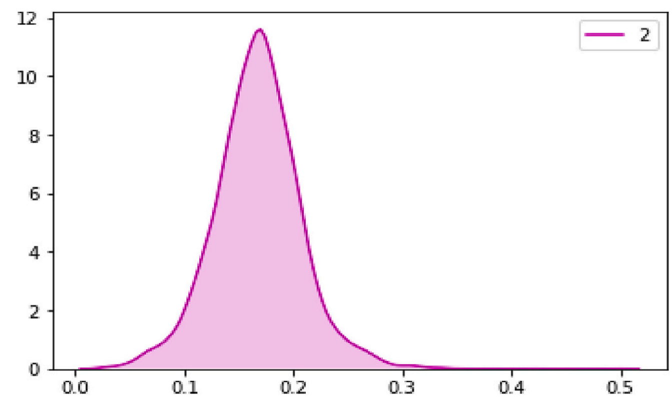

Fig. 13. Distribution of EV charging station repair parameter.

As shown in Fig. 14, the features are ordered from the most to the least significant. We predicted the required power in these regions based on the significance of the parameters. The inclusion of location-based parameters is essential for the prediction of the power demand for EVs. These parameters can be classified into three distinct categories:

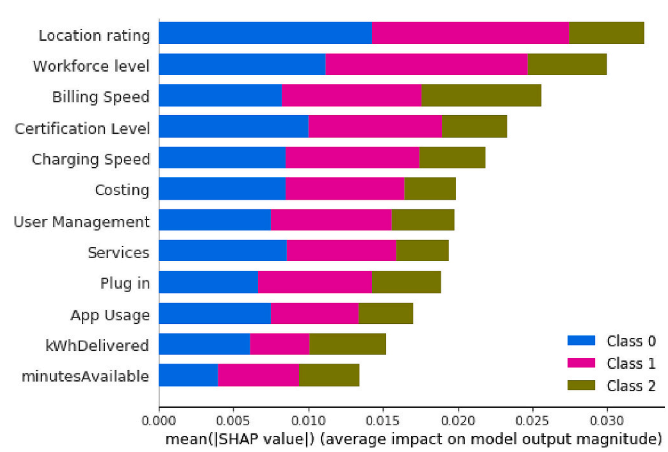

Fig. 14. Location-dependent crucial parameters.

site-specific, regional, and national. The criteria specific to a particular site are contingent upon the precise geographical location of the EV charging station. The factors encompassed in this analysis include the projected quantity of EVs that will utilize the charging station, the mean charging capacity of the EVs, the customary time frame during which charging activities occur, and the prevailing meteorological circumstances.

The geographical location of an electric car charging station determines its regional dimensions, which are influenced by a range of factors. These factors include the mean power tariff in the area, the availability of renewable energy resources, and governmental regulations applicable to EVs. The national specifications of EV charging stations are contingent on the country in which they are situated. Factors influencing the adoption of EVs in the nation encompass the aggregate demand for such vehicles, the government's dedication to mitigating greenhouse gas emissions, and the accessibility of EV infrastructure inside the country.

Through categorization, researchers can discern the most significant criteria in predicting EVs' power demand within a particular geographical area. This can assist in the development of more precise and reliable forecasting models.

The classification of the parameters should be determined by the following factors: the parameters' specificity level. Specific characteristics may exhibit varying levels of detail, with the average charging power of EVs as an example—accessibility of data on parameters. Specific characteristics may present challenges in acquiring data compared with others, such as the government policies concerning EVs—and the influence of parameters on power demand. Certain elements, such as the anticipated quantity of EVs charged at the station, may significantly influence power demand more than others. Through thoroughly examining these elements, researchers can construct a classification system for the characteristics pertinent to their research.

4.5. Data forecasting methods

Forecasting models are one of the many tools that businesses use to forecast sales, basic economics, consumer behavior, and other variables. Corporations employ various forecasting methods that produce varying degrees of knowledge. Exponential smoothing models are used for forecasting because they consider and weigh the most recent observations appropriately. Exponential smoothing is a fixed-model time series prediction approach. Robert G. Brown developed the exponential smoothing technique, which he termed "exponentially weighted moving average." Exponential smoothing is a technique used to predict future values based on the weighted average of previous sequence observations. As more observations are added, the most recent observation is prioritized, and weight loss is organized (Mossali et al., 2020).

Exponential smoothing involves smoothing the original sequence before forecasting the future values of the variable of interest using a smoothed sequence (Mossali et al., 2020). This method is beneficial when parameters related to the time series change over time. The exponential smoothing method predicts future values using the weighted average of previous observations. This method is helpful for forecasting series trends, seasonality, or both. The data in the study (Barrow et al., 2020) are unique in that they do not pertain to traditional restaurants but to United States-based congregate food programs for seniors. However, the estimation of lunch demand in this application is very similar to the estimation of restaurant demand.

The exponential smoothing forecasts various time-series data and is thus simple. The exponential smoothing method predicts the sales, inventory, and economic indices. It predicts the short- and long-term trends—simple, computationally efficient, versatile, and exponential smoothing benefits. The smoothing constant makes the procedure more sensitive and less accurate than more advanced forecasting algorithms. Exponential smoothing can quickly and effectively forecast time series data. This benefits Beginners and simple situations (Mossali et al., 2020).

The recursive exponential smoothing method calculates the current forecast from the previous forecast. This technique is easy to implement and update—the smoothing constant powers exponential smoothing. Recent data weights rely on higher weights for recent data and lower weights for older data. Forecast accuracy requires constant smoothing selection. The time-series data quality determines the optimal a. The exponential smoothing method predicts short—and long-term trends. The exponential smoothing approach is inaccurate for non-stationary or outlier-containing data projections (Barrow et al., 2020).

We examined the trends and seasonal components in Fig. 15 in detail. Until the arrival of the COVID-19 wave, we observed a rising trend and consistent seasonality. As depicted in Fig. 16, we searched for seasonality across months and determined whether any month exhibited significant repeating patterns over time.

