Optimization of EV Charging Stations

Forecasting-Based Scheduling and Optimization of EV Charging Stations for Enhanced Efficiency and User Convenience

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ABSTRACT

The rapid growth of electric vehicles (EVs) has led to a significant increase in demand for charging infrastructure, exerting considerable pressure on power grids and raising concerns about sustainability. This project investigates EV charging patterns to optimize scheduling, reduce grid strain, and minimize reliance on non-renewable energy sources. By forecasting charging demand and analyzing temporal behaviors, station managers and grid operators can implement strategies such as time-based pricing, renewable energy integration, and demand shifting. Using data from credible sources, this study provides actionable insights to enhance grid stability and operational efficiency while supporting a sustainable EV ecosystem.

**KEYWORDS**

Electric Vehicles, Charging Scheduling, Load Demand, Grid Optimization, Data Analysis

**1** **Introduction**

The transition to electric vehicles (EVs) represents a pivotal shift in global energy consumption and carbon reduction efforts. However, this growth in EV adoption has significantly increased the demand for efficient and scalable charging infrastructure. Unmanaged charging behavior not only risks overloading power grids but also increases dependency on non-renewable energy sources, undermining the environmental benefits of EVs. Research indicates that peak demand during EV charging often coincides with high grid usage periods, exacerbating energy costs and environmental impacts. By addressing these challenges, this project holds the potential to optimize energy allocation, prevent power outages, and enable the integration of renewable energy into the charging ecosystem. Effective scheduling and demand forecasting can reduce reliance on fossil fuels, enhance grid stability, and lower operational costs for station managers. As global energy systems evolve, research like this becomes essential to balance EV adoption with sustainable energy practices.

This project is critical for several reasons:

1. **Grid Stability and Reliability**: By forecasting charging demand and optimizing scheduling, grid operators can preemptively address overload risks, preventing outages and ensuring reliable power supply during peak hours ([3]).
2. **Environmental Impact**: Managing EV charging demand can minimize the need for energy production from non-renewable sources, supporting the global goal of reducing greenhouse gas emissions ([4]).
3. **Economic Efficiency**: Time-based pricing and efficient energy scheduling reduce operational costs for both grid operators and EV station managers, making EV charging more cost-effective for users ([3]).
4. **Renewable Energy Integration**: Proactive scheduling facilitates the use of renewable energy sources like solar and wind, enhancing the sustainability of the EV ecosystem ([4]).

By combining data-driven insights with actionable strategies, this project contributes to the development of a resilient and sustainable energy framework for EV charging infrastructure.

2 **Data**

**2.1** **Source of dataset**

The primary dataset is sourced from the Caltech EV data platform ([https://ev.caltech.edu/dataset](https://ev.caltech.edu/dataset)) and the US Energy Information Administration ([https://www.eia.gov](https://www.eia.gov)). These datasets, covering charging sessions from 2018 to 2024, provide comprehensive insights into temporal and seasonal trends. The dataset is for Caltech, JPL, Office 1 is collected and merged and then it is converted into stationdata by aggregating based on the hourly sessions to get date, station, average power, and number of users.

**2.2 Characters of the datasets**

The dataset includes detailed information on EV charging sessions:

‘\_id’: Unique identifier for the record

‘clusterID: Cluster identifier for the station group

‘siteID’: Site identifier where the station is located

‘stationID’: Unique identifier for the station

‘spaceID ‘: Unique identifier for the parking space

‘Connection Time ‘: Time when the vehicle was connected to the station

‘disconnectTime’: Time when the vehicle was disconnected

‘doneChargingTime’; Time when charging was completed

‘chargingTime’: Duration of active charging

‘standbyTime’: Time the vehicle remained plugged in post-charging

‘Session Duration’: Total duration of the session

‘kWhDelivered ‘: Energy delivered during the session (kWh)

’powerkW ‘: Average power delivered during the session (kW) |

‘minpowerkW’ : Minimum power delivered during the session (kW)

The data was pre-processed to ensure consistency, with additional calculations for metrics such as connected time, active charging time, and idle time. All NaN values are being eliminated.

3 **Methodology**

3.1 **Statistical and Machine Learning Models**

**Time-Series Models**: ARIMA and SARIMA models were utilized to forecast seasonal and temporal demand patterns.

**Regression Models**: Random Forest and XGBoost were employed to analyze the impact of various factors on energy consumption.

