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Techno-economic modelling for energy cost minimisation of a university campus to support electric vehicle charging with photovoltaic capacity optimisation

Yan Wu *, Syed Mahfuzul Aziz, Mohammed H. Haque

UniSA, STEM, University of South Australia, Mawson Lakes, SA 5095, Australia

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ABSTRACT

Workplace charging of Electric Vehicles (EV) is a promising approach for transport decarbonization while addressing issues emerging from renewable energy growth. For workplaces, the decision to invest in EV charging infrastructure depends on the overall cost of providing this service. This study proposes a novel modelling approach to minimize the net annual energy cost of a university campus providing EV charging service using optimum capacity solar photovoltaic (PV) systems. The research includes an innovative approach to determine the campus EV charging demand and a novel net annual energy cost minimisation method combining PV size optimisation and EV charging control. A comprehensive analysis is presented to illustrate the influence of EV penetration, charging strategy, charging fees, charger cost and PV generation cost on the campus net annual energy cost. The influence of these parameters are also analysed on the optimal PV capacity, power and energy demand, and PV self-utilisation. Results show that, by using the proposed method, for 25 % EV penetration, the campus's peak demand is reduced by around 12 % and net annual energy cost is reduced by up to 9.2 % while providing free EV charging. The net annual energy cost reduction increases to over 20 % for 100 % EV penetration.

1. Introduction

1.1. Background

Australia has pledged to take stronger action on climate change, namely, reduce greenhouse gas emissions by 43 % from the 2005 levels by 2030 and achieve net-zero emissions by 2050 [1]. To achieve this goal, electrification of transportation is inevitable, and electricity will likely become the main energy source for road transportation. During 2019–20, the Australian transport sector had the largest share of energy consumption (26.5 %) and accounted for 18 % of Australia's greenhouse gas emissions even with the travel restrictions due to COVID-19 [2,3]. Road transport accounted for 72.7 % of total transport energy consumption, out of which small passenger vehicles (cars) accounted for 47 % of road transport emissions (or about 7.5 % of Australia's total greenhouse emissions) [2,3]. To achieve the decarbonization of transport, Australia intends to increase EV penetration to around 25 % by 2030 and over 80 % by 2050 [4,5]. Australian Capital Territory has officially announced to ban the sale of new fossil fuel based cars by 2035 [6]. From 2021, more positive policies have been introduced by state governments to further support EV growth, including financial incentives for EV purchase and investment in charging infrastructure [7]. On the other side, most carmakers around the world have also made public commitments to electrification in line with the goal of decarbonization [7]. For example, the timelines to become 100 % electric have been set by several carmakers: Jaguar Land Rover (2025), Mazda (2030), Nissan (early 2030s), and Honda (2040) [7]. Moreover, the world has begun to witness the emergence of carmakers exclusively dedicated to producing electric vehicles, such as the Automobile Joint Venture Group known as TOGG [8]. However, if the increased electricity demand due to EV charging is met by traditional thermal power stations, the goal of transport decarbonization cannot be achieved.

In Australia, with the strong growth of renewable energy sources, the issues caused by low direct use of renewable generation become apparent year by year. In 2021, renewable energy sources provided 32.5 % of Australia's electricity generation [9]. 37.2 % of this renewable electricity is generated by rooftop solar PV (24.9 %) and large-scale solar PV (12.3 %), making solar the largest contributor to renewable electricity generation in Australia. However, fossil fuel still accounted for 93

* Corresponding author.
E-mail addresses: yan.wu@mymail.unisa.edu.au (Y. Wu), mahfuz.aziz@unisa.edu.au (S.M. Aziz), mohammed.haque@unisa.edu.au (M.H. Haque).

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List of nomenclature

Abbreviations

EV	Electric Vehicle
LCOE	Levelized Cost of Energy
PSO	Particle Swarm Optimisation
PV	Photovoltaic
UniSA	University of South Australia

Indices

$m/d/t$	Index of month/day/time interval
k	Index of individual EV

Parameters and Variables

$P^{EV}_{d,t}$	Aggregated EV charging power in time interval t of day d
AC^{CHGR}	Annual cost of EV chargers
AC^{G}	Annual cost of grid electricity consumption
AC^{PV}	Annual cost of PV generation
AMC^{CHGR}	Annual maintenance cost of EV chargers
AR^{EV}	Annual revenue generated from EV charging fees
$T^{AR}_{k,d}$	Arrival time of k-th EV in day d
BD	Battery degradation factor
CC^{CHGR}	Capital cost of a single EV charger
$P_{k,d,t}$	Charging power of k-th EV in time interval t of day d
$T^{CH}_{k,d}$	Charging start time of k-th EV in day d
$T^{DE}_{k,d}$	Departure time of k-th EV in day d
λ	Electricity tariff
BC_k	EV battery capacity of k-th EV
ηEV	EV charging efficiency
λ^{EV}	EV charging tariff
EE	EV energy economy
PF	EV penetration factor
$P^{EX}_{d,t}$, $P^{IM}_{d,t}$	Export/import power to/from the grid in time interval t of day d
FiT	Feed-in-tariff
$ICAP^{PV\_CR}$	Installed capacity of current PV system
$ICAP^{PV}$	Installed capacity of PV system
r	Interest rate
$LCOE^{PV}$	LCOE for PV generation
Y	Life span of EV charger
LF	Loss factor on electricity bill
SoC^{MAX}	Maximum state of charge of EV battery
SoC^{MIN}	Minimum state of charge of EV battery
MC^{G}	Monthly cost of grid electricity consumption
AEC^{NET}	Net annual energy cost of total electricity consumption
D_m	Number of days in month m
D_y	Number of days in year y
N^{EV}	Number of EVs
T	Number of time intervals in a day
M	Number of months in a year
P^{IM_AY}	Peak power corresponding to Anytime Demand
P^{IM_SR}	Peak power corresponding to Summer Demand
$P^{C}_{d,t}$	Power demand from Campus load in time interval t of day d
$P^{\Delta}_{d,t}$	Power difference between supply and demand
$P^{PV-PU}_{d,t}$	PV output per unit of installed capacity in time interval t of day d
P^{RA}_{k}	Rated charging power of k-th EV
α	Ratio of the number of EVs parked to the number of campus parking bays
SF_d	Scaling-down factor for EV charging demand
SC, SS	Self-consumption, self-sufficiency
$\Omega_{N^{EV}}$	Set of EVs
Ω_{D_m}	Set of days in month m
Ω_{D_y}	Set of days in year y
Ω_{EC}	Set of electricity tariffs for energy consumption
Ω_{M}	Set of months in a year
Ω_{T}	Set of time intervals in a day
$\Omega_{T^{PK}}$	Set of time intervals during peak period in a day
$\Omega_{T^{OFF}}$	Set of time intervals during off-peak period in a day
Δt	Simulation time interval
$SoC_{k,d,t}$	State of charge of k-th EV in time interval t of day d
$DIST_{k,d}$	Travel distance of k-th EV in day d
$P^{PV-CR}_{d,t}$	Output power for the currently installed PV system in time interval t of day d

% of Australia's primary energy mix in 2019–20 [2], and the "duck curve" phenomenon caused by the growing solar generation has already become a challenge for renewable development and decarbonization. The 17 Sustainable Development Goals (SDG) of the United Nations [10] and the harms caused by fossil fuels [11] are summarized in Fig. 1. Clearly, the impacts of using fossil fuels are impeding the progress towards SDG in many ways, particularly in the economic and environmental spheres. Fig. 2 shows the overall electricity demand profile of the Australian National Electricity Market (NEM) in 2010–20 [12]. The high solar generation has led to a significant decrease in grid power demand during the daytime period. Then, in the evening, as solar generation goes down and people return home, the grid power demand increases dramatically. The duck curve will exacerbate if more PV generation enters the grid, and the evening demand increases further due to the home charging of the growing number of EVs.

Workplace charging of EVs can be a sensible approach to mitigate the above problems and has gained attention in recent years. It has been observed in some parts of the world that workplace charging can reduce people's reliance on home charging [13]. In Canada, workplace charging contributed to the reduction of home EV charging from 90 % to 72 % between 2014 and 2019, with free workplace charging accounting for 80 % of the cases. Free workplace charging helps reduce household energy cost [14] and influences EV owners to change their unregulated charging behaviour. The potential benefits of workplace charging include: 1) charging of EVs with renewable energy, 2) increasing the direct utilisation of local renewable energy generation (without entering the grid), 3) reducing home charging of EVs and thus avoiding the increase of grid peak demand during the evening, 4) encouraging EV uptake among private vehicle owners, and 5) bringing us one step closer to green building goals. However, from the perspective of property owners, workplace charging-related costs are the key factors that determine whether to provide this service, which mainly include: 1) capital cost of the EV charging infrastructure, 2) cost of energy used for EV charging, and 3) cost of the on-site solar PV system.

This study proposes an innovative overall energy cost optimisation method for a university campus, which combines EV charging control with campus PV system capacity optimisation. Fig. 3 shows the configuration of the Campus Energy Management System used in this study. The optimisation model is established based on a real campus energy management system at the Mawson Lakes Campus of the University of South Australia (UniSA). The existing campus energy management system is marked with a grid background, and the optimised parts are highlighted within the red dashed rectangles. The existing PV integrated campus energy management system was completed in 2019 based on economic analysis that considered PV cost, campus energy consumption and grid electricity costs at that time. It did not include an assessment of energy demand for EV charging. With the expected increase in EV charging demand and the reduction in PV costs, optimisation of the

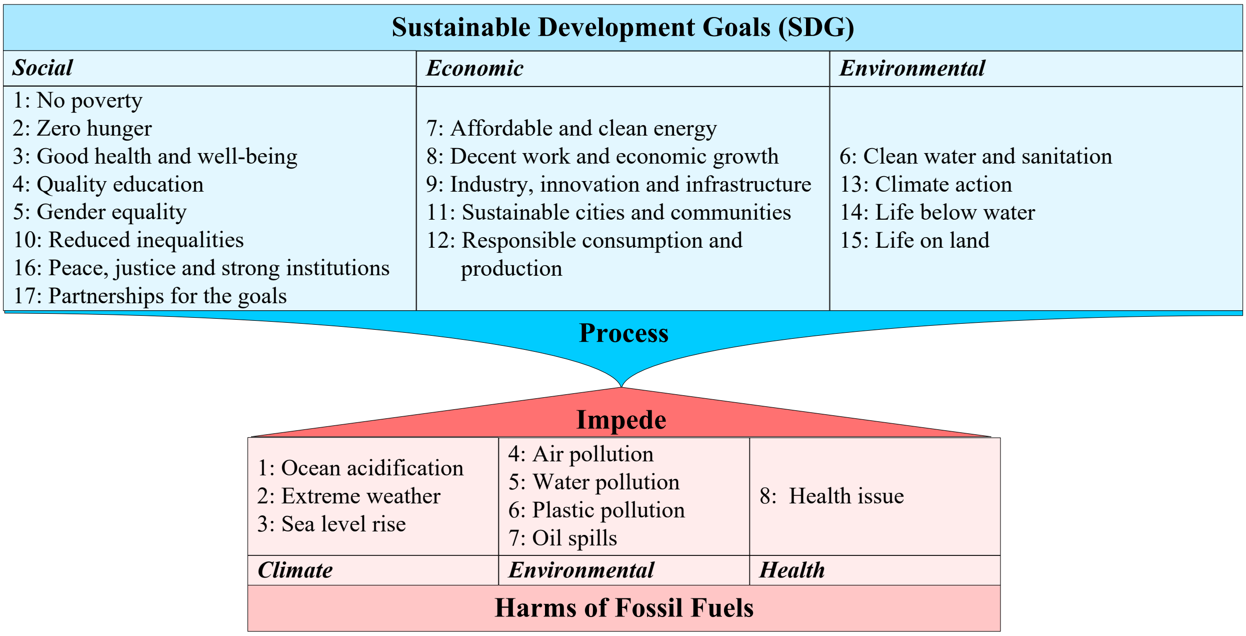


Fig. 1. United Nations' Sustainable Development Goals (SDG) and the harms caused by fossil fuels [10,11].