The seasonality revealed that November and December required the least energy, whereas April and March had high requirements. We used exponential smoothing to forecast values using weighted averages of previous observations. As we return to time, these weights decrease. This implies that more weight is given to recent observations. Exponential Smoothing is used when there is no discernible trend or seasonality in the data. Using this parameter, we attempt to smooth out the level of the series. The level is the definition of the local mean and is mathematically represented as follows:

$$A0 = X0 \tag{1}$$

$$A(t) = \alpha x(t) + (1-\alpha)\, a\,(t-1) \tag{2}$$

$$A(t+1) = \alpha A(t) + \alpha(\alpha-1)\,A(t-1) + \alpha(\alpha-1)^{2^*}\,A(t-2) + \ldots\ldots\ldots \tag{3}$$

As we travel back in time, the weights decrease, and this parameter can be set between 0 and 1 to control the smoothing effect. Fig. 17 demonstrates that the RMSE was 4036.6416, indicating that the forecast could have been more accurate. Because simple exponential smoothing always generates a flat forecast, it should be used only to predict the next data point.

Next, we applied Holt's Model, or Double Exponential Smoothing, considering two properties, level, and trend, resulting in two smoothing parameters. This technique is utilized when there is a trend but no seasonality.

$$\text{Level} : A(t) = (1-\alpha)\,A(t-1) + \alpha x(t) \tag{4}$$

$$\text{Trend} :: P(t) = (1-\beta)\,P\,(t-1) + \beta\,(x(t) - A(t-1)\,) \tag{5}$$

$$\text{Model} : Z(t) = A(t) + P(t) \tag{6}$$

$$\text{Forecasting} : Z(t+n) = A(t) + n.P(t) \tag{7}$$

Fig. 18 displays an RMSE value of 1,787,819, indicating that the power estimation forecasting performs better than the previous model, with a lower RMSE.

Holt-Winter or Triple Exponential Smoothing method: Reclaim seasonality. This model considers the series level, trend, and seasonality. The three smoothing parameters correspond to level, trend, and seasonality. Because the decomposition diagram for our data included trend and seasonal components, we anticipate this model will be more accurate. We also assumed that the model was additive.

$$\text{Level} : A(t) = (1-\alpha)A(t-1) + \alpha x(t) \tag{8}$$

$$\text{Trend} : P(t) = (1-\beta)P(t-1) + \beta(x(t) - A(t-1)\,) \tag{9}$$

$$\text{Seasonal} : Q(t) = (1-\gamma)Q(t-1) + \gamma(x(t) - A(t-1) - P(t-1)\,) \tag{10}$$

$$\text{Model} : Z(t) = (A(t) + P(t)\,)Q(t) \tag{11}$$

$$\text{Forecasting} : Z(t+n) = (A(t) + n.P(t)\,)Q(t) - A + 1 + (n-1)modA \tag{12}$$

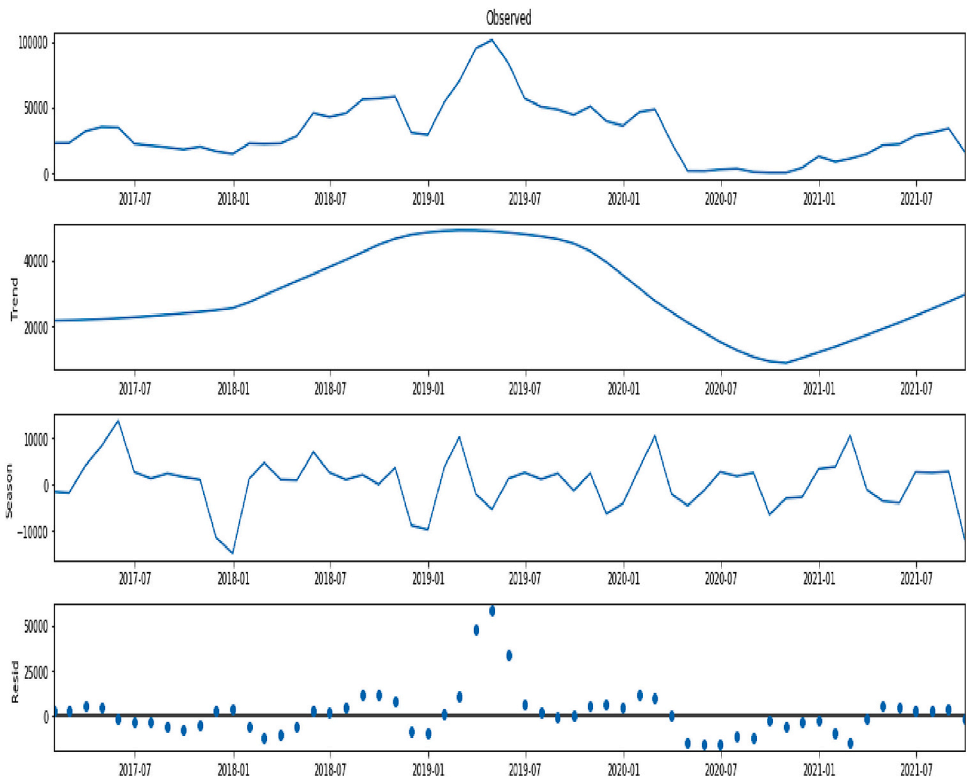

Fig. 15. Seasonal variation and trend over time.

