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AI-Based Solar PV Output Forecasting and Smart EV Charging Optimization Using Linear Regression, Random Forest, and LSTM

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Abstract

The rapid growth of electric vehicles (EVs) and renewable energy systems has increased the need for intelligent energy management solutions. Solar photovoltaic (PV) systems are widely used as clean energy sources for EV charging infrastructure; however, solar power generation is highly dependent on environmental conditions and exhibits significant variability, while EV charging demand changes dynamically based on user behavior and charging patterns. These uncertainties create challenges in balancing energy supply and demand efficiently. To address these issues, this work proposes an AI-based framework for predicting solar PV output and optimizing EV charging operations. Historical solar irradiance and weather data collected from the NASA POWER and Meteostat datasets are used to train machine learning and deep learning models, including Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) networks, while EV charging demand analysis is performed using the ACN (Adaptive Charging Network) dataset. The forecasting performance of the models is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Experimental results show that the LSTM model achieves the highest forecasting accuracy compared to the other models, with an MAE of 0.16, an RMSE of 0.24, and an R^2 score of 0.97, outperforming Random Forest (MAE 0.28, RMSE 0.37, R^2 0.92) and Linear Regression (MAE 0.41, RMSE 0.53, R^2 0.86). The predicted solar output is further integrated with a smart charging optimization strategy, in which EV charging is prioritized during periods of high solar generation using a hierarchical solar-battery-grid allocation approach, to improve renewable energy utilization, reduce grid dependency, and minimize peak load conditions. The proposed system contributes toward sustainable energy management and intelligent EV charging infrastructure for future smart grid applications.

Keywords: *Solar PV Forecasting; Electric Vehicle Charging; Machine Learning; LSTM; Renewable Energy; Smart Grid; Smart Charging Optimization.*

1. INTRODUCTION

1.1 Background

The rapid growth of electric vehicles (EVs) and renewable energy systems is transforming the operation of modern power networks and transportation infrastructure [1]. Electric vehicles are increasingly being adopted worldwide because of their environmental benefits, lower greenhouse gas emissions, and reduced dependence on fossil fuels [2]. At the same time, renewable energy technologies such as solar photovoltaic (PV) systems are gaining significant importance as clean and sustainable energy sources [3], converting sunlight into electrical energy without producing harmful emissions.

However, solar power generation is highly dependent on environmental conditions such as irradiance, temperature, humidity, and cloud cover, and exhibits significant variability throughout the day. EV charging demand simultaneously changes dynamically based on user behavior, travel patterns, and charging preferences [7]. As a result, maintaining a balance between renewable energy availability and charging demand becomes a major challenge for modern energy management systems.

To address these challenges, accurate forecasting of solar PV output becomes essential. Predictive models can estimate future solar power generation using historical weather and irradiance data, enabling better planning and utilization of renewable energy resources [8]. Artificial intelligence (AI) techniques such as machine learning and deep learning have emerged as effective tools for handling complex and nonlinear forecasting problems, capable of analyzing large volumes of environmental data, identifying hidden patterns, and providing accurate predictions of solar PV generation [9]. These forecasting capabilities can further support intelligent EV charging management by scheduling charging operations during periods of high solar energy availability. Integrating AI-based solar forecasting with smart EV charging optimization can therefore significantly improve renewable energy utilization, reduce grid dependency, and contribute toward the development of sustainable smart grid systems [10].

1.2 Problem Statement

One of the major challenges in solar-powered EV charging systems is the unpredictability of solar energy generation. Since solar output changes frequently, it becomes difficult to ensure a stable energy supply for charging vehicles, often leading to inefficient use of available energy. In addition, poor planning of EV charging schedules can result in increased load on the power grid; during peak demand periods, excessive reliance on grid power may cause overloading and reduce system stability. Traditional systems lack the ability to coordinate between solar generation and EV demand effectively, and the absence of predictive coordination between energy generation and consumption makes it difficult to optimize energy distribution and manage resources efficiently. These limitations highlight the need for advanced solutions that can handle dynamic system conditions.

