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Analysis of electricity consumption and thermal storage of domestic electric water heating systems to utilize excess PV generation

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ABSTRACT

Water heating is one of the most energy intensive applications in households and domestic electric water heating systems (DEWH) offer large thermal storage for moving electrical load across the day. This study uses a unique dataset from 410 households and presents a comprehensive analysis of electricity consumption and hot water draw of DEWH for the Australian context. Using the real-world data and thermal energy modelling tool TRNSYS, the study analyses the potential of storing and using excess PV generation in DEWH and investigates the impact of different daily hot water draw profiles, PV and DEWH size on the potential for excess PV utilization. The results show that households on average use 6 kWh of energy for DEWH and 142 L of hot water daily. Potential excess PV utilization is highly dependent on the household's daily hot water draw profile and is also affected by seasonality. On average, excess PV generation from a 4.5 kW PV system can provide 48% of daily DEWH energy for a household with a typical working family profile, which corresponds to a 28% increase in PV self-consumption.

1. Introduction

Water heating is an essential residential energy service and it accounts for around 23%, 14%, and 18% of the residential energy consumption in Australia, European Union and United States respectively [1,2]. Domestic electric water heating systems (DEWH) have widespread installation globally [2]. The majority of DEWH consist of immersive resistive heaters due to their relatively low capital costs; although air-to water heat pumps have also become a popular alternative thanks to their higher energy efficiency [3]. DEWH usually include large water storage tanks which offer large thermal storage capacity.

With recent advancements in efficiency and reductions in equipment costs, rooftop PV has become one of the cheapest forms of electricity generation available for retail electricity consumers [4], while installation rates of rooftop PV are forecasted to continue to grow [5]. By using PV generation within the premises (behind the meter), households can gain environmental benefits by using more renewable energy and financial savings by reducing energy imported from the grid. On the other hand, increasing levels of distributed PV generation may also create challenges for electricity grids, which were originally designed to support unidirectional energy flow. One of the imminent challenges of integrating high levels of distributed PV is the maintenance of safe voltage limits in areas of the grid with high PV export rates [6]. Besides strategies such as control and curtailment of PV generation [7], a more efficient solution for reducing PV export rates, which also maximises emissions abatement from PV, is to increase PV self-consumption rates in households. One way to increase PV self-consumption is to add energy storage behind the meter. However, recent studies [8,9] show that residential battery energy storage systems are not yet economically attractive for the majority of households. An alternative solution is to use DEWH storage tanks to store excess PV generation in the form of thermal energy. This can both reduce the amount of grid energy imported for water heating and increase the PV self-consumption rate. Considering the widespread installation of DEHW and the much lower capital cost compared to battery energy storage systems, DEWH can play an important global role in

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Nomenclature

COP	coefficient of performance
DEWH	domestic electric water heating system
DNSP	distribution network service provider
DSM	demand side management
DTW	Dynamic Time Warping
HWD	hot water draw
NSW	New South Wales
N	number of fully mixed tank segments
PV	photovoltaic
SA	South Australia
SolA	Solar Analytics
ToU	Time of Use
TRNSYS	Transient System Simulation Tool
QLD	Queensland
WD/WE	weekday/weekend

Symbols

A	surface area of DEWH tank
C_k	kth cluster
C_w	specific heat of water
d	day of the year
D	distance metric between two time series
E_{elec}	electrical energy input to DEWH
E_{HWD}	sensible energy for the hot water draw
$E_{heat\ loss}$	energy loss to surroundings
$E_{storage\ cap}$	energy storage capacity of DEWH
$E_{storage\ cap\ min}$	minimum energy storage capacity of DEWH for the tank power to turn on
$E_{storage\ cap\ max}$	max energy storage capacity of DEWH before running out of hot water
$\dot{m}_{house}$	hot water flow rate of the house
$\dot{m}_{tw}$	hot water flow rate from DEWH
$\dot{m}_{mw}$	cold water flow rate from mains
P_{grid}	power imported from grid
$P_{household\ load}$	power used in the household
P_{PV}	gross PV power
$P_{PV_{excess}}$	excess PV power
P_{PV_DEWH}	excess PV power utilized on DEWH
P_{rated}	rated power of DEWH
t	time stamp
t_{full}	time required to fully charge DEWH
$t_{optimal\ excess\ PV}$	optimal excess PV window
T_{to}	DEWH water outlet temperature
T_{ti}	DEWH water inlet/mains temperature
T_{ihw}	ideal household hot water temperature
T_{ts}	DEWH tank segment temperature
T_{env}	ambient air temperature
U	heat loss coefficient
W	minimum Euclidean distance path
η	energy efficiency
γ	recursive optimization search space

supporting the integration of increasing levels of distributed PV and can also provide flexibility for integrating utility-scale variable renewable energy at high penetrations.

Previous DEWH studies have used a bottom-up approach and Time of Use (ToU) surveys collected from households to model and characterize the energy consumption of DEWH according the spatial location, user profile and season [10–12]. More recently, Atikol [13] presented a review of experimental findings on the cooling behaviour of DEWH tanks and on that basis modelled different demand side management strategies for Northern Cyprus with the use of simple timers. Kazmi et al. [14] proposed a reinforcement learning-based method to improve the energy efficiency of DEHW operation through taking occupancy behaviour into account. The method was applied in 32 households in the Netherlands, showing that daily DEWH energy can be greatly reduced through improved understanding of the occupancy behaviour. Other studies focused on characterizing the hot water draw (HWD) from DEWH used in households. Bagge et al. [15] investigated the effect of different time resolutions used for monitoring HWD in an apartment building, showing that peak flow rates were significantly lower when measured over a longer temporal resolution, such as hourly. The authors recommended the use of higher temporal resolutions to increase the accuracy of DEWH simulations. Lomet et al. [16] collected HWD and temperature data from eight homes in France over a period of two years and showed the impact of season, weekday/weekends and occupancy on the daily HWD. Hirohisa et al. [17] collected detailed HWD and temperature data for different end uses such as bath, shower, kitchen and bathroom from four households in Japan. Using this data, the authors built an HWD prediction model and used it in a mixed-linear integer programming (MILP) algorithm to develop optimum energy operations of DEWH. Bertrand et al. [18] characterized HWD for different end use appliances for households, hotels and nursing homes at an urban level by using data from previous European surveys, and found that 80% of the HWD was attributed to showers.

Many of these studies pointed out the difficulties of inferring the HWD required to model DEWH operational strategies directly from electricity consumption data. One study done by Paull et al. [19] used pattern matching to extract DEWH consumption from total household electricity and inferred daily hot water draw (HWD) profiles. Although the method showed promise, the authors avoided modelling the impact of temperature stratification of the DEWH tank, and the method assumed there was no HWD when heating, reducing the accuracy and usefulness of the approach. Studies that specifically investigated the impact of different HWD profiles on the performance of solar-combi systems through physical modelling tools [20–23] have emphasized the importance of using realistic daily HWD profiles in energy simulations and demonstrated that the use of simplistic and constant HWD profiles could lead to misleading conclusions. Moreover, most of the real-world HWD profiles reported in the literature were very similar in shape to typical residential electricity consumption profiles, with a morning and evening peak. However, some key differences were also observed, including higher morning or evening consumption and higher day time consumption on weekends and in households with occupants working from home or retired. Due to the limited availability of detailed HWD data, the findings of these previous HWD research [1,21,24–27] are also used in this research for creating various realistic daily HWD profiles from the inferred daily HWD values.

In Australia, distribution network service providers (DNSPs) offer cheaper tariff rates to households to participate in an aggregate DEWH control scheme, often referred to as ‘off-peak’ or ‘controlled load’. The primary goal is to shift the aggregate DEWH demand to network off-peak periods (i.e. 10pm – 7am) through the use of ‘ripple control’ (frequency signals) or simple mechanical timers [28–30]. However, there are a significant number of households that do not currently participate in this type of scheme. For example, Ausgrid, a DNSP operating in New South Wales (NSW) reports that approximately 45% of the DEWH in their network is not controlled and these systems are on continuous connection with access to electricity at all times [28]. Regardless of the DEWH's control scheme, electricity rates for water heating, even on the ‘controlled load’ tariff are generally higher than PV feed in tariffs [16]; therefore, households can gain financial savings by using excess PV generation for water heating. Given that rooftop PV installations exceeded 25% of Australian freestanding houses [31] and the majority of the households own a DEWH [32], Australia is a useful case study for assessing the potential of DEWH to utilize excess PV generation. Despite the significant opportunity, this has not been assessed previously for the Australian context. Previous Australian studies like [33,34] have focused on the modelling and scheduling of aggregate DEWH electricity demand as a network demand side management strategy to reduce peak demand and the impact of tariff design on the effectiveness of load scheduling strategies. Whaley et al. [24] monitored energy consumption and HWD of 12 different types of water heating systems including DEWH, gas heaters and solar-combis in South Australia (SA). The study revealed the energy performance and HWD characteristics for these systems through Transient-System-Simulation-Tool TRNSYS [27] modelling. Vieira et al. [27] collected HWD data from 27 households with different water heating systems and different sized water tanks located in the greater region of Brisbane. The study analysed and modelled the energy performance of the different water heating systems and emphasized the importance of HWD, tank size and electricity tariff selection in the optimization of energy operations. A government initiative program, Residential End Use Monitoring Program (REMP) [1] collected detailed HWD data from five Victorian households and revealed annual, monthly and typical daily HWD profiles for the studied households. Willis et al. [35] used household survey information from 151 households in the Gold Coast region to study the relationship between socio-demographic factors and HWD. Nguyen et al. [36] collected detailed HWD from 252 households located in South East Queensland (QLD) and disaggregated water flow trace signatures into end use categories such as shower, kitchen, washers etc.

