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Enhancing Urban Energy Resilience: Vehicle-to-Grid (V2G) Strategies within Electric Scooter Battery Swapping Ecosystems

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ABSTRACT

With the global rise in electric scooter adoption and the expansion of battery swapping stations (BSSs), particularly in Taiwan—home to the world's densest network of these facilities—these stations are increasingly recognized as crucial energy storage hubs that enhance grid stability. This study introduces a smart energy management system designed for optimal charge and discharge management of BSSs, using Taiwan as a practical example. Central to our approach is a vehicle-to-grid (V2G) strategy, which, through hourly resolution analyses, assesses the impacts on grid peak demand, operational costs, and emissions. Our results indicate that V2G significantly reduces peak power demand by 110.1% compared to traditional charging methods and lowers operating costs by 18.9% through energy arbitrage. Although current emission reductions are modest due to Taiwan's limited renewable installed capacity, projections demonstrate that emissions could rise by 2% without strategic emission management. Our proposed V2G strategy targets both peak shaving and low-emission charging periods, potentially reducing emissions by 12.8% and supporting national sustainability targets. Furthermore, a comparative analysis shows that V2G is effective in both urban and rural settings, with rural areas achieving greater reductions in peak power usage and costs due to their higher idle battery capacity. This emphasizes the importance of tailored energy management strategies and underscores the critical role of well-designed BSS charging strategies in moving towards a sustainable, net-zero future.

Nomenclature

Acronyms	
CEI	Carbon Emission Intensity
EM	Emission Management
REF	Reference
SEMS	Smart Energy Management System
Indices and Sets	
i	Indices for fuels or energy sources
j	Indices for greenhouse gases emitted
K	Set of data points within time interval
k	Indices for time points
M	Set of BSSs
m	Indices for BSSs
T	Set of times
t	Indices for time
Parameters	

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Parameters	
A	Maximum charging and discharging capacity per hour (batteries / hour)
A_a	Additional charging capacity (batteries / hour)
BRC	Battery replacement cost (TWD / battery)
BRE	Battery replacement emission ($kgCO_2eq$ / battery)
CL_{DoD}	Cycle life of batteries at a specific DoD (cycles)
DoD	Depth of discharge (%)
d_t	Battery swap demands in time interval from t to $t+1$ (swaps)
$EF_{i,j}$	Emission factor of fuel i for GHG j ($kgCO_2eq$ / kJ)
EP_t	Energy price at time t (TWD / kWh)
$G_{i,t}$	Gross electricity generation by fuel i at time t (kWh)
GWP_j	Global warming potentials of GHG j ($kgCO_2eq$ / kWh)
LHV_i	Lower heating value of fuel i (kJ / kg)
N	Maximum battery capacity of the BSS (batteries)
$N_{i,t}$	Net electricity generation by fuel i at time t (kWh)
N_r	Number of reserved batteries (batteries)
n_t	Count of fully charged batteries at the t^{th} time point (batteries)
$n_{t,\,deplete}$	Number of depleted batteries at time t (batteries)

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Parameters	
$n_{t,\ excess}$	Excess fully charged batteries available during peak hours (batteries)
P_r	Propotion of reserved batteries (%)
Q	Capacity of each battery (kWh)
T_e	Time of the end of peak hours (-)
γ	Proportion of additional charging capacity (%)
η	Charging and discharging efficiency factor (%)
μ	Energy sell-to-buy price ratio (-)

Variables	
a_t^+	Number of batteries to charge in time interval from t to $t+1$ (batteries)
a_t^-	Number of batteries to discharge in time interval from t to $t+1$ (batteries)
$a_{t,\ require}^+$	Number of batteries needed to meet the next period's requirements at time t (batteries)
BDC_t	Battery degradation cost in time interval from t to $t+1$ (TWD)
BDE_t	Battery degradation emission in time interval from t to $t+1$ ($kgCO_2eq$)
CE_t	Carbon emissions from the power grid's thermal generating units at time t ($kgCO_2eq$)
CEI_t	Carbon emission intensity at time t ($kgCO_2eq$ / kWh)
ECC_t	Energy consumption cost in time interval from t to $t+1$ (TWD)
ECE_t	Energy consumption emission in time interval from t to $t+1$ ($kgCO_2eq$)
e_t^+	Energy requirements for charging in time interval from t to $t+1$ (kWh)
e_t^-	Energy requirements for discharging in time interval from t to $t+1$ (kWh)
$n_{t,\ require}$	Number of fully charged batteries required at time t (batteries)
OC	Operating cost (TWD)
OE	Operating emission ($kgCO_2eq$)
TCC_t	Total number of charged cycles in time interval from t to $t+1$ (cycles)

1. Introduction

1.1. Background and Related Works

Amidst the global shift towards the electrification of transportation and the concurrent enhancement of charging infrastructure, the number of electric vehicles (EVs) has experienced a significant increase, marking a 60% growth in 2022 compared to the previous year (IEA, 2024). This burgeoning growth in EV adoption is expected to drive electricity consumption up to 200,000 GWh by 2025, which represents a more than threefold increase from the levels recorded in 2022 (IEA, 2024). Such a rapid surge in EV usage will introduce substantial challenges to grid stability if there is no proper energy management. Moreover, increasing electricity demand will likely lead to more greenhouse gas emissions for regions that heavily rely on fossil fuel power generation (Kapustin and Grushevenko, 2020), which ironically counteracts the environmental benefits EVs aim to provide.

In response to these emerging challenges, the Vehicle-to-Grid (V2G) technique has been introduced and has since garnered significant interest within the academic and industrial fields (Bibak and Tekiner-Moğulkoç, 2021a; Deb et al., 2022; Energy Networks Association, 2017; European Commission, 2020; Han et al., 2018; Lempriere, 2020; Veolia, 2024). V2G technology leverages the battery storage capabilities of EVs, allowing them to function as dynamic energy storage solutions that enhance grid stability. By acting as virtual power plants, V2G systems are crucial in alleviating peak load stresses on the grid, enhancing the grid's capacity to integrate renewable energy sources, and aiding in voltage regulation. One application of this technology is in residential areas where heat pumps, especially during colder months, place considerable demand on the electricity grid. This increased demand can strain the grid when combined with high levels of EV penetration. However, V2G technology offers a solution by allowing EVs to discharge energy back into the grid, effectively buffering peak loads and enhancing grid resilience and stability (Dik et al., 2024). Numerous studies have demonstrated the effectiveness of V2G as a grid buffer (Bibak and Tekiner-Moğulkoç, 2021b; Drude et al., 2014; Liu et al., 2013; Mwasilu et al., 2014; Tchagang and Yoo, 2020; Zheng et al., 2021), underscoring the pivotal role of V2G in modern energy strategies.

Notable initiatives, such as the City-Zen project by the European Union that has identified Amsterdam as a pilot city for V2G technologies, aim to cultivate sustainable and resilient urban energy ecosystems (European Commission, 2020). Similarly, North London has embarked on the establishment of the world's most extensive V2G project focusing on electric buses, deploying an initial fleet of 28 zero-emission buses with plans to expand the fleet to 100 units (Lempriere, 2020).

Despite the considerable promise of V2G technology, its real-world application is contingent upon the establishment of extensive infrastructural frameworks (García-Villalobos et al., 2015; Guo et al., 2016). The feasibility of V2G charging faces uncertainties, particularly regarding drivers' willingness to engage in energy-sharing initiatives (Mwasilu et al., 2014). This hesitation largely stems from concerns that bi-directional charging could accelerate battery wear and tear (van Heuveln et al., 2021), a significant issue since the battery represents the most costly component of an EV (Chien et al., 2023; Mauler et al., 2021). These challenges spotlight the potential of an alternative method for energy replenishment: battery swapping. Unlike traditional charging methods that require lengthy periods to recharge batteries, battery swapping offers a swift exchange of depleted batteries for ones that are fully charged and ready to use (Ahmad et al., 2020; Vallera et al., 2021). Crucially, the battery swapping model transfers the ownership of the expensive batteries from the vehicle owner to the service provider. This arrangement facilitates the greater availability of these batteries for grid-support services, presenting a viable and efficient pathway for the integration of V2G technology in environments equipped with battery swap stations (Ahmad et al., 2020).

Recent advancements in battery swapping systems designed for four-wheelers have spurred a reassessment of their economic and operational feasibility within electric vehicle frameworks. Research in this area has led to the development of various optimization strategies aimed at enhancing the efficiency and profitability of these systems. Notably, Sarker et al. (2015) introduced a day-ahead scheduling framework leveraging Battery-to-Grid (B2G) services, considering battery degradation, market price fluctuations, and demand uncertainty. Their model also supports energy transfer between batteries (Battery-to-Battery, B2B) when economically beneficial. Liang et al. (2017) examined optimal battey swapping station (BSS) operation from an investor's perspective, proposing ordered charging and discharging strategies and conducting scenario and sensitivity analyses to identify key influencing factors. Widrick et al. (2018) developed a Markov decision process model to optimize charging and discharging at EV battery swap stations under nonstationary conditions, presenting practical benchmark policies for effective management. Gao et al. (2020) proposed a deep reinforcement learning-based optimization model to minimize BSS operating costs, utilizing deep deterministic policy gradient to dynamically control multiple charging piles based on real-time data. Collectively, these innovative strategies highlight the potential of battery swapping stations not only to streamline the integration of V2G technology but also to enhance the economic and environmental sustainability of electric mobility for four-wheelers.

In addition to four-wheelers, the trend toward electric two-wheelers is swiftly ascending in terms of electric mobility, especially in the Asia-Pacific region (IEA, 2023). The rise in popularity of these vehicles globally can be attributed to their relative affordability, which offers an accessible avenue to private vehicle ownership. Additionally, their compact size provides a solution to the demands of quick, efficient transport that also saves on space—an appealing prospect in densely populated areas. Furthermore, their environmentally friendly characteristics align with a growing societal push towards greener transportation alternatives (Chien et al., 2023; Kjærup et al., 2021). The design of these smaller electric scooters allows for a simplified battery-swapping process, as their lightweight batteries can be exchanged manually without the need for complex mechanical systems. This not only reduces the infrastructure costs associated with constructing battery swap stations but also improves the user experience by speeding up the battery replacement process, making battery swapping an economically viable and preferred method for recharging electric two- and three-wheelers (Ahmad et al., 2020; Nimit, 2023).

Historically, research on V2G technologies has primarily centered on four-wheeled electric vehicles. Yet, as electric scooters (e-scooters) become more prevalent and battery swap networks grow, there emerges a clear necessity for V2G strategies tailored for electric two-wheelers. Despite their potential, these strategies are underexplored, marking a crucial area for further development. Moreover, while numerous studies have investigated the economic benefits of V2G, such as reducing energy costs (Abdelfattah et al., 2024; Bhatti and Salam, 2018; Brinkel et al., 2020; Gao et al., 2020; Hao et al., 2023; Javadi and Baghramian, 2024; Liang et al., 2017; Sarkar et al., 2024; Sarker et al., 2015; Widrick et al., 2018; Yusuf et al., 2023) or moderating peak loads (Abdelfattah et al., 2024; Bhatti and Salam, 2018; Brinkel et al., 2020; Javadi and Baghramian, 2024; Liang et al., 2017; Yusuf et al., 2023; Zheng et al., 2021), the environmental impacts and V2G's contribution to carbon reduction are often overlooked.

