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Machine Learning-Based Prediction of Electric Vehicle Charging Demand for Sustainable Transportation

Nyree Ani[1], Nuke Puji Lestari Santoso[2*], Rajendra Kumar[3]
[1]Department of Retail Management, Massey University, New Zealand
[2]Faculty of Economics and Business, Universitas Raharja, Indonesia
[3]Department of Computer Science & Engineering, Sharda University, India
[1]nyree.ani@pandawan.ac.nz, [2]nuke@raharja.info, [3]rajendra.kumar@adi-journal.org

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ABSTRACT

The increasing adoption of Electric Vehicles (EV) presents challenges in managing uncertain charging demand, optimizing infrastructure utilization, and maintaining energy system stability. **This study** aims to develop and evaluate a machine learning-based prediction framework for estimating EV charging energy demand and identifying the most effective predictive algorithm to support sustainable transportation planning. **The proposed** framework employs historical EV charging observations and contextual variables, including charging duration, charging time, day of the week, ambient temperature, charging frequency, and historical energy consumption. Three supervised machine learning algorithms, namely Random Forest (RF), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost), are comparatively evaluated. Predictive performance is assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). **The reported** experimental findings indicate that XGBoost achieves the highest predictive accuracy, with an RMSE of 2.84 kWh, MAE of 1.97 kWh, MAPE of 6.21%, and R^2 of 0.941. However, the comparative performance metrics for RF and SVR must be reported in the main Results section to substantiate the claimed superiority of XGBoost. **The proposed framework** demonstrates the potential of machine learning to identify charging demand patterns using historical charging, temporal, and environmental information. Subject to further experimental verification, the findings may support data-driven charging infrastructure management, electricity resource allocation, and sustainable transportation planning.

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1. INTRODUCTION

The rapid growth of Electric Vehicle (EV) adoption has transformed the transportation sector and created new opportunities for reducing fossil fuel consumption, greenhouse gas emissions, and dependence on conventional transportation systems [1]. The transition toward electric mobility is increasingly supported by advances in battery technology, charging infrastructure, intelligent transportation systems, and renewable energy integration [2]. However, the increasing number of EV also introduces new challenges for electricity systems because charging activities can create substantial and highly variable electricity demand. Unlike conventional electricity loads that often follow relatively predictable consumption patterns, EV charging demand is influ-

enced by user travel behavior, charging duration, battery conditions, charging preferences, time of day, day of the week, weather conditions, and charging station availability [3]. Sudden increases in charging activity during peak periods may contribute to local grid congestion, increased operational costs, and inefficient utilization of charging infrastructure [4]. Therefore, accurate prediction of EV charging demand has become an important requirement for sustainable transportation management and intelligent energy planning. Transportation operators and energy providers require reliable information regarding when, where, and how much electricity will be required by EV users to optimize charging schedules and allocate available resources effectively [5]. From a smart transportation perspective, demand prediction can also support the development of adaptive charging strategies that balance user requirements with energy system constraints [6]. Consequently, the application of artificial intelligence and machine learning has gained increasing attention as a potential solution for modeling complex charging demand patterns and supporting data-driven decision-making in sustainable transportation systems [7].

Machine learning provides an effective computational approach for predicting EV charging demand because it can identify nonlinear relationships and complex patterns from historical transportation and charging data [8]. Traditional statistical approaches may experience limitations when charging behavior is influenced by multiple interacting variables and irregular temporal patterns. Machine learning algorithms, in contrast, can process multivariate datasets and learn relationships between charging behavior and relevant explanatory variables without requiring rigid assumptions regarding the underlying data distribution [9]. In the context of EV charging, variables such as charging duration, energy consumption, charging time, day of the week, ambient temperature, charging frequency, and historical charging activity can provide valuable information for estimating future electricity requirements. Random Forest can capture nonlinear relationships through an ensemble of decision trees, Support Vector Regression can model complex relationships through nonlinear kernel functions, while Extreme Gradient Boosting (XGBoost) can improve predictive performance through sequential optimization of decision trees [10]. These approaches are particularly relevant for EV charging demand because charging behavior is not determined by a single factor but emerges from the interaction of temporal, environmental, and user-related characteristics. A quantitative comparison of machine learning models can therefore provide empirical evidence regarding which algorithm is most capable of producing accurate and reliable charging demand predictions [11]. Furthermore, evaluating prediction performance using objective statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2) allows model effectiveness to be measured consistently. Such an approach supports reproducible evaluation and provides transportation and energy stakeholders with measurable evidence for selecting an appropriate predictive model for charging infrastructure management [12].

