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AI-Based Prediction and Optimization of Electric Vehicle Charging Demand Integrated with Solar Power Generation

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Abstract

The rapid growth of electric vehicles (EVs) has increased the demand for efficient charging infrastructure and intelligent energy management systems. Simultaneously, the integration of renewable energy sources, particularly solar power, has emerged as a sustainable solution for reducing dependence on conventional electricity generation. However, the intermittent nature of solar energy and the dynamic behaviour of EV charging demand present significant challenges for effective energy utilization and grid stability. This study proposes a machine learning and deep learning-based framework for forecasting EV charging demand and integrating it with solar energy generation. The Boulder EV Charging Station Dataset and the NASA POWER Solar Dataset were used to analyse charging behaviour and solar energy availability. Data preprocessing techniques including cleaning, feature extraction, and normalization were applied to improve data quality. Four predictive models, namely Linear Regression, Random Forest, XGBoost, and Long Short-Term Memory (LSTM), were implemented and evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Linear Regression achieved an R^2 of 0.84, while Random Forest and XGBoost improved performance to 0.92 and 0.95 respectively. The LSTM model achieved the highest accuracy, with an MAE of 0.18, RMSE of 0.28, and R^2 of 0.97, owing to its ability to capture temporal dependencies in time-series data. The integration of solar forecasting with charging demand prediction enabled identification of optimal charging periods, supporting load shifting, improved renewable utilization, and reduced grid dependency.

Keywords: *Electric Vehicle Charging Demand, Solar Energy Forecasting, Machine Learning, LSTM, Smart Grid.*

1. INTRODUCTION

The shift toward cleaner and more sustainable energy sources has gained significant momentum in recent years [1], [2]. One of the major developments in this transition is the increasing use of electric vehicles (EVs), which helps reduce dependence on conventional fossil fuels and lower harmful emissions. At the same time, solar photovoltaic (PV) systems have become a popular choice for generating renewable electricity due to their availability and environmental benefits. Combining EV technology with solar energy has the potential to create a more efficient and eco-friendly power system, particularly in the context of future smart grids [3]. However, both EV charging demand and solar power generation are highly variable: solar output depends on sunlight intensity, weather conditions, and time of day [4], while charging demand is influenced by user habits, travel patterns, and daily routines, which may not always align with solar availability [5].

This mismatch between generation and consumption can result in inefficient use of renewable energy, where excess solar power goes unused during the day while high evening demand increases reliance on the conventional grid [6]. Predictive modelling plays an important role in overcoming these challenges. By analysing historical data related to EV charging behaviour and solar energy generation, machine learning techniques can be used to identify patterns and make accurate predictions that support more effective energy planning and management. The main aim of this work was to develop a data-driven system that predicts EV charging demand and aligns it with solar energy availability, thereby enhancing renewable utilization and supporting the development of a more reliable and sustainable power system.

1.1 Problem Statement

The rapid adoption of EVs has significantly increased demand for charging infrastructure and electricity consumption, introducing challenges related to load management, peak demand, grid congestion, and energy scheduling. Traditional charging systems generally operate without considering future demand patterns or renewable energy availability, resulting in inefficient utilization and increased dependence on grid electricity. At the same time, the intermittent and weather-dependent nature of solar power makes it difficult to ensure a continuous supply. Existing approaches often address demand prediction and renewable forecasting independently, and conventional statistical methods struggle to capture the nonlinear, time-dependent relationships present in charging and environmental data. There is therefore a need for an intelligent framework

that forecasts EV charging demand and solar availability jointly, and integrates both to optimize charging schedules, improve renewable utilization, and support sustainable smart-grid operation.

1.2 Scope and Objective of the Work

The proposed work aims to develop an efficient system that predicts EV charging demand using historical data patterns while simultaneously estimating solar power generation based on weather and irradiance information. By combining these two predictions, the study seeks to improve energy utilization and reduce stress on the power grid. Machine learning techniques were used to build and evaluate the models to ensure reliable performance, supporting better planning and management of energy in systems where EVs and solar power are used together.