1.3 Need for AI-Based Prediction

Artificial intelligence offers a powerful approach to address these challenges, as AI models are capable of analyzing complex and nonlinear relationships between different variables, making them suitable for dynamic energy systems [6]. By using historical weather data, AI can predict solar power output with higher accuracy; in addition to solar forecasting, AI can also be used to predict EV charging demand [11], allowing the system to understand usage patterns and adjust charging schedules accordingly. With these capabilities, AI enables smart energy management by aligning energy supply with demand, and AI-based systems can adapt to changing conditions and continuously improve their performance over time [12], making them more effective than traditional methods in handling real-world scenarios.

1.4 Objectives of the Work

The main objective of this work is to develop an AI-based model for predicting solar PV output using historical weather data, and to analyze how these predictions can be used to improve EV charging infrastructure. Specific objectives include: (i) collecting and preprocessing solar irradiance, weather, and EV charging data from the NASA POWER, Meteostat, and ACN datasets; (ii) implementing and comparing Linear Regression, Random Forest, and LSTM models for solar PV output forecasting; (iii) evaluating forecasting performance using MAE, RMSE, and R^2 metrics; (iv) analyzing EV charging demand patterns, including peak charging periods, charging duration, and energy consumption; and (v) designing a smart charging optimization strategy that aligns EV charging schedules with predicted solar generation to maximize renewable energy utilization and reduce dependency on the grid.

2. LITERATURE REVIEW

Accurate forecasting of solar PV output is essential for effective renewable energy management, and researchers have applied statistical, machine learning, and deep learning approaches to this problem. Solar PV output prediction models generally rely on historical irradiance, temperature, and weather data as input features, with more advanced models incorporating additional atmospheric parameters to improve prediction accuracy. In parallel, EV charging infrastructure research has emphasized the

coordination of charging operations with grid conditions and renewable energy availability, while AI in energy systems - including regression models, random forests, and neural networks - has been widely used for predicting energy generation and consumption; deep learning techniques such as LSTM networks are particularly effective for time-series forecasting given their ability to capture temporal dependencies in solar output and demand data. Smart charging systems build on these capabilities by using load shifting and demand response strategies, scheduling charging during off-peak hours or periods of high renewable generation, and relying on advanced control algorithms and real-time data analysis to make these decisions.

Hassan [2] presented an approach for managing energy in renewable microgrids by combining machine learning with advanced optimization, using Gaussian Process modeling to predict hybrid EV charging demand and the Krill Herd Algorithm for system optimization, showing that intelligent, coordinated charging control can reduce operational costs and improve efficiency. Sheik et al. [3] presented an approach to optimizing EV charging using solar power forecasting, scheduling charging based on predicted solar availability using an ANN model to reduce costs and improve sustainability, demonstrating that combining solar prediction with smart scheduling can significantly lower costs and even enable net-zero energy operation in EV charging stations.

Zhang et al. [13] examined EV charging demand prediction using explainable machine learning techniques, identifying XGBoost as the most accurate among the evaluated models and using SHAP analysis to show how factors such as renewable energy usage and grid conditions influence charging behavior, revealing a strong link between increased renewable adoption and rising EV demand. D'Ulizia et al. [14] proposed an AI-driven integrated management model for sustainable EV charging infrastructure comprising four interconnected layers - Eco-Design, Digital Tools, Risk Management, and Governance - providing a holistic architecture that improves resilience and operational efficiency while supporting sustainable energy goals. Sumanasena et al. [15] presented a comprehensive AI framework for electric vehicle infrastructure management addressing distributed energy resource management, charging demand variability, and grid stability, using AI techniques for charge-demand profiling, data augmentation, demand forecasting, explainability, and charging optimization, with experimental evaluation on real-world data confirming effective support for sustainable EV adoption.

