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An Adaptive Fuzzy Logical Controller for a Two Area Load Frequency Control Problem

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Abstract

The increasing adoption of electric vehicles (EVs) and solar energy sources has significantly transformed modern electrical power systems. However, the integration of large-scale EV charging and solar power generation introduces challenges such as power imbalance, voltage fluctuations, peak load stress, and grid instability. This paper proposes a data-driven smart grid framework using machine learning and deep learning techniques for intelligent energy management. The proposed system uses the NASA POWER dataset for solar and weather information and the ACN-Data EV Charging dataset for charging-behavior analysis. Four models — Linear Regression, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) — are implemented for forecasting solar power generation and EV charging demand, and an intelligent smart-charging strategy is developed to schedule EV charging during periods of high solar availability. Simulation results show that the proposed approach improves renewable energy utilization from 61% to 84%, reduces peak load demand from 82 kW to 61 kW, and enhances grid stability. Among all implemented models, LSTM achieved the highest forecasting accuracy (95.1%, RMSE = 2.40, MAE = 1.65), outperforming Random Forest, SVM, and Linear Regression. The proposed framework offers an efficient, reliable, data-driven solution for future smart grid systems with high EV and solar penetration.

Keywords: Data-Driven Modeling, Electric Vehicles, Solar Energy Integration, Machine Learning, Smart Grid.

I. INTRODUCTION

The rapid growth of global energy demand and rising environmental concerns have accelerated the transition toward sustainable and clean energy technologies [1]. Conventional power generation depends heavily on fossil fuels, which contribute significantly to greenhouse-gas emissions. Among clean-technology options, electric vehicles (EVs) and solar photovoltaic (PV) systems have emerged as two major components of future smart energy systems [2]. EVs reduce air pollution and fossil-fuel dependency, but large-scale charging infrastructure introduces challenges: simultaneous charging of multiple vehicles during peak hours can cause grid congestion, voltage instability, and transformer overloading [3].

Solar PV energy is one of the most widely adopted renewable sources because of its clean, abundant, and cost-effective nature [4]. However, solar generation is highly dependent on environmental conditions such as irradiance, cloud cover, and temperature, making it intermittent. Balancing generation and demand becomes especially difficult when variable solar output and uncertain EV charging demand occur together, since traditional grid-management methods are often insufficient for such dynamic, nonlinear conditions [5].

Data-driven modeling, using artificial intelligence (AI), machine learning (ML), and deep learning, offers a powerful alternative: such models learn complex, nonlinear relationships directly from historical and real-time data rather than relying on fixed assumptions, enabling accurate forecasting of solar generation and EV demand and supporting proactive, intelligent grid control [6]. Unlike traditional power-system models, which are largely deterministic and struggle with dynamic, nonlinear conditions, data-driven approaches continuously improve as more operational data becomes available, allowing system operators to anticipate — rather than merely react to — power imbalances caused by EV charging and solar variability.

The absence of proper coordination between generation and demand can lead to power imbalance, voltage fluctuation, reduced power quality, and inefficient utilization of available renewable resources. Addressing this requires not only accurate forecasting but also an active optimization layer that translates predictions into concrete scheduling decisions. This paper develops a data-driven smart grid framework that forecasts solar power generation and EV charging demand using Linear Regression, Random Forest, SVM, and LSTM, and applies an intelligent smart-charging strategy to align EV charging with solar availability, reducing peak load stress and improving renewable energy utilization and grid stability.

II. LITERATURE REVIEW

Debnath et al. [1] proposed a hybrid AI framework for identifying power-quality disturbances in electrical networks, demonstrating the value of AI-based diagnostics for grid reliability. Bhargava [2] reviewed the integration of renewable energy and AI in EV charging within smart-grid-connected systems, highlighting the growing role of intelligent coordination. Khademhamedani et al. [3] presented a data-driven optimization framework for EV charging that integrates real-time data, ML predictions, and optimization to coordinate charging schedules with renewable availability, reporting reduced peak demand and improved voltage stability. Palomino and Parvania [4] analyzed data-driven risk assessment of joint EV and solar operation in distribution networks.

Choumal et al. [7] used a big-data analytics framework based on Apache Spark to apply machine learning for short-term forecasting of PV generation and EV charging demand, showing how data-driven methods uncover usage patterns to support decision-making. Ahsan et al. [8] reviewed the evolution of smart grids toward data-centric, next-generation systems, emphasizing IoT, edge computing, and agent-based control for managing complex and uncertain grid conditions. Calero et al. [9] proposed a two-level deep-reinforcement-learning controller for coordinating EV charging in residential distribution systems with high PV penetration, improving charging coordination and preventing transformer overloading.