Previous research on the assessment of the potential of DEWH to utilize excess PV generation has also been limited in other parts of the world. Although some European studies [37,38] focused this subject, in the former, the model was only tested on a single unit and results were only presented for a single day, and in the latter [38] the model was based on DEWH with dynamic and remotely controllable thermostat settings whereas a great majority of installed DEWH have fixed thermostat settings. Considering the identified gaps, the main contributions of this study can be listed as below:

- The study uses a unique and recent real-world dataset at five minutely resolution over a full calendar year from 410 households with rooftop PV and DEWH located in capital cities of Sydney (NSW), Brisbane (QLD) and Adelaide (SA).
- The study presents a comprehensive analysis of the electricity consumption of DEWH and reveals the impact of different DNSP control schemes, location and seasons and determines typical daily seasonal and weekday/weekend profiles. Due to the large number of households and high-resolution DEWH data, this makes a significant contribution to the existing DEWH characterization literature in Australia as well as globally.
- The study analyses the potential of utilizing excess PV generation as thermal storage in DEWH and shows the impact of different daily HWD profiles, PV and DEWH size on the potential of excess PV utilization. To the author's knowledge this is the first comprehensive study assessing this potential, especially for the Australian context.
- The findings of research can inform DNSPs and energy companies in Australia and other parts of the world in developing effective demand side management strategies using DEWH and PV.

The remainder of the paper is organized as follows: Section 2 presents the dataset and methodology. Section 3 presents the results and provides important discussions. Section 4 concludes the paper.

2. Methodology & dataset

This section is divided in three parts. The first part describes the methods used for analysing the DEWH electricity consumption. The second part describes the methods used for inferring daily HWD and creating HWD profiles. The third part describes the assessment of excess PV utilization on DEWH. Fig. 1 outlines the methodology steps and sections containing the detailed methods and results.

2.1. Dataset

The dataset consists of 410 households located in Australia with 100 households in Sydney, 250 households in Brisbane and 60 households in Adelaide. The data for these households was provided by Solar Analytics Pty. Ltd., an Australian company specialized in automated monitoring and energy management services for solar households [39]. The metering equipment measures gross PV generation and household electricity load, as well as any other appliances that have dedicated sub-circuits (i.e., DEWH). Data from each household consists of one complete year between 10/18/2018 and 10/17/2019 in 5 minutely resolution. Each household's data-set is accompanied by temperature data collected from the nearest Bureau of Meteorology (BOM) weather station [40]. 273 households have DEWH on a continuous connection and the remaining 137 are on off-peak connection, controlled by the network operator. Descriptive statistics for the complete household fleet are shown in Fig. 2. The DEWHs with power rating lower than 1.8 kW are heat pumps (~10%) and the remaining 90% are standard immersive resistive type.

2.2. Analysis of DEWH electricity consumption

Firstly, the average daily electricity consumption of each 5-minutely interval is found across the year by location and connection type as shown in Eqn. (1). Further analysis is carried out to investigate the distributions of daily DEWH electricity consumption across months in relation to the regional temperature.

$$for \left\{ \begin{array}{l} type : continuous, off - peak \\ location : Adelaide, Brisbane, Sydney \\ day : 1 \ldots 365 \end{array} \right\}$$

$$: E_{DEWH^{type,location,day}_{avg_{t=1\ldots288}}} = \sum_{i}^{N_{type\&location\&day}} E_{DEWH_i}\Big|_{t=1\ldots288} \quad (1)$$

To discover typical daily electricity profiles of DEWH, K-means clustering is applied whose optimization objective is given in Eqn. (2) [41]. The clustering analyses is applied separately for each connection type, season, and weekday (WD) and weekend (WE) profiles.

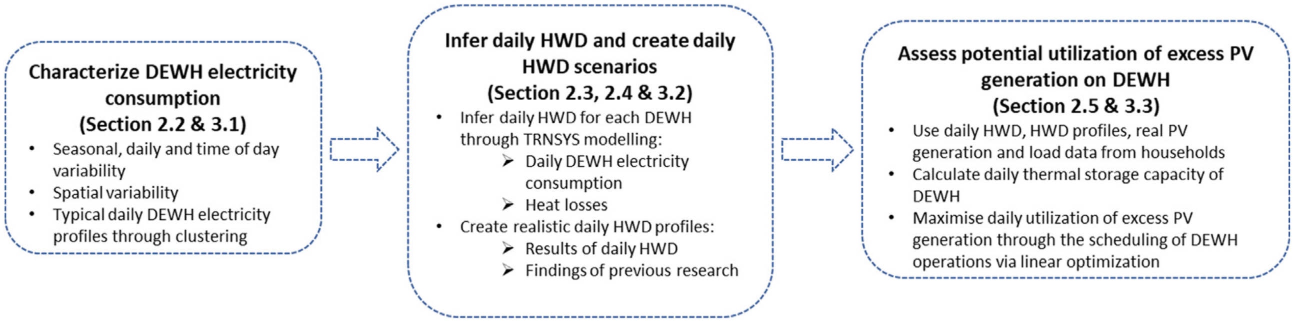

Fig. 1. Steps of the methodology.

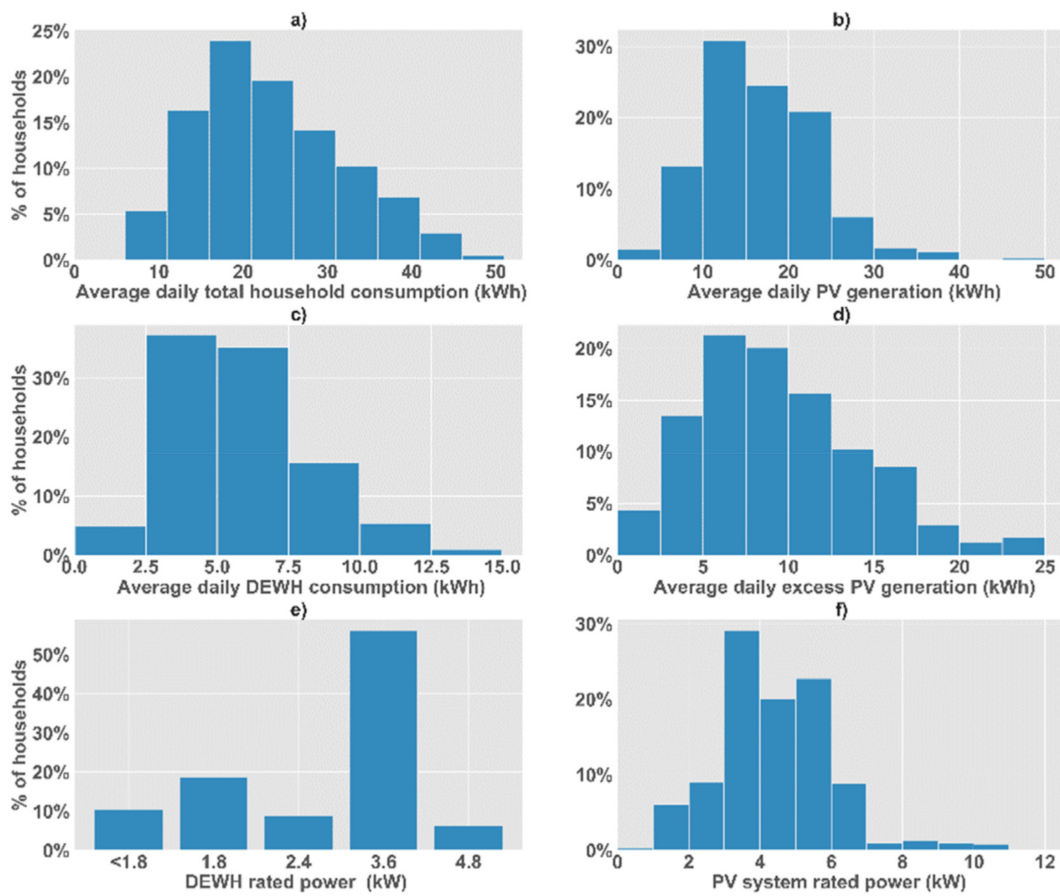

Fig. 2. Histograms of a) average daily total household consumption (kWh), b) average daily PV generation (kWh), c) average daily DEWH consumption (kWh), d) average daily excess PV generation (kWh), e) DEWH power rating (kW), f) PV system rater power (kW).

