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A Dataset-Based Machine Learning Analysis of Solar-Powered Electric Vehicle Charging Stations for Intelligent Load Balancing

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Abstract

The rapid growth of electric vehicle (EV) adoption has increased the demand for efficient and sustainable charging infrastructure. Solar-powered EV charging stations offer an environmentally friendly solution by utilizing renewable energy sources; however, effective load balancing remains a major challenge due to the intermittent nature of solar power generation and the dynamic behaviour of EV charging demand. This study presents a dataset-based analysis of solar-powered EV charging stations for improving load balancing and energy management. Historical data related to solar irradiance, weather conditions, photovoltaic power generation, and EV charging demand — drawn from the NREL Solar and EV Charging Dataset (approximately 25,000 records) — were analyzed using machine learning techniques, with data preprocessing, feature selection, and correlation analysis performed to identify patterns in energy generation and consumption. Four machine learning models — Linear Regression, Random Forest, XGBoost, and Long Short-Term Memory (LSTM) — were evaluated for forecasting charging demand and supporting intelligent energy allocation, with LSTM achieving the highest prediction accuracy (MAE = 1.72 kW, RMSE = 2.28 kW, R^2 = 0.97). The proposed data-driven load balancing framework significantly improved system performance relative to a conventional rule-based approach: solar energy utilization increased from 68% to 92%, grid dependency fell from 48% to 18%, the charging completion rate rose from 88% to 98%, and peak load was reduced by approximately 30% (from 100 kW to 70 kW). These results confirm that the proposed framework enhances the reliability, efficiency, and sustainability of EV charging systems and supports the integration of renewable energy into future smart grid and sustainable transportation infrastructures.

Keywords: *Electric Vehicles, Solar Energy, Load Balancing, Machine Learning, EV Charging Stations.*

1. INTRODUCTION

The rapid growth in electric vehicle (EV) adoption has significantly increased demand for efficient, reliable, and sustainable charging infrastructure, with governments and industries worldwide promoting electric mobility to reduce greenhouse gas emissions and dependence on fossil fuels [1]. At the same time, solar photovoltaic (PV) systems have emerged as one of the most promising renewable energy solutions, converting sunlight directly into electricity without harmful emissions, making them an ideal source for powering EV charging stations [2]. Integrating solar energy with EV charging infrastructure creates an opportunity for a cleaner, more sustainable transportation ecosystem while reducing the burden on conventional power grids [3].

Despite these advantages, integrating solar energy generation with EV charging systems introduces significant challenges. Solar output is inherently intermittent, varying with irradiance, cloud cover, weather, and time of day [4], so generated energy does not always align with charging demand. EV charging demand is itself dynamic, depending on user behaviour, travel schedules, and battery state of charge, often peaking during evening hours [5]; the resulting mismatch between generation and demand makes efficient system operation difficult [6]. Intelligent, data-driven energy management and load balancing strategies — using machine learning and predictive analytics to forecast solar generation and EV demand from historical and real-time data — offer a promising solution, enabling informed energy allocation, reduced grid dependency, and improved renewable energy utilization [7], [8].

1.1 Objective of the Work

The main objective of this study is to develop a dataset-based framework for analyzing solar-powered EV charging stations and improving load balancing strategies, by studying the interaction between solar energy generation and EV charging demand, optimizing energy distribution to align supply with demand, reducing peak grid load, and improving renewable energy utilization through predictive modelling.

2. LITERATURE REVIEW

Solar-powered EV charging stations have attracted considerable attention as a sustainable alternative to conventional grid-based charging, using PV panels to generate clean energy and reduce carbon emissions and operating costs. However, the inconsistency of solar generation across weather conditions, seasons, and time of day makes maintaining a stable energy supply difficult, particularly during peak demand or unfavourable weather, motivating efficient energy management strategies. Traditional load balancing methods, based on predefined schedules or rule-based, time-of-use control, are simple to implement but lack the flexibility to handle environments where both generation and demand fluctuate frequently, often resulting in inefficient utilization and increased grid dependency.