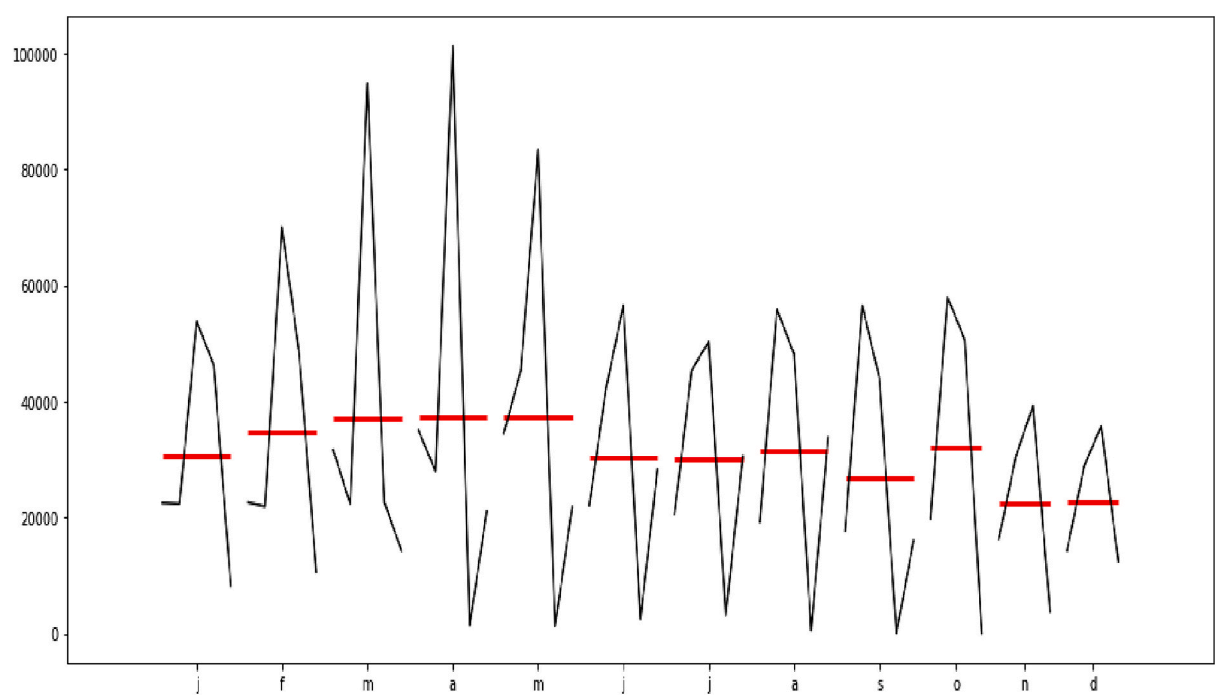

Fig. 16. Monthly Seasonality for electricity.

Determining the most suitable value for the smoothing parameter is contingent on the specific attributes and properties of the time-series data. The ideal value can be selected using several methodologies, such as trial and error, optimality criteria, and cross-validation.

The smoothing parameter can have a substantial effect on forecasting accuracy. An increase in the value of the smoothing parameter is likely to result in forecasts that are more sensitive to current data, although this may also lead to increased volatility. A decrease in the value of the smoothing parameter is associated with a decrease in the responsiveness of forecasts to current data. However, this decrease in responsiveness may also result in a decrease in forecast accuracy. Determining the most suitable value for the smoothing parameter is contingent upon the specific attributes inherent in the power requirement data of EVs.

Further investigation is warranted to examine the influence of the

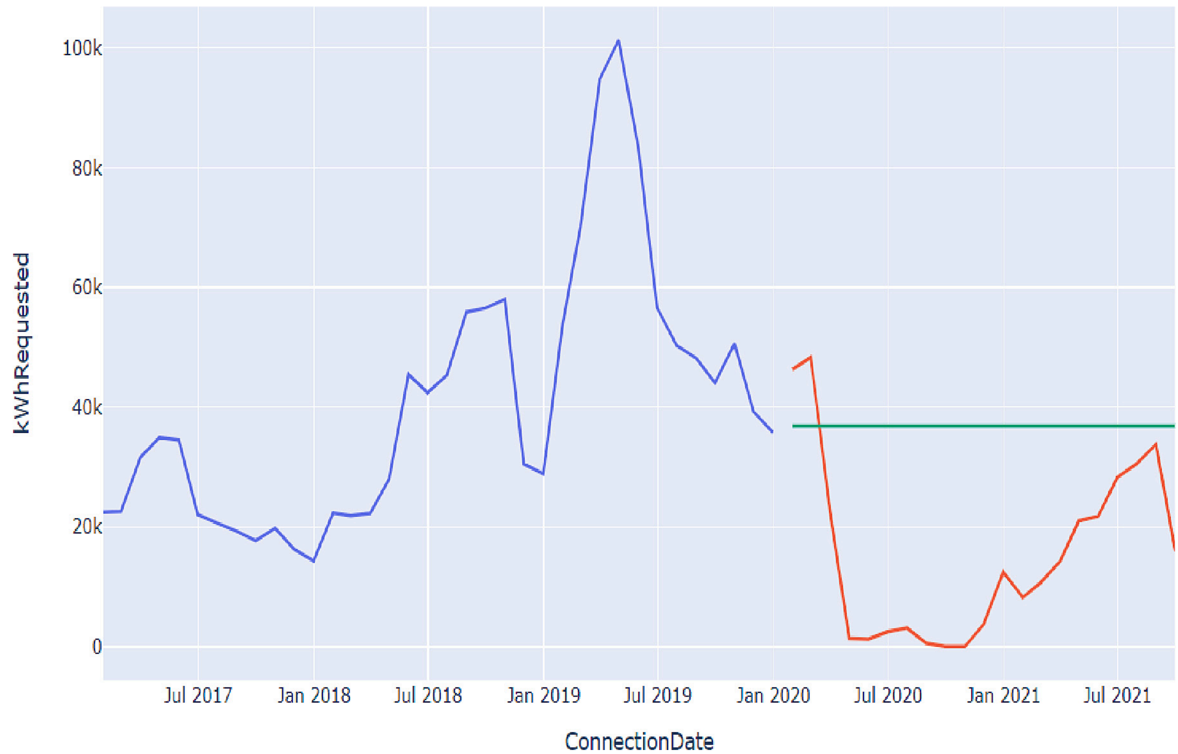

Fig. 17. Forecasting over simple exponential smoothing.

