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Flexibility estimation of electric vehicles and its impact on the future power grid

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ABSTRACT

Electric vehicles offer environmental benefits but pose challenges to power grids during peak demand. This study introduces a method to optimize electric vehicle charging and incorporate vehicle-to-grid technology, aiming to minimize electricity costs and electric vehicle loads during peak periods. Two models are developed to evaluate electric vehicle owners' willingness to participate in both non-vehicle-to-grid and vehicle-to-grid scenarios, providing insights into future peak demand increases and potential reductions through optimization.

A case study in Texas, USA, utilizing data from the Pecan Street database, reveals that by 2030, the increase in peak electric vehicle charging demand could exceed the current levels by over 4.7 times. This surge is up to 3.16% of the total electricity demand in Texas. However, with the implementation of the proposed optimization methods, electric vehicles could potentially feed about 747 MWh of energy back into the grid, effectively transforming them from energy consumers to suppliers during high-demand periods. This demonstrates the crucial role that electric vehicles, coupled with strategic charging and vehicle-to-grid technologies, can play in not only mitigating emissions but also in enhancing grid stability and efficiency.

1. Introduction

The 21st Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) held in Paris in 2015, was a pivotal event where the Paris Agreement was adopted, marking a global commitment to reducing carbon emissions and addressing climate change. This conference catalyzed an upsurge in the adoption of renewable energy worldwide [1].

Despite ongoing efforts, the automotive sector remains a major contributor to greenhouse gas emissions, with an average vehicle emitting over 5 tons annually [2]. To combat this, there has been a significant global shift towards electric vehicles (EVs), marked by a notable increase in sales. In 2019, EV sales reached 2.1 million units [3]. By 2023, this number had skyrocketed to approximately 14 million [4], over six times the sales figures from 2018; additionally, nearly 18% of all car sales in 2023 were electric [5]. This robust growth indicates the rapid expansion of the EV market.

However, this surge in EVs presents its own set of challenges for the electrical grid, leading to concerns about increased peak demands and the potential for grid overloading [6]. This issue highlights the importance of examining the impact of EVs on peak energy demand to ensure a reliable energy supply [7].

Grid operators are tasked with a dual challenge: providing an adequate supply to meet increasing demand and confirming that the infrastructure, both in terms of transmission and distribution networks, is robust enough to support this growth. In residential areas, the focus is more acute on distribution networks, which must consider the grid's operational flexibility. Operational flexibility is the grid's ability to swiftly adapt to changing energy demands and supply while maintaining a steady and reliable service. This encompasses the control and forecast of distributed energy resources (DERs), quick adaptation to demand and supply shifts, ensuring system stability through inertia and frequency regulation, implementing demand response (DR) initiatives, leveraging smart grid technologies, utilizing energy storage, and enforcing supportive grid policies and market mechanisms.

In this paper, we intend to project the anticipated demands of EV charging in the next few years, with a particular focus on how DR and vehicle-to-grid (V2G) strategies could shape this demand. The analysis provided aims to equip grid operators with essential data for informed decision-making, allowing for proactive updates to the grid. This forward-planning is crucial for accommodating the expected rise in EV adoption while maintaining grid reliability and efficiency.

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Nomenclature

Abbreviations:

CDDPG:	Control Deep Deterministic Policy Gradient
C-VF:	Coordinated Valley-Filling
C-VF-PS:	Coordinated Valley-Filling and Peak-Shaving
DRL:	Deep Reinforcement Learning
DSOs:	Distribution System Operators
EV:	Electric Vehicle
ERCOT:	Electric Reliability Council of Texas
FOMO:	Fear of Missing Out
HEMS:	Home Energy Management Systems
IoT:	Internet of Things
LTSA:	Long-Term System Assessment
ML:	Machine Learning
PV:	Photovoltaic
SHINES:	Sustainable and Holistic Integration of Energy Storage and Solar Photovoltaics
SoC:	State of Charge
ToU:	Time-of-Use
UNFCCC:	United Nations Framework Convention on Climate Change
V2G:	Vehicle-to-Grid
ZCMES:	Zero-Carbon Multi-Energy System

Indices and Sets

h:	Home index, where $h \in \{H\}$ and H represents the set of all homes
t:	Time step index, where $t \in \{1, \dots, T\}$ and T is the total number of time steps
i:	Appliance index, where $i \in \{I\}$ and I represents the set of all appliances
d:	Day index, where $d \in \{D\}$ and D represents the total number of days
s:	Scenario index, with $s = \{s1, s2\}$

Parameters and Variables:

β_t:	Incentive given to customer at time t
β_t^{max}:	Maximum possible incentive rate at time t
$C_{h,EV}^{s1}, C_{h,EV}^{s2}, C_{h,EV}^{s3}$:	Total electricity costs for the EV in home h in scenarios 1, 2, and 3, respectively
$C_{h,EV}^{bat}$:	Capacity of home h's EV battery
$\Delta E_{EV,current}^{opt,peak}$:	Current EV peak demand reduction after optimization
$\Delta E_{EV,future}^{opt,peak}$:	Future EV peak demand reduction after optimization
$E_{EV,current}^{bl,peak}$:	Current baseline peak energy consumption without optimization
$E_{EV,current}^{opt,peak}, E_{EV,future}^{opt,peak}$:	Current and future energy consumption of EVs within the peak period
η^{ch}, η^{dis}:	Charging and discharging efficiency of the battery
$N_{EV}^{dataset}, N_{EV}^{state}, N_{EV}^{future}$:	Number of EVs in the dataset, currently in the state, and expected in the future
P^{opt}, P^{ch}, P^{dis}:	The power consumption of the EV after optimization, the average charging power, and the discharging power, respectively
$SoC, SoC^{min}, SoC^{max}$:	State of Charge of the EV, and minimum and maximum acceptable SoC
$t_{h,d,beg}^{opt}, t_{h,d,end}^{opt}$:	Beginning and ending time for EV optimization at home h on day d
t_{beg}, t_{end}:	Beginning and ending time of peak periods
T_{peak}:	Time periods designated as peak periods by the DR provider
V^{aux}:	Auxiliary variables
$\tau^{ahead,max}, \tau^{delay,max}, \tau^{ahead,act}, \tau^{delay,act}$:	Maximum allowable and actual time shifts ahead of and delays from the original charging schedule in the baseline
τ^{max}:	The maximum allowable and actual time deviation from the original operation schedule
$\rho_t^{ToU}, \rho_t^{feed-in,EV}, \rho_t^{feed-in,EV,max}$:	Time-of-Use tariffs, feed-in tariffs for EVs at time t, and maximum feed-in tariffs for EVs at time t
ρ_t^{DAM}:	Day-ahead market tariffs at time t
m_1, m_2:	Weighting factors for economic concerns in Scenario 1, time deviation concerns in Scenario 1, respectively
$n1, n2, n3$:	Weighting factors for incentive concern, V2G reward concern, and inconvenience due to scheduling differences in Scenario 2, respectively
$u^{opt,ch}, u^{opt,dis}, u^{bl,ch}$:	Binary indicators of the EV's charging and discharging status under optimized and baseline schedules
$\omega_{h,EV,d,t}^{s1}, \omega_{h,EV,d,t}^{s2}$:	Willingness of home h's EV owners on day d at time t in Scenarios 1 and 2

2. Literature review

The reliability of power grids, essential for meeting consistent and growing energy demands, faces substantial challenges, particularly during crises. A notable instance was the 2021 winter storm in Texas, leading to extensive power outages and escalated energy costs [8]. In addressing such challenges, strategies to enhance grid reliability are increasingly important. DR strategies, especially those involving EVs, are emerging as a key solution. This paper explores the role of EVs in enhancing grid reliability, examining the potential benefits and the necessary technological advancements.

2.1. Electric vehicle strategies for enhancing grid reliability

EVs offer promising strategies for improving the reliability of power grids. Through innovative technologies such as optimal charging and V2G systems, they contribute significantly to immediate grid stability concerns and the long-term development of sustainable and resilient energy systems. The following subsections explore various facets of EV integration, detailing how they assist in building a more robust and efficient power grid.

One key aspect of this integration is the V2G concept, which not only helps in reducing peak energy demand but also provides financial benefits for EV owners. This concept has been effectively demonstrated in Shanghai's V2G systems sensitivity analysis [9]. Moreover, smart charging and V2G in microgrids have shown a considerable reduction in peak demand [10]. The V2G Logical Control algorithm, focusing on cost minimization, has also displayed considerable savings in charging costs [11].

To enhance grid reliability, optimizing storage capacity is crucial for managing peak demand. Techniques like Monte Carlo simulation play a vital role in assessing how various parameters affect storage optimization [12]. Ref. [13] illustrates how EV charging stations can stabilize the grid by integrating with renewable energy and storage systems. Furthermore, V2G technology extends beyond load management, offering ancillary services such as grid frequency and voltage regulation, which are cost-effective solutions [14]. The integration of solar power with EV batteries to reduce peak demand represents another innovative strategy [15]. The Zero-Carbon Multi-Energy System (ZCMES) concept categorizes electricity usage of EVs into electric, heating, and cooling applications, optimizing charging and discharging schedules while addressing the uncertainties associated with renewable energy sources [16].

2.1.1. Machine learning in electric vehicle charging optimization

As the landscape of EV integration evolves, machine learning (ML) technologies, particularly Deep Reinforcement Learning (DRL), are emerging as pivotal tools in optimizing EV charging processes. DRL models, leveraging neural networks, are adept at adapting to real-time pricing to optimize charging schedules, thereby reducing costs [17]. Techniques like safe DRL ensure efficient EV charging scheduling, guaranteeing a full charge at departure while also minimizing costs [18]. The Control Deep Deterministic Policy Gradient (CDDPG) algorithm, for instance, is designed to meet specific State of Charge (SoC) requirements while keeping costs low, without the necessity of a full battery charge at departure [19]. The integration of the Internet of Things (IoT) with EV charging, as explored in [20], facilitates the identification of optimal charging stations, taking into account factors like cost and distance. Additionally, DRL is employed to minimize the total charging time at public stations [21]. Predictive analytics-based ML strategies also play a significant role in optimizing V2G operations, thereby leading to considerable energy savings [22].

The study by Qiu et al. highlights that most EVs are charged at residential locations [23], with the assumption that each residential property is equipped with its own charging facility. This assumption eliminates the need to consider several factors that are typically relevant in non-residential settings. These factors include the availability of charging facilities, the waiting time for charging, the level of charging power, and the proximity to charging stations.

