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Research paper

An assessment of electric vehicles and vehicle to grid operations for residential microgrids

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ABSTRACT

Electric Vehicles (EVs) are a rapidly growing technology which can lower greenhouse-gas emissions in the transport and energy sectors. The EV batteries can discharge the stored energy back to grid, also known as Vehicle-to-Grid (V2G) which can support the integration of variable distributed renewable generation. Previous research identified financial barriers to the implementation of V2G, however, recent advancements in battery technology present new opportunities to make V2G technology viable. Using the current and predicted EV technology trends, this paper evaluates the annual operation and benefits of EVs and V2G in a microgrid environment and demonstrates different modes of operation. Guided by the gaps identified in the literature, one of the main contributions of this research is to uncover the impact of EV charging scenarios on the V2G operations. Furthermore, the research reveals the interactions between V2G and variable renewable generation coupled with utility scale battery over yearlong simulations to assess seasonal characteristics of V2G operations, which was mostly unexplored to date. Simulation results indicate that the operation of V2G in an optimised microgrid environment improves the economic operation of the system and reduces the levelized cost of electricity by up to 5.7%. Additionally, V2G provides more benefit to grids with higher solar generation proportion The results suggest that the latest advancements in EV technology have improved the economic viability of V2G as well as its potential to improve grid efficiency through providing additional storage capacity and peak demand management.

1. Introduction

According to the International Panel on Climate Change (IPCC), transport represents 14% of the anthropogenic greenhouse gas emissions globally and the introduction of electric vehicles (EVs) is seen as a viable path for reducing emissions in the sector (Kempton et al., 2001; Intergovernmental Panel on Climate Change, 2014). More recent reports by International Energy Agency (IEA) global EV outlook report (Till Bunsen et al., 2019) shows that sales of EVs are rapidly increasing worldwide and by 2020 there were already 10.2 million passenger car EVs. This rapid growth of EV sales and the increase of battery capacities in EVs will require grids to adapt to the new EV load and its effects on load shape, peak demand, ramp rates and frequency/voltage deviations. At present, there is limited understanding of the potential impact of EVs on the electricity grid and how to sustainably integrate EVs with current renewable energy generation technologies. This is because EVs are a relatively new technology and only more recently started attracting global investment.

EV electric load covers a significant portion of the average household energy use when charged at home. Hence, the increasing level of EV penetration is expected to have a significant impact on the network peak demand, especially in charging locations, such as residential areas and in retail and workplaces that provide charging infrastructure. Although EVs will increase electricity demand on the grid, they are also capable of providing power back to the grid, known as Vehicle-to-Grid (V2G). While V2G presents an attractive solution to reduce the negative impacts of EV load, early research has indicated limitations in implementing the technology, particularly due to battery degradation and high operational costs. On the other hand, the EV industry has continually lowered costs by developing cheaper batteries with higher capacities, which changes the dynamics of EV charging and the economic viability of V2G.

Earlier research on V2G was focused on battery degradation modelling (Peterson et al., 2010a,b; Bishop et al., 2013; Hoke et al., 2014). Peterson et al. developed a degradation model based on experimental data of battery cycling in lab conditions. Similarly, Hoke developed a temperature dependent degradation model. Bishop et al. modelled the degradation effects caused by V2G operations on plug in hybrid electric vehicles (PHEV). Other authors developed optimisation algorithms for EV charging and

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Table 1
Summary of V2G economic viability research.

V2G economic model	Grid type	Battery capacity	V2G services	Optimisation	EV load	Time frame	Continuous	Degradation model
Lund and Kempton (2008)	Large country size grid (Denmark) with renewables	30 kWh	Energy	–	0%–100% EV penetration	1 week	Yes	Kempton and Tomić (2005)
Peterson et al. (2010a,b)	Boston,	16 kWh	Energy	–	–	1 year	–	Peterson et al. (2010a,b)
Igualada et al. (2014)	Residential Microgrid	16 kWh	Energy	CPLEX	–	24 h	Yes	DOD and cycling
Drude et al. (2014)	Urban region of Florianópolis, Brazil	25 kWh	Ancillary and Frequency control	–	250 EV fleet	1 year	–	DOD degradation model
Freeman et al. (2017)	New York City metropolitan area	40–100 kWh	Energy	–	–	Peak demand hours over 5 years	–	Kempton and Tomić (2005) DOD
Li et al. (2020)	Shanghai	24–85 kWh	Energy (Peak shaving only)	–	–	Peak hours over several days	–	–
Habib et al. (2020)	Residential microgrid	21.6 kWh	Energy	Particle swarm optimisation	80–700 EV fleet	1 day	–	–

V2G discharging to reduce the operational costs of individual EVs (Ortega-Vazques and Kintner-Meyer, 2015; Liu et al., 2015; Di Somma et al., 2020). Several studies looked at V2G economics in large and micro electricity grids and assessed V2G's capability as ancillary and load balancing services (Tomić and Kempton, 2007; Freeman et al., 2017; Habib et al., 2020; Li et al., 2020; Di Somma et al., 2020). Freeman et al. (2017) looked at the economic feasibility from an EV owner perspective, indicating that smart V2G charging and discharging for grid benefits can result in losses for individual EV owners. Others highlighted key considerations for the viability and implementation of V2G and its potential benefits of reducing peak demand and energy costs. However, many of these studies evaluated the interaction of V2G on legacy grids, with the operation of incumbent generation technologies, based on historical operational behaviours. Therefore, more research is needed to assess the competitiveness of V2G in future electricity grids, including higher penetration of renewables and utility battery storage technologies. Another shortcoming of previous studies was the fact that they assessed V2G operation only over a short-term period (i.e., days, weeks) and did not take the longer-term operations of EV battery into account and its impact on V2G availability and the grid. This is an important limitation which needs to be addressed considering the significant seasonal variations in user behaviour and operational capacity and characteristics of renewable generation technologies and EV batteries.

In EV research, V2G availability (the ability of an EV to provide V2G during a given period) is an important consideration, as an EV is a dynamic asset that can only provide V2G when it is plugged into the grid, it is not charging, and it has sufficient stored energy to allow for discharging. The V2G availability is therefore highly dependent on the charging behaviour of the EV owner such as: charging times, range anxiety (the fear of a vehicle driver that there is insufficient range to meet their requirements) and the State of Charge (SOC). Previous research indicated that EV charging scenario has not been investigated in much detail by previous studies mainly due to limitations of the available datasets (Sovacool et al., 2018).

Table 1 presents a summary of the previous V2G economic viability research and categorises the parameters used in each model. Apart from the issues discussed above, another important identified shortcoming of the previous literature is that most of the degradation models based on DOD and cycling have been proven to be inaccurate or inadequate (Peterson et al., 2010a,b). Moreover, most of these studies used outdated EV battery capacity and considering the most recent advances in technology, new research is required to re-evaluate operational efficiency, costs, and limitations of V2G operations considering more recent battery capacity and costs.

With the introduction of utility scale battery storage into networks around the world, it is also unclear how V2G would interact competitively in an environment with dedicated grid battery storage systems. To represent realistic future grid scenarios, this factor needs to be considered. This paper develops a comprehensive V2G model and evaluates its operational and economic performance and viability for current and future microgrid environments. Considering the significant role that V2G can play in the integration of EVs, this paper aims to assess the economic viability of V2G by addressing the limitations identified by previous research. The novelty and unique contributions of this study are listed below:

- Investigate the impact of different EV charging scenarios on the V2G operations by using a large and comprehensive dataset including thousands of vehicles with detailed travel survey data.
- Assess continuous EV battery and V2G operations over a complete year.
- Incorporate latest advancements in EV battery technology and capacity by using recent EV vehicles and most up to date battery degradation models.
- Reveal interactions and competitiveness of EV and V2G by evaluating its operation in a microgrid environment with utility scale battery.
- Investigate the impact of EV demand and V2G on peak demand times and demand shape by assessing different EV charging scenarios.

The analysis is conducted using openCEM, an open source capacity expansion tool for Australian Energy Markets (ITP Analytics, 2020) to simulate the long term (annual) operation, viability and competitiveness of V2G for different microgrid generation mixes, including utility scale battery storage. The remainder of the paper is organised as follows. Section 2 describes the methodology of this study. Section 3 presents the results and discussions for the microgrid simulations and Section 4 presents concluding remarks.

