

MULTI MODEL EV CHARGING DEMAND FORECASTING WITH REAL TIME OPTIMIZATION

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Abstract

The increase in electric mobility usage has created a strong need for efficient charging infrastructure and intelligent demand management systems. Charging demand depends on battery capacity, charging rate, traffic and weather conditions. Now a days charging stations are facing overload, long waiting hours, and inefficient energy usage. In this project different forecasting models are used to predict EV charging demand. The performance of these models is measured using evaluation metrics. A hybrid ensemble model is developed to improve reliability. The system also includes an optimization technique to reduce sudden load variations and improve charging station efficiency. Infrastructure planning is performed to estimate the number of charging units required. A Streamlit dashboard is implemented for visualization, it displays forecasting results, comparison graphs, residual error analysis, optimization impact, and charging requirements. This system helps station operators, fleet managers, smart city developers make better decisions for charging management.

Keywords- Electric vehicles, Charging demand forecast, Hybrid Ensemble model, Streamlit dashboard, Infrastructure Planning, Machine Learning

1. Introduction

Electric Vehicles are playing an important role in modern transportation. It helps to reduce fuel consumption and pollution. As the increase in electric vehicles, the demand for charging stations also increases. So, proper management and planning of EV charging infrastructure is very much important.

The major challenges faced in EV charging stations is the variation in charging demand due to traffic and, weather, battery level, user behaviour. The project focuses on developing a machine learning based charging demand forecasting system by using multiple forecasting models. Each model predicts future demand by analyzing the data. A hybrid forecasting approach uses multiple models for better demand predictions.

The project includes Linear Regression, Random Forest, ARIMA, and LSTM models for demand prediction. MAE, RMSE, and MAPE evaluation metrics help to compare their performance. A hybrid model is implemented to improve prediction stability. Optimization helps in improving charging station performance.

The system showcases how libraries like Pandas, NumPy, Scikit-learn, TensorFlow, Matplotlib, and Streamlit can come together to predict future demand of charging stations.

A Streamlit dashboard is developed to display forecasting graphs, model comparison results, optimization analysis, residual errors, infrastructure output in a detailed way.

2. Related Work

Khan et al. [1] (2023) proposed a deep learning-based EV charging demand forecasting framework using LSTM and attention mechanisms. Their work demonstrated on forecasting accuracy and machine learning algorithms to predict charging demand.

Zhang et al. [2] (2024) developed a hybrid ML model by combining Random Forest and time-series forecasting techniques. The proposed model achieved better forecasting performance compared to conventional machine learning approaches.

Patel and Sharma [4] (2025) explored the use of AI-driven charging infrastructure planning using forecasting models and optimization techniques. Their research highlighted the importance of demand prediction, charger deployment requirements and smart city development.

Linear Regression is a simple machine learning method used for prediction problems. It helps identify the relationship between input parameters and output demand.

According to **Zhang et al. [5]** Random Forest achieved reliable prediction performance by capturing complex interactions among charging-related factors such as traffic conditions, weather variations, and charging behavior.

Wang et al. [6] (2024) uses ARIMA models to analyze historical EV charging demand data and predict future charging loads. According to their work ARIMA can successfully identify trends, seasonal variations, and temporal patterns in charging behavior.

Deep learning technique have gained significant attention for forecasting of electric vehicles charging demand due to complex temporal patterns. In a recent study, **Khan et al. [7]** explored LSTM-based forecasting framework that analyzed historical charging data to learn long-term dependencies in charging behavior. The LSTM model achieved higher prediction accuracy than conventional forecasting

methods, making it suitable for supporting future EV adoption and infrastructure planning.

3. Materials and Methods

The proposed system consists of two main modules: height monitoring and damage detection. The overall structure is illustrated using block diagrams and flowcharts.