Sumon Rashid et al. [10] developed a hybrid CNN-BiLSTM model for seasonal PV forecasting combined with a genetic-algorithm-based coordination strategy to align EV charging with PV availability, improving voltage stability and reducing losses on the IEEE 13-bus test system. Jiang et al. [11] presented a data-driven method for fast uncertainty assessment of distribution systems with correlated EV charging and renewable generation. Arif and Milanovic [12] examined data-driven distribution-system expansion planning under high EV and PV penetration, while Conti et al. [13] reviewed optimization and machine-learning approaches for EV management in distribution networks.

Zhao et al. [14] proposed a data-driven framework for large-scale prediction of EV charging energy, and Elghanam et al. [15] developed a spatial-regression approach for EV electricity-demand modeling. Across these studies, solar irradiance and EV charging duration consistently emerge as the dominant drivers of forecasting accuracy, ensemble and deep-learning methods outperform simple regression, and coordinated, AI-based charging strategies reliably improve grid stability. However, most existing work addresses solar forecasting, EV demand forecasting, or charging optimization in isolation rather than as an integrated, jointly-evaluated framework — a gap the present study addresses by combining solar forecasting, EV demand prediction, and smart-charging optimization within a single data-driven pipeline.

Taken together, the surveyed literature indicates three consistent trends relevant to this work: first, deep-learning models such as LSTM and CNN-BiLSTM consistently achieve lower forecasting error than classical regression on renewable-generation and EV-demand time series; second, coordination frameworks that combine forecasting with optimization (genetic algorithms, reinforcement learning, or rule-based scheduling) achieve measurably better grid outcomes than forecasting alone; and third, evaluation is rarely

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performed on a common dataset and metric set across models, which motivates the standardized, side-by-side comparison of Linear Regression, SVM, Random Forest, and LSTM undertaken in Section IV.

III. METHODOLOGY

A. Proposed System Architecture

The proposed architecture integrates a solar PV system, EV charging stations, smart-grid infrastructure, a data-acquisition module, a machine-learning prediction module, and an optimization and energy-management system, as illustrated in Fig. 1. The PV system generates power based on solar irradiance and weather conditions, while EV charging stations represent the dynamic load component, whose demand depends on user behavior and time of use. The data-acquisition module continuously collects solar, weather, EV-charging, and load-demand data, which is processed by the machine-learning prediction module (Linear Regression, Random Forest, SVM, and LSTM) to forecast solar generation and EV demand. The optimization module then uses these forecasts to schedule EV charging during periods of high solar availability, reducing peak load stress and improving renewable utilization.

The smart-grid infrastructure layer enables bidirectional communication and real-time monitoring between generation, distribution, and consumption components, which is what allows the forecasts produced by the prediction module to be translated into actionable charging schedules rather than remaining passive estimates. This closed-loop design — forecast, decide, act, and re-forecast — is central to the framework's ability to respond to both slow seasonal shifts in solar availability and fast day-to-day changes in EV charging behavior.

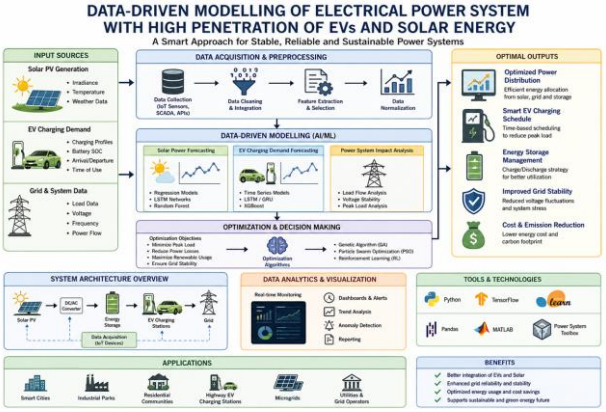


Fig. 1. Data-driven modeling framework for electrical power systems with high EV and solar penetration.

B. Data Collection

Solar and weather data is obtained from the NASA POWER platform, providing satellite-based meteorological and renewable-energy parameters, summarized in Table 1. EV charging-behavior data is obtained from the ACN-Data EV Charging dataset developed by the Adaptive Charging Network, summarized in Table 2. Hourly load-demand data is additionally used to analyze peak and off-peak consumption patterns.