2. Methodology

To evaluate the impacts of EVs and assess the economic viability of V2G on microgrids over a calendar year, a residential microgrid model was developed using Smart Grid Smart City (SGSC) data (Australian Goverment, 2014). 1000 households were randomly selected from this dataset to generate the annual demand profile for the micro-grid in half-hourly temporal resolution. According to vehicle ownership statistics (Australian Bureau of Statistics, 2019), on average, a household owns 1.54 vehicles which corresponds to a total of 1540 vehicles for the micro-grid. Four different EV ownership penetration scenarios were studied: 25%, 50%, 75% and 100%. The study incorporated the following modelling parameters which are discussed in more detail in the following sections:

- Battery degradation and economic impacts of V2G

- EV demand and V2G availability under different charging scenarios and EV penetration scenarios
- Different microgrid generation mixes including diesel, wind, solar and utility scale battery

2.1. Economic impact of V2G

EVs primary function is transportation and V2G can only take place when EVs are not being used for transportation. To enable V2G functionality, bidirectional charging infrastructure is needed which has become an essential component of the EV transition (Weintraub, 2020).

In the first set of simulations (Sections 3.1 and 3.2), it was assumed that the additional cost of bidirectional charging equipment would be carried by the EV owner and therefore, V2G did not bear any capital cost other than battery degradation which is discussed in more detail next. To investigate another scenario where the V2G charging infrastructure cost is accounted as the V2G technology capital cost, a sensitivity analysis was conducted and presented in Section 3.3.

Earlier research indicated that discharging EV battery for V2G purposes served the grid needs however, it resulted in revenue loss for the EV owners (Freeman et al., 2017). As a result, in this work it is assumed that charging of EVs is primarily dictated by the individual owner's travel needs and V2G remains as an opportunistic endeavour. Apart from the capital cost of V2G bidirectional charging equipment which is assumed to be carried by the EV owner, the operational cost of V2G includes the cost of the energy to charge the battery and the associated degradation costs from the additional battery operation, as shown in Eq. (1) derived from Kempton and Tomić (2005).

$$C_{v2g} = \frac{C_{charge}}{\eta_{inv}} + C_{deg} \tag{1}$$

where C_{v2g} is the cost of providing V2G in \$/MWh, C_{charge} is the price of charging the battery in \$/MWh, η_{inv} is the round-trip efficiency of the battery, and C_{deg} is the cost associated with battery degradation due to V2G in \$/MWh. The charging price C_{charge} is normally set by the retail market and may vary across different regions and time of the day. In this study an average cost of energy is assumed for charging based on the average cost of the microgrid energy delivery (\$/MWh). Furthermore, the study considered static modelling for V2G interactions and the variations in individual V2G charging power was ignored. This was because the study focused on aggregate average EV and V2G charging profiles for the microgrid and the openCEM did not allow dynamic modelling of individual V2G operations. Future research aims to incorporate dynamic V2G modelling in higher temporal resolution to better reflect real world charging operations.

2.1.1. Cost of EV battery degradation

A generalised model of battery degradation was used in this paper developed by Wang et al. (2014) which accounts for temperature, charge rate and DOD (Eq. (2)). The model splits the degradation into calendar and cycling ageing, but for V2G, only cycling ageing is considered as the calendar ageing can be regarded as a sunk cost:

$$Q_{loss\%} = \left(a \cdot T^2 + b \cdot T + C\right) \cdot e^{((d \cdot T + e) I_{rate})} \cdot Ah_{throughput} \tag{2}$$

where $Q_{loss\%}$ is the percentage capacity loss of the battery, a, b, C, d, e are empirically fitted pre-exponential parameters of a temperature function as seen in Table 2. I_{rate} is the C-rate of battery, and $Ah_{throughput}$ represents the amount of charge delivered by the battery during cycling:

Table 2
Cycling degradation coefficients (Wang et al., 2014).

Coefficient values and units			
a =	8.61E−6 (Ah^{-1}· K^{-2})	I_{rate} =	C-rate
b =	5.13E−3 (Ah^{-1}· K^{-1})	T =	Kelvin
c =	7.63E−1 (Ah^{-1})		
d =	6.7E−3 (K^{-1}· C-rate^{-1})		
e =	2.35 (C-rate^{-1})		

Table 3
V2G operation and degradation cost assumptions for a battery pack from Tesla model S (cell type 16850).

V2G operating cost assumptions	Value	Units
Battery pack capacity	75	kWh
Number of cells	6,216	
Module size	444	Cells
Number of modules (1p14s)	14	
Module configuration	74p6s	
Amps charging (cell)	0.6544	Amp
Voltage cell (nominal)	3.8	V
Voltage module (nominal)	22.8	V
Charge rate (level 2)	7.2	kW
Inverter efficiency	0.92	
C-rate	0.19	
Microgrid avg. energy cost	160	\$/MWh
Battery capital cost	238,000	\$/MWh
Discharging/Charging Temperature	313	K
Ah throughput	0.6544	
$Q_{loss\%}$ (per vehicle 1 h discharge @ 7.2 kW)	5.65E−04	% loss
Cost of degradation	15.2	\$/MWh
Total cost of V2G @ 7.2 kW	203	\$/MWh

Based on the percentage loss in Eq. (2) the overall degradation cost is calculated using Eq. (3):

$$C_{deg} = \frac{\frac{Q_{loss\%}}{100} \cdot B_{capacity} \cdot B_{cost}}{V_d \cdot \eta_{inv}} \tag{3}$$

where $Q_{loss\%}$ is the degradation percentage at a given discharge rate, $B_{capacity}$ is the individual vehicle battery capacity in kWh, B_{cost} is the capital cost of the battery in \$/kWh, V_d is the total vehicle discharge rate in kWh, and η_{inv} is the roundtrip battery efficiency.

Using Eq. (3) in conjunction with Eq. (1), the degradation cost of V2G at a given discharge rate was calculated for a Tesla model 3/S battery, with the battery parameters provided in Table 3. Tesla model S was used as the default EV model, since it is the most sold EV model (JATO, 2018). Although Tesla model S battery capacity (75 kWh) is slightly larger than current average EV batteries, a battery capacity around 70–80 kWh represents future growth trends (Till Bunsen et al., 2019). Based on Eq. (3), the estimated V2G operation cost was calculated at 203 AU\$/MWh. The details for battery parameters and assumptions are summarised in Table 3.

2.2. EV load profiles and charging scenarios

This section gives details on the studied EV load profiles and battery charging & discharging scenarios. As explained in Section 1, V2G availability depends on:

- The state of EV (i.e., charging, in transit, parked)
- EV state of charge (SoC) to meet the next travel requirements and V2G dispatch.
- EV bidirectional charging infrastructure availability.

To estimate the availability of V2G and EV power demand, dataset from the Victorian Integrated Survey of Travel and Activity (VISTA) (Victoria State Government, 2018) was used. This dataset is based on travel surveys performed between 2012–2016 on 18,152

Table 4
Summary of EV parameters and charging scenarios.

EV parameters	Value	Reference
Electric vehicle	Tesla Model 3/S	
Battery capacity	75 kWh	
Battery roundtrip efficiency	0.85	(Schäuble et al., 2017)
Fuel economy	0.28 kWh/km	(Dunckley and Alexander, 2018)
Charging rate (level 2)	7.2 kW	(JET Charge, 2020; Dunckley and Alexander, 2018)
Charging limitation	Only start charging if battery SOC < 60%	(Dunckley and Alexander, 2018)
Charging locations	Dedicated (off street) parking at home or work	

Table 5
Charging tariff structure.

Charging scenario	Charging time	Tariff remarks
Opportunity	All day	Does not avoid peaks
Night	10 pm–7 am	Avoids morning and evening demand peaks
Night + Midday	10 pm–3 pm	Avoids evening demand peak

households in Melbourne and surrounding suburbs. The VISTA data is categorised by vehicle ID and trip ID. Each trip contains details of date, time of departure, time of arrival, trip length, parking location at end of trip and purpose of trip. The details for the EV movement modelling and V2G availability used in this work can be found in O'Neill et al. (2019).

Current day EV ranges can meet the majority of metropolitan commutes, hence this research assumes that EV owners are likely to have similar travel patterns with conventional vehicle owners in urban environments (O'Neill et al., 2019). For this reason, 1540 commuter vehicles were randomly selected from the VISTA dataset and their travel survey patterns were assumed to represent the EV fleet of the modelled micro-grid. The required SOC at the beginning of each charging cycle was assumed to be 60% or less based on the analysis from Dunckley and Alexander (2018) and Energeia (2018). Table 4 summarises the main assumptions and restrictions used in the simulation of the EV load profiles.

