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A Smart Solar-Powered EV Charging Station with LSTM-Based Demand Forecasting and Real-Time Data Analytics

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Abstract

The growing use of electric vehicles has created a strong need for efficient and reliable charging systems. To meet this demand in a sustainable way, solar-powered EV charging stations are gaining attention as they use clean and renewable energy. However, one of the main challenges in such systems is managing the balance between solar energy generation and the varying demand for EV charging, since solar power depends on weather conditions and time of day, while EV usage patterns are not constant. This work presents the design of a smart EV charging station that combines solar energy with real-time data analytics. The system collects information such as solar output, battery status, and charging demand through sensors, and uses a Long Short-Term Memory (LSTM) neural network trained on the NREL EV Charging Dataset to forecast future charging demand. Based on these forecasts, a smart charging controller intelligently allocates solar, battery, and grid energy under high, moderate, and low solar generation scenarios. The forecasting model achieved a Mean Absolute Error (MAE) of 0.82, a Root Mean Square Error (RMSE) of 1.14, and a Mean Absolute Percentage Error (MAPE) of 4.67%, confirming high prediction accuracy. The proposed smart charging strategy achieved a solar energy utilization rate of 84%, a battery utilization rate of 72%, a 31% reduction in grid dependency, and a charging efficiency of 92%. With real-time monitoring and intelligent control, the system ensures better load management, reduced dependency on the power grid, and improved user convenience, supporting the development of smart, efficient, and environmentally friendly EV charging solutions.

Keywords: *Electric Vehicles (EVs); Solar Energy; Smart Charging Station; Data Analytics; LSTM; Renewable Energy.*

1. INTRODUCTION

1.1 Background

Electric vehicles (EVs) have emerged as one of the most promising solutions for achieving sustainable transportation and reducing the environmental impact associated with conventional internal combustion engine vehicles [1]. Unlike traditional vehicles that rely on gasoline or diesel, EVs operate using electrical energy stored in rechargeable batteries, producing zero tailpipe emissions and significantly reducing air pollution. As a result, governments, industries, and consumers worldwide are increasingly adopting EV technology, creating a growing demand for efficient and reliable charging infrastructure.

Solar-powered EV charging stations have gained significant attention in recent years for their ability to provide clean and sustainable energy, reducing dependence on conventional power sources and lowering carbon emissions [15]. However, one of the main challenges in such systems is managing the balance between solar energy generation and the varying demand for EV charging: solar power depends on weather conditions, cloud cover, and time of day [2], while EV usage patterns are not constant, making it difficult to maintain efficient operation throughout the day.

Real-time data analytics and machine learning offer an effective way to address this challenge. These technologies allow charging stations to continuously monitor energy generation, battery storage levels, charging demand, and environmental conditions, and to forecast future charging demand from historical and real-time data [6]. Battery energy storage systems can

further be integrated with solar-powered charging stations to store excess renewable energy during periods of high generation and supply it during periods of low solar availability. The combination of solar energy generation, battery storage, real-time monitoring, and predictive analytics therefore enables the development of intelligent charging systems that can improve charging efficiency, reduce grid dependency, and enhance overall system reliability.

1.2 Problem Statement

Traditional EV charging stations mainly depend on grid electricity and lack intelligent control systems, making them unable to manage dynamic energy conditions effectively. In solar-powered charging stations the problem becomes more complex due to fluctuations in energy generation: during periods of low solar output, the system may rely heavily on the grid, while excess energy during peak generation may go unused. This leads to inefficient energy utilization, increased load on the grid, and reduced overall system performance.

1.3 Need for Smart Charging and Data Analytics

To overcome these challenges, smart charging systems that can adapt to real-time conditions are required. Real-time data analytics plays a key role in achieving this by processing data collected from sensors and user activity [13]; by analyzing parameters such as solar generation, battery status, and charging demand, the system can make informed decisions about energy distribution, optimize charging schedules, reduce peak load, and improve overall efficiency [14]. Such systems can adjust operations dynamically, ensuring better use of available energy resources while enhancing both system performance and user convenience.

