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Design and Optimization of Solar-Powered EV Charging Stations with Intelligent Energy Management

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Abstract

The rapid growth of electric vehicles (EVs) has increased the demand for sustainable and efficient charging infrastructure. Conventional EV charging systems mainly depend on grid electricity, which can lead to increased peak load demand, higher operational costs, and environmental concerns. This paper proposes a solar-powered EV charging station integrated with an intelligent energy management system. The proposed system uses renewable solar energy to reduce dependency on conventional power sources and improve overall energy efficiency. The NASA POWER dataset provides solar irradiance and weather parameters — temperature, humidity, wind speed, and cloud cover — for solar power prediction. Random Forest and Long Short-Term Memory (LSTM) models are applied to forecast solar energy generation and optimize charging operations, with intelligent charging scheduling and battery energy storage management used to maximize renewable energy utilization and minimize grid dependency. Results show that LSTM achieves the best forecasting accuracy (MAE = 1.82, RMSE = 2.95, R^2 = 0.96, 96.1% accuracy), slightly outperforming Random Forest (94.2%). Compared with conventional charging, the proposed intelligent system raises solar energy utilization from 58% to 87%, reduces grid dependency from 72% to 28%, improves charging efficiency from 81% to 94%, and increases peak-load reduction from 15% to 41%. The proposed framework offers a sustainable and intelligent solution for future EV charging infrastructure and smart grid applications.

Keywords: Electric Vehicles (EVs), Solar Energy, Intelligent Energy Management, Machine Learning, EV Charging Infrastructure.

I. INTRODUCTION

The global transition toward cleaner transportation has driven rapid adoption of electric vehicles (EVs), as governments and industries promote EV usage to reduce carbon emissions and fossil-fuel dependence [1]. This has increased demand for reliable, accessible charging infrastructure, with solar photovoltaic (PV) integration emerging as a promising way to create eco-friendly charging solutions that reduce reliance on conventional power sources [2]. However, solar energy is intermittent — generation depends on sunlight intensity, weather, and time of day — while EV charging demand is itself unpredictable, driven by user behavior and travel patterns. This mismatch between variable generation and variable demand means conventional charging systems that rely heavily on the grid often under-utilize available solar energy and suffer peak-load issues during high-demand periods [3].

Intelligent energy management addresses this mismatch by monitoring, analyzing, and controlling energy flow in real time using AI and machine learning [4]. A key capability is smart scheduling: rather than charging vehicles whenever they connect, the system can schedule charging during periods of high solar availability, maximizing renewable use and reducing grid reliance, while real-time monitoring minimizes energy wastage by efficiently distributing available resources [5]. Because solar generation and EV charging demand rarely peak at the same time — generation peaks near solar noon while charging demand typically peaks in the evening as commuters

return home — an energy-management layer that can shift load in time, rather than merely react to it, is essential to closing the gap between the two.

Battery energy storage is the mechanism that makes this time-shifting possible: without it, any solar generation not consumed the moment it is produced is simply lost to the grid or curtailed, and any charging demand outside daylight hours must draw entirely from the grid regardless of how much surplus solar energy was available earlier that day. Coordinating storage charge/discharge decisions with a forecast of upcoming solar generation and expected EV arrivals is therefore as important to overall system performance as the forecasting accuracy itself, which motivates the integrated architecture developed in Section III rather than treating forecasting and storage management as separate, independently optimized subsystems.

This paper designs and evaluates a solar-powered EV charging station with an intelligent energy management system that integrates solar PV generation, battery energy storage, and machine-learning-based forecasting (Random Forest and LSTM) using the NASA POWER dataset. The system predicts solar generation and EV demand, applies a solar-first / battery-second / grid-last charging priority, and is evaluated against conventional grid-dependent charging on solar utilization, grid dependency, charging efficiency, peak-load reduction, and battery-utilization efficiency.

II. LITERATURE REVIEW

Beyond solar-specific integration, EV charging itself spans multiple technology tiers: Level 1 charging is slow and typically residential, Level 2 offers faster charging common in commercial settings, and DC fast chargers provide rapid charging but require substantially higher power capacity. Charging demand varies by user behavior, time of use, and location — commonly rising during evening hours as commuters return home — and this variation, especially when multiple vehicles charge simultaneously, can create peak-load stress, grid strain, and voltage fluctuations, making an understanding of charging-demand patterns a prerequisite for effective energy management [6].