Research Gap

Despite the progress made in solar energy forecasting and EV charging management, most existing studies address these areas independently. Many works focus on predicting solar PV output without considering how the predicted energy will be used in EV charging systems, while other studies analyze EV charging demand without incorporating the variability of renewable energy sources. This lack of integration limits the effectiveness of current solutions in real-world applications. There is a clear need for a unified approach that combines solar PV prediction with EV charging optimization, enabling better alignment of energy supply with demand, reduced grid dependency, and improved overall system efficiency. This work addresses that gap by developing a comprehensive framework that links AI-based solar forecasting with intelligent EV charging strategies, as presented in Section 3.

3. RESEARCH METHODOLOGY

This section presents the methodology adopted for developing the proposed AI-based solar PV output forecasting and EV charging optimization framework, covering the system architecture, data collection and preprocessing, the three forecasting models (Linear Regression, Random Forest, and LSTM), EV charging demand analysis, the smart charging optimization strategy, and performance evaluation metrics.

3.1 System Architecture

The proposed system is designed to intelligently coordinate solar power generation and EV charging demand using artificial intelligence techniques. The complete system consists of four major components: a solar PV generation system, a weather data

acquisition system, an AI-based prediction module, and an EV charging optimization module. Weather and solar irradiance data collected from the NASA POWER and Meteostat datasets are provided as input to the AI-based Prediction Module, which implements Linear Regression, Random Forest, and LSTM models to estimate future solar PV power generation. Based on the predicted solar output, together with EV charging demand data from the ACN dataset, the EV Charging Optimization Module schedules charging operations to maximize the use of solar energy, reduce peak load, and minimize grid dependency. The complete workflow is illustrated in Figure 1.

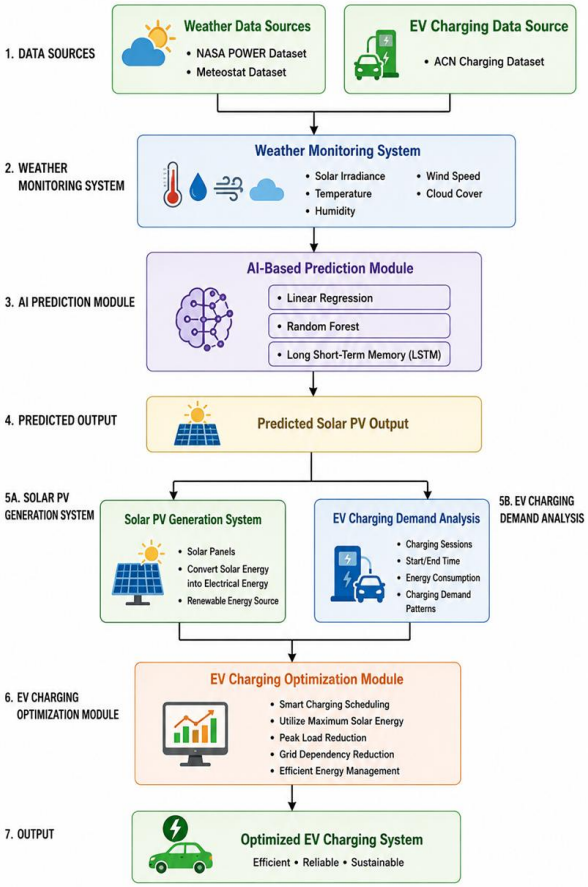


Figure 1: Workflow of AI-Based Solar PV Output Forecasting and EV Charging Optimization System

3.2 Data Collection

Solar irradiance data is collected from the NASA POWER database, which provides location-specific solar and meteorological data that can be downloaded using latitude and longitude coordinates. A sample of the solar irradiance dataset used in this study is presented in Table 1. Additional weather parameters - atmospheric pressure, dew point temperature, wind speed, and cloud cover - are collected from the Meteostat platform to further improve prediction accuracy, while EV charging demand data, including charging duration and energy consumption, is obtained from the ACN (Adaptive Charging Network) dataset. The combination of these three data sources, summarized in Table 2, provides a comprehensive foundation for solar forecasting, weather analysis, and EV charging demand analysis.