**Data Visualization**: Matplotlib and Seaborn were used to create visual representations of energy usage, session duration, and grid load trends.

**3.2 Optimization Strategies**

1. Shifting peak-time sessions to off-peak hours to reduce grid strain.

2. Implementing time-based pricing models to incentivize efficient charging behavior.

3. Integrating renewable energy sources like solar and wind to power charging stations.

4. Exploring the use of EV batteries for energy redistribution during extended standby times, with user consent.

4 **Results**

* 1. **What is the seasonal charging behavior of EV charging vehicles?**

1. **Yearly Charging Users Behavior**

A substantial increase in charging users can be observed between 2019 and 2020, indicating the rapid adoption of EVs. However, a significant drop in 2021 is evident, which could be attributed to external factors such as the COVID-19 pandemic or changes in mobility patterns. This highlights the need for adaptive strategies to handle fluctuating demands.

1. **Daily Charging Users Behavior**

Peaks in usage occur consistently, reflecting daily commuting patterns and possibly evening charging sessions. The sharp decline during certain periods suggests either seasonal effects or interruptions in service availability. Such data reinforces the importance of forecasting to anticipate and manage daily variations effectively**.**

1. **Weekly Charging Users Behavior**

Weekends, particularly Sunday, record minimal activity. This pattern aligns with work-related charging needs, emphasizing the potential to optimize grid operations during weekdays while incentivizing weekend usage.

1. **Monthly Charging Users Behavior**

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**Figure 1: Monthly Charging Users**

This chart provides a detailed view of monthly usage patterns. High usage during January and February could correspond to post-holiday travel and colder weather, which increases energy consumption for heating EVs. The decline from March to August indicates reduced demand, possibly tied to warmer weather and vacation periods, followed by an uptick in the fall months. This reinforces the value of seasonal strategies for load management.

4.2. **How is daily, weekly, monthly and yearly Load Demand of EV charging?**

1. **Yearly Load Demand**

A steady increase from 2019 to 2020, reflecting the growing adoption of EVs and charging infrastructure expansion. However, in 2021, there is a marked decline, potentially due to reduced mobility caused by the pandemic or other external factors. This highlights the need for resilient energy management strategies to adapt to fluctuations in demand.

1. **Daily Load Demand**

Daily energy consumption trends exhibit consistent peaks and troughs, indicating regular patterns likely influenced by commuter behaviors. The highest energy demand typically occurs in the evening hours, aligning with users returning home and plugging in their vehicles for overnight charging. Periods of lower demand may represent weekends or holidays, emphasizing the need for forecasting tools to anticipate daily variations.

1. **Weekly Load Demand**

The weekly energy consumption graph highlights that weekdays, especially Monday through Thursday, are characterized by significantly higher energy usage compared to weekends. This trend suggests that most charging sessions occur in correlation with work commutes. Lower weekend demand underscores the opportunity to shift some weekday load to off-peak weekend hours via pricing incentives or flexible scheduling.

1. **Monthly Load Demand**

A graph of blue bars

Description automatically generated with medium confidence

**Figure 2: Monthly Load Demand**

The monthly analysis reveals high energy demand in January and February, likely due to colder weather and associated energy needs for heating EVs. The demand diminishes during the summer months, suggesting a possible correlation with vacation periods or lower commuting activity. It then rises again in the fall, consistent with increased travel and cooling requirements during transitional weather conditions. This underscores the importance of seasonally adaptive strategies for managing energy allocation.

* 1. **What is the average duration of charging sessions, and how does it vary across different stations?**

The visualized data of average charging times across different stations highlights a substantial variation in charging behavior. These variations can be analyzed in terms of the percentage of connected time utilized for active charging

**Utilization Efficiency**: Across most stations, the percentage of connected time spent actively charging is lower than expected, often around 60-80%. This inefficiency may be due to users leaving vehicles plugged in post-charging (idle or standby time).

**Station-Specific Patterns**: Some stations exhibit significantly higher average charging times, potentially influenced by high-demand usage patterns, equipment variations, or differences in user behavior. Stations with shorter average charging times may indicate either optimized scheduling or lower energy needs.

**Distribution of Charging Durations**: The differences in average charging times reflect the heterogeneity in vehicle battery capacities, charging rates, and user preferences for charging schedules.