This reduction in complexity and training requirements for ML methods in residential charging scenarios leads to a preference for simpler, conventional algorithms. Home charging, being simpler and more direct compared to public or commercial charging scenarios, creates an ideal setting for the use of less complex algorithms, such as mixed-integer programming.

2.1.2. Conventional algorithms for electric vehicle charging optimization

Efficient optimization of EV charging schedules can be achieved through conventional algorithms like mixed-integer programming. These algorithms aim to minimize energy costs for EV owners and manage peak demand for grid operators, ensuring a balance between the dynamic needs of power grids and EV usage [24]. A prominent example is the robust V2G framework that employs a two-layer control algorithm, which not only reduces EV charging costs but also stabilizes grid voltage and frequency, enhancing grid reliability [25].

The consideration of battery degradation in charging schedules is another important aspect, and the study in [26] offers insights for sustainable EV operation. To improve energy consumption efficiency, strategies like Coordinated Valley-Filling (C-VF) and Peak-Shaving (C-VF-PS) have been developed to reduce load variance [27]. The feasibility of rescheduling EV charging to off-peak hours to alleviate grid stress and offer cost benefits is also being explored [18]. Furthermore, the integration of renewable energy sources, such as photovoltaic (PV) systems, with EV charging infrastructure is examined to encourage sustainable energy use and lessen dependence on conventional power sources [28]. These conventional algorithms and strategies play a vital role in enhancing EV charging optimization and contribute significantly to the progression towards more sustainable energy systems.

The algorithms of EV optimization are only one side of the spectrum. On the other hand, EV owners' willingness will significantly influence EV flexibility.

2.1.3. Electric vehicle owners' willingness impact on electric vehicle flexibility

EV owners' participation in DR programs is a crucial part of broader customer engagement in such initiatives [29]. To better understand this participation, numerous studies have employed Home Energy Management Systems (HEMS). These systems are essential for investigating demand flexibility in residential homes, including the specific demand flexibility associated with EVs. This paper concentrates on EV flexibility.

EV flexibility primarily encompasses the implementation of optimal charging schedules to reduce peak electricity demand, known as EV demand flexibility [30]. This strategy not only alleviates grid load during peak times but also includes the ability of EVs to return energy to the grid via V2G technology, thereby enhancing grid stability and efficiency [31]. Additionally, HEMS play a pivotal role in this ecosystem. They not only manage EV charging but also shift the operation of household appliances from peak to off-peak hours. This showcases their effectiveness in automated energy management [32] and in integrating residential PV systems to optimize EV charging [33].

However, the efficiency of HEMS is often hindered by the absence of smart control for individual appliances in many residential homes. This limitation underscores the importance of customer participation and willingness in successful DR programs. The unpredictability of customer energy use decisions significantly affects EV flexibility [34], making accurate assessment of customer willingness crucial for reliable flexibility estimation and to prevent incorrect energy demand forecasts that could jeopardize grid reliability [35].

Customer willingness to participate in DR programs is influenced by several factors. Incentives play a key role in shaping willingness within incentive-based DR programs [34]. Additionally, factors like consumer habits, demand-side management through smart technologies, regulatory policies, and technical interventions including ML and gamification for personalized recommendations influence customer behavior in energy conservation [35]. Demographic elements such as income, age [36], and location also affect energy use behavior [37]. Furthermore, consumer behavior in DR programs is influenced by financial and environmental motivations, trust in and familiarity with technology, perceived risks and control, the complexity and effort required for participation, and individual user characteristics and routines [38]. However, Ref. [39] focuses on designing customer willingness at the appliance level but overlooks the aspect of customer willingness related to the fear of missing out (FOMO) on savings [40], a significant factor in enhancing customer response to discounts.

To address these challenges, we propose a methodology to assess willingness at the appliance level, considering economic, comfort, and adaptation factors, aiming to enhance the effectiveness of DR programs. This methodology will be detailed in Section 3.

2.2. Research gaps and contributions

Our research aims to address several significant gaps in the current research of EV integration into power grids. These gaps underscore critical areas that require further exploration to develop effective grid management strategies, especially as EV adoption continues to rise rapidly.

2.2.1. Research gaps

- **Challenges in Modeling EV Demand during Peak Periods**: Despite numerous studies exploring EV flexibility, there remains a notable gap in estimating accurately EV peak demand with the increasing EV adoption. The complexity of predicting EV charging demand during peak periods [41] underscores the need for models that accurately account for future uncertainties and complexities [42], including EV owners' charging behaviors [43].
- **Customer Willingness in DR Programs**: The willingness of customers to participate in EV DR programs, particularly in residential settings, is crucial. Assumptions of ideal customer responsiveness can pose significant risks to grid reliability. It is essential to incorporate real-world behaviors such as the FOMO phenomenon to more accurately reflect customer behavior and improve participation rates in DR programs.
- **Adjusting Incentive Rates to Enhance EV Flexibility**: While incentive rates in DR programs are designed to encourage customer participation, there is limited research on how these rates can be strategically adjusted to influence EV flexibility and, consequently, enhance the reliability of distribution networks. This gap signifies the need for detailed studies on the optimization of incentive structures to maximize their effectiveness.
- **Future Energy Consumption of EVs**: Research on the future energy consumption of EVs is crucial but remains limited. As the number of EVs continues to grow, this increase in energy demand could significantly challenge the grid [44]. While short-term EV charging demand has been forecasted [45], few studies focus on long-term forecasting of EV charging demand and its flexibility in the future. Understanding and planning for these long-term needs are essential to ensure grid stability and prevent supply shortages.

Addressing these gaps through rigorous empirical research and advanced modeling techniques is fundamental to developing robust grid management strategies that can adapt to the evolving landscape of vehicle electrification.

2.2.2. Contributions

This study focuses on evaluating future EV charging demand and its flexibility through optimal charging schedules and V2G technologies. These areas are critical in relation to DR programs and for assessing the long-term impact of EV adoption on grid stability. Utilizing real-world charging data, the research will analyze peak demand scenarios under various conditions and investigate barriers to EV owner participation in DR programs. This comprehensive approach is designed to equip grid operators, distribution system operators (DSOs), and electricity retailers with strategies necessary to manage the escalating EV charging demand effectively. Ultimately, the research aims to provide actionable guidance to grid operators and policymakers, facilitating informed decisions for grid reinforcement and expansion plans. This initiative is crucial for developing robust grid management strategies that can adapt to the evolving landscape of vehicle electrification, ensuring a resilient and efficient energy infrastructure.

The contributions of this paper are as follows:

- **Modeling EV Demand during Peak Periods:** This study utilizes real-world charging data to accurately model and predict future EV charging demand under various scenarios. This addresses the significant gap in estimating the EV charging peak demand under the continued increasing EV adoption, where the complexities [41], uncertainties [42], and customer behaviors [43] are considered in the model. The approach could help grid operators and policymakers in making informed decisions about grid reinforcement and expansion strategies.
- **Improving Customer Participation in DR Programs:** The accuracy of estimating EV flexibility is enhanced by developing two equations for EV owners' willingness that incorporate the FOMO phenomenon. This contribution addresses the gap concerning ideal customer responsiveness and its risks to grid reliability, reflecting more realistic customer behavior in DR programs.
- **Impact of Incentive Rates on EV Flexibility:** A comprehensive sensitivity analysis is carried out to investigate how different incentive rates affect EV flexibility and the reliability of distribution networks. This responds to the identified gap where few studies have explored the adjustment of incentive rates to influence EV flexibility effectively.
- **Exploring Future Energy Consumption of EVs:**This study examines potential energy reductions achievable through optimal charging schedules and V2G technologies to address the gap concerning future energy consumption of EVs and its impact on grid supply [44]. This analysis prepares grid operators, DSOs, and retailers for the challenges posed by increasing numbers of EVs.
- **Case Study Analysis:** Case studies are carried out that provide insights into barriers to EV owner participation in DR programs and strategies to mitigate these challenges. This contribution complements the above theoretical findings and offers actionable recommendations for enhancing grid management and customer engagement in DR initiatives.

These contributions collectively address the gaps in literature and practice by providing comprehensive, empirically supported solutions and strategies for effective integration of EVs into the power grid.

The following paper is organized as follows: Section 3 outlines the methodology, detailing approaches for analyzing future EV charging demand and flexibility during peak periods. Section 4 presents two case studies on the financial background and incentive impacts on EV flexibility and charging costs. Section 5 summarizes the key findings, discusses implications, and suggests future research directions.

3. Methodology

In this section, the methodology is outlined for optimizing EV operations. This includes investigating EV flexibility through optimal charging schedules and V2G technology, as well as forecasting future EV charging demand and potential load reduction during peak periods.

3.1. Problem introduction and assumptions

This study uses real-time data from Pecan Dataport, a comprehensive database capturing minute-level electricity consumption patterns for various appliances, including EV charging sessions [46]. The energy consumption of an EV in the hth household is defined as the baseline scenario, where the EV solely draws energy from the grid without V2G interaction or optimized charging schedules.

Key assumptions in this study are:

- EVs are parked, powered off, and ready for charging or V2G when not in use.
- All EVs are fully charged at the end of each baseline charging session, equating the energy drawn from the grid to the energy used since the last charge.
- All EVs will remain undriven after their charging or discharging periods end on that day.

3.2. Scenario introduction

Based on the baseline, two scenarios are developed to minimize EV charging costs and enhance demand flexibility:

Scenario 1: Optimal Charging Schedules without V2G

- Utilizes a nonlinear model and a genetic algorithm to generate optimal charging schedules.
- Offers incentives for energy reduction during peak periods, encouraging customer participation in DR programs.

Scenario 2: Integration of V2G Technology

- Incorporates both optimal charging schedules and V2G technology.
- Rewards customers for selling electricity back to the grid, enhancing demand flexibility.

In both scenarios, assuming that the availability of charging and V2G facilities when EVs are parked. The study aims to minimize daily charging costs for EV owners over a fixed number of days $[0, D]$, with D representing the total days and T time steps within each day at interval Δt. The dataset covers H households, each potentially owning one EV. Peak periods, denoted as T_{peak}, are set by the DR provider based on area energy consumption.