2. LITERATURE REVIEW

Early energy demand forecasting relied mainly on traditional statistical techniques such as linear regression and basic time-series models, which are useful for identifying simple trends but struggle with the complex, nonlinear relationships common in real-world power systems. With the growth of artificial intelligence, techniques such as Random Forest, Support Vector Machines, and Artificial Neural Networks have shown significant improvements in forecasting accuracy by learning from large datasets and adapting to changing conditions. In solar forecasting, early ARIMA-based models have progressively given way to neural networks and, more recently, Long Short-Term Memory (LSTM) networks, which are well suited to time-dependent data and long-term dependencies.

Sarker et al. [1] proposed an AI-driven optimization framework that integrates EV charging with solar PV and battery energy storage systems (BESS) in high-density residential environments, demonstrating improved coordination between generation and demand. Prajapati et al. [2] reviewed the challenges, opportunities, and future perspectives of AI integration in solar-powered EV charging systems, highlighting data quality and scalability as key barriers. Sajjad et al. [3] developed data-driven AI models using historical weather and load data to support renewable energy-based smart EV charging stations, reporting improved forecasting reliability. Shibl et al. [4] proposed a machine learning-based EV charging management approach considering fast charging and vehicle-to-grid (V2G) operation, improving scheduling efficiency. Bilal et al. [5] carried out a techno-economic and environmental analysis of grid-connected EV charging stations using AI-based algorithms, showing reduced operating cost and emissions.

Khare et al. [6] modelled the cost optimization and management of a grid-connected, solar-powered EV charging station, demonstrating economic benefits of renewable integration. Shern et al. [7] applied AI optimization for user prediction and efficient energy distribution within EV smart charging systems, improving resource allocation. Ghenai et al. [8] developed artificial neural network-based models for short-term forecasting of solar PV power output and battery state-of-charge at solar EV charging stations, achieving reliable short-horizon predictions. Mazhar et al. [9] compared several machine learning methods for EV charging within smart grids, reporting that ensemble and boosting methods generally outperformed simple regression baselines. Chandra et al. [10] proposed optimal scheduling of solar-powered EV charging stations in a radial distribution system using opposition-based competitive swarm optimization, improving voltage profiles and reducing losses.

Franco et al. [11] analysed real-world EV charging data and emphasized that charging demand is not constant and is heavily influenced by user habits such as daily routines and travel patterns, highlighting the need for accurate demand prediction to ensure smooth grid operation. Dang et al. [12] compared traditional and deep learning models for time-series prediction and proposed a hybrid XGBoost-DL approach that achieved improved forecasting reliability. Wang et al. [13] studied uncertainty in photovoltaic power prediction by comparing Bayesian deep learning and shallow neural models, developing an LSTM-based Bayesian model that improved short-term forecasting accuracy. Clement-Nyns et al. [14] proposed a smart charging approach that schedules EV charging during off-peak hours or when renewable energy is available, improving overall grid stability. Lund and Kempton [15] explored the broader concept of integrating EVs into renewable energy systems, suggesting that EVs can act as flexible loads whose charging is adjusted based on renewable availability, opening new possibilities for balancing energy supply and demand.

Although significant progress has been made in both EV demand prediction and solar forecasting individually [1]–[15], most studies treat them as separate problems, and few attempt to combine both into a single, integrated framework. This creates a gap in achieving efficient, coordinated energy management. The present study addresses this gap by developing a data-driven approach that links EV charging demand forecasting with solar energy availability prediction for improved coordination and utilization.

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3. RESEARCH METHODOLOGY

This study develops an AI-based framework for predicting EV charging demand and integrating it with solar power generation forecasts. The workflow consists of data acquisition, preprocessing, feature engineering, model development and training, performance evaluation, and charging optimization. Two real-world datasets were used: the Boulder EV Charging Station Dataset, providing charging session records (start/end time, duration, energy consumed, and station identification), and the NASA POWER Solar Dataset, providing solar irradiance, temperature, humidity, and wind speed. The overall system architecture, shown in Figure 1, comprises five stages — data acquisition, preprocessing, a prediction module for both EV demand and solar generation, an optimization module for demand-solar matching and load shifting, and an output/visualization stage.