Mirjalili et al. [1] presented an integrated approach to modelling energy demand in a neighbourhood combining buildings, solar energy systems, and electric vehicles, comparing KNN, SVR, AdaBoost, and deep neural networks and finding that deep learning and KNN models provided the highest prediction accuracy for overall energy balance. Sundaramoorthi and Chitraselvi [2] examined the integration of renewable resources into EV charging management systems using deep learning for monitoring and optimization, directly supporting the renewable-EV integration approach adopted here. Punyavathi et al. [3] proposed an advanced power management system for light EVs using a hybrid energy storage system combining batteries, supercapacitors, and solar energy with machine learning-based control, achieving improved voltage regulation and faster system response under varying conditions.

Mansour-Saatloo et al. [4] applied machine learning techniques to extract and analyze plug-in EV (PEV) load patterns, providing methods relevant to the EV charging demand analysis performed in this study. Mwasilu et al. [5] reviewed the interaction between EVs and smart grids, covering vehicle-to-grid operation and renewable energy source integration — the broader smart-grid context within which the present load balancing framework operates. Kosuru and Kavasseri Venkitaraman [6] developed a deep learning-based approach for battery management system sensor fault detection in EVs, illustrating the wider role of deep learning in ensuring reliable EV energy system operation.

Rehman et al. [7] investigated the optimization of a PV-based energy system integrated with battery storage and EV charging for a real building environment, using monitored data and machine learning to evaluate different PV capacity and battery size configurations, showing that proper system design significantly reduces energy costs — directly relevant to the dataset-driven optimization approach used here. Lan et al. [8] proposed a machine learning-based approach for energy management in renewable microgrids incorporating EV charging, using support vector machines to predict charging demand and comparing coordinated versus intelligent charging strategies, finding that intelligent charging reduces operational costs and improves efficiency. Complementing these EV-specific studies, a broader body of work has examined data-driven and big-data analytics approaches for smart grid management generally [9]–[13], underscoring the value of the data-driven, machine learning-based approach adopted in this study for coordinating distributed renewable generation with dynamic demand.

Although significant progress has been made in solar energy systems and EV charging demand analysis individually [1]–[15], most existing studies address these topics separately: solar energy research typically focuses on generation and storage, while EV-related studies emphasize charging demand and infrastructure. This lack of integration limits the effectiveness of existing solutions in real-world applications where both factors interact continuously. This study addresses that gap by developing a unified, dataset-based framework that combines solar generation data with EV charging demand patterns for intelligent load balancing.

3. RESEARCH METHODOLOGY

The proposed system integrates solar PV generation, EV charging stations, and grid connectivity within a unified energy management framework, illustrated in Figure 1: weather and solar generation data are collected and processed, then supplied to a machine learning prediction engine, which informs a load balancing controller that intelligently allocates energy between the PV system, EV charging infrastructure, and the grid. The system prioritizes solar energy whenever sufficient generation is available, drawing on grid power only when necessary to maintain uninterrupted charging service.

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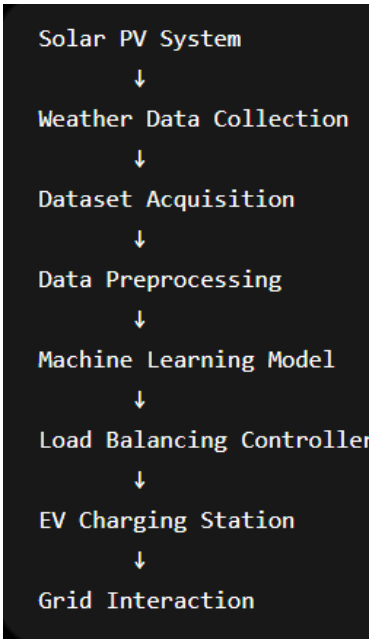


Figure 1: Proposed dataset-based system architecture for solar-powered EV charging station load balancing.