For charging the EVs, three scenarios were developed to reflect common charging tariffs offered to EV owners today: Opportunity, Night, and Midday. Opportunity represents the charging scenarios where EV owners can charge their vehicle any time during the day as long as the vehicle is parked and minimum SOC criteria is satisfied. Night represents charging EV during times to avoid morning and night peak demand periods and Night + Midday represents charging EV during times to avoid evening peak demand. Studying these different charging scenarios are useful to investigate the impacts of different charging times on the peak demand and cost of energy of the Microgrid. The details for the studied charging times and tariffs are summarised in Table 5.

2.3. Microgrid model

Microgrid simulations were carried in openCEM which is an 'open source' electricity grid modelling tool developed by ITP Analytics (ITP Analytics, 2020) in collaboration with the University of New South Wales and University of Melbourne. The tool is originally designed to model the Australian National Electricity Market (NEM) and optimise grid operation and investment. The results of the optimisation include the required capacity and capacity factors (CF) of each generation unit to meet demand with lowest capital and operational cost as measured by levelized cost of electricity-LCOE (i.e., lowest LCOE via the global minima).

For this research, openCEM was modified to simulate and optimise a microgrid in isolation mode with V2G capabilities. The model can be adapted to be grid connected by adding regions and nodes within parameters, but this was out of the scope of this paper. openCEM used the aggregate EV charging load as a trace in addition to the microgrid's electricity load when optimising microgrid LCOE. openCEM did not optimise individual EV movement which was modelled separately for the described VISTA dataset in O'Neill et al. (2019). Market failures such as market power were not included in the simulations. This assumes that all participants (generators) in the grid are operating to lower grid cost rather than improve their own profits.

2.3.1. Microgrid demand

The residential electricity demand was based on data from the Smart Grid Smart City (SGSC) program (Australian Goverment, 2014). 1000 household size was chosen to reflect a micro grid, large enough to incorporate a fleet of EVs with a wide range of charging patterns. Based on data from the Australian Bureau of Statistics (Australian Bureau of Statistics, 2019), each household was assumed to own, on average, 1.54 vehicles (1540 EVs for the studied microgrid). The aggregate EV load was obtained by using the charging profiles generated from the VISTA dataset (see Section 2.2). This was combined with the residential electricity demand to generate the total demand of the micro grid. Four different EV penetration levels were assumed for the study (25%, 50%, 75% and 100%) each resulted in different total electricity demand of the microgrid. The EV demand and charging patterns are created based on the VISTA travel survey and previous trials. openCEM model optimises the aggregate EV charging demand based on the survey data and studied charging scenarios. The current method can be adapted to incorporate new trends of EV charging and produce new demand profiles for the openCEM model

2.3.2. Microgrid generation technologies

The microgrid included the following generation technologies for a hybrid renewable energy microgrid: solar photovoltaic (PV), wind, diesel generator, utility battery storage and V2G. Each generation capacity was determined by openCEM optimisation to achieve best LCOE. The capital and operation and maintenance (O&M) costs of all of these technologies was based on Australian Energy Market Operator's (AEMO) 2019–20 Scenarios, Inputs and Assumptions Workbook (AEMO, 2019) which are presented in Table 6. The costs for V2G were given in Section 2.1.

Table 6
Microgrid generation capital and operational costs (AEMO, 2019).

	PV single axis tracking	Utility Battery 2 h	Diesel	V2G	Wind
Capital (AU$/kW)	1,370	1,424	1,430	0–1000	1,893
Fixed O&M (FOM) (AU$/kW/yr)	17.90	9.92	15.27	–	44.6
Variable O&M (VOM) (AU$/MWh)	–	–	11.29	203	3.31
Heat rate (GJ/MWh)	–	–	7.89	–	–
Fuel cost (AU$/GJ)	–	–	37.71	–	–

Table 7
Microgrid parameters and assumptions.

Microgrid parameters	Value	Reference
Microgrid type	Residential	
Microgrid size	1000 households	
Number of cars	1540	Australian Bureau of Statistics (2019)
Demand profile	Residential SGSC (2013)	Australian Goverment (2014)
Generators	Solar PV, Diesel, Utility Battery 2 h, Wind, V2G	ITP Analytics (2020)
Reliability standard	99.998%	AEMO (2018)
Min synchronous generation	0%	
Microgrid climate (location)	NSW	
Discount rate	5%	
Carbon price	None	
Emission limitations	None	

2.3.3. Microgrid operational assumptions

Other than generation and demand, there are several parameters which can influence the microgrid operation, including environmental policy requirements, such as carbon tax or limits, technical operational requirements, such as reliability and synchronous generation requirement and financial considerations, such as capital expenditure discount rates. Synchronous generation requirement represents the minimum percentage of synchronous generation required to provide inertia for systems security and stability with high penetration of renewable energy generation. However, recent research has shown the ability of utility battery storage to emulate the benefits of synchronous generation (Ramirez et al., 2018) therefore, no minimum threshold was set for synchronous generation. The microgrid model did not include any emission limitations, minimum reserves or carbon pricing, and used a 5% discount rate (Deans, 2020) to evaluate annualised capital costs of generation. Table 7 summarises the microgrid specifications and assumptions used in simulations.

The variable generation sources including solar, wind, and V2G use availability profiles to set the generation capacity at any given period. These profiles present the percentage of total capacity that is available at any given time. The wind and solar profiles were based on data collected from AEMO wind and solar generators in NSW (AEMO, 2020) for a full year at 30 min resolution.

2.4. Generation scenarios

Three microgrid generation scenarios are investigated using the chosen generation technologies:

1. Solar microgrid — solar PV, diesel, and battery storage
2. Wind microgrid — wind, diesel, and battery storage microgrid
3. Wind + Solar microgrid — solar PV, wind, diesel, and battery storage microgrid

Each generation scenario was simulated using five EV charging scenarios to explore the impacts of EV penetration and charging scenarios on V2G utilisation and microgrid's economic efficiency:

1. Base scenario (no EV and no V2G)
2. Opportunity EV charging with no V2G,
3. Opportunity EV charging with V2G,
4. Night EV charging with V2G
5. Midday EV charging with V2G.

The base scenario consists of a microgrid with solar PV and/or wind, diesel, and battery storage (2 h), but no EV and no V2G. Each EV charging scenario was simulated using four EV penetration levels: 25%, 50%, 75% and 100%. Table 8 presents the simulation matrix for the study (all scenarios include diesel generation and battery storage).

3. Results and discussion

3.1. Economic analysis of different scenarios

The EV residential demand profile used for the microgrid scenarios is presented in Fig. 1. It can be seen how different charging scenarios impact the total electricity profile and peak demand times. This in turn impact the operations of V2G in the grid as discussed in the following sections.

The optimised LCOE results for the three microgrid environments; Solar, Wind and Solar + Wind are presented in Fig. 2. The results are given for each of the four EV penetration level and five EV charging scenarios. For the Opportunity charging scenarios, addition of V2G reduced LCOE in the range of 5 to 10% compared to the without V2G option. The additional storage provided by the V2G reduced the required capacity of other generators, resulting in a lower capital expenditure in the microgrid. The lowest LCOE for solar microgrid was achieved for Opportunity with V2G charging, which was closely followed by Midday charging (153.5 $/MWh and 154.1 $/MWh respectively). The lowest LCOE of 137 $/MWh was obtained for the Solar + Wind microgrid for Midday charging at 25% EV penetration. The availability of both wind and solar resources reduced the reliance on diesel generation and utility battery storage resulting in lowest LCOE.

The difference between the base scenario (no EVs) and Opportunity charging without V2G remained marginal. Especially for Solar and Solar + Wind microgrids, the latter scenario resulted in lower LCOE as seen in Fig. 2(a) and (c). The addition of EV demand would have increased the LCOE due to increased micro-grid demand, however, because the large proportion of EV demand fell into daytime, it flattened the demand curve resulting in better

Table 8
Microgrid simulation scenario matrix.