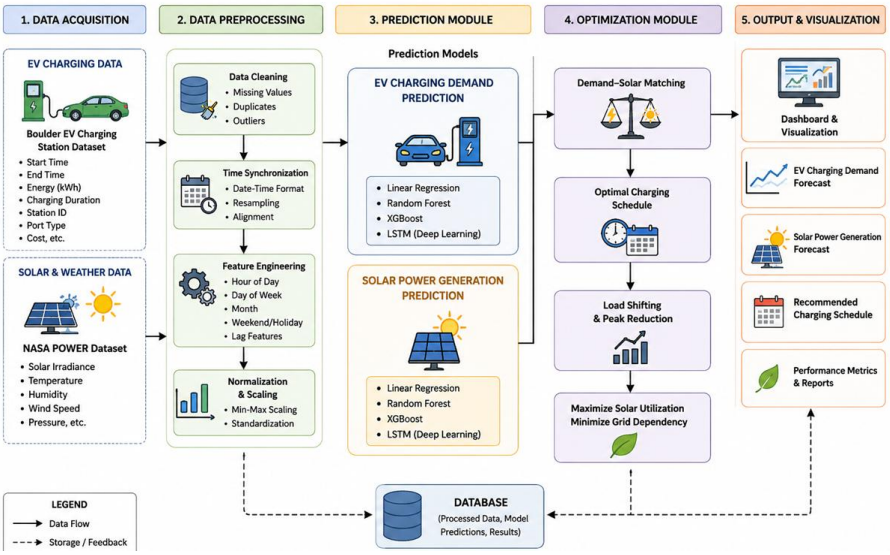


Figure 1: Proposed system architecture for EV charging demand forecasting and solar energy integration.

3.1 Data Preprocessing

As illustrated in Figure 2, raw data were cleaned by identifying and treating missing values through imputation or removal, detecting and removing duplicate records, and applying outlier detection to abnormal charging sessions and weather readings. Time-based features — hour of day, day of week, month, and weekend indicator — were extracted from timestamps, and charging duration was derived from session start/end times. Min-Max scaling was applied to normalize feature values to a common 0–1 range, with standardization applied where necessary to improve model convergence and prevent large-magnitude variables from dominating training.

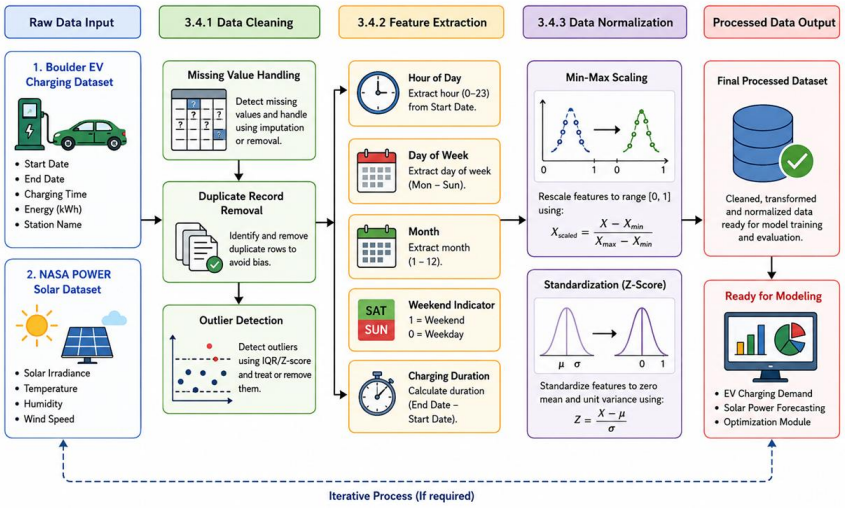


Figure 2: Data preprocessing workflow applied to the Boulder EV charging and NASA POWER solar datasets.

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3.2 Predictive Models

Four models representing different learning paradigms were implemented and compared:

Linear Regression establishes a linear relationship between input features and charging demand, fitted using least squares. It served as an interpretable baseline model.

Random Forest is an ensemble of decision trees trained on randomly selected subsets of data and features, with predictions obtained by averaging individual tree outputs. This reduces variance and captures nonlinear relationships more effectively than linear models.

XGBoost (Extreme Gradient Boosting) builds decision trees sequentially, with each tree correcting the errors of its predecessors. Regularization terms limit overfitting, and the model efficiently handles missing values and large feature sets. A learning rate of 0.1 was used after hyperparameter tuning.

