Evaluating EV User Behavior on Aggregator Smart Charging with ESS and Real-Time Pricing-Based Demand Response

Aakash Kumar[1], Draupathi Chin

1 United Machinery Technologies (Russia)

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Abstract

With rising global electricity consumption, governments prioritize energy efficiency and the integration of electric vehicles (EVs) into energy markets. This study evaluates EV aggregator strategies using a smart charging method that modulates charging power rates based on user preferences. Simulations in Quito's distribution system assess various actions' impacts on aggregator costs and technical conditions. The study focuses on demand response (DR) strategies, particularly for residential areas, exploring EVs' potential as energy storage via vehicle-to-home (V2H) and vehicle-to-grid (V2G) options. It introduces a collaborative evaluation of dynamic-pricing and peak power limiting-based DR strategies, incorporating bi-directional EV and energy storage system (ESS) use. A novel mixed-integer linear programming (MILP) model for home energy management (HEM) integrates distributed renewable energy, V2H/V2G capabilities, and two-way ESS energy trading and diverse DR strategies. This comprehensive approach assesses the impact of EV owner preferences and ESS availability on reducing total electricity costs through case studies.

Introduction

The future of power systems faces challenges due to population growth and the push for increased green energy adoption. In response, policies emphasize the development of smart grids (SGs), which integrate various engineering techniques to create reliable, secure, and efficient grids maximizing renewable energy use [1]. Key SG functions include enhancing fault detection, deploying distributed energy resources, improving building energy efficiency, and integrating demand response and demand-side management techniques [2]. These strategies involve microgrids, control and communications, and sensing and measurement. Electric vehicles present a promising technology for SGs, offering significant battery storage capacity that can benefit the grid [3]. However, widespread EV adoption can strain the power grid, causing issues like voltage deviations, distribution losses, peak load increases, high investment costs, and transformer lifespan reduction [4]. Effective management of EV fleets and understanding charging behavior are essential [5].

Previous studies have explored various EV charging management opportunities in SGs, including vehicle-to-home strategies, peak shaving and valley filling using vehicle-to-grid systems, efficient EV charging methodologies through multi-objective optimization, and decentralized load management using evolutionary game dynamics [6][7]. Other research has focused on smart charger design and evaluation, introducing bidirectional smart chargers, voltage-based controllers, and model predictive control methods [8]. To enhance EV charging management, the concept of an EV aggregator has been introduced, which efficiently manages a large number of EV chargers [9]. This aggregator requires a smart charging infrastructure and aims to optimize the economic and technical aspects of EVs. However, some charging management methods may be efficient for the grid but may not meet user expectations, potentially discouraging EV adoption. Addressing this, a smart charging methodology for EV aggregators was proposed, considering different customer choice products (CCPs) based on EV user preferences [10]. This methodology optimizes charging power modulation to achieve cost savings while maintaining grid reliability [11]. However, many studies assume fixed parameters based on local user preferences, overlooking variations due to regional differences in user behavior.

This paper aims to assess various strategies based on different input parameters applicable to the smart charging methodology. It presents multiple test results, suggesting that these EV aggregator strategies can be tailored to grid conditions and user preferences. Also, the paper discusses the deregulation of the electric power industry and the importance of smart grid and smart households [12]. Smart grid vision aims to enhance electricity utilization efficiency from production to end-user, accommodating all generation and storage options and enabling consumer participation [13]. Demand-side actions for smart households focus on demand response (DR) strategies, allowing utility-consumer interaction. DR strategies aim to shift consumer electric usage from peak to off-peak periods to optimize smart grid operation efficiency [14]. Enabling technologies for residential DR activities include home energy management (HEM) systems and smart meters. With the rise of electric vehicles (EVs), understanding their energy needs and potential as grid resources is crucial [15]. EVs present both challenges and opportunities, with their energy requirements sometimes exceeding individual home power capacities [16]. This paper introduces a mixed-integer linear programming (MILP) model for HEM structures to investigate a collaborative evaluation of dynamic-pricing based DR strategies, distributed renewable energy generation, EV-to-home (V2H) capabilities, two-way EV energy trading (V2G), and energy storage systems [17]. The paper conducts various case studies assessing the impacts of these components under different DR strategies, evaluating consumer electricity bill reduction performance and utilizing real-time load demand and distributed energy resource production data for comparisons.