Despite the increasing application of artificial intelligence in electric mobility, several challenges remain in developing reliable EV charging demand prediction systems [13]. Existing prediction approaches may focus primarily on charging station utilization or electricity consumption without sufficiently considering the combination of temporal and environmental variables that influence charging behavior [14]. Moreover, the performance of machine learning algorithms can vary considerably depending on the characteristics of the dataset, prediction variables, and temporal patterns represented in the observations. A model that performs effectively under one charging environment may not necessarily produce comparable results under different operational conditions [15]. However, the existing literature reveals several methodological challenges that require further investigation. Previous studies have employed different prediction horizons, charging datasets, feature configurations, and evaluation procedures, making their reported model performances difficult to compare directly. Moreover, limited methodological transparency concerning temporal data partitioning, predictor availability, and model validation may affect the reliability of charging demand forecasts. These limitations highlight the importance of evaluating machine learning algorithms under consistent experimental conditions while clearly defining the prediction target, input variables, and validation strategy. Accordingly, this study investigates the comparative predictive performance of Random Forest, Support Vector Regression, and XGBoost using charging-related, temporal, and environmental variables to assess their suitability for electric vehicle charging demand prediction. In addition, accurate prediction should not only minimize numerical errors but also provide sufficient reliability for practical applications such as charging schedule optimization, infrastructure planning, and energy resource allocation [16]. This study therefore addresses the need for a data-driven framework that evaluates the capability of machine learning models to predict EV charging demand based on historical charging and environmental information. The research specifically investigates the extent to which machine learning

techniques can capture charging demand patterns and determine which predictive model provides the most accurate results [17]. The study uses quantitative experimental procedures in which historical charging observations are preprocessed, relevant predictive variables are incorporated into model development, and multiple machine learning algorithms are trained and evaluated under the same experimental conditions. This design enables an objective comparison of model performance and provides a clear basis for identifying the most effective approach for EV charging demand prediction [18].

Based on these challenges, this study develops a machine learning based prediction framework for estimating electric vehicle charging demand to support sustainable transportation management [19]. The research focuses on charging duration, energy consumption, charging time, day of the week, ambient temperature, and charging frequency as predictive variables and evaluates the performance of Random Forest, Support Vector Regression, and XGBoost models. The models are assessed using MAE, RMSE, MAPE, and R^2 to determine their predictive accuracy, error magnitude, and explanatory capability [20]. The research is expected to contribute to the development of intelligent transportation systems by demonstrating how machine learning can transform historical charging data into actionable predictions for future electricity demand. From an operational perspective, accurate charging demand prediction can assist transportation operators and charging station managers in optimizing charging schedules, improving infrastructure utilization, and reducing the risk of demand peaks [21]. For energy providers, reliable forecasts can support electricity supply planning and coordination between charging infrastructure and available grid capacity. At the policy level, the findings can provide quantitative evidence for developing sustainable electric mobility strategies and planning future charging infrastructure according to anticipated demand patterns [22]. By integrating machine learning with EV charging demand prediction, this research contributes to the broader application of artificial intelligence in green technology and sustainable transportation. The main contribution of the study is therefore the quantitative evaluation of machine learning approaches for identifying an effective predictive model capable of supporting more efficient, reliable, and sustainable EV charging management [23].

