International Journal of Advanced Computer Technology
ISSN: 2319-7900 www.ijact.org Volume 13, Issue 3, June 2024

Developing Priority-Based Control Mechanisms for Grid Ancillary Services through Plug-In Electric Vehicle Charging and Discharging

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Abstract

The increasing integration of renewable energy sources into power grids presents challenges for maintaining grid stability and providing essential ancillary services such as frequency regulation, voltage support, and reserve capacity. Plug-in electric vehicles (PEVs) have emerged as a flexible resource for delivering these services through controlled charging and discharging. However, the efficient coordination of large fleets of PEVs to support the grid while minimizing impacts on user convenience remains a challenge. This paper proposes a novel priority-based control mechanism that optimizes the participation of PEVs in ancillary services based on vehicle state of charge (SOC), trip schedules, grid requirements, and the availability of distributed generation resources. The proposed system assigns priorities to individual PEVs, enabling a dynamic response to grid needs while accounting for user preferences and vehicle readiness. The control strategy is evaluated through simulations that model the interaction between PEVs and the grid under various conditions. Results demonstrate that the priority-based control mechanism significantly improves grid stability and reduces energy costs while ensuring that user mobility requirements are met. These findings suggest that the proposed approach can enhance the role of PEVs in grid management and facilitate the transition to a more resilient and sustainable energy system. Future work will explore the integration of real-time pricing mechanisms and the broader implementation of vehicle-to-grid (V2G) capabilities.

Keywords: Energy Storage Systems, Grid Ancillary Services, Priority-Based Control Mechanisms, Renewable Energy Integration.

1. Introduction

The global transition towards cleaner and more sustainable energy systems has led to a significant increase in the integration of renewable energy sources such as solar and wind into power grids. While these resources offer environmental and economic benefits, they also introduce variability and uncertainty in power generation, which poses challenges to maintaining grid stability. As a result, grid operators increasingly rely on ancillary services—such as frequency regulation, voltage control, and spinning reserves—to ensure reliable operation of the grid. Plug-in electric vehicles (PEVs) are rapidly gaining popularity as an eco-friendly alternative to conventional internal combustion engine vehicles. With the growing number of PEVs, they represent a substantial and largely untapped resource for supporting grid ancillary services. By managing their charging and discharging schedules, PEVs can help mitigate fluctuations in power supply and demand, contributing to grid stability. This is particularly relevant in the context of vehicle-to-grid (V2G) technology, where PEVs can return energy stored in their batteries back to the grid. However, optimizing the coordination of large fleets of PEVs for grid services presents several challenges.

A key issue is the need to balance grid requirements with the preferences of vehicle owners, who may have specific schedules for charging or driving. Uncontrolled or poorly managed PEV integration into grid operations could lead to undesirable effects, such as increased grid congestion, inefficient use of energy, or reduced availability of vehicles for user trips. To address these challenges, there is a need for sophisticated control mechanisms that prioritize PEV charging and discharging in a way that benefits both the grid and the vehicle owners. This paper proposes a priority-based control mechanism for PEVs that optimizes their participation in grid ancillary services while considering factors such as vehicle state of charge (SOC), user preferences, trip schedules, and the availability of distributed generation from renewable sources. By assigning dynamic priorities to vehicles, the system ensures that PEVs with higher grid service potential and flexibility are utilized more efficiently while maintaining a balance between user convenience and grid stability. As the adoption of renewable energy sources such as wind and solar power increases, electrical grids face growing challenges in maintaining stability due to the intermittent and unpredictable nature of these energy sources. Ancillary services, including frequency regulation, voltage control, and reserve capacity, play a critical role in ensuring grid reliability. However, conventional methods for providing ancillary services, often reliant on fossil fuel-based power plants, are becoming less efficient and more costly in the context of a rapidly evolving energy landscape. Plug-in Electric Vehicles (PEVs) have the potential to address critical grid challenges by functioning as distributed energy resources (DERs) capable of providing ancillary services through managed charging and discharging. By helping balance power supply and demand, mitigating frequency deviations, and supporting voltage control, PEVs can play a pivotal role in enhancing grid stability. However, their large-scale integration into grid operations presents several challenges. Uncontrolled PEV charging and discharging can result in grid congestion, voltage imbalances, and higher energy costs due to the inadequacy of existing control strategies in dynamically managing PEV fleets. Balancing user convenience, such as driving schedules and state of charge, with grid stability needs is another significant issue, as current approaches often fail to prioritize vehicle participation effectively while meeting user mobility requirements.