1.4 Objectives of the Work

The main objective of this work is to design a smart EV charging station that integrates solar energy with real-time data analytics for efficient operation. Specific objectives include: (i) optimizing the use of solar power for EV charging to reduce dependency on the conventional power grid; (ii) improving energy utilization efficiency by minimizing wastage and balancing supply and demand; (iii) developing an LSTM-based demand forecasting model to support proactive energy allocation; (iv) designing a smart charging strategy capable of adapting to high, moderate, and low solar generation conditions; and (v) enabling real-time monitoring and control to allow continuous observation of system performance and rapid response to changing conditions. The overall system architecture is illustrated in Figure 1.

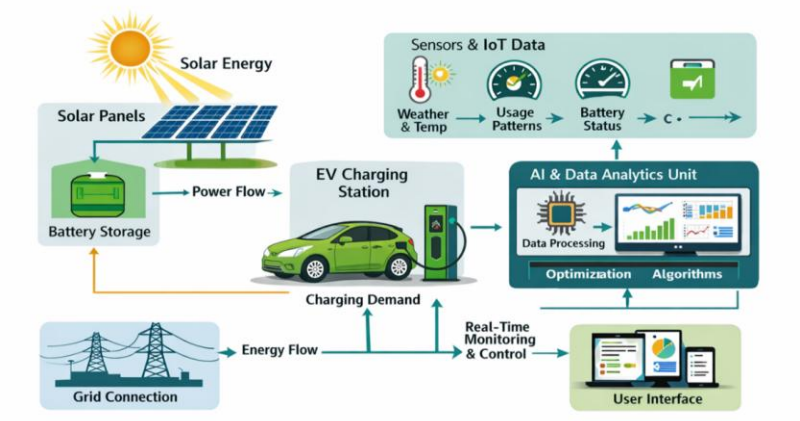


Figure 1: Smart EV Charging Station Using Solar Energy and Real-Time Data Analytics

2. LITERATURE REVIEW

Solar-powered EV charging stations have gained significant attention for their ability to provide clean and sustainable energy, but the variability of solar generation - caused by weather conditions, cloud cover, and time of day - makes it difficult to maintain a steady power supply for charging, particularly during peak demand periods [15]. Smart charging technologies address this by optimizing charging schedules based on energy availability, user demand, and grid conditions, shifting load to off-peak hours or periods of high renewable generation; however, implementing smart charging requires sophisticated algorithms and real-time decision-making capabilities, especially for systems with variable energy sources such as solar power.

Data analytics and machine learning have become essential tools for improving efficiency and decision-making in modern energy systems, with regression models and neural networks widely used to predict energy demand and optimize resource allocation. In the context of EV charging, such techniques help forecast charging demand, estimate energy consumption, and optimize charging schedules, leading to better utilization of available energy resources. Real-time monitoring, supported by IoT technologies, further enables continuous tracking of solar generation, battery status, charging demand, and environmental conditions, allowing quick decision-making, fault detection, and remote access and control.

Barman et al. [11] provided a comprehensive overview of renewable energy integration in EV charging systems, discussing various renewable sources, energy storage technologies, and smart charging strategies used worldwide, along with challenges related to grid integration, infrastructure, and system optimization. Manousakis et al. [12] presented a detailed review of the integration of electric vehicles and renewable energy sources into modern power systems, categorizing existing research by optimization approach and highlighting commonly used tools such as MATLAB and techniques such as particle swarm optimization.

Aldossary et al. [4] proposed an advanced forecasting approach (SARLDNet) for EV charging stations that combines deep learning with feature selection and signal processing to improve prediction accuracy, demonstrating better performance than traditional models such as LSTM and ARIMA on long-term real-world data, and highlighting the importance of accurate forecasting for load management and cloud-based real-time decision-making. Kannayeram et al. [13] proposed a hybrid energy system for EV charging stations integrating renewable energy, grid supply, and vehicle-to-grid technology, combining a forensic-based investigation method with an optimization algorithm (FBI-ATLA) to improve efficiency and reduce cost. Ra et al. [14] proposed a solar-battery integrated EV charging station with switchable-glazing-based passive HVAC support, combining rooftop solar PV with a Vanadium Redox Flow Battery and an IoT-based smart energy management strategy validated under sunny, cloudy, and grid-outage conditions. Hafeez et al. [15] proposed a comprehensive data-driven demand-side management framework for a solar-powered EV charging station integrated with a microgrid, using a deep-learning-based control strategy to optimize energy distribution and schedule charging during off-peak periods, demonstrating effective peak demand compensation and reduced grid stress in a 24-hour case study.