Parameter	Description	Unit
Solar Irradiance	Solar radiation received	W/m²
Temperature	Ambient atmospheric temperature	°C
Humidity	Moisture content in air	%
Wind Speed	Speed of wind flow	m/s

TABLE 1. PARAMETERS USED FROM THE NASA POWER DATASET

Parameter	Description	Unit
Charging Start Time	Time charging begins	HH:MM
Charging End Time	Time charging ends	HH:MM
Charging Duration	Total charging period	Hours
Energy Consumption	Energy delivered	kWh

TABLE 2. PARAMETERS USED FROM THE ACN-DATA EV CHARGING DATASET

C. Data Preprocessing

Missing values, arising from sensor failures or communication errors, were handled using interpolation and mean-filling methods, reducing all six monitored parameters from a small number of missing entries to zero (Table 3). All input features were then scaled to a common [0, 1] range using Min–Max normalization, since raw features such as solar irradiance (0–1000 W/m²) and EV charging duration (0–8 hours) differ by orders of magnitude; normalization improved training stability, convergence speed, and prediction accuracy.

Dataset Parameter	Missing (Before)	Missing (After)	Method
Solar Irradiance	18	0	Interpolation
Temperature	12	0	Mean Filling
Humidity	10	0	Mean Filling
Wind Speed	8	0	Interpolation
EV Charging Duration	15	0	Mean Filling
Energy Consumption	11	0	Interpolation

TABLE 3. MISSING VALUE HANDLING RESULTS

D. Forecasting Models

Linear Regression was used as a baseline model for solar output and load estimation, fitting a linear relationship between input weather/load parameters and the target output. Random Forest, an ensemble of decision trees, was applied to EV demand forecasting because of its ability to capture nonlinear charging-behavior patterns while reducing overfitting. Support Vector Machine (SVM) was used to classify load conditions and predict demand variation by identifying an optimal separating hyperplane in a higher-dimensional feature space, which is effective for multidimensional, nonlinear grid data.

Long Short-Term Memory (LSTM), a deep-learning variant of recurrent neural networks, was used for both solar power forecasting and EV charging-demand prediction because solar generation and charging demand vary continuously with time. LSTM's memory cells retain information from earlier time steps, enabling it to model long-term temporal dependencies in sequential data more effectively than models that treat observations independently.

- Linear Regression: simple, fast, interpretable baseline for solar/load estimation.
- Random Forest: high accuracy, handles nonlinear EV charging patterns, reduces overfitting.
- SVM: strong generalization for multidimensional load/demand classification.
- LSTM: captures long-term temporal dependencies for solar and EV time-series forecasting.

E. Smart Charging Optimization Strategy

Using the LSTM solar forecast and the Random Forest/LSTM EV-demand forecast, a smart-charging strategy shifts EV charging load from evening peak hours toward periods of high solar availability around midday, instead of allowing uncoordinated charging whenever vehicles connect. The objectives of the strategy are to reduce peak load stress, improve renewable energy utilization, optimize EV charging schedules, and improve grid stability, by continuously monitoring solar generation and EV demand forecasts to make charging-allocation decisions.

F. Performance Evaluation Metrics and Tools

Model accuracy was evaluated using RMSE, MAE, and prediction accuracy:

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

$$MAE = (1/n)\ \Sigma\ |yi - \hat{y}i| \quad ...(2)$$

$$Accuracy = (Correct\ Predictions / Total\ Predictions) \times 100 \quad ...(3)$$

where yi is the actual value, ŷi the predicted value, and n the number of observations. Lower RMSE/MAE and higher accuracy indicate better forecasting performance. The framework was implemented in Python using Pandas, NumPy, Matplotlib, Scikit-learn, and TensorFlow/Keras (Table 4).

Tool / Library	Purpose
Python / Jupyter Notebook	Implementation & simulation
Pandas / NumPy	Data preprocessing

Tool / Library	Purpose
Scikit-learn	LR, RF, SVM models
TensorFlow / Keras	LSTM deep learning
Matplotlib	Visualization

TABLE 4. SOFTWARE TOOLS AND LIBRARIES USED

IV. RESULTS AND DISCUSSION

A. Solar Power Forecasting

The LSTM model was trained on NASA POWER solar and weather data to forecast solar power generation. Fig. 2 compares actual and predicted solar output across a representative day: the predicted curve closely follows the actual generation profile, accurately capturing the midday peak and low morning/evening output, with only minor deviations during rapidly changing weather. The model achieved RMSE = 2.15, MAE = 1.42, and 96.4% accuracy (Table 5), confirming that LSTM effectively learns solar generation patterns from historical weather data.

