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A Random Forest-Based Approach for Hourly Electric Vehicle Charging Energy Consumption forecasting

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Abstract- ***The rapid growth in the adoption of electric vehicles (EVs) has increased the need for efficient management of EV charging demand and stable power grid operation. accurate forecasting of EV charging energy consumption is essential for smart grid management and charging infrastructure planning. existing forecasting approaches are commonly based on statistical techniques or deep learning models; however, many of these methods require large datasets, high computational resources, or lack interpretability. this paper presents a random forest-based approach for forecasting hourly EV charging energy consumption. the implemented framework utilizes temporal features and vehicle count information to predict hourly charging demand. the dataset was preprocessed and aggregated at an hourly level to capture variations in charging behavior over time. experimental results demonstrate that the random forest model is capable of capturing EV charging demand patterns and provides reasonable prediction accuracy for hourly energy consumption forecasting.***

Keywords—Electric Vehicles, Charging Demand Forecasting, Machine Learning, Random Forest, Energy Consumption Prediction, Vehicle Count Feature, Hourly Load Forecasting, Smart Grid

I. INTRODUCTION

A.Background of the Study

with the increasing demand for sustainable transportation, the adoption of electric vehicles (evs) has grown significantly in recent years. governments and industries are increasingly promoting electric mobility as part of efforts to reduce carbon emissions and dependence on fossil fuels. as the number of electric vehicles continues to increase, the need for efficient and reliable charging infrastructure also becomes more important.
however, the dynamic and unpredictable nature of ev charging demand creates challenges for power distribution networks. several factors influence charging behavior, including user habits, charging time, and vehicle usage patterns. therefore, accurate forecasting of ev charging energy consumption is essential for efficient energy management and stable grid operation.

accurate prediction of ev charging demand can support better energy distribution, improve charging station management, and reduce the risk of network overload.

B.Problem Statement

traditional load forecasting approaches were primarily designed for conventional residential and industrial electricity consumption patterns. these methods are often based on linear statistical relationships and may not effectively capture the nonlinear behavior associated with ev charging activities.

with the increasing adoption of electric vehicles, there is a growing need for forecasting approaches capable of handling large amounts of charging-related data and identifying complex relationships between variables. inaccurate prediction of ev charging demand may negatively affect energy distribution efficiency, increase operational costs, and reduce grid stability.

therefore, there is a need for machine learning-based forecasting methods capable of improving the prediction of hourly ev charging energy consumption.

C.Motivation

accurate forecasting of ev charging demand provides several benefits, including improved grid stability, better planning of charging infrastructure, and more efficient utilization of energy resources. machine learning techniques are capable of modeling complex relationships within large datasets and have demonstrated promising performance in energy forecasting applications.

the motivation of this work is to implement a random forest-based forecasting approach capable of predicting hourly ev charging energy consumption using temporal and vehicle count features.

D.Objectives of the Study

the objectives of this research are as follows:

1. to review existing machine learning approaches used for ev charging demand forecasting.

2. to implement a random forest-based model for forecasting ev charging energy consumption.

3. to incorporate vehicle count information as one of the input features in the forecasting process.

4. to predict hourly energy demand for electric vehicle charging stations.

5. to evaluate the performance of the implemented model using appropriate evaluation metrics.

E.Contributions of the Paper

the main contributions of this work are summarized as follows:

- an overview of machine learning approaches used for ev charging demand forecasting.
- analysis of datasets and forecasting techniques used in existing studies.
- implementation of a random forest-based model for hourly ev charging energy consumption forecasting.
- incorporation of vehicle count and temporal features in the forecasting framework.
- evaluation of the forecasting performance using real ev charging data.

II. RELATED WORK

A.Traditional Forecasting Approaches

Earlier attempts to predict demand for electric vehicles (EVs) relied mainly on statistical and impact assessment models. Rahman and Shrestha [11] were the first to investigate the effects of EV charging on the electricity network, providing a basis for further analysis of their relationship. More theoretical work was done by Clement-Nyns et al. [12] and Fernandez et al. [14], using mathematical models to determine the strain on residential electricity distribution networks, primarily focusing on voltage variations and transformer loading. Traditional techniques tended to address the problem from a power system stability point of view, demonstrated by Masoum et al. [10] and Pillai et al. [6], analyzing the reliability of the grid. While these approaches provided valuable information regarding infrastructure needs, as discussed in Habib et al. [18]'s review of EV technology and the scheduling methods by Silva and Catalao [20], they often lacked the ability to account for current drivers' uncertainty.