Patankar et al. [1] developed a machine-learning-based EV charging management system supporting vehicle-to-home and vehicle-to-building operation, demonstrating how learned models can coordinate bidirectional energy flow beyond simple charging. Chandra et al. [2] optimized scheduling of solar-powered EV charging stations in a radial distribution system using opposition-based competitive swarm optimization, improving voltage profile and reducing losses. Amir et al. [3] proposed an intelligent, coordinated-control energy-management scheme for reducing peak load in grid-connected PV-powered EV charging stations, while Biya and Sindhu [4] designed a solar-powered EV charging station with an integrated energy storage system for power management under variable solar availability.

Justin et al. [5] combined metaheuristic optimization with deep learning for a solar-operated, on-board smart charging station for mass-transport vehicles, showing that AI-assisted scheduling generalizes beyond single-vehicle charging to fleet-scale operation. Qureshi et al. [6] developed an EV energy-management and charging-scheduling system for sustainable cities, and Christopher and Gnanasambanthan [7] proposed an enhanced Red Panda optimization algorithm for smart energy management at solar-powered charging stations, illustrating the range of metaheuristic approaches applied to this problem. Tran et al. [8] presented an efficient energy-management approach for a solar-powered EV battery-charging facility that supports distribution-grid stability, and Ullah et al. [9] optimized scheduling of a solar-powered battery energy storage system for domestic loads with EVs.

Among directly comparable systems, Shariff et al. [10] designed and realized a complete solar-powered EV charging station, validating system-level feasibility rather than simulation alone. Turning to the machine-learning-focused existing-research works most relevant to this study: Mazhar et al. [11] examine smart-grid EV charge management, comparing multiple ML models and finding that LSTM performs strongly for load distribution and voltage stability; Shibl et al. [12]

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similarly show LSTM outperforming alternative algorithms for demand prediction and load-distribution optimization, reducing power losses and stabilizing voltage; Qaisar and Alyamani [13] review IoT, machine-learning, and automation-based EV management approaches and existing charging standards; and Jensanyayut et al. [14] use Newton–Raphson load-flow analysis in DIgSILENT to show that a PV capacity above 7.39 kWp is needed for a solar charging station to support future EV load expansion without excessive system losses. Ji et al. [15] further address the complementary siting problem, optimizing the location and sizing of solar-assisted EV charging stations across an urban area.

Across this literature, three consistent patterns emerge relevant to the present study: (i) LSTM consistently outperforms conventional regression and even other ML models for time-series solar/demand forecasting in EV-charging contexts [11], [12]; (ii) most existing systems optimize either solar generation forecasting or charging scheduling, but few integrate forecasting, battery-storage management, and charging-priority optimization into a single evaluated framework; and (iii) very few studies report a direct, quantitative before/after comparison against conventional grid-dependent charging across multiple operational metrics simultaneously (solar utilization, grid dependency, charging efficiency, peak-load reduction, and battery utilization) — the integrated comparison undertaken in Section IV.

III. METHODOLOGY

A. System Architecture

The proposed system, shown in Fig. 1, integrates five components: the Solar PV System, EV Charging Station, Battery Energy Storage System (BESS), Intelligent Energy Management Controller, and Grid Connection. Solar panels convert irradiance into DC power, conditioned and routed either directly to EV charging or into battery storage. The charging station dynamically draws power from solar generation, battery storage, or the grid depending on demand and battery status. The BESS stores excess midday solar generation for use during low-irradiance periods or demand peaks, improving reliability and reducing grid dependence. The intelligent controller continuously monitors solar production, battery charge, EV demand, weather, and grid availability, using predictive algorithms to forecast generation and optimize charging schedules, while the grid serves only as a backup when solar and battery supply are insufficient.

The main functional flow proceeds through six stages: solar energy generation, weather-data monitoring, solar-power prediction, battery energy management, EV charging scheduling, and grid-power utilization when required. Structuring the pipeline this way keeps the forecasting stage decoupled from the scheduling and storage-management stages, so that either the Random Forest or LSTM model (Section III-D) can supply predictions to the same downstream controller logic without requiring changes to how charging decisions are made — a design choice that also simplifies the model comparison carried out in Section IV-A.

