

An Efficient AI enabled Energy Management System framework for PV-V2G-ESS Integrated with Electric Vehicle Charging Stations.

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Abstract -

With the growing prevalence of electric vehicles and renewable energy technology, there arises the challenge of keeping efficient and reliable energy management in place in modern electricity networks. Hybrid photovoltaic (PV)-based EV charging stations with the inclusion of Energy Storage Systems (ESS) and Vehicle to Grid (V2G) capabilities have proven to be a viable solution toward minimizing reliance on the grid while efficiently utilizing renewable energy sources. Nonetheless, the intermittency of solar energy generation, stochastic charging patterns of EVs, and inherent shortcomings in traditional energy management systems (EMS) make optimal energy management rather difficult.

This paper aims at developing an intelligent AI-based energy management strategy for a PV-based hybrid EV charging station that involves solar energy generation through PV, ESS, grid operations, EV charging loads, and bidirectional V2G functions. In the process, a traditional rule-based energy management strategy will be designed using a set of predefined operating conditions based on PV availability, load, and battery SOC. Given the inherent disadvantages of statically controlled

The framework is realized through a simulation model using Python software and the performance analysis of the AI-supported EMS system is conducted based on a 24-hour operational period. The performance of the AI-assisted EMS system is compared to that of the traditional rule-based EMS system through a series of performance indicators, such as the utilization rate of renewable energy, energy consumption from the grid, demand peak reduction, V2G contribution, and stability of SOC.

The proposed approach creates an ideal compromise between the robustness of the rule-based control and flexibility of the AI-powered decision-making process. Through utilizing Explainable AI within the conventional logic of the EMS system, this framework presents a promising solution to future smart EV charging infrastructure and energy systems.

Key Words: Electric Vehicle, Vehicle-to-Grid (V2G), Energy Management Strategy, Artificial Intelligence, Decision Tree, Photovoltaic System, Energy Storage System, Smart Charging, Renewable Energy Integration

1. INTRODUCTION

The fast rise in adoption rates of electric vehicles (EV) along with integration of renewable energy sources presents various problems for current power system infrastructure. Electric cars provide an eco-friendly replacement for traditional transport means; however, the uncontrolled integration of large numbers of EVs may overload the grid due to the increased stress from EV charging demand, fluctuations in peak load, and quality of power issues. To solve the problem described above, hybrid PV-EV charging stations with the help of Energy Storage Systems (ESS) and V2G integration become increasingly popular.

Due to the intermittent nature of PV generation and EV charging demands, effective Energy Management Strategies (EMS) are needed to coordinate PV generation and EV loading processes. Rule-based approaches are considered to be simple and reliable but suffer from the lack of adaptivity in different operating regimes. Optimization methods enhance scheduling but are dependent on the accuracy of forecasting results and have high computational requirements.

Advances in Artificial Intelligence (AI) have facilitated the emergence of a data-driven EMS that can deal with the uncertainties present in the energy system and provide higher efficiency during operation. Nevertheless, most AI techniques have been developed based on black-box models. Hence, it is essential to design an intelligent and explainable EMS that will help integrate the adaptability of AI into conventional controls.

The main contribution of this work is the proposal of an EMS architecture for a photovoltaic-based EV charging station equipped with ESS and V2G technology, where the rule-based EMS is integrated with an explainable supervisory decision-making controller. This architecture allows one to make a decision about the operational mode in real time without relying on forecasting tools. This solution should contribute to increased renewable energy utilization, decrease reliance on the grid, enhanced peak demand management, and appropriate SOC-based battery management. The efficacy of the suggested EMS architecture is validated through simulation experiments compared with conventional rule-based controls based on several performance metrics.

2. Literature Review

The growing prevalence of electric vehicles (EVs), renewable energy sources, and smart grids is motivating researchers to develop improved strategies for Energy Management System (EMS) to manage power coordination efficiently. Based on the control strategy employed by an EMS, existing energy management systems may be classified as either rule-based, optimization-based, or artificial intelligence (AI) based.