Long Short-Term Memory (LSTM) networks are a specialized recurrent architecture with memory cells and input, forget, and output gates that regulate information flow (Figure 3), allowing the model to retain relevant history over long sequences while mitigating the vanishing-gradient problem. Given the inherently time-dependent nature of both charging demand and solar irradiance, LSTM was adopted as the primary deep learning model and trained for 50 epochs.

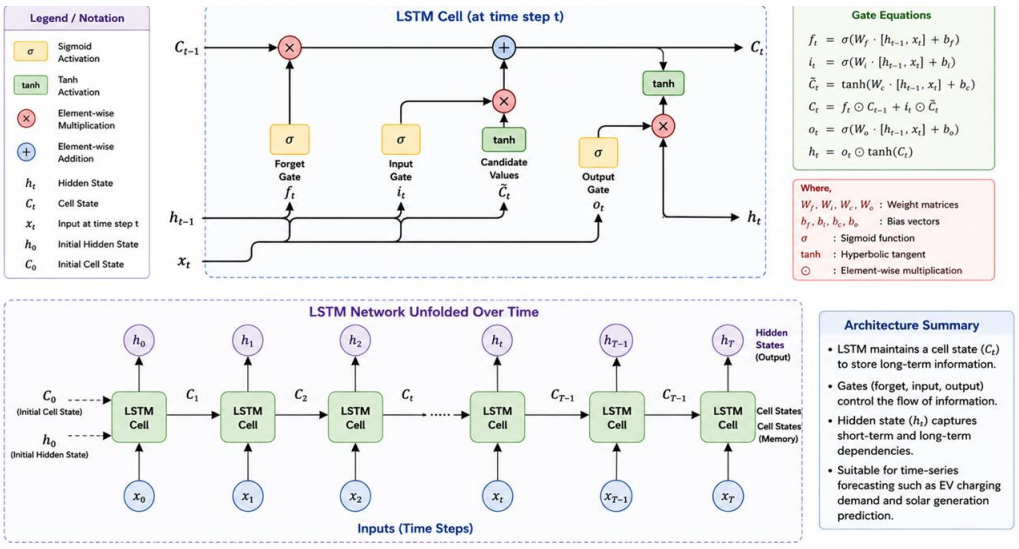


Figure 3: LSTM network architecture showing the internal gating mechanism and the unfolded structure over time.

3.3 Training, Testing, and Evaluation

The dataset was split 80:20 into training and testing subsets, providing sufficient data for learning while preserving an unbiased test set. Random Forest was configured with 100 estimators, XGBoost used a learning rate of 0.1, and LSTM was trained for 50 epochs (Table 1). Model performance was evaluated using three standard regression metrics: Mean Absolute Error (MAE), which measures average absolute prediction error; Root Mean Square Error (RMSE), which penalizes larger errors more heavily by squaring deviations before averaging; and the Coefficient of Determination (R^2), which indicates the proportion of variance in charging demand explained by the model, with values closer to 1 indicating a better fit.

Table 1: Model Hyperparameters

Model	Key Parameter(s)
Random Forest	n_estimators = 100
XGBoost	learning_rate = 0.1
LSTM	Epochs = 50

3.4 Demand–Solar Integration Framework

The final stage integrates forecasted EV charging demand with predicted solar generation to identify optimal charging windows — time intervals coinciding with high solar irradiance and sufficient renewable availability. A load-shifting strategy is incorporated whereby charging demand that would normally occur during peak grid hours is shifted toward periods of higher solar generation, reducing electrical grid stress, minimizing peak demand, and increasing renewable energy utilization.

4. RESULTS AND DISCUSSION

The Boulder dataset comprised 25,438 charging sessions across 18 stations, with an average energy consumption of 11.72 kWh and an average session duration of 2.85 hours. The NASA POWER dataset provided an average solar irradiance of 512.4 W/m², average temperature of 22.8 °C, average relative humidity of 58.6%, and average wind speed of 3.9 m/s, confirming sufficient variability in both datasets to support robust forecasting (Table 2). After cleaning, 1,214 of the original 25,438 records were removed owing to missing values, duplicates, or outlier conditions, leaving 24,224 records for model development.