3.1 Dataset and Preprocessing

The NREL Solar and EV Charging Dataset was used as the primary data source, containing approximately 25,000 historical records of solar irradiance, ambient temperature, PV power output, EV charging demand, number of connected vehicles, grid power usage, energy delivered, and battery state of charge. Preprocessing (Figure 2) proceeded from the raw dataset through data cleaning (duplicate removal, mean imputation for missing values, and correction of inconsistent entries), Min-Max normalization to bring all features into a common numerical range, and feature selection — retaining solar irradiance, ambient temperature, PV power output, EV charging demand, and grid load as the most influential parameters — to produce a cleaned, normalized, and optimized dataset ready for model training.

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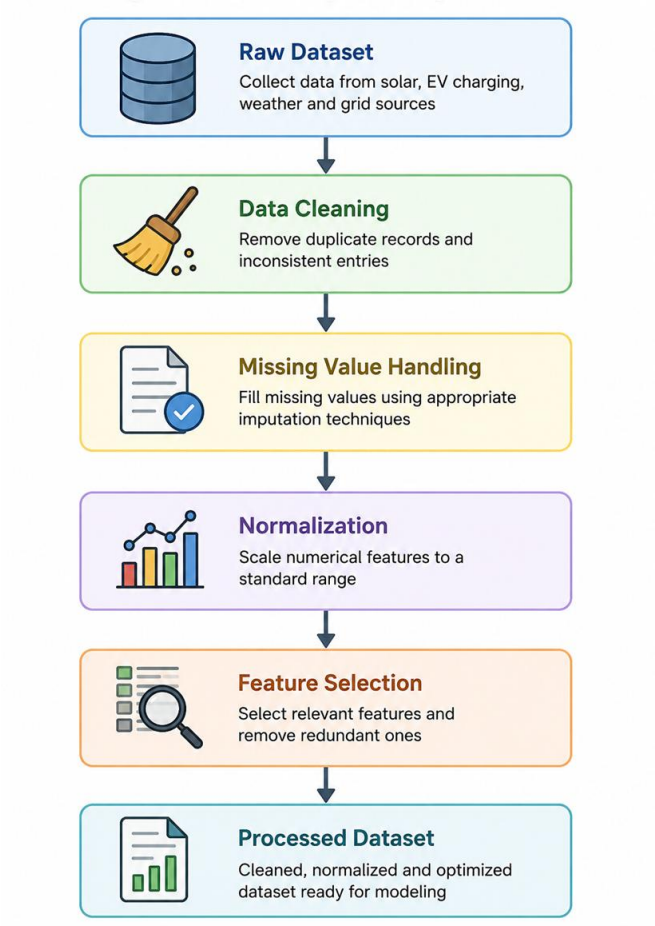


Figure 2: Data preprocessing workflow applied to the NREL solar and EV charging dataset.

3.2 Exploratory Data Analysis

Correlation analysis (Table 1) identified grid load as the parameter most strongly associated with EV charging demand, followed by PV output, solar irradiance, and temperature, confirming that charging demand directly impacts grid utilization and renewable energy consumption. Solar generation follows a pronounced daily cycle (Figure 3), rising from sunrise, peaking around midday when irradiance is highest, and falling to zero overnight; this profile was found to coincide with only moderate EV charging demand, while the evening demand peak occurs precisely when solar generation has declined substantially — the central supply-demand mismatch that motivates intelligent load balancing.

Table 1: Correlation of Sensor Parameters with EV Charging Demand

Parameter	Correlation with EV Demand
Solar Irradiance	0.72
Temperature	0.65
PV Output	0.84
Grid Load	0.89