$$minimize_{C_1,\ldots C_k}\left\{\sum_{k=1}^{K}\frac{1}{|C_k|}\sum_{i,i'\in C_k}\sum_{j=1}^{N}(D)^2\right\} \tag{2}$$

where, K is the number of clusters, C_k is the kth cluster, $|C_k|$ is the number of daily DEWH electricity profiles in the kth cluster, N is the number of points contained in the daily DEWH electricity load profile (i.e. 288 for 5-minutely data), j is the time step (i.e. 1 to 288 for 5-minutely daily profile), i is the normalized daily DEWH electricity load profiles that are assigned to one of the clusters C_k and D is the distance metric used to measure the distance between two daily electricity profiles. As previously demonstrated by Refs. [42,43] and validated by clustering experiments, Dynamic Time Warping (DTW) is highly effective for measuring the similarity between electricity load profiles, with mathematical description given in Eqns. (3)–(5):

$$\begin{aligned} Q &= Q_1, Q_2, \ldots Q_n \\ R &= R_1, R_2, \ldots R_n \end{aligned} \tag{3}$$

$$\begin{aligned} w_k &= (Q_i - R_j)^2 \\ W &= w_1, w_2, \ldots w_k \end{aligned} \tag{4}$$

$$W^* = argmin_W\left(\sqrt{\sum_{k=1}^{K} w_k}\right) \tag{5}$$

where Q and R are two independent time series objects with the same length n, w_k is the squared Euclidean distance between the i^{th} and j^{th} elements of Q and R respectively. Considering n time steps of each time series, there are a total of $n \ x \ n$ distance points between the two time series objects which are represented by w_k. W corresponds to a specific path of the distances consisting of n number of w_k. Therefore, W^* is the path where the cumulative Euclidean distance of the W path is minimised. The optimal distance path W^* is found using dynamic programming with the recursive function given in (6).

$$\gamma(i,j) = d(q_i, r_j) + \min(\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)) \tag{6}$$

where $d(q_i, r_j)$ is the Euclidean distance between the i^{th} and j^{th} timesteps of the time series objects and γ represents the recursive search space where the minimum distance is searched amongst the surrounding times steps of i and j. An important criterion for the K-means technique is that the user needs to specify the number of clusters. To determine the optimum number of clusters, a clustering validity index, Davies Bouldin metric [44] was used, alongside visual inspection of the clustering outcomes as recommended by Ref. [45]. Through experimentation with a range of clusters between two to ten, five clusters was found to be the optimum number for the daily DEWH electricity profiles.

2.3. Inferring daily hot water use (l/day)

The dataset did not include the actual HWD, which is very rarely metered in DEWH installations. However, HWD is needed for calculating the available thermal storage capacity of a DEWH tank throughout the day, which in turn is needed to calculate the potential utilization of excess PV generation. As discussed in Section 1, using DEWH electricity consumption to infer the exact timing of HWD can be challenging, especially at an intra-daily temporal resolution like 5-minutely or hourly. However, at the daily level, the impact of the transient effects become less significant, and it is more feasible to infer daily HWD from electricity data. For this reason, firstly, daily HWD (l/day) is estimated for each household.

To accurately model the temperature stratification, energy dynamics and associated tank losses from the tank, TRNSYS [46] is used. The analysis is carried out for each household separately according to their DEWH electricity data. Eqns. (7)–(11) [47] describe the energy modelling of the DEWH for inferring the daily HWD.

$$E_{elec} \times \eta = E_{HWD} + E_{heat\ \ loss} \tag{7}$$

$$E_{HWD} = \dot{m}_{tw} C_w (T_{to} - T_{ti}) \tag{8}$$

$$\dot{m}_{house} = \dot{m}_{tw} + \dot{m}_{mw} \tag{9}$$

$$\dot{m}_{tw}(T_{to} - T_{ihw}) = \dot{m}_{mw}(T_{ihw} - T_{ti}) \tag{10}$$

$$E_{heat\ \ loss} = \sum_{s=1}^{N} U\ A_{ts}(T_{ts} - T_{env}) \tag{11}$$

where E_{elec}, E_{HWD}, $E_{heat\ \ loss}$ are the rates of electrical energy input to the tank, sensible energy provided for HWD and heat loss to the environment respectively. η is the energy efficiency of the DEWH which is assumed equal to 1 for the resistive element, while for heat pumps a coefficient of performance (COP) between 2 and 5 was used based on the ambient temperature [48]. $\dot{m}_{house}$, $\dot{m}_{tw}$, $\dot{m}_{mw}$ are the water mass flow rate for; HWD used in the house, HWD from the tank, and cold water used from the mains in the mixing valve to obtain the hot water temperature used in the household, respectively. T_{to}, T_{ti}, T_{ihw}, T_{ts} and T_{env} are tank hot water outlet temperature, cold water temperature from the mains at the inlet of the tank and the mixing valve, ideal hot water temperature used in the house, tank's different segment temperatures, and ambient air temperature respectively. C_w is the specific heat of the water. N, U, A are the number of fully mixed tank segments, heat loss coefficient between the tank and its environment per unit area and tank segment's area, respectively. As the studied data-set largely consists of freestanding households occupied by families, a standard hot water tank size of 315 L was chosen as it is the most commonly used DEWH tank size for Australian households [49]. The ambient temperatures for the studied regions were taken from the respective BOM weather stations and cold water temperatures were taken from relevant Australian Standards [25]. These and other DEWH modelling parameters are summarized in Table 1. In the next step, inferred daily HWD values are turned into daily HWD profiles with the aid of previous findings of HWD literature.

2.4. Daily HWD profile scenarios

In the absence of real monitored HWD data, we create scenarios representing a wide range of possible HWD profiles to assess the impact of different HWD behaviors on the potential for excess PV utilization. To create daily HWD profile scenarios, the shape of profiles from previous studies which collected real HWD data are scaled to match the daily aggregate HWD results (l/day) found in Section 3.3. Thirty typical daily HWD profiles were collected from Refs. [1,21,24–27] and grouped into six typical daily HWD profile groups as shown in Fig. 3, by the clustering method described in Section 2.2, assessed by both Davies Bouldin metric and visual inspection to give a wide range habitual HWD profiles. The average of each of the six HWD profile groups were normalized and expressed as a percentage of total daily HWD value. Among the 30 typical daily HWD profiles, 3 profiles were clustered in Fig. 3a and f and the remaining 24 typical daily HWD profiles were distributed evenly across the remaining 4 groups (Fig. 3b, c, d and e). Fig. 3b and d shows high similarity with some of the typical working family HWD profiles presented in Ref. [2] for UK and European countries however, some other HWD profiles presented in Ref. [2] show the evening peak consumption later in the night which reflects the differences of lifestyle and consumption habits between European and Australian households. Apart from the typical working family HWD profiles, Fig. 3c and f also resembles the HWD profiles previously presented for Finnish and Canadian households presented in Refs. [22,50] respectively. Each of the six normalized HWD profiles were multiplied by each of the daily HWD values found in Section 2.3 to create six daily HWD profiles for each household.

2.5. Assessment of excess PV utilization on DEWH

To assess potential utilization of excess PV generation, simulations are run for each household by using each daily HWD profile presented in Fig. 3, inferred daily hot water use found in Section 2.3 and household's year worth of monitored real PV generation and electricity load data. The assessment of excess PV utilization is focused on a typical PV generation window from 7 a.m. to 5 p.m. and outside 7 a.m. to 5 p.m. window, the DEWH tank operated normally according to its default thermostat control. At the time of the latest recorded daily DEWH heating before 7 a.m., the tank is

Table 1
TRNSYS modelling parameters.