3.3. Scenario 1: Optimal charging schedules without vehicle-to-grid

In Scenario 1, the objective is to explore the impact of optimal charging schedules on EVs, especially excluding V2G technology. The focus is on evaluating EV flexibility, particularly in terms of the power consumption after optimization, $P^{opt}_{h,EV,d,t}$. This metric is calculated for each household h across various days d and time intervals t, post-optimization, as shown in (1):

$$P^{opt}_{h,EV,d,t} = u^{opt,ch}_{h,EV,d,t}\omega^{s1}_{h,EV,d,t}P^{ch}_{h,EV} + u^{bl,ch}_{h,EV,d,t}(1-\omega^{s1}_{h,EV,d,t})P^{ch}_{h,EV} \tag{1}$$

Here, the variables $u^{bl,ch}_{h,EV,d,t}$ and $u^{opt,ch}_{h,EV,d,t}$ are binary indicators of the EV's charging status under baseline and optimized schedules, respectively. The average charging power of the EV at home h is denoted as $P^{ch}_{h,EV}$. The critical factor in this scenario is the decision of EV owners to either comply with the optimized charging schedule or stick to regular charging patterns, significantly influencing the power consumption, $P^{opt}_{h,EV,d,t}$.

A key aspect of this study is the 'willingness' of EV owners to switch to these optimized charging schedules, represented by $\omega^{s1}_{h,EV,d,t}$. This willingness, crucial for evaluating the adoption of optimal charging strategies, is developed from Eq. (3) in [39] and is described in (2).

$$\omega^{s1}_{h,EV,d,t} = m_1\frac{(\beta_t)^2}{(\beta^{\max}_t)^2} + m_2\frac{\beta_t}{\beta^{\max}_t}f_{h,EV,d,t} \tag{2}$$

In (2), β_t represents the incentive rate provided by electricity retailers to customers at time t, and $\beta^{\max}_t$ denotes the maximum incentive rate that retailers can offer to customers. Note that $\beta^{\max}_t$ in this paper is determined by the average difference between the retail ToU prices for customers and the day-ahead market prices in the wholesale market during peak periods, as shown in Eq. (26). The parameters m_1 and m_2 weigh economic considerations and time deviation concerns, respectively. The flexibility of the charging schedule is captured by $f_{h,EV,d,t}$, which is outlined in (3):

$$f_{h,EV,d,t} = \begin{cases} \frac{\left|\tau^{ahead,max}_{h,EV,d,t} - |\tau^{ahead,act}_{h,EV,d,t}|\right|}{|\tau^{ahead,max}_{h,EV,d,t}|}, & \text{if } |\tau^{ahead,act}_{h,EV,d,t}| > 0 \\ \frac{\left|\tau^{delay,max}_{h,EV,d,t} - |\tau^{delay,act}_{h,EV,d,t}|\right|}{|\tau^{delay,max}_{h,EV,d,t}|}, & \text{if } |\tau^{delay,act}_{h,EV,d,t}| > 0 \\ 1, & \text{if } \tau^{ahead,act}_{h,EV,d,t} = 0, \\ & \quad \& \quad \tau^{delay,act}_{h,EV,d,t} = 0 \end{cases} \tag{3}$$

Here the term $\frac{\tau^{\max}_{h,i,t} - |\tau^{\text{act}}_{h,i,t}|}{\tau^{\max}_{h,i,t}}$ from [39] is substituted with a similar one in (3). This change is made to address the potential inaccuracies in the EV charging schedule. The original equation considers the maximum deviation ($\tau^{max}_{h,i,t}$) between the optimal and baseline schedules, which could result in inaccuracies when EVs are actively being used.

To cope with it, $\tau^{max}_{h,i,t}$ is split into two components: the maximum allowable shift ahead of time ($\tau^{ahead,max}_{h,i,t}$) and the maximum allowable delay time ($\tau^{delay,max}_{h,i,t}$). This split allows EV owners to preset these values based on the knowledge of when the EVs will be in use, thereby avoiding inaccurate schedules generated by the optimization process.

Similarly, the actual time deviation ($\tau^{act}_{h,i,t}$) is divided into the actual time ahead of the baseline operation time ($\tau^{ahead,act}_{h,i,t}$) and the actual delay time from the baseline operation time ($\tau^{delay,act}_{h,i,t}$). This division enables the application of different conditions for more accurate scheduling.

The first term in (2) reflects the impact of economic incentives on customer decisions. This term uses the square of the ratio of the current incentive to the maximum possible incentive, introducing a nonlinear emphasis on the importance of the retailer's incentive. This squared ratio is a key aspect of the equation, highlighting the principle of increasing marginal significance based on consumer behavior. In retail and e-commerce, there is evidence that as discounts or incentives near their maximum levels, consumers experience a heightened sense of urgency and perceive higher value, often due to diminishing marginal utility and the FOMO phenomenon seen in market trends [40]. This reaction is not simply linear; the incremental value of an offer nearing its peak resonates strongly with consumers, leading to a disproportionately large response. For instance, during peak discount events like Black Friday, consumer purchasing behavior intensifies significantly compared to other days with marginally lower discounts. This is because the FOMO on substantial savings drives a surge in purchases. The squared term in the equation reflects a particular behavioral detail: as incentives get closer to their maximum possible value, customers become increasingly likely to react. However, this reaction is not straightforward or proportional; it changes at a rate that is not consistent as the incentives increase [47].

The second term in (2) addresses the effect of incentives, suggesting that EV owners might be less motivated to respond in the absence of such benefits. With the incentive, customer response will be based on the consideration of the inconvenience level.

This scenario also ensures that EVs receive a sufficient charge by requiring the charging duration in the optimized schedule to match the baseline, as mandated by constraint (4).

$$\sum_{t=1}^{T} u^{\text{bl,ch}}_{h,EV,d,t} = \sum_{t=1}^{T} u^{\text{opt,ch}}_{h,EV,d,t} \tag{4}$$

Furthermore, to ensure continuous charging, Eq. (5) mandates alignment of the charging process with the baseline period. This involves setting the optimization beginning ($t^{opt}_{h,d,beg}$) and ending time ($t^{opt}_{h,d,end}$) within a permissible time range, which are adjusted to accommodate the maximum allowable shifts. In Scenario 1, where no V2G activity occurs, the EV is required to charge continuously, which is consistent with the baseline.

$$\begin{aligned} &\sum_{t=t^{\text{opt}}_{h,d,\text{beg}}}^{t^{\text{opt}}_{h,d,\text{end}}-\left(\sum_{a=1}^{T} u^{\text{bl,ch}}_{h,\text{EV},d,a}-1\right)} u^{\text{opt,ch}}_{h,\text{EV},d,t}u^{\text{opt,ch}}_{h,\text{EV},d,t+1} \\ &u^{\text{opt,ch}}_{h,\text{EV},d,t+2}\cdots u^{\text{opt,ch}}_{h,\text{EV},d,t+\left(\sum_{a=1}^{T} u^{\text{bl,ch}}_{h,\text{EV},d,a}-1\right)} \geq 1 \end{aligned} \tag{5}$$

Assuming the EV is charged only once a day. If the binary variable $u^{opt,ch}_{h,EV,d,t}$ is equal to 1, then the EV is charging at time t, otherwise it equals 0 and EV is not charging at time t.

For the EV to maintain continuous charging within the optimization periods, there should be at least $\sum_{t=1}^{T} u^{bl,ch}_{h,i,t}$ consecutive times where $u^{opt,ch}_{h,i,t}$ equals 1, between the optimization beginning time ($t^{opt}_{h,d,beg}$) and the optimization ending time ($t^{opt}_{h,d,end}$). Therefore, the sequence $u^{opt,ch}_{h,EV,d,t}$, $u^{opt,ch}_{h,EV,d,t+1}$, $u^{opt,ch}_{h,EV,d,t+2}$, $\ldots$, $u^{opt,ch}_{h,EV,d,t+\left(\sum_{a=1}^{T} u^{bl,ch}_{h,EV,d,a}-1\right)}$ should all be equal to 1, ensuring that the EV continues to charge without interruption.

However, this equation introduces a mixed-integer nonlinear constraint, impacting optimization efficiency. To address this, we introduce a new auxiliary variable $V^{aux}_{h,\text{EV},d,t}$ as follows:

$$V^{aux}_{h,\text{EV},d,t} = u^{opt,ch}_{h,EV,d,t}u^{opt,ch}_{h,EV,d,t+1}u^{opt,ch}_{h,EV,d,t+2}\cdots u^{opt,ch}_{h,EV,d,t+\left(\sum_{a=1}^{T} u^{bl,ch}_{h,EV,d,a}-1\right)},$$

where $t = t^{opt}_{h,d,beg}, t^{opt}_{h,d,beg}+1, t^{opt}_{h,d,beg}+2, \ldots, t^{opt}_{h,d,end} - (\sum_{a=1}^{T} u^{bl,ch}_{h,EV,d,a} - 1)$. It is worth noting that $\sum_{a=1}^{T} u^{\mathrm{bl,ch}}_{h,\mathrm{EV},d,a}$ is the total charging time of the day for the EV. When EV charging optimization starts. Then, Eq. (5) can be linearized using Eqs. (6)–(8).

$$V^{aux}_{h,\mathrm{EV},d,t} \le u^{\mathrm{opt,ch}}_{h,\mathrm{EV},d,t+k},\ \text{where } k = 0,1,2,\ldots,\left(\sum_{a=1}^{T} u^{\mathrm{bl,ch}}_{h,\mathrm{EV},d,a} - 1\right) \tag{6}$$

$$V^{aux}_{h,\mathrm{EV},d,t} \ge \sum_{k=0}^{\sum_{a=1}^{T} u^{\mathrm{bl,ch}}_{h,\mathrm{EV},d,a}-1} u^{\mathrm{opt,ch}}_{h,\mathrm{EV},d,t} - \sum_{a=1}^{T} u^{\mathrm{bl,ch}}_{h,\mathrm{EV},d,a} + 1 \tag{7}$$

$$\sum_{t=t^{opt}_{h,d,beg}}^{t^{opt}_{h,d,end}-\left(\sum_{a=1}^{T} u^{bl,ch}_{h,EV,d,a}-1\right)} V^{aux}_{h,\mathrm{EV},d,t} \ge 1 \tag{8}$$

Note that Eqs. (6)–(7) ensure that $V^{aux}_{h,EV,d,t} = 1$ if and only if all of $u^{opt,ch}_{h,EV,d,t+k}$ are all 1, where $k = 0,1,\ldots\left(\sum_{a=1}^{T} u^{\mathrm{bl,ch}}_{h,\mathrm{EV},d,a} - 1\right)$.

This formulation improves the efficiency of the optimization by linearizing this constraint, while still ensuring continuous charging during the specified periods.

The practical application of these constraints means that if an EV starts charging at a particular time under the optimized schedule, it should continue for the same duration as outlined in the baseline. Thus, depending on the time shifts, different cases of (3) are utilized. For instance, if a baseline schedule has an EV charging from 1:00 pm to 3:00 pm and the customer allows a one-hour earlier shift, the optimized schedule could run from 12:30 pm to 2:30 pm. In this case, the actual time deviation for charging earlier is considered, while the delay deviation is disregarded, applying the first case of (3) for power consumption calculations.