	Solar Microgrid					Wind microgrid					Solar + Wind Microgrid				
	Base Scenario	No V2G	Opp.	Midday	Night	Base Scenario	No V2G	Opp.	Midday	Night	Base Scenario	No V2G	Opp.	Midday	Night
Generation															
Solar PV	✓	✓	✓	✓	✓	-	-	-	-	-	✓	✓	✓	✓	✓
Wind	-	-	-	-	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
V2G	-	-	✓	✓	✓	-	-	✓	✓	✓	-	-	✓	✓	✓
Demand															
With EV demand	-	✓	✓	✓	✓	-	✓	✓	✓	✓	-	✓	✓	✓	✓
Without EV demand	✓	-	-	-	-	✓	-	-	-	-	✓	-	-	-	-
EV charging regime															
Opportunity	-	✓	✓	-	-	-	✓	✓	-	-	-	✓	✓	-	-
Midday	-	-	-	✓	-	-	-	-	✓	-	-	-	-	✓	-
Night	-	-	-	-	✓	-	-	-	-	✓	-	-	-	-	✓

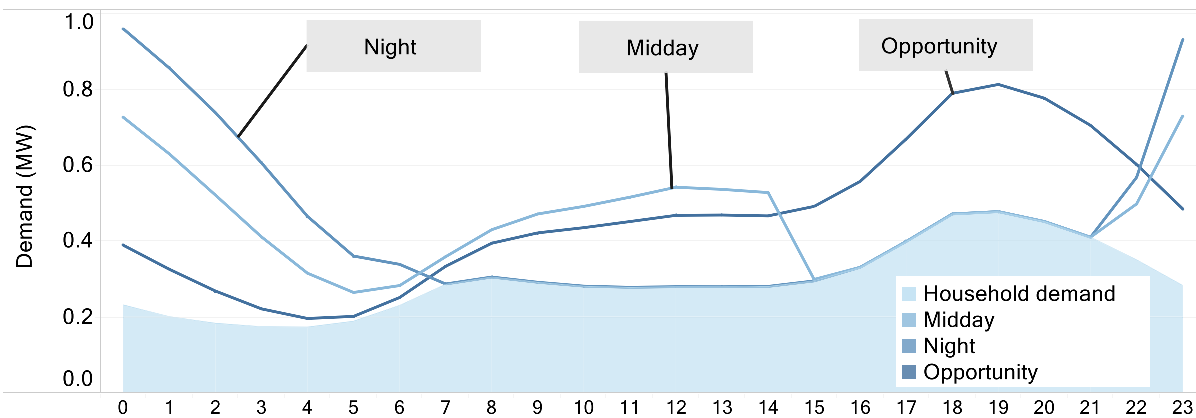

Fig. 1. Average daily residential demand profile with different EV charging scenarios.

utilisation of solar and battery storage which compensated the increased costs due to higher micro-grid demand. In parallel with this finding, the LCOE remained the same or reduced by a marginal amount as the EV penetration increased for Opportunity and Midday charging scenarios. This is because increasing EV demand during the day further flattened the electricity demand profile, resulting in further improvement in self-consumption of the solar generation.

On average, Opportunity with V2G, Midday with V2G, and Night with V2G resulted in an LCOE across all EV penetrations of 154.2 $/MWh, 154.3 $/MWh and 186.5 $/MWh respectively. The reason behind the higher LCOE for the Night charging scenario is because of the lower utilisation of solar generation and increased dependence on diesel generation to compensate for the increased nigh time demand. For the Night charging scenario, increased EV penetration increased the LCOE as microgrid could not utilise solar generation for the increasing EV demand. As seen in Fig. 1, EV demand through night charging surpassed the existing peak and created a new peak demand later in the night. Therefore, the Night charging scenario shifts the timing of existing off peak tariff times from late night towards daytime. This indicates the importance of careful planning for EV charging tariffs to shift the EV demand towards daytime to smooth the demand curve and better utilise solar generation. The impact of different tariff designs on EV charging demand and V2G arbitrage should be further investigated in future research.

The results for the Wind microgrid seen in Fig. 2(b) shows similar patterns to the solar microgrid scenarios for the Opportunity charging, where including V2G reduced LCOE up to 9 $/MWh (4.6% reduction). However, different than solar microgrids, Night charging scenarios at lower EV penetrations resulted in similar LCOE with other charging scenarios in the Wind microgrid. This is mainly attributed to the higher availability of wind generation at night reducing the reliance of diesel generation to meet night time EV demand. Another difference of wind microgrid is the impact of EV demand on cost. Compared to the solar microgrids where the addition of EV demand slightly reduced LCOE cost, addition of EV demand slightly increased the cost at higher penetrations. It is important to note that wind microgrid could have resulted in better LCOE results in other geographical locations where the wind resource is better matched with EV demand profile.

As mentioned previously, the presented LCOE figures represent the cost of generation and do not consider network augmentation costs that may be needed. The additional EV load may require some network augmentation as it will make up a significant proportion of the network demand. However, the utilisation of V2G could also help to reduce this need of network augmentation.

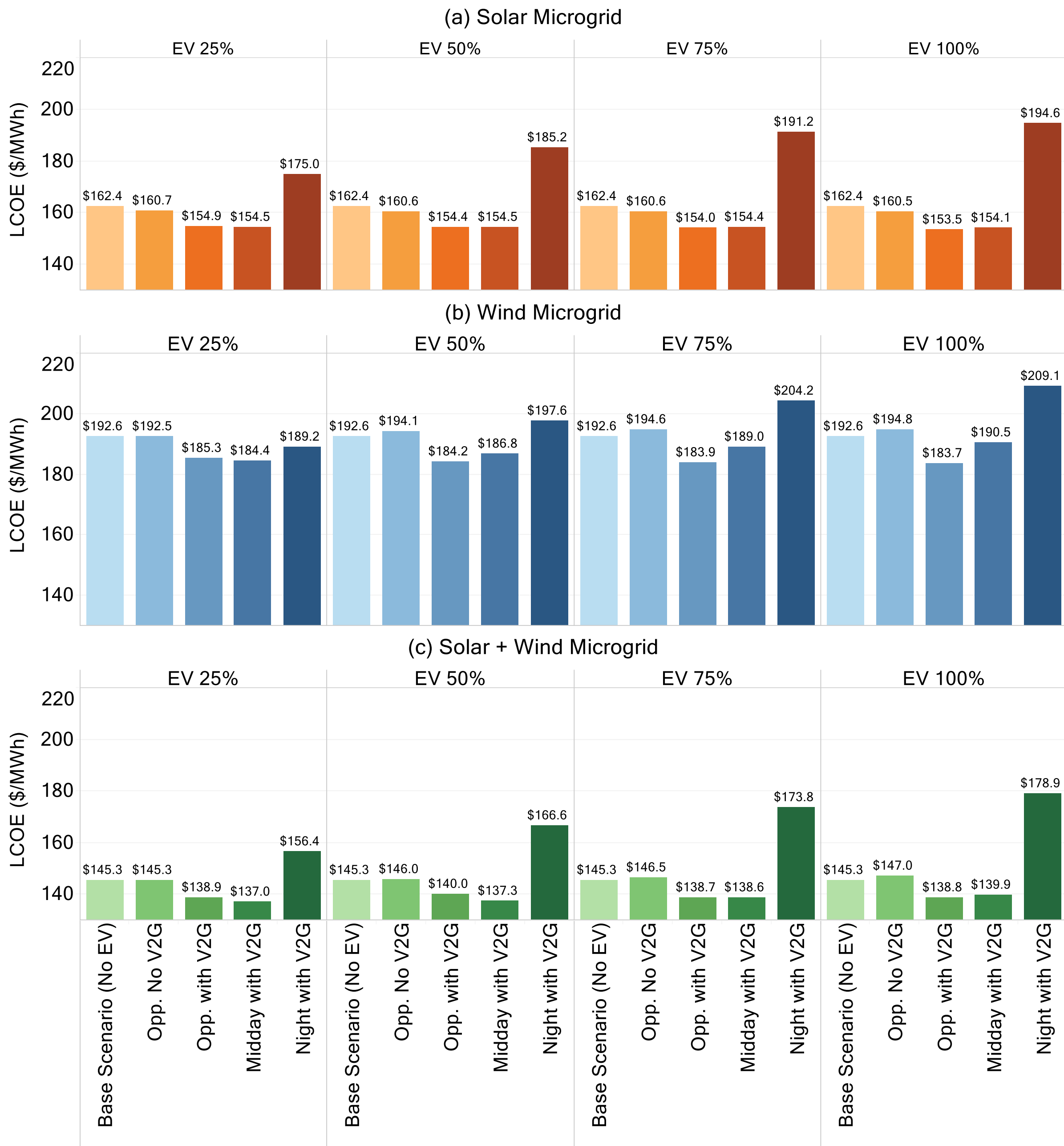

Fig. 2. LCOE of Base, Opp. No V2G, Opp. with V2G, Night, Midday scenarios at different EV penetrations for (a) Solar microgrid, (b) Wind microgrid, (c) Solar + Wind microgrid.