Research Gap

Despite significant advancements in solar-powered EV charging and smart energy management, many existing studies treat these components separately: solar energy systems are often analyzed without considering real-time charging demand, while smart charging techniques may not fully incorporate renewable energy variability. This lack of integration limits the effectiveness of current solutions in real-world scenarios. There is a clear need for a unified approach that combines solar energy generation, smart charging, and real-time data analytics into a single system capable of improving energy utilization, reducing dependency on the grid, and enhancing overall system performance. This work addresses that gap through the LSTM-forecasting-driven smart charging framework presented in Section 3.

3. RESEARCH METHODOLOGY

This section presents the methodology adopted for designing the proposed smart, solar-powered EV charging station, covering the overall system architecture, dataset description, data preprocessing, LSTM-based demand forecasting, the smart charging strategy, performance evaluation metrics, and the simulation environment.

3.1 Overview and System Architecture

The proposed system integrates renewable energy generation, battery energy storage, EV charging infrastructure, and machine-learning-based forecasting to optimize energy utilization and reduce dependence on the conventional power grid. As illustrated in Figure 1, solar panels supply power to a battery storage system and, together with the grid connection, to the EV charging station. Sensors and IoT data - weather and temperature, usage patterns, and battery status - feed an AI and Data Analytics Unit that performs data processing and applies optimization algorithms, while a user interface provides real-time monitoring and control. The methodology consists of five major stages: data collection, data preprocessing, demand forecasting using machine learning, smart charging strategy design, and performance evaluation.

3.2 Dataset Description and Collection

The study uses the National Renewable Energy Laboratory (NREL) EV Charging Dataset, which contains historical EV charging station records collected from charging infrastructure deployed across various locations, including timestamp, station ID, session duration, energy delivered, charger type, start/end time, and power consumption. To estimate solar power generation and renewable energy availability, weather-related parameters and solar irradiance data - solar irradiance, temperature, battery state of charge, and grid energy usage - are integrated with the EV charging dataset. The key dataset attributes used in this study are summarized in Table 1.

Table 1: Dataset Attributes

Attribute / Parameter	Description
Timestamp	Date and time of charging session
Session Duration	Charging duration
Energy Delivered (kWh)	Energy supplied to EV
Power Consumption	Charging power demand
Solar Irradiance	Available solar energy
Temperature	Ambient temperature
Battery State of Charge	Available stored energy
Grid Energy Usage	Energy imported from grid

3.3 Data Preprocessing

Raw datasets often contain missing values, duplicate records, outliers, and inconsistencies that can affect model performance. Data preprocessing was therefore applied to identify and correct incomplete charging records, remove duplicate records, and normalize feature values. The processed dataset was then divided into training and testing subsets, with 80% of the data allocated for training the LSTM forecasting model and the remaining 20% reserved for testing and validation, as summarized in Table 2.

3.4 Demand Forecasting Using Machine Learning

A Long Short-Term Memory (LSTM) neural network - a specialized type of Recurrent Neural Network designed to process sequential and time-series data - is employed for EV charging demand forecasting. The forecasting model is trained using historical charging demand, charging duration, and energy delivered (demand-side factors), together with solar irradiance,

ambient temperature, and battery state of charge (supply-side factors), and outputs future charging demand (kW) and expected energy consumption (kWh). The network consists of an input layer that receives historical charging and environmental data, one or more LSTM hidden layers that learn temporal dependencies and extract patterns from the sequential data, and a final dense output layer that generates the forecasted values. The relationship between historical observations and forecasted demand is expressed as:

$$D_t = f(X_{t-1}, X_{t-2}, ..., X_{t-n}) \quad ...(1)$$

where D_t is the forecasted charging demand at time t, X_{t-1}, X_{t-2}, ..., X_{t-n} are historical charging observations, and f(·) is the non-linear mapping function learned by the LSTM network. The forecasting results are provided to the smart energy management system, which uses the predicted demand to determine the optimal utilization of solar power, battery storage, and grid energy.