Previous studies have not comprehensively explored the integration of vital factors such as implicit costs and emissions from operations and battery degradation, which are crucial for validating the effectiveness of V2G strategies in lightweight battery-swapping systems. Our research addresses these gaps, as detailed in Table 1, by thoroughly assessing the impacts of e-scooter battery swap stations on both grid stability and environmental sustainability. This study extends the dialogue on V2G by evaluating the impact of e-scooter swap stations on grid stability and environmental sustainability. Focusing on Taiwan's dense two-wheeler landscape (Ministry of Transportation and Communications, 2024), where the e-scooter market has expanded notably, we examine the tangible effects of V2G implementation. These include reductions in operating costs, effective management of peak electricity demand, and crucially, potential decreases in emissions as part of Taiwan's goal to achieve net-zero emissions by 2050 (National Development Council, 2022). The widespread adoption of battery swapping, led predominantly by industry giant Gogoro (2024a), makes Taiwan an exemplary case for studying the practical applications of V2G technologies.

1.2. Paper Contributions

With Gogoro's network of GoStations now surpassing traditional fuel stations (Gogoro, 2024b; Ministry of Economic Affairs, 2024), Taiwan provides a distinct platform for exploring V2G applications within electric mobility. This study leverages real operational data from Gogoro's extensive network, enhancing the real-world relevance and robustness of our findings. By analyzing V2G integration within the electric scooter battery-swapping framework from an environmental perspective, our research offers substantial contributions to the field, presenting actionable insights for the advancement of urban energy systems. This research demonstrates the dual benefits of V2G systems: their ability to enhance grid management and their capacity to drive down carbon emissions. Integrating carbon emission considerations into the charging and discharging algorithms of swap stations is an innovative approach that positions our study at the forefront of research in this area.

As the shift towards electrified two-wheelers gains momentum and more battery-swapping ecosystems emerge, our study offers a template for how such energy management systems can align with global sustainability targets. This research thus provides a comprehensive framework that can inform policy and operational strategies, pushing the envelope for V2G technology and aiding in the broader transition toward a net-zero future. The primary novelties of this work are outlined as follows:

1. **First Comprehensive Exploration:** This study represents the first comprehensive exploration of V2G strategies tailored specifically for small-scale electric vehicle BSSs, examining potential benefits not previously addressed.
2. **Extension Beyond Economic Advantages:** It extends beyond the well-documented economic benefits of V2G, such as energy cost reductions and peak load management, to assess its environmental impacts, including an in-depth evaluation of V2G's role in carbon reduction—a critical area that has often been neglected.
3. **Employment of Real Operational Data:** The study employs actual operational data from Gogoro's extensive network across Taiwan, significantly enhancing the study's real-world applicability and the robustness of its findings.
4. **Detailed Sensitivity Analysis and Urban-Rural Comparison:** It provides a detailed sensitivity analysis along with an urban-rural comparison, emphasizing key parameters that influence the effectiveness of V2G technologies.

The remainder of this paper is organized as follows. Section 2 details the model framework and methodology, providing an in-depth look at the design and analysis of the V2G strategies. Section 3 delves into the outcomes and benefits of implementing the V2G strategy, which includes a thorough sensitivity analysis and comparisons between urban and rural settings. Section 4 concludes the discussion by summarizing the key findings. Lastly, Section 5 proposes directions for future research, setting the stage for subsequent investigations in this field.

2. Method and Data

2.1. Model Framework Overview

Fig. 1 outlines the smart energy management system (SEMS) which integrates advanced V2G capabilities, showcasing the structured approach our study employs to analyze energy solutions within the

Table 1
Comparative summary of V2G strategy studies

Reference	EV Type & Recharging Method	Peak Reduction	Economic Analysis		Environmental Analysis		Sensitivity Analysis
			Operating	Battery	Operating	Battery	
(Liang et al., 2017)	4W Battery Swap	✓	✓	✓	-	-	✓
(Sarker et al., 2015)	4W Battery Swap	-	✓	✓	-	-	-
(Widrick et al., 2018)	4W Battery Swap	-	✓	✓	-	-	✓
(Gao et al., 2020)	e-Bus Battery Swap	-	✓	-	-	-	-
(Hoehne and Chester, 2016)	4W Plug-in	-	-	-	✓	-	-
(Bhatti and Salam, 2018)	4W Plug-in	✓	✓	-	-	-	-
(Brinkel et al., 2020)	4W Plug-in	✓	✓	✓	✓	✓	
(Zheng et al., 2021)	4W Plug-in	✓	-	-	-	-	-
(Hao et al., 2023)	4W Plug-in	-	✓	-	-	-	✓
(Yusuf et al., 2023)	HDEV/LDEV Plug-in	✓	✓	✓	-	-	-
(Sarkar et al., 2024)	4W Plug-in	-	✓	✓	-	-	-
(Javadi and Baghramian, 2024)	4W Plug-in	✓	✓	✓	✓	-	-
(Abdelfattah et al., 2024)	e-Bus Plug-in	✓	✓	-	-	-	-
This Paper	2W Battery Swap	✓	✓	✓	✓	✓	✓

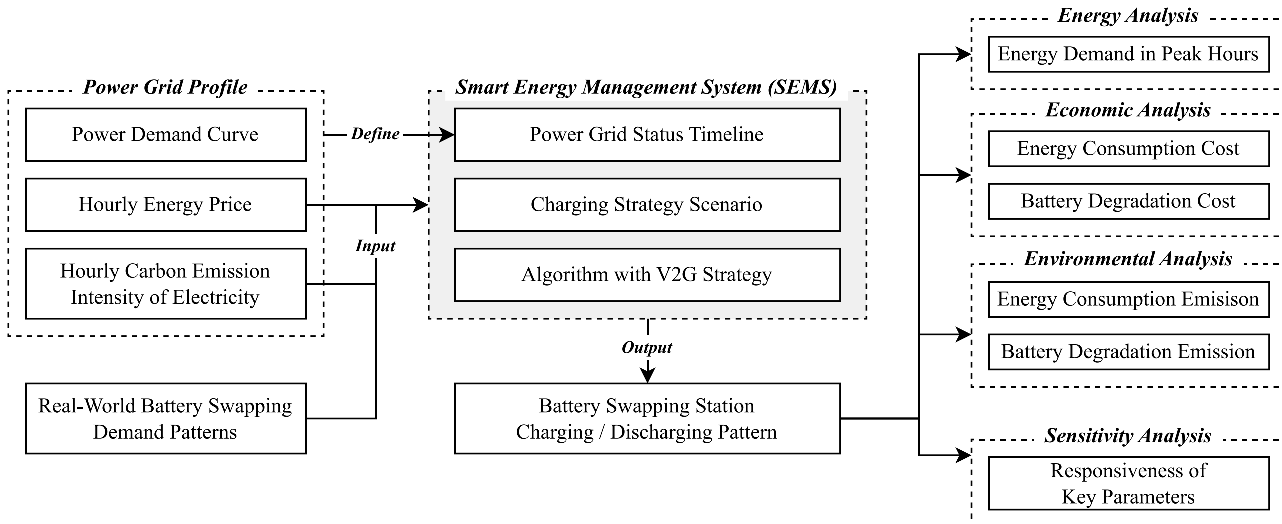

Fig. 1. Methodology framework of the smart energy management system (SEMS)

electrical grid. Our research begins with a comprehensive analysis of the existing grid profile, assessing critical elements such as power demand curves, time-of-use electricity pricing, and hourly carbon emissions. By examining grid performance on an hourly basis, our methodology strategically identifies periods of peak demand to help mitigate excessive loads on power generators, as well as low-carbon emission intervals that are ideal for scheduling charging times at battery swapping stations. This dual-focused evaluation approach not only aids in effective load management but also promotes a balanced distribution of energy across the grid, enhancing overall grid stability and efficiency.

Advancing from this foundational analysis, our approach involves detailed scenario-based simulations that assess the potential impacts of various charging and discharging patterns at battery swapping stations. These scenarios provide a framework for a holistic evaluation encompassing energy utilization, economic implications, and environmental outcomes. The insights gained from this comprehensive assessment are further refined through a sensitivity analysis, which examines the responsiveness of our model to changes in key operational parameters. This methodological structure ensures that our analysis not only captures the complexities of grid interactions but also underscores practical

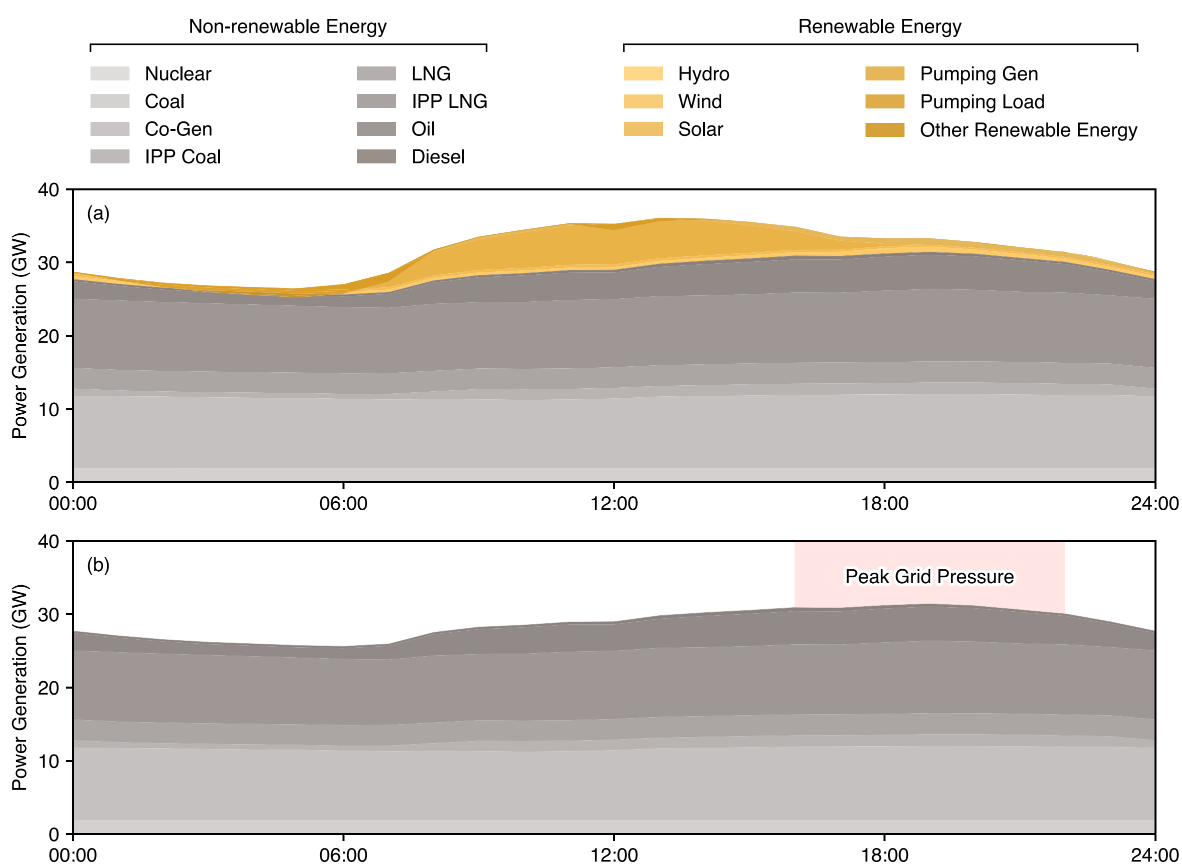

Fig. 2. Daily electricity generation profile in Taiwan in June 2023: (a) With renewable energy sources included; and (b) Excluding renewable energy sources, highlighting peak demand times.

strategies for enhancing the efficacy of V2G technologies.

2.2. Determining Peak Hours for Grid Stability and Carbon Impact

This section aims to provide an in-depth evaluation of peak energy consumption periods in Taiwan from two critical standpoints: grid stability and carbon impact. From an electrical grid perspective, we identify and examine times of high demand, which necessitate a strategic reduction in electricity consumption to enhance the resilience and reliability of the power system. From an environmental perspective, we analyze Taiwan's power generation mix and compute the carbon intensity of electricity during different time periods, shedding light on the potential climate change mitigation benefits that could be realized through the strategic integration of V2G technologies.