3.2. Microgrid and V2G operation – Opportunity charging scenario

The results presented in Section 3.1 showed that V2G reduced microgrid LCOE. Specifically, the Opportunity charging scenario with V2G resulted in the lowest LCOE outcome for the studied microgrid. To better understand the utilisation of V2G under this charging scenario, V2G dispatch and microgrid operation trends are further analysed in this section.

The generation capacities and capacity factors (CF) of all generators for the different scenarios are presented in Fig. 3 for the 25% EV penetration, illustrating how each microgrid operates at its optimised cost. Daily dispatch of each microgrid generation is presented in Fig. 4 for a 10-day period during winter to further investigate the timing of the dispatch of the generation technologies. It is important to remind the reader that the V2G capacity is based on the number of EVs (1540 for this microgrid) and their availability is extracted from the VISTA dataset (see Section 2.2). Hence, V2G capacity is fixed and not optimised by openCEM. However, V2G does have a variable operation and maintenance cost as given in 2.1 which allows openCEM to optimise the V2G dispatch throughout annual operation.

The results in Figs. 3 and 4(a) show that the Solar microgrid operates as a large solar PV and battery system supported by diesel generator. Solar PV meets the day demand and charges the utility scale battery, which is discharged at night. The diesel generator is used at night to provide baseload and operates at near max capacity, while the utility battery ramps up and down to meet the remaining demand. V2G is utilised on the 6th and 13th of July to either meet night time peak demand, or as a backup when the utility battery did not have enough SOC to meet

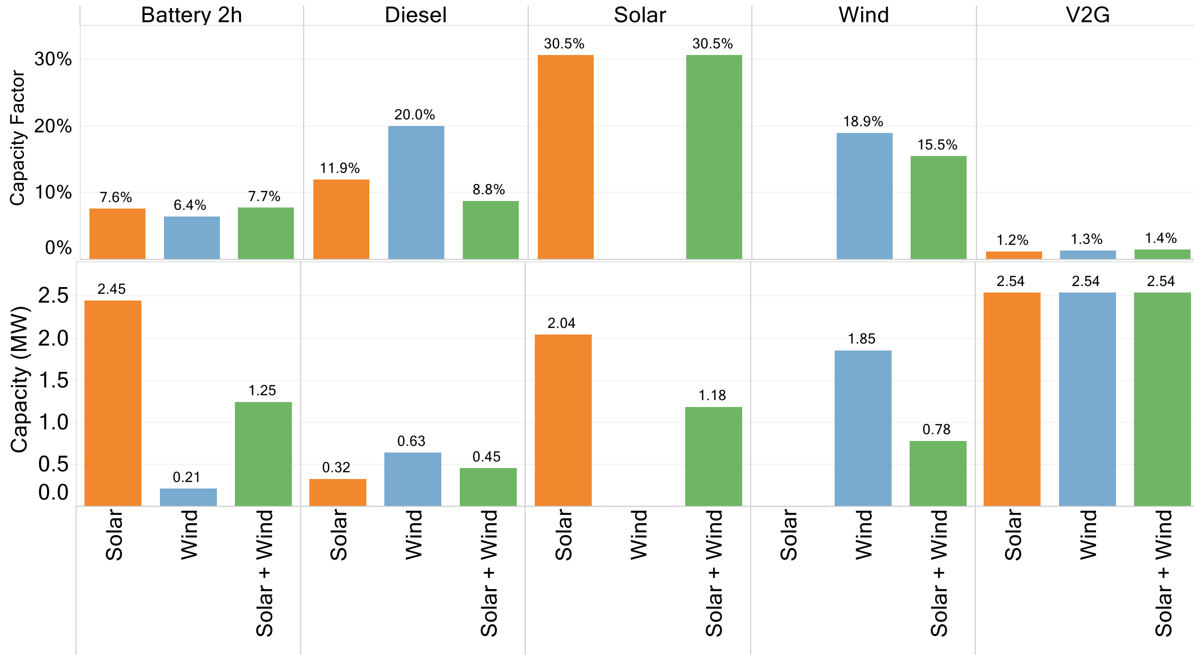

Fig. 3. Opportunity charging with V2G scenario (25% EV Penetration) generation capacity and capacity factor for different generation technologies.

the night demand, especially on the 13th of July with low solar generation.

The results of the Wind microgrid simulation show a significant difference to the Solar microgrid operation as shown in Fig. 4(b). While the Solar microgrid oversizes the solar PV and utility battery capacity to meet night demand, the Wind microgrid has a lower utility battery capacity since the wind generation is spread throughout the day. On the other hand, smaller utility battery increases microgrid's reliance on diesel generation at times when wind generation is low or not available, especially observed between 10th–13th of July. Therefore, the operational and capital costs of Wind microgrid were higher than the Solar microgrid. V2G plays a similar role for the Wind microgrid and helps to meet the peak demand especially during night times.

As expected, the Solar + Wind microgrid operates as a hybrid of the two microgrids. However, due to the lower cost of solar generation this microgrid mainly operates as a PV and storage system, like the Solar microgrid. The wind generation is also used when available, to reduce the reliance on diesel as seen in Fig. 4(c) especially between 4th–6th of July. Furthermore, the availability of wind reduces the need to oversize the PV and utility battery storage capacity. Once again, V2G helps to meet the peak demand especially during night times. Although Fig. 4 shows highest utilisation of V2G for the Wind microgrid, annual capacity factor of V2G was highest for the Solar + Wind microgrid, but only by a small margin (1.2%, 1.3% and 1.4% respectively, for the three microgrids).

The EV demand profiles seen in Fig. 1 shows that there are significant number of EVs that charge at night, even for the Opportunity and Midday charging scenarios such that EV charging load represents the majority of the night time load. Considering this, the EVs providing V2G at night would in theory be charging other EVs in the grid. This may seem counterproductive, but it can make financial sense for the microgrid especially depending on the availability of solar generation and EV owners charging behaviour. For example, an EV owner which was able to charge the vehicle during midday and has excess storage after the commute for V2G may be provide a certain proportion of another EV's storage, which did not have the opportunity to charge at midday and requires charging for travel needs for the following day.

Fig. 5 presents a comparison across the different charging scenarios for the average V2G capacity factors of four different EV penetration levels for the Solar and Wind microgrids. It is seen that the Wind microgrid uses V2G to meet peak demand to a greater extent than the Solar microgrid. This is because Wind microgrid has lower utility battery storage capacity which creates additional opportunities for V2G to be called on to meet microgrid demand, specifically when wind generation is low or at peak demand times. This implies that a higher degradation of the EV batteries would occur in wind based microgrids. Another important point which is not highlighted in Fig. 5 is that V2G capacity factor reduces with increasing EV penetration. This is because V2G is mostly needed for occasional peak shaving events and although the EV and peak demand increases with EV penetration, at higher EV penetration levels, smaller proportion of the increased V2G capacity is utilised.

Fig. 6 presents the analysis of V2G dispatch times in more detail, which shows three microgrids and V2G dispatch for the month of January for the Opportunity charging scenario at 25% EV penetration. Although previous results showed that V2G has a low CF, it is seen that it can be dispatched regularly throughout month especially on days with high peak demand, or low wind or solar generation. Supporting previous findings, V2G is dispatched more often in the Wind and Solar + Wind microgrids compared to the Solar microgrid. As seen, V2G provided almost entire demand on some of the peak demand events.

Fig. 7 presents a more detailed time of day analysis of V2G dispatch over the entire simulation year for three microgrid scenarios. The bar chart indicates the number of V2G dispatch instances over the year at a given hour (left y-axis). The circles show the average capacity of V2G dispatch at the given hour (right y-axis). Although Fig. 7 shows the results for the Opportunity charging at the 25% EV penetration, similar trends are observed at other EV penetrations.

