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An Intelligent Python-Based Energy Distribution Framework for Optimizing Solar-EV Charging Allocation Using Linear Programming

Tahreem Fatima Mohd. Abdul Muqsit[1], Prof. Ms. Alfiya A. Mahat[2]

[1]PG Scholar, Department of Electrical Engineering (Electrical Power System), MSS's College of Engineering and Technology, Nagewadi, Jalna, Maharashtra, India

[2]Assistant Professor, Department of Electrical Engineering, MSS's College of Engineering and Technology, Nagewadi, Jalna, Maharashtra, India

(Affiliated to Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra - 431004)

Abstract

The increasing adoption of electric vehicles (EVs) and renewable energy resources has created a need for efficient energy management systems capable of balancing energy generation and consumption. Solar photovoltaic (PV) systems offer a sustainable source of electricity for EV charging; however, the intermittent nature of solar energy and the varying charging demand of EVs pose significant operational challenges. This work presents an intelligent energy distribution framework for optimizing energy allocation between solar power generation and EV charging loads using Python-based optimization techniques. The study utilizes solar generation data and the Kaggle EV Charging Dataset to analyze charging demand patterns and available renewable energy. Data preprocessing and exploratory analysis are performed to improve data quality and identify key energy consumption trends. An optimization model based on linear programming is developed to maximize solar energy utilization while minimizing grid dependency and operational costs. The proposed framework intelligently allocates available solar energy to EV charging requirements and ensures efficient energy utilization under varying operating conditions. Experimental results demonstrate significant improvements in solar energy usage, reduction in grid power consumption, lower charging costs, and enhanced charging completion rates: solar energy utilization increased from 68% to 92%, grid dependency fell from 47% to 18%, daily charging costs were reduced by 29%, and the EV charging completion rate improved from 88% to 98%. The findings confirm that intelligent optimization techniques can effectively support sustainable EV charging infrastructure and contribute to the development of future smart grid energy management systems.

Keywords: *Electric Vehicles; Solar Energy; Energy Distribution; Optimization; Linear Programming; Smart Grid.*

1. INTRODUCTION

1.1 Background

The rapid advancement of technology and increasing environmental concerns have accelerated the global transition toward sustainable energy systems [1]. Among the various renewable energy options, solar photovoltaic (PV) technology has emerged as one of the most promising and widely adopted solutions due to its abundance, eco-friendliness, and declining installation costs, while electric vehicles (EVs) have gained considerable attention as an effective alternative to conventional fuel-powered vehicles because of their ability to reduce carbon emissions and improve energy efficiency.

The increasing penetration of EVs is creating new opportunities as well as challenges for modern power systems [5]. EV charging requires a substantial amount of electrical energy, and large-scale, uncoordinated charging activity can lead to peak demand conditions, voltage instability, transformer overloading, increased power losses, and higher electricity costs [6]. Integrating renewable energy sources, particularly solar power, with EV charging infrastructure offers a practical solution for reducing grid dependency and supporting sustainable transportation. However, solar power generation is inherently intermittent and varies with weather conditions, seasonal changes, and irradiance levels, creating challenges in maintaining a balance between energy generation and EV charging demand: during periods of low solar generation, additional power must be drawn from the grid, while excess solar energy generated during peak sunlight hours may be wasted if not properly utilized.

Recent advancements in optimization techniques and data analytics have enabled the development of smart energy management systems capable of making intelligent, real-time decisions [9]. Python-based optimization tools provide a powerful and flexible platform for modeling energy systems, analyzing large datasets, and implementing optimization algorithms that can forecast energy demand, allocate available solar energy efficiently, schedule EV charging operations, and minimize operational costs. In this context, the present work develops an intelligent energy distribution framework that optimizes energy allocation between solar generation and EV charging loads using Python-based linear programming, thereby enhancing renewable energy utilization, reducing grid dependency, and improving overall system efficiency.

1.2 Problem Statement

The increasing adoption of electric vehicles introduces substantial charging demand on existing power distribution networks. Uncontrolled EV charging can cause peak load conditions, increased power losses, voltage instability, and higher operational costs. Although solar energy can help satisfy EV charging requirements, its variable nature makes efficient utilization difficult, and traditional energy management approaches often fail to dynamically balance solar generation and EV charging demand. There is therefore a need for an intelligent optimization framework capable of efficiently distributing available solar energy to EV loads while minimizing grid dependency and improving overall system performance.