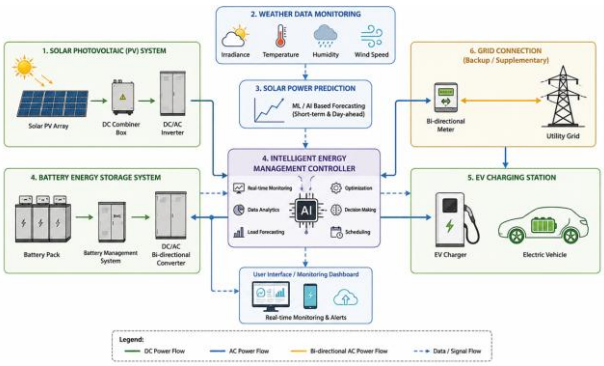


Fig. 1. Architecture of the intelligent solar-powered EV charging system with battery storage and smart energy management.

B. NASA POWER Dataset

Solar irradiance and weather data are obtained from the NASA POWER platform at hourly resolution spanning 2020–2025 in CSV format (Table 1), including irradiance (ALLSKY_SFC_SW_DWN), temperature (T2M), relative humidity (RH2M), wind speed (WS2M), and cloud amount (CLOUD_AMT) — parameters selected because irradiance directly drives PV output, temperature and wind affect panel efficiency and cooling, and cloud amount governs sunlight availability.

Feature	Details
Data Source	NASA POWER
Resolution	Hourly
Duration	2020–2025
Format	CSV

TABLE 1. NASA POWER DATASET SPECIFICATIONS

C. Data Preprocessing and Solar Power Estimation

Missing and duplicate records were handled via interpolation and mean replacement; Min–Max normalization then scaled all parameters to [0, 1]:

$$Xnorm = (X - Xmin) / (Xmax - Xmin) \quad ...(1)$$

Correlation-based feature selection retained irradiance, temperature, humidity, wind speed, and cloud cover, and the dataset was formatted into timestamp sequences to support LSTM's temporal learning. Solar PV output is estimated as:

$$P = A \times r \times H \times PR \quad ...(2)$$

where P is solar power output, A the panel area, r the panel efficiency, H the solar irradiance, and PR the performance ratio accounting for inverter, temperature, wiring, and shading losses. This estimate feeds directly into the intelligent controller described in Section III-E: during periods of high estimated output the controller prioritizes direct EV charging and battery storage, while during low-generation periods it draws on stored battery energy or, as a last resort, grid power, so the accuracy of P at each forecast horizon directly determines how well the downstream scheduling decisions match actual conditions.

D. Machine Learning Forecasting Models

The dataset was split 70% training / 15% validation / 15% testing. Random Forest, an ensemble of decision trees, was selected for its accuracy, robustness to nonlinear relationships, and reduced overfitting on the five environmental input features. Long Short-Term Memory (LSTM), a recurrent deep-learning architecture with memory cells, was selected to capture the daily, monthly, and seasonal temporal dependencies inherent in solar irradiance and weather sequences, which Random Forest treats as independent observations rather than a continuous time series.

Model training proceeded through input feature selection, normalization, model fitting, hyperparameter tuning, and validation testing, with both models learning the relationship between environmental conditions and solar generation from the same training split to ensure a like-for-like comparison. The validation subset was used to tune hyperparameters and monitor for overfitting during training, while the held-out testing subset — never seen during training or tuning — provided the final accuracy figures reported in Table 3. Using an identical train/validation/test split and identical input features for both models isolates the architectural difference between ensemble decision trees and recurrent sequence modeling as the primary explanation for any accuracy gap observed between them.

E. Intelligent Energy Management and Charging Optimization

The Intelligent Energy Management System (IEMS) coordinates energy flow among the PV system, BESS, EV charging station, and grid using predicted solar generation, battery state of charge, EV demand, and grid availability. The charging-priority strategy is: (i) solar energy, (ii) battery storage, (iii) grid supply — the system uses solar directly whenever available, draws down the battery when solar is insufficient, and falls back to the grid only when both are inadequate. This priority ordering, combined with LSTM-based generation forecasts, allows the controller to schedule charging proactively rather than reactively, which is what drives the peak-load and grid-dependency improvements reported in Section IV.