Additionally, frequent charging and discharging for grid services can accelerate battery degradation and increase operational costs, reducing the appeal of vehicle-to-grid (V2G) solutions for vehicle owners. Moreover, the lack of effective priority-based control mechanisms remains a critical gap, as existing algorithms do not adequately optimize PEV participation by considering factors such as state of charge, trip schedules, and grid service needs, thereby limiting the potential benefits to the grid without compromising user satisfaction or battery life. To address these issues, it is essential to develop an intelligent, priority-based control mechanism that optimizes PEV charging and discharging schedules to support grid ancillary services while balancing user needs and minimizing battery degradation. Such a solution would enable PEVs to contribute to grid stability more effectively, enhance the efficiency of renewable energy integration, and reduce energy costs for both grid operators and PEV owners. This work primarily focuses on three key objectives: load flattening, maximizing plug-in electric vehicle (PEV) storage usage, and minimizing the cost of PEV charging. Initially, energy demand zones for load flattening are identified, and the Water Filling Algorithm (WFA) is employed to achieve optimal energy distribution (OED) across intervals within these zones. To optimize PEV storage usage, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is used for vehicle prioritization, ensuring enhanced storage exploitation while reducing the cost of charging (CoC). Furthermore, a Multi-Objective Genetic Algorithm (MOGA) is utilized to determine the optimal power transaction (OPT) between the grid and PEVs, aiming to balance load flattening and maintain voltage regulation effectively. The remainder of this paper is structured as follows: Section 2 reviews related work in the fields of grid ancillary services and PEV integration. Section 3 presents the system model and assumptions. Section 4 describes the proposed priority-based control algorithm and its implementation. Section 5 discusses the results of simulations conducted to evaluate the system's performance. Finally, Section 6 offers conclusions and suggests potential directions for future research.

2. Literature Review

The reviewed literature provides a comprehensive understanding of how plug-in electric vehicles (PEVs) can be integrated into power grids to offer ancillary services, addressing challenges such as grid stability, battery degradation, and the development of effective control strategies. This section presents related works in the fields of grid ancillary services and PEV integration. S. Pal et al. (2023) propose a two-layer optimization method designed to smooth utility power demand, regulate grid frequency, and minimize the daily costs associated with PEV charging and discharging. A. Dubey et al. (2022) explore strategies for controlling nationwide fleets of electric vehicles to provide bi-directional ancillary services. Similarly, S. Sinha et al. (2022) emphasize load frequency control through vehicle-to-grid (V2G) systems, highlighting their effectiveness in maintaining grid stability. M. Yilmaz et al. (2015) examine the role of PEV chargers in delivering ancillary services and their impact on grid integration. Addressing battery concerns, S. Saxena et al. (2022) analyze battery degradation in PEVs caused by frequent charging and discharging cycles. R. Gadh et al. (2014) discuss architectural and algorithmic solutions for integrating large-scale PEVs into power grids, focusing on their effects on grid infrastructure and ancillary services. Y. Wang et al. (2022) provide an extensive overview of battery energy storage systems, including PEVs, and their roles in ancillary services like frequency regulation and voltage support. A. Sharma et al. (2022) investigate the impact of PEV integration on grid systems, particularly when combined with renewable energy sources, and propose strategies to address associated challenges. S. A. Pour Mousavi et al. (2015) introduce a partial differential equation (PDE) approach to model and control PEV fleets for ancillary service provision. Lastly, M. A. Ortega-Vazquez et al. (2016) review aggregation-based management models for PEVs, offering a structured approach to integrating diverse modelling techniques effectively.

3. System Model and Assumptions

A comprehensive system model is essential to developing a priority-based control mechanism for Plug-in Electric Vehicles (PEVs) that optimizes their participation in grid ancillary services. This model integrates the interaction between the grid, PEVs, and the control mechanism to coordinate charging and discharging activities based on grid needs and vehicle priorities.

Grid Model:- It is represented as an interconnected system tasked with maintaining voltage stability and frequency regulation while addressing real-time power demand. Ancillary services provided by the grid include frequency regulation, which balances power supply and demand to maintain stable grid frequency, voltage control to stabilize voltage levels (especially with variable renewable generation), and spinning reserves for rapid response to sudden fluctuations in demand or supply. PEVs, as distributed energy resources, contribute to these services by charging during low-demand periods (when renewable generation is high) and discharging energy back to the grid during high-demand periods.