1.3 Aim and Objectives of the Work

The aim of this work is to develop an intelligent energy distribution system that optimally allocates solar-generated electricity to EV charging loads using Python-based optimization techniques for enhanced energy efficiency and reduced grid dependency. The specific objectives are to: (i) collect and analyze solar generation and EV charging datasets; (ii) preprocess and prepare the data for optimization analysis; (iii) model solar power generation and EV charging demand profiles; (iv) develop an intelligent energy allocation framework using Python-based linear programming; (v) maximize solar energy utilization while minimizing grid power dependency, energy losses, and operational costs; and (vi) evaluate the performance of the proposed system using solar utilization rate, grid dependency, energy cost reduction, charging completion rate, and peak load reduction as performance metrics.

1.4 Scope of the Work

The scope of this work is limited to software-based modeling and simulation - solar energy generation analysis, EV charging demand assessment, energy allocation optimization, grid dependency reduction, cost-effective charging management, and Python-based performance evaluation - and does not include hardware implementation.

2. LITERATURE REVIEW

The rapid growth of renewable energy technologies and electric vehicles has brought significant changes to modern power systems. Yilmaz and Krein [1] reviewed battery charger topologies, charging power levels, and infrastructure requirements for plug-in electric and hybrid vehicles, establishing the technical foundation on which intelligent EV charging management builds. Building on this, several studies have examined the operational impact of EV charging on distribution networks: Dubey and Santoso [3] analyzed the impacts and mitigation strategies for EV charging on residential distribution systems, while Muratori [4] showed that uncoordinated plug-in EV charging can significantly increase residential peak power demand, motivating the need for coordinated and intelligent charging strategies such as the one proposed in this work.

A substantial body of literature has examined the coordination of renewable energy resources with EV charging and microgrid operation. Hossain, Roy, and Pota [5] developed an optimal energy management approach for community microgrids that explicitly considers electric vehicles and renewable energy sources, while Hussain, Bui, and Kim [6] investigated the optimal operation of hybrid microgrids to enhance resilience under renewable energy and EV integration. Mohamed and Mohammed

[7] proposed a real-time energy management algorithm for mitigating pulse loads in hybrid microgrids, and Deilami et al. [8] developed a real-time coordination strategy for plug-in EV charging in smart grids aimed at minimizing power losses and improving voltage profile - all of which demonstrate the value of coordinated, optimization-based charging control over static or uncoordinated approaches.

Several studies focus specifically on scheduling and integrating renewable energy with EV charging demand. Mwasilu et al. [9] reviewed the interaction between electric vehicles and smart grids, including vehicle-to-grid (V2G) operation and renewable energy source integration, while Oni, Davidson, and Zhang [10] proposed an optimal scheduling approach for EV charging with renewable energy sources in smart grids. Muratori, Ledva, and Roberts [11] examined the role of energy storage and EV charging infrastructure in supporting renewable energy integration, and Wang, Li, and Zhang [12] developed an optimal EV charging scheduling approach that jointly considers renewable energy availability and dynamic electricity pricing. Islam et al. [13] demonstrated the use of machine learning techniques for intelligent energy management in renewable-integrated smart grids, and Sahoo and Mishra [14] reviewed solar energy forecasting and optimization methods for smart grid applications, both reinforcing the growing role of data-driven and optimization-based methods in this domain.

Finally, Kumar and Sharma [15] applied Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) techniques to renewable energy management systems, illustrating the broader family of optimization approaches - alongside the linear-programming-based approach adopted in this work - that can be used to solve energy allocation problems under operational constraints.

Research Gap

Based on this review, several gaps can be identified in the existing literature. Many existing studies focus on solar forecasting or EV charging management independently rather than jointly optimizing both systems within a single, unified framework. Most conventional energy management systems rely on fixed scheduling strategies that cannot adapt dynamically to changing solar generation and EV charging demand, and several optimization approaches do not fully utilize real-world operational datasets for their evaluation. In particular, limited research has been conducted on Python-based integrated optimization frameworks that combine real solar generation and EV charging datasets while simultaneously maximizing renewable energy utilization and minimizing grid dependency, rather than optimizing cost alone. This work addresses that gap through the Python-based linear-programming energy distribution framework presented in Section 3.