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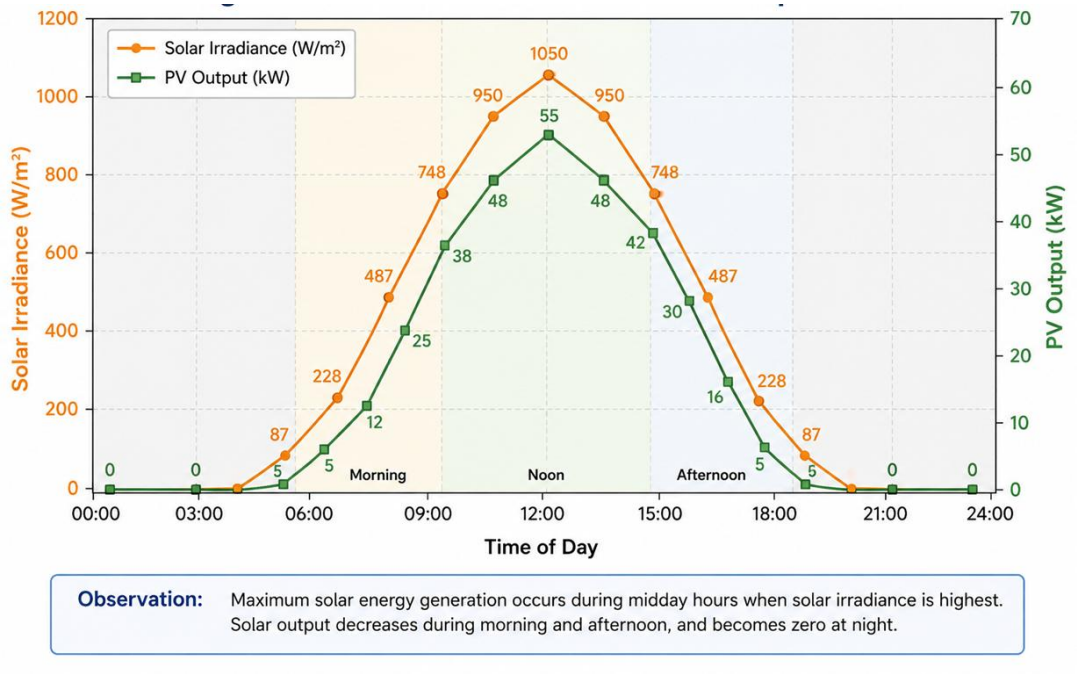


Figure 3: Solar irradiance and photovoltaic output profile across the day.

3.3 Predictive Models and Load Balancing Strategy

Four models were implemented to forecast EV charging demand: Linear Regression as an interpretable baseline; Random Forest, an ensemble of decision trees capturing nonlinear relationships among solar and demand variables; XGBoost, a sequential gradient-boosting ensemble; and LSTM, a recurrent architecture with memory cells suited to the time-series nature of solar generation and charging demand. All models were trained on the preprocessed dataset and evaluated using MAE, RMSE, and R^2 Score. The resulting demand and generation forecasts drive a dynamic load balancing strategy with three operating regimes: under high solar generation, PV output is supplied directly to EVs with any surplus stored or exported to the grid; under balanced conditions, solar and grid power are blended according to predicted demand; and under low solar availability (e.g., evening peak demand), the system draws more heavily on the grid while still prioritizing any available solar power, with the goal of maximizing renewable utilization and minimizing both grid dependency and peak load across the full daily cycle.