DEWH tank parameter	Value	DEWH tank parameter	Value
C_W(kJ/kg.K)	4.19	Heat loss coefficient U (kj/hr.m^3.K)	3
Water density (kg/l)	1	Number of fully mixed segments	6
Tank diameter	0.32 m	Tank height	1.8 m
Height of each node	0.3 m	Initial water temperature of segments	60 °C (top) – 20 °C (bottom) in 10 °C degree increments
Node containing thermostat	1 (top)	Node containing resistive heating element	6 (bottom)
Thermostat set point temperature (°C)	60	Dead-band temperature (°C)	10
Cold water temperature -T_{ti} (°C) [25]	11–23 °C	Household hot water temperature - T_{ihw} (°C) [2]	45 °C

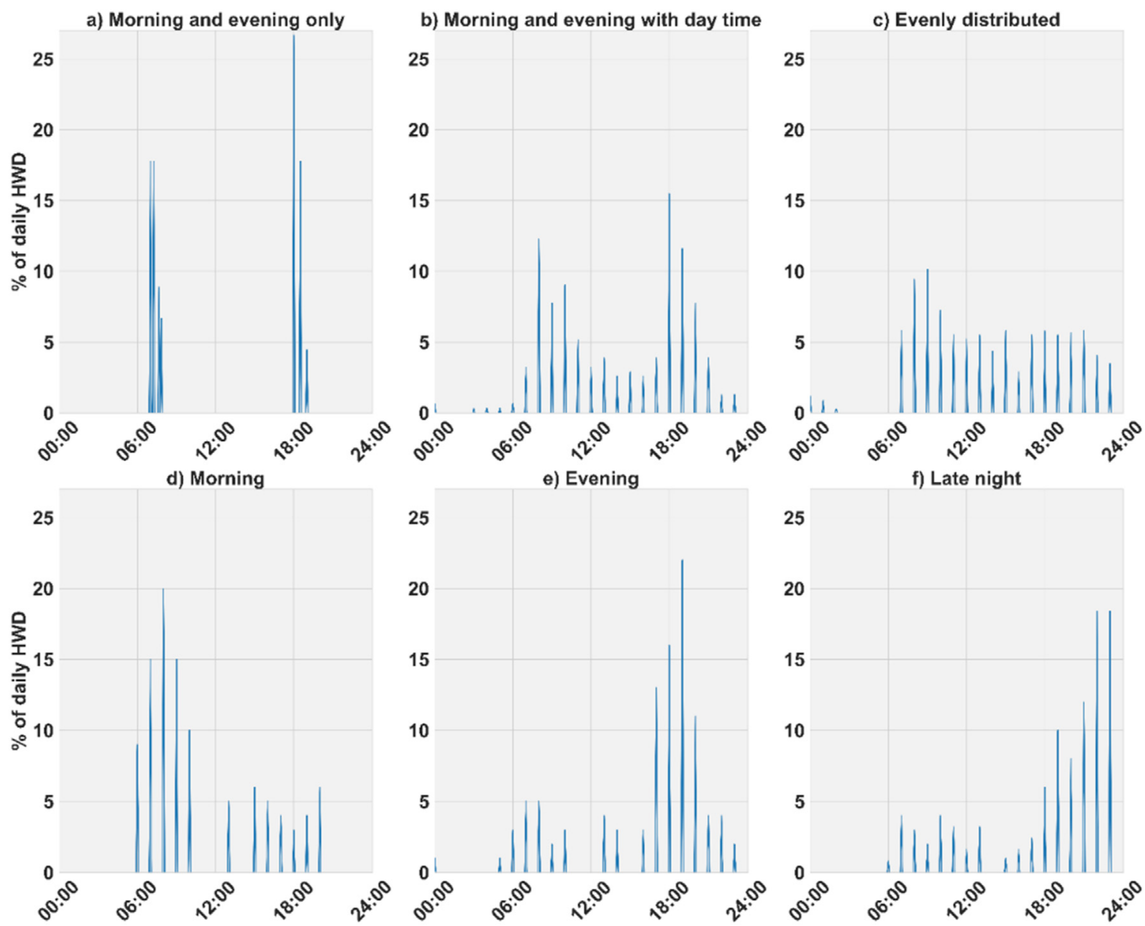

Fig. 3. Six HWD profiles found through clustering typical HWD profiles taken from Refs. [1,21,24,25]: a) Morning and evening only, b) Morning and evening with day time, c) Evenly distributed, d) Morning, e) Evening, f) Late night.

assumed to be thermally fully charged. Simulations used linear programming (LP) [51] with the objective of maximizing the utilization of daily excess PV generation for water heating as expressed in Eqn. (12). The optimization had thermal storage and power flow constraints to obtain the required power balance and make sure the DEWH tank had sufficient thermal energy for household's HWD as described in the following Eqs. (13)–(19). DEWH tank's initial temperature state, thermostat set point and thermal parameters were presented in Table 1.

$$\textit{for } d : 1 \ldots 365 \textit{ and } t : 7am \ldots 5pm, \quad \textit{maximize} \sum_{t=7am}^{t=5\,pm} P_{PV\_DEWH_{d,t}} \tag{12}$$

$$E_{storage\ \ cap_{d,t}} = E_{storage\ cap\ _{d,t-1}} + \int_{t-1}^{t} P_{HWD_{d,t}} + \int_{t-1}^{t} P_{heat\ loss_{d,t}} - \int_{t-1}^{t} P_{rated} \times DEWH_{status_{d,t}} \tag{13}$$

$$E_{storage\ \ cap_{d,\ \ 7am}} = \sum_{t=t_{latest\ \ heating}}^{7am} E_{heat\ \ loss_{d,t}} \tag{14}$$

$$E_{storage\ \ cap_{d,t}} \leq E_{storage\ \ cap\ \ max} \tag{15}$$

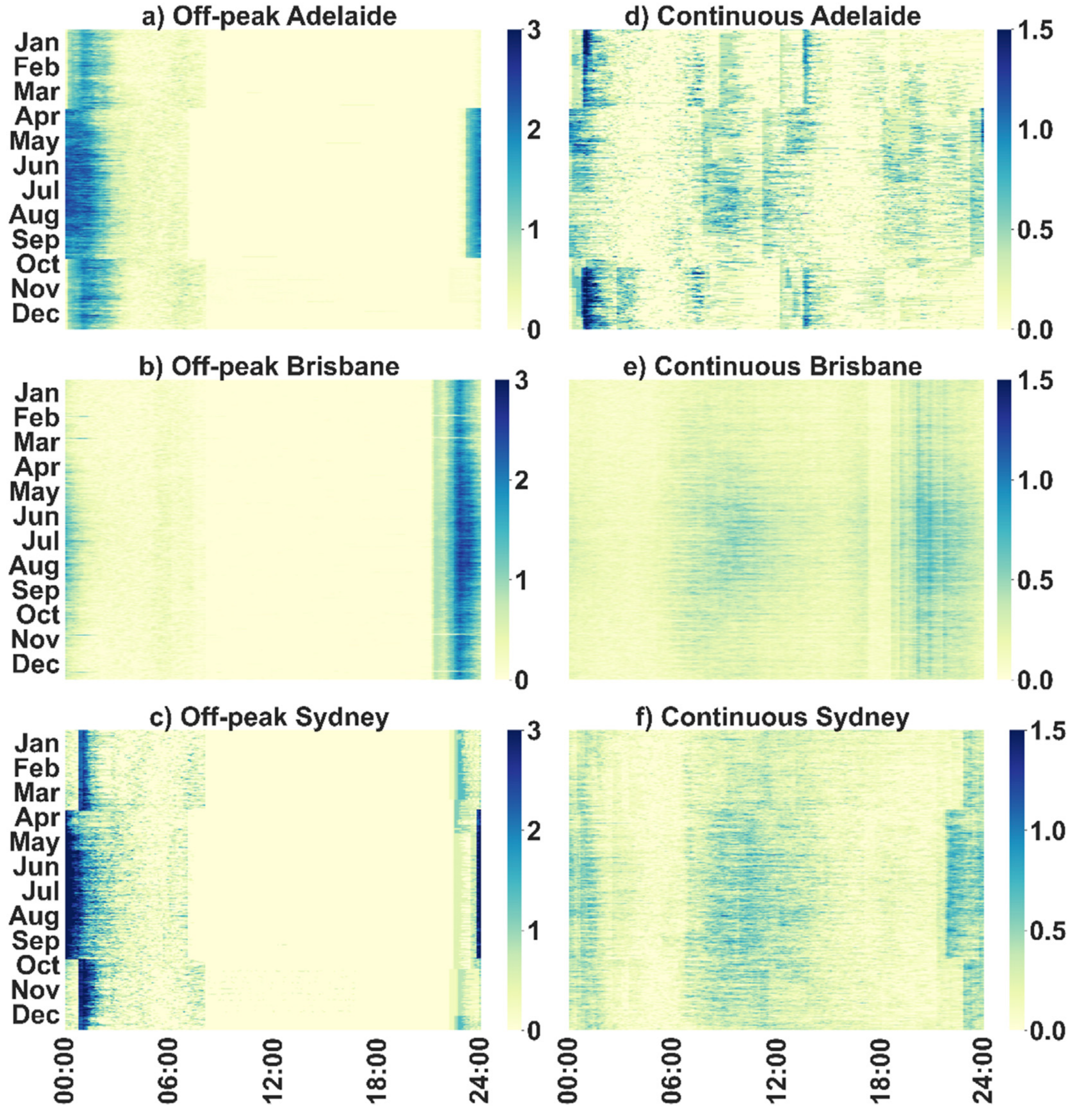

Fig. 4. Average daily power (kW) across the year and time of day for different types of DEWH in different regions: a) Off-peak NSW, b) Off-peak SA, c) Off-peak QLD, d) Continuous NSW, e) Continuous SA, f) Continuous QLD.