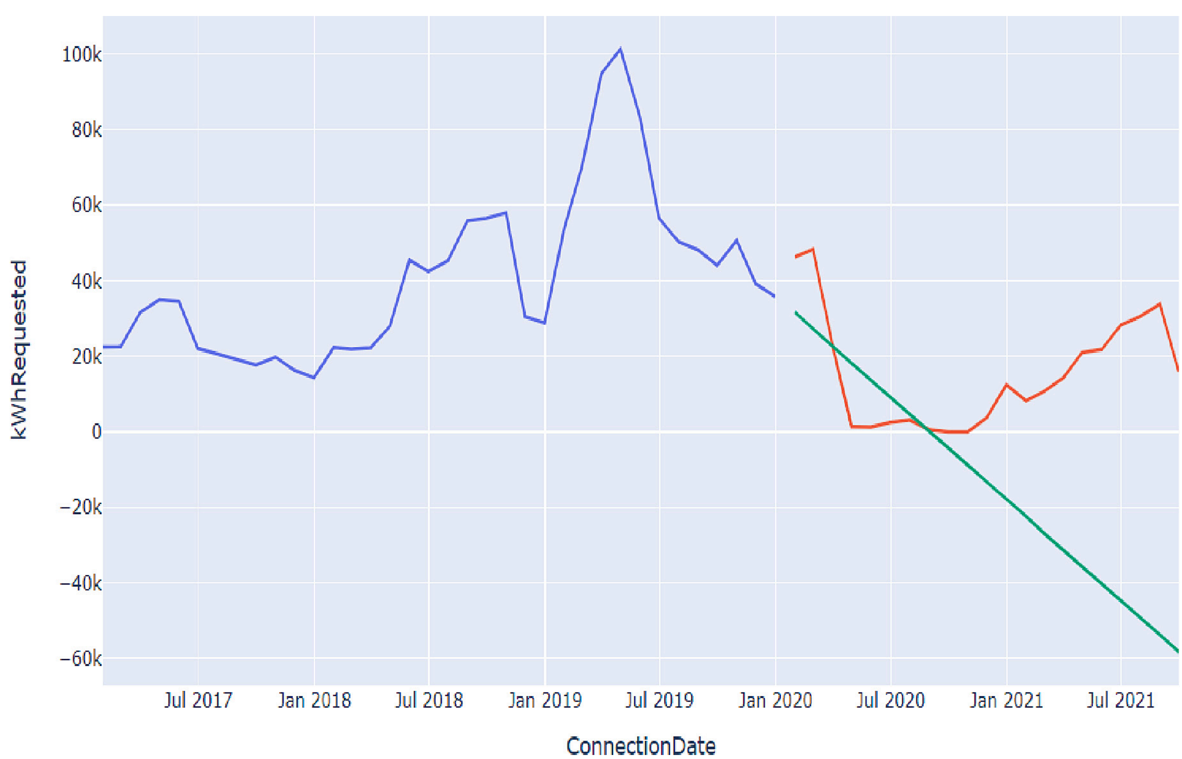

Fig. 18. Forecasting using dual exponential smoothing.

smoothing parameter on the prediction accuracy. Researchers can employ cross-validation to assess the influence of various smoothing parameter values on forecast accuracy. An increase in the value of the smoothing parameter is likely to result in forecasts that are more sensitive to current data, although this may also lead to increased volatility. A decrease in the value of the smoothing parameter is associated with a decrease in the responsiveness of forecasts to current data. However, this decrease in responsiveness may also result in a decrease in forecast accuracy.

Fig. 19 shows that the forecasted model with an RMSE of 982.64 provides the best value. Nevertheless, we observe that seasonality and trends are not observed when classifying based solely on location;

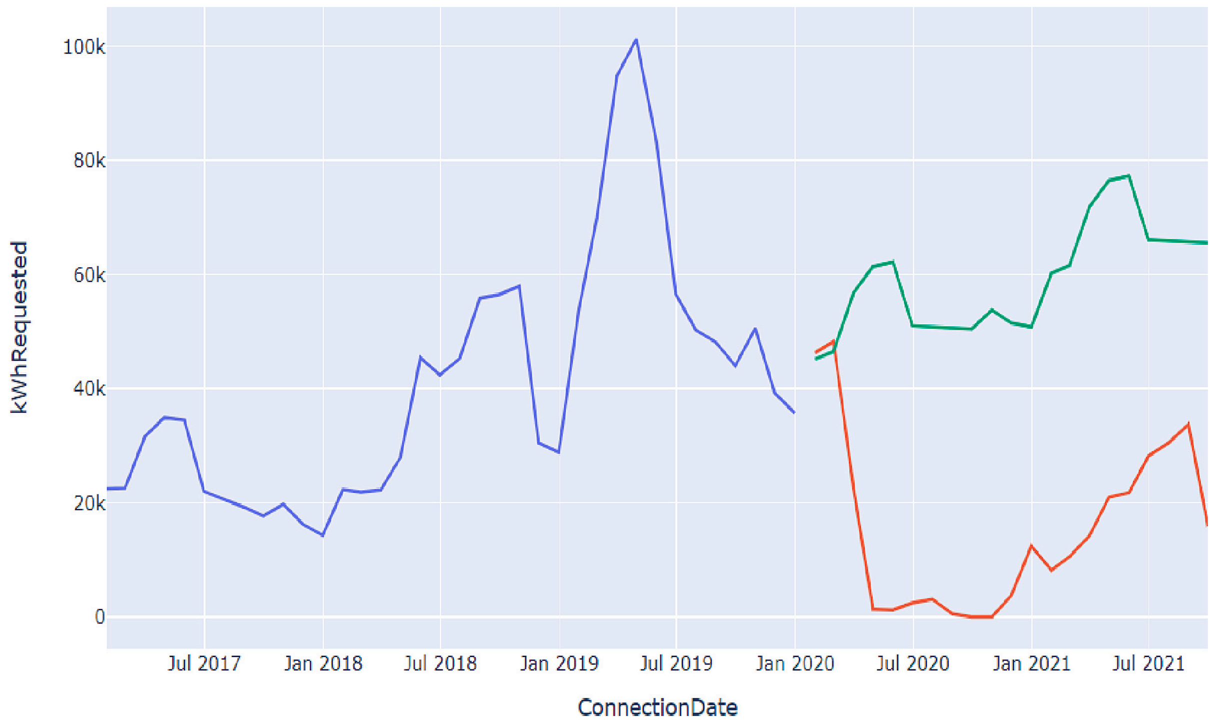

Fig. 19. Prediction using triple exponential smoothing.

therefore, we evaluate the customer data using the RTM method and then forecast the values. RTM - The term "customer recency" refers to the most recent purchase made by a customer. Frequency refers to the frequency with which a customer purchases something, whereas monetary value refers to the monetary value of the purchase. Therefore, we plotted Fig. 19 to determine a customer's proximity to a particular date, allowing us to determine how recently a consumer purchased an EV charging station.

5. Result analysis

The largest sector in the histogram shown in Fig. 20 shows that most customers visited the charging station within the first 50 days. Fig. 21 illustrates the frequency with which customers visit the EV charging station. These findings suggest that customers frequently require power to charge their EVs. Additionally, it is worth noting that many customers visited the station between 50 and 100 days after their previous visit, as indicated by the second-largest sector in the histogram.

Most customers in the primary sector typically visit the charging station within the first 0–100 days, suggesting a need for regular power. To better understand their financial contributions, Fig. 22 was plotted to represent their visits to charge their EVs at the station.