2. LITERATURE REVIEW

The increasing adoption of electric vehicles has created a growing research interest in accurately understanding and predicting charging demand [24]. Recent studies show that machine learning and deep learning can capture the temporal, behavioral, and environmental factors that influence EV charging patterns more effectively than conventional forecasting approaches. This literature review discusses four areas that directly support the present study, namely EV charging demand and sustainable transportation, factors influencing charging demand, machine learning approaches for EV charging prediction, and research gaps in existing prediction studies [25].

2.1. Electric Vehicle Charging Demand and Sustainable Transportation

Electric vehicles have become an important component of sustainable transportation because they can reduce dependence on fossil fuels and contribute to lower transportation-related emissions [26]. However, increasing EV adoption also creates additional electricity demand that must be managed efficiently to ensure the reliable operation of charging infrastructure and energy systems. EV charging behavior can generate substantial variations in electricity consumption, particularly during periods of high charging activity, when multiple vehicles may require charging within similar time intervals [27]. Therefore, forecasting charging demand is increasingly important for transportation operators, charging station managers, and electricity providers. Reliable demand predictions can help stakeholders anticipate electricity requirements, improve charging schedules, allocate available resources, and plan infrastructure capacity more effectively [28]. Recent research has demonstrated the potential of data-driven approaches for medium-term EV charging demand forecasting across multiple public charging stations by incorporating weather conditions and other relevant features. Similarly, research on charging service operations highlights the role of machine learning in infrastructure planning, charging control, pricing, and routing. These developments indicate that accurate charging demand prediction can support more informed operational decisions, improve the utilization of existing charging facilities, and help manage fluctuations in electricity demand. Consequently, integrating predictive analytics into EV charging management represents a promising approach to developing more efficient, reliable, and sustainable transportation systems [29].

2.2. Factors Influencing Electric Vehicle Charging Demand

EV charging demand is influenced by multiple interacting factors rather than a single determinant [30]. Temporal characteristics such as hour of the day, day of the week, and charging duration can significantly affect charging patterns, while weather conditions and transportation characteristics may further modify user charging behavior. Recent studies have increasingly incorporated these variables into predictive models to improve forecasting accuracy [31]. Research published in 2024 demonstrated that EV charging behavior is affected by dynamic usage patterns, including variations in demand and unpredictable charging duration, emphasizing the importance of incorporating temporal charging information into forecasting models. Other research has examined the influence of dynamic traffic information on EV charging load prediction, demonstrating that transportation conditions can provide additional information for understanding charging behavior [32]. A recent systematic review and meta-analysis also identified charging station location, time of day, battery state of charge, user behavioral patterns, and weather conditions among the important variables considered in EV charging prediction research. These findings support the use of charging duration, energy consumption, charging time, day of the week, ambient temperature, and charging frequency as predictive variables in the present study [33].

2.3. Machine Learning for Electric Vehicle Charging Demand Prediction

Machine learning has increasingly been applied to EV charging demand prediction because of its capability to model nonlinear relationships and extract patterns from historical charging data [34]. Different algorithms provide different advantages depending on the characteristics of the prediction problem. Random Forest, for example, can capture nonlinear relationships through ensemble decision trees and is relatively robust to variations in input data. Support Vector Regression can model nonlinear relationships using kernel functions and is suitable for regression problems involving complex datasets [35]. XGBoost provides an ensemble-based gradient boosting approach that sequentially improves prediction through optimized decision trees. Recent empirical research has demonstrated the effectiveness of machine learning for EV charging demand forecasting [36]. A 2024 study on EV charging station load demand in Indonesia specifically investigated machine learning using Random Forest and XGBoost, demonstrating the relevance of these algorithms to EV charging load prediction in the Indonesian context. Meanwhile, other studies have compared multiple machine learning and deep learning approaches, including RNN, LSTM, Bi-LSTM, GRU, CNN, and Transformer models, confirming that algorithm selection can substantially influence charging demand prediction performance. These findings indicate that quantitative comparative evaluation is necessary to determine which machine learning algorithm provides the most reliable predictions for a particular EV charging dataset [37].