In the Solar microgrid most of the instances of V2G dispatch are between 5 pm to 6 am when solar generation is low or not available and peak V2G dispatch is observed at 7 pm as a means of peak demand shaving. In the Wind microgrid, V2G dispatch instances are higher and distributed more evenly across the day

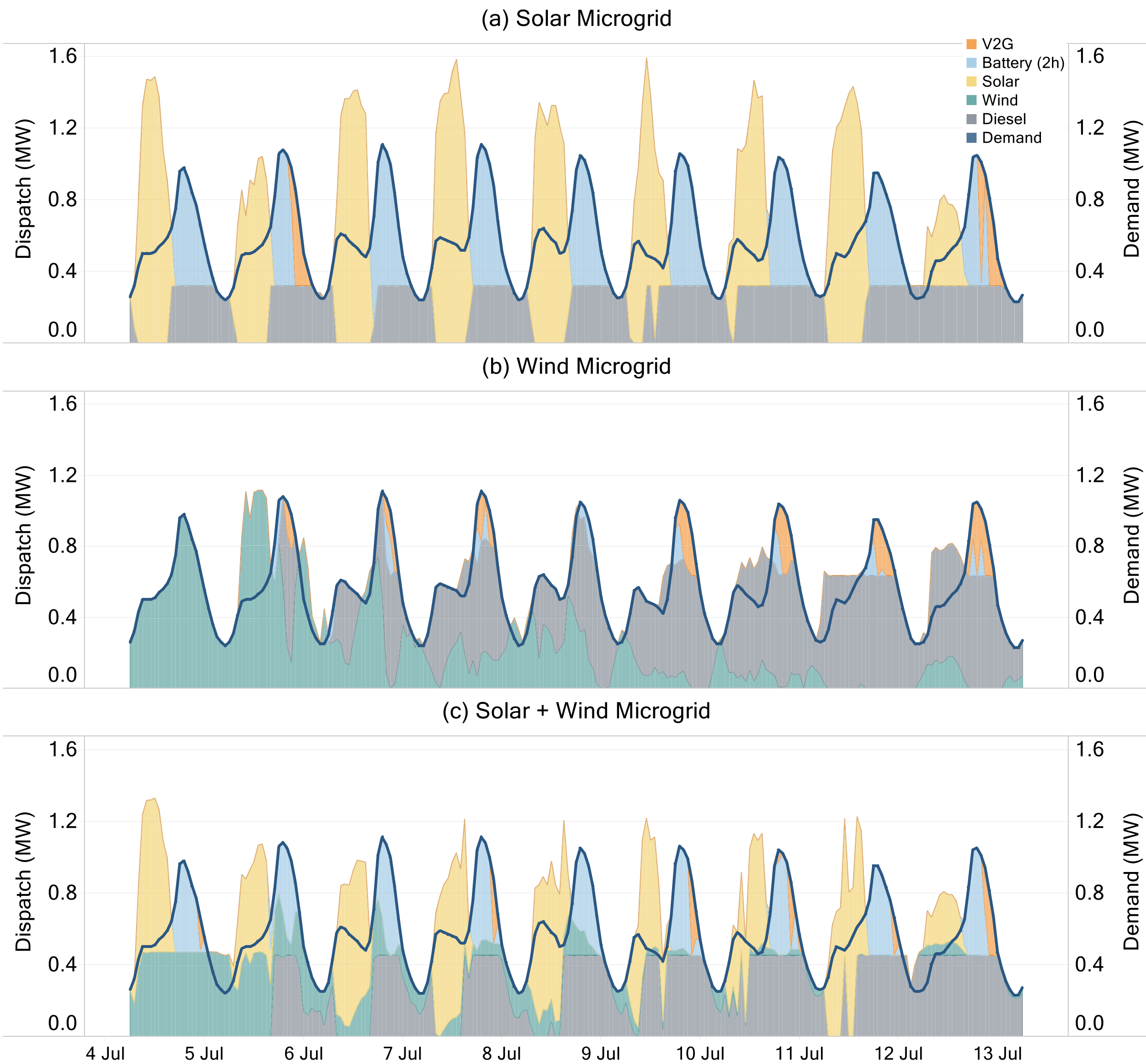

Fig. 4. Opportunity charging at 25% EV penetration for 10-day dispatch period in July (a) Solar microgrid (b) Wind microgrid, (c) Solar + Wind microgrid.

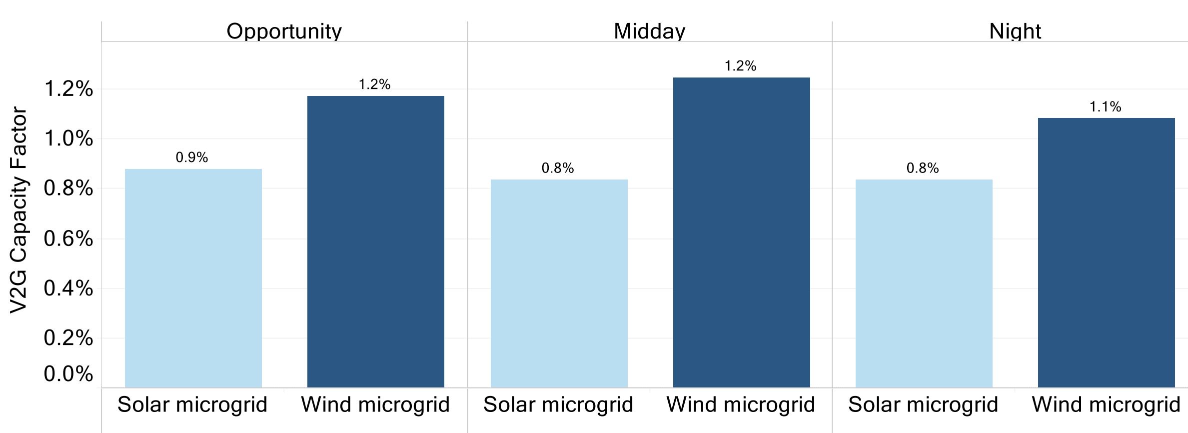

Fig. 5. Average capacity factor (CF) of V2G of four different EV penetration levels in Wind and Solar microgrids.

compared to the Solar Microgrid. However, the utilised average V2G capacity is lower than the Solar microgrid. Furthermore, the peak V2G dispatch is observed at midday. Solar + Wind microgrid represent Solar microgrid the characteristic such that V2G is only dispatched during night time and peak V2G dispatch is observed at 7 pm. However, the V2G dispatch count is higher than Solar microgrid. These results support previous findings such that the use of V2G is highly related to the capacity of existing utility