PEV Fleet Model:- The PEV fleet comprises numerous vehicles with varying attributes, such as state of charge (SOC), user trip schedules, and battery capacity. SOC reflects the current battery charge, determining a vehicle's ability to discharge energy to the grid. User trip schedules define when vehicles need to be charged to meet mobility requirements and when they are idle for grid services. Battery capacity and degradation are also crucial factors, as repeated charging and discharging cycles wear out batteries. The model incorporates these aspects to optimize PEV participation in ancillary services while minimizing battery wear and ensuring user convenience.

Control Mechanism: The proposed control mechanism dynamically prioritizes PEV charging and discharging activities based on multiple factors. Vehicles with higher SOC or available capacity are prioritized for discharging during grid needs, while those required for trips soon are deprioritized to preserve mobility. Grid demands for ancillary services, such as frequency regulation or voltage control, and the availability of distributed generation (e.g., solar or wind) influence priority assignments. The control system operates in real time, using a centralized algorithm to adjust priorities in response to evolving grid conditions and vehicle statuses. Smart grid infrastructure facilitates communication between the grid and PEVs, enabling coordinated decision-making.

Assumptions:- Key assumptions underpin the model's operation. A smart grid infrastructure and reliable communication network are presumed, ensuring real-time interaction between PEVs and the grid. Renewable energy is assumed to constitute a significant portion of the grid's supply, introducing variability that the system addresses. Accurate battery degradation models are incorporated to mitigate wear, and user participation is assumed to be incentivized by cost savings or compensation. While user mobility needs are considered, grid stability remains the system's top priority, requiring occasional flexibility from users during grid stress.

Energy Pricing Model:- The model incorporates a dynamic pricing strategy where energy prices vary with grid demand and renewable generation levels. This enables PEVs to optimize charging and discharging activities, such as charging during low-price, high-renewable generation periods and discharging during high-price, high-demand intervals. This pricing model aligns user incentives with grid requirements, promoting efficient energy use and supporting grid stability. This comprehensive framework ensures effective PEV integration into grid operations, addressing challenges while leveraging the potential of PEVs to enhance grid reliability and sustainability.

4. Proposed Methodology

This article outlines the proposed control strategy for optimizing the integration of Plug-in Electric Vehicles (PEVs) into the grid. The strategy involves optimal energy distribution using the Water Filling Algorithm (WFA) and optimal power transaction using a Multi-Objective Genetic Algorithm (MOGA). From the utility's perspective, the primary objective is achieving load flattening while maintaining bus voltage limits. The control strategy is implemented in three distinct stages, each contributing to efficient grid operations and cost minimization. In the initial stage, the WFA is employed to distribute the total available energy from PEVs optimally across all time intervals in each zone. This distribution accounts for the uncertainty of PEV availability for grid support, ensuring that energy resources are allocated reliably and effectively. The second stage utilizes MOGA to determine the Optimal Power Transaction (OPT) between the grid and PEVs. This optimization focuses on two critical objectives: load flattening, which balances energy supply and demand, and voltage regulation, which ensures grid stability under varying conditions. In the final stage, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is applied for vehicle prioritization. This approach maximizes the utilization of PEV storage capacity while minimizing the Cost of Charging (CoC). The ANFIS mechanism dynamically prioritizes vehicles based on grid requirements, state of charge, and user mobility needs, achieving an optimal balance between user convenience and grid support. The article also examines the impact of Optimal Energy Distribution (OED) and OPT on load flattening

ISSN: 2319-7900 www.ijact.org Volume 13, Issue 3, June 2024

and voltage regulation. Various scenarios are analyzed in the ANFIS prioritization process, highlighting their effects on total PEV power availability and the depreciation of charging costs. The results demonstrate the effectiveness of the proposed strategy in enhancing grid operations and improving the efficiency of PEV integration.