2.2.1. Grid Demand Profiles

Upon examining the electricity generation data for Taiwan (Taipower Company, 2020), with a focus on the output excluding renewable sources, it becomes apparent that conventional power plants often experience their peak demand between 4:00 PM and 10:00 PM, a time when demand exceeds the 75th percentile of their capacity. This observation is represented in Fig. 2 using June 2023 data for illustrative purposes. The Taipower Company's time-of-use electricity pricing during these hours on summer weekdays reinforces this observation; rates can increase substantially, at times quadrupling those of off-peak periods (Taipower Company, 2023). Such a pricing strategy is likely intended to temper demand during these high-stress periods for the grid. Recognizing the significance of this data, the 4:00 PM to 10:00 PM interval is identified as the peak grid pressure interval. This time frame is thus essential for the strategic implementation of V2G technologies, as it represents a period where the grid is most vulnerable and can benefit greatly from the stabilizing influence that V2G can provide.

2.2.2. Hourly Carbon Intensity of Electricity Generation

To evaluate the carbon emissions associated with energy consumption, we utilize the bottom-up electricity emission intensity evaluation method developed by Tseng et al. (Tseng and Hsieh, 2023). This approach enables us to compute Taiwan's hourly grid carbon intensity (expressed as $kgCO_2eq$ per kWh) by accounting for emissions at the unit level of generation, allowing us to foresee emission intensity fluctuations over time, particularly as the penetration of solar power generation changes. The carbon emission intensity (CEI) at any given time t is calculated using the following Equation (1) and the resulting emission intensity curves are shown in Fig. 3.

$$CEI_t = \frac{CE_t}{\sum_i N_{i,\,t}} = \frac{\sum_i \sum_j G_{i,\,t} \times EF_{i,\,j} \times LHV_i \times GWP_j}{\sum_i N_{i,\,t}} \tag{1}$$

where CE_t represents the total carbon emissions from the power grid's thermal generating units (such as coal, natural gas, and oil) at time t ($kgCO_2eq$); $G_{i,\,t}$ and $N_{i,\,t}$ represent the gross and net electricity generation by fuel i at time t (kWh), respectively; $EF_{i,\,j}$ denotes the emission factor of fuel i for greenhouse gas (GHG) j ($kgCO_2eq$ / kJ); LHV_i is the lower heating value of fuel i (kJ / kg); GWP_j represents the global warming potentials of GHG j ($kgCO_2eq$ / kWh); i represents different types of fuels or energy sources, including coal, natural gas, oil, nuclear, and renewables; j represents different types of GHG emissions, including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). These parameters are derived from the IPCC guidelines for GHG inventories (Eggleston et al., 2006; Solomon et al., 2007) and Taiwan's electricity company reports (Taipower Company, 2019).

Upon reviewing the emission intensity curves, we identify periods with low emission intensity, particularly from 8:00 AM to 4:00 PM. During these hours, energy generation relies more on cleaner sources, making it a preferable time for V2G charging activities to take place to reduce the overall carbon emissions footprint effectively. The findings also indicate that while solar PV generation substantially reduces emission intensities at midday, its impact diminishes in the evening. As a result, there is a pronounced disparity between daytime and nighttime emission levels, with nighttime periods associated with higher carbon emissions due to less availability of solar energy. This dynamic emphasizes the need for energy strategies that account for these variations to enhance the overall efficiency of emissions reduction.

2.2.3. Integrating Grid Stability and Carbon Intensity Data

By integrating data on grid demand with emission intensity, we can identify critical periods within the grid's daily cycle. This integration is illustrated in Fig. 4, where we map out the electricity generation curve and emission intensities to identify strategic times for V2G interventions. Our approach reduces power consumption at e-scooter battery swapping stations (BSSs) during peak hours and, where possible, directs stored energy back to the grid to alleviate pressure. Conversely, we shift BSS charging operations outside these intervals. Armed with insights from hourly emission intensities, our scheduling can be fine-tuned to lessen the strain on the grid and minimize the carbon footprint of V2G operations. The methodology we employ balances the dual goals of enhancing grid stability and promoting environmental sustainability. By synchronizing BSS activities with times of lower emissions, the role of V2G technology in fostering a more sustainable energy

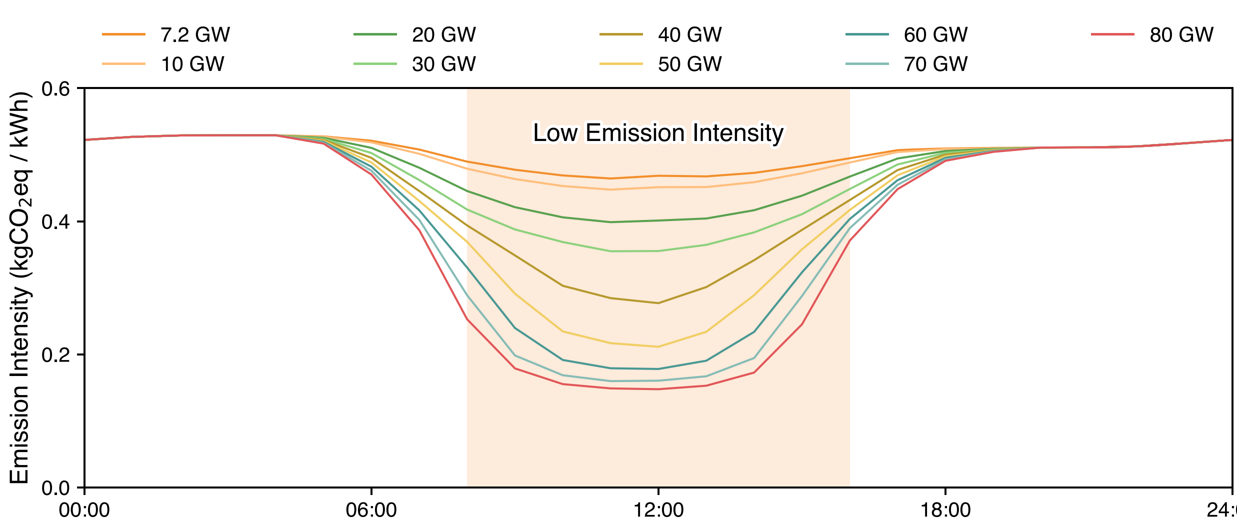

Fig. 3. Hourly emission intensity curve: Assessing the impact of solar photovoltaic (PV) installation on overall emission levels throughout the day.

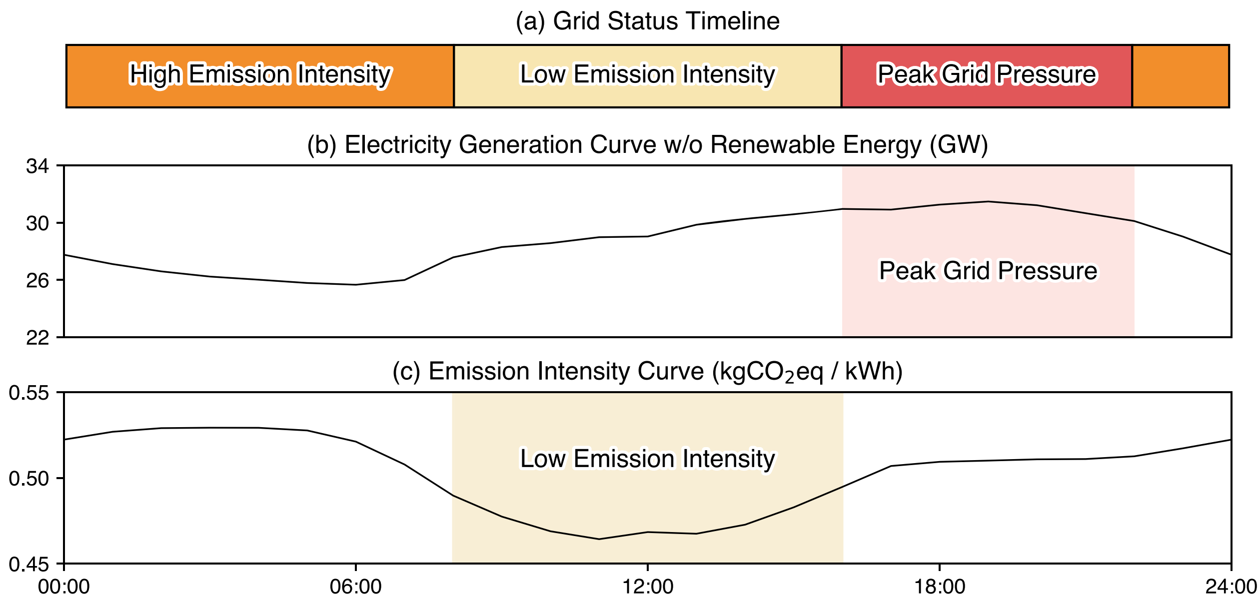

Fig. 4. (a) Integrated grid status timeline: (b) Illustrates the grid's operational phases with a focus on non-renewable energy generation and (c) Details the emission intensity fluctuations, identifying opportune moments for grid support and environmental benefits.

framework could be significantly amplified.

2.3. Development of Charging Strategy Scenarios

To rigorously evaluate the impact of varied charging strategies on the electrical grid, we design a scenario analysis that delineates three distinct charging strategies, informed by the integrated grid status timeline as shown in Fig. 5. Each scenario outlines a distinct approach to battery charging at swapping stations, ranging from continuous charging to strategic charging based on grid demand and carbon emission considerations.

Firstly, we propose a Reference (REF) scenario as our control. Under this scenario, battery swapping stations begin charging incoming batteries immediately upon arrival, continuing until all batteries are fully charged. This approach is called the active charging strategy. Secondly, we integrate V2G bi-directional charging capabilities. Aiming to reduce net energy demand during peak grid pressure intervals, swap stations will use historical battery swap demand patterns to guide their charging operations, ensuring that just enough batteries are charged to meet expected swapping needs. Any excess fully charged batteries provide an opportunity for the station to contribute energy back to the grid during times of high demand. This approach is defined as the passive charging strategy. Finally, our third scenario incorporates an Emission Management strategy (V2G + EM) into the V2G framework, that is, we integrate carbon emission considerations into the charging and discharging algorithms. This strategy is designed to minimize carbon impacts by reducing charging activities during high-emission intensity periods, an approach we call the intermediate charging strategy. In contrast, charging is more aggressive during low emission intensity periods, aligning with the environmental objectives of V2G implementation.

2.4. Data Collection and Preprocessing

For this study, we compile real-world data on the fully charged battery inventory from 2520 stations within the Powered by Gogoro Network (PBGN) throughout Taiwan (Gogoro, 2024b; Mowd, 2024). This data simulates the weekly patterns of user battery swaps and the charging and discharging schedules of service providers, capturing activity from Monday to Sunday.

Given the difficulty of directly obtaining precise battery swap demand data, we derive an estimation based on the changes in fully charged battery quantities over time. Fig. 6 showcases a segment of the dataset representing the fluctuating number of fully charged batteries at each station across an 8-day span, with updates approximately every 20 minutes. We deduce battery swap demands within different intervals using Equation (2). It's important to note, however, that this estimation approach has its limitations. For instance, it may not capture concurrent events of battery swaps and charges—if two batteries are swapped out

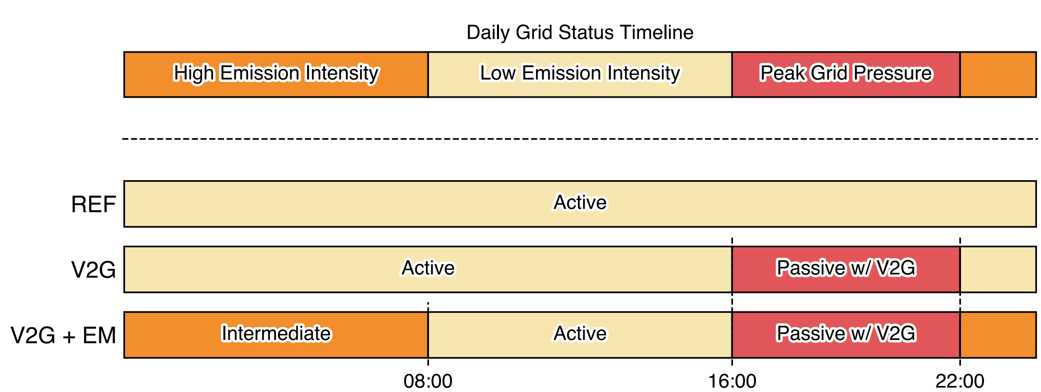

Fig. 5. Charging strategy against grid dynamics: Illustrating the integration of different charging approaches with key grid status time points identified at 8:00 AM, 4:00 PM, and 10:00 PM.