* 1. **What percentage of connected time is spent charging, and how does this vary across stations?**

**A graph of lines with numbers and numbers

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**Figure 3: Percentage of charging time per station**

The chart illustrates the percentage of connected time spent actively charging across various stations over the months. Key insights from the data include:

**General Observations**:

**Charging Efficiency**: The percentage of connected time utilized for charging varies significantly across stations and months, ranging from approximately 50% to 100%. This indicates differing user behaviors and station characteristics.

**Monthly Fluctuations**: Some months show consistently higher charging time percentages, suggesting a higher proportion of users who unplug promptly after charging. Other months experience more idle time, where vehicles remain connected even after charging is complete.

**Variation Across Stations**:

**Station Utilization Patterns**: Stations with higher charging percentages are likely influenced by factors such as user awareness, active management, or automated systems that discourage idle time.

**Seasonal Impact**: Seasonal changes may also influence charging efficiency, as weather conditions affect energy consumption and user behavior.

4.5. **How are the tariffs across different periods**?

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**Figure 4: Hourly Tariffs**

The graph illustrates the variation in electricity tariffs across different time periods for three tiers. Here are the key observations:

**Tier 1 Rates**: The baseline tariff (Tier 1) remains consistent over all observed periods at approximately $0.08/kWh. This stability in Tier 1 rates ensures affordability for low-energy users.

**Tier 2 Rates**: Tier 2 rates remain constant at approximately $0.14/kWh across the periods. This moderate rate applies to users exceeding the baseline threshold, incentivizing conservative energy use.

**Tier 3 Rates**: The Tier 3 rates exhibit significant fluctuations, peaking during the summer months (June-September). The highest rate observed is approximately $0.22/kWh, which aligns with increased demand during warmer months. This variation reflects seasonal adjustments aimed at managing peak energy loads and discouraging excessive energy consumption during high-demand periods.

4.6 **What is the potential impact on grid load if we shift a percentage of charging sessions from peak to off-peak hours, and how would this affect overall charging costs?**

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**Figure 5: Before and After Scheduling**

The chart compares the grid load before and after shifting a portion of EV charging sessions from peak to off-peak hours. Here are the key insights:

**Impact on Grid Load**

**Original Grid Load**: The original load profile indicates significant peaks during late evening hours (around 8 PM to 10 PM), likely caused by simultaneous charging as users return home from work.

**Shifted Grid Load**: By redistributing charging sessions to off-peak hours (early morning or midday), the revised load profile shows a reduction in peak load and a more even distribution of demand throughout the day.

**Overall Reduction**: Peak grid load is reduced by approximately 20-25%, alleviating stress on the grid and lowering the risk of outages.

**Impact on Charging Costs**

**Cost Efficiency**: Shifting charging to off-peak hours, when electricity tariffs are lower, can significantly reduce overall charging costs for users. This is especially relevant in systems employing time-of-use pricing models.

**Incentives for Adoption**: Lower energy costs during off-peak hours encourage users to participate in such programs, enhancing the effectiveness of grid management strategies.

5 **Discussion**

5.**1 Caveats**:

* **Data Completeness**:

Some sessions lack critical fields (e.g., user inputs, min\_kWh), leading to incomplete analysis and reduced insight into user behavior.

* **Data Quality**:

Missing, null, or malformed values (e.g., incomplete timestamps or doneChargingTime) could introduce inaccuracies in derived metrics such as session duration and power calculations.

* **Privacy Constraints**:

User data is anonymized, restricting longitudinal studies of individual charging behavior but ensuring compliance with privacy standards.

* **Error-Prone Data**:

Outliers and anomalies in energy delivery (e.g., extremely low or high kWhDelivered) need additional validation to avoid skewing results.

**5.2 Overcome the errors**:

* **Improve Data Completeness**:

Implement mechanisms to fill missing fields through data interpolation or external sources where possible.

Collaborate with data providers to ensure consistent recording of critical metrics such as min\_kWh and doneChargingTime.

* **Expand Temporal and Spatial Scope**: Incorporate additional datasets from diverse geographic locations and timeframes to improve representativeness. Use simulation or synthetic data to model trends in areas where real data is unavailable.
* **Mitigate Privacy and Anonymization Constraints**: Consider aggregate-level or pseudonymized data for longitudinal analysis while maintaining user privacy. Use clustering or grouping techniques to infer patterns without needing individual user-level data.
* **Handle Outliers and Anomalies**: Introduce automated anomaly detection systems to flag and exclude improbable values from the analysis.
* **Optimize Scalability and Performance**: Leverage distributed computing frameworks (e.g., Apache Spark) for processing large datasets efficiently.
* **Improve Model Assumptions and Validation**: Perform hyperparameter tuning for forecasting and optimization models using grid search or automated tools.

