

Article

Optimal Vehicle-to-Grid Strategies for Energy Sharing Management Using Electric School Buses

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Abstract: In today's power systems, electric vehicles (EVs) constitute a significant factor influencing electricity dynamics, with their important role anticipated in future smart grid systems. An important feature of electric vehicles is their dual capability to both charge and discharge energy to/from their battery storage. Notably, the discharge capability enables them to offer vehicle-to-grid (V2G) services. However, most V2G research focuses on passenger cars, which typically already have their own specific usage purposes and various traveling schedules. This situation may pose practical challenges in providing ancillary services to the grid. Conversely, electric school buses (ESBs) exhibit a more predictable usage pattern, often deployed at specific times and remaining idle for extended periods. This makes ESBs more practical for delivering V2G services, especially when prompted by incentive price signals from grid or utility companies (UC) requesting peak shaving services. In this paper, we introduce a V2G energy sharing model focusing on ESBs in various schools in a single community by formulating the problem as a leader–follower game. In this model, the UC assumes the role of the leader, determining the optimal incentive price to offer followers for discharging energy from their battery storage. The UC aims to minimize additional costs from generating energy during peak demand. On the other hand, schools in a community possessing multiple ESBs act as followers, seeking the optimal quantity of discharged energy from their battery storage. They aim to maximize utility by responding to the UC's incentive price. The results demonstrate that the proposed model and algorithm significantly aid the UC in reducing the additional cost of energy generation during peak periods by 36% compared to solely generating all electricity independently. Furthermore, they substantially reduce the utility bills for schools by up to 22.6% and lower the peak-to-average ratio of the system by up to 9.5%.

Keywords: electric school bus; vehicle-to-grid; energy sharing management; peak shaving; Stackelberg game



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1. Introduction

Today, the number of Internal Combustion Engine Vehicles (ICEVs) on the road is steadily being replaced by Electric Vehicles (EVs). This shift is facilitated by the decreasing prices of EVs, making them more affordable. EVs offer numerous advantages over ICEVs, such as their environmentally friendly nature, energy efficiency, high performance, and low maintenance costs. In the USA, approximately 58% of harmful greenhouse gas emissions come from the power and transportation sectors [1]. ICEVs contribute to emissions that are not only detrimental to the environment, causing climate change issues, but also pose health risks to humans, leading to various diseases [2].

The development of Information and Communication Technology (ICT) has led to the transformation of the traditional grid into a smart grid [3], enabling various entities to communicate and be controlled efficiently. An important aspect of this transformation is

the integration of EVs, which possess the capability of charging and discharging from/to their battery storage. As the number of EVs on the road continues to rise, coupled with advancements in modern two-way communication and control systems, the charging and discharging of EVs can be effectively controlled and managed.

Currently, research in electric vehicle (EV) technology is gaining widespread attention, with a particular focus on grid-to-vehicle (G2V) and vehicle-to-grid (V2G) systems, both of which can be considered part of energy sharing management schemes that incorporate EVs into the smart grid. In G2V research, the emphasis is on understanding the behavior of EVs and developing methods to manage and control the charging operations of EV batteries. This involves utilizing energy from sources such as the utility grid and renewable energy resources (RE). On the other hand, V2G research explores the potential of EVs to provide ancillary services to the grid by discharging energy from their batteries back into the grid. The battery storage in EVs serves as an excellent supply source capable of responding almost in real-time and can address the problem of the intermittent nature of RE [4]. V2G has the potential to support the grid with various ancillary services, including peak shaving, frequency regulation, voltage regulation, and spinning reserve [5]. EV owners can derive benefits by charging their batteries during non-peak periods when electricity prices and generation costs are low. Subsequently, they can provide V2G services to assist the grid during peak periods when electricity prices and generation costs are high.

However, the majority of G2V and V2G research primarily concentrates on personal passenger EVs. These vehicles, designed for individual transportation with diverse schedules and purposes, typically have smaller battery capacities, resulting in a lower willingness and interest to participate in ancillary services [6]. The real-world implementation of V2G programs with this type of EV may prove challenging. In contrast, electric school buses (ESBs) follow specific schedules and routes [7,8], often remaining parked in idle mode. Schools that own ESBs would find participation in V2G programs beneficial, ensuring a high willingness to engage in ancillary services. Traditionally, school buses have been powered using diesel engines, emitting harmful pollutants that can negatively impact the health of students [9], particularly young children in primary schools. However, there has been a positive shift in the transportation sector. The price of electric buses (EBs) has decreased significantly compared to several years ago, particularly in the early 2000s [1]. This reduction in cost, coupled with growing environmental awareness, has led to initiatives in the USA aimed at transforming 500,000 diesel buses into electric ones [10]. This transformative effort aligns with the broader goal of fostering cleaner and more sustainable school transportation. Due to their predictability and substantial battery storage capacities, ESBs are well-suited for providing V2G services. This makes them a compelling choice for contributing to grid stability and benefiting both schools and the UC.

Typically, generated electricity needs to be matched all the time with the electric demand. When multiple high-consumption electric appliances are simultaneously activated, it can result in a surge in overall energy demand, leading to peak periods. During these peak periods, UCs are required to operate peak-generation power plants, incurring significant expenses to meet the additional demand. These peak power plants are not only economically inefficient; they are also environmentally harmful [11].

To tackle this challenge, a potential solution involves offering peak shaving services to various groups of EVs or battery packs. The UC can leverage the fast response capabilities of energy storage units on the demand side to discharge stored energy into the grid. This approach assists the UC in mitigating peak demand and reducing additional costs. Electric vehicles, for instance, can be charged at lower prices during non-peak demand periods and discharge energy back to the grid during peak demand periods, such as early evening, offering benefits for their participation in this program. Given the suitability of ESBs for providing peak shaving services, they should play an important role in peak shaving programs. However, a single ESB may not be capable of discharging a sufficient amount of energy to participate in such a program. Therefore, it is essential for a school, which

can aggregate the discharged energy from multiple ESBs within its location, to act as a participant in peak shaving programs.

In this paper, we introduce a novel V2G model for a peak shaving problem that incorporates ESBs inside schools within a community. The problem is formulated as a Stackelberg game, where the UC assumes the role of a leader. The UC issues information about the peak shaving program, particularly the incentive unit price offered to schools for providing the service. The UC aims to minimize the additional cost associated with meeting peak demand. Simultaneously, schools in the community act as followers, negotiating the optimal discharged energy from their ESBs and determining the discharge hours during peak periods to maximize their utility.

The main contributions of this paper can be summarized as follows:

- A V2G model incorporating ESBs in a community is proposed which includes the additional cost model of UC and the utility model of schools that possess a number of ESBs. The UC tries to minimize the additional cost to cover peak demand periods, while schools in a community try to maximize their utility using the stored energy inside their ESBs.
- A two-level Stackelberg game model is introduced to capture the interaction between two types of players, that is a UC and schools who possess a number of ESBs, both of the players trying to negotiate to establish the optimal incentive price and the discharged energy for the peak shaving program. Also, the existence and uniqueness of the Stackelberg equilibrium is proven and guaranteed.
- The optimal energy-price (OEP) equilibrium algorithm is introduced to achieve the Stackelberg equilibrium, where no player can increase their utility by unilaterally changing their strategies from this equilibrium.

This paper is structured as follows: Section 2 provides a literature review of related works. Section 3 outlines the system model of the proposed V2G model, including the UC and the school model. In Section 4, the Stackelberg game is detailed. This section covers the game formulation, the proof of existence and uniqueness, and the algorithm to achieve equilibrium. The simulation results are presented and discussed in Section 5. Finally, Section 6 provides conclusions and possible future research directions.

2. Related Works

This section provides a review of the literature related to G2V and V2G research for various types of EVs, including personal passenger EVs, Electric Taxis (ETs), Electric Buses (EBs), and Electric School Buses (ESBs).

Research in the field has predominantly concentrated on personal passenger cars for both G2V and V2G operations. Several studies have made explorations into G2V research, particularly incorporating personal EVs [12–17]. In [12], the authors proposed a G2V model between the grid and groups of personal EVs using a non-cooperative game between the personal EVs and the energy supplier. In this model, the grid aims to maximize its revenue with limited supplied energy, while the personal EVs aim to minimize their charging cost. The proposed algorithm was introduced and assessed through simulations, demonstrating that the EVs in the proposed model can obtain higher utility compared to PSO and equally distributed methods. A power scheduling scheme for an EV charging station (CS) is proposed in [13]. The paper analyzes the benefits for multiple parties by formalizing the problem as a game theory interaction between CS and EV users. The results reveal that the proposed power management scheme is feasible for an actual environment, reducing the electricity cost by up to 8.6%. The authors in [14] proposed a charging scheme focused on public EV CS, aiming to determine the charging time, pairing between CS-EVs, and pricing using game theory along with a matching algorithm. The findings indicate that the proposed scheme can enhance the performance of the charging system. In [15], a study on the EV charging problem in intelligent transportation systems was conducted, consisting of CS and EGVs, where CS aims to maximize its revenue, and EVs aim to find the proper CS with the lowest charging cost, considering the willingness of the EVs. This work

proposed the LOBACH algorithm to find the optimal solution, which was then compared to existing works, where it outperformed other approaches. A novel charging scheme for EVs inside smart communities integrated with RE is proposed in [16]. The authors consider three parties in the model: the grid, aggregators (AGGs), and EVs, where a trust model is introduced to enable EVs to select an AGG for charging, as information needs to be shared between each entity involved. The analysis results show that the proposed scheme is effective compared with traditional schemes. The authors in [17] presented a charging strategy for EV CS equipped with Photovoltaic (PV) panels, considering day-ahead pricing. They introduce a profit model for CS operators and a cost model for EVs. This work studies the model using a game-theoretic approach. The proposed model is verified through results that show an increase in CS operator profit and reduced charging cost for EVs.