$$DEWH_{status_{d,t}} = \begin{cases} 1 \ if \ E_{storage \ cap_{d,t}} > E_{storage \ cap \ min} \\ 0 \ if \ E_{storage \ cap_{d,t}} \le E_{storage \ cap \ min} \end{cases} \quad (16)$$

$$P_{PVexcess_{d,t}} = \text{maximum}\left(P_{PV_{d,t}} - P_{household \ load_{d,t}}, 0\right) \quad (17)$$

$$P_{PV\_DEWH_{d,t}} = \text{minimum}\left(P_{PVexcess_{d,t}}, P_{rated}\right) \times DEWH_{status_{d,t}} \quad (18)$$

$$P_{rated} \times DEWH_{status_{d,t}} = P_{PV\_DEWH_{d,t}} + P_{grid_{d,t}} \quad (19)$$

where, d is day of year, t is 5-minutely simulation time step between 7 a.m. & 5 p.m., $P_{PV\_DEWH_{d,t}}$ is the excess PV generation utilized on DEWH tank, $E_{storage \ cap_{d,t}}$ is the available thermal storage capacity of DEWH tank, $P_{HWD_{d,t}}$, $P_{heat \ loss_{d,t}}$ P_{rated} are the power spent for household's HWD, power lost to ambient and rated power of DEWH tank respectively, $DEWH_{status_{d,t}}$ is the binary (on/off) power state of the DEWH tank for each day and time-step. $E_{storage \ cap \ max}$ is the maximum thermal storage capacity of the DEWH tank before causing run out of hot water (i.e., insufficient water temperature), $E_{storage \ cap \ min}$ is the minimum required thermal storage capacity for $DEWH_{status_{d,t}}$ to be 'on', based on the DEWH tank's thermostat set-point and dead-band temperatures (Table 1). $P_{PVexcess_{d,t}}$, $P_{PV_{d,t}}$, $P_{household \ load_{d,t}}$ are the excess PV generation power, gross PV generation power and household load respectively, for each day and time-step. Finally, $P_{grid_{d,t}}$ is the required imported power from the grid during utilization of $P_{PVexcess_{d,t}}$ whenever available $P_{PVexcess_{d,t}}$ is smaller than P_{rated}. The studied linear optimization gave the global maximum for the utilized excess PV generation for each daily household simulation and studied HWD profiles.

3. Results and discussion

3.1. Analysis of DEWH electricity consumption

Fig. 4 presents a heatmap of the average power (kW) of the 410 DEWH in each 5-minutely period of the year, according to connection type and location. The highest average power drawn by

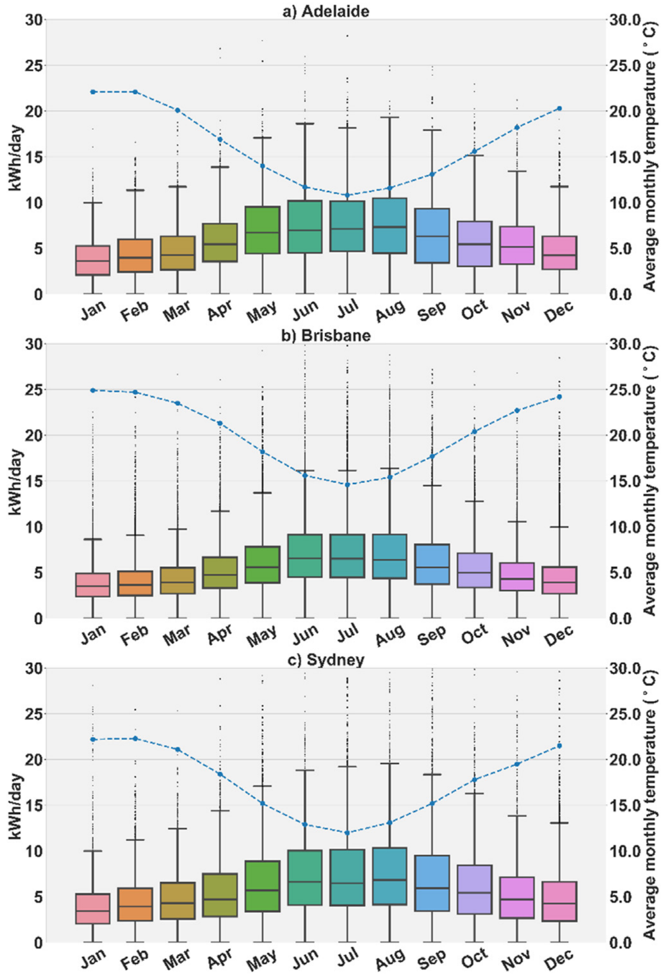

Fig. 5. Monthly distribution of daily DEWH electricity consumption (kWh/day) for sites in: a) Adelaide, b) Brisbane, c) Sydney.

off-peak DEWH is significantly greater than the continuous type for all locations. This is unsurprising as the off-peak DEWH has a restricted operation window (10pm − 7am) to fully charge the tank. Fig. 4 a) and c) show that the off-peak DEWH operation in Adelaide and Sydney show a shift between summer and winter months. This is because the hot water is operated according to daylight savings time, which is not corrected for in the meter data. The off-peak DEWH in Brisbane doesn't show this shift is because there is no daylight savings in Brisbane (Fig. 4 b). For every region, most of the off-peak heating occurs from 10 p.m. to 2 a.m., with some top-up heating from 4 a.m. to 7 a.m. to compensate for the heat losses throughout the night. In contrast to off-peak DEWH, the average continuous DEWH power is more evenly distributed throughout the day yet, it is relatively higher during the morning and evening periods, which correlates with some of the HWD profiles shown in Fig. 3.

Fig. 5 presents the distribution of daily DEWH electricity consumption (kWh/day) across the year for the three locations, together with the average monthly temperature. The distributions follow similar patterns in all locations relative to the temperature. Daily DEWH electricity consumption is highest during winter and lowest during summer. DEWHs in Adelaide have a slightly higher daily average consumption of 6.4 kWh followed by Sydney with 6.3 kWh and Brisbane with 5.6 kWh. The lower consumption in Brisbane is due to higher regional temperatures. The daily average DEWH electricity consumption results fall under the medium load case according to European Standards [2] and low load case according to the Australian and New Zealand Standards [25]. It is important to emphasize that around 10% of the DEWH systems in this study are heat-pumps and therefore the reported results would be slightly higher if all systems were standard immersive resistive type.

The typical daily electricity profiles of DEWH are presented in Fig. 6, where sub-figures a to p) show five cluster centroids (C1 to C5) for each season, weekday (WD)/weekend (WE) and connection types. For each of the continuous DEWH shown in Fig. 6 a-h), at least one of the profiles corresponds to the typical working family electricity profile, with morning and evening peaks such as C3, C1 and C2 in Fig. 6 d), f) and h) respectively. Furthermore, one of the typical profiles shows minimal electricity consumption of DEWH throughout the day representing household's unoccupied days with no HWD as confirmed by the households' respective daily electricity consumption. Typical profiles such as C5 and C2 in Fig. 6 a) and h) have long uninterrupted operation with consistent power output. These profiles represent daily heat-pump profiles with relatively low and continuous output. These results clearly show the high variability of typical daily electricity profiles across different continuous DEWH systems especially compared to the reference average daily profiles presented in relevant standards [25]. The resultant typical working family electricity profiles show high similarities with the profiles presented in previous Australian [27] and European studies [12,15] but some of the profiles presented in this study has day time loads that are more equally distributed across the day compared to profiles with morning and evening peaks. It is important to note the alignment between some of the typical profiles and the studied HWD profiles given in Fig. 3. For example, the morning dominant HWD of Fig. 3 e) corresponds to profiles such as C3 in Fig. 6 c), d), and f). Night and late night dominant HWD given in Fig. 3 e) and f) shows similarity to C2 in Fig. 6 b), g). Although some typical profiles vary in magnitude and shape between weekday and weekends, others show high similarities such as C2 and C3 in Fig. 6 c) and d) and C1 in Fig. 6 e) and f).

In contrast to the continuous DEWH, typical profiles for off-peak connection show highly similar characteristics for all seasons and weekdays/weekends. Although there are slight time differences, the peak heating occurs between 10 p.m. and 2 a.m. with a tail end towards 7 a.m. reflecting the supplementary heating to off-set the heat losses. The similarity between typical daily profiles of off-peak DEWH is due to control by DNSPs and household behaviour has less of an impact on the shape and magnitude of these profiles. The presented typical daily off-peak profile shapes show similarities to the annual average off-peak profiles reported in Ref. [27] however, the profiles presented here capture the tail end of the late night heating by the help of the studied clustering method compared to using simple averaging.

