Regional and Remote Communities Reliability Fund Microgrid

MyTown Microgrid

Residential load profiles for Heyfield, Victoria

Heyfield local energy options: techno-economic analysis

Milestone 5.2a – May 2023

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Key support

Federation University Australia

Wattwatchers Digital Energy

AusNet Services

Heyfield Community Resource Centre

Latrobe Valley Authority

About the project

MyTown Microgrid is an innovative, multi-year, multi-stakeholder project that aims to undertake a detailed data-led microgrid feasibility for the town of Heyfield (Victoria), built on a platform of deep community engagement and capacity building.

The project received funding under the Australian Government's Regional and Remote Communities Reliability Fund Microgrids stage 1 funding round. It also received funding from the Latrobe Valley Authority as part of the Gippsland Smart Specialisation Strategy.

Citation

Mohseni, S., Rutovitz, J., Smith, H., McCoy, T. (2023) Residential load profiles for Heyfield, Victoria. Prepared for the Regional and Remote Communities Reliability Fund.

Executive Summary

The MyTown Microgrid project is developing an innovative data-led approach to microgrids and other local energy solutions, starting with the town of Heyfield in Victoria. Built on a platform of deep community engagement and capacity building, the project is also creating the knowledge and tools to make it faster, easier, and cheaper for other regional communities to understand the proposition for microgrids and complementary local energy solutions for their towns.

This report focuses on providing high-quality, representative, and scalable typical load and sub-load profiles for rural communities by using data from energy monitoring devices in Heyfield. The load profiles provide information about the average electricity consumption patterns of the community, including peak loads and low energy usage times.

The profiles are based on data from 107 Wattwatchers devices installed in 96 houses in Heyfield. The data includes information on energy consumption from 1 July 2021 to 30 June 2022 with data aggregated to hourly resolution, which is used to create load profiles that can be adjusted based on household size and electrical equipment ownership, such as rooftop solar photovoltaic (PV), different hot water types, and heating and cooling (HVAC) systems.

The derived load profiles are available as a resource for other communities and will be used to analyse local energy solutions in Heyfield, in particular the business cases for load flexibility, community batteries, energy efficiency upgrades, and community retailer/aggregator models.

What is a typical load profile and why is it important?

Typical load profiles represent the average electricity consumption of a group of similar customers, such as households or commercial customers, over a period of time, such as a day or a year. The profiles are usually derived from actual meter readings of a sample of customers and are then statistically analysed to determine the typical or average consumption pattern of the group.

Typical load profiles can provide valuable insights into how electricity is consumed by a specific area or customer group, making them useful for a variety of purposes, such as:

- *Analysing the business case:* for local energy options, such as renewable energy installations, flexible demand, energy efficiency, or microgrids. The first step is usually to gain an estimate of both the hour-by-hour load and the overall energy consumption.
- *Designing and optimising energy systems, particularly in greenfield developments:* by using load profiles to inform the design of localised renewable and sustainable energy systems. The load profiles help to ensure that the energy system is optimised to meet the specific energy needs of the area or customer group.
- *Demand-side management:* identifying the sub-loads with the greatest potential impact on reducing peak demand. This can help develop effective strategies to shift demand away from peak periods or reduce overall energy consumption during peak hours.
- *Evaluating the effectiveness of energy efficiency measures:* by comparing the actual load profile with the expected profile after the implementation of energy efficiency measures, such as switching to heat pump water heaters. This can inform the development of effective energy-saving schemes and technologies.

How did we derive the typical load and sub-load profiles?

We carried out the following process for deriving typical load and sub-load profiles (Figure E1):

1. *Data collection:* The initial step involved collecting energy consumption data from a sample of customers over a specified period of time.
2. *Data pre-processing:* The data was pre-processed to eliminate errors and outliers. This included data cleaning and imputation using standard techniques to eliminate errant and missing values.

3. *Data classification and aggregation:* The data was then classified according to various household characteristics (such as HVAC ownership) and aggregated in hourly time intervals.
4. *Deriving typical load profiles:* Typical load and sub-load profiles were then derived by averaging the aggregated electricity consumption over each hourly period. This was undertaken on a month-by-month basis to maximise the number of eligible devices for inclusion.
5. *Typical load profiles*: To avoid small data sets, these were built up by adding the appropriate sub-load profiles, for example the appropriate water heating profile scaled for the number of occupants, the household-level HVAC profile where appropriate, and the relevant underlying household-level load, which included non-(major) heating plus appliances and lighting (non-water-heating) profile.