On the other hand, there are studies in the literature on V2G research [18–21]. The work in [18] presents a utility maximization algorithm for the V2G scheme. The system comprises EVs and an AGG, both aiming to maximize their own utility. The results demonstrate that the proposed algorithm can increase utility by up to 50% compared to conventional methods. In [19], the authors proposed a planning strategy framework to optimize and manage optimal EV charging and discharging operations, aiming to enhance the flexibility and efficiency of a microgrid. The problem was formulated as a non-cooperative game involving the distribution company, CS, and EVs. The findings reveal that the proposed framework can increase the flexibility and efficiency of a microgrid by 0.3% and 67.4%, respectively, compared to a case study. A V2G model is proposed in [20], where the study is conducted between multiple AGGs and a number of EVs to determine the optimal V2G pricing. The game theory model is formulated with the objective of maximizing the utility of both AGGs and EVs. The simulation is verified with three AGGs and 2000 EVs, demonstrating the effectiveness of the proposed model. The authors in [21] proposed a V2G pricing model with demand response based on game theory, where the players involved are AGGs and EVs trying to maximize their objectives by setting optimal strategies. The results confirm the feasibility of the proposed model, ensuring the maximum benefit of all parties. In [22], an approach is presented for scheduling household EV usage for V2G and vehicle-to-home services, using UK data and dynamic electricity pricing. The simulation results show that the proposed approach effectively reduces electricity bills. It was found that the main factors influencing this reduction are the energy price and the number of EVs.

Some work has focused on G2V and V2G applications involving ETs in their system [23–26]. The optimization of dispatch for ETs and CS is studied in [23]. ETs aim to choose a suitable CS for charging while minimizing their cost, and CS sets the charging price. The model is formulated using game theory, and a practical situation is simulated for analysis. Ma et al. [24] studied a charging problem involving CSs and ETs. ETs aim to select a CS with the lowest electricity charging cost, while CS adjusts the charging price based on regional hotspot information of ETs to maximize its revenue. The results confirmed that the proposed model effectively reduces the charging cost of ETs and guarantees CS's revenue. In [25], a multi-objective optimization problem is formulated for the coordinated charging strategy of ETs. The goal is to maximize the utilization of charging facilities, minimize load imbalance, and minimize electricity charging costs. The particle swarm algorithm is employed for optimization. The results confirm the improvement in efficiency, better load balance, and electricity cost benefits. In [26], a charging coordination problem for ETs is studied to decrease the charging cost. The goal is to decide when and where to charge ETs by utilizing real-time information with a two-stage decision process. The analysis reveals that the proposed approach can effectively decrease the charging cost of ETs, increase the utilization of CSs, and flatten the charging demand profile for the power grid.

In recent years, there has been research studying G2V and V2G for EBs [27–29] and ESBs [1,7,8]. In [27], a novel bus-to-grid concept is introduced, allowing the bus operator to generate revenue from both fare collection and through providing ancillary services to the grid. Non-linear optimization problems are formulated to maximize the bus operator's profit and determine the optimal bus charging plan. The simulation employs bus line

data and time-of-day pricing to verify the proposed concept. The work proposed by Yang et al. [28] introduced an optimization model for dispatching EBs to participate in carbon trading and the peak shaving market. The goal is to minimize the bus company's daily cost and also reduce load fluctuations. The results reveal that the daily cost, load fluctuations, and carbon emissions are reduced compared to the disorderly dispatch of EBs. The operation of EBs integrated with dynamic market prices for load congestion management is studied in [29]. Bi-level optimization is employed to determine electricity market clearing and bus planning. The experimental results show that the engagement of EBs can alleviate network congestion and reduce energy loss by 7.2%. Manzolli et al. [30] focus on the charging scheduling problem of EBs. An optimization model is designed to minimize the charging costs while also participating in a V2G scheme. This study demonstrates that it is economically viable for EBs to sell electricity back to the grid. One study [31] developed an optimization model for scheduling battery swapping stations for EBs, aimed at minimizing running costs while considering operational requirements. A savings cost index was proposed, which confirmed the economic viability of the concept.

There is limited literature on V2G research specifically focused on ESBs. Ercan et al. [1] focus on the environmental benefits of using V2G technology with ESBs instead of producing more electricity through traditional power plants, which release harmful emissions. The results reveal that ESBs can reduce greenhouse gas emissions by 1420 tons of carbon dioxide. In [7], the paper develops an ESBs V2G model to study the effect of integrating the ESBs with V2G capability into the grid. The aim is to minimize peak load periods and reduce carbon dioxide emissions using DC fast chargers in a centralized fashion. The simulation results show that using ESBs with V2G capability can decrease dependency on peak power plants and avoid carbon emissions of up to 1130 tons per day. An analysis to evaluate the cost and benefit of using V2G-capable ESBs is performed in [8]. Many factors are considered, including electricity cost, fuel cost, battery cost, health benefits, and the ancillary service market. The findings reveal that V2G-capable ESBs can save the school expenses by USD 6070 per set in net present value. One study [32] explored the integration of ESBs for V2G purposes into the US electrical system, which is powered using solar energy, utilizing Geographic Information Systems (GIS) data. The results indicate that the integration of ESBs for V2G purposes can benefit both communities and schools.

For various reasons, it becomes evident that ESBs are the most suitable EVs for performing V2G service to the grid, given their characteristics of predictability, consistent availability, and large storage capacity, as stated above. However, the existing literature primarily focuses on minimizing overall electricity costs through a centralized entity, such as a bus operator or grid operator. To the best of our knowledge, no research study has addressed the V2G problem for ESBs while considering the interests of multiple entities involved in the system. This consideration is crucial for the practical implementation of V2G solutions in the real world, where the interests of various stakeholders must be taken into account to realize the maximum benefits for each entity. Consequently, this work employs a game-theoretic approach to investigate the problem, aiming for a more realistic exploration of the dynamics involving multiple entities.

3. System Model

3.1. Preliminaries

3.1.1. Overview of the Model

Figure 1 depicts the conceptual illustration of the vehicle-to-grid model in a community. This model comprises a utility company and multiple schools, each possessing several electric school buses. The involved parties can be explained as follows:

- **Utility company (UC):** It is assumed that the utility company (UC) can accurately forecast the upcoming peak demand and predict the additional energy required for generation. However, power plants generating peak energy during peak durations typically incur very high running costs, posing a considerable financial burden for UC if it was to generate all the required energy during peak times independently. In

a community comprising several schools, each with multiple ESBs equipped with battery storage, these ESBs can play a crucial role in supplying the needed energy. Consequently, UC initiates communication by sending incentive price signals and peak duration information to schools before the peak period, engaging in negotiations for the provision of discharged energy from their ESBs. The incentive price offered by UC is set lower than the unit cost it would incur to generate all electricity independently. While UC still needs to generate the remaining energy that ESBs do not cover, the quantity is reduced, resulting in a substantial decrease in unit costs compared to when UC generates all the energy. Therefore, UC can effectively minimize the cost of generating additional energy during peak periods with the assistance of ESBs in schools within the community.

- **Schools:** Within a community, there exists a collection of schools, each consisting of a number of ESBs. These ESBs possess the capability to offer V2G services to the UC, specifically engaging in peak shaving activities by receiving incentive prices for providing discharged energy to the UC. The unit incentive price that UC sends to schools will be higher than the unit price at which the schools charge their ESBs during non-peak periods, meaning the school will benefit from providing this service to the UC. Upon receiving the incentive signal from UC, each school responds by determining the optimal quantity of the discharged energy to submit back to UC. Additionally, the school strategically identifies the most favorable time-duration to provide the V2G service, aiming to maximize their overall benefit from participating in the program.

The proposed V2G model consists of two levels: the UC level and the schools' level. Initially, at the upper level, the UC anticipates the forthcoming peak period and demand. It initiates negotiations for the V2G program by issuing an incentive signal (p_{uc}^t) to schools within the community. This incentive price is related to the projected amount of peak demand. Subsequently, at the lower level, each school in the community responds to the provided incentive prices by determining and submitting the optimal quantity of discharged energy from their ESBs' batteries to maximize their individual benefits through participation in the V2G program.

The set of schools is denoted as $\mathcal{N} = 1, 2, \dots, N$, where $n \in \mathcal{N}$ and N is the total number of schools in the system. Every school has the ability to offer V2G service by using the energy that is stored in its ESB battery. Prior to the peak period, the UC has the ability to initiate the peak shaving program by sending an incentive pricing signal.