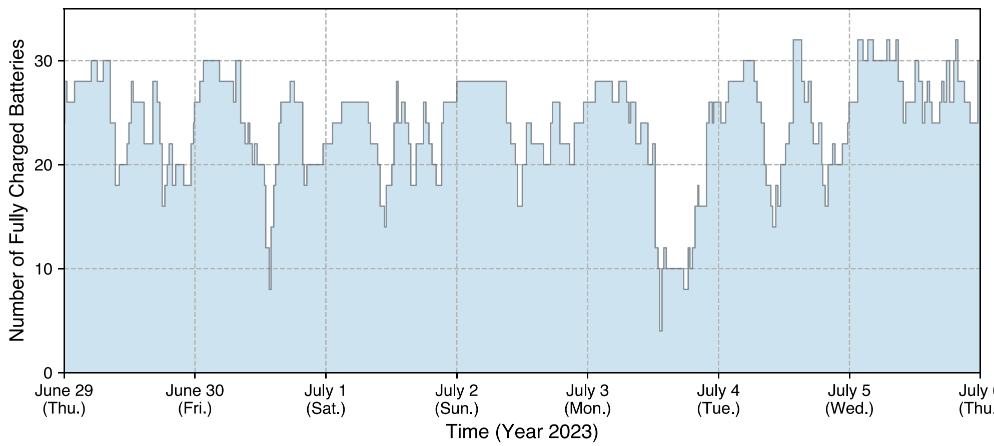

Fig. 6. Sample fully charged battery quantity curve: Illustrating the temporal pattern of battery availability at the stations, with the y-axis quantifying the count of fully charged batteries at each recorded timestamp.

and two are charged within the same interval, these swaps would not be reflected in the demand estimation.

$$d_t = \begin{cases} \sum_{k=1}^{K} |n_{k+1} - n_k|, & \text{if } n_{k+1} < n_k \\ 0, & \text{if } n_{k+1} \geq n_k \end{cases} \tag{2}$$

where d_t represents the battery swap demands in any given time interval from t to $t+1$ (swaps); K denotes the number of data points within the time interval (data points); n_k indicates the count of fully charged batteries at the k^{th} time point (batteries).

2.5. Constructing the Smart Energy Management System (SEMS)

2.5.1. SEMS Process Flow for Charging and Discharging

In the development of the SEMS model, we consider the specific charging and discharging profiles of e-scooter batteries and ensure the synchronization of these processes across all networked BSSs. Our SEMS model presupposes that every BSS is fully integrated with the grid and prepared for bidirectional charging. Fig. 7 outlines the operational procedure for the SEMS, which coordinates activities across Taiwan's extensive network of BSSs. Over a typical week, or 168-hour cycle, SEMS processes activities at each of the 2,520 BSSs, responding dynamically to the unique battery-swapping demands of each location. The system operates on an hourly cycle, where projected battery requirements for the forthcoming two hours are calculated using historical usage patterns. This approach enables SEMS to decide whether a station should charge batteries in anticipation of upcoming demand or discharge surplus energy back to the grid based on its current capacity and grid requirements.

2.5.2. Dynamic Management and Event Scheduling

Given the modest capacity of individual swappable e-scooter batteries, typically around 1.5 kWh as reported by Gogoro (Gogoro, 2024c), and challenges in tracking individual usage accurately, our model assumes that returned batteries generally maintain a 20% state of charge (SoC). This is based on operator guidelines recommending users to swap batteries before they drop to 20% to alleviate range anxiety. The model simulates the charging process at a 1C rate. Due to the general unavailability of detailed specifications for swapping units, we rely on Level 2 charging station norms to presume that each swapping unit operates consistently at 7 kW (EVBox, 2023; Pod Point, 2024; Tesla, 2024). This setup allows each BSS to charge up to five batteries concurrently. The dynamics of the SEMS are clarified through detailed notation, emphasizing the timing of swapping events within the system:

1. **Decision Time Set**: The model divides time into discrete periods from 0 to 167 (i.e., $t = \{0, \ldots, 167\}$), covering all hours across a week, beginning at midnight (12:00 AM) on Monday.
2. **Station Status at Time t**: Denoted by $n_t = \{0, 1, \ldots, N\}$, where N is the maximum battery capacity of the station, reflecting the number of fully charged batteries available at any decision point.
3. **Action at Time t**: Decision to charge (a_t^+) or discharge (a_t^-) at time t are modeled as follows:

$$\begin{cases} a_t^+ = \{0, 1, \ldots, \min(n_{t,deplete}, A)\} \\ a_t^- = \{0, 1, \ldots, \min(n_t, A)\} \end{cases} \tag{3}$$

Here, $n_{t,\ deplete} = N - n_t$ indicates depleted batteries at a 20% SoC, and A represents the station's maximum charging and discharging capacity per hour (batteries/hour). Each swapping unit is assumed to operate with a consistent 7 kW charging power (EVBox, 2023; Pod Point, 2024; Tesla, 2024), enabling simultaneous charging of up to 5 batteries per unit per hour. Positive action implies charging, and negative implies discharging, with no overlap in the same period.

To adapt to fluctuating user demands and ensure a buffer against unexpected surges, a reserve of batteries, N_r, is maintained:

$$N_r = N \times P_r \tag{4}$$

where P_r is the designated reservation proportion, set to 10% for this study.

2.5.3. Strategic Charging and Discharging

The charging strategy is based on historical swapping demand data, balancing the need for a ready supply of charged batteries with maintaining a reserve for emergencies. The required stock of batteries for the next hour, $n_{t+1,\ require}$, is calculated as:

$$n_{t+1,require} = d_t + d_{t+1} + N_r \tag{5}$$

where $n_{t+1,\ require}$ represents the targeted number of ready-to-use batteries for the next hour, d_t is the current demand, d_{t+1} is the anticipated demand for the next hour.

Within our SEMS, we implement three distinct charging strategies—active, passive, and intermediate—tailored to address both operational efficiency and environmental concerns. These strategies, along with their specific charging (a_t^+) and discharging (a_t^-) actions, are detailed in Fig. 8 and guided by Algorithm 1.

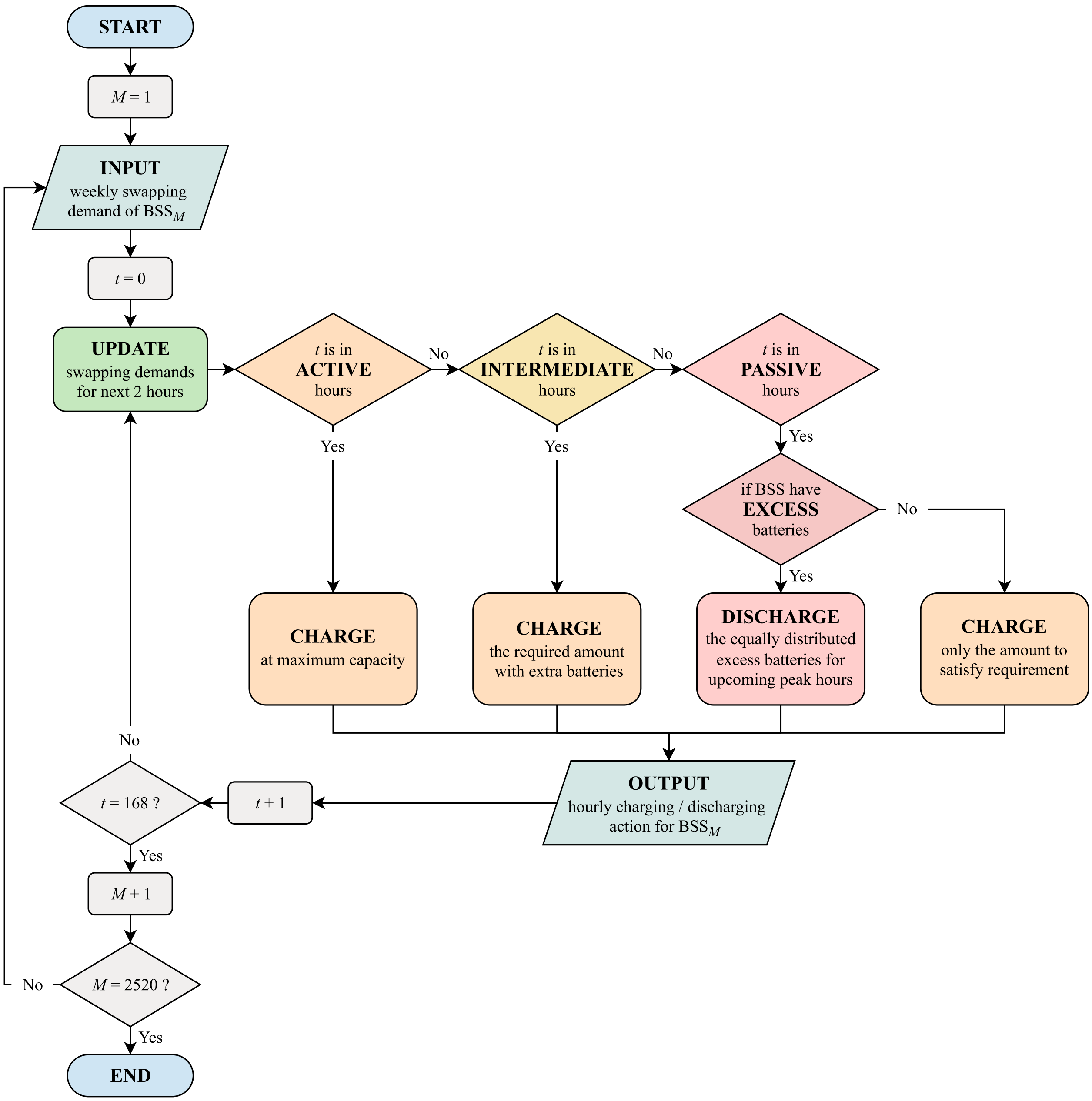

Fig. 7. SEMS decision-making flowchart for charging and discharging activities

1. **Active Charging Strategy (Fig. 8(a)):** This approach involves charging during specific time intervals that are optimal for energy replenishment. During these periods, BSSs operate at their maximum charging capacity, ensuring batteries are swiftly recharged and ready for deployment.
2. **Passive Charging Strategy (Fig. 8(b)-(c)):** Under this strategy, we prioritize the energy contribution of the stations over their charging demands, particularly during peak demand times when energy conservation and grid support are crucial. In such scenarios, BSSs charge batteries just enough to meet immediate needs, maintaining a basic level of readiness, denoted as $n_{t+1,\ require}$. Any surplus energy is then redirected back to the grid, enhancing overall grid stability.
3. **Intermediate Charging Strategy (Fig. 8(d)):** This strategy is activated during periods marked by operational constraints, such as high electricity emission intensities. Here, BSSs charge at a rate that lies between the active and passive strategies. The goal is to effectively manage the power demand without exacerbating carbon impacts, striking a balance between immediate energy needs and longer-term ecological considerations.