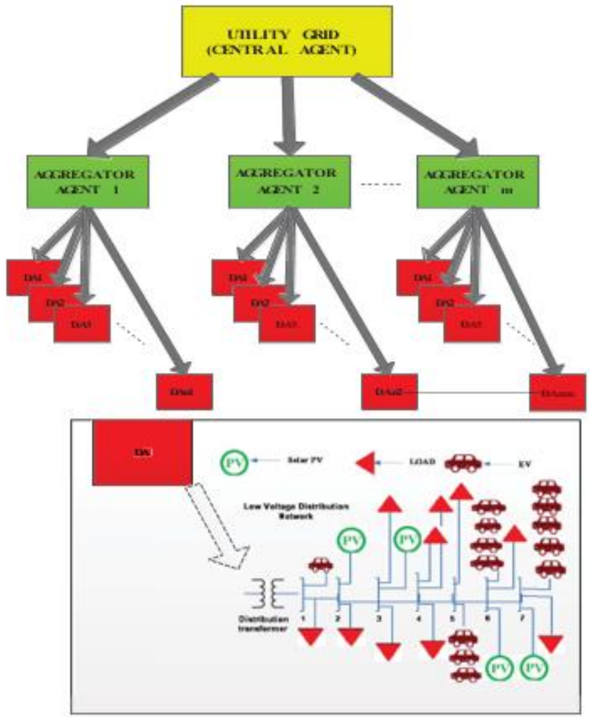

Fig. 1 Three-layer multi-agent-based EMS (top) and residential network under distribution agent (bottom)

4.1 Multi-Agent-Based EMS

The proposed Energy Management System (EMS) consists of three layers of agents designed to coordinate the operation of Plug-in Electric Vehicles (PEVs) and solar PV systems. As shown in Fig. 1, the top layer represents the main grid, which acts as the central agent (slack bus). This central agent controls the amount of power delivered to the next layer, termed the aggregator agent (AA). The AA then sets power transaction limits, referred to as specified power, for each distributed agent (DA) in the third layer. The primary objective of the DA is to manage power consumption in line with the specified power set by the AA. At the central agent level, the primary goal is to minimize spinning reserve requirements by strategically scheduling power demand across all distribution areas.

The stochastic nature of renewable energy sources (RES) significantly impacts spinning reserves. This challenge can be addressed by scheduling loads and managing energy storage at the local level (DA level), a task indirectly assigned by the AA through specified power limits. For this study, the specified power is treated as a constant reference for load flattening at the AA level throughout the day. The focus of this work is on the DA level, aiming to achieve a flat load profile by leveraging PEV storage while ensuring voltage limits are not violated. At the beginning of each zone, the total energy available from PEVs for grid support is estimated. Based on the projected power demand within the zone, the total energy requirement and the interval-specific energy needs for load flattening are calculated. The Water Filling Algorithm (WFA) is employed to determine the Optimal Energy Distribution (OED) for each interval, optimizing the use of PEV energy according to the energy needs of the zone. Vehicle prioritization is also implemented to maximize PEV power availability while minimizing the Cost of Charging (CoC). The voltage at each bus is maintained within the acceptable range of 0.9–1.1 p.u. by regulating power transactions between PEVs and the bus. This regulation is achieved by setting the Optimal Power Transaction (OPT) between PEVs and the grid for each time interval using a Multi-Objective Genetic Algorithm (MOGA). MOGA minimizes deviations in grid power demand (\(\Delta P \)) to ensure a flat load profile while maintaining voltage stability across all buses. The DA continuously monitors bus voltages and the state of charge (SoC) of PEVs. Fixed power rates are assigned to EVs, and the Aggregate Power Transaction (APT) is compared with the OPT to determine further inclusion of PEVs based on their priority. However, APT is constrained by voltage limits, and the DA may compromise on load flattening under extreme voltage conditions. From the perspective of the central agent, the key objective is to dispatch power to all AAs in a manner that minimizes total spinning reserve requirements. Each AA is tasked with allocating specified power intake to individual DAs, considering the average load demand of each DA. For simulation purposes, the average load demand is treated as the specified power. The DA's role is to maintain the net power demand close to the specified power, effectively ensuring a flat load profile with the specified power serving as the reference.