3.5 Smart Charging Strategy

The smart charging strategy dynamically allocates energy based on forecasted charging demand, available solar power generation, battery state of charge, and grid availability, prioritizing renewable energy utilization while minimizing dependence on conventional grid power. Based on the relationship between charging demand and available solar energy, the system operates under three scenarios. In Case 1 (high solar generation), solar generation exceeds charging demand, EVs are charged directly from solar energy, and any excess is stored in the battery. In Case 2 (moderate solar generation), solar energy is used as the primary source but is insufficient to meet demand alone, so the battery storage system supplies the remaining energy. In Case 3 (low solar generation), the battery becomes the primary source, and if its state of charge falls below a predefined threshold, grid power is activated as a backup to ensure continuous charging. This hierarchical priority - solar energy, then battery storage, then grid power - reduces operational costs, minimizes grid dependency, improves battery utilization, and enhances the sustainability of the charging infrastructure.

3.6 Performance Evaluation Metrics

The forecasting model is evaluated using three standard statistical error metrics. Mean Absolute Error (MAE) measures the average absolute difference between actual and predicted values; Root Mean Square Error (RMSE) evaluates the square root of the average squared prediction error and penalizes larger errors more heavily; and Mean Absolute Percentage Error (MAPE) expresses forecasting error as a percentage, making results easier to interpret and compare. The energy management performance of the smart charging strategy is further assessed using solar energy utilization rate, battery utilization rate, grid dependency reduction, and charging efficiency.

3.7 Simulation Environment

The proposed smart EV charging station is implemented and evaluated using a Python-based simulation environment within Jupyter Notebook, selected for its extensive support for data analysis, machine learning, visualization, and scientific computing. The experimental configuration adopted for implementation is summarized in Table 2.

Table 2: Experimental Configuration

Parameter	Value
Dataset	NREL EV Charging Dataset
Training Data	80%
Testing Data	20%
Forecasting Model	LSTM
Programming Language	Python

Parameter	Value
Development Platform	Jupyter Notebook
Evaluation Metrics	MAE, RMSE, MAPE

4. RESULTS AND DISCUSSION

4.1 Experimental Setup and Data Analysis

The proposed framework was implemented using the experimental configuration summarized in Table 2, with the NREL EV Charging Dataset providing historical charging records. Analysis of the collected data revealed considerable fluctuations in charging demand throughout the day: charging activity was generally lower during early-morning hours and gradually increased as users began their daily activities, reaching a peak during business hours and evening periods, largely attributable to workplace charging activity, commuting patterns, and increased vehicle usage during daytime hours. Charging duration and energy consumption also varied significantly depending on battery status, charging requirements, and charger type, with energy consumption following recurring daily patterns similar to charging demand.

The distribution of EV charging demand observed in the dataset is illustrated in Figure 2, which highlights the fluctuation in charging demand across different time intervals and provides a clear view of peak and off-peak charging periods, generally consistent with the 16:00-20:00 evening peak identified in the forecasting analysis of Section 4.2.