To encourage EV owners to respond, the objective is to minimize the EV charging cost, $C^{s1}_{h,EV}$, of home h over D days, as calculated in (9). In the big parentheses, the first part calculates the EV charging costs, including the EV following the optimal charging schedule and following the schedule in the baseline. The second part is the incentive provided to the EV owners, who shift the EV charging schedule from peak periods T_{peak} to other periods.

$$\min C^{s1}_{h,EV} = \sum_{d=1}^{D} \Bigg\{ \sum_{t=1}^{T} P^{opt}_{h,EV,d,t} \rho^{ToU}_{t} \Delta t - \sum_{t\in T_{peak}} \omega^{s1}_{h,EV,d,t} P^{ch}_{h,EV} \beta_t (u^{bl,ch}_{h,EV,d,t} - u^{opt,ch}_{h,EV,d,t}) \Delta t \Bigg\} \tag{9}$$

The current energy consumption of EVs in the dataset within the peak period T_{peak} in Scenario 1, $E^{opt,s1,peak}_{EV,current}$, is

$$E^{opt,s1,peak}_{EV,current} = \sum_{h=1}^{H} \sum_{d=1}^{D} \sum_{t\in T_{peak}} P^{opt}_{h,EV,d,t} \Delta t \tag{10}$$

By comparing the current peak energy consumption in the baseline and in Scenario 1, the peak demand reduction, $\Delta E^{opt,s1,peak}_{EV,current}$, is,

$$\Delta E^{opt,s1,peak}_{EV,current} = E^{bl,peak}_{EV,current} - E^{opt,s1,peak}_{EV,current} \tag{11}$$

where the peak demand in the baseline is calculated as,

$$E^{bl,peak}_{EV,current} = \sum_{h=1}^{H} \sum_{d=1}^{D} \sum_{t\in T_{peak}} u^{bl,ch}_{h,EV,d,t} P^{ch}_{h,EV} \Delta t \tag{12}$$

Assume the current total number of EVs in the state, N^{state}_{EV}, and the expected total number of EVs in the future, N^{future}_{EV}, are known. Additionally, the current total number of EVs in the dataset, $N^{dataset}_{EV}$, is obtained from the data. Since the current EV energy consumption in the dataset $E^{opt,s1,peak}_{EV,current}$ is calculated by (10), the average EV energy consumption in the dataset is $\frac{E^{opt,s1,peak}_{EV,current}}{N^{dataset}_{EV}}$. Assuming the average energy consumption of EV will be the same in the future, the peak energy consumption with increased EVs in the future, $E^{opt,s1,peak}_{EV,future}$, is,

$$E^{opt,s1,peak}_{EV,future} = \frac{N^{future}_{EV}}{N^{dataset}_{EV}} E^{opt,s1,peak}_{EV,current} \tag{13}$$

Therefore, comparing with the current peak energy consumption $E^{bl,peak}_{EV,current}$ in the baseline, the increment of EV peak energy consumption in the future without optimization, $\Delta E^{bl,peak}_{EV,future}$, is calculated as,

$$\Delta E^{bl,peak}_{EV,future} = \frac{N^{future}_{EV}}{N^{dataset}_{EV}} E^{bl,peak}_{EV,current} - \frac{N^{state}_{EV}}{N^{dataset}_{EV}} E^{bl,peak}_{EV,current} \tag{14}$$

where the first part is the future energy consumption without optimization (the same as the baseline) in the future, and the second part is the current energy consumption without optimization in the state. Moreover, the peak demand increment after optimization, $\Delta E^{opt,s1,peak}_{EV,future}$, is,

$$\Delta E^{opt,s1,peak}_{EV,future} = E^{opt,s1,peak}_{EV,future} - \frac{N^{state}_{EV}}{N^{dataset}_{EV}} E^{bl,peak}_{EV,current} \tag{15}$$

3.4. Scenario 2: Integration of vehicle-to-grid technology

In Scenario 2, not only optimal charging schedules but also V2G technology is applied to increase demand flexibility from EVs. The average discharging power of an EV battery under V2G is denoted by $P^{dis}_{h,EV}$. It is crucial to note that the battery cannot perform charging and discharging operations concurrently. Therefore, two binary variables are introduced. One is $u^{opt,ch}_{h,EV,d,t}$ for the optimal charging schedule, which has been introduced in Scenario 1. Another variable is the optimal discharging schedule for V2G, $u^{opt,dis}_{h,EV,d,t}$. It is equal to 1 when the battery is discharging, and 0 when it is not. The relationship is mathematically formulated as shown in (16).

$$u^{opt,ch}_{h,EV,d,t} + u^{opt,dis}_{h,EV,d,t} \le 1 \tag{16}$$

Note that it is permissible for both $u^{opt,ch}_{h,EV,d,t}$ and $u^{opt,dis}_{h,EV,d,t}$ to be equal to 0 from (16), which indicates an idle scenario.

The SoC of the EV at home h during time step t, denoted as $SoC_{h,EV,d,t}$, is determined based on (17) when the EV is stationary and connected for charging or V2G.

$$SoC_{h,EV,d,t} = SoC_{h,EV,d,t-1} + (u^{opt,ch}_{h,EV,d,t} P^{ch}_{h,EV} \eta^{ch}_{h} \Delta t - \frac{u^{opt,dis}_{h,EV,d,t} P^{dis}_{h,EV}}{\eta^{dis}_{h}} \Delta t)/C^{bat}_{h,EV} \tag{17}$$

In (17), the parameter, $C^{bat}_{h,EV}$, represents the capacity of the EV battery. The charging efficiency and discharging efficiency of the battery are denoted by η^{ch}_{h} and η^{dis}_{h}, respectively.

When the EV is ready to drive away, the SoC should be within the acceptable range as in (18).

$$SoC^{min}_{h,EV} \le SoC_{h,EV,d,t^{opt}_{h,d,end}} \le SoC^{max}_{h,EV} \tag{18}$$

When an EV owner is unwilling to take the optimal schedule, the EV will keep charging as in the baseline. Similarly, if the EV is unwilling to sell electricity to the grid via V2G, there is no V2G because no V2G is applied in the baseline. According to the survey in [48], when SoC is less than 0.55, customers will charge EVs because of range anxiety. Moreover, the average EV daily trip in the U.S. is less than 50 km [49]. It is also pointed out that the popular EV model in the market is Telsa Model 3, and its standard model can drive 491 km [50]. Considering driving behaviors, and traffic conditions, the real range is about 360 km. Therefore, to ensure energy for trips of the next day, 15% of capacity is added to the minimum allowable energy in this paper. That is, the minimum SoC of the battery, $SoC^{min}_{h,EV}$, is set as 70%. Besides, to increase the battery life, the maximum SoC of the battery, $SoC^{max}_{h,EV}$, is set as 80% [51].

Besides, to enhance the model's accuracy in predicting EV demand over D days, the SoC at the initial time when the EV is parked and begins to charge or discharge on day d, denoted as $t^{opt}_{h,d,beg}$, is introduced. Considering that all EVs in the dataset are fully charged at the end of each baseline charging session, it is assumed that the EV's energy usage (including trips and other energy consumption by in-car facilities such as air conditioners, audio systems, etc.) is equivalent to the energy charged from the grid on the current day, expressed as $\sum_{t=1}^{T} u^{bl,ch}_{h,EV,d,t} P^{ch}_{h,EV} \eta^{ch}_{h} \Delta t$. A random input, varying from 10% to 100%, is applied to the SoC for the first day (d=1). Subsequently, the $SoC_{h,EV,d,t^{opt}_{h,d,beg}}$ for the following days will be determined (19).

$$SoC_{h,EV,d,t^{opt}_{h,d,beg}} = SoC_{h,EV,d-1,t^{opt}_{h,d-1,end}} - \frac{\sum_{t=1}^{T} u^{bl,ch}_{h,EV,d,t} P^{ch}_{h,EV} \eta^{ch}_{h} \Delta t}{C^{bat}_{h,EV}} \quad \text{if } d > 1, \tag{19}$$

The objective function (20) in Scenario 2 is similar to the one in (9) for Scenario 1.

$$\min C^{s2}_{h,EV} = \sum_{d=1}^{D} \Bigg\{ \sum_{t=1}^{T} [u^{opt,ch}_{h,EV,d,t} \omega^{s2}_{h,EV,d,t} P^{ch}_{h,EV} \rho^{ToU}_{t} + u^{bl,ch}_{h,EV,d,t} (1-\omega^{s2}_{h,EV,d,t}) P^{ch}_{h,EV} \rho^{ToU}_{t} - u^{opt,dis}_{h,EV,d,t} \omega^{s2}_{h,EV,d,t} P^{dis}_{h,EV} \rho^{feed-in,EV}_{t}] \cdot \Delta t - \sum_{t \in T_{peak}} \omega^{s2}_{h,EV,d,t} P^{ch}_{h,EV} \beta_t (u^{bl,ch}_{h,EV,d,t} - u^{opt,ch}_{h,EV,d,t}) \Delta t \Bigg\} \tag{20}$$

In both cases, the goal is to minimize the charging costs incurred to the EV owner at home h.