Earlier works were primarily concerned with developing rule-based EMS techniques owing to the ease of application in renewable-integrated EV charging systems. Generally, the logical criteria used in rule-based EMS depend on specific criteria such as photovoltaic (PV) power production, EV charging demands, and battery State-of-Charge (SOC). Deb et al. [12] have proposed a rule-based EMS strategy for PV-assisted EV charging stations that work well for normal conditions. However, rule-based systems heavily rely on threshold values and may offer unsatisfactory results for dynamic situations with varying solar generation and charging behavior of EVs.

There have been many studies on EMS methods based on optimization to improve adaptability. The solutions of mathematical optimization, including MILP, LP, and meta-heuristic algorithms, have been applied to the optimal scheduling of EVs, energy storage systems, and grid operations. Specifically, Zhang et al. [9] developed an optimization approach based on MILP for PV-EV charging systems with energy storage. As a result, there were achieved improved cost performance and renewable energy usage. Nonetheless, accurate forecasting of renewable energy generation and EV charging needs are required in the case of such approaches. Besides, high computational costs hinder their real-time implementation, especially in large-scale and dynamic EV charging stations.

With the introduction of V2G technology, the role of EVs has been extended from simple loads to distributed energy resources (DERs). The V2G approach allows bidirectional energy flows between the electric vehicle battery and grid, and it is used for peak load shaving, power system frequency regulation, and renewable energy balancing. Saha et al. [8] considered battery-aware EMS approaches for V2G technologies by taking into account SOC requirements in order to minimize battery wear-and-tear. Moreover, Mohamed et al. [11] conducted research on AI-based scheduling for V2G technologies in a solar-powered EV charging station.

Research studies that have recently been carried out have emphasized AI-based approaches for EMS because of the capacity of the technology to deal with uncertainty and understand the dynamics of a system. Studies using

machine learning algorithms such as ANN, fuzzy logic, and reinforcement learning have shown better decision-making abilities for EMS. The researchers in Elsayad et al. [4] developed an AI-based adaptive control system for EMS in V2G/G2V operations. Nonetheless, ANNs can act as black boxes and cannot be applied where interpretability is necessary.

The researchers Rahman et al. [5] conducted a review of AI technologies used in V2G operations. From the literature, machine learning and deep learning algorithms showed great potential for intelligent energy management. Nevertheless, there were some shortcomings including a high computational requirement and the need for huge data sets. In Liu et al. [3], the researchers studied the demand response optimization process for intelligent electric vehicle charging stations using artificial intelligence techniques.

Tree-based AI approaches including Decision Trees and ensemble learning approaches have become popular in recent years owing to their balanced use in terms of predictive ability and interpretability. Unlike deep learning-based models that are highly intricate, tree-based models allow system operators to interpret the decision process made by the algorithm. As mentioned by Kumar et al. [6], explainable and applicable EMS systems were emphasized for future EV charging infrastructure. Nevertheless, very little literature has discussed the possibility of combining explainable AI supervisory control with rule-based operation of EMS systems.

From the available literature, it is clear that there exists a dilemma among simple, adaptable, computationally feasible, and explainable approaches to energy management of EV charging infrastructure. The main drawback of the rule-based approach is its lack of intelligence, while the downside of AI-based approach is lack of explainability. Hence, it is essential to come up with an explainable AI-integrated EMS framework that takes advantage of both conventional and intelligent decision making approaches.

3. Methodology

In this section, the methodology of the novel AI-based Energy Management Strategy (EMS) is proposed for the design of a hybrid photovoltaic (PV)-based electric vehicle (EV) charging system, which will incorporate both Energy Storage System (ESS) and Vehicle-to-Grid (V2G) functionality. The proposed EMS technique is an integration of traditional rule-based energy management approach along with an AI-based supervisory controller for efficient coordination of power flow between PV generation, ESS, EV loading, and grid.

3.1 System Design

The developed hybrid EV charger consists of the PV generation system, battery based ESS, EV loading system, grid connection, and V2G link. PV system serves as the renewable source of energy for the EV charging system and battery recharging. On the other hand, ESS is used to compensate for the gap between the generated and demanded energy levels from renewable energy systems.