5.3 **Future Scope**:

**Scalability and Expansion**: Data Inclusion: Extend the dataset to include more sites, diverse geographies, and additional timeframes. This would allow the analysis to capture broader EV charging trends. Integration with Other Data Sources: Incorporate data from external sources, such as weather patterns, traffic data, or renewable energy generation, to enrich the analysis and improve decision-making.

**Advanced Forecasting Models**: Deep Learning Integration: Experiment with advanced deep learning models (e.g., LSTMs, Transformers) to predict charging demand and optimize station usage.

**Dynamic Pricing Strategies**: Integrate real-time electricity pricing data to develop predictive models that optimize cost-efficiency for both users and providers.

**Real-Time Optimization**: Adaptive Scheduling: Implement real-time optimization algorithms that dynamically allocate charging sessions based on changing conditions, such as grid load or user priorities.

**Energy Management**: Integrate battery storage and renewable energy systems to provide a more sustainable and efficient charging infrastructure.

**User Behavior Analysis**: Longitudinal Studies: Analyze changes in user behavior over time to better understand trends and adapt to evolving needs.

**Segmentation and Personalization**: Identify user segments and offer personalized recommendations or incentives, such as off-peak discounts.

**Policy and Sustainability Impact**: Policy Simulation: Model the effects of various governmental policies (e.g., subsidies for off-peak charging) on user behavior and grid efficiency.

**Carbon Footprint Analysis**: Estimate the environmental impact of charging sessions and propose strategies for reducing the carbon footprint through renewable energy integration.

**Policy Advocacy and Societal Impact**: Use the findings from the project to advocate for infrastructure improvements and policies that support widespread EV adoption, reducing reliance on fossil fuels and contributing to climate goals

6 **Conclusion**

This study provides comprehensive insights into EV charging behaviors, infrastructure utilization, and grid management strategies. The key findings are as follows:

**Load Management**: EV charging demands exhibit clear temporal and seasonal patterns, with peak usage during weekday evenings and winter months. Effective demand forecasting and scheduling strategies can mitigate these peaks, reducing grid strain.

**Energy Efficiency**: On average, 70% of connected time is utilized for active charging, with the remainder as idle time. Implementing idle fees and educating users can significantly improve station availability and efficiency.

**Tariff and Cost Optimization**: Tiered and dynamic pricing strategies, such as higher rates during peak hours and lower rates during off-peak hours, incentivize users to shift charging sessions. This reduces energy costs and ensures equitable access to charging infrastructure.

**Renewable Integration**: Aligning charging schedules with renewable energy availability (e.g., solar during midday) enhances sustainability and minimizes reliance on non-renewable energy sources.

**Grid Stability**: Shifting a portion of peak-time charging to off-peak hours reduces peak grid load by 20-25%, demonstrating the feasibility of scalable solutions to manage increasing EV adoption.

These findings emphasize the importance of data-driven approaches to EV infrastructure management. By leveraging forecasting models, time-based tariffs, and user education, stakeholders can ensure a sustainable, cost-effective, and efficient EV ecosystem.

ACKNOWLEDGMENTS

I want to sincerely thank Weijie Pang, my professor, for giving me the chance to work on this project and for his crucial advice. The findings and insights in this report have been greatly influenced by your mentoring.

I would also like to thank Zachary J. Lee, Tongxin Li, and Steven H. Low, the authors of the paper ACN-Data: Analysis and Applications of an Open EV Charging Dataset. The analysis carried out in this project has been based on the dataset and insights this effort has supplied. The breadth of this study has been enhanced by your tremendously inspired contribution to the field of EV charging research.

We appreciate your help and contributions to the advancement of research on EV charging infrastructure.

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Conference Short Name:WOODSTOCK’18

Conference Location:El Paso, Texas USA

ISBN:978-1-4503-0000-0/18/06

Year:2018

Date:June

Copyright Year:2018

Copyright Statement:rightsretained

DOI:10.1145/1234567890

RRH: F. Surname et al.

Price:$15.00