B.Machine Learning Approaches

The evolution of the field has seen a definitive shift toward data-driven computational models. Rashid et al. [1] and Wu et al. [22] categorize this transition in their extensive surveys, noting that machine learning offers superior adaptability to complex datasets. Optimization strategies, such as the flexible charging proposed by Sundstrom and Binding [13] and the decentralized control developed by Ma et al. [16], now rely on these predictive insights to balance load. Strategic infrastructure planning, explored by Deb et al. [4] and Xiang et al. [5], similarly utilizes computational forecasting to optimize station locations. High-performance models have recently dominated the literature; Zhang et al. [2] demonstrated the accuracy of deep learning for short-term demand, while Wang et al. [8] and Gao et al. [21] introduced robust and hybrid models to handle data uncertainty. Despite these advances, reviews by Kong et al. [3] and Xu et al. [7] highlight a persistent need for models that balance computational efficiency with interpretability, providing the rationale for the Random Forest approach utilized in this research.

III. COMPARATIVE ANALYSIS OF EXISTING METHODS

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TABLE I
Comparative Summary of Machine Learning Approaches for EV Charging Demand Forecasting

Authors (Year)	Application Domain	ML Models Used	Key Findings	Remarks / Effectiveness
Mamunur Rashid et al. (2024)	EV charging demand forecasting (survey/taxonomy)	Statistical, ML, DL (RF, SVR, LSTM)	ML/DL outperform statistical methods; temporal and weather features are critical	Establishes theoretical foundation for supervised ML in hourly forecasting
Yashvi Mudgal et al. (2025)	Cluster-based EV network forecasting and peak demand management	SVM, RF, K-means clustering	Cluster-wise modeling improves accuracy (reduced RMSE, MAE)	Handles data heterogeneity across multiple charging stations
Seyedmehdi Khaleghian et al. (2025)	Station-level utilization prediction	RF, XGBoost, OLS	Tree-based models outperform linear models; temporal features dominate	Supports feature selection based on vehicle count and time variables
Madan Mohan Reddy Nune et al. (2025)	IoT-based short-term load forecasting	SVR (RBF kernel)	Captures nonlinear patterns effectively; lower RMSE than statistical methods	Demonstrates effectiveness of real-time sensor data
Lubos Buzna et al. (2023)	EV load forecasting for smart grid planning	ARIMA, SARIMA, RF, SVR, ANN	RF and SVR outperform time-series models	Strong comparative validation supporting ML approaches
Xingshuai Huang et al. (2022)	Short-term charging station load forecasting	RF, Gradient Boosting, ANN (Ensemble)	Ensemble methods reduce RMSE; RF is robust and interpretable	Closely aligns with Random Forest-based methodology

Table I provides a comparison of the effectiveness and methodology aspects of various machine learning techniques used for predicting charging loads in electric vehicles (EVs). It shows that ensemble and decision tree algorithms such as Random Forest and Gradient Boosting have higher prediction accuracy and stability, while also being capable of modeling the time and non-linear characteristics of EV charging.

IV. IDENTIFIED RESEARCH GAPS

While there have been numerous advancements in the area of predicting EV charging demand, there are still a few limitations associated with the existing literature on this topic. Firstly, while much focus has been placed on optimization or energy management, demand prediction becomes an insignificant aspect within this context. Secondly, the existing studies use datasets that consist of data from one charging station only, limiting the ability of these models to be generalized. Additionally, certain important factors such as number of vehicles and charging time are not incorporated within the predictive model framework. Lastly, despite positive findings associated with the ensemble learning methods, less attention has been paid to developing interpretable models.

V. PROPOSED METHODOLOGY

A.System Overview

the implemented framework aims to forecast hourly electric vehicle (ev) charging energy consumption using a machine learning approach based on random forest regression. the methodology includes preprocessing ev charging session data and aggregating the charging demand at an hourly level. features such as hour of the day, day of the week, and vehicle count are extracted for analysis.

the preprocessed dataset is then used to train the random forest model in order to learn the relationship between the input features and energy consumption. the trained model is subsequently used to predict hourly energy demand at ev charging stations.