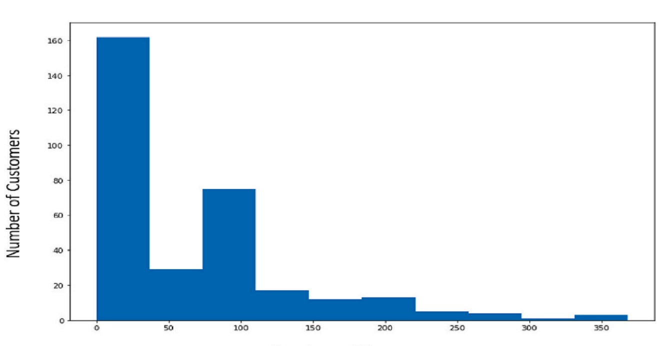

Fig. 20. Customer's recency using an EV charging station.

The research indicates that most customers typically pay around 75,000 Indian rupees at charging stations, suggesting a preference for lower-cost power at regular intervals. Additionally, the overall value of customers visiting the EV charging station is assessed by examining Fig. 23.

In the current analysis, we utilized a hierarchical scoring system to categorize the overall score. A score greater than two is designated as "Mid-Value," while a score greater than five is designated as "High-Value." Conversely, a score less than two is designated as "Low-Value." We aim to evaluate the dataset based on customer segments and forecast the power requirement considering seasonality and trends. To achieve this, we plotted the dataset shown in Fig. 24.

In hierarchical score systems, the expressions "overall score" and "mid-value" denote varying levels of specificity within the grading framework. The overall score refers to the final assessment, which considers all aspects of the hierarchy. It serves as a comprehensive evaluation for decision-making and comparisons. However, the mid-value signifies the score at a mid-level within the hierarchy, encapsulating a particular subcategory or group of factors contributing to the overall score. This can be likened to the scores for individual branches within a tree, whereas the overall score represents the entire tree.

These mid-values offer valuable insights into the most critical factors in the final evaluation. The overall score depends on the allocation and consolidation of mid-values. The system may assign varying degrees of significance to different subcategories, which is evident in how mid-values are combined to arrive at the final score. Therefore, scrutinizing overall and mid-values provides a more refined perception of the hierarchical score system. This enables one to appreciate the bigger picture while examining each component's health.

The trends and seasonal components in Fig. 25 were analyzed in detail. A rising trend existed until the emergence of the COVID-19 wave, and consistent seasonality was observed throughout the timeframe. Fig. 26 demonstrates the methodical examination of seasonality across various months, revealing recurring patterns deviating from the norm.

The findings of our analysis indicate that monthly power consumption exhibits a consistent pattern, with a notable upward trend observed from June to August. This trend may be attributed to local festivals and

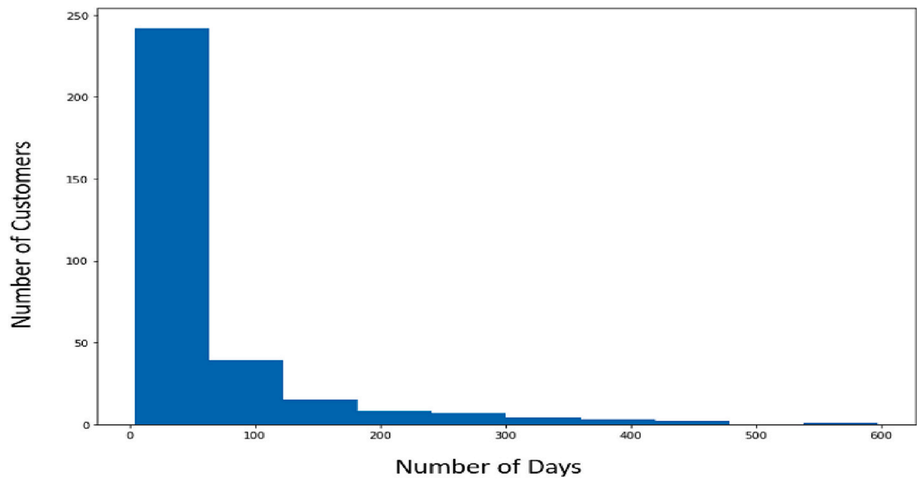

Fig. 21. Customer visitation frequency using an EV charging station.

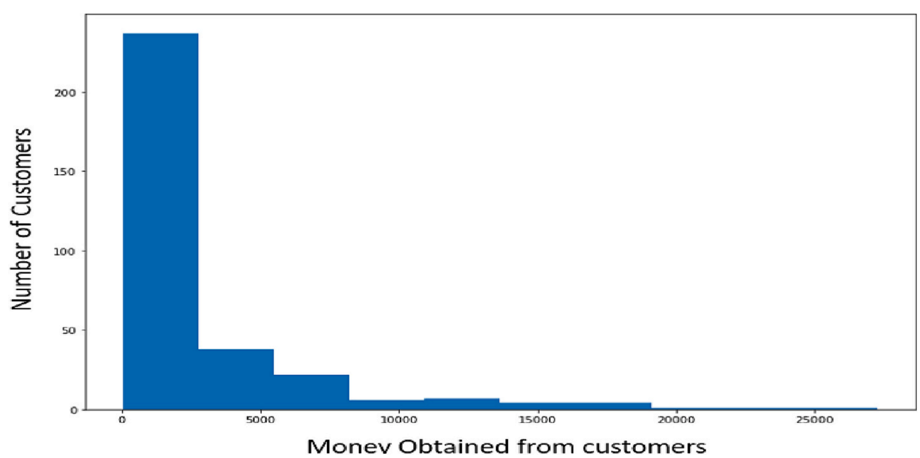

Fig. 22. The monetary value of using an EV charging station.

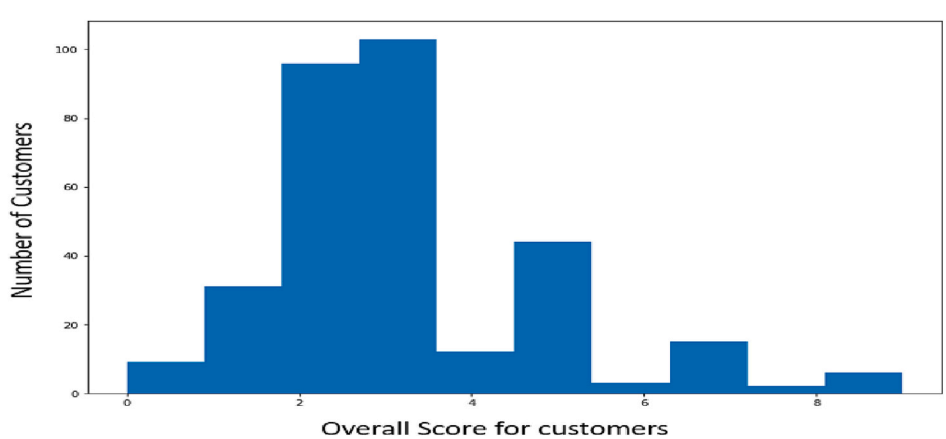

Fig. 23. The customer's overall value Visiting the Classified EV charging station based on ratings.

fairs in the area. Considering these findings, we proceeded to the forecasting stage, employing the previously described forecasting models for the location classification model. Furthermore, we endeavored to separate the data into test and training sets, as shown in Fig. 27.