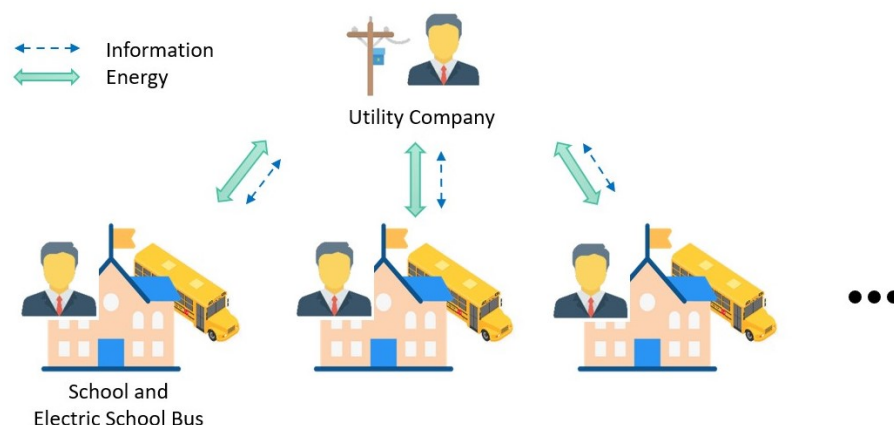


Figure 1. Conceptual illustration of vehicle-to-grid model in a community.

3.1.2. Technologies for Implementation

This energy sharing management can be implemented by utilizing the following technologies:

- **Bidirectional converter:** To enable electric school buses (ESBs) to charge from the grid and discharge back to it, a bidirectional converter is essential at the charging point. This converter consists of an AC/DC converter and a DC/DC converter. When ESBs charge from the grid, the AC/DC converter converts electricity from AC to DC, which then passes through the DC/DC converter to match the voltage of the ESBs. Conversely, during discharge from ESBs to the grid, the DC electricity from the ESBs' batteries is converted back to AC form and supplied to the grid, as illustrated in Figure 2.

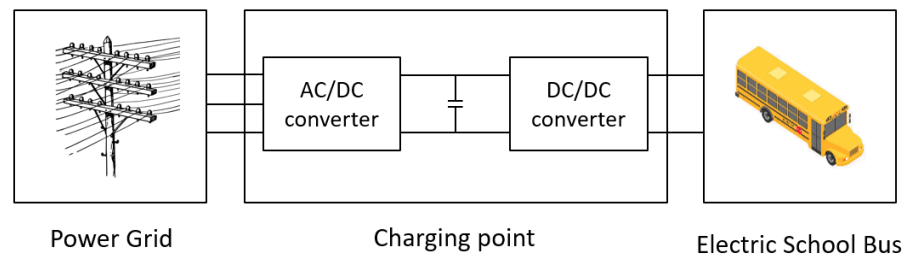


Figure 2. Power flow diagram for G2V and V2G [33].

- **Advanced metering infrastructure (AMI):** Smart meters are crucial components in the smart grid, playing an essential role not only in accurately measuring electrical parameters but also in facilitating communication and control. They might even be capable of providing timely forecasts of energy demand, either day-ahead or during the day. Smart meters for users and prosumers will be installed at sites where the demand and generation occur, such as homes, charging stations, and buildings. The communication capabilities of smart meters can be enhanced through various technologies. Wireless options like WiMAX or wired solutions through power line communication (PLC) enable efficient two-way communication between different entities in the system. This connectivity is essential for real-time data exchange and grid management. The effective operation of the smart grid requires specific functionalities from AMI, such as bidirectional energy measurement and communication, seamless connectivity, and adequate memory storage. These capabilities ensure that all parts of the grid are integrated and that data flows smoothly to support grid management and optimization.
- **Communication protocol:** In future complex smart grid networks, there will be a high frequency of communication, including numerous requests and acknowledgments between entities. The communication between sensors and smart meters can be achieved using wireless communication technologies or PLC. These methods enable efficient data exchange and monitoring within the smart grid infrastructure. The communication between smart meters and aggregators or operators can utilize wireless networks such as WiMAX, 3G, and 4G. These technologies provide reliable and rapid data transmission, essential for effective grid management and operations. The selected communication technologies should be capable of covering wide areas, offer connectivity at any time, and incur low operational costs. The standard for EV charging station communication is ISO/IEC 15118 [34], which outlines the protocol for communication between electric vehicles and charging stations. Meanwhile, the standard for communication between charging stations and the grid is IEC 61850 [35], which is used for substation automation and enables interoperability and communication between various grid components.

3.2. Utility Company

3.2.1. Energy Cost Function

The generation cost, $C_{gen}^t(D^t)$, denotes the cost required to generate the energy to serve all demand loads D^t during time t . The widely used and accepted assumptions for the cost function are as follows:

- (1) The cost function is an increasing function with the generated energy [36,37].

$$C_{gen}^t(D_1^t) \leq C_{gen}^t(D_2^t), \quad \forall D_1^t \leq D_2^t, \quad t \in \mathcal{T} \quad (1)$$

- (2) The cost function is strictly convex [38].

$$C_{gen}^t(\theta D_1^t + (1 - \theta)D_2^t) < \theta C_{gen}^t(D_1^t) + (1 - \theta)C_{gen}^t(D_2^t) \quad (2)$$

where $0 < \theta < 1$, $D_1^t, D_2^t > 0$, and $D_1^t < D_2^t$.

In this work, the quadratic cost function that satisfied the above assumption is utilized as follows [36,37,39,40]:

$$C_{gen}^t(D^t) = a(D^t)^2 + bD^t \quad (3)$$

where a and b are coefficients of the generation cost function at t , and D^t represents the amount of generated energy.

The unit dynamic electricity price for each t can be calculated by $p^t = \frac{C_{gen}^t(D^t)}{D^t}$; hence, the unit price is as follows:

$$p^t = aD^t + b \quad (4)$$

This price can be employed to calculate the cost of charging ESBs during typically non-peak hours as well.

3.2.2. Utility of UC

The UC aims to fulfil the required demand D_{req}^t by generating energy from its generators, along with procuring discharged energy from ESBs. This is achieved through V2G services, where the UC sends incentive price signals to schools, prompting them to discharge the stored energy in ESBs' batteries.

We define D_{peak}^t , D_{base}^t , and D_{req}^t as the peak demand, base demand, and the required demand resulting from the difference between peak and base demand at time t . This can be written as follows:

$$D_{req}^t = D_{peak}^t - D_{base}^t \quad (5)$$

When the peak shaving program is executed, the total amount of discharged energy from ESBs from all the schools for performing peak shaving is the following:

$$E_{V2G}^t = \sum_{n \in \mathcal{N}} x_n^t \quad (6)$$

where x_n^t is the discharged energy from school n at time t .

The new reduced peak demand after ESBs help to shave the original peak demand D_{peak}^t can be written as follows:

$$D_{peak,new}^t = D_{peak}^t - E_{V2G}^t \quad (7)$$

Hence, the total additional cost incurred by the UC from energy generation and the V2G program to meet the total demand in the community D_{peak}^t with a base demand of D_{base}^t is as follows:

$$U_{uc}^t(p_{uc}^t) = p_{uc}^t E_{V2G}^t + C_{gen}^t(D_{peak,new}^t) - C_{gen}^t(D_{base}^t) \quad (8)$$

Here, p_{uc}^t represents the incentive price for providing peak shaving service, paid by the UC to schools.

Equation (8) comprises three terms. The first term represents the cost of paying incentives to schools for providing the V2G service. The second and third terms denote the generation costs for the new reduced peak demand and base demand, respectively. The subtraction between these two generation cost terms is employed to determine the additional generation cost incurred for producing the extra energy necessary to meet the energy level after subtracting the energy supplied from the V2G program.

Upon substituting (3) into (8), the total additional cost of UC is reformulated as follows:

$$U_{uc}^t(p_{uc}^t) = p_{uc}^t E_{V2G}^t + [a(D_{peak,new}^t)^2 + b(D_{peak,new}^t) - a(D_{base}^t)^2 - bD_{base}^t] \quad (9)$$

Therefore, the total additional cost of UC consists of two parts: (1) The cost of paying incentives to schools to provide discharged energy from their ESBs. (2) The cost of generating the new reduced peak demand minus the cost that is already incurred at the base demand.

The objective of UC is to minimize this additional cost during peak periods by selecting the proper incentive price p_{uc}^t while ensuring the delivered energy matches the peak demand within the community.

$$\min_{p_{uc}^{min} \leq p_{uc}^t \leq p_{uc}^{max}} U_{uc}^t(p_{uc}^t) \quad (10)$$

3.3. Schools

3.3.1. Battery Dynamics

The State-of-Charge (SoC) of a school's ESBs can increase over time during the day by charging the batteries. It can decrease by discharging the stored energy to provide the V2G service to the UC and during traveling in the typical schedule of ESBs in the morning and afternoon. The battery dynamics of school n 's ESBs can be represented as follows:

$$SoC_n^{t+1} = SoC_n^t + s_1^t \frac{D_{ch}^t}{ESS} - s_2^t \frac{x_n^t}{ESS} - s_3^t \frac{\omega d_n}{h_d \cdot ESS} \quad (11)$$

where SoC_n^t and SoC_n^{t+1} represent the SoC at the beginning of time t and the SoC at the beginning of the next time slot for school n 's ESBs, respectively. D_{ch}^t denotes the charging energy into the school's ESBs in timeslot t , ESS represents the battery capacity of ESBs in school n , ω is the energy consumption rate per distance of ESBs during traveling, d_n is the distance needed to travel of ESBs in school n , and h_d is the number of hours used in the driving service each round. s_1^t is the state indicating whether the school's ESB is in charging operation during the timeslot t . s_2^t is the state showing whether the school's ESB is in discharging operation during the timeslot t , and s_3^t is the state representing whether the ESBs are currently in use for travel or not.