The EV electricity charging price, ρ^{ToU}_{t}, is usually a time-of-use (ToU) tariff. The feed-in price is denoted by $\rho^{feed-in,EV}_{t}$, and the willingness of EV owners to apply optimal charging schedule and V2G is represented by $\omega^{s2}_{h,EV,d,t}$. In (20), the charging costs of the EV are divided into two parts: the cost under optimal charging schedules and the cost under baseline schedules. Scenario 2 involves both V2G and optimal charging schedules. Therefore, the cost function (20) must also take into account the benefit obtained by customers from selling electricity back to the grid. This benefit is represented in the third part of the equation, which accounts for the revenue generated by selling electricity to the grid. The final part of the equation represents the reward received by EV owners for participating in the DR program, utilizing the optimal charging schedules and the incentive rate β_t. It is important to note that this incentive is only provided during peak periods. The willingness of EV owners to participate in V2G and the optimal charging schedule is expressed as (21),

$$\omega^{s2}_{h,EV,d,t} = n_1 \frac{(\beta_t)^2}{(\beta^{\max}_t)^2} + n_2 \frac{\rho^{feed-in,EV}_{t}}{\rho^{feed-in,EV,max}_{t}} \frac{\beta_t}{\beta^{\max}_t} + n_3 \frac{\tau^{max}_{h,EV,d,t} - |\tau^{act}_{h,EV,d,t}|}{|\tau^{\max}_{h,EV,d,t}|} \frac{\beta_t}{\beta^{\max}_t} \tag{21}$$

where n_1, n_2, and n_3 are the weighting factors for incentive concern, V2G reward concern, and inconvenience concern (due to the difference between the optimal charging schedule and the schedule in the baseline), respectively. The maximum EV feed-in price is denoted by $\rho^{feed-in,EV,max}_{t}$. The reason that the feed-in prices are considered in (21) is to account for the impact on electricity costs for EV owners. Noted that the EV owner can sell the electricity to the grid all day; however, the incentive is only granted to customers who shift charging schedules from peak periods to other periods. Therefore, the total peak energy consumption $E^{opt,s2,peak}_{h,EV,current}$ of EVs at home h in Scenario 2 is calculated as follows.

$$E^{opt,s2,peak}_{h,EV,current} = \sum_{d=1}^{D} \Bigg\{ \sum_{t \in T_{peak}} [u^{opt,ch}_{h,EV,d,t} \omega^{s2}_{h,EV,d,t} P^{ch}_{h,EV} + u^{bl,ch}_{h,EV,d,t} \cdot (1-\omega^{s2}_{h,EV,d,t}) P^{ch}_{h,EV} - u^{opt,dis}_{h,EV,d,t} \omega^{s2}_{h,EV,d,t} P^{dis}_{h,EV}] \Delta t \Bigg\} \tag{22}$$

The total energy consumption consists of three components: the energy obtained from the grid according to the optimal charging schedules, the energy obtained from the grid following the same schedule as the baseline, and the energy sold back to the grid. By comparing the current peak energy consumption in the baseline and Scenario 2, the peak demand reduction in Scenario 2, $\Delta E^{opt,s2,peak}_{EV,current}$, is,

$$\Delta E^{opt,s2,peak}_{EV,current} = E^{bl,peak}_{EV,current} - \sum_{h=1}^{H} E^{opt,s2,peak}_{h,EV,current} \tag{23}$$

where the peak energy consumption $E^{bl,peak}_{EV,current}$ in the baseline is calculated by (12). The future peak energy consumption with increased EVs and V2G strategies, $E^{opt,s2,peak}_{EV,future}$, is,

$$E^{opt,s2,peak}_{EV,future} = \frac{N^{future}_{EV}}{N^{dataset}_{EV}} \sum_{h=1}^{H} E^{opt,s2,peak}_{h,EV,current} \tag{24}$$

By comparing the current energy consumption in the state, the future peak energy increment is calculated as (25),

$$\Delta E^{opt,s2,peak}_{EV,future} = E^{opt,s2,peak}_{EV,future} - \frac{N^{state}_{EV}}{N^{dataset}_{EV}} E^{bl,peak}_{EV,current} \tag{25}$$

3.5. Flow chart of electric vehicle optimization

This section outlines the EV optimization process illustrated by Fig. 1.

The process begins with the input of electricity prices (including ToU and feed-in prices from electricity retailers) and EV data from a database. The data include the power consumption of EVs at each time step, sourced from [46]. The optimization process considers EV owners' preferences for maximum allowable time deviations from their original schedules $\tau^{ahead,max}_{h,EV,d,t}$, $\tau^{delay,max}_{h,EV,d,t}$, and $\tau^{max}_{h,EV,d,t}$. The incentive rate is predetermined. The home index (h) and day index (d) are set to 1. The optimization model involves two main scenarios:

Scenario 1: Optimal Charging Scheduling Only

This scenario generates an optimal charging schedule to minimize electricity costs for home h. It ensures the total and continuous charging time (See (4) and (5)).

Scenario 2: Optimal Charging Scheduling with V2G

This scenario generates both charging and discharging schedules. It ensures the SoC remains within allowable limits when the EV is disconnected (See (18)).

If any constraint is not met, the optimization process restarts to generate a new optimal schedule. If all constraints are met, the process records the daily electricity costs, the willingness of home h's EV owners at each time t on day d, the SoC of the battery in Scenario 2, and the optimal charging or discharging schedule.

The process then checks if day d equals the total days for simulation, D. If not, d is incremented by 1, and the optimization repeats for the next day. If $d = D$, then d is reset to 1 and h is incremented by 1, to start the optimization for the next home. This process continues until h exceeds H, indicating that all homes have minimized their electricity costs.

After that, all data on the current and future number of EVs are input to the optimization model. This allows the calculation of EV flexibility in the dataset (See (10) for Scenario 1, (23) for Scenario 2) and the future peak demand increment without optimization (See (14) for Scenario 1, (24) for Scenario 2). After optimization, the future peak demand increment is recalculated (See (15) for Scenario 1, and (25) for Scenario 2).

Finally, the potential for future EV flexibility is calculated, demonstrating the impact of optimization on peak demand reduction. Note that the optimization problem can be solved by the 'ga' solver in Matlab.

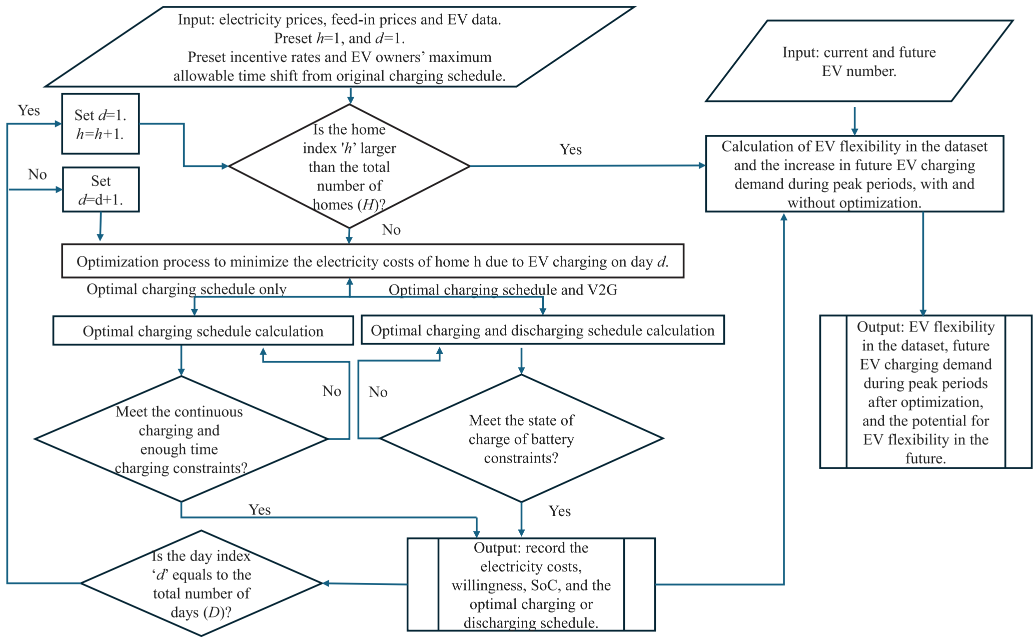

Fig. 1. Flow chart of EV optimization.

4. Case study

This section outlines our case studies designed to assess the impact of EVs on grid stability and electricity demand. We utilize detailed data from the Pecan Street Dataport [46], examining how increased EV adoption influences grid management and energy consumption patterns. These studies are crucial for developing strategies that effectively accommodate rising EV numbers while ensuring grid efficiency and reliability.

4.1. Current and future electric vehicle numbers

By August 1, 2023, there are over 211,000 registered EVs in Texas, U.S. [52]. The Electric Reliability Council of Texas (ERCOT), the independent system operator for Texas, uses its Long-Term System Assessment (LTSA) [53] to forecast that this number could grow to 1 million by 2030 [54]. This forecast is crucial for planning the expansion of Texas's extra-high voltage (345-kV) system over the next ten to fifteen years to ensure the grid can handle the expected increase in demand. The accurate assessment of the impact on grid reliability due to this projected surge in EV numbers is increasingly important. By utilizing current and projected EV numbers, along with EV charging data from our dataset, the present and future EV charging demand and flexibility in Texas are estimated. This estimation is conducted using (13) and (15) for Scenario 1, and (24) and (25) for Scenario 2.

Two simulations are conducted using high-resolution data from Austin, Texas, sourced from Pecan Street Dataport [46]. The data include energy usage recorded each minute from 98 homes, with approximately 96 EVs involved. It encompasses a broad spectrum of EV models, from new to old, which enables the modeling of energy consumption patterns across a diverse array of EV models. This diversity supports the accurate calculation of average energy consumption.

Additionally, the EV numbers are listed in Table 1, which also includes data on the present and estimated future registrations of EVs in Texas, U.S.

4.2. Case studies on electric vehicle flexibility and incentive impact

This subsection conducts two case studies using the previously discussed data. These studies explore how EV flexibility in response to electricity demand varies across different socioeconomic regions and how changes in incentive rates can impact EV integration strategies.

Table 1
EV Numbers [46,52,54].

EVs in the dataset	Current EVs in Texas	Projected EVs in Texas by 2030
96	211,000	1,000,000

4.2.1. Case study 1: Electric vehicle flexibility across income levels

This case study utilizes historical data to assess EV flexibility during peak electricity demand across regions with varying income levels. By analyzing energy usage patterns and integration strategies in diverse economic backgrounds, we explore how socioeconomic factors affect the adoption of optimization strategies like optimal charging schedules and V2G technology.

4.2.2. Case study 2: Impact of incentive rates on electric vehicle integration

Following insights from our data analysis, this case study conducts a sensitivity analysis to evaluate how different incentive rates affect EV flexibility, the electricity costs of EV owners, and the future peak demand increment due to EVs. This analysis provides essential insights for grid operators, DSOs, and electricity retailers, aiding in the preparation and management of the rising prevalence of EVs. The findings underscore how incentive adjustments could enhance grid management and support a transition to a more sustainable and efficient energy system.

4.3. Electricity tariffs

Electricity pricing and feed-in rates, as provided by Austin Energy, one of the main electricity suppliers in Austin, are detailed in Table 2 [55]. Austin Energy is also part of the "Sustainable and Holistic Integration of Energy Storage and Solar Photovoltaics" (SHINES) project, which aims to improve methods of electrical generation, delivery, and consumption. This project incorporates a wide range of resources, including utility-scale energy storage systems, residential and commercial energy storage systems, smart inverters, real-time data transmission, a distributed energy resource optimizer, and a V2G component [56].