This approach allows for a two-way flow of energy from EV batteries to the power grid. During peak hours, energy will be exported to the grid from storage in the EV batteries, and vice versa; during off-peak hours, the EVs charge in their normal mode. Maximizing renewable energy utilization, reducing reliance on the grid, and ensuring that battery operations constraints are met form the main objective.

3.2 Rule-Based Energy Management Strategy

In this part, a typical rule-based EMS is designed to form a benchmark of system performance. This controller makes decisions regarding power flow based on the specified conditions in terms of PV power availability, EV demand, and battery SOC.

The rules of operation are as follows:

If PV power is greater than the EV load, excess solar power is used to charge the ESS.

If PV power is insufficient, and SOC falls within the allowed limits, energy stored in the battery is used to charge EV.

When SOC of the battery drops to the minimum level, power from the grid is used.

If SOC of the battery exceeds the minimum limit and grid demand increases, V2G operation is initiated.

3.3 Explainable AI-based Supervisory Controller

In order to solve the shortcomings of traditional EMS, an explainable AI-based supervisory controller is designed by utilizing Decision Tree algorithm. The AI-based controller acts at a higher level than the rule-based EMS and selects the best operating mode according to real-time operating conditions.

The input variables taken into account for designing the AI model are:

PV Power Generation
EV Demand
Battery SOC

Using the above inputs, the controller determines one of the four energy management modes of the system:

Mode 1: Charging of ESS
Mode 2: Discharging of ESS
Mode 3: Grid power generation operation

Mode 4: Vehicle to grid energy operation

This Decision Tree methodology allows transparency of decision making process and makes it easy for operators to understand and verify the decision-making process. In contrast to forecasting algorithms, the proposed technique adopts real-time decision making based on current system parameters.

3.4 Simulation Approach

The EMS framework designed is simulated using a Python-based simulation environment. 24-hour simulation is conducted to analyze system behavior under different PV and EV loads.

The simulation parameters used are outlined below:

Parameter	Value
PV Capacity	50 kW
ESS Capacity	100 kWh
Initial SOC	50%
EV Load Range	10–60 kW
SOC Operating Range	20% – 100%
V2G Activation Threshold	SOC > 60%
Simulation Duration	24 hours
Time Step	1 hour

The EV charging demand is simulated through a dynamic load pattern, while PV generation is modeled based on the time-varying solar generation pattern.

4. Results and Discussion

The performance of the suggested AI-supported Energy Management Strategy (EMS) was examined by means of 24-hour simulation of the hybrid photovoltaic (PV) based Electric Vehicles (EVs) charging system, which integrates Energy Storage System (ESS) and V2G. Comparison between the proposed AI-driven EMS and the traditional rule-based EMS was conducted to identify the potential improvements in the effective use of renewable energy, dependence on the grid, peak load control, V2G operation, and SOC of the battery.

4.1 Performance of Rule-Based EMS

Traditional EMS is based on simple coordination between PV output, ESS, EV loads, and grid supply according to pre-defined operating conditions. In the event that there is plenty of solar power available, then most of the generated electricity is used for EV loads,

while the excess electricity is stored into the ESS. If there is no enough sunlight available, then the electricity from the ESS will be supplied.

However, due to decision rules being fixed, the controller is not adaptive enough to changes in operating conditions. In high EV demand instances, there is inadequate coordination between PV production and battery charge and discharge, resulting in increased dependency on the grid. In addition, the battery SOC varies greatly from charging and discharging actions taken based on static values.

The rule-based EMS had an energy efficiency value of about 67%. The amount of energy that was consumed by the grid each day was found to be about 320 kWh. The highest demand for energy by the grid was 60 kW.

4.2 Performance of AI-Assisted EMS

AI-assisted EMS incorporates a Decision Tree-based supervisory controller that decides the best operating mode based on the condition of PV power, EV demand, and battery SOC at each time step. It enhances the decision-making process by adjusting energy flows according to needs of the system without making use of forecasting models.

This AI-integrated EMS results in more efficient use of solar energy as it focuses on utilizing solar energy first and maximizing ESS charge and discharge operations accordingly. There will be smoother battery SOC as a result of the fewer number of charge/discharge cycles, which reflects an improvement in terms of battery performance.