The state s_1^t , s_2^t , and s_3^t can be expressed as follows:

$$s_1^t = \begin{cases} 1, & \text{charging} \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

$$s_2^t = \begin{cases} 1, & \text{discharging} \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

$$s_3^t = \begin{cases} 1, & \text{traveling} \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

The SoC of school n at the beginning of the next timeslot SoC_n^{t+1} as in (11) can be computed using the following four terms:

- (1) SoC at the beginning of time slot, SoC_n^t ;
- (2) The amount of charged SoC in time slot t ;
- (3) The amount of discharged SoC in time slot t ;
- (4) The amount of SoC usage for the travel of ESBs in school n in time slot t .

Furthermore, it is typically imperative for the SoC to remain within the capacity limitations to extend the battery's lifespan as follows:

$$SoC_n^{min} \leq SoC_n^t \leq SoC_n^{max} \quad (15)$$

where SoC_n^{min} and SoC_n^{max} represent the minimum SoC and maximum SoC at the time t of the school n 's ESBs.

Each school possesses a number of ESBs that can be utilized to provide the peak shaving program by discharging the stored energy inside their ESBs' battery. Therefore, the maximum available stored energy to be discharged is calculated as the difference between the State-of-Charge (SoC) at that time t and the minimum SoC, which can be converted to kWh by multiplying the battery capacity, ESS_n .

$$E_n^t = (SoC_n^t - SoC_n^{min})ESS_n \quad (16)$$

Here, E_n^t is the maximum energy in kWh that can be discharged by school n 's ESBs.

3.3.2. Utility of Schools

The utility function of each school n at time t comprises two terms: satisfaction derived from retaining stored energy inside ESBs' batteries and monetary profit from participating in the peak shaving program.

$$U_n^t = \psi_n^t(e_n^t) + (p_{uc}^t - p_{avg}^t)x_n \quad (17)$$

where e_n^t is the remaining energy in the school's ESBs that can be further utilized after discharging energy for x_n^t , and the p_{avg}^t is the average charging price per unit of energy constituting the current amount of stored capacity.

$$e_n^t = E_n^t - x_n^t \quad (18)$$

$$p_{avg}^t = \frac{1}{\sum_{t=1}^{t-1} D_{ch}^t} \sum_{t=1}^{t-1} p^t D_{ch}^t \quad (19)$$

where p^t denotes the dynamic price calculated by (4).

We define the satisfaction function $\psi_n^t(e_n^t)$, representing the level of satisfaction obtained from having a certain amount of stored energy in ESBs.

The satisfaction function must satisfy the following properties:

- (1) The satisfaction function is a non-decreasing function. Each school is always more satisfied with more energy stored inside their ESBs' battery until it reaches the maximum level of stored energy.

$$\frac{\partial \psi_n^t}{\partial x_n^t} \geq 0 \quad (20)$$

- (2) The marginal benefit is a non-increasing function, meaning that the satisfaction level increases less per unit of stored energy as the level of energy in storage increases, eventually reaching a saturated level.

$$\frac{\partial^2 \psi_n^t}{\partial x_n^t{}^2} \leq 0 \quad (21)$$

Therefore, in this work, we employ the quadratic satisfaction function, a widely accepted and utilized form in the literature [36,40,41].

$$\psi(e_n^t) = \lambda_n e_n^t - \frac{\theta_n}{2} (e_n^t)^2 \quad (22)$$

where λ_n is the preference parameter of school n , distinguishing it from other schools, and θ_n stands for the quadratic function's predefined constant.

Therefore, from (16)–(18) and (22), we can reformulate the utility function of a school n as:

$$U_n^t = \lambda_n (E_n^t - x_n^t) - \frac{\theta_n}{2} (E_n^t - x_n^t)^2 + (p_{uc}^t - p_{avg}^t) x_n \quad (23)$$

This utility function represents the trade-off between providing discharged energy to UC for monetary profit and retaining stored energy in the ESBs' battery for satisfaction. In other words, if school n provides more energy to the UC, their satisfaction level decreases due to the low remaining energy in the ESBs' battery, but they will earn higher monetary profit. Conversely, if they preserve more stored energy in the ESBs' battery and discharge less, they will make less profit from the V2G service, but their satisfaction level stays high. Therefore, each school aims to maximize its utility by determining the optimal value of x_n^t as follows:

$$\max_{x_n^{t,min} \leq x_n^t \leq x_n^{t,max}} U_n^t(x_n^t) \quad (24)$$

4. Stackelberg Game among Players

The Stackelberg game is a non-cooperative game that examines situations where a hierarchy exists among players. It was first introduced by Heinrich von Stackelberg [42]. In this game, the leader selects the action (strategy) first, and then the followers observe the leader's strategy and decide on their own strategies by choosing the "best response strategy" that maximizes their utility function. The leader is also aware of this, so they select a strategy that maximizes their own utility. The solution to the game is known as the "Stackelberg equilibrium", where no player can increase their utility by unilaterally deviating from their best response strategy. The hierarchical nature of the Stackelberg game makes it highly suitable for modeling the interaction between multiple parties in a smart grid problem.

4.1. Game Formulation

In this paper, a Stackelberg game is formulated, where UC is the leader aiming to minimize its cost function by determining the optimal incentive price (p_{uc}^t). In contrast, schools that own ESBs are the followers trying to maximize their utility function by finding the optimal amount of discharged energy from their ESBs' battery (x_n^t) for the V2G service in response to the incentive price issued by UC. The game can be formally defined as follows:

$$\mathcal{S} = \{(\mathcal{N} \cup \{UC\}), \{\mathcal{X}_n^t\}_n, p_{uc}^t, \{U_n^t\}_{n \in \mathcal{N}}, U_{uc}^t\} \quad (25)$$

which consists of the following components:

- (1) **Players:** The set of schools owning ESBs $\mathcal{N}$ as followers determines their optimal discharged energy for the peak shaving program, and the UC as the leader decides on the incentive price paid to schools for providing peak shaving service.
- (2) **Strategies:** Each school n decides on the amount of discharged energy, $x_n^t \in \mathcal{X}_n^t$, to maximize its payoff. The UC decides on the optimal incentive price, p_{uc}^t , to minimize its additional cost in meeting the demand within a community.
- (3) **Payoffs:** The utility of school n owning ESBs, $U_n^t(x_n)$, as described in (23), and the additional cost to cover additional peak demand in the community of the UC, $U_{uc}^t(p_{uc})$, as shown in (9), where the payoffs for both types of players depend on the strategies of the other players.

Definition 1. For the proposed two-level Stackelberg game in (25), a set of strategies $(\mathbf{x}_n^{t*}, p_{uc}^{t*})$ constitutes a Stackelberg equilibrium if and only if the following set of conditions is satisfied:

$$U_n^t(\mathbf{x}^{t*}, p_{uc}^{t*}) \geq U_n^t(x_n^t, \mathbf{x}_{-n}^{t*}, p_{uc}^{t*}) \quad (26)$$

$$U_{uc}^t(\mathbf{x}^{t*}, p_{uc}^{t*}) \leq U_{uc}^t(\mathbf{x}^{t*}, p_{uc}^t) \quad (27)$$

where $\mathbf{x}_{-n}^{t*} = \{x_1^{t*}, x_2^{t*}, \dots, x_{n-1}^{t*}, x_{n+1}^{t*}, \dots, x_N^{t*}\}$ is the optimal strategies of all the schools in time slot t except for the school n . Hence, the optimal strategies of all the schools in the community in time slot t can be expressed as $\mathbf{x}^{t*} = \{x_n^{t*}, \mathbf{x}_{-n}^{t*}\}$.

The Equations (26) and (27) imply that when all players are at the Stackelberg equilibrium, no schools can increase its utility by deviating from x_n^{t*} , and the UC cannot reduce any more cost by selecting a different incentive price other than p_{uc}^{t*} .

4.2. Existence and Uniqueness of the Equilibrium

It is possible that the equilibrium in the game does not always exist. Therefore, investigating whether the equilibrium exists or not is needed for the proposed game model. To examine this, we apply the *backward induction* technique to determine the game's equilibrium. The first step is to find the optimal strategies of each follower. Then, given the optimal strategies from the followers, the existence of the optimal strategy of the leader can be proved. Thus, the existence of the equilibrium will be established.

Theorem 1. There exists a unique Stackelberg equilibrium in the proposed two-level Stackelberg game among UC and schools that satisfies (26) and (27).

Proof. The first step of the proof initiates at the lower level by identifying the best response of each school, which is the optimal discharged energy of the school's ESBs (x_n^{t*}), responding to the UC's strategy (p_{uc}^t) in the upper level. From the best response information of the schools, we can then trace back to determine whether the UC has an existing optimal strategy or not. The mathematical proof is presented as follows:

(1) Lower level: optimal discharged energy of schools

Given the strategy from the leader p_{uc}^t sent from UC in the upper level, the best response strategy for each school n in the lower level can be obtained by taking the first-order derivative of U_n^t in (23), with respect to x_n^t :

$$\frac{\partial U_n^t}{\partial x_n^t} = -\lambda_n + p_{uc}^t - p_{avg}^t + \theta_n x_n^t + \theta_n E_n^t \quad (28)$$

Let (28) equal to zero, the optimal discharged energy of school n that maximizes its utility function can be obtained as follows:

$$x_n^{t*} = \frac{-\lambda_n + p_{uc}^t - p_{avg}^t}{\theta_n} + E_n^t \quad (29)$$

Then, the second-order derivative of U_n^t is as follows:

$$\frac{\partial^2 U_n^t}{\partial x_n^{t2}} = -\theta_{m,n} < 0 \quad (30)$$

Since the second-order derivative of U_n^t is always negative as in (30) due to $\theta_n > 0$, it means that U_n^t is strictly concave with respect to x_n^t . Therefore, the best response strategy of the school n as in (29) is guaranteed to be unique and optimal.