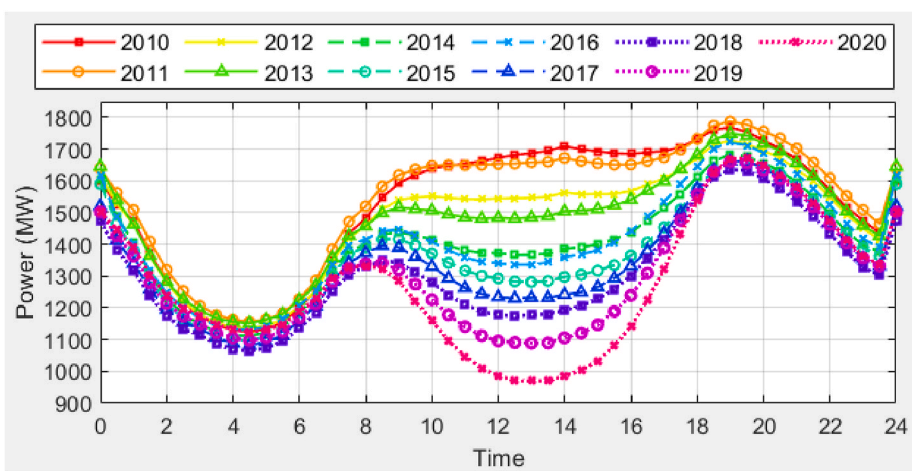


Fig. 2. Duck curve in Australia 2010–2020 [12].

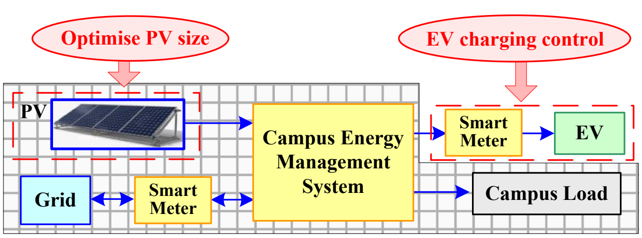


Fig. 3. Configuration of the campus energy management system.

campus energy system is required to enable the current campus energy management system to achieve optimal economic performance while facilitating workplace charging and contributing to Australia's carbon reduction goals.

1.2. *Literature review*

The integration of PV and EV in the energy management system of a workplace has been a popular topic within the power system and renewable energy fields in recent years. To the best of the authors' knowledge, no existing study combines workplace EV charging control with PV capacity optimisation to minimize workplace electricity costs. Furthermore, the impacts of EV charging strategies on optimal PV sizing, and the joint impacts of these strategies and PV optimisation on the energy cost and renewable energy utilisation have not been studied for workplaces previously. A summary of the existing studies, their objectives and limitations are given in Table 1. The remainder of this section presents a review of these studies.

The study in Ref. [15] presents an optimal system schedule for a campus micro gird by comparing different energy management strategies to reduce operational cost and increase self-consumption of renewable energy. And the study in Ref. [16] proposes components' capacity optimisation method to minimize total operating cost and investigates the impacts of various financial incentives for a campus micro gird. However, EV charging demand is not considered in Refs. [15,16]. Integrating PV generation and EV charging demand into buildings [17], examines the energy and economic performance of various

Table 1
Summary of objectives, key features and limitations of the existing studies.

Ref.	Objectives of the study	Features included		
		PV sizing	EV control	Others
[15]	1) Reduce operational cost 2) Increase self-consumption of Distribution Generation	×	No EV	–
[16]	Minimize total operating cost	✓		–
[17]	Examine energy and economic performance	×	×	–
[18]	Environmental, energy and economic analysis			–
[19]	1) Net or nearly zero-energy target 2) Energy and economic assessment	×	✓	–
[20]	Minimize daily system cost			24-hour simulation only
[21]	Maximize profit of charging service			–
[22]	Minimize daily electricity consumption cost			–
[23]	Minimize operational cost of bus charging station			–
[24]	1) Exam techno-economic feasibility 2) Release energy congestion 3) Minimize energy-based operational cost			–
[25]	1) Assess energy generation 2) Reduce carbon emission 3) Analyse cost-benefit	✓	×	–
[26]	Maximize economic and environmental benefit for fast charging station			PV is used only to charge EV
[27]	1) Maximum usage of PV to charge EVs 2) Minimize CO_2 emission 3) Reduce operating cost			Electric bus only
[28]	1) Maximize self-consumption of PV energy 2) Maximize autonomy			Lightweight EVs (13.8 kWh)
[29]	Optimise self-consumption and self-sufficiency	✓	✓	PV is used to only charge EV
This study	1) Minimize net annual energy cost with free EV charging service 2) Analyse the influence of EV penetration, EV charging strategy, EV charging fees, EV charger subsidies, and PV generation cost on the net annual energy cost, optimal PV size, power and energy demands, and PV self-consumption and self-sufficiency of the campus 3) Perform year-round simulation and reveal seasonal impacts on optimisation	✓	✓	–

configurations of the energy management system. For commercial buildings [18], analyses the environmental, energy and economic impacts of increasing EV penetration. However, only a fixed PV capacity is used in Refs. [17,18], and EV charging control is not considered.

To achieve the net-zero-energy target for office buildings, an energy management method including EV charging control is proposed in Ref. [19], and the energy and economic performances are assessed. In Ref. [20], to minimize the daily energy consumption cost, EV charging schemes and energy management strategies are proposed for a grid-connected smart building considering photovoltaics using the demand response method. From the perspective of commercial building owners [21], proposes a real-time management method for EV charging to maximize the profit from providing the charging services. Based on Time-of-Use tariff, a method of optimising power priority is used in Ref. [22] to minimize the daily cost of electricity consumption for a campus microgrid. In Ref. [23], the effects of three energy management strategies and various charging schemes are examined for two charging rates to reduce the operational cost of a bus charging station. A multi-objective method combining EV charging control, system energy management and off-peak electricity tariff is proposed in Ref. [24], aiming to release the network energy congestion. Although EV charging strategies in presence of renewable generation have been investigated in the studies mentioned above, none of these studies has considered PV capacity optimisation.

Although PV sizing techniques have been employed by some researchers to optimise EV and PV integrated systems, EV charging control is not considered in these studies. Reference [25] presents a study that assesses the energy and environmental performance for an academic institution, and performs cost analysis to find the most economic system configuration. A planning and optimisation method for campus EV fast-charging station is proposed in Ref. [26] to achieve maximum economic and environmental benefits; however, the PV generation is only used to charge EVs and the campus energy consumption is not considered. To maximize renewable utilisation, minimize CO_2 emission and reduce operating costs, a PV optimisation method for the campus is proposed in Ref. [27]; however, this study only considers the charging demand of campus electric buses. In Ref. [28], four configurations with PV sizing are analysed to achieve maximum self-consumption of PV energy and system autonomy for a campus PV-EV charging station; however, this study is focused on lightweight EVs' charging demand and does not present economic analysis.

Combining the optimal PV sizing and smart EV charging [29], presents a study on workplace charging stations aiming at improving the system's self-consumption and self-sufficiency; however, the solar PV output is only used for EV charging and the local loads of the workplace are not considered.

1.3. Contributions

The aim of this study is to optimise the PV system in a university campus considering increasing EV charging demand, and to perform economic as well as energy and power flow analysis. The main contributions of the paper are.

1) Propose a novel net annual energy cost (net AEC) minimisation method for a campus combining EV charging control with PV capacity optimisation.
2) Develop a new modelling approach for the estimation of campus EV charging demand throughout the year. This modelling approach is built on the vehicle parking distribution extracted from the Victorian

Integrated Survey of Travel and Activity (VISTA) [30] and validated against real year-round vehicle parking data collected from an Australian university campus. The approach considers the impact of working and non-working days during both teaching and non-teaching periods on the number of vehicles parked on the campus.

3) Present comprehensive cost optimisation results and critical analysis for the University of South Australia's Mawson Lakes Campus Energy Management System using the actual electricity billing mechanism for a 'High Voltage connection customer'.

New findings from this study include the influence of EV penetration, EV charging strategy, EV charging fees, EV charger subsidies and PV generation cost on the campus's net AEC, optimal PV size, power and energy demand, PV self-consumption and self-sufficiency. Using the campus load and PV generation data, simulation is conducted for the full year to incorporate the effects of seasonal variations. The proposed method is expected to facilitate cost-effective integration of workplace EV charging with optimally sized PV. The proposed models are applicable to any campus or workplace provided the relevant campus/workplace data are supplied to the proposed optimisation algorithm.

1.4. Paper organisation

The remainder of this paper is organized as follows: Section 2 presents the existing PV integrated campus energy management system in UniSA Mawson Lakes campus and the current electricity billing mechanism. Section 3 presents the overall optimisation model, the cost-based objective function and the factors used to assess the local utilisation (self-consumption and self-sufficiency) of renewable energy. Section 4 presents the modelling of the EV usage demand, electricity consumption and various EV charging strategies. In Section 5, the optimisation results for different charging strategies are compared. It also presents the power flow analysis of the campus energy management system, the seasonal impacts and various sensitivity analysis using key system parameters. Finally, Section 6 concludes the paper's achievements, discusses the limitations and recommends future works.

2. Existing PV system and billing mechanism

2.1. Campus PV generation and energy consumption

The existing solar PV system in UniSA's Mawson Lakes Campus consists of rooftop solar panels on 18 buildings and ground-mounted solar panels. A section of the ground-mounted panels is shown in Fig. 4. The PV output is used to supply the campus load and excess PV energy, if any, is exported to the grid. Thus, the PV generation reduces the campus power demand and the amount of energy imported from the grid and therefore reduces the campus's energy cost.