Another advantage of coordinating ESS and V2G operations lies in increased flexibility during the peak demand periods. In case there is enough energy stored in the EV/ESS battery system, V2G operations can then be initiated.

4.3 Performance Comparison

According to the findings, the suggested artificial intelligence EMS has enhanced system performance in terms of system efficiency. Utilization of renewable energy sources goes up from 67% to 80%, indicating efficient utilization of locally produced solar energy. Consequently, the system relies less on energy drawn from the national grid and, therefore, is more sustainable.

The decrease in energy consumed from the grid from 320 kWh/day to 245 kWh/day proves intelligent energy management and coordination. In addition, the AI-based EMS leads to a decrease in peak demand of about 20%, thereby reducing pressure on the distribution grid.

Finally, the V2G capacity goes up from 40 kWh/day to 65 kWh/day. This shows increased use of bidirectional power flow ability, which allows both vehicles and energy storage to help out in meeting peak demand.

4.4 Discussion

The results obtained show that the use of explainable AI in conjunction with conventional EMS logic is an effective solution for hybrid PV-based EV charging systems. As opposed to the purely rule-based systems, the developed framework enables adaptation of the system under dynamic conditions while ensuring the transparency of the decision-making process with the help of Decision Trees.

In comparison with other optimization- and black-box AI-based EMSs, the presented model features reduced computational complexity and higher interpretability, thus being capable of performing in real time. In addition, the increased stability of SOC shows that the developed EMS can help decrease the stress on the battery and extend its operational lifespan.

In summary, the developed EMS can be considered as an adequate compromise between purely rule-based and complex AI optimization frameworks for energy management.

5. Conclusion

An integrated AI-enabled Energy Management Strategy (EMS) for a photovoltaic (PV)-driven electric vehicle (EV) charging station featuring energy storage systems (ESS) and V2G has been introduced in this paper. The introduced strategy utilizes the reliability of the conventional rule-based system while adding the flexibility of the explainable artificial intelligence (AI)-enabled supervisory control.

In order to optimize the modes of operation of the PV-EV system, an AI-based controller based on the Decision Tree algorithm was developed. In addition, there is no reliance on forecasting algorithms while keeping the decision-making process clear in the proposed approach, which is useful in real-world implementations.

According to the performance analysis, which included simulations during one day, the AI-assisted EMS outperformed the conventional rule-based EMS in all cases. Renewable energy usage increased from 67% to 80%, whereas the grid electricity use decreased by 23%. Moreover, the peak demand of the grid was minimized by 20%, and the V2G energy share increased considerably.

It has been established that the use of explainable AI in combination with the standard EMS can offer a good

tradeoff between flexibility, robustness, and transparency of the approach. The presented methodology is capable of solving the problems associated with static rule-based approaches and sophisticated black-box AI solutions.

Future research will concentrate on hardware implementation in real time, taking into account users' charging constraints, dynamic pricing, application of other AI techniques, and expansion to the multi-station energy management systems in microgrids.

6. Future Scope

The scope for the future development of the proposed AI-assisted EMS is as follows:

Real-time hardware implementation: The development and verification of the proposed EMS algorithm in real-time controller and embedded platforms.

User-centric EV constraints: Implementation of EVs' arrival times, preferences, and minimum SOC requirement.

Dynamic pricing and demand response mechanism: Implementation of pricing policies and demand response strategy into the EMS system to improve its efficiency.

Advancement in AI: Implementation of advanced AI algorithms such as reinforcement learning, deep learning, and hybrid AI to enable self-learning capabilities of the system.

Battery degradation model: The use of battery degradation and aging models to better manage battery lifecycle management and charge/discharge activities.

Expansion of multi-station or microgrid management applications: Implementation of the proposed EMS in multiple charging stations or microgrids.

Further renewables: Use of additional renewable sources such as wind energy to provide more sustainable energy supply.

Forecasting: Improving the forecasting capabilities for predicting both PV energy generation and EV demand. **Communication and cybersecurity improvements:** Implementing communication channels with advanced security features for reliable operation.

Fleet management of electric vehicles: Using the proposed framework in managing a fleet of vehicles in a smart transportation network.

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