3.2. Inferring daily hot water draw

The distribution of the resultant HWD (l/day) is presented in Fig. 7 with histograms alongside respective means shown with vertical lines. Fig. 7 a) shows the distribution of the daily HWD for continuous and off-peak connections. Both distributions are skewed to the right and the average daily HWD is 140 l/day and 136 l/day for continuous and off-peak DEWH, respectively. Fig. 7 b) presents the distribution of daily HWD across Adelaide, Brisbane, and Sydney. All distributions show a similar right skew, and on average the HWD is lowest in Brisbane with 130 l/day followed by 147 l/day in Adelaide and 153 l/day in Sydney. The distribution of HWD in Adelaide shows similarities with the results of a previous study which monitored HWD from 12 households from the same

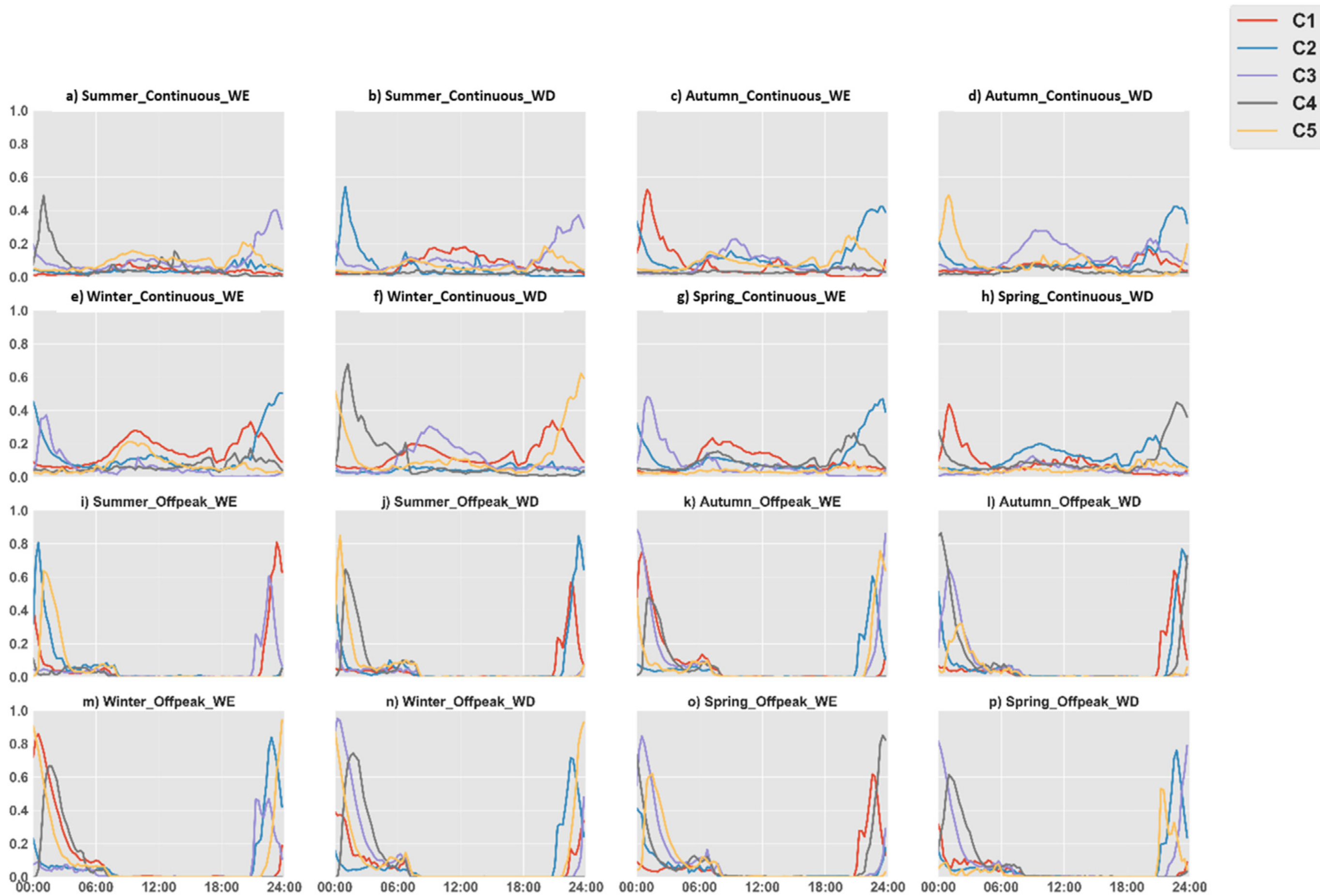

Fig. 6. Normalized seasonal weekday (WD) and weekend (WE) cluster centroids of daily DEWH electricity profiles for continuous and off-peak connections.

region [24]. The average daily HWD results for Brisbane (130 l/day) is lower compared to a previous for the nearby Gold Coast region (157 l/day) [35]. The HWD results reported in this study falls under small to medium category according to figures reported in Australian and New Zealand standards [25]. Fig. 7 c) shows the distribution and averages of daily HWD across months. The distributions follow a similar trend as that shown in Fig. 5, which supports previous findings [2,24] that households habitually use more hot water in colder months. This would also explain why HWD is lower in Brisbane with year-round higher temperature compared to Adelaide and Sydney. Fig. 7 d) presents the distribution and averages of daily HWD grouped by weekdays, which shows little variance of HWD between different days of the week, and more importantly, no clear difference is found between the amount of daily HWD on weekdays and weekends. It is important to emphasize that the inferred daily HWD results in this study had significantly larger number of households than previous studies carried out in the same locations.

3.3. Assessment of excess PV utilization on DEWH

Fig. 8 presents daily examples of simulated DEWH control to maximise the utilization of excess PV generation compared to normal operation for selected off-peak (Fig. 8 a) and continuous DEWH systems (Fig. 8 b). Both DEWH has 3.6 kW rated power and the households have 4 kW and 3.6 kW PV systems, respectively. The days are randomly chosen and have partially cloudy conditions. As shown in Fig. 8 a), the simulation for the off-peak household shifts around two-thirds of daily heating to the middle of the day to utilize excess PV and the remaining heating is done between 4:00–5:00am to provide sufficient energy to meet morning HWD. As a result of the shifted day time heating, some power is imported from the grid, yet the majority (90%) is provided by excess PV. In Fig. 8 b), the normal heating operations are scattered across the day whereas as a result of the simulations 90% of the daily heating is provided by utilizing excess PV generation without requiring grid imports. The remaining heating is left at 5:00 a.m. to provide sufficient energy to meet morning HWD. In each example, the total daily energy spent on DEWH in the normal and simulated cases is very similar. This is important because if utilizing excess PV generation results in higher energy use, it may not be beneficial for the household.

One of the objectives of the simulations is to explore the impact of the different HWD profiles shown in Fig. 3 on the potential utilization of excess PV generation. Fig. 9 presents the distribution and summary statistics of the average excess PV utilization for each of the HWD profiles applied to all of the household daily DEWH consumption, using violin plots. As shown in vertical distributions of the violin plots, all HWD profiles show a right skewed distribution. The morning dominant HWD profile (Fig. 3 d) results in the highest excess PV utilization, with an average of 3.3 kWh/day. This is because the DEWH tank has the highest thermal storage capacity during the PV generation window after the majority of the HWD has been used in the morning. On the other hand, evening and late night dominant HWD (Fig. 3 e and f) have the lowest excess PV utilization with an average 1.8 kWh/day. This is because the