The installed AC capacity of the campus PV system is 1365 kW, and Fig. 5 shows the power flow of the campus energy management system for one week in March (end of summer) and one week in August (winter). The peak load demand of the campus is around 2300 kW. The campus PV system can meet some of this demand during the day and very small amount of power is exported to the grid because there isn't much excess PV generation. Fig. 5 illustrates the variations in load demand between weekdays and weekends as well as the seasonal variations. The typical summer curve shown in Fig. 5 (a) is taken from March when there is abundant sunlight on most of the days and the PV system output can almost reach its rated capacity at noon. In contrast, as shown in Fig. 5 (b), fewer days in winter have good solar radiation and the solar generation has significantly lower peaks than in summer, so the rated PV output cannot be reached. Compared to the workdays, the campus load demand during the weekends (days 6 and 7) is relatively low and remains almost at the same level as night-time. The PV power output per kW of installed PV capacity during time interval t of day d ($P_{d,t}^{PV-PU}$) can be obtained from the current campus PV output ($P_{d,t}^{PV-CR}$) and the current installed PV capacity ($ICAP^{PV-CR}$).

$$P_{d,t}^{PV-PU} = P_{d,t}^{PV-CR} \Big/ ICAP^{PV-CR}; \forall t \in \Omega_T, \forall d \in \Omega_{D_y} \quad (1)$$

where, Ω_T and Ω_{D_y} represent the set of time intervals in a day and the set of days in year y.

2.2. Electricity billing mechanism

The complete electricity bill of the Mawson Lakes campus for a month can be found in Table A.1 of the Appendix. There are fourteen charge items grouped into five categories. The 'Charges' column lists all fourteen items, the next two columns show the energy 'Usage' and 'Unit Price' (λ) for each item, and the last two columns show the 'Loss Factor' and the total charge for each item. As can be seen from Table A.1, the campus electricity costs comprise the following.

- Items 1, 2, 3, 4, 5, 11 and 13 represent charges based on the total energy consumption

Fig. 4. Picture of part of the UniSA Mawson Lakes Campus PV system.

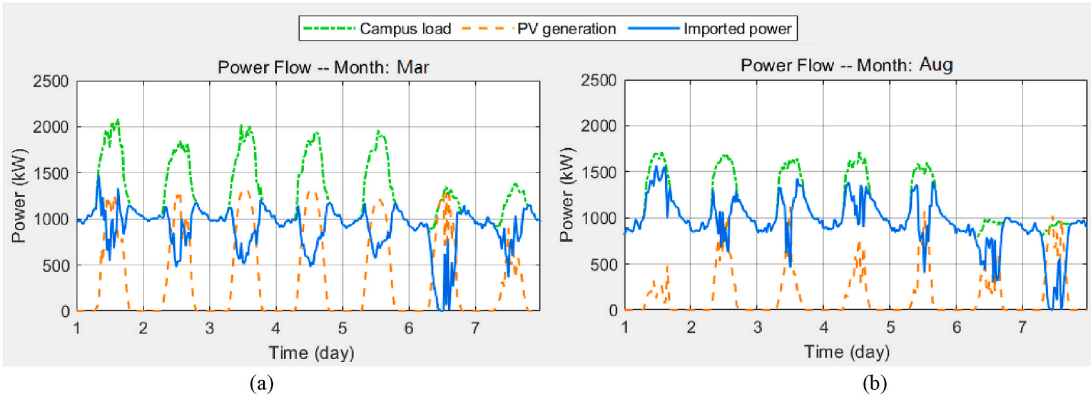


Fig. 5. Campus load and existing PV generation in (a) March – summer and (b) August – winter.

- Items 6 and 7 account for charges due to peak and off-peak energy consumption respectively
- Items 8 and 9 are charges for kVA demand
- Items 10 and 12 represent daily network and market operator charges respectively
- Item 14 is the annual meter charge.

Note that the university is classified as a business customer. As such, it is subject to the High Voltage Business Annual Demand (HVAD) charges shown in items 6–10 of Table A.1. Currently, the campus does not earn any revenue for excess PV energy exported to the grid, that is, the *feed-in-tariff* (*FiT*) is zero. The monthly variation in the retail price of electricity λ_1 (refer to item 1 in Table A.1) is shown in Fig. A.1 with the annual average value presented by the red dashed line. In this study, the 2021 rates are used for λ_1. To investigate the effects of varying λ_1 on the optimisation results, sensitivity analysis is performed in the results section. For clarity, the tariff structures of items 6, 7, 8 and 9 from the bill of Table A.1 are illustrated in Fig. A.2 of the Appendix along with a brief explanation.

The mathematical expression for calculating the monthly cost (MC^G) of campus electricity consumption from the grid is represented by (2).

$$MC^G(m) = \overbrace{\sum_{d\in\Omega_{D_m}}\sum_{t\in\Omega_T}\left(P^{IM}_{d,t}\times\Delta t\right)\times\sum_{j\in\Omega_{D_{EC}}}(LF_j\times\lambda_j)}^{energy\ consumption\ cost}+$$
$$\overbrace{\sum_{d\in\Omega_{D_m}}\left(\sum_{t\in\Omega_{TPK}}P^{IM}_{d,t}\times\Delta t\times\lambda_6+\sum_{t\in\Omega_{TOFF}}P^{IM}_{d,t}\times\Delta t\times\lambda_7\right)}^{peak-offpeak\ energy\ consumption\ cost}+$$
$$\overbrace{\left[P^{IM-SR}\times\lambda_8+P^{IM-AY}\times\lambda_9\right]\times D_m}^{power\ demand\ cost}+$$
$$\overbrace{\left[\lambda_{10}+\lambda_{12}+\left(\lambda_{14}/D_y\right)\right]\times D_m}^{operator,network\ \&\ meter\ charge}-\overbrace{\sum_{d\in\Omega_{D_m}}\sum_{t\in\Omega_T}\left(P^{EX}_{d,t}\times\Delta t\times FiT\right)}^{energy\ exporting\ revenue} \quad (2)$$

where, $\Omega_{D_{EC}} = \{1,2,3,4,5,11,13\}$. Δt is the simulation time interval (30 min in this study) and LF is the corresponding loss factor. $P^{IM}_{d,t}$ and $P^{EX}_{d,t}$ represent the power imported/exported from/to the grid in time interval t of day d, respectively. m, d and t are the indices for months, days and time intervals, respectively. T is the number of time intervals in a day, and D_m is the number of days in month m. Ω_{D_m} represents the set of days in month m. Referring to Fig. A.2 of the Appendix, $\Omega_{T^{PK}}$ and $\Omega_{T^{OFF}}$ represent the set of time intervals during the peak and off-peak periods for billing items 6 and 7, respectively; P^{IN-SR} and P^{IN-AY} are contracted peak Summer Demand and Anytime Demand for billing items 8 and 9, respectively.

The annual cost (AC^G) of campus grid electricity consumption is the sum of the twelve monthly costs (MC^G), as shown in (3). Here, M is the number of months in the year and Ω_M is the set of months.

$$AC^G = \sum_{m\in\Omega_M} MC^G(m) \quad (3)$$

Clearly, the billing mechanism for relatively large workplaces such as a university campus is relatively complex, and a number of factors affect the campus electricity cost. At the same time, the cost and availability of adequate PV-generated energy to meet future growth in EV charging demand will impact upon the campus electricity costs. Therefore, there is a need to consider realistic EV charging demand and charging strategies to develop rigorous analytical methods for the optimisation of campus PV capacity so that future EV growth can be supported without escalating the overall electricity costs of the campus.

3. Optimisation method

Fig. 6 shows the overall flow chart of the optimisation method that uses an objective function to achieve the minimum net annual energy cost (net AEC) by finding the optimal PV size. The technical and economic parameters used in this study are given later in Section 5. In this study, the optimisation model is implemented using the built-in PSO solver in MATLAB running on a Windows PC having an Intel Core i5-8500T Processor and 4 GB RAM. Other optimisation algorithms can also be used, such as Genetic Algorithm and Firefly Algorithm [31]. The reasons for choosing PSO for this study include, but are not limited to, a straightforward syntax for modelling power system flow control, effective memory utilisation and stable performance of the optimisation solution (largely independent of the problem size and nonlinearity) [31]. The PSO solver has been successfully applied in many studies to solve optimisation problems in power systems [32–34].

3.1. Objective function

The model aims to minimize the net annual energy cost of the campus electricity consumption (AEC^{NET}), and the installed PV capacity ($ICAP^{PV}$) is used as the decision variable. The objective function is represented by (4). It includes the annual cost of grid electricity consumption (AC^G) given by (3), the annual cost of PV generation (AC^{PV}), the annual cost of EV chargers (AC^{CHGR}), and the annual revenue from the EV charging fees collected (AR^{EV}).

$$\begin{gathered} Min\{AEC^{NET}(ICAP^{PV})\} = \\ Min\{AC^G + AC^{PV}(ICAP^{PV}) + AC^{CHGR} - AR^{EV}\} \end{gathered} \quad (4)$$

$$\text{subject to} \begin{cases} System\ constraints \\ EV\ charging\ strategies \end{cases}.$$

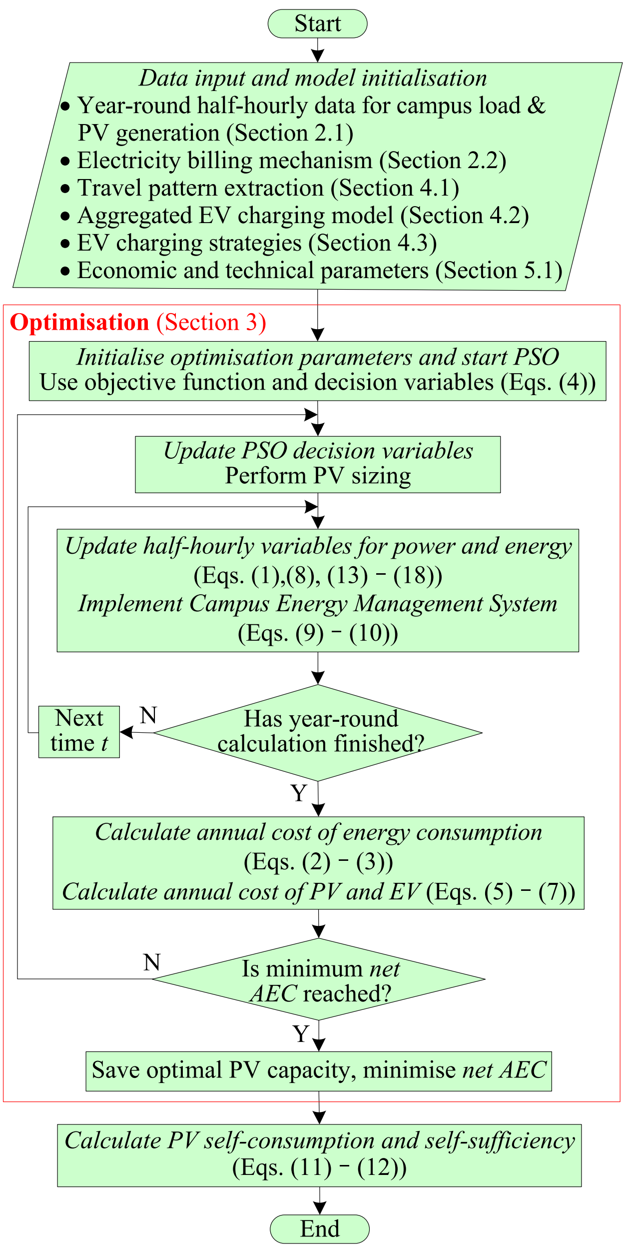


Fig. 6. Overall flowchart of the proposed optimisation method.