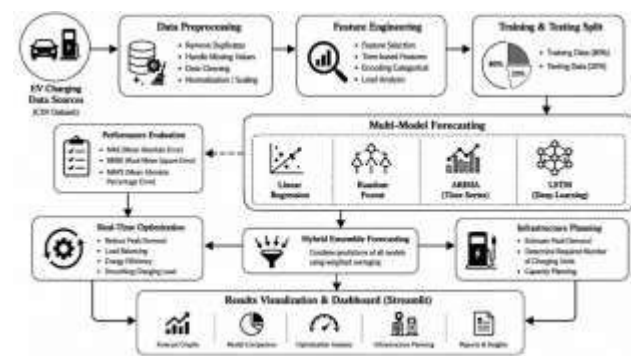


FIGURE 1.1 ARCHITECTURE OF THE PROPOSED EV CHARGING FORECASTING SYSTEM

The first stage is data collection. Data is collected from CSV datasets containing charging parameters like battery capacity, charging rate, queue time, traffic conditions, weather conditions, charging load, and station capacity. In preprocessing stage to improve the quality and reliability of the data. At this stage duplicates, missing values, are removed from the data. Cleaned data is passed through feature engineering, it helps to modifying the raw data into meaningful, informative representation for machine learning model. It helps forecasting models to understand charging demand behavior and improves prediction stability. It also reduces the influence of irrelevant features in the dataset. Training the data set is for model development, and then predict the test data. Dataset splitting helps avoid overfitting and improves reliability. In this project hybrid ensemble model is used to predict different model outputs. Linear-Regression used to identify linear relationships between charging parameters and charging demand. Random Forest is an ensemble learning model by using multiple decision trees it improves prediction

accuracy. ARIMA is a time series forecasting technique used for analyzing historical charging demand patterns. LSTM is a deep learning model capable of learning long term charging demand behavior from sequential data.

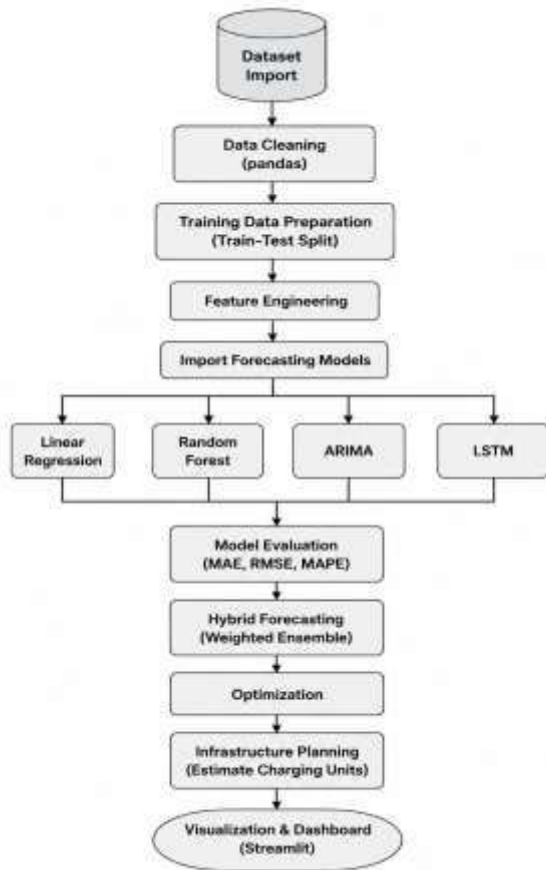


Figure 1.2 Flow Chart.

The first stage is importing the dataset, which contains charging-related parameters like battery capacity, charging rate, queue time, traffic conditions, weather conditions, temperature, and charging load.

Data cleaning is a preprocessed technique used to improve the quality and consistency of the dataset.

In the next stage the dataset is divided into training data and testing data. 80% of the data for training the model and 20% for testing the model. The `train_test_split()` function from Scikit-learn for dataset splitting. EDA(Exploratory Data Analysis):

Activities performed, Dataset summary

Missing value analysis, Correlation analysis Charging Demand Distribution, Detection of Outlier, Identification of Trend. Residual analysis helps in evaluate forecasting and prediction errors.

In this system linear regression is used estimate electric vehicle charging demand. It analyzes the relationship charging load and parameters, like battery capacity, state of charge, traffic conditions, queue time, and charging rate. Random Forest improves the performance by learning complex relationships in EV charging data. ARIMA is used into the system to analyze historical charging demand trends, time series and forecast future charging requirements. LSTM used for long term temporal patterns in data. Hybrid model is used to predict which forecasting technique works better. And Streamlit dashboard is developed to upload datasets, compare model performance, optimization results, and estimation of charging infrastructure requirements in real time.

4. Results and Discussion

The Multi-Model EV Charging Demand Forecasting System uses ML and DL techniques to generate accurate EV charging demand predictions and support intelligent infrastructure planning. The system analyzes charging-related parameters such as battery capacity, charging rate, queue time, traffic conditions, weather conditions, and charging load to forecast future charging demand patterns.