B.Workflow

he implemented workflow consists of several interconnected stages. first, historical ev charging session records are collected from the selected dataset. the data is then preprocessed to handle inconsistencies and missing values. after preprocessing, the dataset is aggregated into hourly records to align with the forecasting objective. next, feature engineering is performed to generate temporal features such as hour of the day and day of the week. vehicle count information is also incorporated to represent the number of charging sessions occurring within a given hour. the processed dataset is subsequently divided into training and testing sets.

the random forest regression model is trained using the selected input features. finally, the model performance is evaluated using metrics such as mean absolute error (mae) and root mean square error (rmse).

C.Dataset

the dataset used in this work consists of historical ev charging session records. each record contains information related to ev charging activities, including charging start time, charging duration, and energy consumption measured in kilowatt-hours (kwh).

to align with the forecasting objective, the charging data is aggregated at an hourly level. in addition to the original variables, an engineered feature representing vehicle count per hour is incorporated. this feature indicates the number of vehicles charging during a specific hour and contributes to capturing variations in charging demand.

furthermore, temporal features such as hour of the day and day of the week are extracted to model charging behavior patterns over time. the final dataset used for training includes these engineered features together with the aggregated hourly energy consumption values.

the target variable used for forecasting is the hourly aggregated energy consumption measured in kwh.

VI. IMPLIMENTATION METHODOLOGY

a machine learning-based approach was implemented to forecast hourly aggregated electric vehicle (ev) charging energy consumption using the random forest regression algorithm. the implementation process consisted of several stages, including data

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preprocessing, feature engineering, model training, performance evaluation, and visualization.

A. Data preprocessing

the dataset used in this work contains detailed ev charging session records, including timestamps, vehicle-related information, and charging energy consumption values. the charging start time for each session was converted into a datetime format to facilitate temporal analysis.data cleaning procedures were performed to remove missing or invalid entries and ensure consistency within the dataset before model training.

B. Hourly Aggregation

to support hourly energy consumption forecasting, the charging session data was aggregated at an hourly level. the charging start time of each session was used to extract hourly information and generate time-based variables.

the dataset was grouped according to the hour of the day, and the following values were calculated:

i. hourly aggregated charging energy consumption
ii. vehicle count per hour

this aggregation process enabled the analysis of charging demand variations across different periods of the day.

C. Training and Testing

to preserve the temporal sequence of the charging data, the dataset was divided chronologically into training and testing subsets. the split was performed as follows:

- training set: 80%
- testing set: 20%

this approach allowed the model to be evaluated using unseen future data while maintaining the chronological structure of the forecasting problem.

D. Model Evaluation

the forecasting performance of the random forest model was evaluated using mean absolute error (mae).

the experimental results produced an mae of approximately 30.51 kwh, indicating that the model achieved a reasonable level of prediction accuracy for hourly ev charging energy consumption forecasting.

E. Visualization

several visualizations were generated to analyze charging demand patterns and evaluate model performance. these visualizations include:

- hourly ev charging energy demand
- actual versus predicted energy consumption
- feature importance analysis
- vehicle count versus energy consumption

the generated graphs support the interpretation of charging behavior patterns and help validate the effectiveness of the forecasting model.

VII. RESULTS AND DISCUSSION

A. Model Performance

the hourly aggregated ev charging energy demand was analyzed to identify variations in energy consumption throughout the day. the results indicate noticeable fluctuations in charging demand across different hours, with hourly energy consumption values ranging from approximately 43.88 kwh to 326.42 kwh.

higher demand levels are observed during specific periods of the day, reflecting variations in charging activity and vehicle usage behavior. these observations demonstrate that ev charging demand is dynamic and influenced by temporal factors.

the identified hourly demand patterns highlight the importance of incorporating time-based features into the forecasting model to improve prediction performance.

B. Energy Demand Analysis

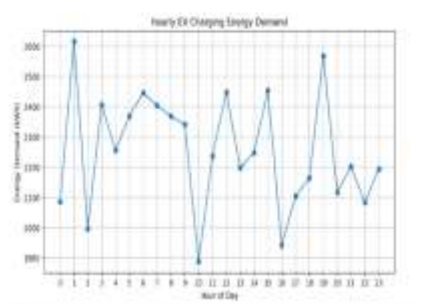

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Figure 1: Hourly aggregated EV charging energy demand by hour of the day.

The hourly aggregated EV charging energy demand was analyzed to identify variations in energy consumption throughout the day. The results indicate noticeable fluctuations in charging demand across different hours, with energy consumption values ranging from approximately 1,900 to 2,650 kWh per hour.