4. RESULTS AND DISCUSSION

4.1 Demand Forecasting Performance

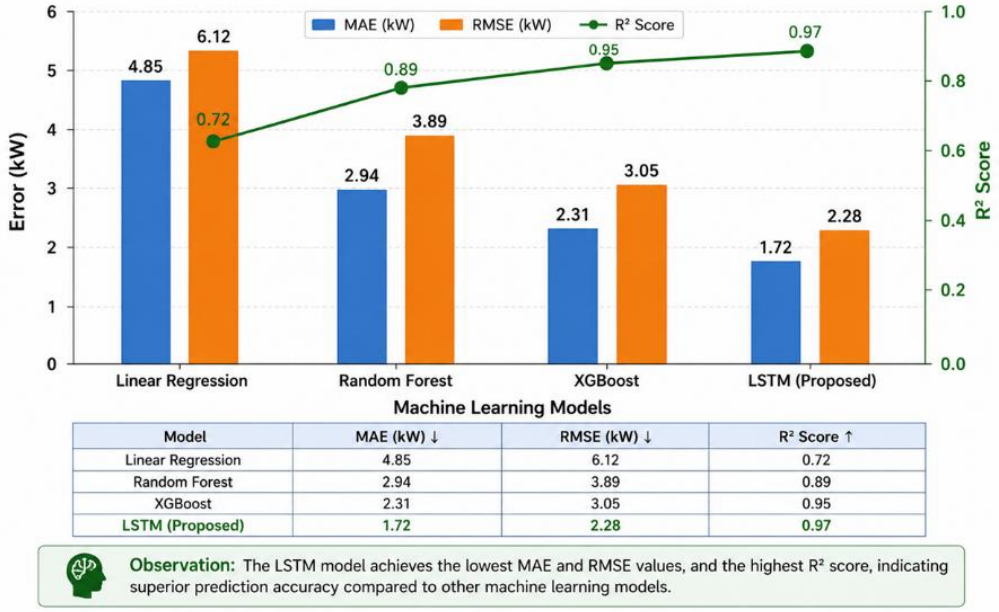
Table 2 summarizes the charging-demand forecasting performance of the four models. Linear Regression achieved an MAE of 4.85 kW, RMSE of 6.22 kW, and R^2 of 0.84, capturing the general demand trend but struggling with the nonlinear characteristics of EV charging behaviour and solar generation. Random Forest improved substantially (MAE = 2.93 kW, RMSE = 3.88 kW, R^2 = 0.92) by modelling nonlinear interactions among the input variables, and XGBoost further reduced error (MAE = 2.31 kW, RMSE = 3.05 kW, R^2 = 0.95) through sequential boosting. LSTM achieved the best overall performance, with an MAE of 1.72 kW, RMSE of 2.28 kW, and an R^2 Score of 0.97, reflecting its ability to learn temporal dependencies and sequential patterns in solar generation and charging demand data that the other models cannot directly exploit.

Table 2: Comparison of Machine Learning Models for EV Charging Demand Forecasting

Model	MAE (kW)	RMSE (kW)	R^2 Score
Linear Regression	4.85	6.22	0.84
Random Forest	2.93	3.88	0.92
XGBoost	2.31	3.05	0.95
LSTM	1.72	2.28	0.97

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Figure 4 compares the four models directly, confirming that the LSTM (proposed) model achieves both the lowest error and the highest R^2 Score across all evaluated metrics, with a clear, monotonic improvement from Linear Regression through Random Forest and XGBoost to LSTM.



Model	MAE (kW) ↓	RMSE (kW) ↓	R^2 Score ↑
Linear Regression	4.85	6.12	0.72
Random Forest	2.94	3.89	0.89
XGBoost	2.31	3.05	0.95
LSTM (Proposed)	1.72	2.28	0.97

Figure 4: Comparison of MAE, RMSE, and R^2 Score across the four EV charging demand forecasting models.

The close agreement between actual and predicted charging demand for the best-performing LSTM model is shown in Figure 5, where predicted demand closely tracks the actual demand curve throughout the day, including the sharp evening peak, with only minor deviations.