Algorithm 1 details the operational logic for each hour, adjusting actions based on the strategy in place and current battery levels. If the hour is within active charging times, a_t^+ is maximized to fill all available slots for charging, and a_t^- is set to zero. During intermediate times, a_t^+ meets the required battery demand plus an additional reserve to accommodate unexpected needs, while a_t^- remains zero. $a_{t,\ require}^+$ denotes the number of batteries to meet the demand for the next period ($= n_{t+1,\ require} - n_t$). Additionally, A_a represents the extra batteries to be charged during intermediate periods (batteries/hour), set at 40% of the maximum charging capacity ($= \gamma \times A$). This 40% level is derived from empirical analysis and optimization based on real-world data from battery-swapping demand, striking a balance between feasibility and operational functionality. This strategy ensures that the BSS has a higher availability of fully charged batteries compared to passive hours,

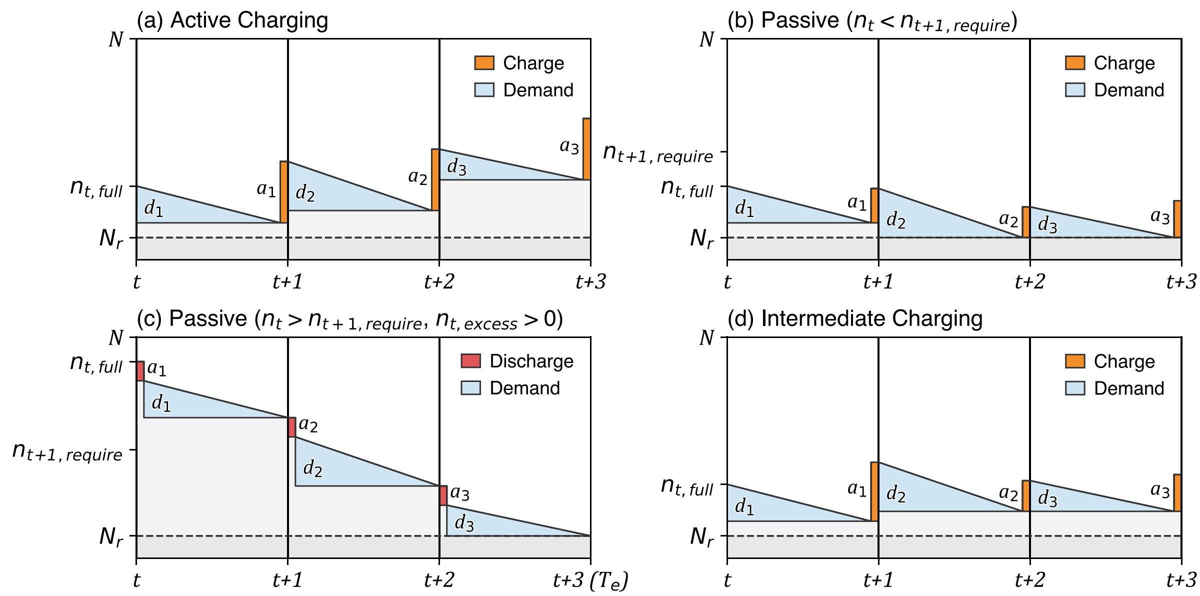

Fig. 8. Operational dynamics within the SEMS under (a) active charging, passive charging (b) without and (c) with surplus energy, and (d) intermediate charging. Note: Charging phases (in orange) conclude at the end of each period, while discharging phases (in red) commences at the start of each period. The light-blue shaded areas represent the demand for battery swaps, indicating real-time usage rates.

enhancing operational readiness. In passive times, if excess battery capacity is available, charging is minimized or halted, and excess energy is potentially discharged back to the grid. $n_{t,\ excess}$ is the surplus of fully charged batteries available during peak times, subtracting the upcoming demand from the current stock ($= n_t - \sum_{t=t}^{T_e} d_t - N_r$, where T_e indicates the end of the peak period, which is 10 PM for every weekday).

The number of fully charged batteries at the end of each hour (n_{t+1}) is updated to reflect the balance after accounting for batteries charged (a_t^+), discharged (a_t^-), and used (d_t). The formula is:

$$n_{t+1} = n_t + a_t^+ - a_t^- - d_t \tag{6}$$

The energy requirements for charging (e_t^+) and discharging (e_t^-) over an hour are calculated with the following equations:

$$e_t^+ = \frac{a_t^+ \times Q \times DoD}{\eta} \tag{7}$$

$$e_t^- = a_t^- \times Q \times DoD \times \eta \tag{8}$$

where Q represents the battery capacity, set at 1.5 kWh (Gogoro, 2024c); DoD indicates the depth of discharge, maintained at 70%, following Park et al. (Park et al., 2023) to optimize battery life and safety between a charge state of 20% and 90%; η denotes to efficiency, accounting for energy conversion and transmission losses during charging and discharging. We adopt a 90% efficiency rate, corroborated by findings from the existing literature (Battery University, 2019; European Commission et al., 2021; Schram et al., 2020).

2.6. *Assessing Economic and Environmental Outcomes*

2.6.1. *Economic Cost*

With the Taipower Company's implementation of time-of-use electricity pricing (Taipower Company, 2023), EV charging and swapping stations conform to a variable rate structure. In summer, for instance, the cost of electricity during peak hours is set at 8.35 TWD per kWh, while off-peak hours enjoy a reduced rate of 2.05 TWD per kWh. Beyond these fluctuating energy rates, the V2G system's intensified battery use and the associated charge-discharge cycles can exacerbate battery capacity fade (Guo et al., 2019), leading to significant replacement costs. Battery longevity is affected by various factors, including depth of discharge (DoD) and cycle count. The operating cost in our simulation is computed using the following equations:

$$OC = \sum_{m=1}^{M} \sum_{t=0}^{T} (ECC_t + BDC_t) \tag{9}$$

$$ECC_t = \left(e_t^+ - e_t^- \times \mu\right) \times EP_t \tag{10}$$

$$BDC_t = \frac{TCC_t}{CL_{DoD}} \times BRC \tag{11}$$

Here, the term OC represents the aggregate operating costs accumulated over a week (TWD), where M corresponds to the complete count of BSSs (stations), numbering 2,520 in total (Gogoro, 2024b). T encompasses all 168 hourly segments that constitute a week (-). The two primary constituents of OC are ECC_t, denoting the cost of energy consumed at time t (TWD), and BDC_t, signifying the costs arising from battery degradation during the same period (TWD). The variable μ represents the price ratio of electricity for discharging to charging (-), which is set at 1 in our baseline scenario. This setting assumes that the cost of discharging one unit of energy from the batteries is equivalent to the cost of charging one unit. However, this ratio may vary in practical applications due to external factors such as subsidies or economic incentives, which aim to promote participation in V2G program (Huang and Wu, 2019). EP_t is the energy price at time t (TWD / kWh), influenced by time-of-use rates. TCC_t is the total number of charged cycles at time t (cycles); CL_{DoD} represents the cycle life of a battery at a given DoD (cycles), defined as the total number of charge-discharge cycles the battery can undergo before its capacity degrades to 80% of its initial state of health. Assuming a baseline DoD of 70%, the battery's cycle life is set at 2,020 cycles (ELERIX, 2015); BRC is the cost of battery replacement (TWD / battery), which is set at 278 USD (9,071 TWD), reflecting insights from PBGN operators in July 2023. Operators indicated that replacement costs could be twice the market price due to the enhanced durability and waterproof casing of each smart battery. With lithium-ion battery packs projected to cost 139 USD per kWh in 2023 (BloombergNEF, 2023), this estimate incorporates the exchange rate of 32.63 TWD per USD (Bank of Taiwan, 2024).

2.6.2. *Carbon Emissions*

For a thorough analysis of carbon emissions associated with the

Algorithm 1
Smart Energy Management System (SEMS)

Input: Strategy timeline, state of BSS, swapping demands, charging / discharging rate / efficiency, batteries for reserve

Output: BSS power demand for each hour

foreach BSS in all stations in Taiwan (2,520 BSSs) do
  for each hour in a week (0 to 167) do
    if hour is in active hours **then**
      $a_t^+ = \min(n_{t,deplete}, A)$
      $a_t^- = 0$
    else if hour is in intermediate hours **then**
      $a_t^+ = \min(a_{t,require}^+ + A_a, n_{t,deplete}, A)$
      $a_t^- = 0$
    else if hour is in passive hours **and** $n_t < n_{t+1,require}$ **then**
      $a_t^+ = \min(a_{t,require}^+, n_{t,deplete}, A)$
      $a_t^- = 0$
    else if hour is in passive hours **and** $n_t > n_{t+1,require}$ **and** $n_{t,excess} > 0$ **then**
      Equally distribute excess batteries to upcoming peak hours
      $a_t^+ = 0$
      $a_t^- = \min(n_{t,excess}/(T_e - t), A)$
    end if
  end for
end foreach

SEMS, we assess the emissions from both the operational phase, which includes energy production, and the emissions attributable to the manufacturing of batteries. Utilizing the methodology from section 2.1.2, we evaluate hourly carbon emissions, accounting for electricity consumption fluctuations and grid emission intensity variations. To estimate the carbon footprint of battery replacements, we factor in cycle counts alongside the comprehensive lifecycle carbon emissions of the batteries. Incorporating insights from Schneider et al.'s research on the lifecycle emissions of PBGN batteries (Schneider et al., 2023), we measure the carbon emissions linked to battery disposal. Carbon emissions in the simulation are determined by the following equations:

$$OE = \sum_{m=1}^{M} \sum_{t=0}^{T} (ECE_t + BDE_t) \tag{12}$$

$$ECE_t = \left(e_t^+ - e_t^-\right) \times CEI_t \tag{13}$$

$$BDE_t = \frac{TCC_t}{CL_{DoD}} \times BRE \tag{14}$$

where OE represents the total operating carbon emission accumulated over a week ($kgCO_2eq$); ECE_t reflects the energy consumption emission at time t ($kgCO_2eq$); BDE_t accounts for the emissions due to battery degradation at time t ($kgCO_2eq$); CEI_t indicates the carbon emission intensity at time t ($kgCO_2eq$ / kWh); BRE is the carbon emissions associated with battery replacement ($kgCO_2eq$ / battery). As reported by Schneider et al., the life cycle emissions of PBGN batteries amount to 32.07 $kgCO_2eq$ per kWh (Schneider et al., 2023).