Within the SHINES project spearheaded by Austin Energy, the feed-in price for V2G technology is aligned with the residential solar energy rate, both adjusted to 9.7¢/kWh as part of the retailer's secondary

Table 2
Electricity tariff [55–57].

Period	Time	ToU tariff (Summer)	Feed-in tariffs from the retailer	Maximum feed-in tariffs from the retailers
Peak Period	15:00-18:00	\$0.16616/kWh	\$0.09700/kWh	\$0.14000/kWh
Other Period	00:00-14:59	\$0.09256/kWh	\$0.09700/kWh	\$0.14000/kWh
	18:01-23:59	\$0.09256/kWh	\$0.09700/kWh	\$0.14000/kWh

Table 3
Weighting factors [58].

Weighting factors	Rich Areas	Poor Areas
m_1	0.1450	0.3610
m_2	0.8550	0.6290
n_1	0.1450	0.3610
n_2	0.4275	0.3145
n_3	0.4275	0.3145

SHINES programs [55]. This rate, set by Austin Energy, is a strategic decision to encourage the adoption of renewable energy sources and V2G technologies among its customers.

However, it is important to note that the maximum feed-in price for this case study is capped at 14¢/kWh, as determined by the ERCOT, which operates the grid in Texas. ERCOT's setting of this higher rate serves as the upper limit for feed-in tariffs in the region, under which Austin Energy operates and sets its own rates for the SHINES project [57].

Additionally, the maximum incentive rate in this paper is calculated as (26), where ρ_t^{DAM} is the electricity prices in the day-ahead market, obtained from Energy Online, managed by LCG Consulting [59].

$$\beta_t^{\max} = \frac{\sum_{t=t_{\text{beg}}}^{t_{\text{end}}} \left(\rho_t^{ToU} - \rho_t^{DAM} \right)}{t_{end} - t_{beg} + 1} \tag{26}$$

Eq. (26) represents that $\beta_t^{\max}$ is calculated as the average discrepancy between the ToU prices and day-ahead market prices among the peak periods. The reason for this is that retailers can benefit from DR programs when the incentive rate does not exceed the average difference between the ToU retail prices charged to customers and the day-ahead market wholesale prices paid by retailers. In this paper, the day-ahead market prices for June 1st, 2021, were selected, and based on the calculations, $\beta_t^{\max}$ is determined to be \$0.12.

4.4. Weighting factors of willingness to respond

Since a city or a state must include varieties of rich suburbs, poor suburbs, and mixed suburbs, the weighting factors' values are set as Table 3 [39], where m_1 and m_2 are used in Scenario 1, applying only optimal charging schedules for shifting peak demand. The rest of the weighting factors (n_1, n_2 and n_3) are applied in Scenario 2, where the EV can not only shift the charging schedules but also sell electricity to the grid.

4.5. Simulation results

To compare the EV flexibility in scenarios 1 and 2, two examples of a weekly EV energy consumption for low-income areas are shown in Figs. 2 and Fig. 3.

Fig. 2 illustrates the total energy consumption of EVs before and after optimization in Scenario 1. The gray dash-dotted line represents the weekly energy consumption of all EVs in the dataset, while the blue solid line denotes the target energy consumption, reflecting the total energy without considering willingness.

As shown in Fig. 2, there is a noticeable spike in energy consumption from day 0 to day 1 during the peak period, indicating that this is when energy consumption reaches its highest level for the day. After optimization, this peak shifts slightly earlier, occurring just before the peak period.

It is important to note that EVs are optimized only near or during peak periods. In periods without optimization, the total energy consumption after optimization (represented by the blue curve) and the baseline energy consumption (represented by the gray curve) remain the same. This rule also applies to the total energy consumption that considers willingness (represented by the red curve). These trends could be illustrated and observed by the small dots (in blue and red) along the gray curve.

Fig. 2 shows the total energy consumption of EVs before and after optimization in Scenario 1. The gray dash-dotted curve represents the weekly energy consumption of all EVs in the dataset, while the blue solid line represents the target energy consumption, reflecting total energy consumption without considering willingness after optimization. As shown in Fig. 2, from day 0 to day 1, there is a noticeable spike during the peak period, indicating that this time experiences the highest energy consumption of the day. After optimization, this peak shifts slightly earlier, occurring just before the peak period.

Taking into account customers' willingness to engage in DR programs, some customers choose to adopt the new charging schedules, while others stick to the baseline schedules. Examining the red dotted line in Fig. 2 (total energy consumption with consideration of willingness), it becomes evident that during peak periods, the red curve is lower than the gray curve (baseline), but higher than the baseline and lower than the blue curve (desired energy consumption) during the periods slightly ahead of the peak periods.

Note that optimization only occurs near or during the electricity peak periods. In periods without optimization, the total energy after optimization (blue curve) matches the baseline energy consumption (gray curve), as no adjustments are made. This also applies when considering willingness. This pattern is indicated by small dots (blue and red) along the gray curve, highlighting areas of consistent energy consumption.

Similarly, in Fig. 3, the total energy consumption of EVs before and after optimization in Scenario 2 is depicted. The gray, blue, and red curves represent the total energy of EVs in the baseline, without and with consideration of willingness, respectively. In contrast to Fig. 2, the blue curve in Fig. 3 during peak periods does not remain at 0 kWh; instead, it shows negative values, indicating that EVs are supplying electricity through V2G to the grid during peak periods to gain benefits. As EVs discharge during peak times, more energy is required to charge them outside of these peak periods to satisfy the constraint in (18). Consequently, the blue curve in Figs. 3 exhibits higher spikes compared to Fig. 2 in the time leading up to peak periods.

In summary, Figs. 2 and 3 illustrate energy consumption in scenarios 1 and 2. Considering customer willingness reveals the disparity in total energy consumption compared to scenarios without such consideration. Neglecting customer willingness in DR programs can yield inaccurate outcomes for retailers, DSOs, and grid operators, potentially leading to wrong decision-making and posing a threat to grid stability.

4.5.1. Case study 1

This case study will examine the charging requirements of a growing number of EVs in the next few years, exploring how demand flexibility might vary under various scenarios. Additionally, it will investigate how demand flexibility varies across different financial sectors when subjected to a uniform incentive rate of \$0.05 per kWh.

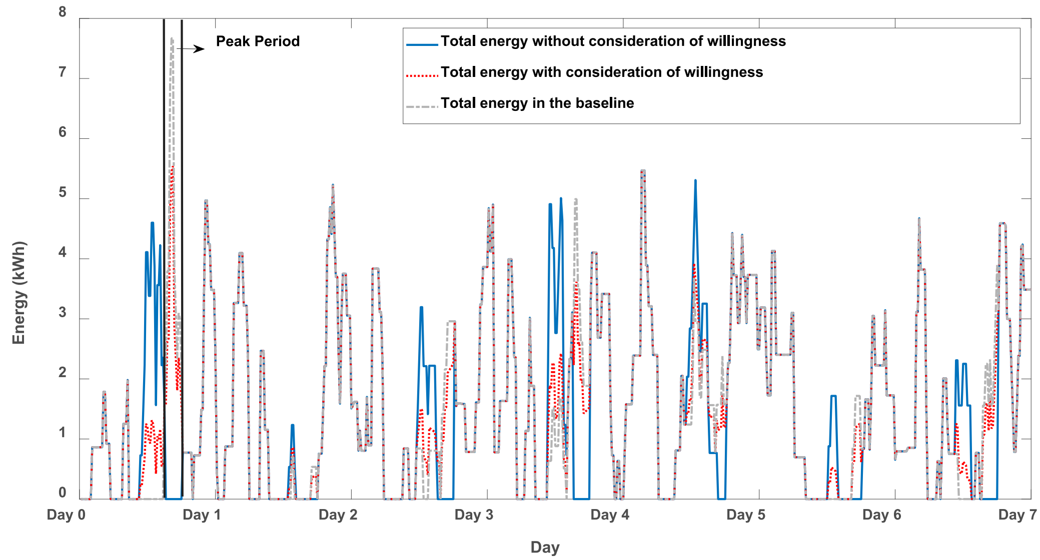

Fig. 2. Energy curve of low-income areas in Scenario 1.

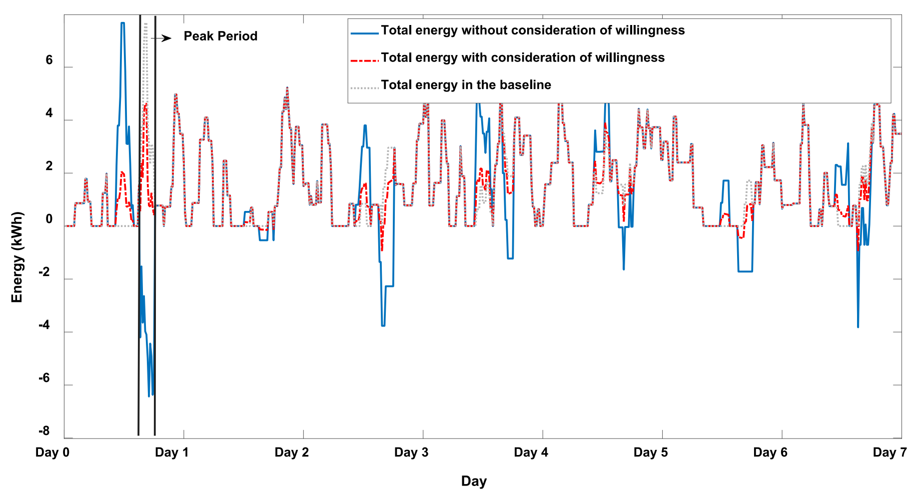

Fig. 3. Energy curve of low-income areas in Scenario 2.

Table 4
Analysis of weekly energy consumption and charging costs of EVs for high-income areas, with future prediction.

Scenario Index	Baseline	Scenario 1	Scenario 2
Incentive rate ($/kWh)	0	0.05	0.05
Current peak demand of the dataset (kWh)	162.340	118.614	85.023
Current peak demand reduction of the dataset (kWh)	0	43.726	77.316
Current total energy of the dataset (kWh)	1036.291	1036.291	1004.118
Current total energy consumption reduction of the dataset (kWh)	0	0	32.173
Current total cost of the dataset ($)	108.155	102.889	87.431
Current total cost reduction of the dataset ($)	0	5.266	20.724
Current peak demand in Texas (MWh)	356.902	260.772	186.923
Future peak demand in Texas (MWh)	1691.037	1235.566	885.659
Future peak demand increment in Texas (MWh)	1334.135	878.664	528.757

Table 4 provides a comprehensive overview of the weekly energy consumption and charging costs of EVs in high-income areas, along with future predictions. This table reveals significant differences in charging costs and peak energy reduction between scenarios 1 and 2. Specifically, in Scenario 1, there is a decrease in charging costs from $108.155 to $102.889, amounting to a reduction of 4.869%. In contrast, Scenario 2 showcases a more substantial decrease in these costs, lowering them to $87.431, which represents a 19.161% reduction from the baseline. The greater cost reduction observed in Scenario 2 can be attributed to the opportunity afforded to EV owners to sell electricity back to the grid at a feed-in price during peak periods, a feature that is absent in Scenario 1.