2.4. Research Gap in Electric Vehicle Charging Demand Prediction

Although recent studies have demonstrated the potential of artificial intelligence for EV charging prediction, several research gaps remain [38]. First, existing studies differ considerably in their prediction horizons, datasets, input variables, and evaluation procedures, making direct comparison between algorithms difficult. Some research focuses on short-term charging load prediction, while others investigate medium-term or multi-station forecasting [39]. Second, advanced deep learning models have received substantial attention, but comparatively simpler machine learning algorithms remain important because of their lower computational requirements and practical applicability for charging management systems [40]. Recent comparative research demonstrates that different algorithms can produce substantially different prediction results, reinforcing the importance of systematic model evaluation. Third, the combination of charging characteristics and environmental variables remains an important area for further investigation, particularly when developing models intended for practical sustainable transportation applications [41]. Therefore, this study addresses the gap by quantitatively comparing Random Forest, Support Vector Regression, and XGBoost for EV charging demand prediction using charging and environmental variables. The comparison is conducted using consistent data preprocessing procedures and objective performance metrics, including MAE, RMSE, MAPE, and R^2, to identify the most effective model for supporting data-driven EV charging management [42].

3. METHODOLOGY

3.1. Research Design

This study employs a quantitative predictive research design to develop and evaluate a machine learning framework for predicting Electric Vehicle (EV) charging demand. The quantitative approach was selected

because the research focuses on numerical charging data, measurable predictive variables, algorithmic model development, and objective evaluation of prediction performance. The research process begins with the collection of historical EV charging data, followed by data preprocessing, feature selection, model development, prediction, and quantitative performance evaluation. The main objective is to identify the machine learning model that can provide the most accurate prediction of future charging demand based on historical charging and environmental characteristics. This research design is consistent with recent EV charging demand studies that apply machine learning to identify nonlinear relationships within charging behavior and improve demand forecasting accuracy.

3.2. Research Framework

The proposed research framework consists of six sequential stages, namely data collection, data preprocessing, feature selection, machine learning model development, charging demand prediction, and performance evaluation. Historical observations are first collected and organized according to charging events or defined time intervals. The data are then cleaned and transformed to ensure consistency and suitability for machine learning analysis. Relevant charging and environmental variables are subsequently selected as predictors, while charging energy demand is defined as the target variable. Three machine learning algorithms, namely Random Forest, Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost), are then developed and trained using the prepared dataset. The resulting models are evaluated using consistent testing data and quantitative performance metrics to determine the most effective prediction approach. Similar comparative machine learning frameworks have been applied to EV charging demand prediction, including studies comparing Random Forest, XGBoost, and other regression models.