We show various exponential models in Figs. 28, 29, 30, and 31.

Fig. 31 illustrates Forecasting over Triple Exponential Smoothing in greater detail.

Before commencing our analysis, we would like to study seasonality analysis techniques. Additive and multiplicative methods are the most widely used techniques for examining the seasonality of Time Series. The seasonal pattern's magnitude in the data depends on the data's magnitude, indicating that seasonality follows multiplicative models. However, the additive model's magnitude of seasonality remained constant over time.

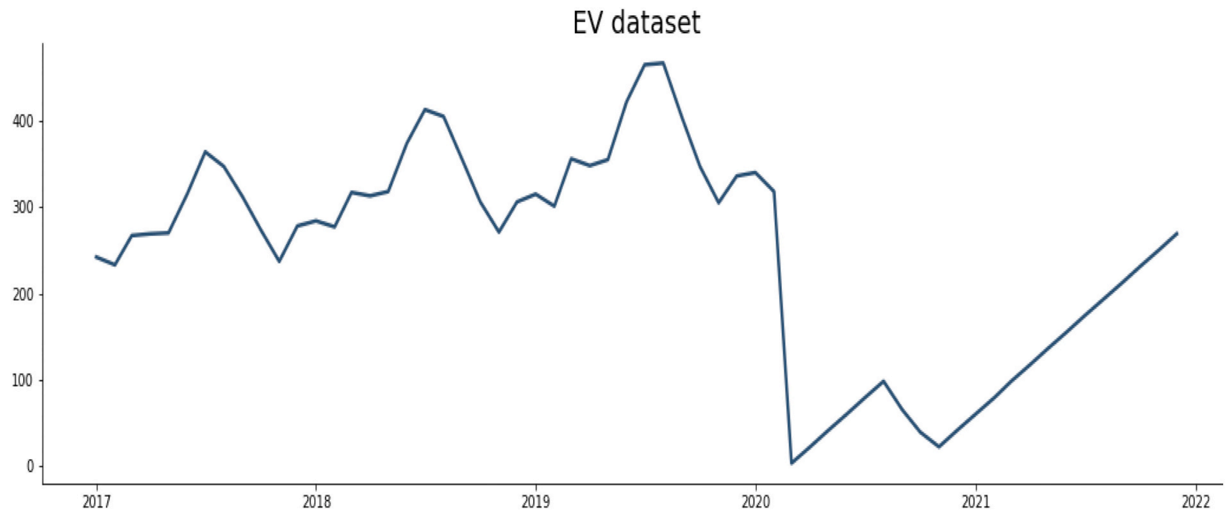

Fig. 24. The initial power demand of the customer visiting the EV charging station.

Fig. 25. Seasonality and trend graph for a customer segment over time.

In the context of Random Forest, location, charging speed, minutes available, and power demanded all play a significant role in the prediction. All features, except for app usage, cost, and plug type, significantly impact the forecast. These results may result from the Random's tendency to overfit or closely follow the training data. However, when we assigned the location to specific classes based on their intended use, we discovered that parking slots, such as charging stations, fuel stations, and public parking lots, substantially affected the prediction model. Variables such as billing speed, certification level, available minutes, workforce, and cost directly affect the prediction of the most efficient charging stations for customers.

Furthermore, our findings indicate that most customers visited charging stations between 50 and 100 days, and this trend is also observed in the primary sector, suggesting a frequent need for power. Additionally, the average payment made by customers is approximately 75,000 Indian rupees, which suggests that they require energy at a lower cost because of their regular power needs and fall within the mid-value category based on their overall scores.

Our optimized character demand forecasting revealed that July (8750 kWh) and November (1105 kWh) had the lowest and highest power demand, respectively. Using a prediction-based method, charging stations can provide stable power. However, it is essential to note that our analysis assumes that charging stations do not contain batteries, and any excess electricity generated that is not used for recharging is sent to the grid. Implementing a local energy storage system could mitigate the impact of short-term output variability on charging times; however,

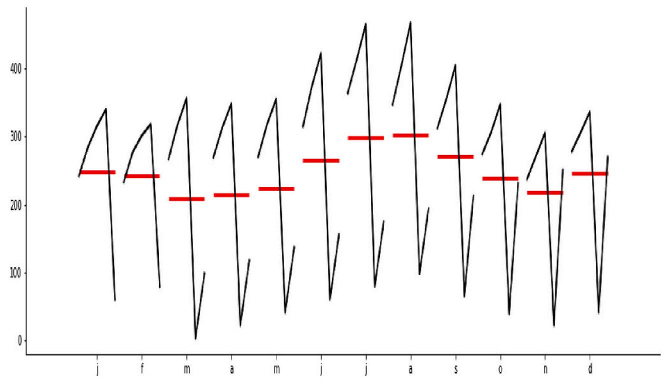

Fig. 26. Seasonality every month for electricity.

further research is required in this area.

6. Managerial implication

The findings have significant implications for management. The study suggests that the advantage of market orientation may vary depending on the composition of a company's supply- and demand-side power components. Additionally, this study identifies the crucial elements likely to encourage or deter the establishment of a charging station within market customer orientation. Because managers have the authority to alter these variables, they can modify them to strengthen the market orientation of their companies. Ultimately, our findings provide managers with a comprehensive grasp of market orientation, including how to attain it and its anticipated consequences.

However, firms that gather and act on market intelligence tend to surpass their competitors and achieve more excellent customer and employee satisfaction. They need more engagement in market-oriented activities to guarantee their success. Market intelligence may be of questionable quality, or marketing strategies developed in response to such intelligence may not be effectively executed. A market-driven approach may fail to produce desired operational results in such cases. Using AI- and ML-based decision support systems for EV power requirements presents significant managerial considerations.