Table 2: Summary of Datasets Used

Dataset	Parameter	Value
Boulder EV Charging	Total Sessions	25,438
Boulder EV Charging	Stations	18
Boulder EV Charging	Average Energy (kWh)	11.72
Boulder EV Charging	Average Duration (Hours)	2.85
NASA POWER Solar	Solar Irradiance (W/m²)	512.4
NASA POWER Solar	Temperature (°C)	22.8
NASA POWER Solar	Relative Humidity (%)	58.6
NASA POWER Solar	Wind Speed (m/s)	3.9

Exploratory analysis revealed clear temporal structure in charging behaviour. As shown in Figure 4, average charging demand is lowest during late-night and early-morning hours and rises steadily through the day, peaking between 18:00 and 20:00 as users return home from work — a pattern consistent with commuting-driven charging behaviour and directly relevant to aligning charging with solar availability, which is naturally highest around midday.

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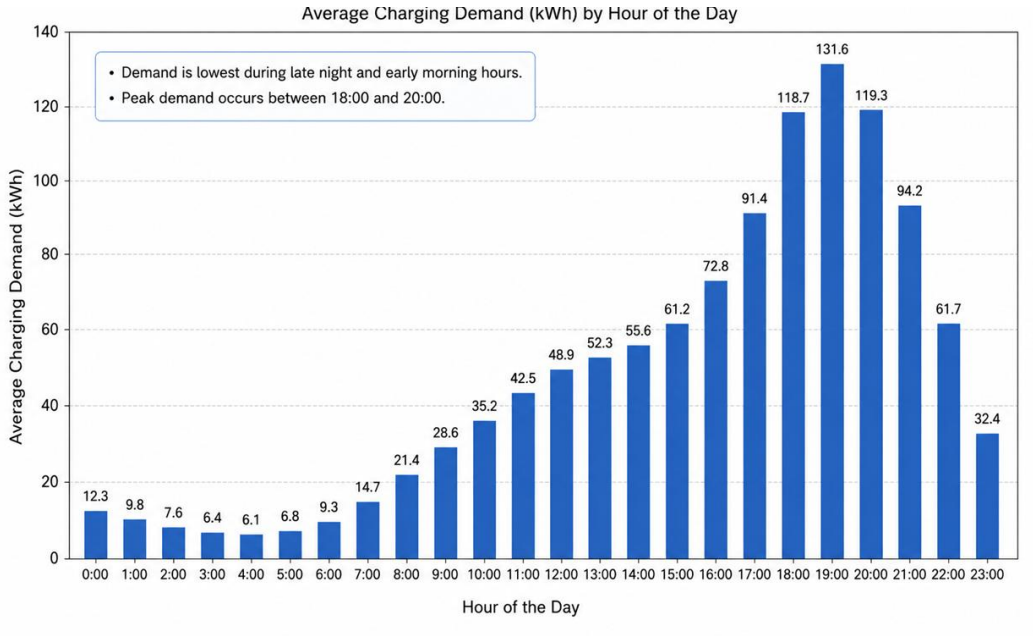


Figure 4: Hourly distribution of average EV charging demand, showing evening peak load.

4.1 Model Performance

Each model was trained on the same 80:20 split and evaluated on identical test data. Linear Regression achieved an MAE of 0.45, RMSE of 0.62, and R^2 of 0.84, capturing the overall demand trend but showing larger deviations during rapid fluctuations due to its linear assumption. Random Forest improved substantially on this baseline, reducing MAE to 0.29 and RMSE to 0.41 while raising R^2 to 0.92, reflecting its ability to model nonlinear interactions among charging and weather variables. XGBoost further improved performance (MAE = 0.24, RMSE = 0.35, R^2 = 0.95) through its sequential error-correcting boosting mechanism and regularization. The LSTM model achieved the best results overall, with an MAE of 0.18, RMSE of 0.28, and R^2 of 0.97, reflecting its capacity to learn long-term temporal dependencies and nonlinear sequential patterns in both charging and solar data. The complete comparison is summarized in Table 3 and Figure 6.