4.2 Proposed PEV control strategy

In this work, equal importance is given to both utility operators and customers while utilizing PEVs for grid support. The control strategy aims to achieve load flattening by ensuring voltage regulation and accommodating customer flexibility, including trip requirements. The overall PEV control strategy employs the Water Filling Algorithm (WFA) to distribute available energy optimally across time intervals within each zone. The day-ahead forecast of load demand, combined with solar PV generation data, is used to determine the energy requirements for each zone and interval. WFA facilitates the scheduling of PEVs in advance, taking into account their mobility patterns and energy needs to support load flattening. Details of the WFA are discussed later in this section. Prioritization plays a critical role in the control strategy, with two main objectives: maximizing battery storage utilization and minimizing the Cost of Charging (CoC). The timing of battery usage is crucial as it determines the power availability in subsequent intervals. For instance, if a PEV with a low State of Charge (SoC) is used heavily in the early intervals of a discharging zone, it may become unavailable for grid support as its SoC is depleted, effectively setting its power rate to zero. This situation highlights a challenge: even if excess energy is available at a given time, SoC constraints may limit the ability to meet power requirements. Prioritization helps the utility operator decide which PEVs to utilize first, streamlining this complex decision-making process. Voltage regulation is integral to achieving load flattening and is accomplished through active power transactions between PEVs and the grid. In this work, a Multi-Objective Genetic Algorithm (MOGA) is employed to determine the Optimal Power Transaction (OPT) for each interval, ensuring voltage limits are maintained while using PEVs for load flattening. Active power transactions are the primary focus for voltage regulation, as the goal is to address active power imbalances. In low-voltage residential distribution networks, voltage deviations are typically allowed within the range of 0.9 to 1.1 per unit (p.u.). Based on prioritization, PEVs are incrementally added to meet the grid's requirements when the Aggregate Power Transaction (APT) falls short of the OPT in each interval. However, if the voltage at any bus reaches its maximum allowable limit during charging or discharging, the power demand for load flattening is adjusted to ensure compliance with voltage constraints. This approach balances the dual objectives of maintaining voltage regulation and achieving a flattened load profile while respecting the operational limits of the distribution network. Optimal energy distribution among the intervals in each zone is done using WFA, and the MOGA decides the optimal power transaction between the grid and PEVs in each interval.

4.3 Zones of Energy Need

The residential distribution network considered in this work consists of solar PV, houses, and PEVs. The load curve is shaped by the algebraic sum of load demand, solar PV power, and PEV charging load, as shown in Equation 1.

$$\mathrm{Ptotal(t)=Pload(t)+Psolar(t)+PPEV(t)} \qquad (1)$$

Where $P_{total}(t)$ is the total power at time t, $P_{load}(t)$ is the load demand at time t, $P_{solar}(t)$ is the solar PV power at time t, and $P_{PEV}(t)$ is the PEV charging load at time t.

The specified grid power serves as the reference for flattening the load curve. Equation 2 gives the energy demand from PEVs to support load flattening.

$$E_{PEV}(t)=E_{load}(t)-E_{grid}(t) \qquad (2)$$

Where $E_{PEV}(t)$ is the energy required from PEVs at time t, $E_{load}(t)$ is the total energy required by the load at time t, and $E_{grid}(t)$ is the specified energy from the grid at time t.

Since we are dealing with storage units, the load demand is considered in terms of energy, as illustrated in Fig. 2, over 96-time intervals.

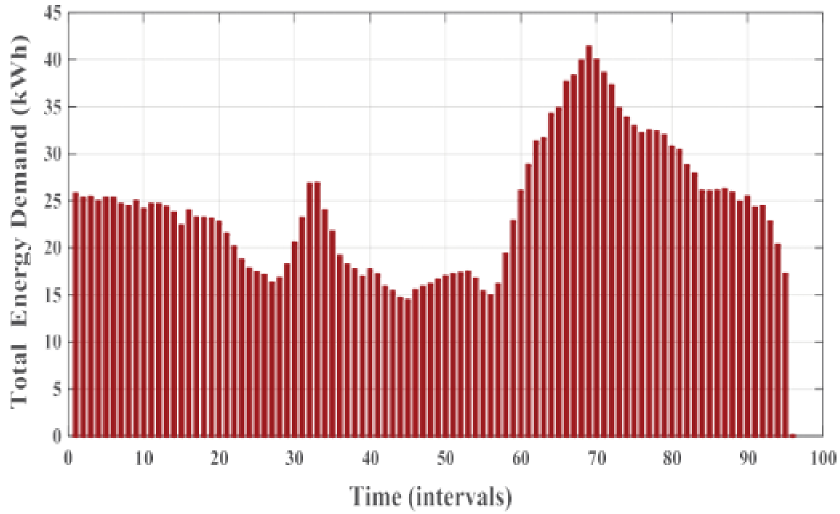

Fig. 2 Total energy demand from the main grid during 96 intervals

4.4 Formulation of Objectives

In this work, three key objectives are considered: load flattening, voltage regulation, and revenue maximization/minimizing the cost of charging.

Load Flattening:- The objective of load flattening is represented by Equation 3, where ΔPΔP is the difference between the specified grid power (in this case, the average load demand of 65 kW) and the actual power drawn from the grid. Equation 3.

$$\Delta P = P_{specified} - P_{actual} - P_{PEV} \quad (3)$$

In this equation, PPEVPPEV refers to the aggregate power used from PEVs in load flattening, with "+" indicating the charging zone (Grid-to-Vehicle, G2V) and "-" indicating the discharging zone (Vehicle-to-Grid, V2G). The Optimal Energy Distribution (OED) derived from the Water Filling Algorithm (WFA) provides the optimal energy usage for each interval, which is used as a constraint in the Multi-Objective Genetic Algorithm (MOGA) optimization process.