(2) Upper level: optimal incentive price of UC

Given the best-response strategy of followers from the lower level in (29), we can calculate the summation of all the discharged energy from the school's ESBs for peak shaving service E_{V2G}^t as follows:

$$\begin{aligned} E_{V2G}^t &= \sum_{n \in \mathcal{N}} \left(\frac{-\lambda_n + p_{uc}^t - p_{avg}^t}{\theta_n} + E_n^t \right) \\ &= \sum_{n \in \mathcal{N}} \left(\frac{-\lambda_n - p_{avg}^t}{\theta_n} + E_n^t \right) + \sum_{n \in \mathcal{N}} \frac{1}{\theta_n} p_{uc}^t \end{aligned} \quad (31)$$

To simplify the expression, we can define new parameters α and β^t as follows:

$$\alpha = \sum_{n \in \mathcal{N}} \frac{1}{\theta_n} \quad (32)$$

$$\beta^t = \sum_{n \in \mathcal{N}} \left(\frac{-\lambda_n - p_{avg}^t}{\theta_n} + E_n^t \right) \quad (33)$$

Therefore, (31) can be rewritten as follows:

$$E_{V2G}^t = \alpha p_{uc}^t + \beta^t \quad (34)$$

The utility function of the UC can be reformulated by substituting the summation of the optimal strategy of the schools from (34) into the UC cost function in (9). Therefore, U_{uc}^t can be reformulated as follows:

$$\begin{aligned} U_{uc}^t(x_n^t, p_{uc}^t) &= p_{uc}^t(\alpha p_{uc}^t + \beta^t) + [a(D_{peak}^t - (\alpha p_{uc}^t + \beta^t))^2 + b(D_{peak}^t - (\alpha p_{uc}^t + \beta^t))] \\ &\quad - [a(D_{base}^t)^2 + bD_{base}^t] \end{aligned} \quad (35)$$

We can determine the first and second-order derivatives of (35) with respect to p_{uc} as follows:

$$\frac{\partial U_{uc}^t}{\partial p_{uc}^t} = 2\alpha p_{uc}^t + \beta^t - 2a\alpha(D_{peak}^t - \alpha p_{uc}^t - \beta^t) - \beta^t \quad (36)$$

$$\frac{\partial^2 U_{uc}^t}{\partial p_{uc}^t{}^2} = 2(a\alpha^2 + \alpha) > 0 \quad (37)$$

Since the value of a and α is positive, the second-order derivative of U_{uc}^t is always positive, as shown in (37). This means that U_{uc}^t is strictly convex with respect to p_{uc}^t . Thus, the optimal solution of the UC is guaranteed to be unique and optimal.

From the above proof, we can see that once the unique and optimal strategy of UC (p_{uc}^{t*}) is found, the unique and optimal strategy of each and every school n can be calculated. Hence, the unique Stackelberg equilibrium in the form of (x^{t*}, p_{uc}^{t*}) exists for the proposed two-level Stackelberg game model and will be found once the optimal UC incentive price is determined. $\square$

4.3. Algorithm for Reaching the Equilibrium

The goal of energy sharing management in this research is to reduce the additional costs associated with generating energy for UC, as well as the electricity costs or bills of schools. Moreover, reducing the peak-to-average ratio of the energy profile is another objective achieved once the peak is shaved. Therefore, in terms of energy sharing management, two periods in the energy profile require management: the valley period and the peak period. During the valley period, the UC tries to smooth out the demand by allocating the charging demand from schools. The allocation of charging energy is coordinated through communication between the UC and schools beforehand. When the UC is informed of the total request demand for charging energy from all schools, it can fill the valley period

and smooth out the energy profile during that time. Consequently, the electricity unit price becomes uniform as the final energy profile is smoothed out, which can be calculated using (4). More importantly, in the peak period, the UC aims to minimize the additional generation cost required to cover the peak demand by providing incentive prices to schools to supply discharged energy to the system. Schools that have been previously charged during the valley period using the cheapest prices can benefit by providing V2G services, discharging the stored energy inside their ESBs to the community, and receiving incentive prices higher than the charging prices previously. Consequently, the peak demand and PAR value can be reduced. Moreover, the costs for the UC and the bills for schools are also decreased.

In this section, we introduce and describe the proposed optimal energy-price (OEP) equilibrium algorithm, designed to achieve game equilibrium in a distributed manner. In this approach, schools are required only to disclose the discharged energy to the UC and nothing else, thereby preserving their privacy. We can see from the previous subsection that the objective function of UC is strictly convex with respect to p_{uc}^t . Hence, enumerating the incentive price p_{uc}^t will lead to the minimum of the UC cost, meaning it is always guaranteed to reach the unique and optimal solution. In the nature of the leader–follower game, to find the Stackelberg equilibrium, we have to find the optimal solution of the leader. To do that, we can enumerate the leader strategy p_{uc}^t from $p_{uc,min}^t$ to $p_{uc,max}^t$, and the optimal solution is the one that minimizes the cost of UC. When the UC's optimal incentive price p_{uc}^{t*} is found, the optimal discharged energy of every n -th school x_n^{t*} will also be found by (29). Hence, the strategy profile (x^{t*}, p_{uc}^{t*}) for the Stackelberg equilibrium is found.

In Algorithm 1, the UC iteratively updates p_{uc}^t from $p_{uc,min}^t$ to $p_{uc,max}^t$. The UC first issues the incentive price p_{uc}^t to all schools. Upon receiving the announced incentive price, each school n calculates the optimal discharged energy it will provide to UC for peak shaving service (x_n^t) that maximizes its utility given p_{uc}^t by (29) and sends this response information back to the UC. The UC gathers all the responses from the schools, then calculates the total discharged energy from schools in the community (6). The UC further calculates the total additional cost it needs to pay to cover the community's demand by (9). It then compares the results with the previously recorded utility of the previous recorded incentive price that makes the utility the lowest so far. If the new one is lower, indicating an improvement, the UC updates the recorded utility value U_{uc}^{t*} . However, if the new one is not less than the recorded utility, the UC ignores the newly calculated utility value and price. The algorithm runs iteratively until the conditions in (26) and (27) are satisfied, indicating that the Stackelberg equilibrium is reached.

Algorithm 1 Optimal Energy-Price (OEP) Equilibrium Algorithm

```

1: UC initialize  $p_{uc}^* = p_{uc}^{min}, U_{uc}^{t*} = C_{gen}^t(D_{peak}^t) - C_{gen}^t(D_{base}^t)$ 
2: for  $p_{uc}^t$  from  $p_{uc}^{min}$  to  $p_{uc}^{max}$  do
3:   Broadcast  $p_{uc}^t$  to all schools in the community
4:   for school  $n \in \mathcal{N}$  in community do
5:     Calculate optimal discharge energy from its ESBs ( $x_n^t$ ) using (29)
6:     Send  $x_n^t$  back to the UC
7:   end for
8:   UC summarizes all the discharged energy from all the schools using (6)
9:   UC calculates the value of its utility function using (9)
10:  if  $U_{uc}^t \leq U_{uc}^{t*}$  then
11:    UC record new incentive price and cost value
12:     $p_{uc}^{t*} = p_{uc}^t, U_{uc}^{t*} = U_{uc}^t$ 
13:  end if
14: end for
15: The equilibrium  $(x^{t*}, p_{uc}^{t*})$  is reached where the cost of UC is minimized
  
```

4.4. Implementation Process

The process can be divided into two stages: G2V is used for filling valleys and typically occurs on a day-ahead basis. Then, V2G for peak shaving takes place during the day when requests for peak shaving are made.

4.4.1. G2V for Valley Filling

The UC attempts to fill up the valley periods by managing and allocating the demand charge energy from schools that need to charge their ESBs.

- (1) First, assume that the UC has accurate forecasting capabilities for the energy profile of a community on a day-ahead basis and announces the valley period that needs to be filled by charging at the school.
- (2) Each school then requests the amount of energy needed to charge its ESBs from the UC.
- (3) The UC allocates the demand to flatten the valley period and sends the relevant information back to the schools for implementation.

4.4.2. V2G for Peak Shaving

During the day, the UC will request V2G services from schools that possess a number of ESBs capable of discharging the energy stored in their batteries.

- (1) The utility company (UC) announces the peak periods and sends an incentive signal to schools before the peak period begins.
- (2) Each school submits the amount of energy they plan to discharge from their electric school buses (ESBs) during the peak period.
- (3) UC calculates its own utility and announces a new price to the schools based on this calculation.
- (4) The process returns to steps 2 and 3 and repeats until an equilibrium is reached.