The integration of advanced forecasting technology brings about significant advantages across various sectors. First, this sophisticated system accurately anticipates the electricity consumption patterns of EVs over diverse timeframes, spanning from days to years. Such foresight empowers utilities to meticulously plan and schedule electricity generation and distribution, ensuring optimal resource allocation. Additionally, it enables utilities to identify peak demand periods and proactively manage electricity supply to meet the burgeoning needs of EV users during these critical times. Furthermore, this technology catalyzes optimizing the placement and capacity of EV charging stations. Through meticulous data analysis, it identifies regions with substantial EV demand. It facilitates the strategic deployment of charging infrastructure, ensuring convenient access for EV owners while alleviating

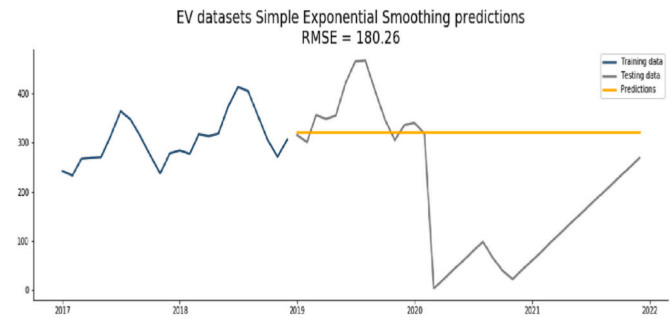

Fig. 28. Forecasting over simple exponential smoothing.

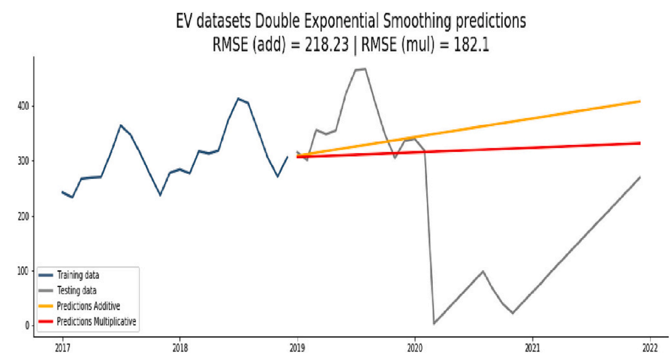

Fig. 29. Forecasting over double exponential smoothing.

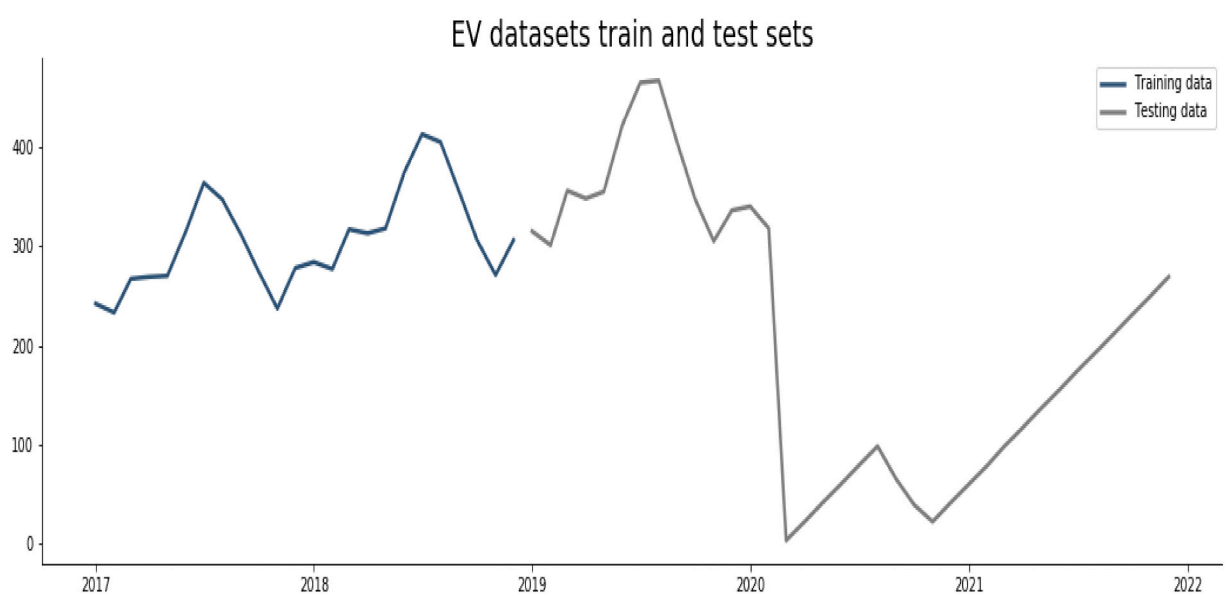

Fig. 27. Test and train for electricity consumption.

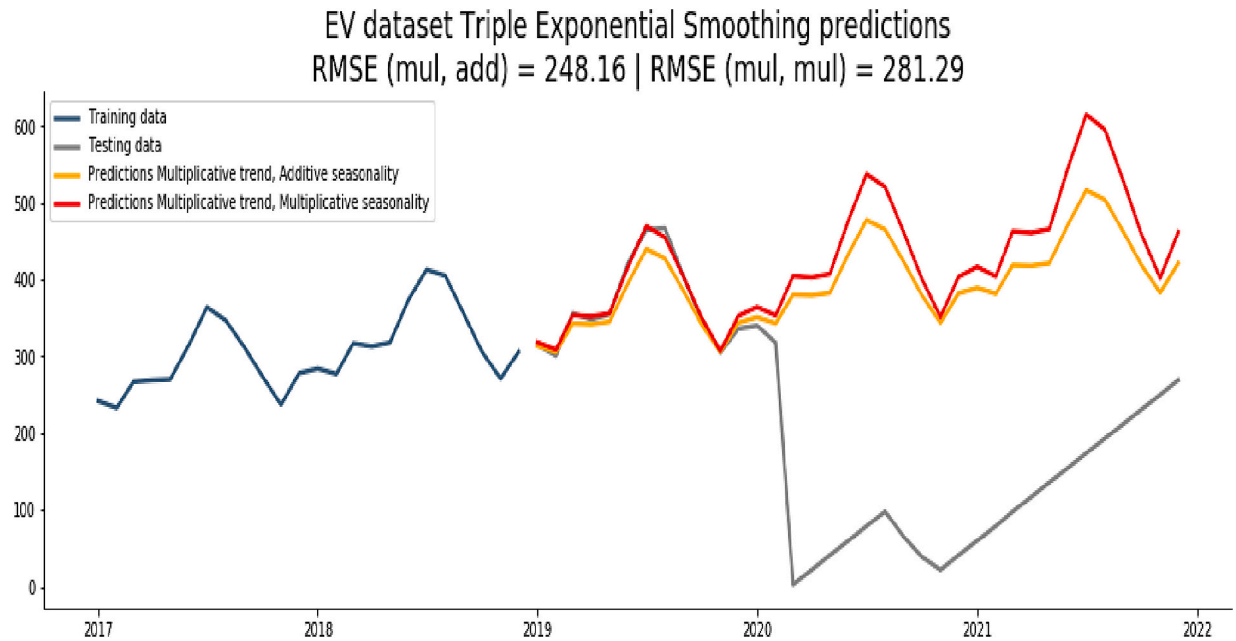

Fig. 30. Forecasting over triple exponential smoothing.