Moreover, the impact on peak demand reduction is more obvious than the cost reduction. Scenario 1 achieves a 26.935% reduction in peak demand, while Scenario 2 reaches 47.626%. This significant disparity highlights the effectiveness of V2G technology. V2G contributes

Table 5
Analysis of weekly energy consumption and charging costs of EVs for low-income areas, with future prediction.

Scenario Index	Baseline	Scenario 1	Scenario 2
Incentive rate ($/kWh)	0	0.05	0.05
Current peak demand of the dataset (kWh)	162.340	112.396	75.531
Current peak demand reduction of the dataset (kWh)	0	49.944	86.809
Current total energy of the dataset (kWh)	1036.291	1036.291	1000.404
Current total energy consumption reduction of the dataset (kWh)	0	0	35.887
Current total cost of the dataset ($)	108.155	102.336	86.259
Current total cost reduction of the dataset ($)	0	5.819	21.896
Current peak demand in Texas (MWh)	356.902	247.102	166.052
Future peak demand in Texas (MWh)	1691.037	1170.794	786.772
Future peak demand increment in Texas (MWh)	1334.135	813.892	429.870

to a higher current peak demand reduction of 77.316 kWh, surpassing the overall reduction of 32.173 kWh. The reason for this discrepancy is the requirement for EVs to maintain sufficient SoC as (18).

Additionally, in Scenario 1, the absence of total energy reduction is due to the implementation of only optimal EV charging schedules, which shift peak demand by charging EVs outside of peak periods. In contrast, Scenario 2 utilizes both optimal charging schedules and V2G technology, resulting in decreases in both peak demand and total energy consumption. In Scenario 2, due to the constraint of (18), EV batteries are only allowed to charge within an acceptable range, falling short of a full charge.

The above results discussed are based on the current number of EVs in the dataset. Considering Texas' registered EV count of 211,000, these vehicles currently consume an estimated 356.9 MWh of energy. Without optimization, the total peak demand by EVs is expected to rise to 1691.037 MWh by 2030, assuming the number of EVs in Texas reaches 1 million. This represents a more than fourfold increase, posing a substantial challenge to the grid's energy supply. However, the application of demand management strategies significantly mitigates this increase in peak demand. Under Scenario 1, the expected future peak energy demand is reduced to 1235.566 MWh, while Scenario 2 further reduces it to 885.659 MWh.

Compared with the current peak demand in Texas in the baseline, the increment in peak demand is 878.664 MWh for Scenario 1. However, this increase is notably lower in Scenario 2, at only 528.757 MWh. This comparison highlights the effectiveness of optimal charging schedules for EVs in reducing peak energy demand. Furthermore, incorporating V2G technology enhances this effect, further increasing EV flexibility.

Given these findings, it becomes evident that policies and promotional strategies by electricity retailers, DSOs, or grid operators are crucial. These strategies should aim to encourage EV owners to participate in demand reduction, such as optimal charging schedules and V2G programs. Through these methods, the pressure on the grid supply can be substantially reduced, contributing to a more sustainable and stable energy future as the adoption of EVs continues to increase.

Additionally, Table 5 lists the weekly energy consumption and charging costs of EVs for low-income areas with future predictions. The analysis in Table 5 shows that with the same incentive rates, low-income areas have greater EV flexibility compared to high-income areas (as indicated in Table 4). Specifically, in low-income areas under Scenario 1, peak demand of EVs is reduced by 49.944 kWh, amounting to 30.765% of the peak demand in the baseline. This reduction is more significant than in high-income areas, where the reduction is only 26.934% of the baseline. In Scenario 2, the peak demand reduction in low-income areas reaches 86.809 kWh, which is 9.493 kWh higher than in high-income areas, reflecting a higher motivation to incentives in low-income areas than in high-income areas.

Moreover, this higher motivation in low-income areas also results in more substantial cost reductions: $5.819 in Scenario 1 and $21.896 in Scenario 2. These reductions exceed those in high-income areas by 10.50% in Scenario 1 and 5.66% in Scenario 2, as Table 4. As the number of EVs grows, the difference between low-income and high-income areas also expands. Currently, peak energy demand in low-income areas is 247.102 MWh in Scenario 1, 13.67 MWh lower than in high-income areas. This difference widens to 20.871 MWh in Scenario 2. By 2030, the anticipated peak demand is 1170.794 MWh in Scenario 1 and 786.772 MWh in Scenario 2 for low-income areas, marking increases of 813.892 MWh and 429.870 MWh from the current baseline, respectively. These increments are 64.772 MWh and 98.887 MWh lower than those in high-income areas in scenarios 1 and 2, respectively.

In conclusion, the comparison between Tables 4 and 5 illustrates that, with the same incentive rate, EV owners in low-income areas exhibit more EV flexibility than counterparts in high-income areas, primarily due to higher motivation to participate in DR/V2G for greater financial benefits from incentives. This discovery offers insights for grid operators, DSOs, and retailers, emphasizing the importance of considering financial factors when developing policies and promotional strategies.

4.5.2. Results comparison with the existing paper

To validate the effectiveness of our EV optimal charging scheduling and V2G model, it is crucial to compare our results, particularly regarding EV flexibility, with those of the existing literature. Ref. [60] develops an optimized scheduling model for private EV charging using an improved particle swarm optimization algorithm. Focusing on ToU electricity pricing, their model aims to minimize peak-to-valley load differences and reduce electricity costs for EV users through optimal charging schedules and V2G technology, aligning closely with our study.

Unlike our approach, Ref. [60] designs scenarios using various participation rates of EV owners, which are set at 30%, 60%, and 100%. According to their results shown in Figs. 4 and 5, with 30% of EVs participating, there is a reduction of 3735 kWh in charging demand during peak periods, which represents a 42.66% decrease from the baseline peak demand of 8755 kWh. When the participation rate increases to 60%, the reduction reaches 64.88%.

In Case Study 1 of our research, we observed that the average willingness of EV owners to participate is between approximately 30.1% and 45.55%, which results in an average reduction of about 50.55% in peak electricity demand due to EV charging during peak periods. These reductions are consistent with the results reported in [60], falling between the 42.66% and 64.88% reductions associated with 30% and 60% EV participation rates, respectively. This comparison serves to validate the accuracy of our models and our assumptions regarding owner willingness.

Moreover, according to Figure 6 in [60], with full participation from EV owners, the total EV charging demand reduction during peak periods could be about 7750 kWh, accounting for an 88.5% reduction of the peak demand. Applying the highest willingness value from our study (45.55%) suggests that their approach could potentially reduce peak demand by 40.31%. However, this 40.31% is significantly lower than the 50.55% peak demand reduction achieved in our study, underlining

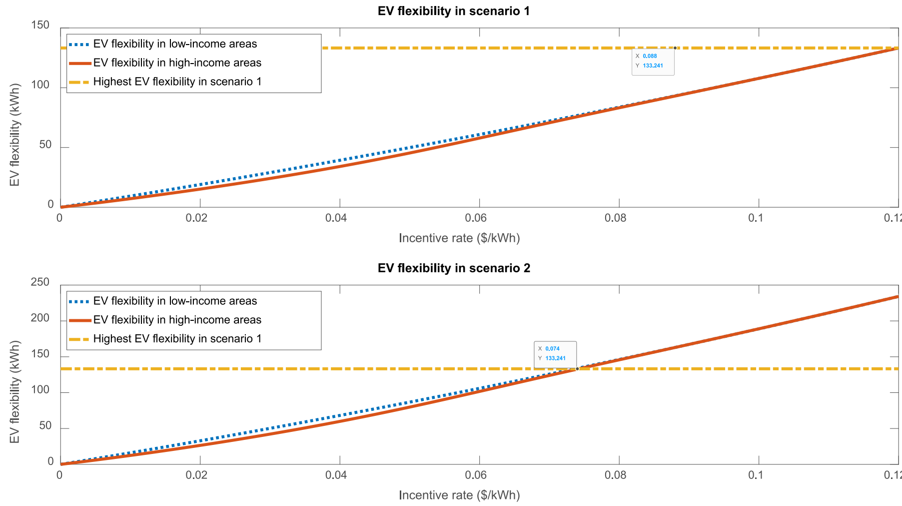

Fig. 4. Sensitivity analysis of EV flexibility in the dataset.

the enhanced effectiveness of our approach in increasing EV flexibility during peak periods.

It is noteworthy that Ref. [60] primarily uses ToU pricing to encourage EV owners to adjust their charging away from peak periods. Our study not only applies ToU pricing but also introduces additional incentives to motivate customer participation further. This comprehensive strategy significantly enhances the outcomes observed in our research, demonstrating the benefits of combining various incentives with ToU pricing.

4.5.3. Case study 2

While Case Study 1 explored the variability in EV flexibility, electricity costs, and future EV charging demands across different financial scenarios, it did not account for the impact of incentives on these factors. To bridge this gap, Case Study 2 employs a sensitivity analysis, utilizing incentive rates that increase incrementally by \$0.001/kWh at each step, starting from \$0/kWh and capping at a maximum of \$0.12/kWh, as calculated in (26). This fine-grained approach to adjusting incentive rates allows us to precisely gauge their influence on EV flexibility, electricity costs, and future peak demand from EVs. The high precision of these increments significantly enhances the sensitivity analysis by providing a detailed resolution of how slight changes in incentives can affect the system's responsiveness. This detailed insight is crucial for designing incentive schemes that are both effective and efficient, ensuring optimal participation from EV owners and maximum benefit to the grid.

Fig. 4 illustrates the trends in EV flexibility in response to increasing incentive rates across different scenarios. The red curves denote high-income areas, while the blue curves represent low-income areas. The yellow curves show the maximum achievable EV flexibility in the two scenarios, revealing that low-income areas exhibit significantly higher EV flexibility compared to high-income areas as incentive rates increase. Notably, at an incentive rate of \$0.32/kWh, the difference in EV flexibility between these areas reaches its maximum, supporting the findings from Case Study 1 which noted a higher willingness to respond in low-income areas.