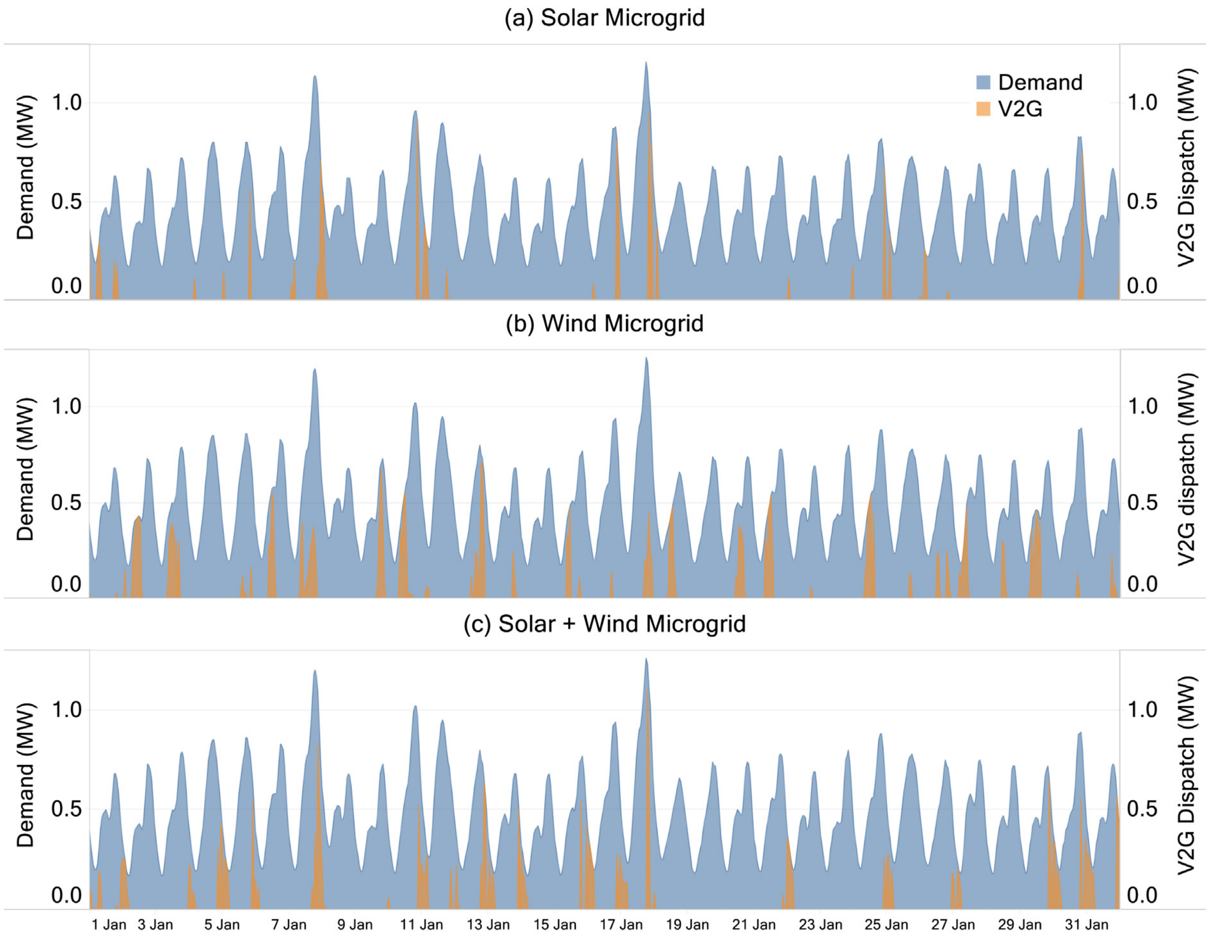

Fig. 6. V2G dispatch across January for Opportunity charging at 25% EV penetration: (a) Solar microgrid, (b) Wind microgrid, (c) Solar + Wind microgrid .

Table 9
V2G energy dispatch over a year (MWh) for Solar, Wind and Solar + Wind microgrids.

	Solar microgrid	Wind microgrid	Solar + Wind microgrid
Annual V2G energy dispatched (MWh/year)	271.6	296.9	316.7
Additional EV degradation per year due to V2G	0.05%	0.06%	0.06%

battery storage for that microgrid. As the solar microgrids have a high reliance on the utility battery storage to meet its night demand, the instances where V2G is required are less. In contrast, as the Wind microgrid is less reliant on utility battery storage, there are more opportunities for V2G.

The increase in V2G dispatch may raise concerns for increased battery degradation due to higher use of battery. To investigate this further, Table 9 presents the total energy dispatched from V2G in each microgrid and additional battery degradation that would occur due to V2G dispatch assuming V2G dispatch is equally distributed across the EV fleet.

As seen in Table 9, the battery degradation percentage due to V2G is relatively small for all microgrid scenarios and therefore V2G would not significantly reduce the life span of the EV battery according to the results of this study. Furthermore, as the EV penetration increases, the degradation is further reduced as V2G dispatch is spread across a larger EV fleet.

During the simulations, it was observed that an average V2G dispatch used relatively low amount of the EV fleet (5%–15%), however during maximum V2G dispatch, this percentage reached up to 51% of the EV fleet for the 25% EV penetration scenario. Even though simulations considered real world travel survey patterns when calculating V2G availability, such high availability of EV fleet may not always be realistic. This raises important questions on system security and reliability when microgrids rely on different levels of V2G dispatch to meet maximum demand. Assessing system security under different V2G dispatch is a future research objective. It was also seen that as EV penetration increased above 50%, the percentage of the EV fleet needed to meet the maximum V2G capacity reduced below 32% of the fleet. This indicates that higher EV penetrations can improve the reliability for systems that rely on V2G dispatch.

The studied openCEM tool optimised the capacity for the chosen generation technologies for the least cost microgrid solution. However, renewable generation penetration may differ in real world according to available resource and location. Apart from the optimal generation mix, simulations with different firmed renewable energy penetration levels were carried to understand the impact of different penetration of renewable energy. The simulation results indicate that microgrids with higher renewable energy penetration have higher utilisation of V2G and utility batteries. However, as renewable energy penetration increased, the growth in V2G and utility battery utilisation slowed down as both are limited by pre-determined capacity. For grids with

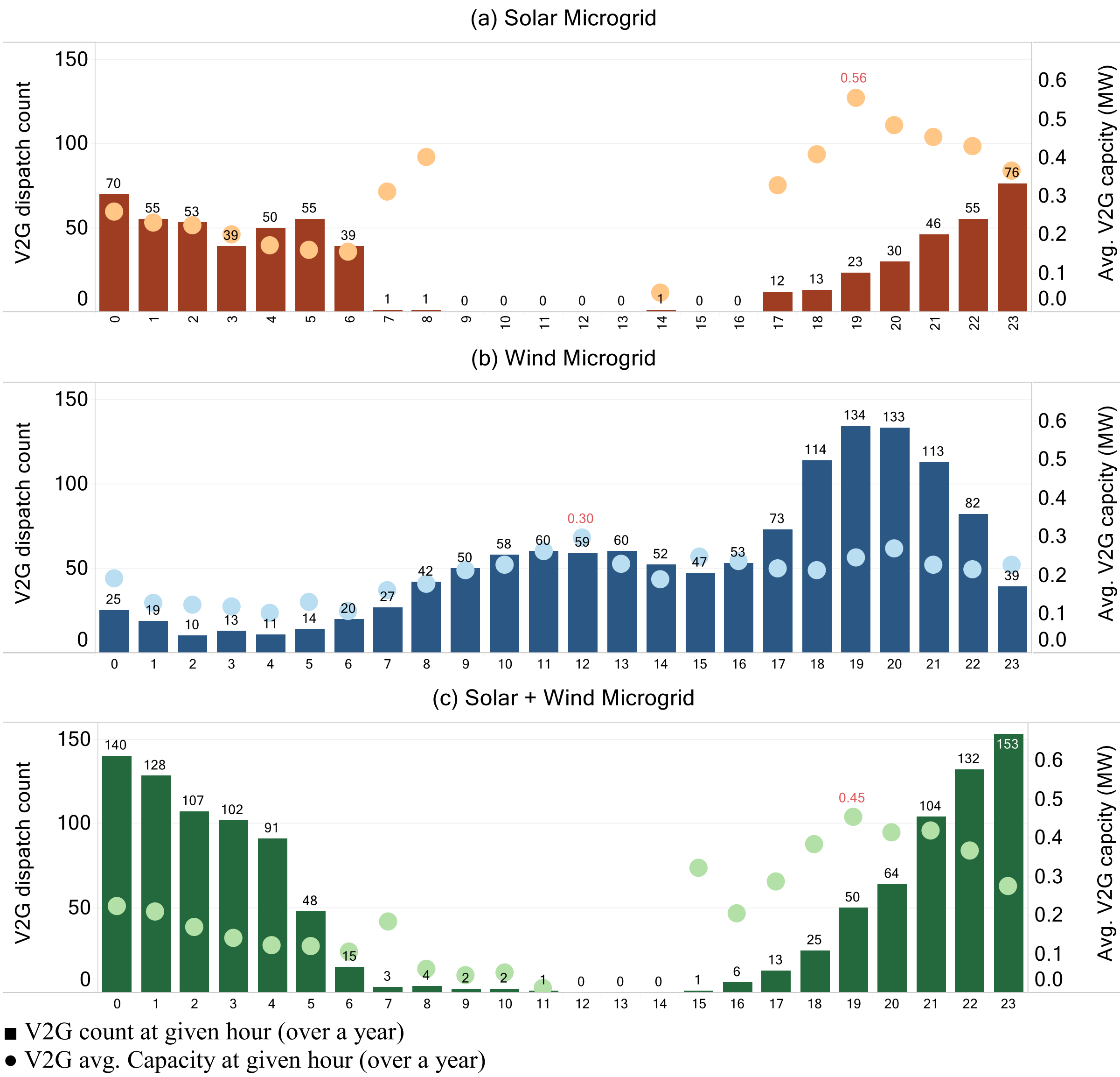

Fig. 7. Number of instances of V2G at a given hour over a year and average capacity of V2G dispatch at a given hour for Opportunity charging at 25% EV penetration (a) Solar microgrid, (b) Wind microgrid (c) Solar + Wind microgrid.

renewable energy penetration below optimum levels, the utilisation of utility storage and V2G decreases as most of the renewable generation is used for the microgrid demand, reducing the available energy for storage. As such, the overall cost of the microgrid increases in both options.