Table 1: Sample NASA POWER Solar Irradiance Dataset

Date	Solar Irradiance (kWh/m²)	Temperature (°C)	Rel. Humidity (%)	Wind Speed (m/s)
01-01-2025	5.6	29.4	62	3.5

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Date	Solar Irradiance (kWh/m²)	Temperature (°C)	Rel. Humidity (%)	Wind Speed (m/s)
02-01-2025	5.2	30.1	58	3.1
03-01-2025	4.8	28.6	65	2.8
04-01-2025	6.1	31.2	54	4.0
05-01-2025	5.9	30.5	57	3.7

Table 2: Datasets Used in the Study

Dataset	Parameters Used	Purpose
NASA POWER	Solar irradiance, temperature, humidity	Solar forecasting
Meteostat	Wind speed, cloud cover, pressure	Weather analysis
ACN Dataset	Charging duration, energy consumption	EV demand analysis

3.3 Data Preprocessing

Since the datasets are collected from different sources, preprocessing is necessary to ensure uniformity, reliability, and suitability for AI model training. The preprocessing workflow, illustrated in Figure 2, consists of four stages: data cleaning (removing duplicate records, handling missing values through interpolation, and removing noise and inconsistent data); normalization (scaling all features to a common [0, 1] range using Min-Max normalization); feature selection (selecting relevant features affecting solar generation - solar irradiance, temperature, humidity, wind speed, and time of day - while removing irrelevant or redundant features); and time-series formation (arranging data in chronological order and constructing input-output sequences using a sliding window, in preparation for LSTM model training).

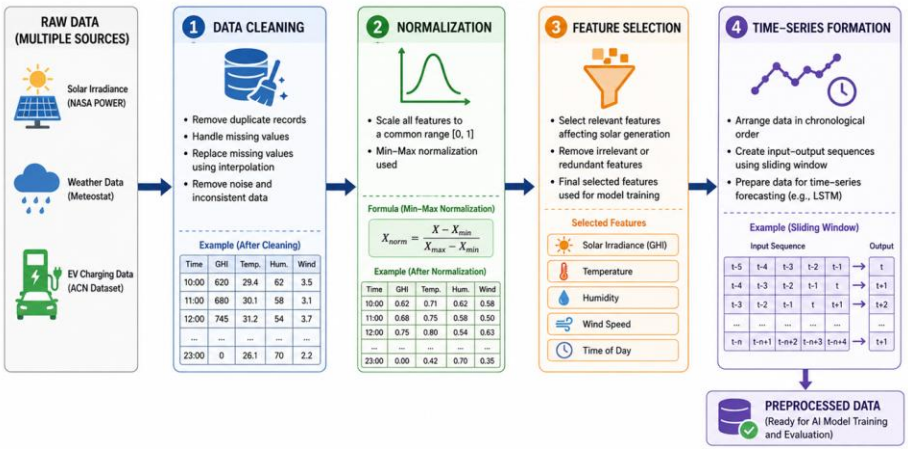


Figure 2: Workflow of Data Preprocessing for Solar PV Forecasting and EV Charging Demand Analysis

3.4 AI-Based Solar PV Prediction Models

Three AI models are implemented and compared for solar PV output forecasting. The Linear Regression model estimates solar PV output as a linear combination of environmental input features and serves as a baseline forecasting method. The Random Forest model is an ensemble learning algorithm that combines multiple decision trees, each independently predicting solar PV output, with the final prediction obtained by averaging the outputs of all trees; this ensemble approach reduces prediction variance and improves forecasting stability compared with Linear Regression, particularly for nonlinear relationships between weather conditions and solar generation.

The Long Short-Term Memory (LSTM) model is a deep learning architecture specifically designed to process sequential and time-series data. Since solar PV generation exhibits strong time-series characteristics, the LSTM model is expected to more effectively learn sequential dependencies and temporal patterns than the other two models. The LSTM network architecture used in this study consists of an input layer, one or more hidden LSTM layers, a dropout layer for regularization, a dense layer, and an output layer that generates the forecasted solar PV output. The input features provided to all three models include solar irradiance, temperature, humidity, wind speed, and (for the LSTM model) a time index.