5. Evaluation Studies

5.1. Simulation Setup

In this section, we evaluate the performance of the proposed V2G model, where both entities, UC and schools, seek to find optimal strategies in response to each other's actions. Given that the USA has the world's largest usage of ESBs, we focus on and utilize data from the USA. The electrical load profile is obtained from the U.S. Energy Information Administration [43]. The daily school schedule is from Rochester Community Schools in Michigan, USA, where the ESBs operate by picking up students in the morning from 6:00 a.m. to 8:00 a.m. and dropping them back home in the afternoon from 3:00 p.m. to 5:00 p.m. [44]. This means that h_d is 2 h. Hence, during these intervals, the ESBs cannot be used for V2G service. At other times, schools that possess ESBs can participate in the V2G peak shaving program, effectively acting as stationary batteries. In this Rochester community, there are approximately 21,000 people of student age [45], and typically in the US, about 38% of students take school buses [46]. Hence, the number of students taking the school bus is around 8000, with each bus accommodating 40–60 students comfortably and up to 80 students at maximum capacity [44]. Hence, the number of ESBs in real-world scenarios in this community should range between 100 and 200 buses. The number of schools (N) in a community is 20, including elementary schools, middle schools, and high schools. Each school possesses 10 buses. Therefore, the total number of ESBs used in the simulation is 200 buses. The preference parameter of schools is randomly selected from the range of [1, 1.2]. The parameter θ is set to 0.001. The ESB with a capacity of 200 kWh is used. The minimum SoC is 20%, and the maximum SoC is 90% [47,48], as this range would prolong the battery life. The ESB travel distance each round is 70 km [7,49]. The energy consumption rate for traveling is 1 kWh/km [50,51]. The maximum charging and discharging power is 60 kW [7,51]. We utilize MATLAB to implement Algorithm 1 in order to find the equilibrium solution.

5.2. Energy Profile Results and Discussion

In this subsection, the energy profile results are compared among three scenarios: charge-after-use (CAU) charging, grid-to-vehicle (G2V) charging, and the proposed optimal energy-price (OEP) V2G model.

- Charge-after-use (CAU) [52]: The ESBs are charged immediately until full after their pick-up and delivery service in the morning and afternoon, following typical human behavior.
- Grid-to-Vehicle (G2V) [53]: This charging involves the ESBs being charged only during the valley period, where the electricity price is the lowest, until full. This typically occurs after midnight until early morning before the service starts, and no discharging energy is provided to the grid.
- Centralized approach (CEN) [22]: This scenario employs centralized control from the UC to maximize the reduction in generation costs by fully utilizing all ESBs to discharge energy during peak periods. This approach does not consider the schools' efforts to maximize their own benefits, but the schools still receive monetary compensation for providing the discharged energy.
- The proposed optimal energy-price (OEP): This scenario utilizes both charging during the lowest price period and discharging energy during peak periods to receive monetary benefits from the utility company.

The profiles are studied across three seasons: winter, spring, and fall, when the school is normally open.

The energy profile in winter in Figure 3 shows that CAU charging will cause high peaks during the morning and evening due to the ESBs charging aligning with the peak energy demand profile. In contrast, G2V only charges during the valley period in the early morning and can be used for travel services in both the morning and afternoon. On the other hand, the proposed OEP algorithm not only fills the valley period during 0–6 a.m. but also helps shave the peak demand during 8–11 a.m., where the original peak demand is reduced by 11.15 MWh.

Figures 4 and 5 show the energy profiles for the spring and fall seasons, where both seasons typically have very similar energy profiles. The results indicate that CAU charging will cause two peak demands after the travel service. G2V charging helps fill the valley in the early morning by charging at the lowest price. On the other hand, the proposed OEP charging and discharging algorithm can help fill the valley during 1–6 a.m. and also reduce the original peak during the evening (6 p.m.–10 p.m.) by 9.3 MWh and 9.7 MWh in spring and fall, respectively.

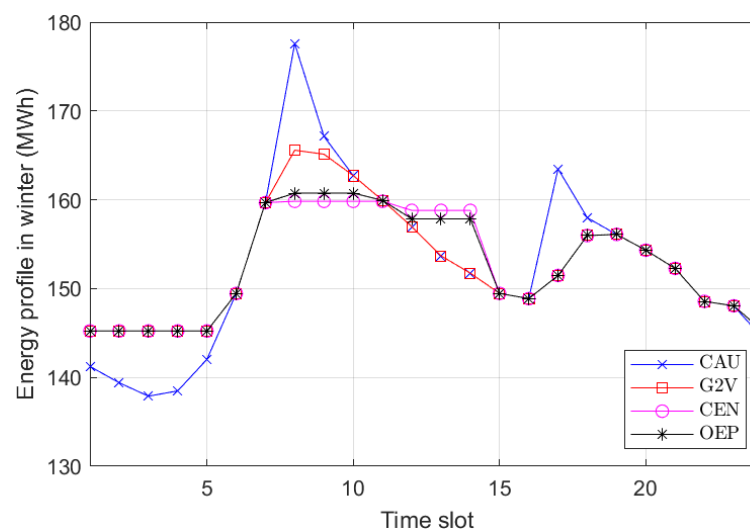


Figure 3. Energy profile in winter.

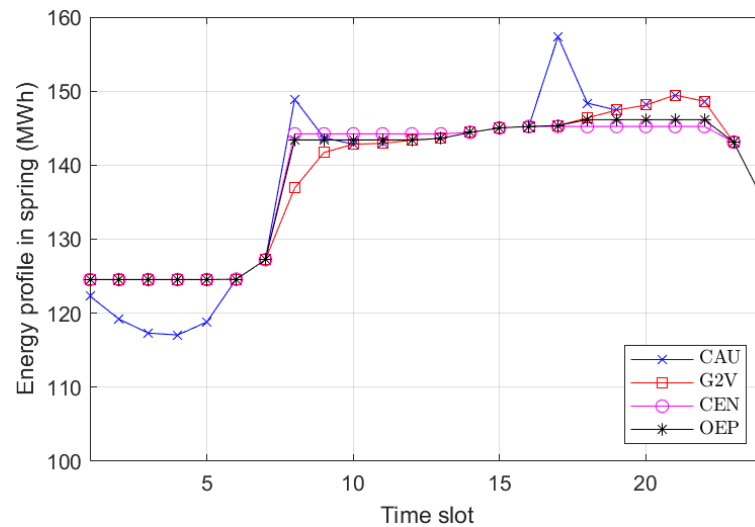


Figure 4. Energy profile in spring.

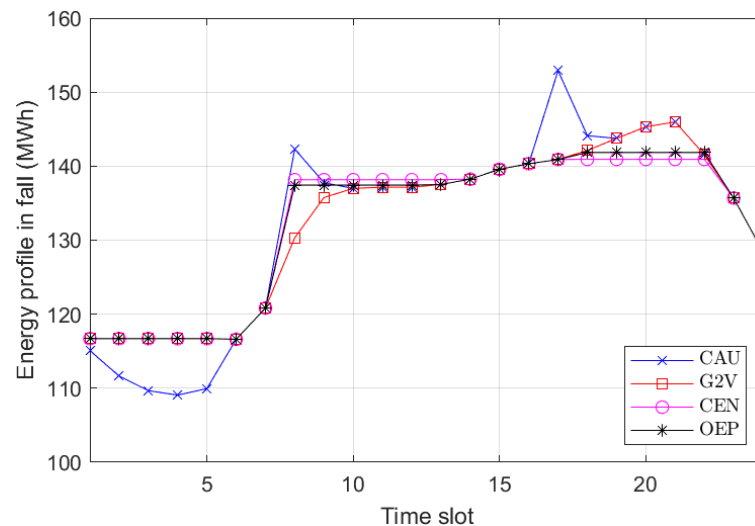


Figure 5. Energy profile in fall.

Table 1 illustrates the percentage reduction results comparing the G2V, CEN, and proposed OEP algorithms with CAU charging across three seasons. The results indicate that the cost for the utility company is reduced the most with the proposed OEP algorithm compared to both G2V and CAU charging. On the other hand, the cost for the UC is reduced the most with the CEN approach, as this centralized strategy primarily focuses on reducing the UC's costs, rather than the bills of the schools. Conversely, the bills of the schools decrease the most with the proposed OEP algorithm, which considers both the cost to the UC and the bills of the schools. As a result, the combined reductions in the cost to the UC and the bills of the schools for CEN and the proposed OEP are 20.27% and 23.16% for winter, 20.84% and 22.68% for spring, and 20.89% and 23.24% for fall, respectively. This shows that, although CEN provides the greatest reduction in the cost to the UC and also significantly lowers the bills of the schools, the total reduction is consistently better with the proposed OEP approach across all seasons. This is because the OEP approach accounts for the benefits to both the UC and the schools. Although the percentage reduction in the total 24 h cost of UC is small due to the typically very high demand compared to the amount that the peak can be shaved out, the effective impact of the proposed OEP algorithm is evident in the significantly reduced additional cost during peak periods, which will be shown and discussed later on. This effectiveness extends to the total bills for all the schools, which can

be reduced by up to 22.61%. Additionally, the peak-to-average ratio is also reduced in the proposed OEP algorithm compared to both G2V and CAU charging by up to 9.5%.

Table 1. Percentage reduction comparing the G2V, CEN, and proposed OEP algorithm with CAU charging over 24 h.