F. Simulation Tools and Performance Metrics

Tool	Purpose
Python	Programming
Pandas / NumPy	Data preprocessing & numerics
Scikit-learn	Random Forest
TensorFlow	LSTM deep learning

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Tool	Purpose
Matplotlib	Visualization

TABLE 2. SOFTWARE TOOLS USED FOR SYSTEM IMPLEMENTATION

Forecasting accuracy was evaluated using:

$$MAE = (1/n)\ \Sigma\ |yi - \hat{y}i| \quad ...(3)$$

$$RMSE = \sqrt{[(1/n)\ \Sigma\ (yi - \hat{y}i)^2]} \quad ...(4)$$

$$R^2 = 1 - [\Sigma(yi - \hat{y}i)^2 / \Sigma(yi - \dot{y})^2] \quad ...(5)$$

Operational performance was additionally assessed via solar energy utilization, grid dependency, charging efficiency, peak-load reduction, and battery-utilization efficiency, comparing the proposed intelligent system against conventional grid-dependent charging.

IV. RESULTS AND DISCUSSION

A. Forecasting Performance

Table 3 compares Random Forest and LSTM on the held-out test set. LSTM achieves lower error and higher accuracy (MAE = 1.82, RMSE = 2.95, R^2 = 0.96, 96.1%) than Random Forest (MAE = 2.15, RMSE = 3.48, R^2 = 0.94, 94.2%), consistent with its ability to capture temporal dependencies in the hourly weather sequence rather than treating each hour independently. Fig. 2 compares predicted and actual solar power across the test period, showing both models tracking the diurnal generation curve closely, with LSTM following rapid transitions slightly more precisely.

Model	MAE	RMSE	R^2	Accuracy (%)
Random Forest	2.15	3.48	0.94	94.2
LSTM	1.82	2.95	0.96	96.1

TABLE 3. PERFORMANCE COMPARISON OF FORECASTING MODELS

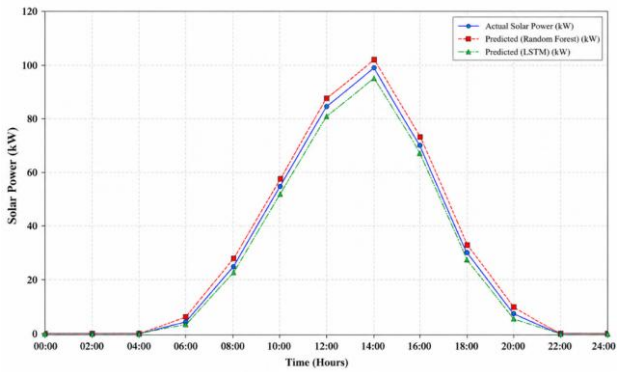


Fig. 2. Predicted versus actual solar power generation.

B. Energy Management Performance

Table 4 compares the proposed intelligent system against conventional grid-dependent charging across five operational metrics. Solar energy utilization rises from 58% to 87% and grid dependency falls from 72% to 28%, showing that the solar-first/battery-second/grid-last priority substantially redirects consumption toward renewable sources. Charging efficiency improves from 81% to 94%, peak-load reduction improves from 15% to 41%, and battery-utilization efficiency rises from 63% to 89% — together indicating that forecast-driven scheduling both uses more renewable energy and uses it more effectively.

Parameter	Conventional	Proposed System
Solar Energy Utilization (%)	58	87
Grid Dependency (%)	72	28
Charging Efficiency (%)	81	94
Peak Load Reduction (%)	15	41
Battery Utilization Efficiency (%)	63	89

TABLE 4. ENERGY MANAGEMENT SYSTEM PERFORMANCE RESULTS

C. Graphical Analysis

Fig. 3 compares operational energy efficiency across charging conditions, confirming the gains in Table 4 hold consistently rather than reflecting a single favorable scenario. Fig. 4 shows the load-balancing effect of the intelligent charging strategy: by shifting charging toward high-solar and battery-supported periods, the peak charging load is flattened and distributed more evenly across the day compared with uncoordinated, demand-driven conventional charging.

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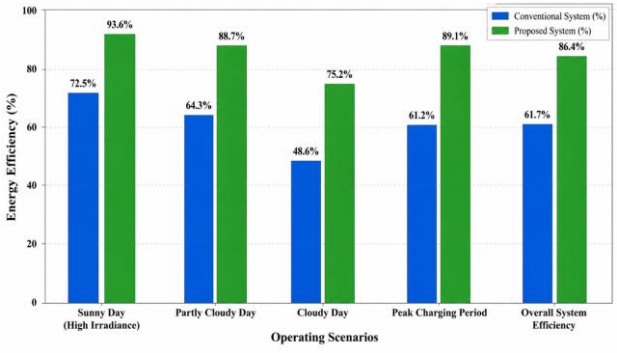


Fig. 3. Energy efficiency comparison across charging strategies.