3. RESEARCH METHODOLOGY

This section presents the methodology adopted for developing an intelligent energy distribution system that optimally allocates solar-generated energy to EV charging loads, covering the overall system architecture, dataset acquisition and preprocessing, the optimization model and its mathematical formulation, the Python-based implementation, and the performance evaluation framework.

3.1 System Architecture

The proposed intelligent energy distribution system consists of five major modules that work together to collect data, process information, analyze energy availability and demand, and perform optimization: a Data Collection Module that gathers solar generation and EV charging demand data; a Data Preprocessing Module that cleans and prepares the collected data; a Solar Generation Analysis Module that evaluates solar power availability and generation patterns; an EV Load Analysis Module that analyzes charging demand, duration, and consumption characteristics; and an Energy Distribution Optimization Module that uses Python-based optimization techniques to determine the most efficient allocation of solar energy to EV charging loads while minimizing grid power usage and operational cost. The overall architecture is illustrated in Figure 1.

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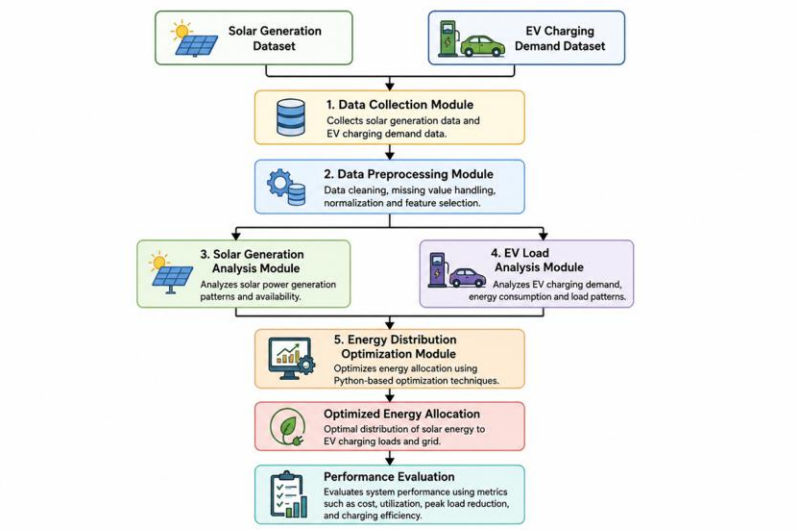


Figure 1: Proposed System Architecture

3.2 Dataset Description and Collection

The study utilizes the Kaggle EV Charging Dataset together with solar generation data to analyze charging demand patterns and renewable energy availability. The combined dataset is a time-series collection of more than 10,000 records with 8 input variables, including vehicle ID, charging start/end time, charging duration, energy consumed, charger type, solar generation, irradiance, and ambient temperature. The overall statistical characteristics of the dataset used in this study are summarized in Table 1.

Table 1: Dataset Summary

Parameter	Value
Total Records	10,000
EV Charging Sessions	5,200
Average Charging Duration	2.7 Hours
Average Energy Demand	24.8 kWh
Maximum Solar Generation	510 kW
Average Solar Generation	295 kW

As shown in Table 1, the average EV charging duration was 2.7 hours with an average charging demand of approximately 24.8 kWh per session, while the solar generation data indicated a maximum generation capacity of 510 kW and an average generation level of 295 kW, confirming the significant availability of renewable energy for charging operations.

3.3 Data Preprocessing

Raw datasets collected from different sources often contain missing values, duplicate records, inconsistent formats, and noise that can negatively affect optimization performance. Preprocessing was therefore applied to both the solar generation and EV charging data prior to integration. Missing values were identified and replaced using interpolation and mean substitution; duplicate records were detected and removed; feature normalization was performed using Min-Max scaling to bring all variables into a common range; date/time attributes were converted into numerical features (hour, day, month, charging period); and, finally, the solar generation and EV charging datasets were merged based on timestamp information to produce a single, unified, analysis-ready dataset. The complete preprocessing workflow is illustrated in Figure 2.