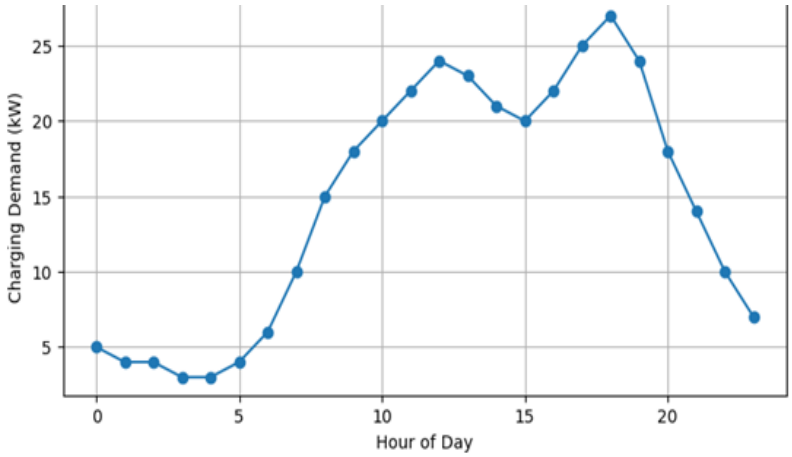


Figure 2: EV Charging Demand Distribution

4.2 Demand Forecasting Results

The LSTM forecasting model was trained on 80% of the dataset and evaluated on the remaining 20%. Figure 3 compares the actual and predicted charging demand obtained from the trained model across a 24-hour period, showing that the predicted demand curve closely follows the actual demand profile, including through the identified 16:00-20:00 peak demand period, with only minor deviations.

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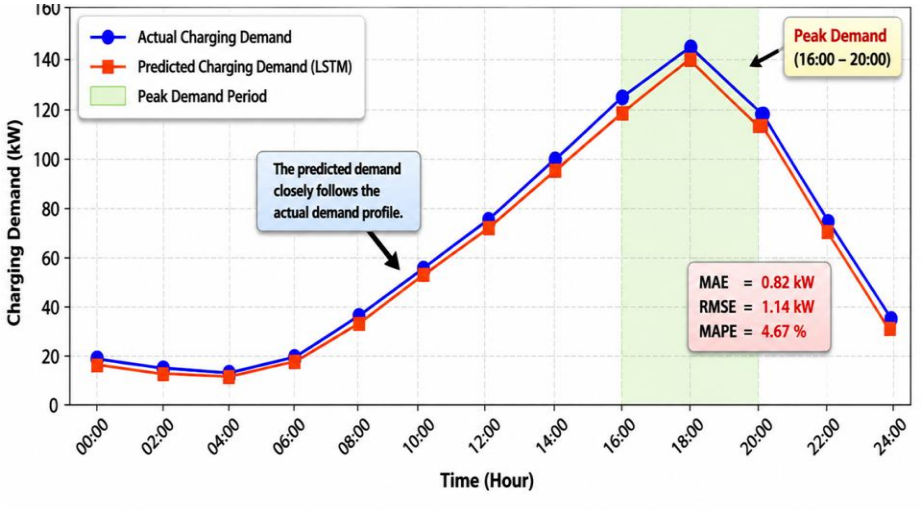


Figure 3: Actual versus Predicted Charging Demand

4.3 Forecasting Performance Evaluation

The forecasting performance obtained from the proposed LSTM model is summarized in Table 3. The model achieved a Mean Absolute Error (MAE) of 0.82, indicating that the average difference between actual and predicted charging demand values is relatively small, and a Root Mean Square Error (RMSE) of 1.14, confirming that significant forecasting deviations occur infrequently and that prediction errors are distributed consistently with limited extreme outliers. The Mean Absolute Percentage Error (MAPE) of 4.67% - below the 5% threshold generally considered to indicate excellent predictive performance - provides further evidence that the LSTM model reliably captures temporal dependencies and recurring charging-demand patterns, confirming its suitability for practical deployment in EV charging infrastructure.

Table 3: Forecasting Performance Metrics

Metric	Value
MAE	0.82 kW
RMSE	1.14 kW
MAPE	4.67%

4.4 Smart Charging Performance Analysis

The smart charging strategy was evaluated under the three representative operating scenarios described in Section 3.5. Under high solar generation (Figure 4), solar PV output of 120 kW exceeded the 80 kW charging demand; the entire demand was met directly from solar energy, the 40 kW surplus was stored in the battery, and grid usage remained at 0 kW.