Table 3: Comparison of Machine Learning and Deep Learning Models

Model	MAE	RMSE	R^2
Linear Regression	0.45	0.62	0.84
Random Forest	0.29	0.41	0.92
XGBoost	0.24	0.35	0.95
LSTM	0.18	0.28	0.97

The close agreement between the LSTM model's predicted and actual charging demand values on the held-out test set is illustrated in Figure 5, where predicted points closely track the 45° perfect-prediction line across the full demand range, with only minor scatter at higher demand levels.

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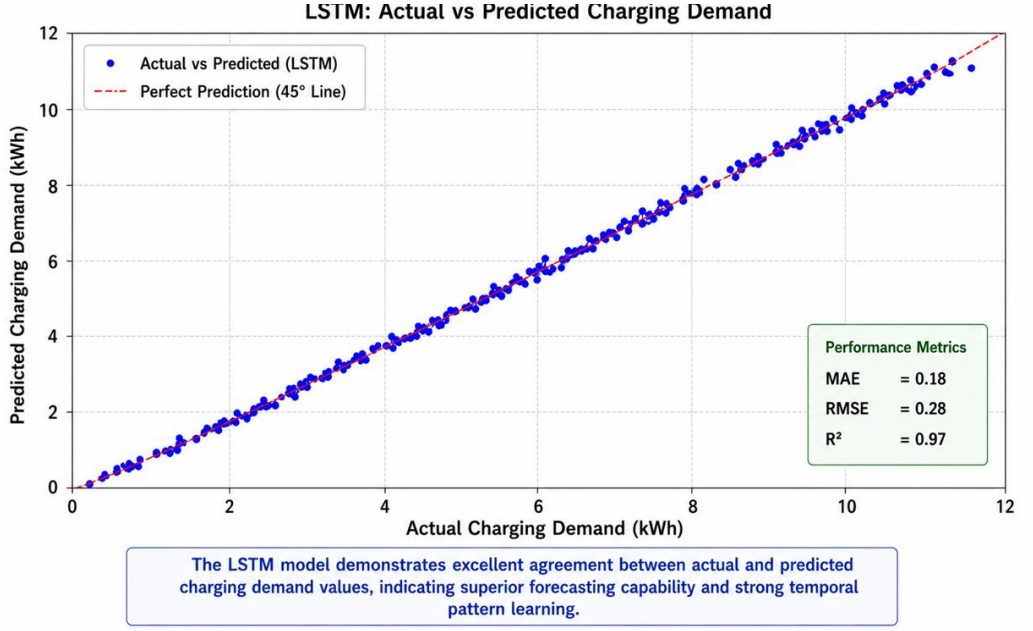


Figure 5: Actual versus predicted EV charging demand for the LSTM model on the test dataset.

The relative performance of all four models across MAE, RMSE, and R^2 is compared directly in Figure 6, which shows a consistent, progressive improvement moving from Linear Regression to Random Forest, XGBoost, and finally LSTM.

4.2 Discussion

The results show a consistent, progressive improvement in forecasting accuracy moving from simple statistical modelling to ensemble learning and finally to deep sequential learning. Error metrics (MAE, RMSE) decreased monotonically while R^2 increased monotonically across Linear Regression, Random Forest, XGBoost, and LSTM, confirming that model complexity aligned with the nonlinear, time-dependent nature of the underlying charging and solar processes is directly rewarded in forecasting accuracy. Linear Regression's assumption of a linear relationship between predictors and demand limited its ability to track rapid fluctuations, whereas the tree-ensemble methods (Random Forest, XGBoost) captured nonlinear feature interactions without requiring explicit transformation of inputs. LSTM's advantage stemmed specifically from its memory-cell and gating architecture (Figure 3), which allowed it to retain relevant historical context — such as recent charging trends and irradiance patterns — while discarding irrelevant information, effectively modelling the sequential dependency inherent to both charging demand and solar generation.