where, the calculation of AC^G is done using (2) and (3), and the remaining terms are calculated using (5) – (7).

$$AC^{PV}\left(ICAP^{PV}\right) = \sum_{d\in\Omega_{D_y}}\sum_{t\in\Omega_T}\left(P_{d,t}^{PV}\times\Delta t\right)\times LCOE^{PV} \tag{5}$$

$$AC^{CHGR} = N^{EV}\times a\times\left[CC^{CHGR}\times\frac{(1+r)^Y\times r}{(1+r)^Y-1}+AMC^{CHGR}\right] \tag{6}$$

$$AR^{EV} = \sum_{d\in\Omega_{D_y}}\sum_{t\in\Omega_T}\left(P_{d,t}^{EV}\times\Delta t\right)\times\lambda^{EV} \tag{7}$$

where, $LCOE^{PV}$ is the Levelized Cost of Energy (*LCOE*) for PV generation and $P_{d,t}^{PV}$ is the PV output power in time interval *t* of day *d* given by (8). N^{EV} is the number of EVs, *a* is the coefficient used to calculate the number of chargers required to support a certain number of EVs. CC^{CHGR} and AMC^{CHGR} represent the capital cost and annual maintenance cost of a single EV charger respectively. The annual investment cost of each EV charger is calculated using the capital recovery factor (CRF) which depends on the interest rate (*r*) and the expected life span of the EV charger (*Y* years) [35]. λ^{EV} is the EV charging fee, and $P_{d,t}^{EV}$ is the aggregated EV charging power in time interval *t* of day *d*. The expression for $P_{d,t}^{EV}$ is introduced in Section 4.2.

$$P_{d,t}^{PV} = P_{d,t}^{PV\_PU}\times ICAP^{PV}; \forall t\in\Omega_T, \forall d\in\Omega_{D_y} \tag{8}$$

Clearly, $P_{d,t}^{PV}$ is calculated using the PV generation per unit ($P_{d,t}^{PV\_PU}$) given by (1) and the PV capacity ($ICAP^{PV}$), which is the optimisation decision variable. Here, the PV capacity is taken as the capacity on the AC side.

3.2. System constraints

The power balance constraints are shown in (9) and (10). Here, $P_{d,t}^{C}$ represents the power demand from the campus load in time interval *t* of day *d*. If the combined campus and EV load demand is higher than the PV output, the power difference ($P_{d,t}^{\Delta}$) will be imported from the grid; however, if there is excess PV generation, the power difference will be exported to the grid.

$$P_{d,t}^{\Delta} = \left(P_{d,t}^{C}+P_{d,t}^{EV}\right)-P_{d,t}^{PV}; \forall t\in\Omega_T, \forall d\in\Omega_{D_y} \tag{9}$$

$$\begin{cases} P_{d,t}^{IM} = P_{d,t}^{\Delta},\ if\ P_{d,t}^{\Delta}>0; \forall t\in\Omega_T, \forall d\in\Omega_{D_y} \\ P_{d,t}^{EX} = -P_{d,t}^{\Delta},\ if\ P_{d,t}^{\Delta}\le 0; \forall t\in\Omega_T, \forall d\in\Omega_{D_y} \end{cases} \tag{10}$$

where, $P_{d,t}^{IM}\times P_{d,t}^{EX} = 0$, because import and export cannot occur simultaneously.

3.3. Renewable energy utilisation

Self-consumption (*SC*) and self-sufficiency (*SS*) are used as indicators of utilisation of the PV system integrated into the campus. The *SC* is defined by (11) as the ratio of the PV energy consumed locally to the total PV generation. The *SS* is defined by (12) as the ratio of PV energy consumed locally to the total local load demand.

$$SC = \left[\sum_{d\in\Omega_{D_y}}\sum_{t\in\Omega_T}\left(P_{d,t}^{PV}-P_{d,t}^{EX}\right)\times\Delta t\right]\Big/\left(\sum_{d\in\Omega_{D_y}}\sum_{t\in\Omega_T}P_{d,t}^{PV}\times\Delta t\right)\times 100\% \tag{11}$$

$$SS = \left[\sum_{d\in\Omega_{D_y}}\sum_{t\in\Omega_T}\left(P_{d,t}^{PV}-P_{d,t}^{EX}\right)\times\Delta t\right]\Big/\left[\sum_{d\in\Omega_{D_y}}\sum_{t\in\Omega_T}\left(P_{d,t}^{C}+P_{d,t}^{EV}\right)\times\Delta t\right]\times 100\% \tag{12}$$

4. Electric vehicle charging model

The EV charging model is implemented using the steps illustrated in the flowchart of Fig. 7 whereby the aggregated EV charging demand of the campus is determined from the raw input data. As shown in Fig. 7, the input data consist of three parts: (1) the first column involves the actual parking data from a campus of the Monash University in the greater Melbourne area, (2) the second column includes vehicle travel data from VISTA [30], and (3) the remaining columns include the technical parameters of the EV, EV penetration, the campus load and PV generation data. Real vehicle parking data for UniSA's Mawson Lakes campus was not available. Therefore, workplace vehicle data from the Victorian Integrated Survey of Travel and Activity (VISTA) [30] is used to estimate the probability distribution of vehicle parking in the Mawson Lakes campus. The parking probability distribution is used to calculate the number of chargers required to charge the EVs parked on the Mawson Lakes campus. The Monash campus parking data is used to

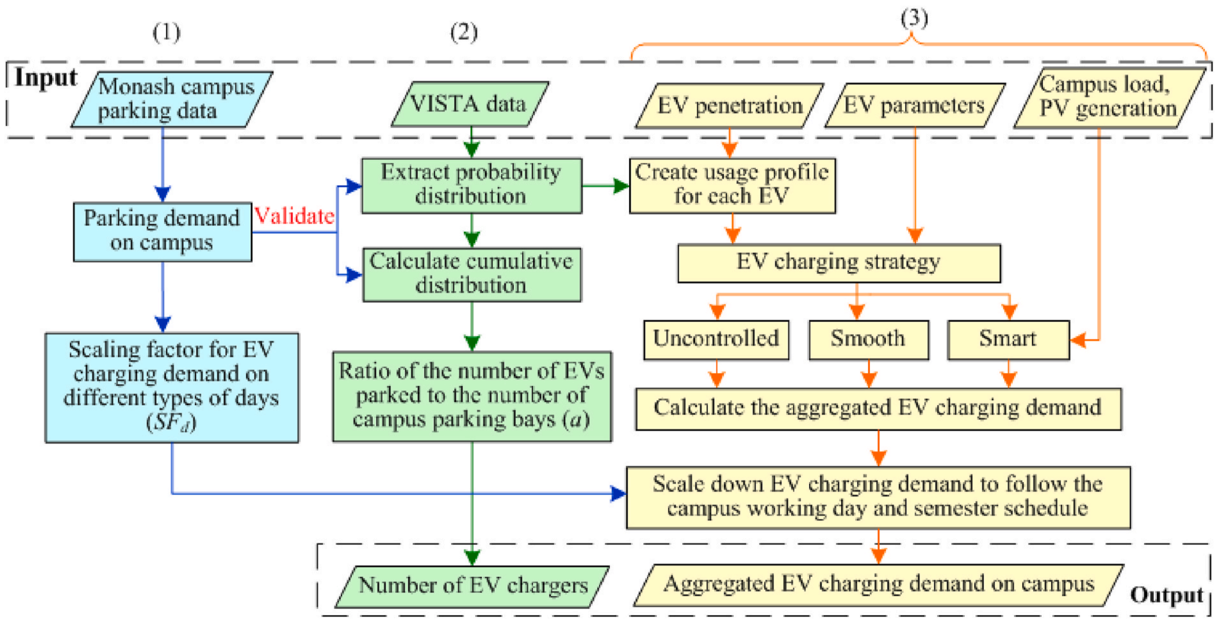


Fig. 7. Flowchart of the proposed EV charging model.

validate the probability distribution of the campus vehicle parking obtained from the VISTA data, and to calculate the scaling factor for EV charging demand on different types of days, for example, working versus non-working days. Based on the third group of input data (EV penetration, technical EV parameters, campus load and PV generation), the EV usage profile (workplace arrival/departure time and daily travel distance) is created individually for each EV using the probability distribution extracted from the VISTA data. This is then used to evaluate three alternative EV charging strategies (*Uncontrolled*, *Smooth* and *Smart*) by calculating the aggregated EV charging demand. The outputs of the EV model are the required number of EV chargers and the aggregated EV charging demand on campus.

4.1. EV usage profile

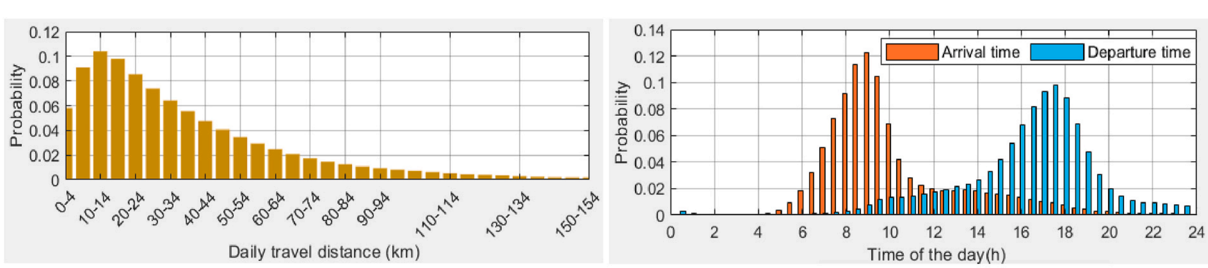
Monte Carlo simulation is used to generate the daily usage profile of each EV throughout the year. The details of the experimental methods and related datasets are given in the accompanying paper to be submitted to the *Data-in-Brief* journal. The method is briefly introduced next.

As stated previously, the raw vehicle travel dataset is sourced from the Victorian Integrated Survey of Travel and Activity (VISTA) [30]. It is assumed that EVs have the same usage demand as conventional private vehicles. Fig. 8 (a) presents the probability distribution of daily travel distance obtained from the raw VISTA data, and Fig. 8 (b) presents probability distribution of workplace vehicle arrival and departure times. In these two figures, 5 km and half-an-hour are used as the distance interval and time interval respectively.

Based on the EV arrival and departure distributions of Fig. 8 (b), the cumulative distributions of EV arrival and departure can be calculated, and the cumulative distribution of EV parking can be obtained as shown in Fig. 9. Based on that, the number of EV chargers required to meet the EV charging demand can be determined. Based on the VISTA dataset, the highest number of workplace EV parking occurs at noon (about 69 %). Therefore, to meet the charging needs of all EV users, the number of EV chargers should be greater than or equal to 69 % of the entire EV fleet (a = 69 %). Here, the impact of the parking location on the charging demand is not considered.