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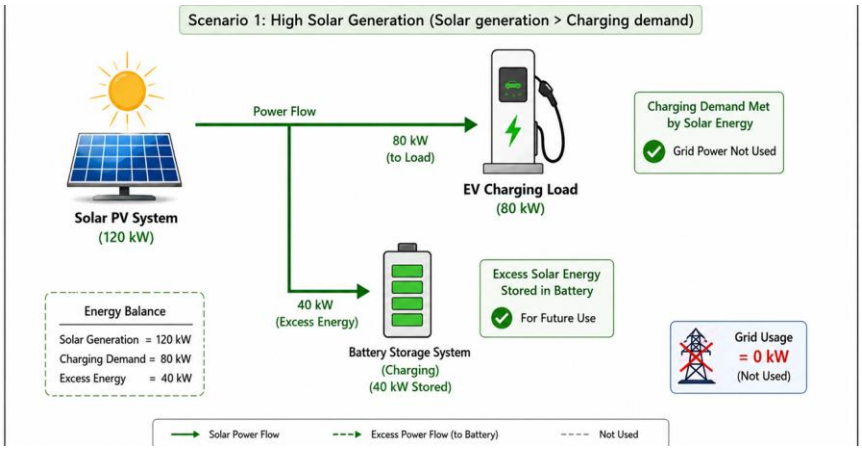


Figure 4: Smart Charging Operation During High Solar Generation

Under moderate solar generation (Figure 5), a 90 kW charging demand was met using 60 kW of solar energy (66.7%) as the primary source, supplemented by 30 kW discharged from the battery (33.3%), with grid usage again at 0 kW - demand fully satisfied without grid support.

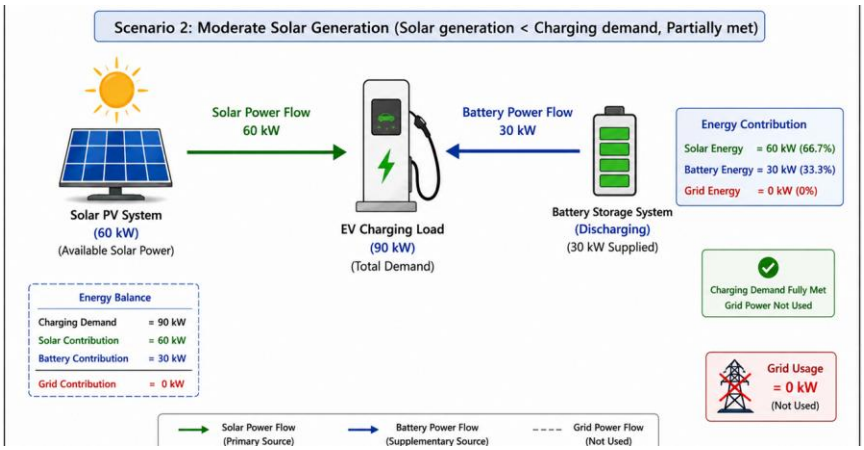


Figure 5: Smart Charging Operation During Moderate Solar Generation

Under low solar generation (Figure 6), the same 90 kW charging demand was met using only 20 kW of solar energy (22.2%), with the battery supplying 40 kW (44.4%) and the grid supplying the remaining 30 kW (33.3%) as a backup source, activated only because the battery state of charge was insufficient to cover the full deficit - illustrating that grid power is accessed only when necessary, minimizing grid dependency while maintaining uninterrupted charging.

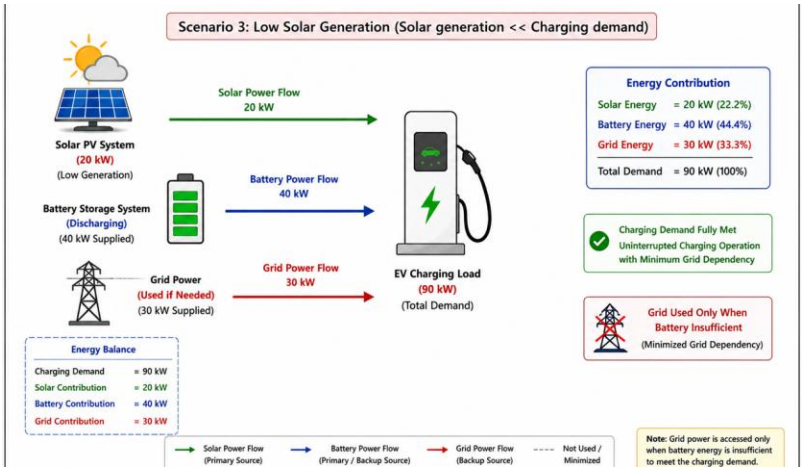


Figure 6: Smart Charging Operation During Low Solar Generation

Together, Figures 4-6 demonstrate the adaptability of the proposed smart charging strategy: the controller maximizes renewable energy utilization when solar generation is abundant, intelligently combines solar power and battery storage under moderate generation, and falls back on battery and, only when necessary, grid power under low solar generation - consistently following the priority order of solar energy, battery storage, and grid power described in Section 3.5.