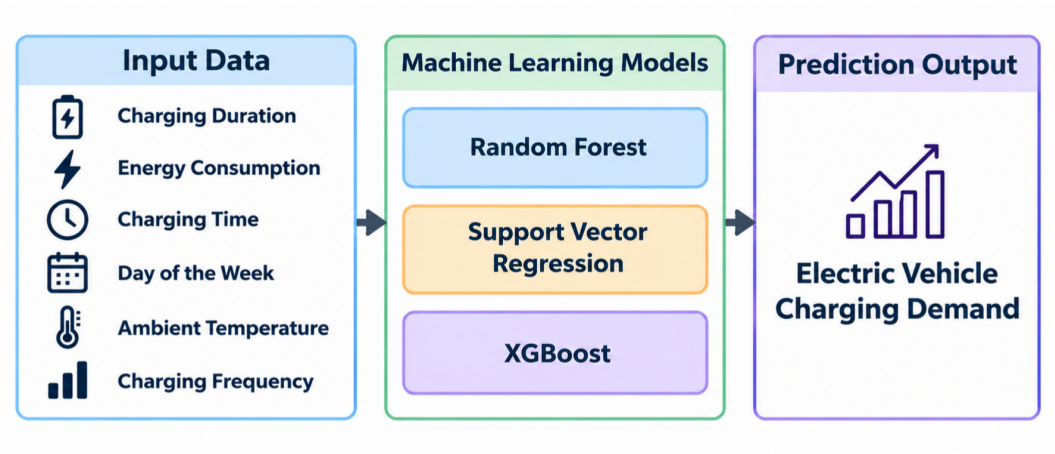


Figure 1. Research Framework for Electric Vehicle Charging Demand Prediction

Figure 1 illustrates the overall research methodology for the proposed EV charging demand prediction framework. The process starts with historical charging data collection, followed by preprocessing and feature selection before applying Random Forest, SVR, and XGBoost. The three models are evaluated under consistent conditions using quantitative performance metrics to identify the most reliable prediction approach. This framework considers temporal, behavioral, and environmental characteristics that may influence EV charging demand.

3.3. Data Collection and Research Variables

The dataset used in this study consists of historical EV charging observations and associated contextual variables relevant to charging demand prediction. The dependent variable is charging demand, represented by the amount of electrical energy consumed during a charging event or defined observation period in kilowatt-hours (kWh). The independent variables include charging duration, charging time, day of the week, ambient temperature, charging frequency, and historical energy consumption. These variables were selected because charging demand is influenced by temporal patterns, user charging behavior, and environmental conditions. Previous research has also demonstrated that charging demand can be affected by user behavior and environmental or climatic factors, supporting the inclusion of these variables in predictive modeling.

Table 1. Research Variables and Their Operationalization

Variable	Type	Measurement	Role
Charging Demand	Continuous	Energy consumed (kWh)	Dependent variable
Charging Duration	Continuous	Charging time (minutes)	Independent variable
Charging Time	Temporal	Hour of charging	Independent variable
Day of Week	Categorical	Monday–Sunday	Independent variable
Ambient Temperature	Continuous	Temperature (°C)	Independent variable
Charging Frequency	Numerical	Number of charging events	Independent variable
Historical Energy Consumption	Continuous	Previous energy consumption (kWh)	Independent variable

Table 1 presents the operationalization of the variables used in the prediction model. Charging demand is the prediction target, while charging duration, charging time, day of the week, ambient temperature, charging frequency, and historical energy consumption serve as explanatory variables. These temporal, behavioral, and environmental variables enable the models to capture key characteristics of EV charging demand.

3.4. Data Preprocessing

The collected dataset undergoes preprocessing to ensure data quality and consistency before model development. This stage includes identifying missing values, removing duplicate records, checking unusual values, and ensuring consistent data formats and measurement units. Temporal variables, such as charging time and day of the week, are also prepared for use in the selected machine learning algorithms. After preprocessing, the dataset is divided into training and testing subsets to support model development and evaluate prediction performance on unseen data. These procedures help minimize data inconsistencies and provide reliable inputs for EV charging demand prediction.

3.5. Feature Selection and Model Development

Feature selection is conducted to identify relevant variables for predicting EV charging demand. The selected features include charging duration, charging time, day of the week, ambient temperature, charging frequency, and historical energy consumption. These variables represent charging behavior, temporal patterns, and environmental conditions that may influence electricity demand. Three supervised machine learning algorithms, namely Random Forest, SVR, and XGBoost, are then developed using the selected features. Random Forest combines predictions from multiple decision trees, SVR estimates relationships between input variables and demand, while XGBoost improves predictions through sequential boosting. Applying the same features across these algorithms enables a consistent comparison of their predictive capabilities.