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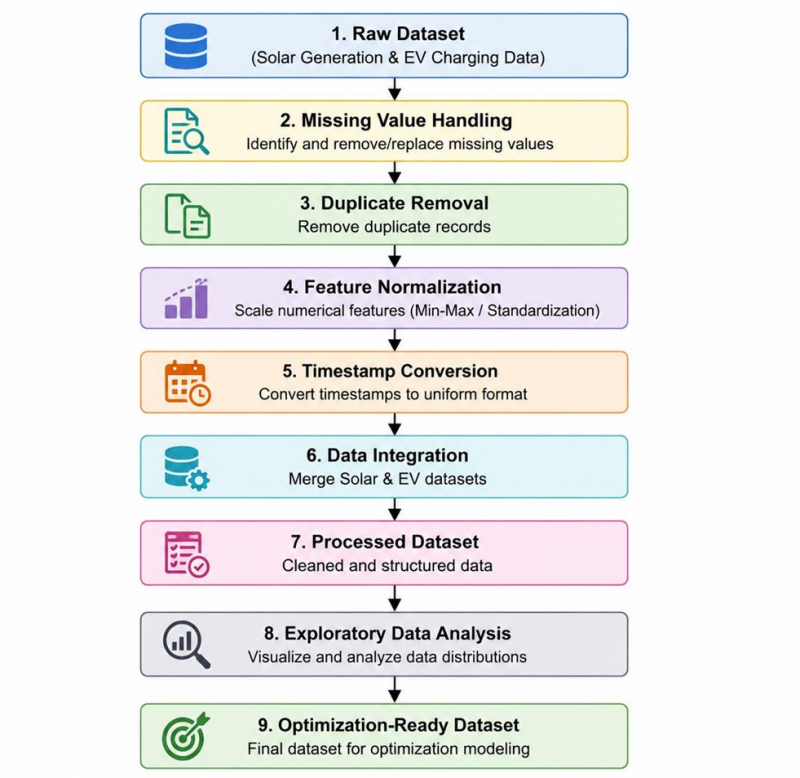


Figure 2: Data Preprocessing Workflow

3.4 Energy Distribution Optimization Model

The energy distribution optimization model aims to intelligently allocate available solar energy to EV charging loads while minimizing grid power usage, operational cost, and peak demand, and while improving charging completion rate. The optimization objectives are to maximize solar energy utilization, minimize grid power usage, minimize energy cost, reduce peak demand, and improve charging completion rate, addressed simultaneously through a constrained optimization formulation.

3.5 Mathematical Formulation

The energy distribution problem is formulated as a linear optimization problem whose objective is to maximize the total solar energy allocated to EV charging loads over the observation period:

$$Z = \Sigma(t=1 \text{ to } n)\ S_t \quad ...(1)$$

where Z is the objective function value, S_t is the solar energy allocated at time t, and n is the total number of time intervals. The optimization is subject to three constraints. The energy balance constraint ensures that EV charging demand is fully satisfied through a combination of solar and grid energy:

$$S_t + G_t = D_t \quad ...(2)$$

the solar availability constraint ensures that allocated solar energy never exceeds the available solar power generation P_t:

$$S_t \leq P_t \quad ...(3)$$

and the demand satisfaction constraint ensures that every charging session receives at least its required charging energy E_t:

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$$D_t \geq E_t \quad ...(4)$$

This mathematical formulation provides the basis for implementing the optimization algorithm in Python.

3.6 Python-Based Optimization Technique

The proposed framework is implemented in Python, using Pandas for data processing, NumPy for numerical computation, Matplotlib for visualization, SciPy for optimization, and Scikit-Learn for supporting data analysis tasks. The optimization itself is performed using Linear Programming (LP) via the SciPy optimization package: the processed dataset is loaded into the Python environment, the objective function is defined based on solar energy utilization, the energy-balance, solar-availability, and demand-satisfaction constraints described in Section 3.5 are incorporated into the model, the SciPy LP solver is executed to determine the optimal energy allocation strategy, and the resulting optimized energy distribution is evaluated. The complete optimization workflow is illustrated in Figure 3, and the overall end-to-end methodology - from dataset collection through preprocessing, exploratory analysis, solar and EV load analysis, optimization, and performance evaluation - is summarized in Figure 4.