4.5 Energy Utilization Analysis

The overall energy management performance of the proposed framework, aggregated across operating conditions, is summarized in Table 4. The system achieved a solar energy utilization rate of 84%, indicating that the majority of available photovoltaic energy was effectively used for EV charging and battery charging operations, and a battery utilization rate of 72%, reflecting effective use of stored renewable energy during periods of reduced solar generation. Grid dependency was reduced by 31% relative to a conventional, non-intelligent charging approach, while the system achieved an overall charging efficiency of 92%, confirming that the integration of LSTM-based demand forecasting with the smart charging strategy substantially improves renewable energy utilization and reduces reliance on grid electricity.

Table 4: Energy Management Performance

Performance Parameter	Value
Solar Energy Utilization	84%
Battery Utilization	72%
Grid Dependency Reduction	31%
Charging Efficiency	92%

4.6 Discussion

The experimental results confirm that combining LSTM-based demand forecasting with a hierarchical, priority-based smart charging strategy (solar, then battery, then grid) enables an EV charging station to adapt effectively to varying solar generation conditions. The low forecasting errors (MAE 0.82, RMSE 1.14, MAPE 4.67%) demonstrate that the LSTM model reliably anticipates future charging demand, enabling the energy management controller to make proactive rather than reactive allocation decisions. This is reflected in the energy utilization results, where 84% solar utilization, 72% battery utilization, a 31% reduction in grid dependency, and 92% charging efficiency were achieved across high, moderate, and low solar generation scenarios, confirming the effectiveness of the proposed framework in enhancing charging station performance while promoting sustainable, renewable-energy-based EV charging.

5. CONCLUSION

This work presented the design and evaluation of a smart EV charging station powered by solar energy and supported by real-time data analytics. The National Renewable Energy Laboratory (NREL) EV Charging Dataset was used to develop and evaluate an LSTM-based forecasting model for predicting future charging demand, together with a smart charging strategy that dynamically allocates solar, battery, and grid energy based on the predicted demand and available solar generation.

The forecasting model achieved low prediction errors (MAE 0.82, RMSE 1.14, MAPE 4.67%), confirming that it reliably captures charging demand patterns from historical charging records and environmental parameters. The proposed smart charging strategy successfully adapted to high, moderate, and low solar generation scenarios, prioritizing solar energy, then battery storage, and finally grid power, and achieved a solar energy utilization rate of 84%, a battery utilization rate of 72%, a 31% reduction in grid dependency, and a charging efficiency of 92%. These results confirm that the integration of machine-learning-based demand forecasting with intelligent, priority-based energy management can significantly enhance the efficiency, reliability, and sustainability of solar-powered EV charging infrastructure, supporting the development of future smart grid and sustainable transportation systems.

FUTURE SCOPE

Although the proposed system demonstrates promising performance, several directions remain open for future work: (i) implementing advanced deep learning models such as Gated Recurrent Units (GRU), Transformer networks, and hybrid forecasting techniques to further improve charging demand prediction accuracy; (ii) incorporating real-time IoT sensors and cloud-based monitoring platforms to enable continuous data collection, remote supervision, and real-time decision-making; (iii) integrating Vehicle-to-Grid (V2G) technology, allowing EVs to supply stored energy back to the grid during peak demand periods; (iv) including additional renewable energy sources such as wind energy and hybrid renewable configurations to improve energy availability and reduce the impact of fluctuations in any single source; (v) applying optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), or Reinforcement Learning to support optimal scheduling of energy resources; (vi) conducting economic analysis and cost optimization - including installation cost, operating cost, return on investment, and lifecycle assessment - to evaluate large-scale commercial deployment; and (vii) validating the proposed framework using real-world charging station deployments and larger datasets collected from multiple charging locations.

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