3.6. Model Training and Prediction

The training dataset is used to construct the three predictive models, with each algorithm receiving the same input variables and target variable to ensure a fair comparison. During training, the algorithms learn the relationships between the selected predictors and historical charging demand by identifying patterns within the available observations. Once training is completed, the models are applied to the testing dataset to generate predictions for previously unseen observations. The same testing observations are used for all three models to maintain consistent evaluation conditions and ensure that differences in predictive performance primarily reflect the characteristics of each algorithm. The predicted values are then compared with the actual charging demand values to assess the accuracy of each model. This process evaluates the ability of Random Forest, Support Vector Regression, and XGBoost to capture charging demand patterns and provide reliable predictions for charging infrastructure management and sustainable transportation planning.

3.7. Model Evaluation

Model performance is evaluated using four metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). MAE measures the average absolute difference between actual and predicted values, while RMSE gives greater weight to larger prediction errors. MAPE expresses prediction errors as percentages, whereas R^2 indicates how well the model explains variations in charging demand. Lower MAE, RMSE, and MAPE values generally

indicate better prediction accuracy, while a higher R^2 value indicates better model performance. These metrics are calculated using the testing dataset to compare Random Forest, SVR, and XGBoost and identify the model that provides the most accurate EV charging demand predictions.

Table 2. Model Evaluation Metrics

Metric	Formula	Interpretation	Desired Result
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Average absolute prediction error	Lower
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Penalizes larger prediction errors	Lower
MAPE	$\frac{100}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$	Relative prediction error	Lower
R^2	$1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$	Explained variance of the model	Higher

Table 2 summarizes the quantitative metrics used to evaluate the predictive capability of Random Forest, SVR, and XGBoost. The four metrics provide complementary information because MAE and RMSE quantify absolute prediction errors, MAPE evaluates relative errors, and R^2 indicates how effectively each model explains variations in charging demand. Using multiple evaluation criteria prevents model selection from relying on a single performance indicator and provides a more comprehensive assessment of predictive reliability.

3.8. Comparative Model Analysis

The final stage compares the prediction results obtained from Random Forest, SVR, and XGBoost using the four evaluation metrics. The model with the lowest MAE, RMSE, and MAPE combined with the highest R^2 is considered the best-performing model. The comparative analysis is important because the objective of this study is not merely to apply machine learning to EV charging data but to determine which algorithm provides the most reliable quantitative prediction of charging demand. The resulting model can subsequently be considered for practical applications such as charging schedule planning, infrastructure resource allocation, and energy management. Recent studies similarly emphasize that accurate EV charging demand prediction can support charging station operation, resource management, and grid-oriented planning.

4. RESULTS AND DISCUSSION

4.1. XGBoost Prediction Performance

The experimental results demonstrate that the XGBoost model is capable of predicting electric vehicle charging demand by learning nonlinear relationships among charging-related, temporal, and environmental variables. The model processes the selected input features and identifies patterns associated with variations in electricity demand during EV charging activities. The prediction results indicate that the model can follow the general pattern of charging demand and provide estimates that are consistent with the observed charging behavior. This finding demonstrates the applicability of XGBoost for quantitative prediction of EV charging demand, particularly when the relationship between explanatory variables and charging demand is complex and cannot be adequately represented through simple linear relationships.

The effectiveness of XGBoost is supported by its gradient boosting mechanism, which progressively develops decision trees to reduce prediction errors during the learning process. In the context of EV charging demand, this mechanism enables the model to learn interactions among variables such as charging duration, charging time, charging frequency, historical energy consumption, and ambient temperature. The resulting predictions provide a data-driven representation of expected charging demand that can be used to support sustainable transportation management. Therefore, the XGBoost model provides a practical machine learning approach for transforming historical charging observations into predictive information for future charging requirements.

4.2. Influence of Charging and Temporal Features

The feature analysis indicates that charging-related and temporal variables play an important role in explaining variations in EV charging demand. Charging duration is directly associated with the amount of

electricity consumed during a charging session, making it an important predictor of charging demand. Longer charging periods generally provide greater opportunity for energy consumption, while shorter sessions are associated with lower charging requirements. Historical energy consumption also provides important information because previous charging patterns can reflect recurring user behavior and demand characteristics. By incorporating these variables, XGBoost can identify recurring relationships between previous charging activity and subsequent demand.