Higher demand levels are observed during specific periods of the day, reflecting increased charging activity and variations in vehicle usage patterns. These observations demonstrate that EV charging demand is dynamic and influenced by temporal factors.

The identified hourly demand patterns highlight the importance of incorporating time-based features, such as hour of the day, into the forecasting model to improve prediction performance.

C. Feature Importance Analysis

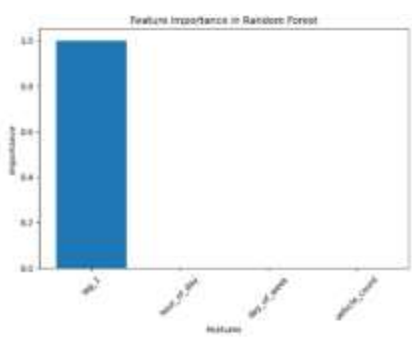

Figure 2: Feature importance obtained from the Random Forest model.

The feature importance analysis reveals that the lag feature (lag_1), representing the previous hour's energy consumption, has the strongest influence on the prediction process. This indicates that historical charging demand plays a significant role in forecasting future energy consumption.

In contrast, features such as hour of the day, day of the week, and vehicle count contribute less to the prediction due to limited variability in the aggregated dataset.

D. Model Prediction Analysis

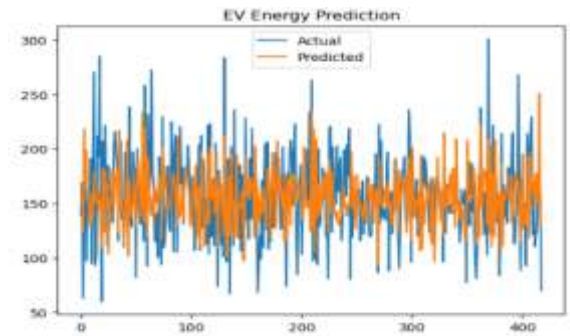

Figure 3: Comparison between actual and predicted energy consumption values.

From the comparison of observed data with forecasted data, it is evident that the model is effective in capturing the overall trend in energy consumption. While the forecasted data generally follows the observed data, there are some discrepancies in the data. The discrepancy becomes more evident at peak demand times due to the unpredictability of sudden changes in charging by users.

E. Discussion

The Random Forest model has been shown to be successfully predictive of the hourly energy demand for Electric Vehicles (EV) charging stations with a good degree of temporal pattern accuracy. Furthermore, it captures the relationship between the features investigated and the energy consumed.

The importance of these results is tempered by the presence of prediction errors caused by the stochastic nature of consumer behaviors in relation to EV charging. Factors contributing to the complexities of EV charging behaviors such as home-to-work arrival times on average for various vehicle types and inconsistent charging durations create further difficulty for forecasting.

The Random Forest model can therefore provide researchers a reliable estimate of energy demands to assist with both Energy Demand Planning and Energy Management for EV Charging Infrastructure.

CONCLUSION

this work implemented a random forest-based model for forecasting hourly electric vehicle charging energy consumption. through data preprocessing and the extraction of temporal and vehicle count features, the model was able to capture important patterns in ev charging behavior.

the experimental results achieved a mean absolute error (mae) of approximately 30.51 kwh, indicating a reasonable level of prediction accuracy for hourly energy demand forecasting. the comparison between actual and predicted values showed that the model successfully follows the general energy demand trends, although some variations remain during peak demand periods.

overall, the results demonstrate that random forest can provide an effective and interpretable approach for ev charging energy consumption forecasting. future improvements may include the incorporation of additional features and further optimization of the forecasting model.

FUTURE SCOPE

future improvements to this work may focus on the integration of additional features that can further enhance forecasting performance, such as weather conditions, electricity pricing, traffic density, and renewable energy availability. incorporating larger and more diverse datasets collected from multiple charging stations and geographic regions may also improve the generalization capability of the forecasting model.

further research may explore the use of advanced machine learning and hybrid forecasting techniques to compare their performance with the random forest approach. optimization methods for smart charging scheduling and energy management can also be integrated with the forecasting framework to support intelligent charging infrastructure and smart grid operations.

in addition, real-time forecasting systems using live charging data may be developed to enable dynamic energy management and improve the operational efficiency of electric vehicle charging stations.

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