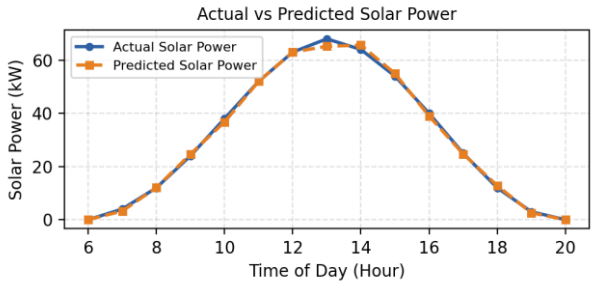


Fig. 2. Actual vs. predicted solar power generation.

Metric	Value
RMSE	2.15
MAE	1.42
Accuracy	96.4%

TABLE 5. SOLAR FORECASTING PERFORMANCE

B. EV Charging Demand Prediction

Random Forest and LSTM were used to forecast EV charging demand. Fig. 3 shows that predicted demand closely tracks the actual charging profile, correctly identifying the evening peak (when users charge after returning home) and the low overnight/early-morning demand. As shown in Table 6, LSTM outperformed Random Forest on every metric (RMSE = 2.40 vs. 3.25; MAE = 1.65 vs. 2.10; accuracy = 95.1% vs. 92.8%), because its recurrent memory cells capture the sequential dependencies in charging behavior more effectively than Random Forest's independent-tree averaging.

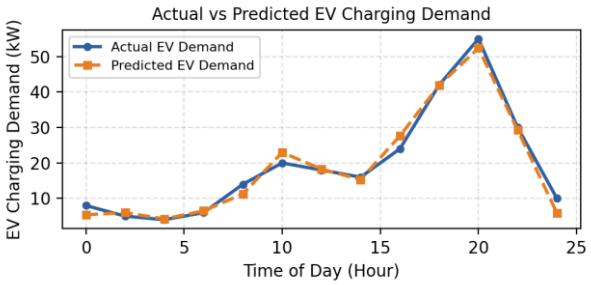


Fig. 3. Actual vs. predicted EV charging demand.

Metric	Random Forest	LSTM
RMSE	3.25	2.40
MAE	2.10	1.65
Accuracy	92.8%	95.1%

TABLE 6. EV CHARGING DEMAND PREDICTION PERFORMANCE

C. Load Demand and Smart-Charging Optimization

Without coordination, most EV users charge during evening hours, concentrating demand and pushing peak load to 82 kW (Fig. 4, "before optimization"). The proposed smart-charging strategy shifts charging toward periods of high solar availability, reducing and flattening the peak to 61 kW and distributing demand more evenly across the day (Table 7). This reduction directly relieves stress on distribution transformers and feeders during the evening peak window.

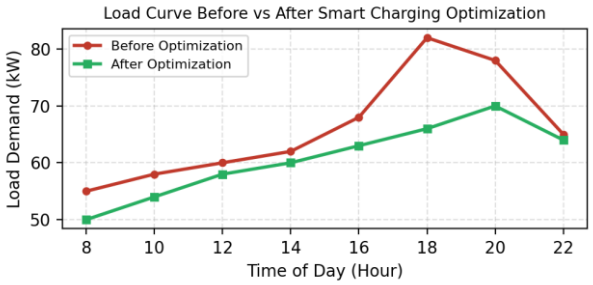


Fig. 4. Load curve before and after smart-charging optimization.

Condition	Peak Load (kW)	Renewable Utilization
Before Optimization	82	61%

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Condition	Peak Load (kW)	Renewable Utilization
After Optimization	61	84%

TABLE 7. PEAK LOAD REDUCTION AND RENEWABLE ENERGY UTILIZATION

As shown in Table 7, shifting EV charging toward midday solar availability raised renewable-energy utilization from 61% to 84%, reducing both wasted solar generation and reliance on conventional grid power. Grid-stability analysis further indicated reduced voltage fluctuations, better load balancing, improved supply–demand coordination, and fewer overload conditions once the smart-charging strategy was active, confirming that coordinated, forecast-driven charging improves operational reliability as well as energy efficiency.