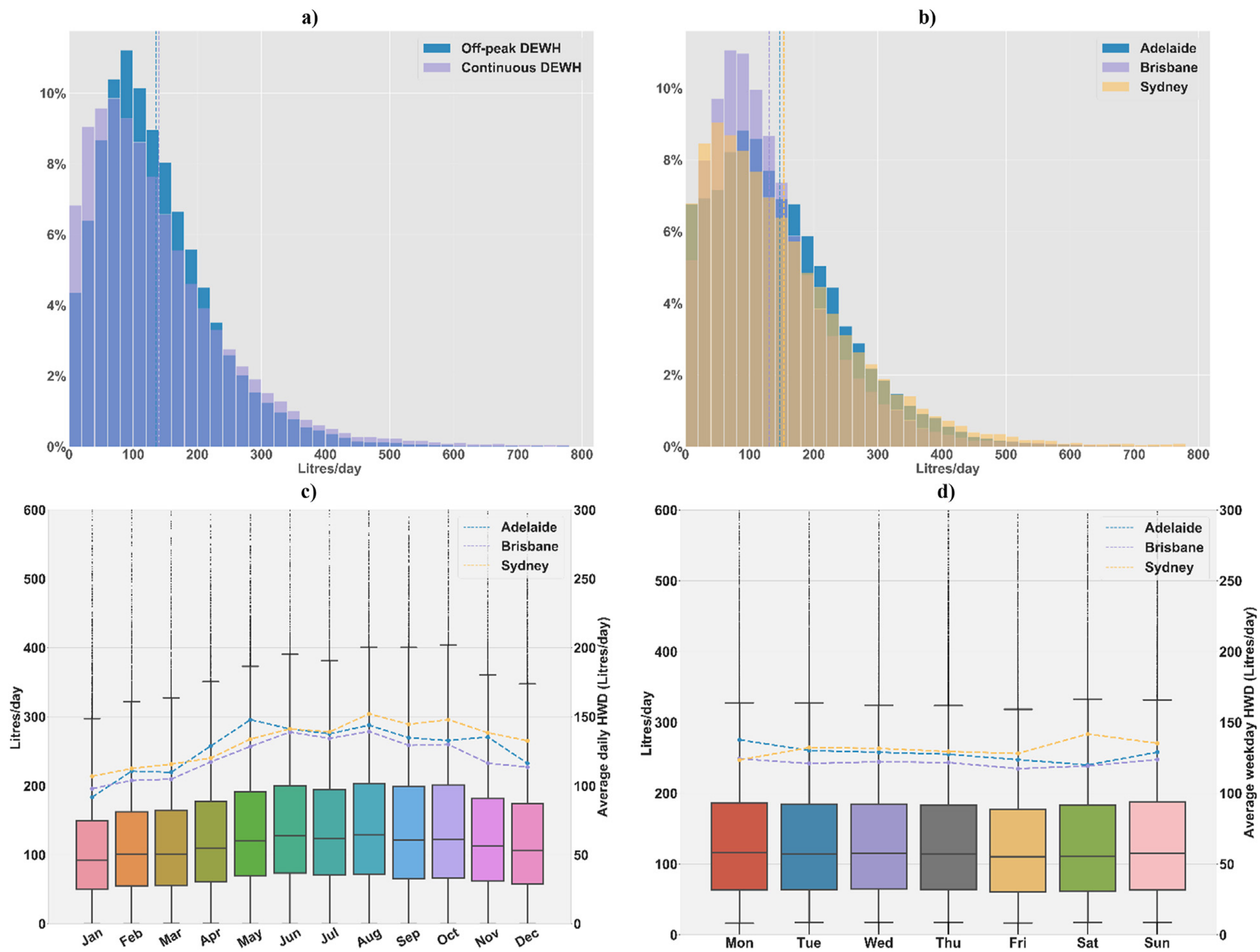

Fig. 7. Daily HWD characterization: a) Histogram of daily HWD for off-peak and continuous DEWH, b) histogram of daily HWD across three regions, c) box plots of daily HWD across months shown with average daily HWD for three regions, d) box plots of daily HWD over weekdays shown with average daily HWD for three regions.

majority of the HWD has been late at night period after which DEWH thermostat triggers charging from the grid to provide sufficient HWD to meet morning HWD. After the tank is fully charged during night, there is less daytime HWD compared to other HWD profiles, and as a result the DEWH tank has less thermal storage capacity to soak up excess PV generation. The remaining three types of HWD profiles (Fig. 3 a, b and c) show similar distributions with an average of 2.6 kWh/day utilization where all types have substantial morning and evening HWD, which is more typical of working family households.

Fig. 10 shows the relationship between the average daily excess PV utilization and PV rated power according to location and DEWH rated power for the morning and evening dominant HWD type a). Generally, having a larger PV system results in higher daily excess PV utilization on DEWH. On average the daily excess PV utilization is 2.9 kWh/day, 2.6 kWh/day and 2.5 kWh/day for Sydney, Adelaide and Brisbane respectively. However, comparing the households with the same PV and DEWH sizes in different regions does not show any clear relationship between the region and the excess PV generation used for DEWH. Further investigating the common PV rated power of 3 kW and 5 kW, it is seen that there is a wide range of excess PV utilization results. One important reason for this is the different daily consumption habits across households impacting the available excess PV generation for water heating. Moreover, the DEWH rated power also impacts the results. Between households with similar daily HWD (l/day), DEWH with smaller rated power results in higher daily excess PV utilization, in fact, for heat pumps and DEWH with 1.8 kW, excess PV generation provides the highest percentage of daily DEWH energy. This is somewhat to be expected as with smaller DEWH power, there is less imports required from the grid and most of the DEWH power can be provided by excess PV generation during the day.

Another important parameter to assess is the required imported energy during the optimal PV generation window. Fig. 11 shows the average daily excess PV utilization on DEWH and corresponding energy imported during the daytime for the 410 households, in order of highest daily excess PV utilization. The figure also presents the percentage of total daily DEWH consumption provided by excess PV utilization. Around half of the households require imports of less than 1/3rd of the energy provided during the solar window , however some households with smaller PV systems and/or higher day time loads have less available excess PV generation and require significant imports during the day as seen with the red spikes. The bottom 10% of households can provide less than 20% of the DEWH via excess PV generation. Some of these households are on off-peak connections with cheaper rates than the regular consumption tariff that would apply for daytime imports and hence may incur financial loss where significant grid imports occur attempting to utilize excess PV on DEWH. On the other hand, for the top 10% of households, excess PV is sufficient to provide at least 90% of daily DEWH consumption and there are significant financial benefits in this strategy.

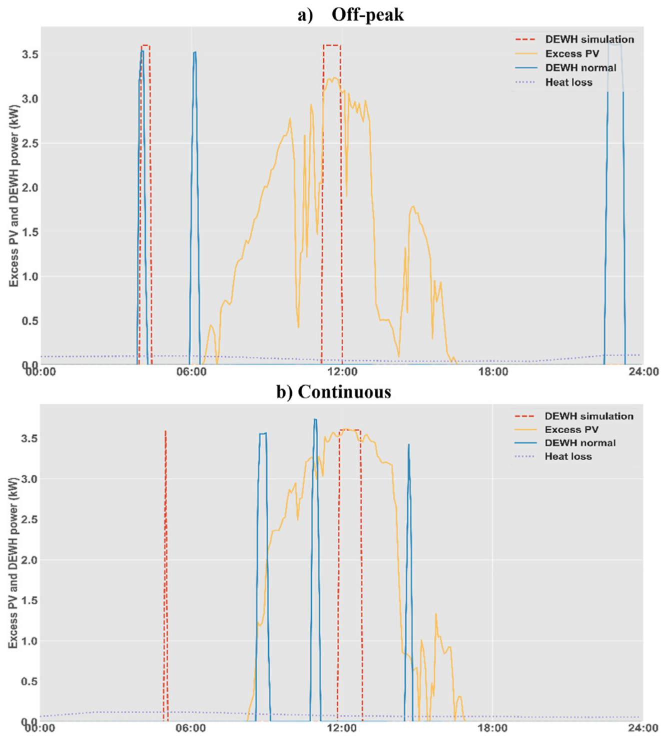

Fig. 8. Example daily simulation vs normal operation for two sites: a) Off-peak, b) Continuous.

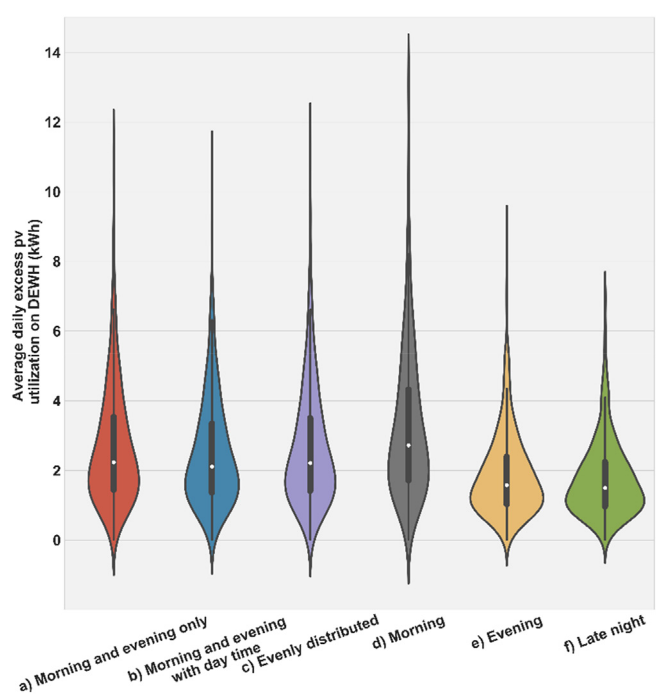

Fig. 9. Distribution of average daily excess PV utilization on DEWH across different daily HWD profiles.

Table 2 provides further details on the seasonal breakdown of the results. Due to the similarity of the obtained results, HWD type a) is presented as representative of a), b) and c) and HWD type e) is presented to represent e) and f).

Spring results in the highest excess PV utilization (kWh) for all HWD profile types and overall, most of daytime heating comes from excess PV (>75%). This is mainly because households have the highest excess PV during spring and there is substantial hot water demand as temperatures gradually increase. Winter has the second highest excess PV utilization but also with a significantly greater proportion of daytime imports. This is because excess PV generation is lowest during winter and DEWH consumption is highest which results in a higher level of imported energy. Surprisingly, Autumn and Summer have very similar excess PV utilization, yet due to greater daily DEWH consumption, the proportion of DEWH provided by excess PV is significantly smaller in Autumn. The proportion of excess PV absorbed by DEWH (i.e., percentage PV self-consumption improvement) is smallest in summer and greatest during winter as households have smaller excess PV and greater daily DEWH consumption in winter. For the typical working family HWD profile type a), on average, 48% of daily DEWH consumption can be provided by excess PV utilization. This corresponds to an average daily PV self-consumption rate improvement of 28%. This also indicates that there is still a significant amount of excess PV to be utilized in other storage applications such as batteries or pre-heating/pre-cooling applications.