Voltage Regulation:- Voltage regulation at the distribution level is achieved using resources such as online tap-changing transformers, capacitor banks, and distributed energy sources (Mehmood, Khawaja Khalid et al., 2018). PEVs serve as an important asset for voltage regulation without the need for additional expenditures. The second objective is to minimize the voltage deviation (ΔVΔV) at each bus by controlling the active power transactions between PEVs and the grid. The power injected into or drawn from the grid is coordinated with the bus voltage deviation and the required active power transactions at each bus where PEVs are connected. In this work, load flattening and voltage regulation are both considered simultaneously without compromising customer flexibility (trip requirements). This ensures that load flattening objectives are met while maintaining voltage limits and respecting trip schedules. By addressing these objectives, this strategy aims to achieve an efficient integration of PEVs into the grid, balancing utility needs with customer preferences.

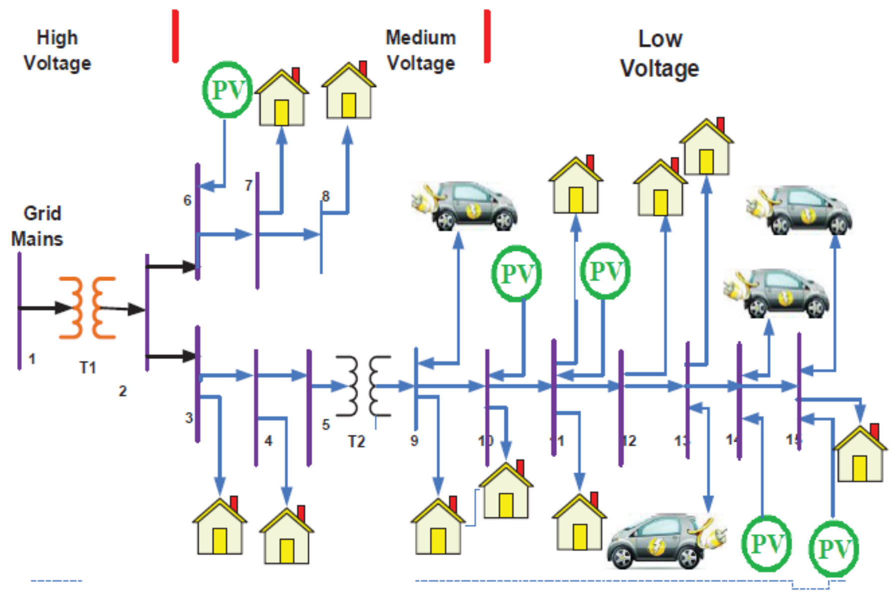

Fig. 3 An active residential distribution network with solar PVs, houses and PEVs.

Table 1 PEV Specifications

SPECIFICATION	BMW i3 REx	Chevrolet Volt	Citroen C-Zero
Capacity (kWh)	22	16	16
Battery type	Li-ion	Li-ion	Li-ion
Charging rate	230V 6-8h	230V 7h	230V 7h
Consumption (kW/100Km)	13.5	16	13.5

5. Results

5.1 Simulation Setup

In this article, the proposed strategy is implemented, and the results are discussed for different cases. A low-voltage active residential distribution network, shown in Fig. 3, is being considered for the implementation of the proposed PEV control strategy. It is assumed that PEV owners are willing to participate in both Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) support based on utility requirements. In return, they will receive incentives for each kilowatt-hour (kWh) of energy transacted between the PEVs and the grid. The active residential distribution network, shown in Fig. 4, consists of residential loads from 120 houses, with 13 PEVs (each having fixed power rates) connected to buses 1, 5, 6, and 7. Additionally, there are four solar PVs located on buses 2, 3, 6, and 7, each capable of generating a maximum of 6 kW. The data required for the simulation is sourced from DiSC, a MATLAB-based smart grid simulation platform (R. Pedersen et al., 2015), which is used to implement the proposed methodology. Three different types of PEVs, with technical specifications such as battery capacity, battery type, and charging rates, as shown in Table 1, are used in this study.