3.5 EV Charging Demand Analysis

EV charging demand data obtained from the ACN dataset is analyzed along four dimensions. Peak charging period analysis identifies the time intervals during which a large number of EVs require charging simultaneously, typically during morning office hours and evening residential charging periods, together with off-peak intervals and load variation throughout the day. Charging duration analysis estimates the average time required per charging session, computed as the mean of individual session durations, and helps identify charging behavior patterns that may increase grid load during peak hours if not managed properly. Energy consumption analysis estimates the total electrical energy required for EV charging operations as the sum of charging power multiplied by charging duration across all sessions, helping determine periods of high charging demand. Charging frequency analysis determines how often EV users access charging stations within a given observation period, computed as the number of charging sessions divided by the observation time, providing insight into station utilization patterns.

3.6 Smart Charging Optimization

The predicted solar PV output generated by the AI forecasting model is integrated with the EV charging demand analysis to optimize charging schedules intelligently. The proposed optimization strategy schedules EV charging operations during periods of high solar power availability and shifts charging demand away from peak grid load periods, following a hierarchical priority of solar energy, then battery storage (where available), then grid power. The major objectives of the strategy are to maximize renewable energy utilization, reduce grid dependency, and avoid peak load conditions. The renewable energy utilization ratio η_RE is defined as the proportion of total EV charging energy supplied from solar generation, and the peak load reduction L_red is defined as the difference between the original peak grid load L_peak and the peak load achieved after applying the smart charging strategy, expressed as a percentage of the original peak load. By coordinating predicted solar availability with charging schedules in this way, the strategy is designed to maximize renewable energy utilization, minimize grid dependency, and reduce operational cost.

3.7 Performance Evaluation Metrics

The forecasting performance of the three AI models is evaluated using three standard statistical metrics. Mean Absolute Error (MAE) measures the average absolute difference between actual and predicted solar PV output values. Root Mean Square Error (RMSE) evaluates the square root of the average squared prediction error, penalizing larger errors more heavily. The Coefficient of Determination (R^2) measures the proportion of variance in the actual solar PV output that is explained by the model's predictions, with values closer to 1 indicating better model fit.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The proposed framework was implemented in Python using the software tools summarized in Table 3, with Pandas and NumPy used for data preprocessing and numerical computation, Scikit-learn used for implementing the Linear Regression and Random Forest models, TensorFlow/Keras used for developing the LSTM deep learning model, and Matplotlib used for visualizing forecasting results.

Table 3: Software Tools Used

Software Tool	Purpose
Python	Model implementation
Pandas	Data preprocessing
NumPy	Numerical computation
Scikit-learn	Machine learning models
TensorFlow / Keras	LSTM implementation
Matplotlib	Graph plotting and visualization

The datasets used for experimental analysis - NASA POWER, Meteostat, and the ACN dataset, summarized earlier in Table 2 - were preprocessed and normalized following the workflow described in Section 3.3 (Figure 2) before being used to train and evaluate the three forecasting models.

4.2 Solar PV Forecasting Results

The Linear Regression model was first evaluated as a baseline forecasting method. Figure 3 compares actual and predicted solar PV output across a 24-hour period, showing that while the model captures the overall daily generation trend, it noticeably under-predicts output around the midday peak, achieving an MAE of 0.41, an RMSE of 0.53, and an R^2 score of 0.86 - indicating that it explains approximately 86% of the variation in solar PV generation but has reduced accuracy when dealing with complex, nonlinear environmental patterns.