% Reduction	Winter			Spring			Fall		
	G2V	CEN	OEP	G2V	CEN	OEP	G2V	CEN	OEP
Cost of UC	0.11	0.71	0.59	0.15	0.79	0.58	0.17	0.85	0.63
Bill of schools	7.75	19.56	22.57	9.10	20.05	22.10	9.80	20.03	22.61
peak-to-average ratio	6.76	11.11	9.48	5.01	8.34	7.12	4.53	8.51	7.24

5.3. Sensitivity Analysis Results and Discussion

We study the characteristics of the proposed OEP V2G model by varying important input parameters, such as the number of schools, battery capacity, and travel distance, while fixing D_{base} at 150 MW and changing D_{req} to 1, 2, 3, 4, and MW. Hence, four different line colors, black, red, blue, and magenta, are used to show different results.

5.3.1. Number of Schools

Figures 6–8 show the normalized incentive price of UC, the total discharged energy from schools in the community, and the percentage reduction in cost of UC when the number of schools varies from 0 to 20.

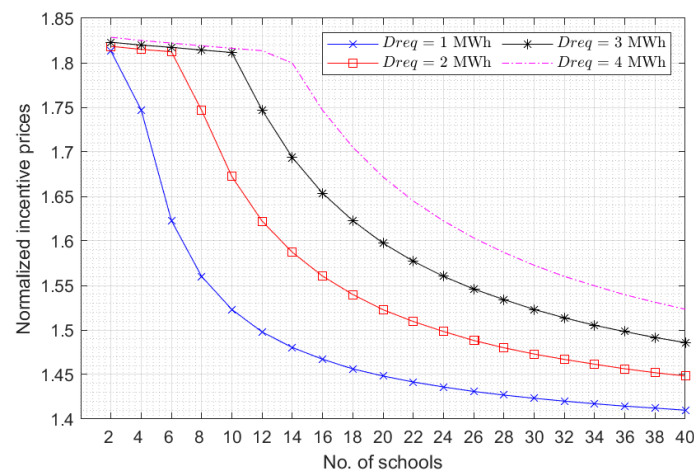


Figure 6. Incentive price of UC vs. number of schools.

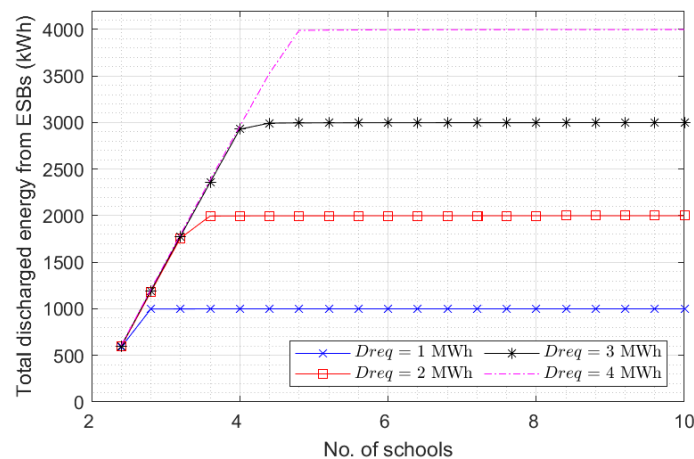


Figure 7. Total discharge energy from ESBs vs. number of schools.

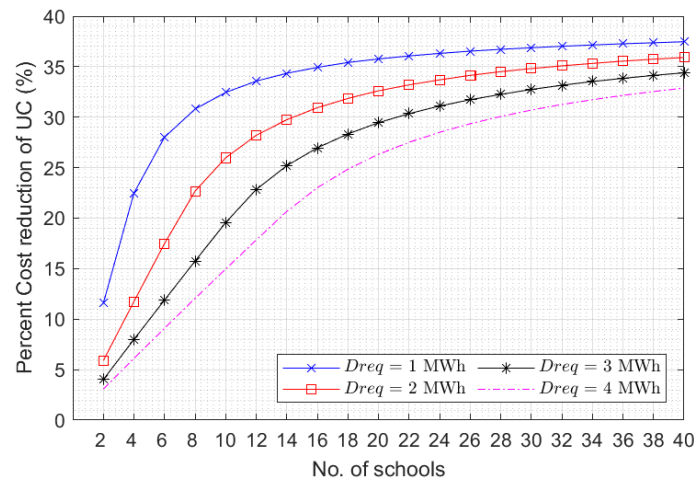


Figure 8. Percentage reduction in cost of UC vs. number of schools.

The result reveals in Figure 6 that the greater number of schools in the community, the lower the incentive price paid by the UC. This is because there is more energy inside the ESBs to be discharged into the system, hence the competition between schools is higher. Each school is willing to accept the lower incentive price while still discharging the same amount of energy. As we expected, as the number of schools increases, the discharged energy and the percentage reduction in the costs of the UC will also increase, as shown in Figures 7 and 8.

Figure 6 shows that when the D_{req} is increased, the incentive price of UC also increases as is expected; this is indicated by the different line colors. Since a higher D_{req} will cause higher unit prices for generation cost, the UC is willing to pay higher incentive prices for the schools to discharge energy from their ESBs to fulfil the D_{req} . Similar to Figure 7, when the D_{req} increases, the total discharged energy also increases. On the other hand, the percentage reduction in the cost of UC decreases when D_{req} is higher, since at a higher peak demand, the cost of generating energy is significantly higher and harder to reduce.

5.3.2. Travel Distance

Figures 9–11 depict the normalized incentive price of UC, the total discharged energy from schools in the community, and the percentage reduction in the cost of UC when the traveling distance varies from 50 km to 120 km.

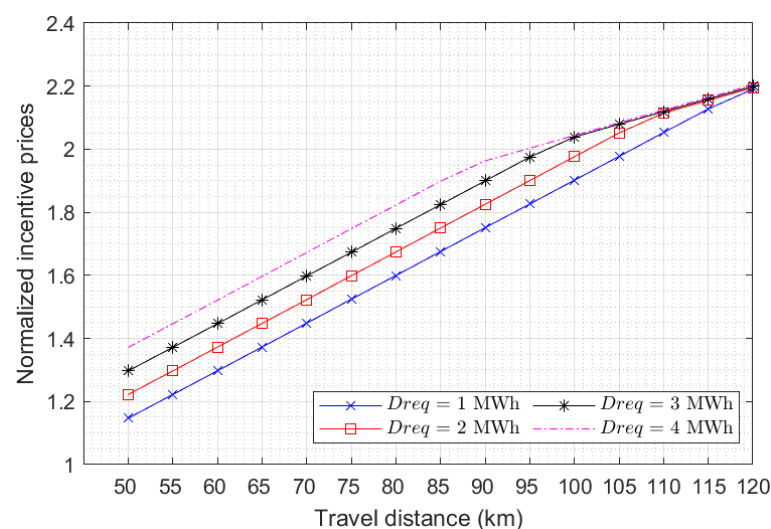


Figure 9. Incentive price of UC vs. daily travel distance of each ESB.

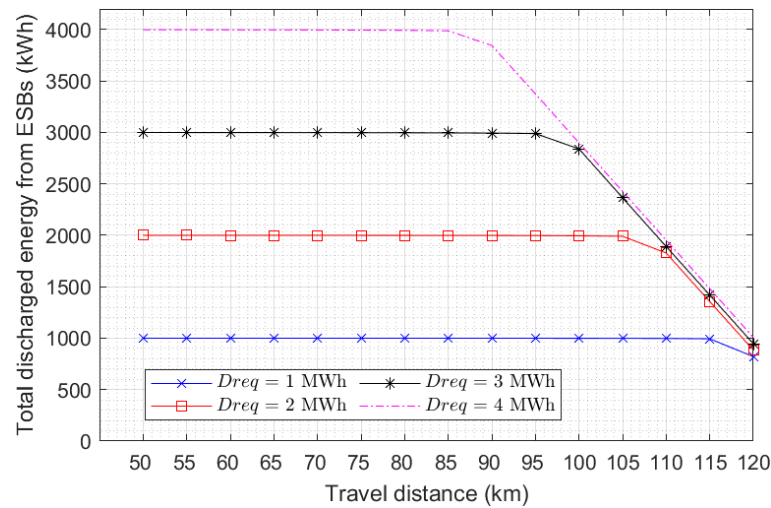


Figure 10. Total discharge energy from ESBs vs. daily travel distance of each ESB.

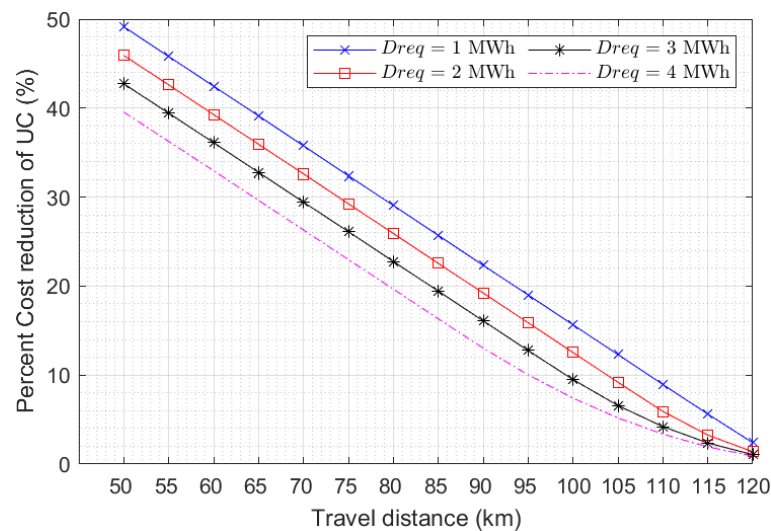


Figure 11. Percentage reduction in cost of UC vs. daily travel distance of each ESB.