The suitability of the above vehicle probability distributions for use in a university campus is ascertained by comparing them with actual parking data collected from a real university campus. Here, the parking data collected from the Monash University's Clayton campus for 2021 is used. The profiles of vehicle parking for Non-Working Days, Non-Semester Working Days and Semester Working Days are shown in Fig. 10 (a)-(c) respectively. Each coloured line represents the number of vehicles on different days and the black line with square markers represents the mean. Comparison of Figs. 9 and 10 reveal that the probability distributions of vehicle parking obtained from the VISTA data have similar patterns to those of the actual vehicle parking profiles for the Monash University's Clayton campus. In addition, the impact of non-workdays and non-semester versus semester workdays respectively on the number of vehicles parked on campus can be estimated from Fig. 10 (a), (b), and (c) respectively. The maximum average number of parked vehicles for non-workday, non-semester workday and semester workday were found to be 13, 778 and 2031, respectively.

Based on the above verification, using the probability distribution



(a) (b)

Fig. 8. Probability distribution of (a) daily travel distance, (b) workplace vehicle arrival and departure times.

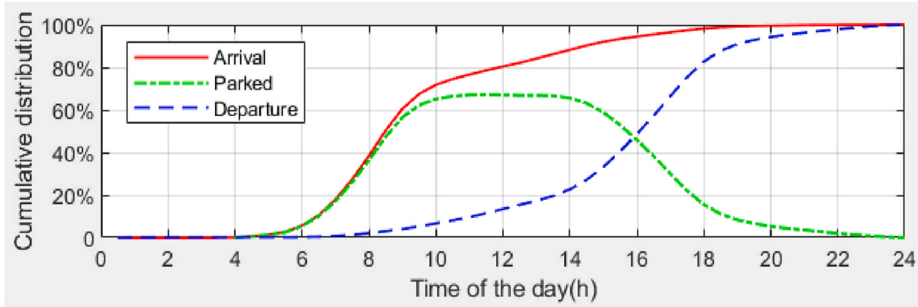


Fig. 9. Cumulative distribution of EV arrival, parking and departure.

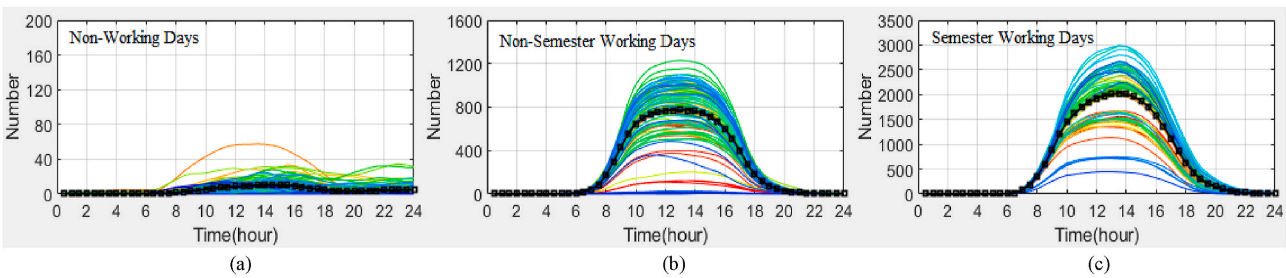


Fig. 10. Number of parking vehicles from Monash data for (a) Non-Working Days, (b) Non-Semester Working Days, and (c) Semester Working Days.

obtained from the VISTA dataset, the year-round EV usage profile is created individually for the desired number of EVs. In this study, the total parking capacity of the Mawson Lakes campus (874 parking bays) is considered to be the maximum EV number and represents 100 % penetration.

4.2. Aggregated EV charging demand

The aggregated EV charging demand ($P^{EV}_{d,t}$) in time interval t of day d is calculated using (13) over a one-year period. A penetration factor (PF) is introduced to represent the charging demands for various EV penetration levels, where $PF = 1$ represents 100 % EV penetration.

$$P^{EV}_{d,t} = \left(\sum_{k \in \Omega_{NEV}} P_{k,d,t}\right) \times SF_d \times PF; \quad \forall t \in \Omega_T, \forall d \in \Omega_{D_y} \tag{13}$$

where $P_{k,d,t}$ is the charging power of the k-th EV in time t of day d. First, $P^{EV}_{d,t}$ is calculated assuming that every day of the year is a semester workday. This is multiplied by a scaling-down factor (SF_d) to determine the actual EV charging demand for each day depending on whether it is a non-workday, a semester workday or a non-semester workday. Based on the results shown in Fig. 10, the values of SF_d are 0.6 %, 38.3 % and 100 % for non-workday, non-semester workday and semester workday, respectively. The semester schedule can be seen from the 2021 academic calendar of UniSA as shown in Table A.2 of the Appendix, and the schedule of working days is the same as that of the state of South Australia for 2021 [36].

Given the daily travel distance, the EV battery's State of Charge (SoC) upon arrival at campus parking can be calculated using (14).

$$SoC_{k,d}\left(T^{AR}_{k,d}\right) = SoC_{k,d}\left(T^{DE}_{k,d}\right) - \left(DIST_{k,d} \times EE\right) \Big/ \left(BC_k \times BD\right); \quad \forall k \in \Omega_{NEV}, \forall d \in \Omega_{D_y} \tag{14}$$

where $T^{AR}_{k,d}$ and $T^{DE}_{k,d}$ represent the arrival and departure times of the k-th EV in day d, respectively. $DIST_{k,d}$ is the travel distance of k-th EV in day d and EE is the EV energy economy. BC_k is the battery capacity of the k-th EV, and BD is the simplified degradation factor for battery capacity fading.

As EVs are charged during the parking period ($T^{AR}_{k,d} \le t \le T^{DE}_{k,d}$), the SoC level of the k-th EV in time interval t of day d is calculated using (15).

$$SoC_{k,d,t} = SoC_{k,d,(t-1)} + \left(P_{k,d,t} \times \Delta t\right) \big/ \left(BC_k \times BD\right); \quad \forall k \in \Omega_{NEV}, \forall t \in \Omega_T, \forall d \in \Omega_{D_y} \tag{15}$$

The EV charging constraints are expressed by (16). The EV charging power cannot be higher than the rated charging power P^{RA}_k, and the lower limit is 0 because vehicle-to-grid power flow is not considered in this study. The EV SoC should satisfy the maximum and minimum limits expressed by (16).

$$\begin{cases} 0 \le P_{k,d,t} \le P^{RA}_k \\ SoC^{MIN} \le SoC_{k,d,t} \le SoC^{MAX} \end{cases} ; \forall k \in \Omega_{NEV}, \forall t \in \Omega_T, \forall d \in \Omega_{D_y} \tag{16}$$

4.3. Charging strategy

The aggregated EV charging demand will significantly affect the campus load demand. In this study, only campus-to-vehicle charging is allowed, which means vehicle-to-campus or vehicle-to-grid power flows are not considered. The three EV charging strategies analysed in this study are described below.

4.3.1. Uncontrolled charging

For *uncontrolled charging*, each EV will begin charging at its rated charging power when it arrives at the parking lot as shown in (17). It is assumed that the EV is charged with the goal of achieving fully charged state by the departure time.

$$T^{CH}_{k,d} = T^{AR}_{k,d}; \forall k \in \Omega_{NEV}, \forall d \in \Omega_{D_y} \tag{17}$$

where $T^{CH}_{k,d}$ represents the charging start time of the k-th EV in day d.

4.3.2. Smooth charging

Under the *uncontrolled charging strategy*, the commencement of EV charging events will be concentrated during the morning peak arrival period, which will lead to a surge in the aggregated charging power

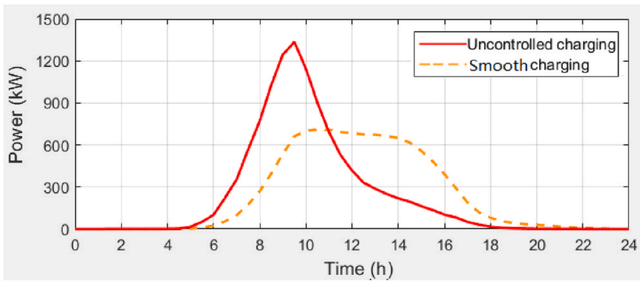


Fig. 11. Charging demand profiles for *uncontrolled* and *smooth EV charging*.

demand. To avoid excessive power demand due to EV charging while considering the parking preferences of EV users, a *smooth charging strategy* is adopted and its impacts on the optimisation results and the system performance will be presented in Section 5. For each EV, charging begins immediately upon arrival as expressed by (17). However, the charging power is calculated using the required charging energy and the EV parking duration as expressed by (18). Here, η^{EV} is the EV charging efficiency.

$$P_{k,d,t} = \frac{\left[SoC^{MAX} - SoC_{k,d}\left(T^{AR}_{k,d}\right)\right] \times (BC_k \times BD)}{\left[T^{DE}_{k,d} - T^{AR}_{k,d}\right] \times \eta^{EV}}; \quad \forall k \in \Omega_{N^{EV}}, \forall t \in \Omega_T, \forall d \in \Omega_{D_y} \tag{18}$$

Fig. 11 compares the campus EV charging demand profiles for *uncontrolled* and *smooth charging* under 100 % EV penetration. It is clear that the profiles for *uncontrolled* and *smooth* EV charging demands have patterns similar to the EV arrival distribution of Fig. 8 (b) and the EV parking distribution of Fig. 9, respectively. Under the *smooth charging strategy*, the peak EV charging demand is reduced to almost half of that for *uncontrolled charging*.

4.3.3. *Smart charging*

The *smart charging strategy* is a simple one, requiring minimal control signal communication. Fig. 12 illustrates this strategy using the months of January and July as examples. The strategy involves the following steps.

a) Estimate the monthly excess PV generated energy by comparing the monthly average PV output profile and the monthly average campus load profile;
b) Calculate the scale-factor by comparing the energy required for *uncontrolled* EV charging and the excess PV energy for each month;
c) Create an EV charging profile for *smart charging* by reshaping the *uncontrolled* EV charging profile to follow the excess PV generation profile as closely as possible. This is to ensure maximum possible utilisation of PV generated energy.

5. Results and analysis

5.1. *Campus case studies*

The proposed methods are tested using year-round simulation with a half-hourly time interval. The number of simulation time intervals for 2021 is 365 days × 48 half-hours = 17,520. Table 2 lists the 4 cases (*Cases 1–4*) that are used to demonstrate the efficacy of the proposed optimisation modelling approach and the various EV charging strategies. *Case 1* represents the existing PV capacity with *uncontrolled* EV charging, and *Case 2–4* represent the three different charging strategies where PV capacity is optimised in each *case* using the proposed

Table 2
Household energy system configurations.

Case	EV charging	PV size
1	Uncontrolled	Existing
2	Uncontrolled	Optimised
3	Smooth	Optimised
4	Smart	Optimised

Table 3
Economic and technical parameters used in this study.