2.7. Defining the Parameters for Sensitivity Analysis

The sensitivity analysis within this research offers a detailed examination of the variability and the inherent uncertainties of our foundational assumptions. It also highlights the extent to which different parameters can influence outcomes, offering insights into the potential impacts of future developments. It is important to note that the upper and lower bounds assigned to the parameters are based on their numerical values and do not suggest the likelihood of particular scenarios occurring. The parameters used in this sensitivity analysis are detailed as follows:

1. **Energy Sell-to-Buy (S/B) Price Ratio:** In the baseline analysis, battery swapping operators are assumed to buy and sell electricity at identical rates, setting the Energy S/B price ratio to 1. However, insights from a discussion in July 2023 with Justin Wu, who holds managerial positions in Gogoro's Impact Office and CEO Office, indicate that operators are willing to pay a premium for green energy to foster sustainable practices. This perspective, supported by the literature (Economic Daily News, 2023; Huang and Wu, 2019), prompts an adjustment of the upper bound of the price ratio to 1.5. Conversely, scenarios where the selling price is lower than the buying price are considered, particularly during power grid congestion hours when tariffs might be applied to selling energy (Huang and Wu, 2019). For these cases, the lower bound of the price ratio is set at 0.8. This dual approach allows for a comprehensive examination of different market conditions and their impact on the financial dynamics of battery swapping operations.
2. **Depth of Discharge (DoD):** Drawing from Park et al.'s research on DoD (Park et al., 2023), a 70% baseline DoD is established, aligning with the most favorable cycle characteristics and safety. An increased 80% DoD serves as the upper bound, while a reduced 60% DoD is positioned as the lower bound.
3. **Energy Loss:** The standard energy loss is fixed at 10%, with older infrastructure that could elevate losses, we set the upper bound at 15%. Considering advancements in technology potentially lowering this loss, we place the lower bound at 5%.
4. **Battery Replacement Cost:** Price projections estimate lithium-ion battery packs to cost about 139 USD per kWh by 2023 (BloombergNEF, 2023), with a potential decline to 75.1 USD per kWh by 2030 (Chen and Hsieh, 2023). Engagements with PBGN operators in July 2023 revealed battery replacement costs could double the market price, partly due to the enhanced durability provided by the robust and waterproof aluminum alloy casing that each smart battery is equipped with. Factoring in the exchange rate of 32.63 TWD to 1 USD (Bank of Taiwan, 2024), the baseline and upper bound for battery replacement costs are set at 278 USD (9,071 TWD), with the lower limit at 150.2 USD (4,902 TWD).
5. **Battery Replacement Emission:** According to research by Schneider et al. (2023) (Schneider et al., 2023), the life cycle emissions of PBGN batteries are quantified at 32.07 $kgCO_2eq$ per kWh. Future projections based on the use of greener energy sources and improved recycling methods anticipate a potential reduction of up to 46% in these emissions (Chen and Hsieh, 2023). Consequently, the baseline and upper bound for battery replacement emissions are maintained at the current level of 32.07 $kgCO_2eq$ per kWh, while the lower bound is set at 54% of this figure, amounting to 17.32 $kgCO_2eq$ per kWh.
6. **Solar PV Capacity:** In step with Taiwan's net-zero emissions target (National Development Council, 2022), the aspiration to reach a

cumulative solar PV capacity of 80 GW by 2050 defines the upper bound. The present installation level of 7.2 GW serves as the baseline and is also considered the lower bound.

7. **Shared Battery Utilization Ratio:** This ratio represents how many electric scooters typically share one battery, derived from dividing the total fleet of electric scooters by the aggregate number of batteries available at swap stations. Distinct variations exist across regions, and for the purpose of this study, we set the baseline at the national average for Taiwan (values for all cities are shown in Table S1), which is 6.78 (e-scooters per battery). The upper and lower bounds are adopted from the highest and lowest regional ratios, with the lower limit at the 25th percentile (5.72) and the upper limit at the 75th percentile (7.13).

Table 2 categorizes each parameter with their respective upper bound, baseline, and lower bound values, offering a structured approach to understand the system's flexibility and responsiveness to change.

Table 2
Sensitivity analysis parameters: Defining bounds for system variability (Exchange rate of 32.63 TWD to 1 USD)

Parameter	Upper Bound	Baseline	Lower Bound
Energy Sell/Buy Price Ratio (-)	1.5	1	0.8
Depth of Discharge (%)	80%	70%	60%
Energy Loss (%)	15%	10%	5%
Battery Replacement Cost (USD / kWh)	278 (9,071 TWD)	278 (9,071 TWD)	150.2 (4,902 TWD)
Battery Replacement Emissions ($kgCO_2eq$ / kWh)	32.07	32.07	17.32
Solar PV Capacity (GW)	80	7.2	7.2
Shared Battery Utilization Ratio (-)	7.13	6.78	5.72

3. Results and Discussion

3.1. Evaluating the V2G Strategy Efficacy

To showcase the efficacy of the V2G strategy, Fig. 9(a) presents an averaged profile of the hourly power dynamics on weekdays[1], highlighting the significant differences between the REF scenario and the V2G strategy. The disparity becomes most pronounced during the peak grid demand times and persists until the early hours of the morning at 6:00 AM. With V2G activated, the net power demand sees a significant reduction during these critical peak times. Especially notable is the time window from 16:00 to 22:00, where battery swapping stations not only meet their energy requirements but also feed excess electricity back into the grid, effectively reversing the net power demand into a positive power supply. Following the peak demand phase, there's a swift increase in charging activities to replenish the batteries in anticipation of the next day's requirements. By 6:00 AM, the convergence of the net power demand curve with that of the REF scenario indicates a successful reserve buildup of fully charged batteries, ready to service the day's demands.

Fig. 9(b)-(d) presents a side-by-side comparison of peak electricity demand, operating costs, and operating carbon emissions between the REF and V2G scenarios. The V2G strategy demonstrates marked effectiveness, evidenced by a 110.1% reduction in net energy demand during peak periods, a 18.9% decrease in costs, and a slight drop in carbon emissions by 1.0%. Diving deeper, the analysis breaks down costs into battery degradation cost and energy consumption cost, and carbon emissions into battery degradation emissions and energy consumption emissions. It's important to note that costs associated with battery degradation account for 60.3% of the total costs in the REF scenario, largely driven by the high battery prices. Adopting the V2G system, despite an 8.0% increase in battery degradation costs from the more frequent charging and discharging cycles relative to the REF scenario, delivers economic gains. A notable 56.5% reduction in energy consumption costs emerges from the strategic adjustment of operational behaviors—charging less during high-tariff peak periods and, instead, feeding energy back to the grid, while increasing charging activities when electricity prices drop. In assessing operating emissions, battery degradation emissions increase by 8.0% under the V2G strategy, a result of more frequent battery cycling. Concurrently, emissions from energy consumption decrease marginally by 1.0%, as the amount of power filled slightly exceeds the power shaved. Additionally, the emission intensities during these periods are comparable, contributing to a slight reduction in overall emissions.

[1] This approach allows for a clear representation of typical weekday performance. Comprehensive results covering the entire week, from Monday to Sunday, are detailed in Figures S1 and S2. These supplementary figures validate the model's stability and reliability, confirming the effectiveness of the V2G strategy in managing energy demands throughout the week.

3.2. Sensitivity Analysis Within the V2G Framework

The interplay between the V2G strategy and the REF scenario, as discussed in Section 3.1, is subject to a range of determinants. To comprehensively understand how these factors influence outcomes, we conduct a sensitivity analysis of key operational metrics—net energy demand during peak grid pressure intervals, the economic aspects of operating costs, and the carbon impact measured by operating emissions. Analyzed parameters include the energy sell-to-buy (S/B) price ratio, the depth of discharge, the extent of energy loss, the costs associated with battery replacement, the emissions resulting from battery replacement, the capacity of solar PV installations, and the ratio of shared battery utilization. The sensitivity range for each parameter is based on their established upper and lower bounds provided in Table 2, with the baseline serving as the reference point for comparison in Fig. 10.

Firstly, the sensitivity of net energy demand within peak grid pressure intervals (Fig. 10(a)) highlights that the variable with the most noticeable impact on the outcome is the ratio of shared battery utilization. Lowering the ratio to 5.72 indicates a robust battery stockpile per e-scooter, enabling BSSs to significantly reduce the V2G-to-REF scenario net energy demand ratio by 8.7%. An increase in ratio to 7.13, on the other hand, tightens battery availability and causes the net energy demand ratio to rise 18.1% compared to the baseline. In addition, the extent of energy loss also plays a critical role in the net energy demand outcomes, swinging the V2G-to-REF scenario ratio from a 3.6% reduction at a 5% energy loss to a minor 3.3% increase at a 15% energy loss case.

Secondly, the operating cost analysis in Fig. 10(b) reveals that the costs associated with battery replacement have the most considerable influence over total operating expenses, followed by DoD and energy S/B price ratio. Reducing battery cost to 4,902 TWD per kWh (150.2 USD/kWh) significantly decreases the operating costs, plummeting the V2G scenario's ratio to 71.3% of the REF scenario. Higher DoD levels necessitate more frequent battery replacements, inflating costs and pushing the V2G scenario's costs to 85.5% of REF when DoD reaches 80%. The energy S/B price ratio also holds sway; increasing the energy selling price 1.5 times higher than the buying price reduces the V2G scenario's operating costs to 76.8% of REF. The ratio of shared battery utilization has less impact on the operating costs, indicating that battery-sharing logistics play a less critical role in cost fluctuations. This is primarily because, given a consistent user base and battery swapping demand, variations in the number of batteries marginally influence the frequency of charging and discharging cycles, leading to only slight adjustments in battery degradation and energy consumption costs.

Lastly, in the environmental aspect showcased in Fig. 10(c), the V2G

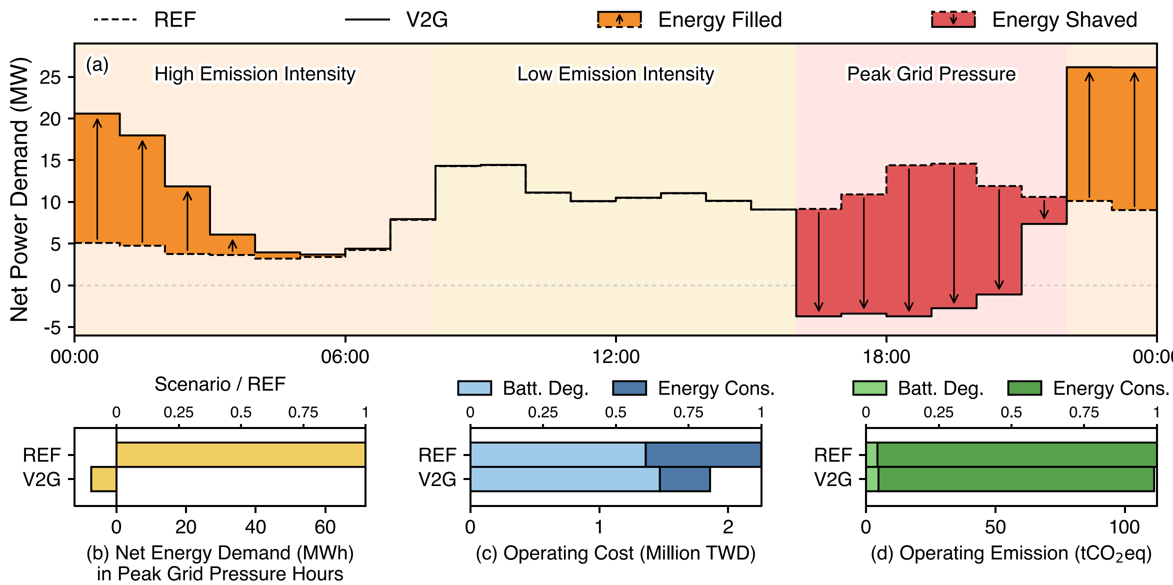

Fig. 9. (a) Daily net power demand fluctuations for REF and V2G scenarios, with the peak demand and high and low emission intensity periods highlighted in light red, orange, and yellow. Panel (b) provides a detailed breakdown of daily net energy demand during peak periods, while panels (c) and (d) focus on operating costs and carbon emissions, respectively. Note: The outcomes presented assume baseline conditions as established in Table 2.

model displays minimal sensitivity to changes across most parameters. Nevertheless, the capacity of solar PV installations stands out to be an exception. With significant charging taking place post-peak demand during the high emission intensity phases, increasing solar PV installations results in higher carbon emissions. This counterintuitive outcome arises because, although solar PV reduces emission intensities during midday, it does not substantially affect the emission levels in the evening. Consequently, the gap between daytime and nighttime emission levels widens, emphasizing the increased carbon emissions associated with intense charging activities during high emission periods. Specifically, as the installed capacity approaches the ambitious 2050 goal of 80 GW, the operational emissions for the V2G scenario exceed those of the REF scenario by more than 2%, marking a significant environmental concern associated with this peak-shaving strategy.