3.3. Sensitivity analysis — V2G charging equipment cost

In previous sections, bidirectional charging equipment cost was assumed to be borne by the EV owner and was not accounted for the capital cost of V2G. In this section, a sensitivity analysis was conducted to assess the impact of bidirectional charging equipment cost on the dispatch and operations of V2G when this cost was considered as V2G technology capital cost. The additional cost of bidirectional charging equipment for V2G is hard to determine as discussed in Section 2.1. Therefore, a range of bidirectional charging equipment cost was studied as a capital cost for the V2G generation, ranging from AU$100-AU$1000. Fig. 8 presents the results for the sensitivity analysis for the Solar microgrid at 25% EV penetration level where individual technology costs are presented on the left *y* axis against the range of V2G capital cost due to bidirectional charging equipment cost. On the right *y* axis, the resultant microgrid LCOE is presented. The results indicate that for V2G to be a competitive generator in this microgrid, it must have a lower LCOE cost than the diesel generator which stands around AU 320 $/MWh. Therefore, V2G can compete with the diesel generator as long as its capital cost is below AU $900. Above this cost, V2G is no longer a competitive technology for the microgrid. This cost figure can be used as a benchmark by future research when V2G is included in the studied generation mix. As the capital costs come down with further technology advancements, V2G will secure its place in microgrid generation mix. This will result in further reductions in the overall LCOE by higher utilisation of V2G.

4. Conclusions and future work

Using simulations of openCEM, this paper discussed the impacts of EV demand and the economic viability of V2G for various microgrid generation mix scenarios over a calendar year. The simulations accounted for battery degradation, EV charging scenarios, different V2G availability scenarios, varying EV penetrations and

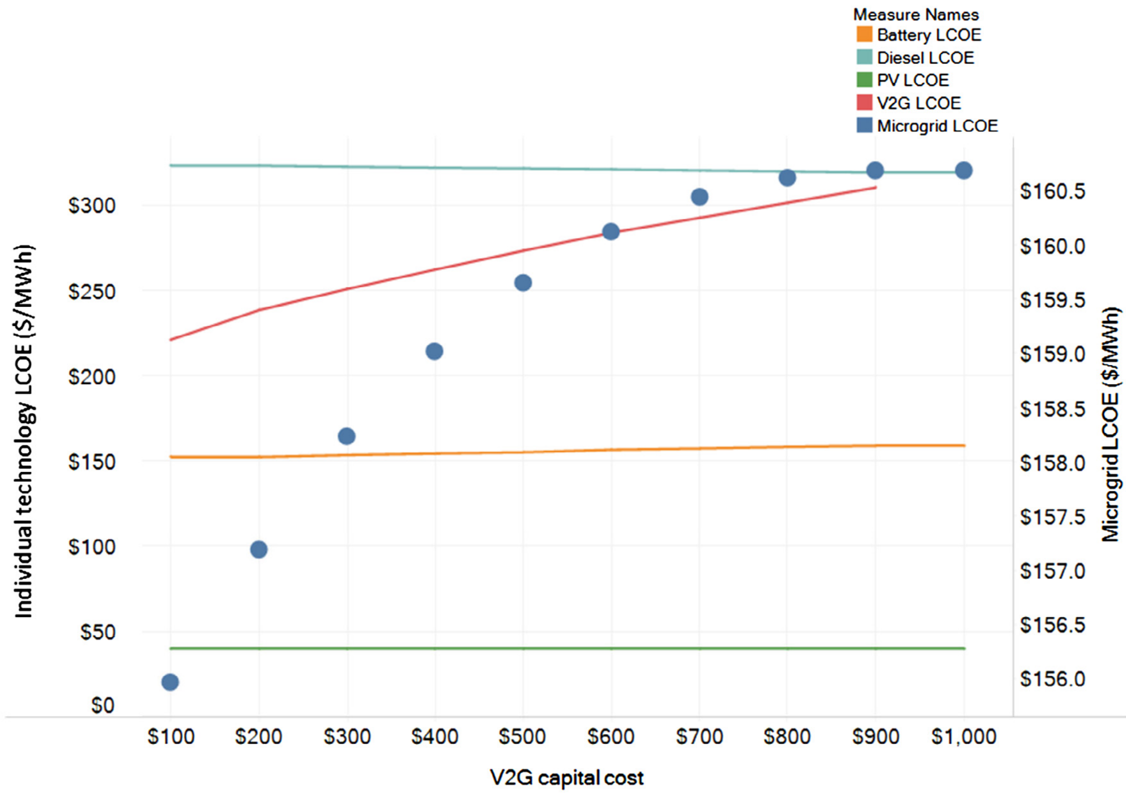

Fig. 8. V2G Bidirectional cost sensitivity analysis (Solar microgrid, 25% EV).

new developments in EV battery technology. The results of the study show that recent advancements in EV battery have diminished the impact of V2G degradation and improved V2G availability. This results in a net benefit to microgrid operations by reducing LCOE. The key findings of these simulations can be summarised as follows:

- V2G resulted on a positive impact on the microgrid LCOE in all scenarios. V2G reduces LCOE grid costs by up to:
  - 9.0 $/MWh (5.4% reduction) for the Solar microgrid (Opportunity charging scenario).
  - 9.0 $/MWh (4.6% reduction) for the Wind microgrid (Opportunity charging scenario)
  - 6.6 $/MWh (4.5% reduction) for the Solar + Wind microgrid. (Opportunity charging scenario)
- The Night charging scenario had higher LCOE in all microgrid environments due to the creation of new peaks later at night. This caused lower utilisation of solar PV and increased dependence on diesel generator. The Opportunity and Midday scenarios showed similar LCOE with one another and are preferable over the Night charging scenario. This highlights the need of appropriate policies and strategies to incentivise the spread of the EV charging load across the day. Infrastructure to allow for EV charging at work, home, and other locations or where EVs may be parked during the day can help to facilitate this.
- High penetration of EVs does not necessarily increase LCOE of microgrids and in some cases a small reduction was seen, such as in the Solar microgrid. This was because EV demand smoothed the overall microgrid demand profile (i.e., reducing the variations between peak and low demand) and daytime EV demand could be provided by solar PV generation which increased the self-consumption rate.
- V2G is best suited to meet peak demand and as additional storage capacity for days with low solar or wind generation. The optimum V2G dispatch depends on the level of utility battery storage in the system. The Solar microgrid required less instances of V2G dispatch compared to the Wind microgrid because the Solar microgrid had higher reliance on utility battery storage to meet the night demand.
- While V2G availability is significantly impacted by travel patterns, there is generally sufficient percentage of fleet available to provide the required V2G dispatch. The reliability on V2G to provide higher percentages of microgrid demand increases with higher EV penetration levels because of increased availability.
- When bidirectional charging equipment cost is considered as V2G capital cost, V2G must have a LCOE lower than diesel generation to be included in the microgrid generation mix. This cost was estimated to be AU$900.

An important limitation of the study is that the simulations did not consider the interactions between V2G and Frequency Control Ancillary Services (FCAS) market and the associated revenue. Moreover, V2G's impact on system strength, reserve and reliability requires further investigation. With increasing levels of EV ownership and V2G opportunities in networks, future research is needed to understand the relationship between V2G and transmission and distribution network capacity constraints. A relevant future research objective is to include a grid connected microgrid scenario and investigate its impact on V2G operations. Intuitively, adding grid connection would bring more competition via other generation technologies that can operate in similar ways with V2G's opportunistic nature (i.e., gas-fired generation). Although this may reduce the utilisation of V2G, such analysis must include additional cost of transmission as well as any constraints on grid import and exports. This is an important area of future research which can bring valuable insights into V2G's role in different micro-grid formations. Finally, studied openCEM modelling had perfect foresight for the EV and household demand which represents an ideal scenario. Under higher demand uncertainty, V2G's opportunistic nature may result in higher utilisation which requires further evaluation. These points comprise the objectives of our future research.

CRediT authorship contribution statement

Daniel O'Neill: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Baran Yildiz:** Conceptualization, Methodology, Software, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Jose I. Bilbao:** Conceptualization, Methodology, Investigation, Writing – review & editing, Project administration.

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.

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