6.2 Prioritization Impact on Utility and Customer

A PEV with a higher State of Charge (SoC) that participates in grid support during the early time intervals of the charging zone will quickly reach its maximum SoC limit (greater than 0.8), making it unavailable for further grid support. Similarly, in the discharging zone, problems arise when the SoC drops to 0.2 or below. During the prioritization process, carried out using an Adaptive Neuro-Fuzzy Inference System (ANFIS), both SoC and laxity are crucial in determining the PEV's availability for grid support in subsequent time intervals. PEVs with higher laxity should be given lower priority, as they have more flexibility to be used later. The Cost of Charging (CoC) for all 13 PEVs at the end of the day is shown in Fig. 5, where a negative value indicates profit (due to participation in grid support when electricity prices are low in the charging zone), and a positive value indicates a cost that the customer must pay.

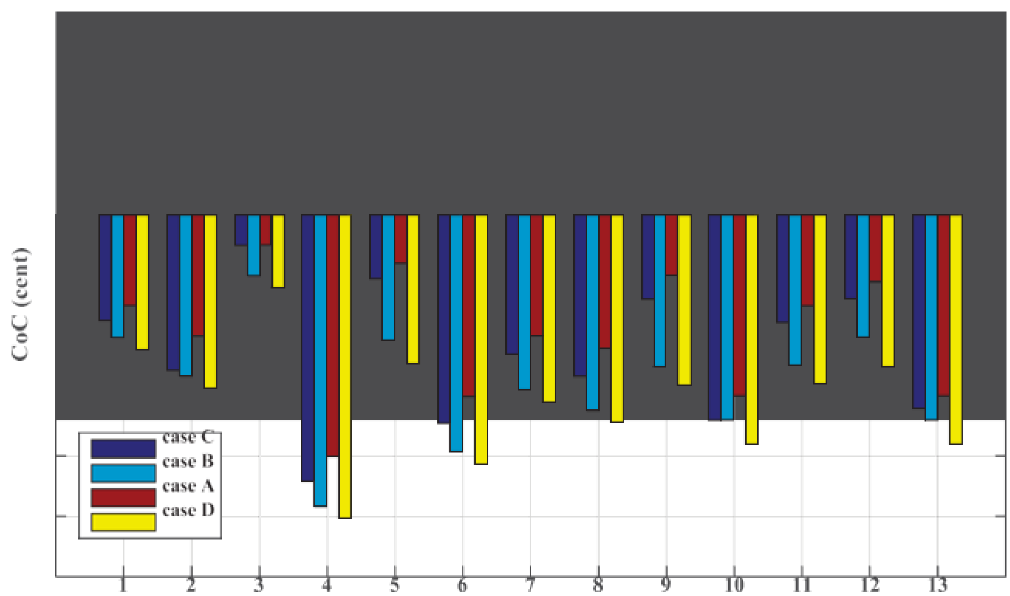

Fig. 4 Impact of ANFIS prioritization on the Cost of charging

The CoC depends on whether the vehicle participates in the charging zone when electricity prices are low and the discharging zone when prices are high. SoC and laxity are essential factors in determining when PEV storage can be used for grid support. For example, a PEV with a lower SoC participating in grid support during the early intervals of the discharging

ISSN: 2319-7900 www.ijact.org Volume 13, Issue 3, June 2024

zone will deplete quickly and become unavailable for further support. On the other hand, a PEV with higher laxity should be given higher priority for grid support based on its SoC. Four different cases are considered in the ANFIS prioritization process for analysis, with the effect of these scenarios on PEV power availability for grid support shown in Fig. 5. In Case A, customer revenue maximization is not considered in the prioritization of PEVs. As both SoC and laxity are key factors in deciding PEV storage usage, maximum power is available from PEVs throughout all intervals of the day. In Case B, the proposed control strategy is implemented, considering all five input decision variables in the prioritization process. In this case, both customer and utility needs are satisfied, resulting in a win-win situation. However, the power availability in Case B may be slightly lower compared to Case A.