In sum, the V2G strategy shows potential in curtailing net energy demand during peak times and in cutting operating costs, yet its effectiveness in diminishing carbon emissions is less assured, revealing a substantial limitation within the V2G concept. Section 3.3 will explore how integrating carbon emission considerations with V2G can change these dynamics and will compare the impacts of standard V2G strategy against those combined with emission management (V2G + EM).

3.3. Advancing Emission Management (EM) within the V2G Framework

3.3.1. Comparison of V2G and V2G + EM Scenarios

Fig. 11(a) contrasts the net power demand curves for the V2G and the V2G + EM strategies. Through enhanced emission management, BSSs significantly reduce their charging activities during the high emission intensity phase following the peak grid pressure section. Instead, they shift charging to periods of low emission intensity, which not only maintains the net power demand alignment during peak periods as seen with V2G, but also promotes outcomes that are more environmentally beneficial.

The comparative analysis depicted in Fig. 11(b)-(d), reveals marginal distinctions between the V2G and V2G + EM strategies. Although the net energy demand during peak grid pressure intervals sees a minor increase of 0.7% with the V2G + EM strategy compared to V2G alone, the integration of an emissions management approach results in a 0.9% decrease in operating costs and a 2.6% reduction in operating emissions. The negligible disparity between the outcomes suggests that, within the current e-scooter energy ecosystem, both V2G and V2G + EM strategies share considerable similarity in effectiveness. The primary reason lies in the minimal variance in the carbon intensity of electricity during peak versus non-peak times, attributable to the current level of solar PV integration within the energy mix. Hence, the benefits of adding an emission management layer for carbon reductions to the strategy are not yet starkly evident. Nonetheless, as the solar PV capacity expands in the coming years, the environmental benefits of the V2G + EM approach are expected to become more significant, underscoring the criticality of including an environmental perspective in strategic energy planning. This assumption is based on the premise that increased solar PV penetration will widen the disparity in carbon intensity between peak and off-peak periods. The subsequent sensitivity analysis will explore this potential in more depth, examining how growing solar PV installations could enhance the climate benefits of V2G + EM strategies.

3.3.2. Sensitivities of Operating Emissions Under V2G and V2G + EM Scenarios

Fig. 12 presents the sensitivity of operating emissions to key factors within the V2G and V2G + EM frameworks. This section delves into the potential of incorporating emission management for carbon footprint reduction, while other aspects, including net energy demand and operating costs, are elaborated upon in Figure S3. A pivotal outcome of this sensitivity analysis is the significant influence of solar PV capacity.

Taiwan's goal of achieving 80 GW of solar energy capacity is expected to dramatically alter the emission intensity during different periods, highlighting the increased relevance of emission management within the renewable energy framework. The analysis indicates that operating emissions under the V2G + EM strategy could be significantly lowered to 87.2% of those in the REF scenario, given the achievement of the 80 GW solar capacity target. This reduction is attributed to the greater difference in emission intensity between day and night resulting from high solar power integration, emphasizing the importance of shifting energy load to periods of lower emissions, particularly during daytime hours. This suggests that strategic adjustments in V2G operations, which may slightly lessen peak shaving efficiency (Figure S3), can lead to notable carbon reductions. The findings suggest that enhanced emission management harmonizes environmental goals with economic efficiency, a crucial synergy for progressing toward a renewable-centric energy system. Emphasizing the need for environmental considerations

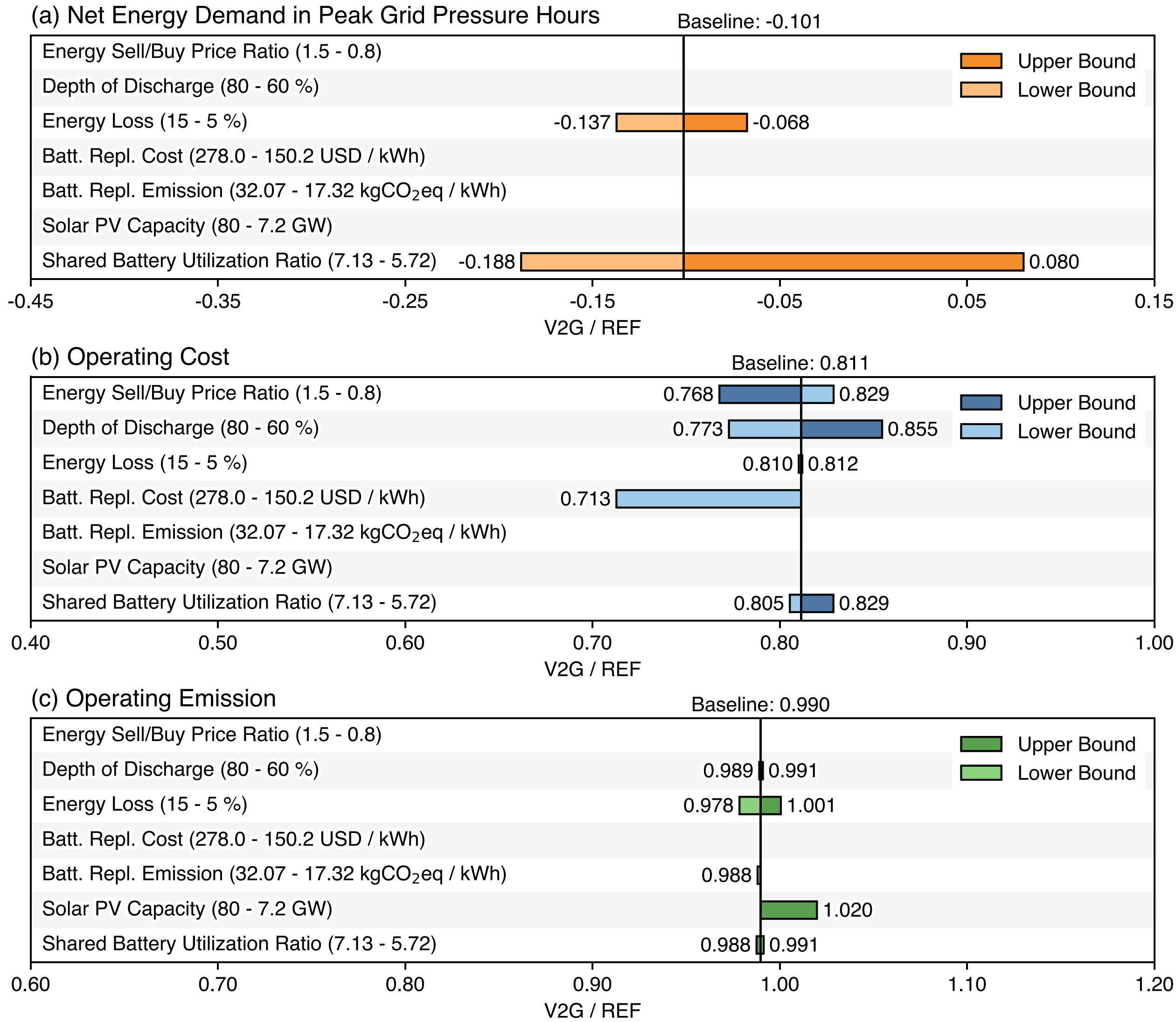

Fig. 10. Sensitivity analysis results for the V2G-to-REF ratio, focusing on the outcomes of (a) the variation in net energy demand during peak periods, (b) the fluctuations in operating costs, and (c) the shifts in operating emissions. Note: Baseline assumptions are outlined in Table 2. For each parameter listed, the numbers in parentheses following the parameter name indicate the range (Upper bound – Lower bound).

in V2G strategy formulation, the V2B + EM scenario underlines a pathway toward a sustainable and economically viable energy landscape.

3.4. Comparative Analysis of V2G Impacts Across Urban and Rural Settings

Fig. 13(a)-(d) presents a detailed analysis of peak power demand shaving, operating cost reductions, and emissions reductions across Taiwan's diverse urban and rural settings. By evaluating urbanization levels alongside shared battery utilization ratios, it's evident that V2G systems in densely populated urban areas effectively reduce peak power demands and operating costs, though these benefits are somewhat more pronounced in rural settings. The complex urban environment, characterized by high operational demands, limits the full potential of V2G strategies but still yields significant benefits. In contrast, rural areas, with their surplus of idle batteries, achieve greater reductions in peak power usage and operating costs. However, their contributions to emissions reductions are less marked than in urban areas, where frequent battery swapping and better integration with renewable energy sources enhance emission control measures.

Fig. 13(f)-(i) examines the daily electricity demand curves for selected urban and rural areas—specifically Taipei City and Kaohsiung City versus Nantou County and Taitung County. The analysis highlights stark differences in electricity usage patterns: urban areas show pronounced peaks during rush hours due to high battery swapping demands, whereas rural areas demonstrate a more consistent demand throughout the day. This distinction highlights the challenges faced by urban areas in mitigating peak electricity demands as effectively as their rural counterparts, though they still manage substantial reductions. This urban-level analysis not only illustrates the varied effectiveness of V2G strategies based on the degree of urbanization but also highlights how rural areas, with their surplus of idle batteries, provide substantial operational benefits and contribute to a more stable grid ecosystem. Meanwhile, urban implementations of V2G at battery swapping stations underscore their potential to significantly enhance environmental benefits, showcasing a strategic approach to urban energy challenges.

4. Conclusion

This study presents the development and application of a comprehensive smart energy management system (SEMS) model, specifically focusing on electric two-wheeler battery swapping stations (BSSs) in Taiwan. This investigation, serving as a pioneering case study to our

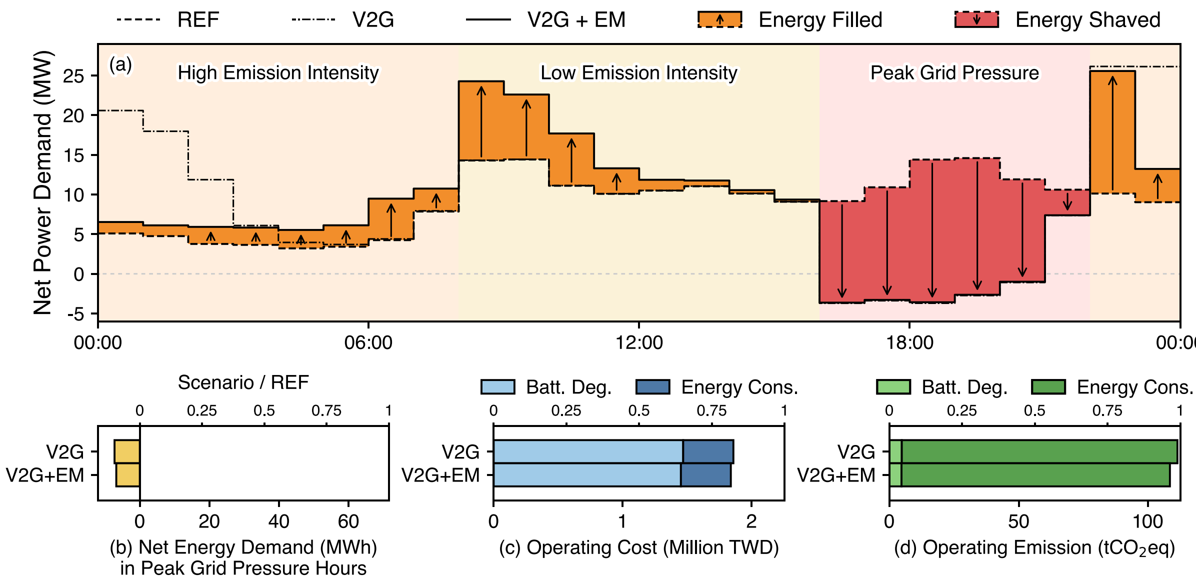

Fig. 11. (a) Daily net power demand fluctuations for REF, V2G and V2G + EM scenarios, with the peak demand and high and low emission intensity periods highlighted in light red, orange, and yellow. Panel (b) provides a detailed breakdown of daily net energy demand during peak periods, while panels (c) and (d) focus on operating costs and carbon emissions, respectively. Note: The outcomes presented assume baseline conditions as established in Table 2.

knowledge, rigorously explores the potential benefits that Vehicle-to-Grid (V2G) strategies could yield when applied specifically to electric scooter (e-scooter) BSSs. At its core, the SEMS model capitalizes on the strategic use of batteries within these stations as energy storage units, enabling flexible scheduling and bidirectional power exchanges with the electrical grid. The overarching aim is to enhance grid stability while offering economic incentives for BSS operators and mitigating the environmental impact.