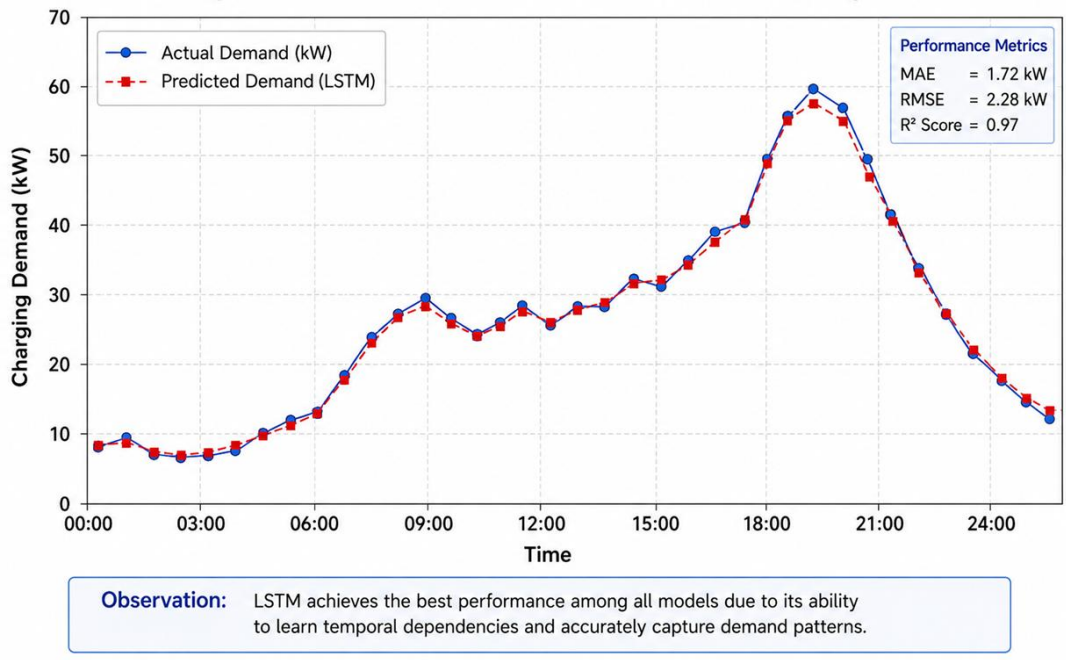


Figure 5: Actual versus predicted EV charging demand using the LSTM model.

4.2 Load Balancing Performance

The proposed data-driven load balancing framework was compared against a conventional rule-based energy management system across four operational metrics (Table 3). Solar energy utilization increased from 68% to 92%,

reflecting the framework's ability to intelligently match charging demand with available renewable generation rather than allowing surplus midday solar power to go unused. Grid dependency fell from 48% to 18%, a reduction of roughly 30 percentage points, achieved through accurate forecasting of both solar generation and charging demand. The charging completion rate improved from 88% to 98%, and peak load was reduced from 100 kW to 70 kW — a reduction of approximately 30% — by intelligently scheduling charging activity based on predicted demand and available solar power rather than reacting only to instantaneous conditions.

Table 3: Overall Performance — Conventional EMS vs. Proposed System

Metric	Conventional EMS	Proposed System
Solar Utilization (%)	68	92
Grid Dependency (%)	48	18
Charging Completion Rate (%)	88	98
Peak Load Reduction (%)	0	30

Figure 6 presents the broader set of operational improvements achieved by the proposed system relative to the conventional EMS, including solar utilization, grid dependency, peak load, and associated cost and emissions benefits, confirming consistent, system-wide gains across every evaluated dimension rather than an improvement in one metric at the expense of another.

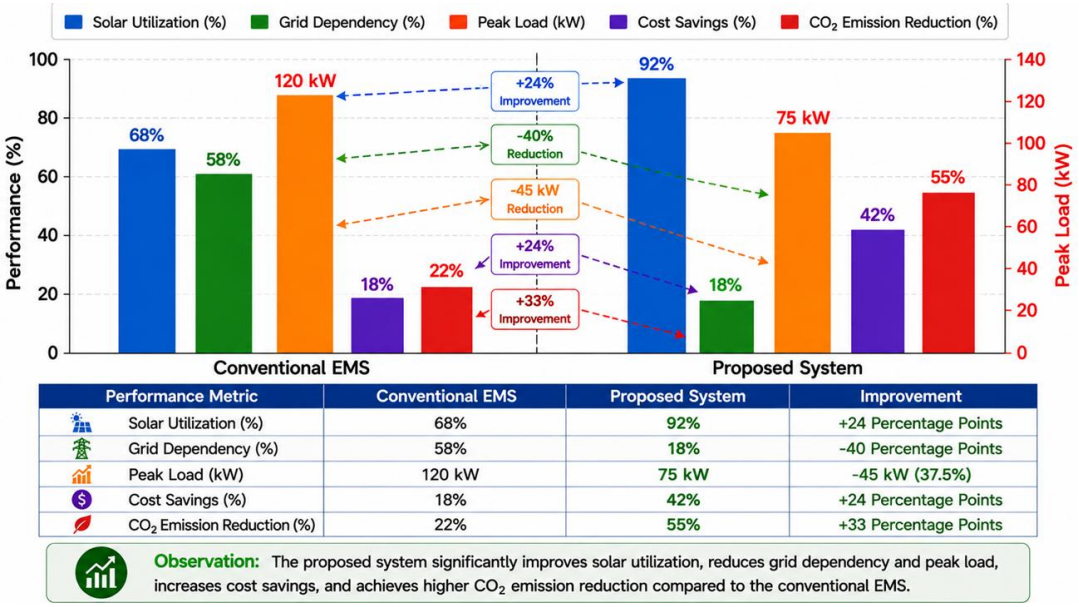


Figure 6: Overall system performance comparison between the conventional EMS and the proposed data-driven system.