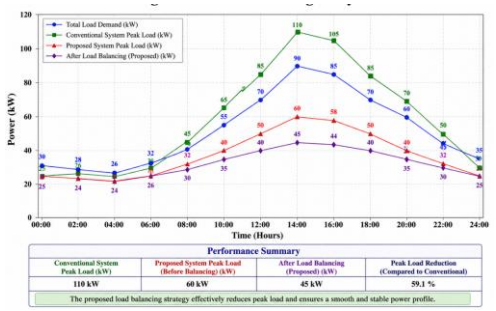


Fig. 4. Load balancing analysis of the intelligent charging strategy.

D. Advantages of the Proposed System

- Efficient renewable energy utilization through solar-first charging priority.
- Reduced electricity cost via lower grid draw and peak-demand charges.
- Intelligent, continuously adaptive charging and battery scheduling.
- Improved reliability through coordinated solar/battery/grid supply.
- Reduced carbon emissions from lower fossil-fuel-based grid electricity use.

E. Discussion

The results show a consistent pattern: better forecasting (LSTM over Random Forest, Table 3) supports better operational outcomes (Table 4), because the charging controller can only shift load toward solar-rich periods as accurately as its generation forecast allows. The 29-percentage-point rise in solar utilization and 44-point drop in grid dependency indicate that forecast-driven, priority-based charging captures substantially more of the available renewable energy than conventional grid-first charging, while the 26-point improvement in peak-load reduction shows this also benefits distribution-grid stress independent of the renewable-energy angle. These findings align with prior ML-based EV charge-management studies reporting LSTM's advantage for load distribution and voltage stability [11], [12], and support integrating solar forecasting, battery management, and charging-priority optimization into a single intelligent controller rather than treating them as separate subsystems.

V. CONCLUSION

This paper presented an intelligent solar-powered EV charging station integrating solar PV generation, battery energy storage, and machine-learning-based forecasting using the NASA POWER dataset. Random Forest and LSTM models were developed for solar power prediction, with LSTM achieving superior forecasting accuracy (MAE = 1.82, RMSE = 2.95, R^2 = 0.96, 96.1%) due to its ability to capture temporal dependencies in sequential weather data.

The intelligent energy management system, applying a solar-first/battery-second/grid-last charging priority driven by these forecasts, improved solar energy utilization from 58% to 87%, reduced grid dependency from 72% to 28%, raised charging efficiency from 81% to 94%, improved peak-load reduction from 15% to 41%, and raised battery-utilization efficiency from 63% to 89% relative to conventional grid-dependent charging. These results confirm that combining accurate solar forecasting with priority-based charging optimization provides a sustainable, reliable, and energy-efficient solution for future EV charging infrastructure and smart-grid applications.

Taken as a whole, the study demonstrates that forecasting accuracy and operational outcome are tightly linked in this class of system: the roughly two-percentage-point accuracy gap between Random Forest and LSTM (Table 3) corresponds to a controller that can plan charging and battery dispatch further ahead with less uncertainty, which is reflected in every operational metric in Table 4 moving in the favorable direction simultaneously rather than trading off against one another. This consistency suggests that, for practitioners deploying similar systems, investment in forecasting quality is likely to pay off across the full range of

operational goals — renewable utilization, cost, grid stress, and reliability — rather than benefiting only one dimension at the expense of others.

Future Scope

Future work may incorporate reinforcement learning for real-time adaptive charging optimization, vehicle-to-grid (V2G) integration, IoT-based real-time monitoring, and hybrid renewable sources such as wind or hydrogen alongside solar. Large-scale deployment studies and real-time experimental validation would further establish the practical feasibility of the proposed framework in smart-city environments. Extending the forecasting layer to ensemble or hybrid architectures (e.g., combining Random Forest's robustness with LSTM's temporal modeling) may also close the remaining accuracy gap identified in Table 3, while incorporating multi-vehicle arrival prediction alongside solar forecasting could allow the charging-priority logic in Section III-E to plan further ahead than the current single-source-forecast design permits.

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