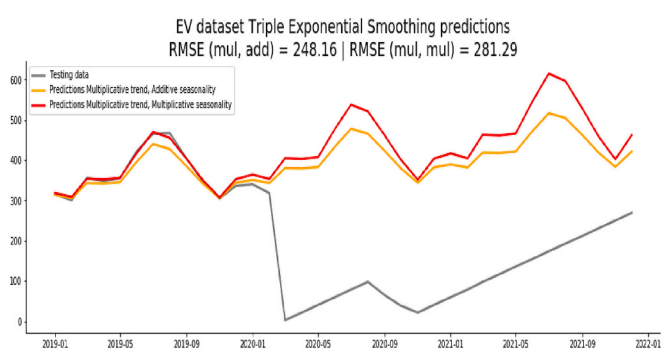

Fig. 31. Detailed forecasting using triple exponential smoothing.

strain on the grid. Moreover, adopting this framework translates into tangible cost savings by optimizing EV charging schedules to coincide with periods of lower electricity rates. Organizations can effectively mitigate grid maintenance and operation expenses by capitalizing on off-peak charging hours, enhancing financial efficiency. Beyond economic benefits, implementing this method fortifies the reliability of electrical power grids. By proactively identifying and addressing potential issues before they escalate into disruptive outages, the system enhances the resilience of critical infrastructure, ensuring uninterrupted access to electricity for consumers and bolstering overall grid stability.

This method aims to enhance the electrical grid's sustainability by minimizing fossil fuel utilization. This technique promotes the efficient use of clean energy by coordinating EV charging with renewable energy sources. Moreover, EVs can be charged using renewable energy sources, such as wind power at night and solar power during the day, contributing to grid stability and the proliferation of renewable energy. Using AI and ML to develop a decision support system for predicting EV power requirements can benefit electric car fleets. This system optimizes the planning, scheduling, and charging infrastructure to reduce costs, increase reliability, and promote sustainability.

Furthermore, this method also presents technological consequences. Specifically, the system must be capable of processing, storing, and analyzing vast amounts of data on time. In addition, the system must be adaptable to environmental shifts, such as an increase in EV availability and the integration of renewable energy sources. Despite these obstacles, AI—and ML-based decision support systems for determining EV power requirements demonstrate great potential. These systems can enhance the efficiency and sustainability of electrical grids.

7. Conclusion and future research direction

This study has crafted a robust framework to discern the pivotal characteristics of EV charging demand. Through the innovative integration of artificial intelligence (AI) and machine learning (ML), the model unveils latent features crucial for precisely calculating EV charging demand. With this methodology in place, the Demand Forecasting module adeptly predicts power consumption across diverse locations and loads, spanning multiple timeframes. Implementing this model's strategies in managerial contexts enables the creation of a feasible charging demand and load zone design. For instance, in areas with heightened charging demand, the model offers insights for optimizing power distribution through strategies like swapping or augmentation. Its adaptable design lends itself well to various scales, from smaller neighborhoods to entire countries, requiring only minor adjustments to suit different case scenarios.

It is crucial to recognize that the proposed model's effectiveness is contingent upon various factors, such as the localized impact of weather conditions and the nuanced influence of marketing strategies on charging demand. These considerations and implications for alternative problem-solving methodologies like robust mathematical models and Deep Learning approaches warrant comprehensive exploration in future research endeavors. One significant limitation of AI- and ML-based decision support systems in estimating EV power requirements is the critical dependence on data availability and quality. The fidelity and reliability of these models are inherently tied to the breadth and accuracy of the datasets they are trained on, necessitating careful attention to real-world representativeness. Moreover, the inherent complexity of AI and ML models poses challenges regarding interpretability and transparency. Understanding the inner workings of these models is essential for ensuring the validity and reliability of their conclusions, necessitating dedicated efforts to unravel their intricacies. Furthermore, the susceptibility of AI and machine-learning models to biases is a pressing concern. These biases, reflective of underlying biases in the training data, can lead to skewed or erroneous decision-making processes, highlighting the need for meticulous bias mitigation strategies. Additionally, security and privacy vulnerabilities represent significant risks associated with AI and ML systems. Threats such as unauthorized data access and system breaches underscore the imperative for robust security measures and proactive risk mitigation strategies.

A comprehensive focus on data gathering and preparation methodologies is paramount in charting future research trajectories. Efforts should be directed towards refining techniques for data cleaning, anonymization, and handling missing data, ensuring the integrity and utility of datasets. Furthermore, pursuing accurate, robust, and interpretable AI and ML models demands exploring novel methodological approaches and a deeper understanding of their operational mechanisms. Transparent and interpretable models are essential for fostering trust and confidence in their outputs. Moreover, advancing model evaluation and validation techniques is critical for ensuring the reliability and applicability of AI and ML solutions. Developing comprehensive evaluation metrics and strategies for assessing accuracy and robustness is essential for effectively gauging model performance. Addressing security and privacy concerns necessitates a multi-faceted approach encompassing the development of stringent security protocols, proactive threat detection mechanisms, and user education initiatives. Safeguarding AI and ML systems against potential vulnerabilities is paramount for upholding data integrity and user privacy.

CRediT authorship contribution statement

Sunil Kumar Jauhar: Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sunil Sethi:** Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Sachin S. Kamble:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization. **Shawn Mathew:** Writing – original draft, Visualization, Resources, Project administration, Methodology. **Amine Belhadi:** Writing – review & editing, Validation, Formal analysis.

Data availability

Data will be made available on request.

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