As incentive rates climb to around \$0.86/kWh, the differences in responsiveness between high-income and low-income areas become less noticeable. At this level, the incentives are sufficient to motivate a similar level of engagement from both high and low-income areas, leading to comparable EV flexibility across these areas. It is crucial to highlight that EV flexibility starts at 0 kWh when there is no incentive (\$0/kWh). This occurs because EV owners lack the motivation to modify their charging behaviors in the absence of incentives, as detailed in (2) and (21). The lack of incentive influence is further reflected in the associated electricity costs and projections for future peak EV demand, as illustrated in Figs. 5 and 6.

Comparing scenarios in Fig. 4, it is evident that Scenario 2, which includes V2G technology, significantly enhances EV flexibility compared to Scenario 1. For example, while the maximum EV flexibility in Scenario 1 is 133.3 kWh, in Scenario 2 it rises to 234.3 kWh, representing approximately 75.7% increase from the flexibility observed in Scenario 1. This significant increase is due to the integration of V2G technology, which not only allows for optimal charging schedule adjustments but also enables EVs to feed electricity back to the grid during peak periods.

In Scenario 2, similar to the trends observed in low-income areas before the incentive exceeds \$0.074/kWh, the difference in EV flexibility between low and high-income areas reaches its maximum at around \$0.3/kWh. This peak corresponds to the incentive rate of \$0.32/kWh in Scenario 1, which maximizes the discrepancy in EV flexibility between the two income areas. This phenomenon indicates that while high-income areas may require significant incentives to alter their behavior, lower-income areas are more responsive at lower incentive rates, demonstrating a higher initial willingness to adapt. This similarity between the two scenarios, where one includes only optimal charging schedules (Scenario 1) and the other incorporates further V2G technology (Scenario 2), suggests that there are threshold levels of incentives beyond which both high and low-income areas noticeably change their energy consumption behaviors. This response is likely influenced by the inherent cost–benefit evaluations made by EV owners from different income areas, assessing the value of shifting their consumption relative to the incentives offered.

Similarly, Fig. 5 demonstrates the shifts in electricity costs with increasing incentives, highlighting that electricity costs of EV in Scenario 1 are higher, at about \$83.7, which is approximately \$13.6 higher than in Scenario 2. This difference arises because EV owners in Scenario 2 are compensated for contributing electricity back to the grid via V2G. A comparison of high-income and low-income areas indicates that while high-income areas are less sensitive to incentives, leading to smaller differences in EV flexibility and electricity costs, as incentives increase, low-income areas show greater responsiveness, as previously observed. Additionally, in Scenario 2, when incentive rates exceed \$0.063/kWh, electricity costs for EV owners drop below those in Scenario 1. These differences in incentive thresholds that lead to optimal outcomes in Scenario 2, as shown in Figs. 4 and 5, reflect the complex interplay between EV operations and variables such as electricity tariffs, feed-in tariffs, and rewards.

The analysis also includes future EV peak demand, as depicted in Fig. 6. Here, Scenario 2 consistently exceeds Scenario 1 in terms of

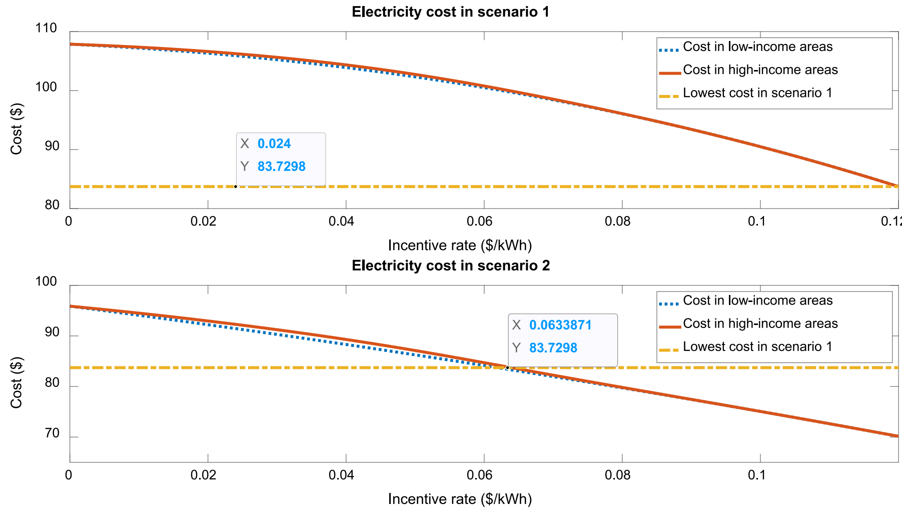

Fig. 5. Sensitivity analysis of electricity costs.

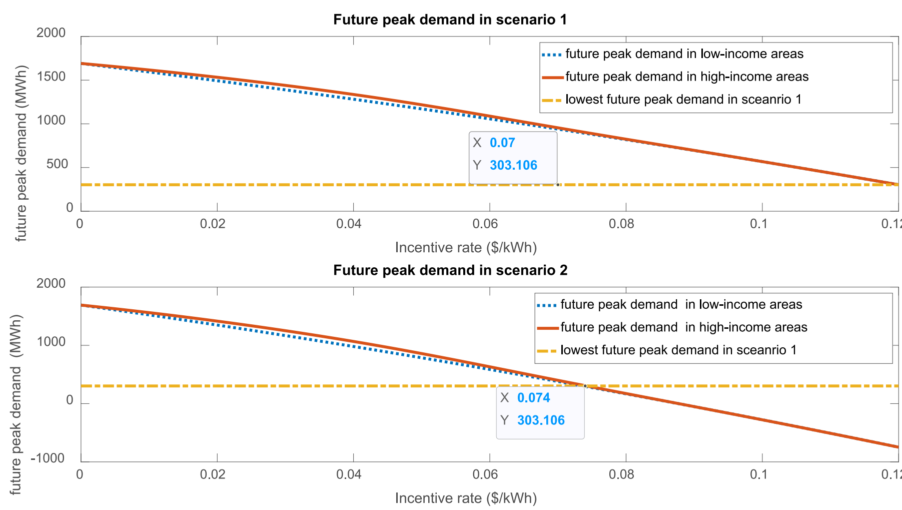

Fig. 6. Sensitivity analysis of future peak demand of EVs.

performance. Notably, in Scenario 2, the peak EV demand can become negative, dropping to a minimum of −747.646 MWh. This indicates the potential of EVs to serve as energy suppliers during peak times. When compared to Scenario 1's lowest future peak demand of 303.106 MWh, Scenario 2 offers a reduction in peak demand exceeding 1050.752 MWh. While the reduction in peak demand for Scenario 1, which falls from approximately 1691.037 MWh to 303.106 MWh (a decrease of 1387.931 MWh), is substantial, Scenario 2 shows an even greater reduction. In Scenario 2, the peak demand potentially decreases by about 2438.683 MWh when the incentive rate is at its maximum.

This scenario provides crucial insights for grid operators, DSOs, and retailers regarding the management of peak demand shortages. The findings indicate a strategic approach for maintaining grid stability: escalating incentives to a substantial level to enhance EV flexibility during acute energy shortages, and subsequently moderating these incentives to an appropriate level when the energy storage situation is less critical.

In summary, Case Study 2 highlights the significant impact of incentives on EV flexibility and electricity costs in high and low-income areas. The study reveals that increased incentives can enhance EV flexibility and reduce electricity costs and peak demand, particularly in scenarios allowing EVs to sell electricity back to the grid. These findings provide actionable insights for grid operators and policymakers, emphasizing the importance of incentive structures in optimizing EV integration into the energy system.

5. Conclusion

This paper analyzes current and future trends in electric vehicle charging demand. From our analysis, we predict a substantial increase in electric vehicle charging demand, potentially rising to five times the current levels by 2030. This surge poses significant challenges to existing grid infrastructures. To mitigate these challenges, we propose two strategies: optimal charging schedules and vehicle-to-grid technology, aimed at reducing peak charging demands and balancing grid loads.

We estimate that in the absence of optimization, electric vehicles will contribute to a peak demand of more than 1.691 GWh by 2030, an increase of 1.3 GWh over the current demand. This increase represents about 3% of the current peak demand in Texas, U.S. [61]. As the number of EVs is expected to surpass the 1 million threshold, the associated demand is likely to escalate significantly, placing substantial pressure on the grid's supply capabilities.

In response, our study designs two models to incentivize customer participation in demand response programs. These models focus on reducing electric vehicle charging costs and consider the rate of customer participation. Applying optimal scheduling could potentially decrease the peak charging demand of electric vehicles by up to 1.387

GWh. With the integration of V2G technology and optimal charging schedules, a substantial peak demand reduction of up to 2.483 GWh is achievable.

Furthermore, two case studies explore the impact of socioeconomic background and incentive rates on electric vehicle flexibility. These studies examine how variations in incentive rates significantly influence electric vehicle owner behavior and the overall demands on the grid as electric vehicle adoption increases. The insights from these case studies are invaluable for grid stakeholders tasked with effectively managing the integration of electric vehicles into energy systems. They highlight the direct effects of policy adjustments on consumer behavior and provide a deeper understanding of how these changes can influence grid stability and efficiency.

This study offers critical insights for grid operators, DSOs, and retailers on the impact of electric vehicles on the power grid. Electric vehicles play a dual role as both energy consumers and storage devices, consuming energy when demand is low and supplying energy back to the grid during high demand periods. Recognizing this dual role is essential for planning grid upgrades and devising strategies to manage potential imbalances between energy supply and demand. These strategies and insights ensure that our recommendations are not only based on realistic scenarios but are also actionable for future grid planning and policy development.

Despite the effective modeling of V2G systems and optimal charging strategies within this study, the current state of battery technology and charging infrastructure may not yet fully support the widespread implementation of these strategies. The existing battery solutions might not adequately accommodate the longevity and efficiency demands required for robust V2G applications at both system-level and node-level of the power grid, and the charging infrastructure may be insufficient for large-scale deployment. Future research should, therefore, focus on advancing battery technology and enhancing the charging infrastructure. This involves exploring battery life extension techniques, improving charging speeds, developing more durable battery components, node-level charging load impact, and expanding the charging infrastructure with smart grid functionalities to manage increased capacities effectively. Such advancements will enhance the practicality and efficiency of V2G technologies and ensure their adaptability to evolving energy systems and increasing EV penetration.

CRediT authorship contribution statement

Jiexiang Wu: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Li Li:** Writing – review & editing, Supervision, Methodology. **Jiangfeng Zhang:** Writing – review & editing, Supervision, Methodology. **Boyi Xiao:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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