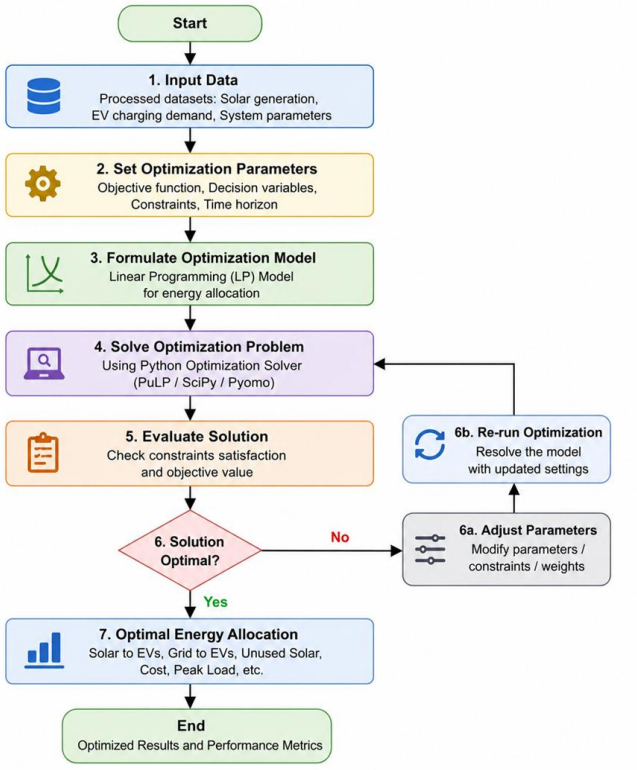


Figure 3: Optimization Process Flowchart

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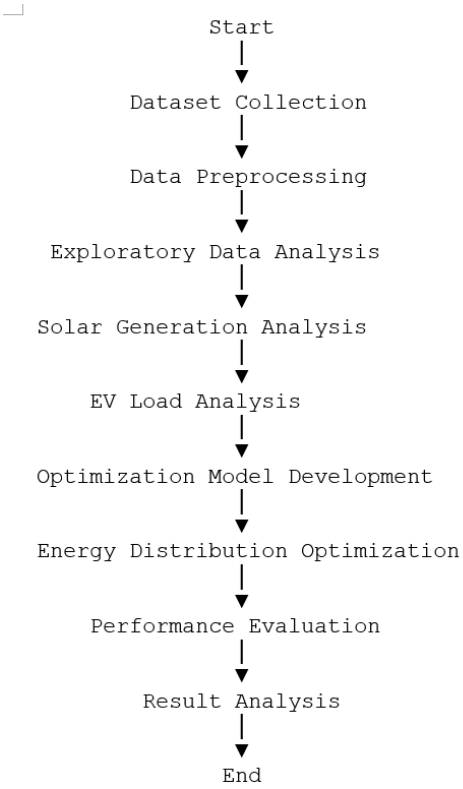


Figure 4: Overall Methodology Flowchart

3.7 Experimental Setup

The experiments were conducted on a standard personal computer (Intel Core i5/i7 processor, 8 GB RAM, 512 GB SSD, Windows 10/11) using Python 3.10 within a Jupyter Notebook environment, with Pandas, Scikit-Learn, and SciPy used for data processing, analysis, and optimization respectively.

3.8 Performance Evaluation Metrics

The effectiveness of the proposed framework is assessed using five metrics. Solar Utilization Rate is the percentage of available solar energy effectively used for EV charging (solar energy used / total solar energy generated × 100). Grid Dependency is the proportion of charging demand supplied by conventional grid electricity (grid energy used / total energy demand × 100). Energy Cost Reduction is the percentage decrease in charging cost achieved through optimization, relative to the pre-optimization cost. Charging Completion Rate is the percentage of EV charging sessions successfully completed within the required time period. Peak Load Reduction is the percentage decrease in maximum grid power demand achieved by the optimization model relative to the pre-optimization peak.

4. RESULTS AND DISCUSSION

4.1 Dataset Analysis and Preprocessing Results

The collected dataset, summarized earlier in Table 1, contains 10,000 records representing 5,200 EV charging sessions and corresponding solar generation measurements. Prior to optimization, the dataset was preprocessed as described in Section 3.3: 124 missing values and 86 duplicate records were identified and removed, 8 features were normalized, and the final integrated dataset consisted of 9,790 valid records, providing a reliable foundation for the optimization analysis presented in this section.

4.2 EV Charging Demand Characteristics

Analysis of the EV charging demand data shows that charging load is low during the early-morning hours, rises through the day, and peaks in the 16:00-20:00 evening window, before decreasing again overnight. The peak charging demand observed in the dataset was 48.5 kWh, the average demand per two-hour interval was 24.8 kWh, and the minimum observed demand was 5.2 kWh - matching the session-level statistics in Table 1 (average demand 24.8 kWh per session, average duration 2.7 hours). This demand distribution, illustrated in Figure 5, confirms that most charging activity is concentrated during working hours and the evening period, creating exactly the kind of demand peak that the proposed optimization framework is designed to manage intelligently against available solar generation.