The results of this study are promising, showing that excess PV utilization can provide a substantial proportion of DEHW consumption, resulting in a significant reduction in required grid imports. It is important to remind that the studied simulations considered household comfort by always keeping tank's thermal energy state above the minimum threshold to prevent running out of hot water. It was shown in a previous study [52] that if households were ok with occasional instances of running out of hot water, the utilization of excess PV generation could provide up to 70% of daily DEWH energy which is higher than the results reported in this study. It is also important to note that potential operational inefficiencies with PV and DEWH tank has not been considered other than heat losses, which may have a further impact on the obtained results. Moreover, there are more sophisticated power modulation techniques (i.e., PV diverters) which could be used for similar excess PV utilization purposes. Future research aims to test different excess PV utilization methods on a wide range of customer groups in the field and further assess the performance and financial implications.

4. Conclusion

Analysis of 410 domestic electric water heating (DEWH) systems located in Adelaide, Brisbane and Sydney revealed average daily electricity consumption is 6 kWh and for continuous DEWH occurs mainly during morning and evening periods, with some daytime consumption. For off-peak DEWH, consumption is focused between 10 p.m. and 2 a.m. with a tail before the cut off period of 7 a.m. Using K-means clustering with dynamic time warping (DTW), five typical daily electricity profiles were found for DEWH and examined in detail for each season and weekday/weekend. These typical profiles can provide useful information for future DEWH research. Using the electricity consumption data and TRNSYS modelling, the study found that average daily hot water draw (HWD) is 130, 147 and 153 l/day for Brisbane, Sydney, and Adelaide regions. Daily HWD is higher in colder months and there is no significant difference in hot water use across different days of the week. The inferred daily HWD were mapped onto daily HWD profiles produced in previous studies, which enabled the comprehensive assessment of excess PV utilization on DEWH. The utilization of excess PV for DEWH is highly dependent on the daily HWD profiles, and heavy morning hot water use promises the highest potential, followed by more regular morning & evening dominant types and evening/late evening dominant types. Excess PV utilization also depends on the

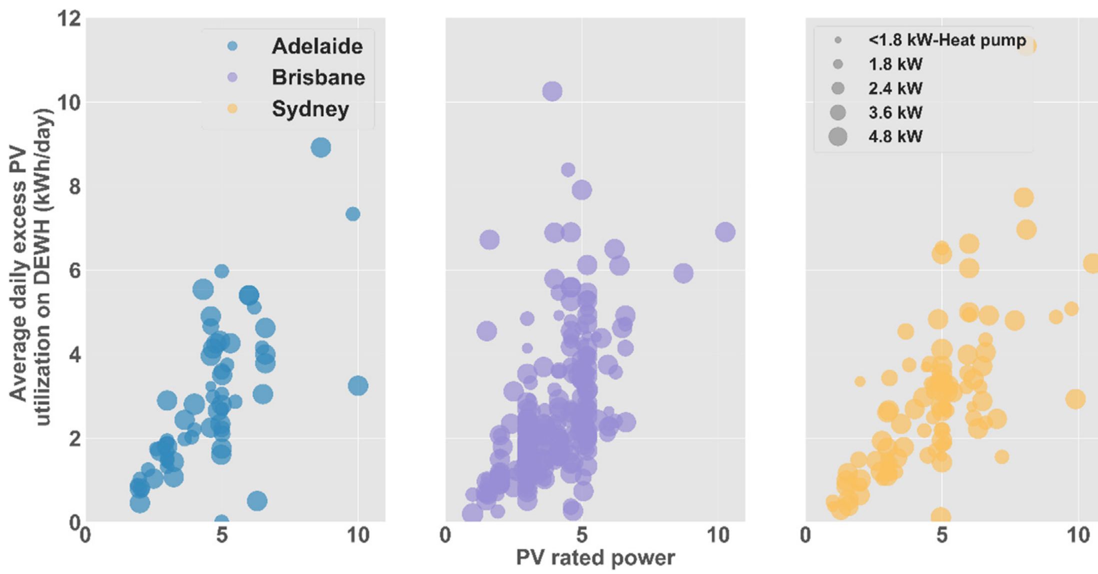

Fig. 10. Scatter of PV rated power (kW) vs. average daily excess PV utilization on DEWH (kWh/day).

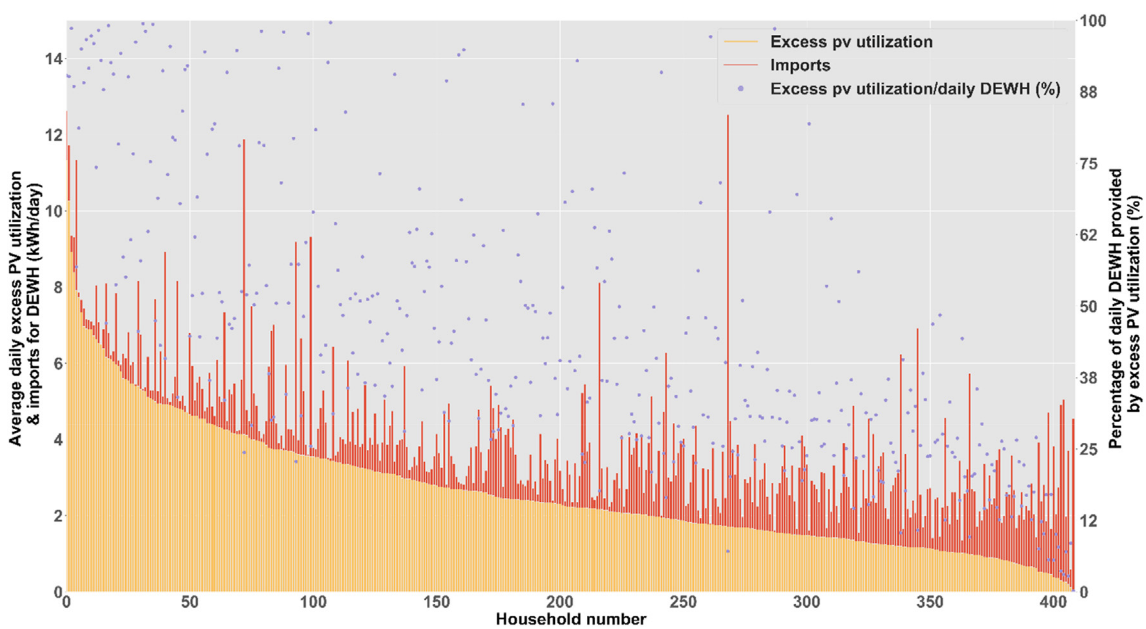

Fig. 11. Average daily excess PV utilization & imports for DEWH during excess PV utilization (kWh) and the percentage of daily DEWH provided by excess PV utilization.

Table 2
Excess PV utilization results for different seasons and HWD types.

	HWD Type a)				HWD Type d)				HWD Type e)			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
Average daily excess PV utilization on DEWH (kWh)	2.4	2.4	2.8	3.2	2.9	2.9	3.4	4.0	1.8	1.7	1.9	2.3
Average daily imports during excess PV utilization (kWh)	0.9	1.2	1.9	1.0	1.1	1.7	2.6	1.4	0.6	0.8	1.2	0.7
Proportion of DEWH energy provided by excess PV utilization (%)	52.4	44.7	41.0	54.1	59.9	51.5	47.8	62.3	41.9	33.9	30.3	41.2
Proportion of excess PV utilized on DEWH (%)	21.2	28.1	37.2	25.1	25.3	33.7	44.7	30.7	15.7	20.2	26.1	17.5

rated power of PV and DEWH. The results reveal that for the typical working family HWD profile, on average 48% of daily HWD can be provided via excess PV which corresponds to a 28% PV self-consumption improvement. Still, there is a significant amount of additional excess PV after supplying DEWH, implying further scope for other battery and thermal storage applications. These results demonstrate that there are significant potential benefits from the utilization of excess PV for DEWH for solar households in reducing their bills, while the reduction in daytime solar exports would have benefits for network operation and can help to facilitate integration of higher penetrations of distributed PV. Future research aims to validate the obtained results through field tests and implement different excess PV utilization methods on different customer groups.

Credit author statement

Baran Yildiz: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Jose I. Bilbao**: Methodology, Writing – review & editing, Supervision, **Mike Roberts**: Software, Investigation, Writing – review & editing, **Simon Heslop**: Investigation, Writing – review & editing, **Jonathon Dore**: Data curation, Resources, Supervision, **Anna Bruce**: Writing – review & editing, Supervision, **Iain MacGill**: Writing – review & editing, Supervision, **Renate J. Egan**: Writing- Review & Editing, Project administration, Funding acquisition. **Alistair B. Sproul**: Writing- Review & Editing, Project administration, Funding acquisition

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This project received grant funding from the Australian Government through the Cooperative Research Centre Projects program (CRC-P). This project used data provided by Solar Analytics Pty., Ltd. for research purposes. Solar Analytics was an industry partner of the CRC-P.

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