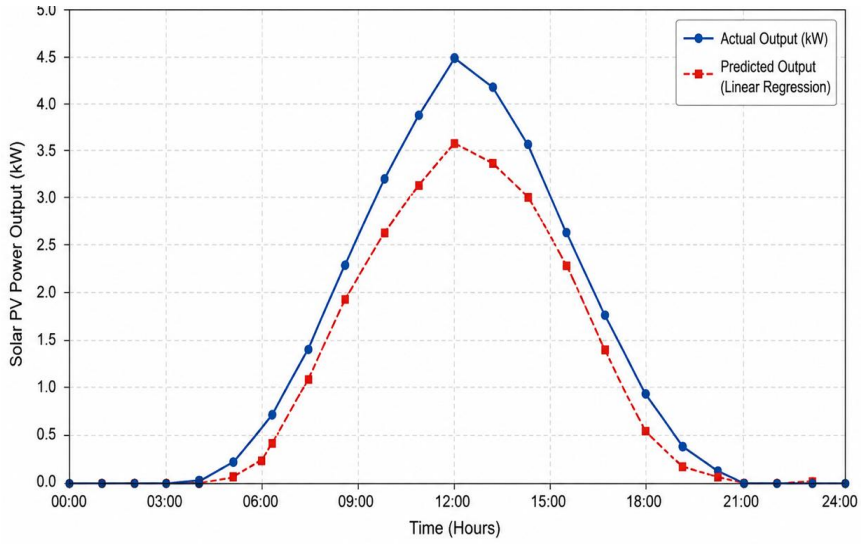


Figure 3: Actual vs Predicted Solar PV Output Using Linear Regression

The Random Forest model, an ensemble approach combining multiple decision trees, was evaluated next. As shown in Figure 4, the predicted output tracks the actual solar generation curve more closely than Linear Regression, particularly around the midday peak, achieving an MAE of 0.28, an RMSE of 0.37, and an R^2 score of 0.92 - a clear improvement over Linear Regression (MAE reduced from 0.41 to 0.28, RMSE from 0.53 to 0.37) that demonstrates the effectiveness of ensemble learning for capturing nonlinear relationships between weather conditions and solar generation.

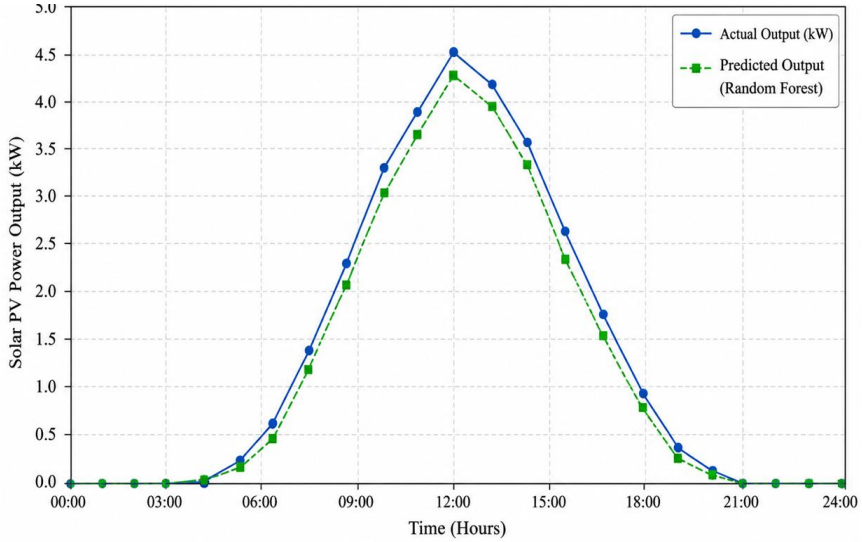


Figure 4: Actual vs Predicted Solar PV Output Using Random Forest

The LSTM deep learning model, designed to capture sequential and temporal dependencies in time-series data, was evaluated last. As shown in Figure 5, the predicted output curve closely matches the actual solar generation curve throughout the day, including around the midday peak, achieving the best performance among all three models with an MAE of 0.16, an RMSE of 0.24, and an R^2 score of 0.97 - indicating that the model explains approximately 97% of the variation in solar PV generation data and confirming its superior ability to learn temporal dependencies, capture sequential weather patterns, and handle nonlinear variations in solar output.