Approach

The Home Energy Management (HEM) system orchestrates smart household operations, integrating price-based signals from the Load Serving Entity (LSE), self-produced small-scale energy, smart appliance consumption, and consumer preferences. The goal is to minimize daily electricity costs by balancing grid energy purchases with energy sold back to the grid through household assets like PV, ESS, and EV. This optimization considers time-varying energy prices and imposes penalties on energy sourced from different resources to prioritize energy sales [18]. The HEM system's core operations are outlined, offering flexibility for specific implementations, such as modeling HVAC systems, water heaters, or customer contract details. The time granularity can be adjusted by selecting ΔT, for example, setting ΔT to 4 for 15-

minute intervals. Constraints define the maximum power drawn from and injected back into the grid, which can be adjusted with time-dependent parameters N1 and N2, respectively. Consumer options and behaviors are represented by setting ESS and EV charging and discharging variables to zero during specific intervals [19]. Different energy selling policies can be modeled by adjusting selling energy variables. Further details on this methodology are available in [20]. The Electric Vehicle aggregator plays a pivotal role in managing EV charging, offering technical services to Distribution System Operators and Transmission System Operators [21]. These services ensure that the "maximum load profile" set by grid operators are not exceeded, preventing grid instability and asset damage [22]. The aggregator optimizes EV charging costs while adhering to technical constraints.

To enhance EV adoption, the methodology introduces three Consumer Charging Profiles (CCPs): green, blue, and red. Each profile offers different charging price and duration options, accommodating user flexibility [23]. Green and blue profiles allow the aggregator to adjust charging rates, while the red profile prioritizes speed, offering the maximum charging rate of 7.2 kW. The aggregator's objective is to minimize daily charging costs, optimize charging patterns for each CCP, and avoid penalty costs by staying within the maximum load profile [24]. Given the complexity of the model and uncertainties in EV user behavior, sensitivity analysis is crucial [25]. This analysis assesses how variations in input parameters, such as minimum required energy, starting charging time delay, and average charging power rates for green and blue CCPs, impact output variables like EV load and charging costs. Monte Carlo simulations are employed to analyze the cost impact of parameter variations through regression analysis, considering 100 simulations per scenario to capture user behavior uncertainties. The HEM system and EV aggregator aim to optimize household energy management and EV charging while considering dynamic pricing, consumer preferences, and grid constraints. Sensitivity analysis and Monte Carlo simulations provide insights into the model's robustness and the impact of variable changes on charging costs, ensuring efficient and user-friendly EV integration into smart grids.

Results and Discussions

To assess the overall impact of various household operational scenarios on consumer electricity bills, we employ an MILP model implemented in GAMS v.24.1.3 using CPLEX v.12 as the solver [24]. The findings from these simulations are elaborated upon in this section. The study uses real-time load demand data from an average Portuguese household spanning 140 square meters and housing four occupants. The household features a variety of electric appliances, such as a fridge, TVs, microwave, washing machine, dishwasher, computer, and oven. Notably, the household relies on a gas-powered water heater. Daily consumption data over a one-month period was collected to derive an average power consumption profile. The household is equipped with a 1 kW small-scale PV system, with its production data normalized based on a measured daily solar farm production profile. The study also considers bi-directional Electric Vehicle (EV) operations, encompassing both Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) functionalities.

The analysis takes into account a Chevy Volt with a 16 kWh battery and a charging station limited to 3.3 kW for both charging and discharging operations. Charging and discharging efficiencies are set at 95%. Initial EV battery energy upon arriving home is assumed to be 8 kWh, with a lower limit of 4.8 kWh to prevent deep-discharging. The Energy Storage

System (ESS) consists of a 1 kWh capacity battery with a charging/discharging rate of 0.2 kW per hour, efficiencies of 95%, and a deep-discharge limit of 0.25 kWh. Notably, no costs associated with using storage facilities like EV and ESS during Home Energy Management (HEM) operations are considered. The study employs a net-metering approach to facilitate two-way energy transactions between the end-user and the utility. Excess energy can be sold back to the grid when available, with a flat rate of 3 cents/kWh paid to the user for such sales. Pricing for grid-sourced energy is based on a dynamic pricing-based Demand Response (DR) scheme.