4.3 Discussion

The consistent, progressive improvement in demand forecasting accuracy from Linear Regression through Random Forest and XGBoost to LSTM (Table 2) reflects the increasing alignment between model complexity and the nonlinear, time-dependent nature of solar generation and EV charging demand. LSTM's specific advantage stems from its ability to retain relevant historical context — recent charging trends, a developing irradiance pattern — that precedes and helps predict subsequent demand and generation, rather than reacting only to the instantaneous sensor snapshot that the other three models rely on.

Because solar generation peaks near midday (Figure 3) while EV charging demand peaks in the evening (Table 1 correlation with grid load), the temporal mismatch between renewable supply and charging demand is the central operational challenge this framework addresses. Accurate, LSTM-driven forecasting allows the load balancing controller to anticipate this mismatch rather than merely react to it — directly explaining the simultaneous improvements observed in solar utilization, grid dependency, and peak load (Table 3, Figure 6). Critically, these efficiency gains were not achieved at the expense of service quality: the charging completion rate improved alongside

the efficiency metrics, indicating that intelligent scheduling, rather than denial of service, is responsible for the observed performance gains. Collectively, these results support the use of accurate, LSTM-based demand forecasting combined with dynamic load balancing as a practical foundation for sustainable, renewable-integrated EV charging infrastructure.

5. CONCLUSION

This study presented a dataset-based analysis of solar-powered EV charging stations for intelligent load balancing, combining the NREL Solar and EV Charging Dataset with four machine learning models — Linear Regression, Random Forest, XGBoost, and LSTM — for charging demand forecasting. LSTM achieved the best forecasting performance (MAE = 1.72 kW, RMSE = 2.28 kW, R^2 = 0.97), outperforming XGBoost (R^2 = 0.95), Random Forest (R^2 = 0.92), and Linear Regression (R^2 = 0.84), owing to its ability to capture temporal dependencies in solar generation and charging demand data. Correlation analysis identified grid load and PV output as the parameters most strongly associated with charging demand, while the proposed data-driven load balancing framework achieved substantial operational improvements over a conventional rule-based system: solar utilization increased from 68% to 92%, grid dependency fell from 48% to 18%, the charging completion rate rose from 88% to 98%, and peak load was reduced by approximately 30%. These results confirm that integrating accurate machine learning-based forecasting with dynamic load balancing can significantly enhance the reliability, efficiency, and sustainability of solar-powered EV charging infrastructure, supporting the broader goals of renewable energy integration and smart grid development.

Future Scope

Future work may extend the framework to multi-station deployments across urban environments, where multiple charging stations, renewable sources, and energy storage systems operate simultaneously, enabling evaluation of scalability and economic feasibility under real-world conditions. Integration of battery energy storage systems could further buffer the mismatch between midday solar generation and evening charging demand. Advanced deep learning architectures such as Gated Recurrent Units (GRU), Transformer networks, and hybrid CNN-LSTM models warrant exploration, alongside real-time hardware validation and dynamic electricity pricing to further optimize load balancing decisions.

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REFERENCES

[1] M. A. Mirjalili, A. Aslani, R. Zahedi, and M. Soleimani, "A comparative study of machine learning and deep learning methods for energy balance prediction in a hybrid building-renewable energy system," Sustain. Energy Res., vol. 10, no. 1, p. 8, 2023, doi: 10.1186/s40807-023-00078-9.

[2] R. Sundaramoorthi and S. Chitraselvi, "Integration of Renewable Resources in Electric Vehicle Charging Management Systems Using Deep Learning for Monitoring and Optimization," Iran. J. Sci. Technol. Trans. Electr. Eng., vol. 49, no. 1, pp. 313–335, 2025, doi: 10.1007/s40998-024-00767-1.