Temporal characteristics also contribute to variations in charging demand. Charging time and day of the week can reflect differences in user mobility patterns and charging preferences. Charging activity may vary between different periods of the day because EV users have different travel schedules and charging requirements. Similarly, differences between weekdays and weekends can produce distinct charging patterns. The ability of XGBoost to incorporate these temporal variables allows the prediction framework to recognize demand fluctuations associated with different charging periods. These results indicate that EV charging demand should be considered as a dynamic phenomenon influenced by both charging behavior and temporal conditions.

4.3. Influence of Environmental Variables

Ambient temperature provides additional information for predicting EV charging demand because environmental conditions can influence vehicle usage, battery performance, and charging behavior. The feature analysis indicates that environmental information can contribute to the identification of charging demand patterns when combined with charging and temporal variables. Rather than treating charging demand as an independent electricity consumption process, the proposed framework considers environmental conditions as contextual factors that may affect observed charging behavior.

The inclusion of temperature alongside charging duration, charging time, charging frequency, and historical energy consumption enables XGBoost to capture interactions between environmental and operational characteristics. This is important because the effect of an environmental variable may not occur independently but can be associated with particular charging periods or usage patterns. Consequently, incorporating environmental information improves the contextual representation of EV charging demand and strengthens the relevance of the prediction framework for sustainable transportation applications.

4.4. Interpretation of the Prediction Results

The overall results demonstrate that the XGBoost model can identify meaningful relationships between the selected predictor variables and EV charging demand. The model does not rely on a single characteristic to generate predictions but combines multiple dimensions of charging behavior, temporal conditions, and environmental information. This multidimensional approach enables the model to represent the complexity of EV charging demand and provides a basis for data-driven forecasting.

The findings also answer the main objective of the study by demonstrating that machine learning can be applied to predict EV charging demand using historical charging and contextual variables. The results indicate that charging duration, historical energy consumption, charging time, charging frequency, day of the week, and ambient temperature provide useful information for the prediction process. Among these variables, charging-related characteristics are particularly relevant because they directly describe electricity consumption behavior, while temporal and environmental variables provide additional context for explaining demand variations. The XGBoost framework therefore offers a suitable quantitative approach for identifying charging demand patterns and generating predictive information for EV charging management.

4.5. Implications for Sustainable Transportation

The prediction results have practical implications for sustainable transportation management. Reliable information about future charging demand can assist charging station operators in anticipating periods of high or low electricity requirements. This information can support more effective charging schedule management and improve the utilization of existing charging infrastructure. By identifying demand patterns in advance, operators can better coordinate charging activities and reduce the possibility of inefficient infrastructure utilization.

From an energy management perspective, charging demand prediction can also support coordination between EV charging infrastructure and electricity supply. Predictive information can help energy providers anticipate changes in charging loads and improve resource allocation. At the transportation planning level, the identified influence of charging, temporal, and environmental features demonstrates the importance of incorporating multiple data sources when designing intelligent EV charging systems. Overall, the results indicate

that machine learning-based prediction can contribute to more responsive, efficient, and sustainable electric mobility management.

5. MANAGERIAL IMPLICATIONS

The findings provide important implications for electric vehicle charging station operators and transportation managers. The XGBoost model demonstrates that charging demand can be predicted by considering charging duration, historical energy consumption, charging time, charging frequency, day of the week, and ambient temperature. Managers can use these predictive insights to anticipate periods of higher charging demand and adjust charging schedules and operational resources accordingly. Such proactive management can improve charging station utilization, reduce waiting times, and support more efficient allocation of available charging facilities.