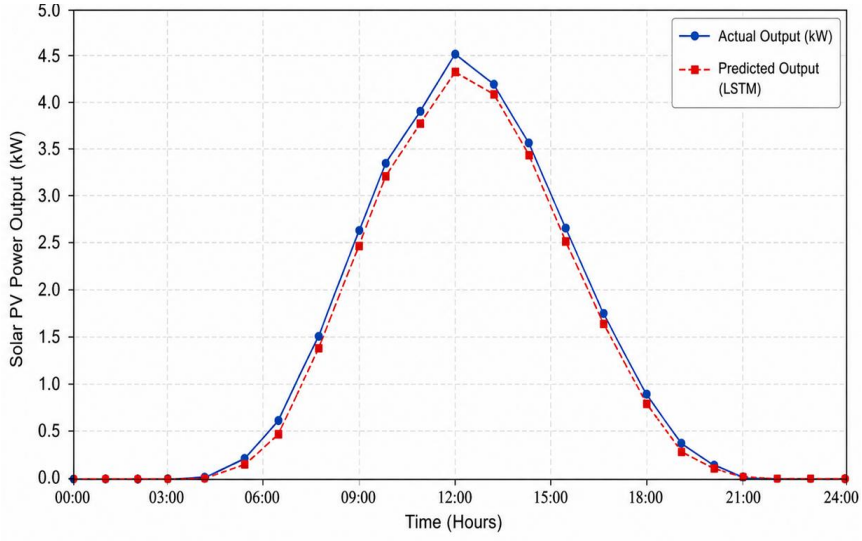


Figure 5: Actual vs Predicted Solar PV Output Using LSTM

4.3 Comparative Analysis of AI Models

A comparative analysis was performed to evaluate the relative effectiveness of the three implemented forecasting models. As summarized in Table 4 and illustrated in Figure 6, the LSTM model outperforms both Random Forest and Linear Regression across all three evaluation metrics, achieving the lowest MAE (0.16) and RMSE (0.24) and the highest R^2 score (0.97). The Linear Regression model produces the highest prediction error because it is unable to effectively capture nonlinear relationships and temporal variations present in solar generation data; Random Forest improves on this through ensemble learning but still

lacks the ability to efficiently learn long-term sequential dependencies. On this basis, the LSTM model is selected as the most suitable forecasting technique for the proposed AI-based solar PV output prediction and EV charging optimization system.

Table 4: Comparative Performance Analysis of AI Models

Model	MAE	RMSE	R^2 Score
Linear Regression	0.41	0.53	0.86
Random Forest	0.28	0.37	0.92
LSTM	0.16	0.24	0.97