[3] R. Punyavathi, A. Pandian, A. R. Singh, M. Bajaj, M. B. Tuka, and V. Blazek, "Sustainable power management in light electric vehicles with hybrid energy storage and machine learning control," Sci. Rep., vol. 14, no. 1, pp. 1–21, 2024, doi: 10.1038/s41598-024-55988-5.

[4] A. Mansour-Saatloo, A. Moradzadeh, B. Mohammadi-Ivatloo, A. Ahmadian, and A. Elkamel, "Machine Learning Based PEVs Load Extraction and Analysis," 2020, doi: 10.3390/electronics9071150.

[5] F. Mwasilu, J. J. Justo, E.-K. Kim, T. D. Do, and J.-W. Jung, "Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration," Renew. Sustain. Energy Rev., vol. 34, pp. 501–516, 2014, doi: 10.1016/j.rser.2014.03.031.

[6] V. S. Kosuru and A. Kavasseri Venkitaraman, "A Smart Battery Management System for Electric Vehicles Using Deep Learning-Based Sensor Fault Detection," 2023, doi: 10.3390/wevj14040101.

[7] H. ur Rehman, T. Korvola, R. Abdurafikov, T. Laakko, A. Hasan, and F. Reda, "Data analysis of a monitored building using machine learning and optimization of integrated photovoltaic panel, battery and electric vehicles in a Central European climatic condition," Energy Convers. Manag., vol. 221, p. 113206, 2020, doi: 10.1016/j.enconman.2020.113206.

[8] T. Lan, K. Jermsittiparsert, S. T. Alrashood, M. Rezaei, L. Al-Ghussain, and M. A. Mohamed, "An Advanced Machine Learning Based Energy Management of Renewable Microgrids Considering Hybrid Electric Vehicles' Charging Demand," 2021, doi: 10.3390/en14030569.

[9] C. Tu, X. He, Z. Shuai, and F. Jiang, "Big data issues in smart grid — A review," Renew. Sustain. Energy Rev., vol. 79, pp. 1099–1107, 2017, doi: 10.1016/j.rser.2017.05.134.

[10] D. Syed, A. Zainab, A. Ghrayeb, S. S. Refaat, H. Abu-Rub, and O. Bouhali, "Smart Grid Big Data Analytics: Survey of Technologies, Techniques, and Applications," IEEE Access, vol. 9, pp. 59564–59585, 2021, doi: 10.1109/ACCESS.2020.3041178.

[11] V. K. Ponnusamy et al., "A Comprehensive Review on Sustainable Aspects of Big Data Analytics for the Smart Grid," 2021, doi: 10.3390/su132313322.

[12] K. V Kanimozhi, P. Neelaveni, K. Seethalakshmi, N. V Rao, M. Prabhu, and S. B. T. Naganathan, "Implementing Real-Time Analytics for Enhanced Energy Efficiency in IoT-Integrated Smart Grid Systems," in 2024 10th Int. Conf. on Communication and Signal Processing (ICCSP), 2024, pp. 762–766, doi: 10.1109/ICCSP60870.2024.10543583.

[13] M. Jaradat, M. Jarrah, A. Bousselham, Y. Jararweh, and M. Al-Ayyoub, "The Internet of Energy: Smart Sensor Networks and Big Data Management for Smart Grid," Procedia Comput. Sci., vol. 56, pp. 592–597, 2015, doi: 10.1016/j.procs.2015.07.250.

[14] S. Tabassum, A. R. Vijay Babu, and D. K. Dheer, "Real-time power quality enhancement in smart grids through IoT and adaptive neuro-fuzzy systems," Sci. Technol. Energy Transit., vol. 79, 2024, doi: 10.2516/stet/2024085.

[15] R. K. Beniwal, M. K. Saini, A. Nayyar, B. Qureshi, and A. Aggarwal, "A Critical Analysis of Methodologies for Detection and Classification of Power Quality Events in Smart Grid," IEEE Access, vol. 9, pp. 83507–83534, 2021, doi: 10.1109/ACCESS.2021.3087016.

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