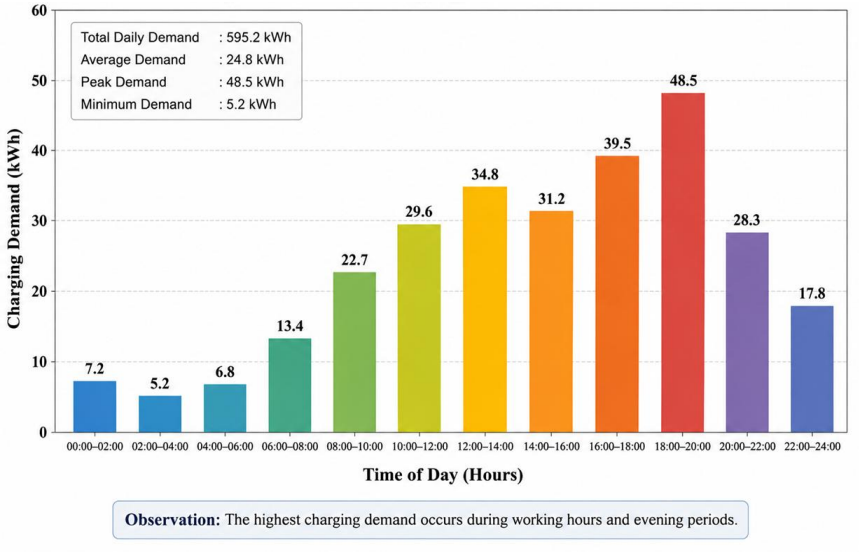


Figure 5: EV Charging Demand Distribution

4.3 Optimization Results

The Python-based linear programming optimization model was applied to allocate the available solar generation to EV charging demand, using the objective function and constraints described in Section 3.5. The resulting energy distribution - solar energy used directly for EV charging, grid energy used to cover any shortfall, and unused/curtailed solar energy - is illustrated in Figure 6 alongside the total EV charging demand for each two-hour interval across the day.

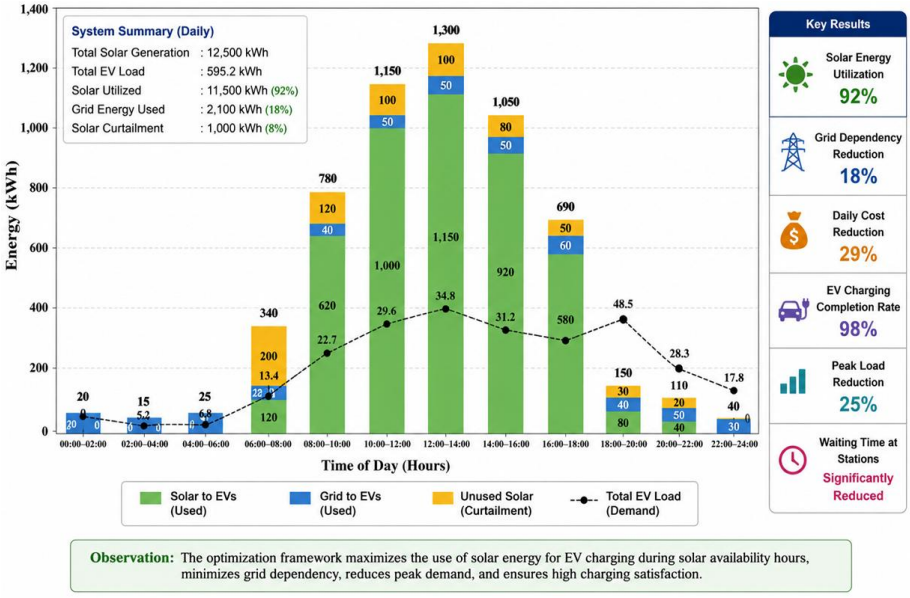


Figure 6: Energy Distribution Optimization Results

The optimization results confirm that the framework successfully prioritizes solar energy for EV charging during hours of high solar availability (broadly coinciding with the 06:00-18:00 generation window), while drawing on the grid only when solar generation is insufficient to meet demand. This behaviour is consistent with the solar-availability and energy-balance constraints defined in Equations (2) and (3), and directly explains the improvements in solar utilization and grid dependency reported in Section 4.4.