Three consumer preference scenarios are analyzed: immediate EV charging, cost-effective EV charging, and cost-effective EV charging combined with V2H during peak demand periods. Monetary values are used to quantify the impact of these preferences on daily household operation costs, facilitating comparative analysis and percentage-based cost reduction assessments. Additional scenarios, such as shifting EV charging to low-price periods post-midnight, are also explored. This strategy reduces costs but may result in off-peak utility load peaks and EV battery idle periods. The study further evaluates the impact of an optimization-based HEM strategy on costs for various scenarios, considering daily electricity prices and regular household load demand patterns. Sensitivity analyses explore the effects of varying minimum required energy for charging, charging start time delays, and consumer preference proportions on costs. The study employs detailed modeling and sensitivity analyses to assess the impacts of various operational and consumer preference scenarios on household electricity costs, providing insights into the optimization potential of HEM strategies and the benefits of dynamic pricing and net-metering in smart household energy management.

Significance of results

The widespread adoption of Electric Vehicles (EVs) poses significant challenges to power systems. Without intelligent charging solutions, EVs could strain the grid, exacerbating technical and cost constraints. EV aggregators emerge as pivotal players capable of managing the uncertainties associated with this new demand. This study delves into the impact of various input parameters on smart charging strategies, recognizing that these parameters can vary widely based on user behavior. Our findings highlight that the most substantial cost variations are linked to the average charging power rate for the green Customer Charging Profile (CCP), showing a 10.26% difference in total EV aggregator costs between the examined lower and upper bounds. The proportion of green CCP and time delay parameters showed differences of 7.03% and 5%, respectively, between their lower and upper bounds.

Conversely, factors like the minimum energy required to charge an EV showed negligible cost variations, with only a 2.03% difference in total EV aggregator costs between the lower and upper bounds. Similarly, variations in the average charging power rate for the blue CCP resulted in a 3.40% cost difference between the lower and upper bounds. While EV aggregators could incentivize users to charge during off-peak hours to maximize benefits, the success of these incentives hinges on aligning charging times with user flexibility. If users perceive a mismatch between charging times and their schedules, they may be reluctant to embrace smart charging solutions. Thus, determining optimal input parameter values that resonate with EV user preferences becomes a critical challenge for EV aggregators. Real-world studies assessing user reactions to incentives are essential for selecting suitable parameter values and fostering adoption of smart charging techniques.

A primary concern in implementing the proposed approach is computational efficiency. For instance, solving the problem for the most recent case took only 0.11 seconds on a Dual Core Laptop with a 2 GHz CPU and 8 GB RAM, offering a glimpse into the computational demands of the methodology. While the model developed and used offline in this study, it can be adapted for online application using dynamic programming. The uncertainty stemming from the deterministic PV system power production curve in offline mode can be managed through forecasting tools commonly employed across various scales of applications. To address uncertainties in dynamic pricing data for upcoming hours, shortening the scheduling horizon to align with the horizon of pricing data received from the Load Serving Entity via smart metering can be effective. Additionally, uncertainties regarding the state-of-energy of Electric Vehicles upon arrival at home can be addressed through a secondary optimization stage, adjusting operation scheduling based on real-time data. Machine learning tools, like neural networks, can also be trained using daily data, potentially reducing the reliance on multi-stage programming.

Conclusion

This paper integrates dynamic-pricing and peak power limiting DR strategies with renewable energy generation, EV V2H and V2G capabilities, and two-way energy trading using V2G and ESS. Utilizing a MILP framework, it models an HEM system with net metering for two-way energy exchange, based on real-world data from a Portuguese family and a PV plant. In a base scenario without HEM or ESS, immediate EV charging sets a cost benchmark. The proposed strategy reduces electricity costs by around 65%, with smart technologies and HEM promising further savings. As smart tech evolves, end-users stand to gain flexibility and economic opportunities, subject to regulatory and installation costs. The methodology is adaptable for wider smart household applications and multi-household optimization from LSEs and household owners' viewpoints. The study evaluates EV user impacts on smart charging across three CCPs, using Monte Carlo simulations for sensitivity analyses of variables like minimum energy, charging delay, and CCP user proportions and rates. Regression analyses reveal variable relationships with EV aggregator costs. Some variables, like minimum energy, minimally affect costs, aligning with user preferences. In contrast, changes in CCP user proportions and up to 3-hour charging delays notably influence costs, with the most significant variations from green CCP average charging power rate fluctuations.

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