The research identifies three distinct grid states based on the daily electricity consumption curve and the carbon emission intensity of electricity generation. In this context, three scenarios are developed for detailed comparative analysis: the Reference (REF) scenario, which represents the current state; the Vehicle-to-Grid (V2G) scenario, demonstrating the application of V2G technology; and the advanced Vehicle-to-Grid with Emission Management (V2G + EM) scenario, which additionally factors in carbon impacts. Using the SEMS model, we examine the performance differences across these scenarios on an hourly basis. This assessment spans a network of 2520 BSSs managed by Gogoro Network throughout Taiwan, enabling us to evaluate the operational improvements and environmental progress catalyzed by the deployment of these advanced energy management strategies.

The study presents several key findings and recommendations: Firstly, the study underscores that under the prevailing demands and scooter electrification rates, the V2G scenario has enabled a majority of Taiwanese BSSs to maintain energy independence during peak demand periods. This strategic implementation leads to a notable reduction in peak electricity consumption by 110.1%, thereby enhancing grid stability. Secondly, the transition to a V2G setup results in a marked decrease in operating costs for BSS operators. Considering that battery degradation costs account for a considerable portion—60.3%—of the total operating expenses, further reductions in battery prices hold the potential for even more significant financial benefits. However, it is observed that merely integrating V2G technology falls short in effectively reducing operating carbon emissions. The lack of a robust emission management strategy might inadvertently escalate environmental impacts. Additionally, our comparative analysis across urban and rural settings demonstrates that V2G strategies effectively manage peak demands and costs in both environments, with rural areas often outperforming urban settings due to higher idle battery availability. This highlights the broader applicability and significant benefits of V2G strategies across varied urbanization levels, promoting more stable and efficient energy management across the grid. Lastly, the research emphasizes the critical role of integrating emission management within the V2G framework. Although this might entail minor trade-offs, such as a

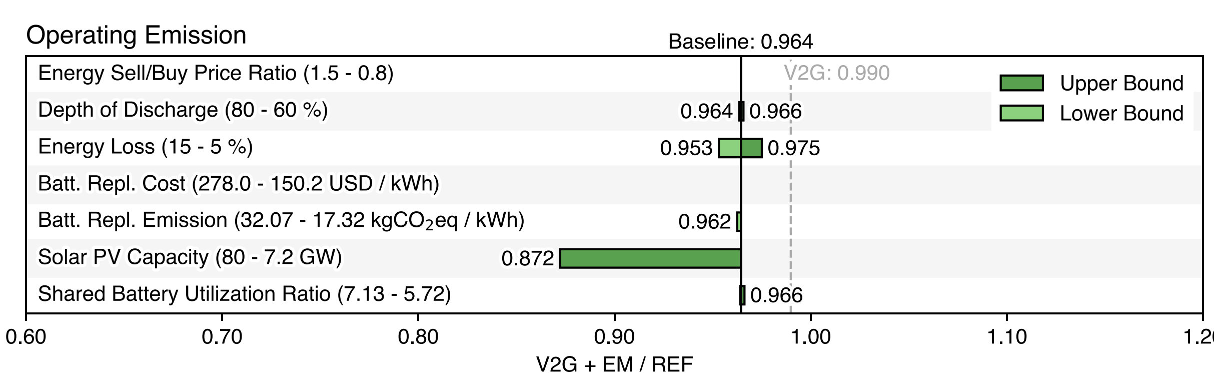

Fig. 12. Sensitivity analysis of operating emissions under the V2G + EM scenario compared to the REF scenario, with the V2G-to-REF ratio presented in a subdued grey line for reference. For a focused view of the V2G scenario, refer to Fig. 10(c). Note: Baseline assumptions are outlined in Table 2. For each parameter listed, the numbers in parentheses following the parameter name indicate the range (Upper bound – Lower bound).

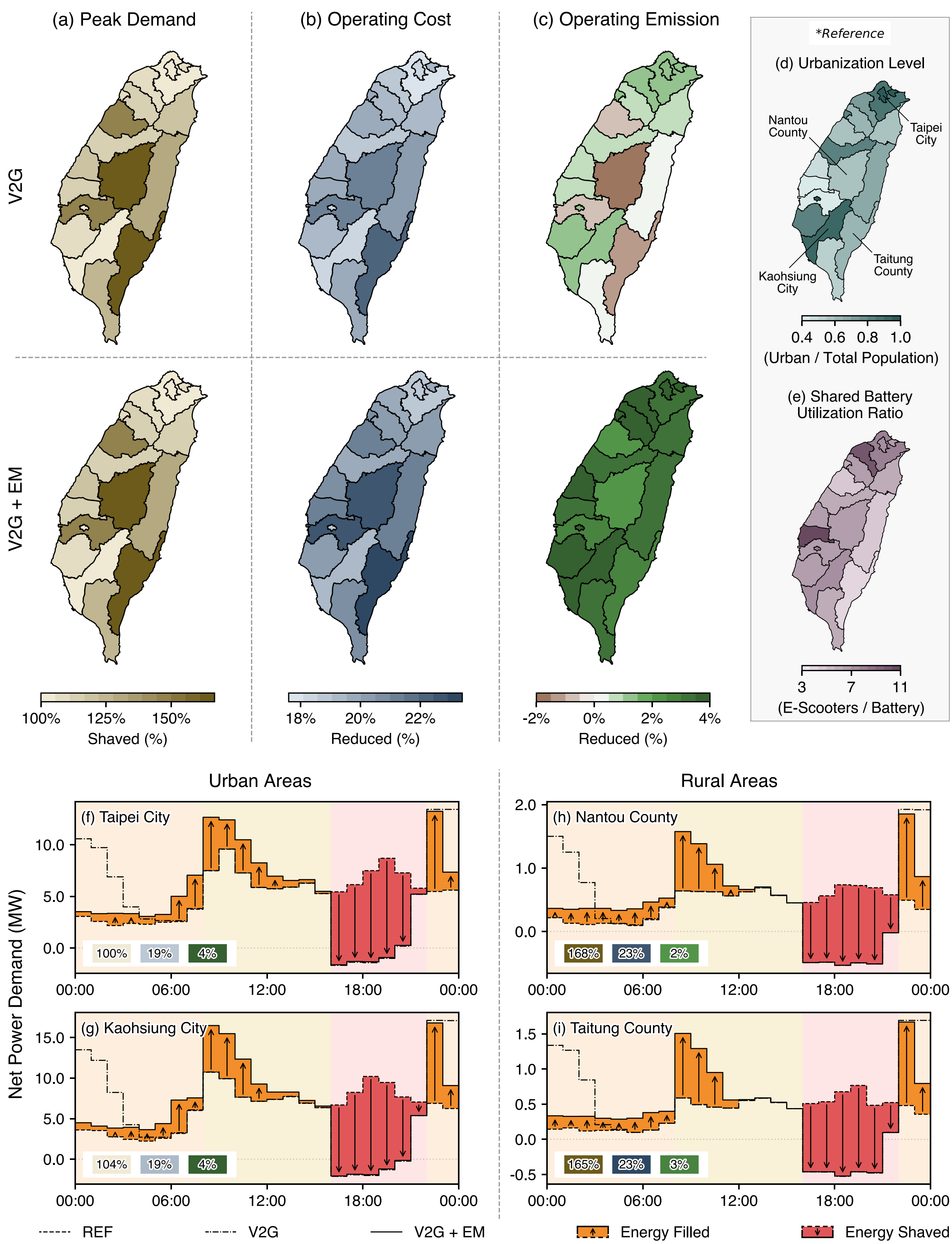

Fig. 13. Comparative heat maps of V2G and V2G+EM scenarios across different cities, illustrating: (a) peak demand shaving, (b) reductions in operating costs, and (c) emissions reductions, with additional maps of (d) urbanization levels and (e) shared battery utilization ratios for reference. Detailed Daily power demand curves for urban versus rural regions: (f) Taipei City, (g) Kaohsiung City contrasted with (h) Nantou County, and (i) Taitung County. Each panel's lower left heatmap quantifies the reductions in peak demand, operating costs, and emissions.

marginal increase in peak electricity demand, the overall benefits, including reductions in costs and emissions, highlight the necessity of a holistic approach to the design and application of V2G systems.

This research addresses a crucial gap in the literature by providing a comprehensive evaluation of V2G benefits, specifically tailored for small-scale BSSs. It introduces an efficient energy management strategy that takes into account the growing prevalence of electric two-wheelers, assessing the potential impacts on BSS operators and the broader electrical grid with a focus on peak demand, operational costs, and carbon emissions. The results are poised to guide policymakers and BSS operators towards strategic V2G technology adoption.

While this research significantly enhances understanding of V2G's potential within the context of e-scooter BSSs in Taiwan, it also acknowledges certain limitations. The study provides a broad evaluation of the potential benefits of V2G, offering a holistic perspective rather than aiming to maximize specific outcomes. Although this is the first comprehensive study in this area, it may not fully capture the full range of advantages that V2G technology can provide. The extensive BSS network across Taiwan, combined with data accessibility limitations, restricts the study's capacity for detailed optimization. Moreover, the study primarily focuses on BSSs operated by the Gogoro Network, which constitutes a large share of Taiwan's e-scooter battery-swapping infrastructure. However, excluding other major providers, such as KYMCO Ionex (Ionex, 2024), may impact the study's general applicability across the entire BSS landscape.

5. Future Scope: Utilizing Swap Stations for Future Mobility Solutions

The potential to expand the applicability and enhance the functionality of V2G technologies is vast and promising. Research can venture into multi-objective optimization that incorporates energy load management, economic factors, and environmental impacts. This approach could refine V2G charging and discharging schedules, maximizing battery utilization while balancing grid demands with environmental and cost considerations. An important expansion involves aligning BSS charging schedules with periods of high renewable energy generation, such as during peak solar and wind outputs. This alignment could significantly mitigate emissions and foster progress towards net-zero targets, enhancing urban energy resilience. Moreover, exploring the integration of swapping stations in vehicle-to-building (V2B) applications could further the agenda for nearly-zero energy buildings (NZEB), optimizing energy use in buildings during peak demand times. Notable recent studies, such as Liu et al. (2023), Lo et al. (2023), and Niveditha and Singaravel (2024), demonstrate how V2B strategies incorporating EVs with renewable energy systems can further enhance grid flexibility, reduce emissions, and balance economic and environmental priorities, underscoring V2B's role in sustainable building energy management.

The rapid adoption of two- and three-wheeler electric vehicles, particularly in Southeast Asia, suggests a substantial scope for its broader V2G adoption. Gogoro's operational footprint, which extends to over 50 cities globally—including major urban centers in India, Indonesia, the Philippines, and China—illustrates the viability of battery-swapping ecosystems beyond Taiwan (Gogoro, 2024a). Expanding the study's scope to incorporate different geographic and economic contexts could yield valuable insights into how grid stability, renewable integration, and local infrastructure nuances impact V2G performance. Comparative research in regions with diverse levels of renewable energy resources or urban density might reveal optimal configurations for V2G systems, enhancing their adaptability and resilience globally.

CRediT authorship contribution statement

Yuan-Hsi Chien: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **I-Yun Lisa Hsieh:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization.

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

Data will be made available on request.

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Supplementary materials

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