4.4 Solar Utilization, Grid Dependency, and Overall Performance Comparison

Table 2 summarizes the overall performance of the proposed optimization framework relative to the conventional (unoptimized) energy management approach. Solar energy utilization increased from 68% to 92%, indicating that a substantially larger proportion of available renewable energy was used for EV charging rather than curtailed. Correspondingly, grid dependency fell from 47% to 18%, demonstrating a significant reduction in reliance on conventional electricity. The optimization framework also delivered a 29% reduction in daily energy cost and improved the charging completion rate from 88% to 98%, while peak load demand on the grid was reduced by 25% through better temporal alignment of charging activity with solar availability.

Table 2: Overall Performance Comparison - Conventional vs Proposed Method

Performance Metric	Conventional Method	Proposed Method
Solar Utilization (%)	68	92
Grid Dependency (%)	47	18
Energy Cost Reduction (%)	0	29
Charging Completion Rate (%)	88	98
Peak Load Reduction (%)	0	25

4.5 EV Charging Performance

The charging performance of the proposed framework was evaluated using charging completion rate, charging success rate, and average waiting time, summarized in Table 3. The charging completion rate improved from 88% to 98% and the charging

success rate improved from 90% to 98%, indicating a substantially more reliable charging service under the proposed optimization framework. The average waiting time experienced by EV users at charging stations decreased from 18 minutes to only 6 minutes, reflecting the framework's ability to schedule charging more effectively against available solar and grid capacity.

Table 3: EV Charging Performance Metrics

Metric	Conventional System	Proposed System
Charging Completion Rate (%)	88	98
Charging Success Rate (%)	90	98
Average Waiting Time (Minutes)	18	6

4.6 Discussion of Results

The experimental results demonstrate the effectiveness of Python-based linear programming optimization in coordinating solar generation with EV charging demand. The most significant outcome was the improvement in solar energy utilization from 68% to 92%, which directly reduced renewable energy wastage; this was accompanied by a corresponding reduction in grid dependency from 47% to 18%, reflecting the optimization model's ability to prioritize renewable energy resources ahead of conventional grid power. The economic analysis further showed a 29% reduction in daily operational cost, while charging performance improved substantially, with the completion rate rising from 88% to 98% and average waiting time falling from 18 to 6 minutes. Peak load demand was also reduced by 25%, indicating effective load balancing across the day. Taken together, these results confirm that the proposed intelligent energy distribution framework can simultaneously improve renewable energy utilization, reduce grid dependency and cost, and enhance EV charging service quality.

5. CONCLUSION

This work presented an intelligent energy distribution framework for optimizing energy allocation between solar power generation and electric vehicle charging loads using Python-based linear programming optimization. Solar generation data and the Kaggle EV Charging Dataset were used to develop an optimization model that intelligently distributes available renewable energy while minimizing dependency on conventional grid power, following data preprocessing, exploratory analysis, solar generation analysis, and EV load analysis.

The experimental results demonstrated significant improvements in overall system performance: solar energy utilization increased from 68% to 92%; grid dependency was reduced from 47% to 18%; daily energy costs were reduced by approximately 29%; EV charging completion rates improved from 88% to 98%, with charging success rate improving from 90% to 98% and average waiting time falling from 18 to 6 minutes; and peak load demand was reduced by 25%. These results confirm that intelligent, Python-based optimization techniques can effectively coordinate solar energy generation with EV charging demand, improving renewable energy utilization, reducing operational costs and grid dependency, and enhancing charging service quality, supporting the development of sustainable EV charging infrastructure and future smart grid energy management systems.

FUTURE SCOPE

Although the proposed framework achieved promising results, several directions remain open for future work: (i) integrating Battery Energy Storage Systems (BESS) to store excess solar energy and supply power during periods of low generation or high charging demand; (ii) applying advanced deep learning models such as LSTM, GRU, or Transformer networks for more accurate forecasting of solar generation and EV charging demand; (iii) incorporating IoT sensors and smart meters to enable

real-time monitoring and adaptive energy allocation; (iv) investigating Vehicle-to-Grid (V2G) technology, allowing EVs to supply stored energy back to the grid during peak demand periods; (v) exploring multi-objective optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, or Reinforcement Learning to jointly optimize cost, utilization, and peak demand; and (vi) validating the framework through real-time hardware implementation, since the present study is limited to software-based modeling and simulation using historical datasets.