Applicable to	Parameters' values
PV	$LCOE^{PV}$ = \$0.06/kWh
EV	η^{pen} = 25 %, η^{EV} = 90 %, η^{ee} = 0.164 kWh/km
	P_{ra}=7.2 kW, BC=40 kWh, Y = 10 years
	SoC^{MIN} = 0.2, SoC^{MAX} = 0.95, CC^{EV}_{chgr} = \$3000 per charger
Project	r = 3 %, FiT = \$0/kWh

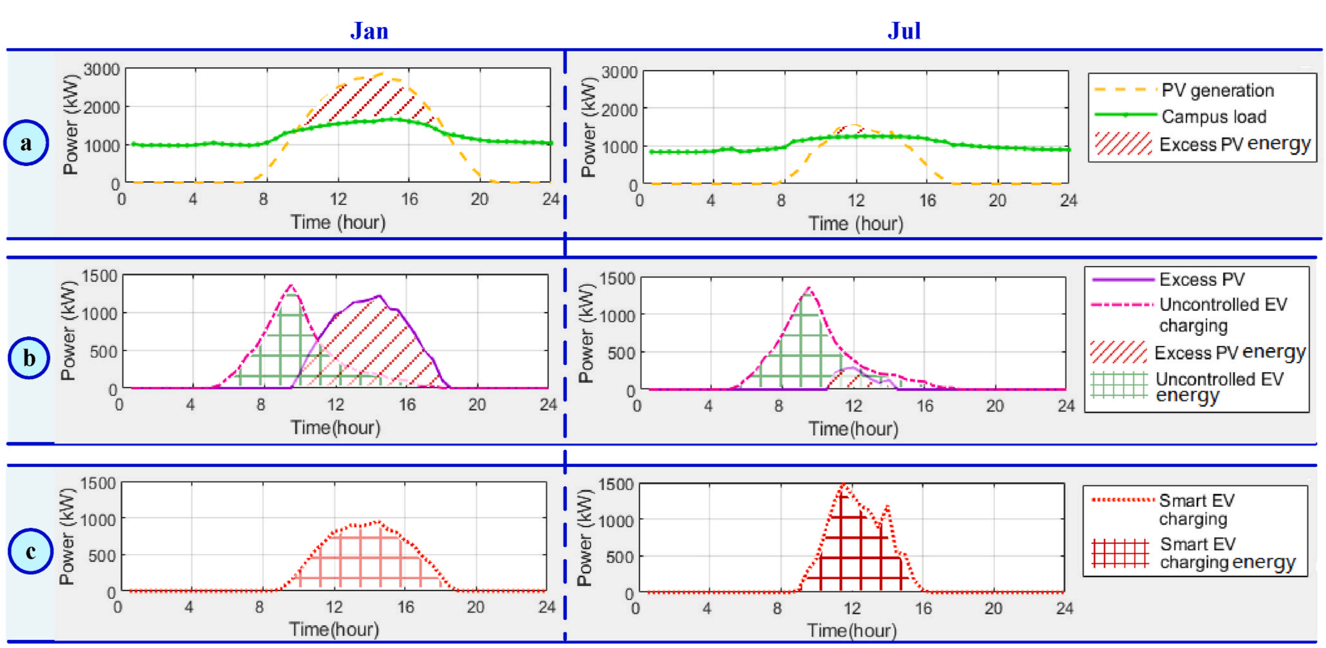


Fig. 12. Illustration of *smart EV charging*.

optimisation method presented in Section 3.

Unless stated otherwise, the economic and technical parameters listed in Table 3 are used throughout this study. The interest rate is set to 3 %. Unless stated otherwise, the workplace charging is assumed to be free and the EV penetration is assumed to be 25 %, which is expected to be reached in Australia by 2030 [4]. For a mid-scale solar PV system (100 kW–5 MW), the *LCOE* is assumed to be \$0.06/kWh including capital cost and operation and maintenance (O&M) cost [37]. The Level 2 EV charger with a rated power of 7.2 kW is used, which is the predominant charger type for workplaces and other destinations [38]. Maximum and minimum EV battery SoC is set to 0.95 and 0.2 respectively. The technical parameters of the EV (battery capacity, charging efficiency and energy economy) are sourced from the Nissan Leaf [39]. The capital cost of a 7.2 kW EV charger was around \$3000 in 2022 in Australia [40]. As the values of some of the economic and technical parameters may vary by region and country, sensitivity analysis is performed where appropriate to illustrate the impacts of these variations.

5.2. Optimal PV size and net annual energy cost

When EV charging is provided for free, Table 4 compares the results for optimal PV capacity and net annual energy cost (net AEC) for the 4 cases listed in Table 2. The changes in net AEC, Summer Demand and Anytime Demand have been calculated for *Cases 2–4* using *Case 1* as a reference. The Summer Demand and Anytime Demand (refer to items 8 and 9 on the bill in Table A.1) are the contracted kVA demand values that are negotiated at the beginning of each billing year based on the actual demand values in the previous year.

Table 4 shows that when EV charging is introduced under the existing PV capacity of 1365 kW (*Case 1*), the net AEC is around \$1.87 million. The optimised PV capacity in each of the *cases* (*2–4*) is more than double the currently installed PV capacity, and therefore the overall PV energy generation cost is much higher. Still, there is a significant reduction in net AEC in each of the cases (*2–4*) even though the campus does not earn any revenue from the EV charging services or from the energy it exports to the grid. The optimisation of PV also has significant effects on peak power reduction. The *smart EV charging* strategy (*Case 4*) offers the highest reduction in net AEC (9.2 %), and peak power demand reductions of 8.4 % (Summer) and 15.9 % (Anytime). The above results did not consider the EV charger maintenance cost. The optimisation results for *Case 4* have been reproduced with the maintenance cost of EV charger ranging from \$100 to \$400 per year. These results are shown as *Case* 4^{+} in Table 4. In *Case* 4^{+}, the optimal capacity of the PV remains the same as that for *Case 4*. The *net AECs* increase with increasing EV charger maintenance costs, however the *net AECs* for *Case* 4^{+} are still lower than that for *Case 1* (without PV optimisation).

The last two columns of Table 4 show the annual imported and exported energies for all cases. Without PV optimisation (*Case 1*), the annual imported energy is ~8.4 GWh and the annual exported energy is 9 MWh. The corresponding self-consumption and self-sufficiency, as calculated using (11) and (12), are 99.7 % and 10.3 % respectively. For the three optimised *cases* (*2–4*), the imported energy decreases by nearly 22 % to ~6.5 GWh. This means that the higher values of the optimised PV capacities are able to supply more energy to meet the local campus load demand and the EV charging demand, however much higher amount of excess PV energy is generated and exported compared to *Case 1*. Consequently, for *Case 2–4*, the self-consumption decreases to around 81.2%–82.2 % and self-sufficiency increases to around 18.4%–19.3 %. In future if an energy storage system is added to the campus EMS, then this excess PV generation can be stored to meet the campus demand when sufficient sunlight isn't available.

Assuming 100 % EV penetration, Table 5 presents the optimisation results when various charging fees are introduced for the *smart charging* strategy (shown as *Case 4**) and compares with the results for *uncontrolled* charging under the existing PV capacity (shown as *Case 1**). Due to increased EV penetration, both the charging demand and the number of charger installations have increased. Consequently, the net AEC for *Case 1** increases to around \$2.18 million compared to \$1.87 million for *Case 1* reported in Table 4 when EV penetration was 25 %. For *smart charging* (*Case 4**), the optimal PV capacity increases to 3846 kW and the net AEC for free EV charging decreases by 10.4 % compared to *Case 1**. Introducing an EV charging fee of \$0.1/kWh can reduce the net AEC by 15.6 % compared to *Case 1**and an EV charging fee of \$0.2/kWh can reduce it by 20.8 %.

Comparing the *smart charging Cases 4 and 4** from Tables 4 and 5 respectively, it is clear that for free EV charging, the net annual energy cost of the campus increases by 14.3 % as the EV penetration increases from 25 % to 100 %. If the university charges \$0.2/kWh for EV charging, then the net annual energy cost of the campus for 100 % penetration (last row in Table 5) is almost the same as that for 25 % penetration with *free charging* (*Case 4* in Table 4). In the Australian economic context, this is a very encouraging result for organisations intending to provide EV charging service in the future.

Table 4
Optimisation results for 25% penetration with free EV charging.

Case	PV size (kW)	Maintenance cost of each EV charger (\$/year)	Net annual energy cost (\$/year)	Change in net annual energy cost (%)	Change in Summer Demand (%)	Change in Anytime Demand (%)	Imported energy (MWh/year)	Exported energy (MWh/year)
1	1365	0	1,867,837	–	–	–	8418	9
2	3126		1,719,950	−8.4	−12.2	−11.9	6588	1012
3	3153		1,712,867	−8.8	−11.3	−19.2	6532	998
4	3165		1,705,915	−9.2	−8.4	−15.9	6486	972
4^{+}	3165	100	1,721,015	−8.6	−8.4	−15.9	6486	972
		200	1,736,115	−7.7				
		300	1,751,215	−6.8				
		400	1,766,315	−6.0				

Table 5
Optimisation results for 100 % penetration with various EV charging fees.

Case	PV size (kW)	EV charging fee (\$/kWh)	Net annual energy cost (\$/year)	Change in net annual energy cost (%)
1*	1365	Free	2,177,658	–
4*	3846	Free	1,950,246	−10.4
		0.1	1,837,128	−15.6
		0.2	1,724,010	−20.8

5.3. Power flow analysis

With 25 % EV penetration, Fig. 13 shows the power flow for the *smart EV charging* strategy (*Case 4*) for a week during the semester period. Fig. 13 (a) shows that in summer (e.g., March) the peak campus demand increases to around 3000 kW, and a large portion of the energy demand due to campus load and EV charging is met by the solar PV. The highest imported power is around 1300 kW and occurs during the night. The highest exported power of 1700 kW occurs during the weekend due to low campus load and low EV charging demand. Fig. 13 (b) shows that in winter (e.g., August), although PV output is much less than that in summer, there is excess PV generation for significant parts of the day. However, spikes in imported power of up to 1600 kW can be seen.