This shows that when the traveling distance is longer, the incentive price will increase. The reason is that when the traveling distance is longer, there is less energy remaining inside the battery of ESBs to discharge after completing traveling tasks. Therefore, the UC is willing to pay a higher incentive for ESBs to discharge to the grid.

And as expected, when the daily travel distance is very high, the total discharged energy is lower, as shown in Figure 10. For the percentage reduction in the cost of UC, it also decreases with increasing distance, as shown in Figure 11.

5.3.3. Battery Capacity of Each ESB

In this subsection, we study the effect of the battery capacity of each ESB by varying the value from 120 kWh to 240 kWh. Figures 12–14 illustrate the incentive price from UC, the total discharged energy from ESBs, and the percentage reduction in UC costs, respectively.

In Figure 12, it is observed that when the battery capacity of each ESB is higher, the incentive price from UC is lower. This is because there will be more energy available to assist UC during peak demand, prompting UC to offer a lower price. Figure 13 demonstrates that increasing the battery capacity leads to a higher total discharged energy, especially when the battery capacity is very low. However, in higher capacity values, the total discharged energy remains unchanged as it already covers the D_{req} .

Regarding the percentage reduction in the cost of UC shown in Figure 14, it is observed that when the battery capacity increases, the percentage reduction also increases, as

expected. This is because there is more stored energy available to assist UC, leading to a greater reduction in cost.

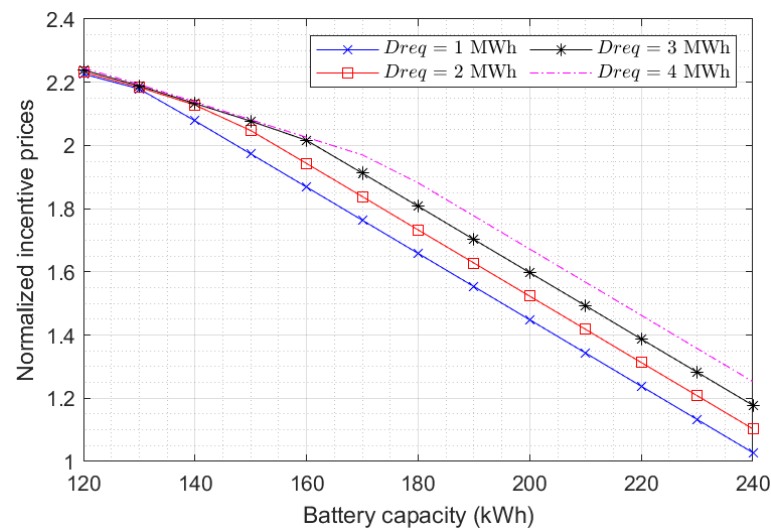


Figure 12. Incentive price of UC vs. battery capacity of each ESB.

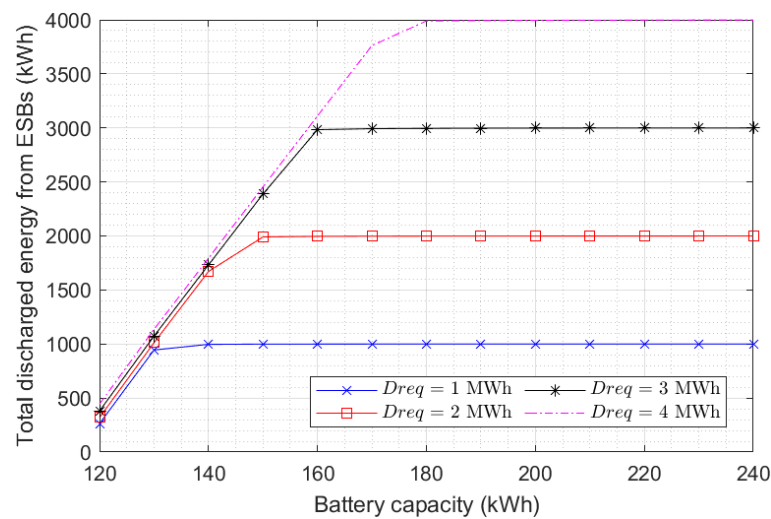


Figure 13. Total discharge energy from ESBs vs. battery capacity of each ESB.

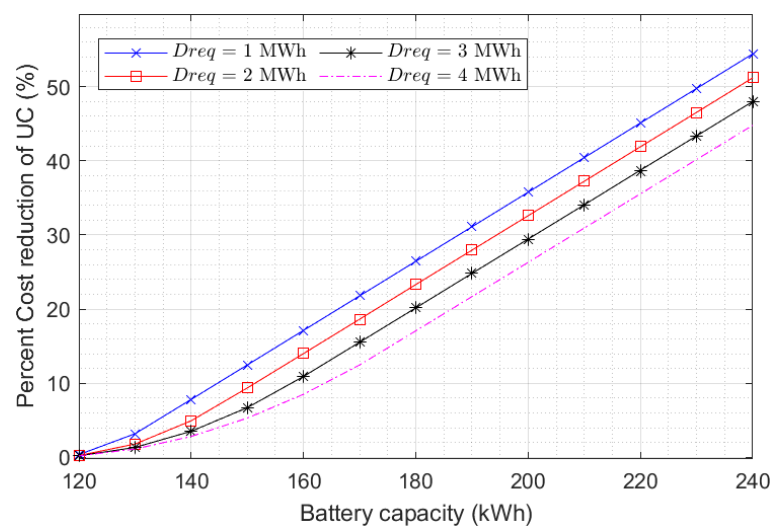


Figure 14. Percentage reduction in cost of UC vs. battery capacity of each ESB.

5.3.4. Optimal Battery Capacity of ESB

Figure 15 illustrates that when the battery capacity for each ESB varies from 120 kWh to 240 kWh, there is an optimal value at which the average utility of each school is maximized; this is 200 kWh, a value we have used in our simulation. Examples of real ESBs that use this amount of battery capacity include the GreenPower: BEAST [54], Blue Bird: All American Electric [55], and Lion Electric: LionD [56].

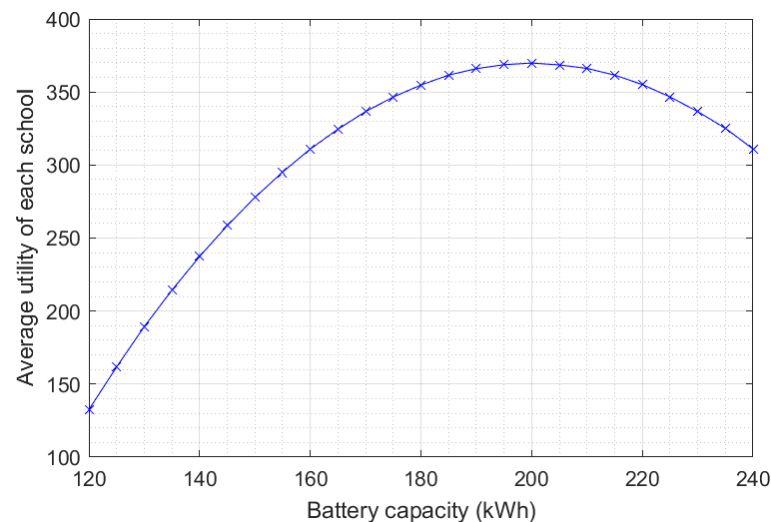


Figure 15. Average utility of each school vs. battery capacity of each ESB.

When utilizing the optimal battery capacity of 200 kWh, with 20 schools as indicated in the community data, a distance of 70 km, and a mean D_{req} of 1 MWh, the effectiveness of the proposed OEP model is demonstrated by significantly reducing the additional generation cost for UC by around 36% during peak periods.

This work possesses some limitations, as it does not consider the effects of battery degradation, which will be a focus in our future research. Some sources suggest that using EV batteries for V2G purposes could result in faster battery degradation and reduced lifespan. However, other studies [57–59] indicate that V2G does not significantly affect battery degradation. Addressing EV battery degradation in detail while performing energy sharing will be one of our near-future research efforts. In this upcoming work, we plan not only to study the mentioned problem but also to examine the performance of the scheme over a more extended period.

6. Conclusions

This paper presents a V2G energy sharing management model for UCs and schools that possess ESBs. Since the ESBs have a predictable usage in terms of time and energy consumption, they are highly suitable for use in peak shaving services, in contrast to personal EVs. The problem is formulated as a Stackelberg game, where a UC is the leader in setting the incentive price for providing the peak shaving service. On the other hand, the followers are the schools, which try to find the optimal discharge energy to help the UC shave the peak. The evaluation is performed in four different scenarios across three different seasons. The sensitivity analysis of the V2G model is also conducted by varying the number of schools, daily travel distance, and battery capacity of each ESB. The effectiveness of the proposed OEP algorithm is demonstrated by a 36% reduction in the additional generation cost for the UC during peak periods and a decrease in electricity bills for schools by up to 22.6%. Furthermore, the peak-to-average ratio is reduced by up to 9.5%. Future research directions could explore the integration of electric buses with other community loads and generation sources, which would provide valuable insights into their mutual impacts and interactions within the system dynamics. Additionally, investigating the direct sharing of stored energy from large batteries, such as those in electric school buses, with other places

like schools or nearby buildings within the community, presents a promising avenue for further study.

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