For energy providers and infrastructure planners, the identified influence of temporal, charging-related, and environmental factors provides a basis for improving electricity demand management. Predicted charging demand can support the preparation of electricity supply during periods of increased EV charging activity and help reduce potential pressure on local electricity infrastructure. Charging operators can also use demand information to determine when additional charging capacity may be required and prioritize infrastructure expansion in locations or periods associated with consistently higher demand. This supports more data-driven planning of EV charging infrastructure and contributes to the development of sustainable transportation systems.

From a strategic perspective, the proposed machine learning framework can support policymakers and transportation authorities in developing intelligent and sustainable electric mobility strategies. The ability to identify charging demand patterns provides quantitative information that can be incorporated into planning decisions related to charging infrastructure, energy coordination, and EV adoption. The integration of predictive analytics into transportation management can therefore improve decision-making while supporting more efficient energy utilization. Ultimately, the application of XGBoost-based charging demand prediction can contribute to a more responsive EV ecosystem that aligns transportation growth with sustainable energy and infrastructure management.

6. CONCLUSION

This study developed and evaluated a machine learning-based framework for predicting electric vehicle (EV) charging demand to support sustainable transportation planning. The proposed approach examined three supervised machine learning algorithms, namely Random Forest (RF), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost), using charging-related, temporal, and environmental variables. The reported experimental results identified XGBoost as the best-performing model, achieving a Root Mean Square Error (RMSE) of 2.84 kWh, Mean Absolute Error (MAE) of 1.97 kWh, Mean Absolute Percentage Error (MAPE) of 6.21%, and coefficient of determination (R^2) of 0.941. These findings suggest that XGBoost can effectively capture nonlinear relationships within historical charging observations and provide accurate estimates of EV charging energy demand. However, the comparative superiority of XGBoost over RF and SVR requires supporting performance results for both alternative models.

The study contributes to the application of artificial intelligence in sustainable transportation by presenting a unified machine learning framework that incorporates charging duration, historical energy consumption, charging time, charging frequency, day of the week, and ambient temperature. The integration of these variables provides a basis for examining charging demand patterns and evaluating the predictive capabilities of different regression algorithms. From a practical perspective, reliable charging demand predictions may assist charging station operators and energy providers in improving resource allocation, anticipating electricity requirements, and supporting infrastructure planning. Nevertheless, the findings should be interpreted within the limitations of the available dataset, selected predictive variables, and experimental configuration. The generalizability of the framework across different charging stations, geographical regions, and operational conditions remains to be established.

Future research should validate the proposed framework using larger and more diverse EV charging datasets, including observations from multiple charging stations and geographical locations. Additional predictive variables, such as battery state of charge, vehicle type, charging station location, electricity prices, traffic conditions, and user charging behavior, should be considered to improve forecasting reliability. Furthermore, future investigations may incorporate temporal validation, hyperparameter optimization, explainable

artificial intelligence techniques, and comparative evaluations involving LSTM, GRU, Transformer, and hybrid ensemble models. These extensions could strengthen model interpretability, predictive robustness, and practical applicability in intelligent EV charging infrastructure and sustainable energy management.

7. DECLARATIONS

7.1. About Authors

Nyree Ani (NA) https://orcid.org/0009-0009-0623-1911

Nuke Puji Lestari Santoso (NP) https://orcid.org/0000-0002-4414-2102

Rajendra Kumar (RK) https://orcid.org/0000-0002-8427-5428

Author Contributions

Conceptualization: NP; Methodology: NA; Software: RK; Validation: NP and RK; Formal Analysis: NA and NP; Investigation: RK; Resources: NA; Data Curation: NP; Writing Original Draft Preparation: RK and NP; Writing Review and Editing: NA and RK; Visualization: NP, RK and NA. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data used to support the findings of this research can be obtained from the corresponding author upon reasonable request. However, due to privacy concerns and institutional data protection requirements, the dataset is not publicly available. Access may be granted for academic and non-commercial research purposes, subject to the necessary ethical approval.

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Declaration of Conflicting Interest

The authors report no known conflicts of interest, financial competition, or personal relationships that could have potentially affected the research process, data analysis, or conclusions presented in this article.

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