D. Comparative Analysis of Machine Learning Models

Table 8 and Fig. 5 compare all four forecasting models on the combined solar/EV forecasting task. Linear Regression showed the weakest performance (RMSE = 5.82, MAE = 4.40, accuracy = 84.5%) because it cannot represent the nonlinear relationship between weather/charging variables and output. SVM improved accuracy to 89.6% by mapping features into a higher-dimensional space, and Random Forest improved further to 92.8% through ensemble averaging across decision trees. LSTM achieved the best overall performance (RMSE = 2.40, MAE = 1.65, accuracy = 95.1%), consistent with its superior ability to model sequential dependencies in time-series solar and EV data.

Model	RMSE	MAE	Accuracy
Linear Regression	5.82	4.40	84.5%
SVM	4.15	3.12	89.6%
Random Forest	3.25	2.10	92.8%
LSTM	2.40	1.65	95.1%

TABLE 8. COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS

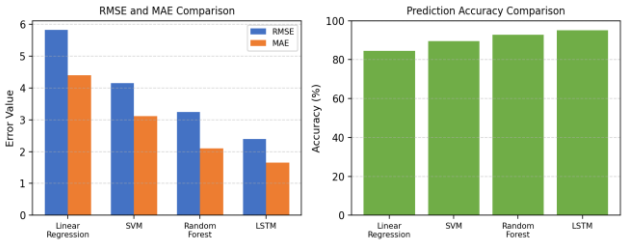


Fig. 5. Comparative RMSE/MAE and accuracy of the forecasting models.

E. Discussion

The results confirm that forecasting accuracy improves consistently from Linear Regression through SVM and Random Forest to LSTM, mirroring the increasing capacity of each method to model nonlinear and temporal structure in solar and EV data. Beyond raw forecasting accuracy, the practical value of the framework lies in combining these forecasts into a coordinated smart-charging strategy: accurate solar and EV-demand predictions are what make it possible to shift charging load to solar-rich hours, which is what ultimately delivers the 26-percentage-point rise in renewable utilization and the 26% cut in peak load observed in Table 7. These findings are consistent with prior coordinated-charging studies [3], [9], [10], and support the use of LSTM-based forecasting as the core predictive engine for smart-grid energy-management systems with high EV and solar penetration.

From a deployment perspective, the accuracy gains of LSTM come at higher training cost than Linear Regression or Random Forest, which is an acceptable trade-off given that solar and EV forecasts are typically retrained on a daily or weekly cadence rather than in real time. The consistent outperformance of LSTM across both the solar-forecasting task (Table 5) and the EV-demand task (Table 6) also suggests that a single recurrent architecture can reasonably serve both prediction roles within one framework, simplifying deployment compared with maintaining separate specialized models for each task.

V. CONCLUSION

This paper presented a data-driven smart grid framework that combines solar power forecasting, EV charging-demand prediction, and smart-charging

optimization using the NASA POWER and ACN-Data EV Charging datasets. Four models — Linear Regression, SVM, Random Forest, and LSTM — were implemented and compared using RMSE, MAE, and accuracy. LSTM achieved the best performance for both solar forecasting (RMSE = 2.15, MAE = 1.42, accuracy = 96.4%) and EV demand forecasting (RMSE = 2.40, MAE = 1.65, accuracy = 95.1%), owing to its ability to capture temporal dependencies in sequential energy data.

The proposed smart-charging strategy, which schedules EV charging during periods of high solar availability, reduced peak load from 82 kW to 61 kW and raised renewable-energy utilization from 61% to 84%, while also improving voltage stability, load balancing, and supply–demand coordination. These results confirm that combining accurate AI-based forecasting with coordinated charging optimization provides an effective, scalable solution for future smart grids with high penetration of EVs and solar energy.

More broadly, the comparative evaluation across four forecasting models demonstrates that model choice materially affects downstream optimization quality: since the smart-charging schedule is only as good as the forecasts feeding it, the accuracy gap between Linear Regression (84.5%) and LSTM (95.1%) translates directly into how reliably charging can be shifted to solar-rich hours without risking under- or over-scheduling. This reinforces the case for deep-learning-based forecasting as a foundational component of future smart-grid energy-management deployments, rather than an optional accuracy enhancement.

Future Scope

Future work may incorporate additional renewable sources such as wind energy and battery energy storage to improve reliability during low-solar periods, and explore advanced architectures such as Transformer networks, hybrid CNN-LSTM models, and reinforcement learning for improved forecasting and adaptive energy management. Vehicle-to-grid (V2G) technology, in which EVs supply stored energy back to the grid during peak demand, is a further promising direction for enhancing grid stability and optimizing energy utilization.

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