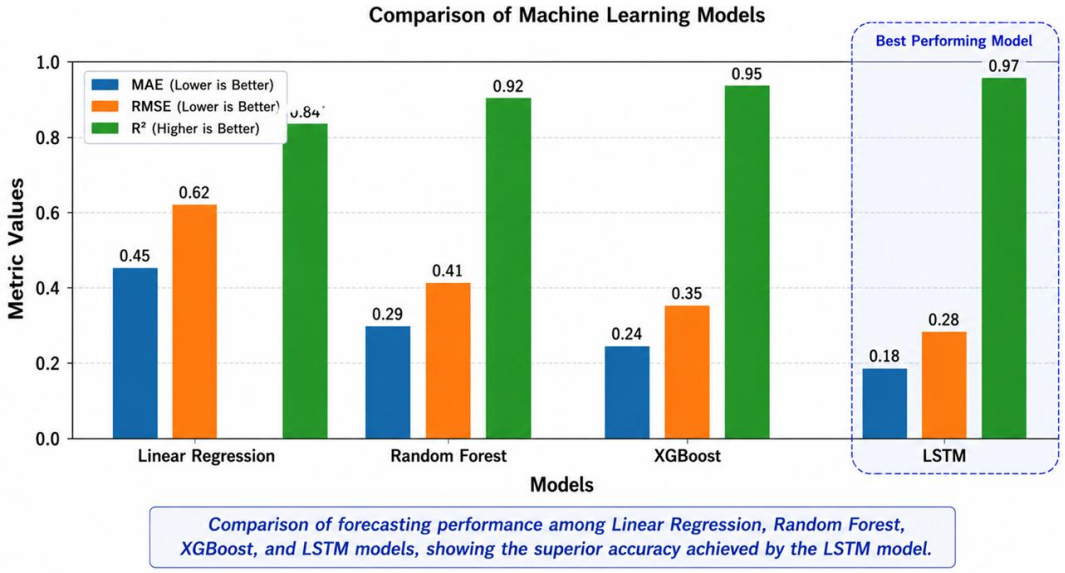


Figure 6: Comparison of MAE, RMSE, and R^2 across the four forecasting models.

The integration of solar forecasting with charging demand prediction enabled identification of charging periods that coincide with high renewable availability. Since peak charging demand (Figure 4) occurs in the evening while solar generation peaks around midday, the proposed framework supports a load-shifting strategy in which demand that would otherwise occur during peak grid hours is redirected toward high-solar-generation windows, increasing the effective utilization of renewable energy that would otherwise be underused or curtailed during low-demand daytime periods. Collectively, these outcomes indicate that the proposed framework can reduce peak electricity demand, ease stress on distribution networks, lower dependence on fossil-fuel-based generation, and support the broader development of intelligent, renewable-integrated smart-grid systems.

5. CONCLUSIONS

This study presented a machine learning and deep learning-based framework for forecasting EV charging demand and integrating it with solar energy generation to support intelligent energy management. Using the Boulder EV Charging Station Dataset and the NASA POWER Solar Dataset, comprehensive preprocessing — cleaning, feature extraction, and normalization — was applied prior to training four predictive models: Linear Regression, Random Forest, XGBoost, and LSTM. All models captured charging demand patterns with reasonable accuracy, but performance differed substantially: Linear Regression achieved $R^2 = 0.84$, Random Forest $R^2 = 0.92$, and XGBoost $R^2 = 0.95$, while LSTM achieved the best overall performance with MAE = 0.18, RMSE = 0.28, and $R^2 = 0.97$, owing to its ability to learn temporal dependencies and nonlinear relationships from historical data. Integrating solar forecasting with demand prediction enabled identification of optimal charging periods, supporting intelligent charging management, greater renewable utilization, reduced grid dependency, and improved grid stability. The study confirms that advanced machine learning and deep learning techniques can meaningfully improve EV charging demand forecasting accuracy and facilitate development of sustainable smart-grid systems, with the proposed framework demonstrating clear effectiveness for this application.

6. FUTURE SCOPE

Future work may utilize larger, more diverse EV charging datasets spanning multiple cities and regions to improve generalization and robustness. Additional environmental and socioeconomic parameters — electricity prices, traffic conditions, user behaviour, and battery state-of-charge — could be incorporated to further improve accuracy. Advanced architectures such as Gated Recurrent Units (GRU), Transformer networks, and hybrid CNN-LSTM models warrant exploration and comparison with the present LSTM approach. Finally, real-time data acquisition from smart charging stations and IoT devices could enable dynamic, adaptive forecasting and charging systems, supporting continued advancement of AI-driven, renewable-integrated smart-grid infrastructure.

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