5.4. Sensitivity analysis

5.4.1. Impacts of PV cost and EV penetration on optimal PV capacity and net annual energy cost

With varying EV penetration and varying LCOE of PV, the variations of net annual energy cost (net AEC) and optimal PV capacity for *Cases 2* and *4* are represented in Fig. 14 by the colour bar and the dashed red lines, respectively. At a fixed *LCOE* of PV, the optimal PV capacity increases with higher EV penetration leading to increases in campus net AEC. For a certain EV penetration, declining *LCOE* of PV increases the optimal PV capacity and decreases net AEC. Comparing Fig. 14 (a) with Fig. 14 (b), although the *smart charging strategy* (*Case 4*) requires higher PV capacity, a lower net AEC can be achieved. For example, if PV LCOE is \$0.08/kWh and EV penetration is 60 %, then the optimal PV capacities

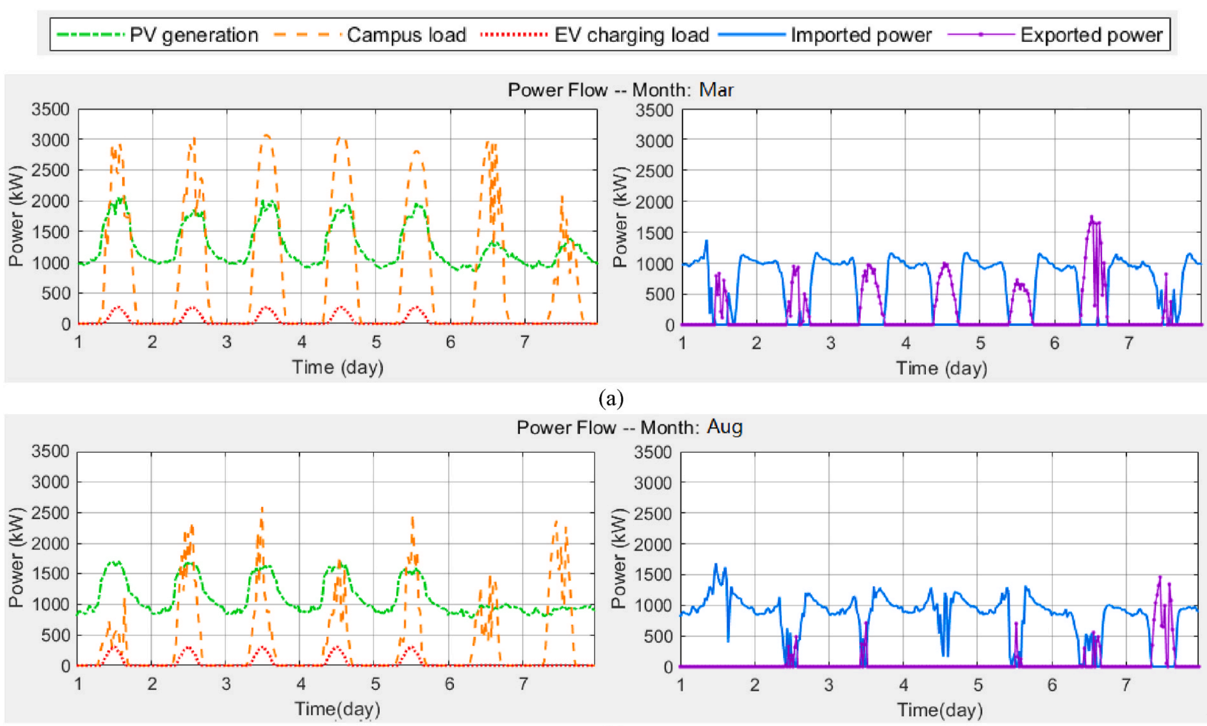


Fig. 13. Power flow of Campus Energy Management System for a week during the semester period for *Case 4* in (a) summer and (b) winter.

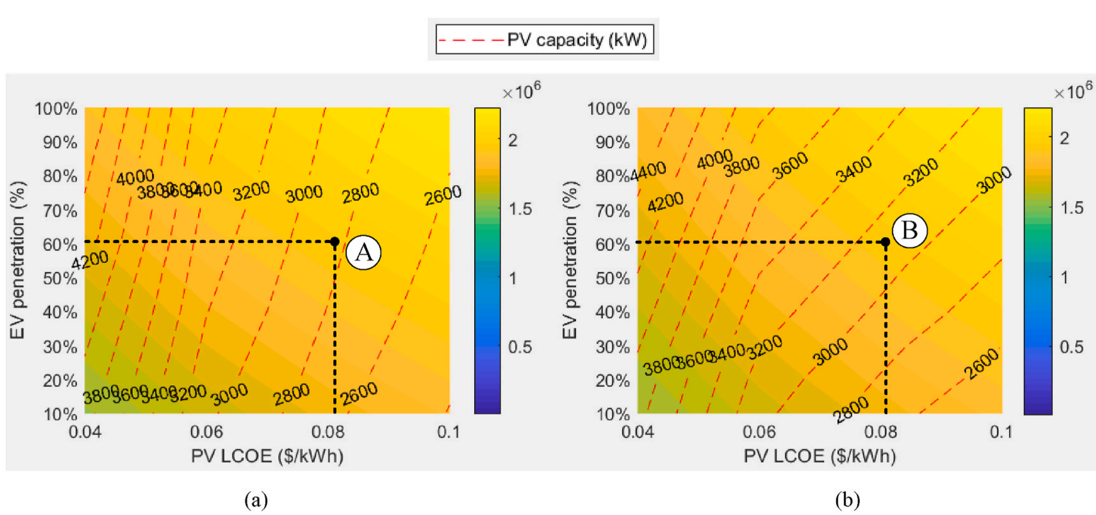


Fig. 14. Variation of net annual energy cost against PV LCOE and EV penetration for (a) *Case 2* and (b) *Case 4*.

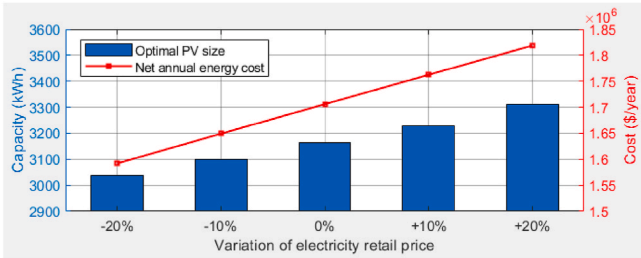


Fig. 15. Variation of net annual energy cost and optimal PV capacity against retail electricity price for the *smart charging strategy* (*Case 4*).

are around 2850 kW and 3150 kW for *Cases 2* and *4* respectively, and the net AECs are $1.95 million and $1.92 million respectively.

5.4.2. Impacts of electricity retail price on net annual energy cost

The retail price of electricity (λ_1 in the bill shown in Table A.1) may fluctuate each year due to factors such as primary energy prices, interest rates etc., although the seasonal pattern of retail electricity prices remains similar. With 25 % EV penetration, Fig. 15 illustrates the sensitivity of net annual energy cost (line graph) and optimal PV capacity (bar chart) to varying λ_1 for *Case 4*, where 0 % indicates the retail electricity price in 2021. The optimal PV capacity and net AEC are represented by blue bars and the red line respectively. As shown, the optimal PV capacity increases with higher retail price leading to an increase in the net AEC; on the contrary, if the retail price of electricity becomes lower then both the optimal PV capacity and the net AEC decrease. For example, with a 10 % reduction in λ_1, the optimal PV capacity reduces to around 3100 kW and the net AEC reduces to $1.65 million.

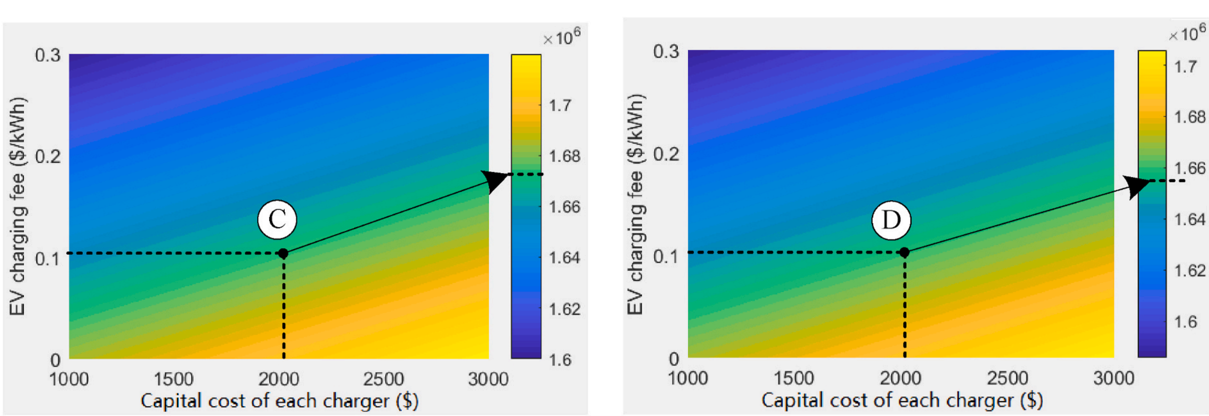
5.4.3. Impacts of EV charger cost and EV charging fee on net annual energy cost

All results in this section are based on 25 % EV penetration. EV charger subsidies have been introduced in several Australian states as part of their EV promotion schemes to keep charging facilities in step with the growth of EVs. Fig. 16 (a) and Fig. 16 (b) illustrate the sensitivity of net annual energy cost (net AEC) to varying EV charger capital costs and varying EV charging fees for the *uncontrolled* (*Case 2*) and the *smart EV charging* (*Case 4*) strategies respectively. The net AEC increases with higher EV charger capital costs and decreases with higher EV charging fees. For example, compared with the results in Tables 4 and if the EV charger capital cost decreases from $3000 to $2000/unit and an EV charging fee of $0.1/kWh is introduced then the net AEC for *uncontrolled charging (Case 2)* reduces from around $1.72 million (see Table 4) to approximately $1.67 million. Under the same scenario, the net AEC for *smart charging* decreases from approximately $1.71 million (see Table 4) to around $1.65 million. Although Fig. 16 (a) and Fig. 16 (b) show almost the same pattern, the *smart EV charging* strategy (*Case 4)* offers a lower net AEC under a given EV charger capital cost and a given EV charging fee.

5.4.4. Impact of PV size on campus energy transaction and cost

Some workplaces and campuses may not have sufficient space available to install large capacity optimally sized PV, while others may have the space available to install even larger PV systems. To illustrate the impact of non-optimal PV capacities, Fig. 17 presents the campus's energy economy, energy usage and PV utilisation for varying PV capacity for *Case 4*. Fig. 17 (a) shows that the net annual energy cost reduces initially with increasing PV capacity. The lowest net AEC (approximately $1.7 million) occurs at a PV capacity of around 3100 kW, which is consistent with the optimisation results presented in Section 5.2. Increasing the PV capacity above this value increases the net AEC, because the increased excess PV energy exported to the grid does not earn any revenue due to zero *Feed-in-Tariff* (*FiT*). Fig. 17 (b) shows the variation of imported energy and PV utilisation with varying PV capacity. When the PV size increases from the current capacity (1365 kW) to 5000 kW, the annual imported energy decreases by almost 30 % (from around 8400 MWh/year to less than 6000 MWh/year). Besides, self-consumption decreases from nearly 100 % to less than 60 %, self-sufficiency increases from around 10 % to over 20 %. Note that when PV size is larger than ~4000 kW, the changes of self-consumption and self-sufficiency slow down, because PV can only provide power for the Campus when there is sunlight and cannot support the campus load during the rest of the time.