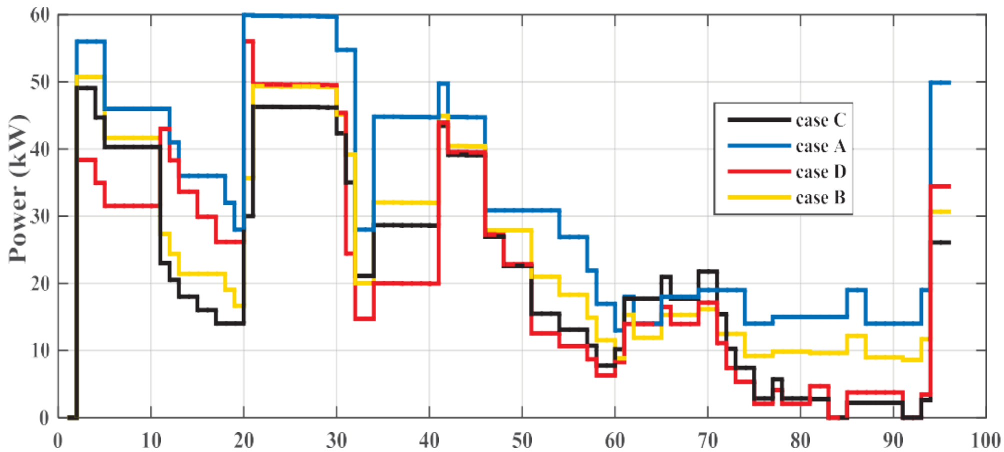

Fig. 5 Impact of ANFIS prioritization on Total PEV power availability

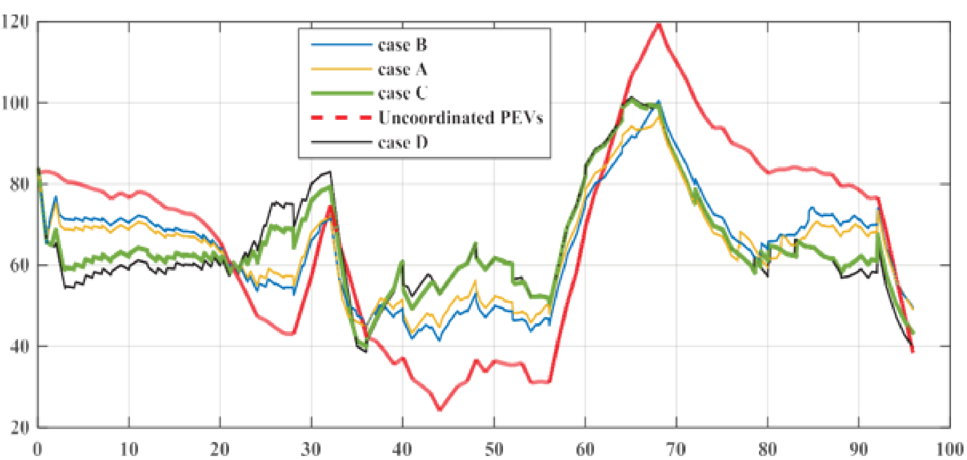

Fig.6 Impact of ANFIS prioritization on Load flattening.

In case C, only SoC is excluded from the decision inputs (of ANFIS), and the effect can be observed in terms of reduced power availability. Finally, case D resembles the collective effect of the absence of laxity and SoC on PEV power availability. In this case, ignoring laxity in decision variables causes sudden PEV charging load (for the trip purpose) and, hence, leads to deviations in ΔP even more. The effect of these four cases on ΔP(load flattening) can be seen in Fig. 6.

7. Conclusion

The integration of renewable energy sources into power grids introduces both opportunities and challenges for maintaining grid stability. As the penetration of intermittent renewable energy increases, ancillary services such as frequency regulation, voltage support, and spinning reserves become critical to ensuring grid reliability. Plug-in Electric Vehicles (PEVs) represent a promising resource for providing these ancillary services due to their energy storage capabilities and widespread availability. However, managing the charging and discharging of large fleets of PEVs in a way that balances grid needs with user convenience requires sophisticated control mechanisms. This paper proposed a novel priority-based control mechanism designed to optimize PEV participation in grid ancillary services. The control system dynamically assigns priorities to PEVs based on factors such as state of charge (SOC), user trip schedules, grid service requirements, and the availability of distributed generation from renewable sources. By prioritizing PEVs with higher flexibility and grid service potential, the mechanism ensures that grid demands are met without compromising the mobility needs of vehicle owners. Simulation results demonstrated that the proposed priority-based control system can significantly enhance grid stability, reduce operational costs, and facilitate the efficient integration of renewable energy.

Furthermore, the mechanism successfully balances the trade-offs between grid performance, user convenience, and battery health, reducing the risks of excessive battery degradation. This approach provides a pathway for PEVs to play a central role in future smart grids, enabling them to function as active contributors to grid management. Future work could explore the real-world implementation of this control mechanism, including the development of incentive structures to encourage greater user participation and the incorporation of real-time energy pricing models. Additionally, expanding the system to include more advanced vehicle-to-grid (V2G) capabilities could further enhance the role of PEVs in supporting grid operations.

In conclusion, the proposed priority-based control mechanism represents a significant step toward unlocking the potential of PEVs in grid ancillary services, contributing to a more resilient, sustainable, and efficient energy system.

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