The proposed system implements multiple forecasting models and Hybrid Ensemble forecasting approach combines the outputs of these models to improve prediction stability and forecasting reliability. The generated forecasting results help charging station operators optimize charging load distribution and improve charging station efficiency.

The system also performs optimization analysis to reduce charging demand fluctuations and improve

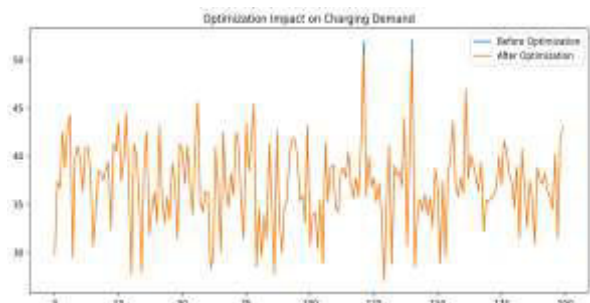


Figure 1.5 Estimated Charging Infrastructure Requirement

energy utilization. Infrastructure planning analysis estimates the required number of charging units based on forecasted peak demand and charging

station capacity. Graphical visualizations and performance comparisons provide better understanding of forecasting accuracy and model behavior.

The Streamlit dashboard provides an interactive interface for displaying forecasting graphs, optimization analysis, model performance comparisons, residual error analysis, and infrastructure planning results. The dashboard enables users to monitor EV charging demand trends in real time and supports intelligent decision-making for future EV charging infrastructure development.

Model	MAE	RMSE	MAPE	Remarks
Linear Regression	8.05	10.10	30.2	Good baseline performance
Random Forest	8.08	10.18	30.3	Better nonlinear prediction
ARIMA	8.60	10.85	33.0	Suitable for time-series forecasting
LSTM	8.60	10.85	33.0	Captures temporal dependencies
Hybrid Ensemble (Proposed)	8.04	10.10	30.1	Best overall performance

Table 1.1 Model Comparison

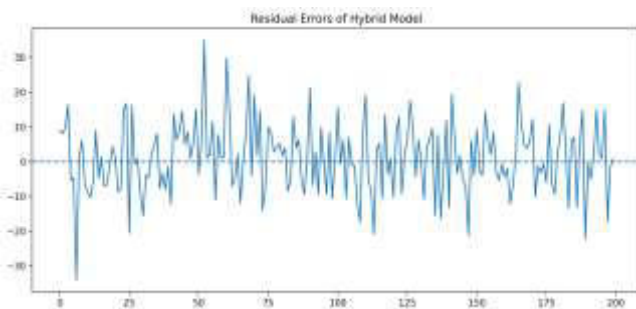


Figure 1.3 Residual Error Analysis

Residual errors represent the difference between actual charging demand and predicted charging demand values. The graph indicates that most forecasting errors are distributed around zero, demonstrating stable forecasting behavior.

The optimized charging demand curve appears smoother indicating improved charging station efficiency and reduced charging load fluctuations.

Displays the estimated number of charging units required based on forecasted peak charging demand and charging station capacity.

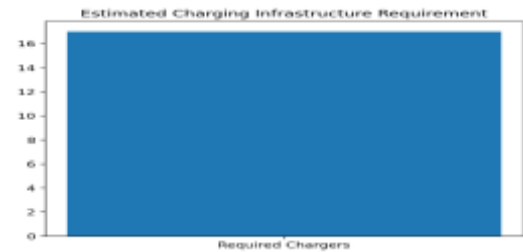


Figure 1.4 Optimization Impact on Charging Demand

5. Conclusion

The proposed system provides an intelligent solution for predicting and managing EV charging demand. The system uses machine learning, deep learning, and time-series forecasting models to analyze charging-related data and generate future demand predictions.

The project implements Linear Regression, Random Forest, ARIMA, and LSTM models. These models are compared using performance metrics such as MAE, RMSE, and MAPE. A Hybrid model is developed to improve forecasting stability and reliability.

The optimization helps to reduce the overloading and improves the station efficiency. The infrastructure planning shows the number of required charging unit. It helps charging station operator to make better decisions.

The Streamlit dashboard displays an interactive forecasting graphs, performance of different model, residual error analysis, optimization impact, and infrastructure planning output. Overall, the proposed system supports smart transportation, efficient energy management, and sustainable EV charging infrastructure planning.

The proposed system can be further enhanced by integrating real-time charging station data collected through IoT devices and smart sensors. Advanced deep learning architectures and reinforcement learning techniques can also be implemented to improve forecasting accuracy and optimization performance.

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