The seasonal variations in the campus's net monthly energy cost are presented in Fig. 18 by comparing the net energy costs for the months of January and July with the average monthly cost. The net annual energy cost (net AEC) shown in Fig. 17 is used to calculate the average monthly cost. Fig. 18 shows that the lowest average monthly cost (around $141,000) occurs at around *Point A*, where the PV size is 3100 kW. January is a typical summer month with plenty of solar irradiation and has a relatively lower retail price of electricity (see Fig. A.1 of the Appendix). The optimal PV size required to achieve the lowest net monthly energy cost in January (around $122,000) is around 2500 kW (*Point B*). In contrast, there is much less sunshine in winter months such as July and the retail price of electricity is much higher (see Fig. A.1 of the Appendix). Consequently, achieving the lowest net monthly energy cost in July requires a much larger PV capacity of around 4500 kW (*Point C*). Note that the lowest net monthly energy cost for July (around $165,000) is much higher than that for January. This indicates the importance of a year-round simulation for system optimisation.



(a) (b)

Fig. 16. Variation of net annual energy cost against EV charging fee and EV charger capital cost for (a) *Case 2* and (b) *Case 4*.

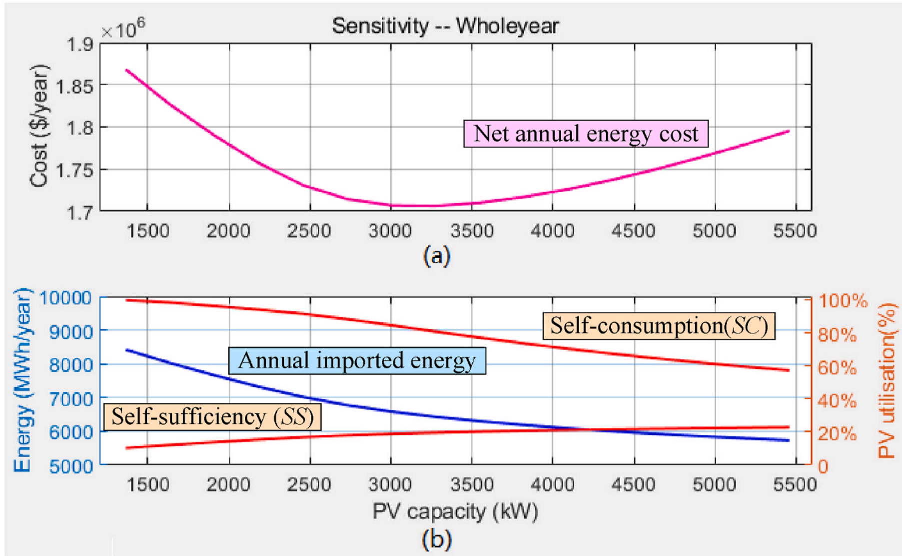


Fig. 17. Impact of PV Size on the Campus' Energy Economy, Energy Usage and PV utilisation for *Case 4*.

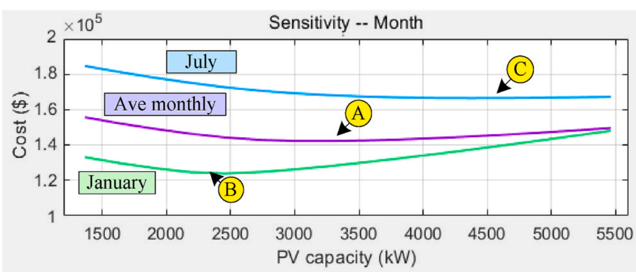


Fig. 18. Seasonal variations in the campus's net monthly energy cost for various PV sizes with *smart charging*.

6. Conclusions

A novel net annual energy cost minimisation method for a campus providing public EV charging service has been proposed. The energy cost is minimised by optimising the PV capacity for a given EV charging strategy. A new modelling approach has been developed to estimate the realistic EV charging demand of the campus based on the analysis of the vehicle travel data (VISTA) and validated against a real campus parking data. The effects of the proposed optimisation method have been tested for various EV charging strategies using the actual campus load and PV generation data for a year. The results reveal that controlled EV charging strategies can lead to reduction in net annual energy cost (net AEC) of the campus provided the campus PV capacity is optimised. Under the existing billing mechanism and levelized cost of electricity (LCOE), the optimal PV capacity is more than double the existing PV capacity of the campus. Other key findings of this study are summarized below.

i. Even with free charging, the deployment of optimised PV capacity along with the proposed *smart* EV charging strategy can reduce the net annual energy cost of the campus by 9.2 % for 25 % EV penetration, and by more than 20 % for 100 % EV penetration.
ii. Because the capacity of optimally sized PV is much larger than the existing capacity, the PV generation is much higher and therefore the imported energy reduces and exported energy increases. Consequently, the system self-sufficiency is increased, however the system self-consumption is reduced. The self-consumption can be increased by storing the excess PV energy in on-campus energy storage devices and utilised when there is insufficient or no solar irradiation.

The optimisation framework based on PV capacity sizing and *smart* EV charging control proposed in this study will help achieve decarbonization of workplaces and reduction in annual energy cost. The proposed models are applicable to any workplace provided the corresponding workplace data are supplied to the optimisation algorithm. Future research for sustainable EV charging at workplaces may explore the economic benefits of adding on-campus energy storage. The proposed optimisation method will then be adapted to incorporate the energy storage systems, further reducing the net annual energy cost incurred by the energy management system and increasing the direct local utilisation of PV. Based on the findings of this study, workplaces can support EV charging without necessarily increasing their annual energy cost through PV capacity optimisation in conjunction with appropriate (*smart*) charging strategies and tariffs.

CRediT authorship contribution statement

Yan Wu: Conceptualization, Methodology, Investigation, Software, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Syed Mahfuzul Aziz:** Supervision, Conceptualization, Methodology, Visualization, Project administration, Writing – review & editing. **Mohammed H. Haque:** Supervision, Conceptualization, Methodology, Visualization, Writing – review & editing.

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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Appendix

Table A.1
Example of UniSA monthly electricity bill for March 2021

Item	Charges	Usage	Unit Price (λ)	Loss Factor (η^{ls})	Total
Retail Charges					
1	PPPT	717,345.600 kWh	$\lambda_1 = 10.4753$ c/kWh	1.05384	$79,189.86
2	PPPT Admin Fee	717,345.600 kWh	$\lambda_2 = 0.2250$ c/kWh	1.05384	$1700.93
Environmental Schemes					
3	LRECs[1]	717,345.600 kWh	$\lambda_3 = 0.6621$ c/kWh	1.05100	$4991.77
4	SRECs[2]	717,345.600 kWh	$\lambda_4 = 1.1146$ c/kWh	1.05100	$8403.31
5	REPS[3]	717,345.600 kWh	$\lambda_5 = 0.2830$ c/kWh	1.05100	$2133.62
Network Charges					
6	HVAD[4] – Peak	331,400.400 kWh	$\lambda_6 = 4.1400$ c/kWh		$13,719.98
7	HVAD – Off Peak	387,222.000 kWh	$\lambda_7 = 2.5900$ c/kWh		$10,029.05
8	HVAD – Summer Demand	1508.080 kVA	$\lambda_8 = 21.4800$ c/kVA/Day		$10,042.00
9	HVAD - Demand	2351.160 kVA	$\lambda_9 = 10.3600$ c/kVA/Day		$7550.99
10	HVAD - Fixed Charges	31 Days	$\lambda_{10} = 41.0959$ \$/Day		$1273.97
Market Operator Charges					
11	AEMO[5] Market Fee	717,345.600 kWh	$\lambda_{11} = 0.0368$ c/kWh	1.05100	$277.45
12	AEMO Market Fee	31 Days	$\lambda_{12} = 0.3633$ c/day	1.00000	$0.11
13	AEMO Ancillary Fee	717,345.600 kWh	$\lambda_{13} = 0.2450$ c/kWh	1.05100	$1847.13
Metering Charges					
14	Meter Charge		$\lambda_{14} = 900.00$ \$/mtr/pa		$76.44

[1] LRECs – Large-Scale Renewable Energy Certificates.
[2] SRECs – Small-Scale Renewable Energy Certificates.
[3] REPS – Retailer Energy Productivity Scheme.
[4] HVAD – High Voltage Business Annual Demand.
[5] AEMO – Australian Energy Market Operator.

Table A.2
Academic calendar of UniSA 2021

Schedule	Semester – 1			Semester – 2		
	Teaching period – 1	Teaching break	Teaching period – 2	Teaching period – 1	Teaching break	Teaching period – 2
Time	1 Mar - 11 Apr	12 Apr –23 Apr	24 Apr – 18 Jun	26 Jul – 19 Sep	20 Sep – 1 Oct	2 Oct – 10 Nov

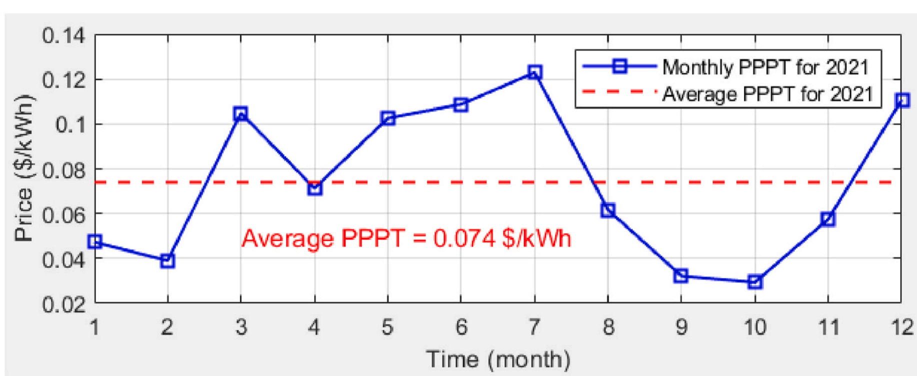

Fig. A.1. Monthly PPPT price (λ_1) for 2021

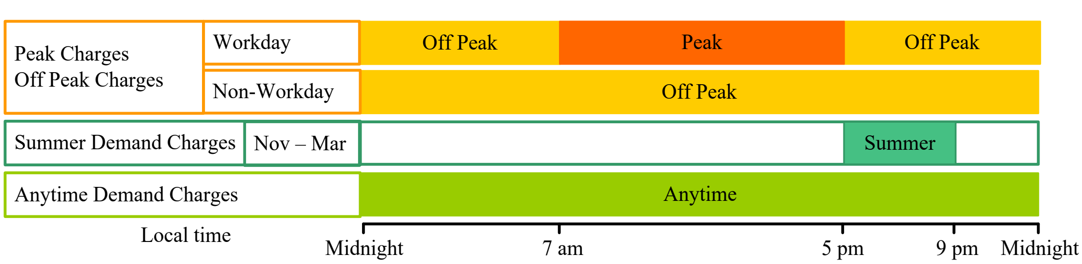

Fig. A.2. Tariff structure of the Network Charges from the bill in Table A.1.

Fig. A.2 shows that, for workdays, the energy consumed during 7 a.m.–5 p.m. is charged at the peak rate (item 6 in Table A.1) and the energy consumed outside these hours is charged at the off-peak rate (item 7). The off-peak charge applies to the non-workday. The Summer Demand charge (item 8) applies during 5 p.m.–9 p.m. for the months of November–December. At other times during these summer months and during the entire months of January–October, the Anytime Demand charge (item 9) is applicable.

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