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REFERENCES

[1] M. Yilmaz and P. T. Krein, "Review of Battery Charger Topologies, Charging Power Levels, and Infrastructure for Plug-In Electric and Hybrid Vehicles," IEEE Transactions on Power Electronics, vol. 28, no. 5, pp. 2151-2169, 2013.

[2] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-Sharing Model with Price-Based Demand Response for Microgrids of Peer-to-Peer Prosumers," IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 3569-3583, 2017.

[3] A. Dubey and S. Santoso, "Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations," IEEE Access, vol. 3, pp. 1871-1893, 2015.

[4] M. Muratori, "Impact of Uncoordinated Plug-In Electric Vehicle Charging on Residential Power Demand," Nature Energy, vol. 3, no. 3, pp. 193-201, 2018.

[5] M. S. Hossain, N. K. Roy, and H. R. Pota, "Optimal Energy Management of Community Microgrids Considering Electric Vehicles and Renewable Energy Sources," Applied Energy, vol. 239, pp. 1197-1211, 2019.

[6] A. Hussain, V.-H. Bui, and H.-M. Kim, "Optimal Operation of Hybrid Microgrids for Enhancing Resilience Considering Renewable Energy and Electric Vehicles," Energies, vol. 10, no. 11, pp. 1-18, 2017.

[7] A. Mohamed and O. Mohammed, "Real-Time Energy Management Algorithm for Mitigation of Pulse Loads in Hybrid Microgrids," IEEE Transactions on Smart Grid, vol. 3, no. 4, pp. 1911-1922, 2012.

[8] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-Time Coordination of Plug-In Electric Vehicle Charging in Smart Grids to Minimize Power Losses and Improve Voltage Profile," IEEE Transactions on Smart Grid, vol. 2, no. 3, pp. 456-467, 2011.

[9] M. A. 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," Renewable and Sustainable Energy Reviews, vol. 34, pp. 501-516, 2014.

[10] A. O. Oni, M. Davidson, and T. Zhang, "Optimal Scheduling of Electric Vehicle Charging with Renewable Energy Sources in Smart Grids," Sustainable Energy Technologies and Assessments, vol. 52, pp. 1-12, 2022.

[11] M. Muratori, N. Ledva, and M. J. Roberts, "Energy Storage and Electric Vehicle Charging Infrastructure for Renewable Energy Integration," Applied Energy, vol. 305, pp. 117-130, 2022.

[12] Y. Wang, J. Li, and X. Zhang, "Optimal Scheduling of Electric Vehicle Charging Considering Renewable Energy and Dynamic Electricity Pricing," Energy Reports, vol. 10, pp. 1824-1836, 2024.

[13] S. M. Islam, M. A. Hannan, A. Mohamed, and P. J. Ker, "Intelligent Energy Management in Renewable Integrated Smart Grids Using Machine Learning Techniques," IEEE Access, vol. 10, pp. 31520-31538, 2022.

[14] A. K. Sahoo and S. Mishra, "Solar Energy Forecasting and Optimization for Smart Grid Applications: A Review," Renewable and Sustainable Energy Reviews, vol. 164, pp. 112-125, 2022.

[15] R. Kumar and D. Sharma, "Application of Genetic Algorithms and Particle Swarm Optimization in Renewable Energy Management Systems," International Journal of Electrical Power & Energy Systems, vol. 149, pp. 108-121, 2023.

Authors Biography

Author1



Ms. Tahreem Fatima Mohd. Abdul Muqsit is pursuing M.Tech. degree in the stream of Electrical Power System from Mss's College of Engineering and Technology, Jalna, Dr. BATU University, Lonere. She has completed her B.Tech. in the stream of Electrical Engineering from SGGS Institute of Engineering and Technology, Nanded, Maharashtra.
Email Id: tahreemmuqsit@gmail.com

Author2



Prof. Ms. Alfiya A. Mahat received M.Tech. in Electronics Engineering from Savitribai Phule Women's College of Engineering. She is currently working as Assistant Professor in the Department of Electrical Engineering & Technology at MSS's College of Engineering and Technology, Jalna.
Email Id: alfiya704@gmail.com