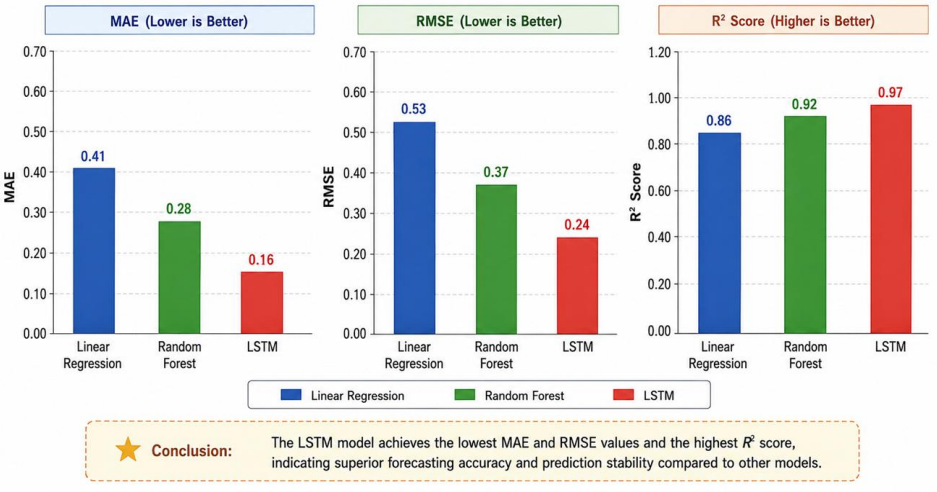


Figure 6: Comparative Performance Analysis of AI Models for Solar PV Forecasting

4.4 Smart Charging Optimization

The LSTM-predicted solar PV output was integrated with the EV charging demand analysis described in Section 3.5 to drive the smart charging optimization strategy defined in Section 3.6, which schedules EV charging during periods of predicted high solar availability and applies a solar-battery-grid priority order to reduce grid dependency and peak load. Given the high forecasting accuracy achieved by the LSTM model ($R^2 = 0.97$), the predicted solar output provides a reliable basis for this scheduling decision. A full quantitative evaluation of the resulting renewable energy utilization rate and peak-load reduction under the smart charging strategy, using metered before/after charging data, is identified as a direct next step building on the forecasting results established in this study.

4.5 Discussion

The experimental results confirm that deep learning significantly outperforms both traditional regression and ensemble-based machine learning for solar PV output forecasting in this study: MAE improved from 0.41 (Linear Regression) to 0.28 (Random Forest) to 0.16 (LSTM), a progression that mirrors the models' increasing ability to capture nonlinear and temporal patterns in solar generation data. The consistency of this improvement across all three metrics (MAE, RMSE, and R^2) and across all three actual-vs-predicted comparisons (Figures 3-5) confirms that the LSTM model provides the most reliable foundation for downstream EV charging optimization, since accurate forecasting is a prerequisite for effectively scheduling charging around solar availability.

5. CONCLUSION

This work presented an AI-based framework for predicting solar photovoltaic (PV) output and optimizing electric vehicle (EV) charging operations. Historical solar irradiance and weather data collected from the NASA POWER and Meteostat datasets were used to train and evaluate three forecasting models - Linear Regression, Random Forest, and LSTM - while EV charging demand data from the ACN dataset was analyzed to understand charging behavior and support charging schedule optimization.

Comparative analysis showed that the LSTM model achieved the best forecasting performance, with an MAE of 0.16, an RMSE of 0.24, and an R^2 score of 0.97, compared with Random Forest (MAE 0.28, RMSE 0.37, R^2 0.92) and Linear Regression (MAE 0.41, RMSE 0.53, R^2 0.86). The LSTM model's ability to capture nonlinear relationships and temporal dependencies in solar generation data makes it the most suitable forecasting technique for the proposed system. The predicted solar PV output was integrated with EV charging demand analysis to inform a smart charging optimization strategy that schedules charging during periods of high solar generation using a solar-battery-grid priority order, with the goal of maximizing renewable energy utilization, reducing grid dependency, and minimizing peak load conditions. The results confirm that AI-based forecasting - particularly LSTM-based solar PV prediction - can play an important role in future smart grid and sustainable transportation systems, and the proposed framework supports the development of intelligent renewable energy management systems capable of improving energy efficiency and environmental sustainability.

FUTURE SCOPE

Although the proposed system achieved promising forecasting results, several directions remain open for future research: (i) conducting a full quantitative evaluation of renewable energy utilization, grid dependency reduction, and peak load reduction achieved by the smart charging optimization strategy using metered before/after charging data; (ii) integrating additional renewable energy sources such as wind power to further diversify the energy supply for EV charging; (iii) exploring hybrid and ensemble deep learning architectures (e.g., CNN-LSTM, GRU, Transformer-based models) to further improve solar PV forecasting accuracy; (iv) incorporating battery energy storage systems to store excess solar energy and further reduce grid dependency during periods of low solar generation; (v) validating the proposed framework using real-time hardware implementation and live EV charging station deployments; and (vi) applying multi-objective optimization techniques such as Particle Swarm Optimization, Genetic Algorithms, or Reinforcement Learning to jointly optimize charging cost, renewable utilization, and grid stability.

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