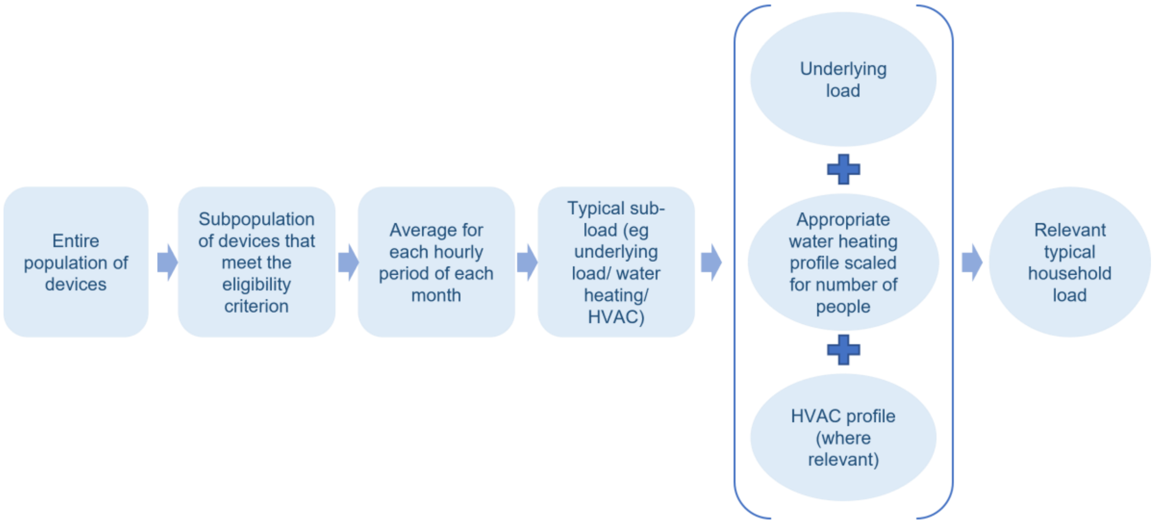

Figure E1 Overview of the method to derive the overall typical load profiles

Deriving the HVAC sub-load profile was straightforward and was derived from all premises with HVAC. Deriving the sub-load profile for water heating was more challenging due to the substantial impact of occupancy on the hot water load. First, we developed two sub-load profiles – one for controlled load, and one for uncontrolled – based on all existing water heating sub-load profiles. The two sub-load profiles were then normalised per person. The hot water sub-load profiles were obtained by scaling back up for the actual number of people. The underlying load was also adjusted to pre-solar load (where relevant) by adding back solar generation records, whilst subtracting actual HVAC and water heating electricity consumption.

Results – overall load

Figure E2 summarises the daily amount of electricity various average houses consume, with the houses categorised as with or without electric hot water, and with or without HVAC.

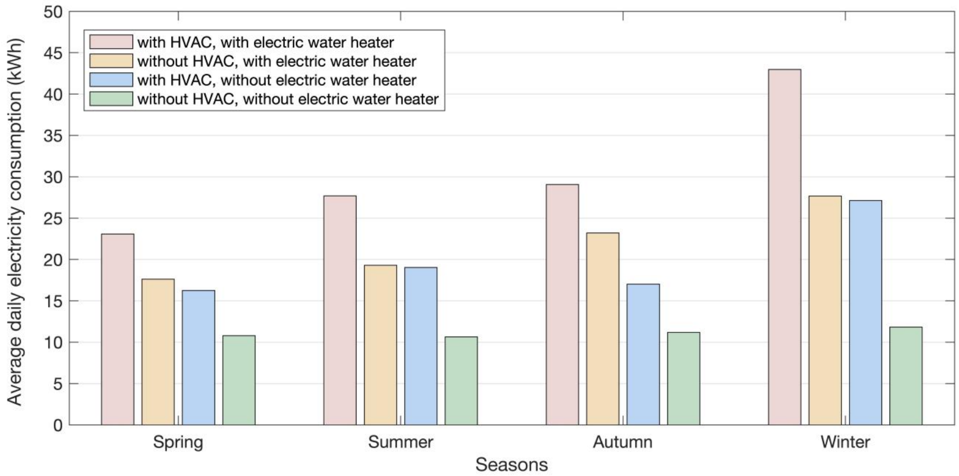

Figure E2 Average daily electricity consumption per season per category of household type

Results – underlying load

Figure E3 shows the derived typical underlying load in a daily seasonal mean (24-hour) format; the profile includes both customers with and without solar. The slight seasonality of the load without electric space and water heating can be explained by the increased need for lighting and unidentified resistive heating loads.

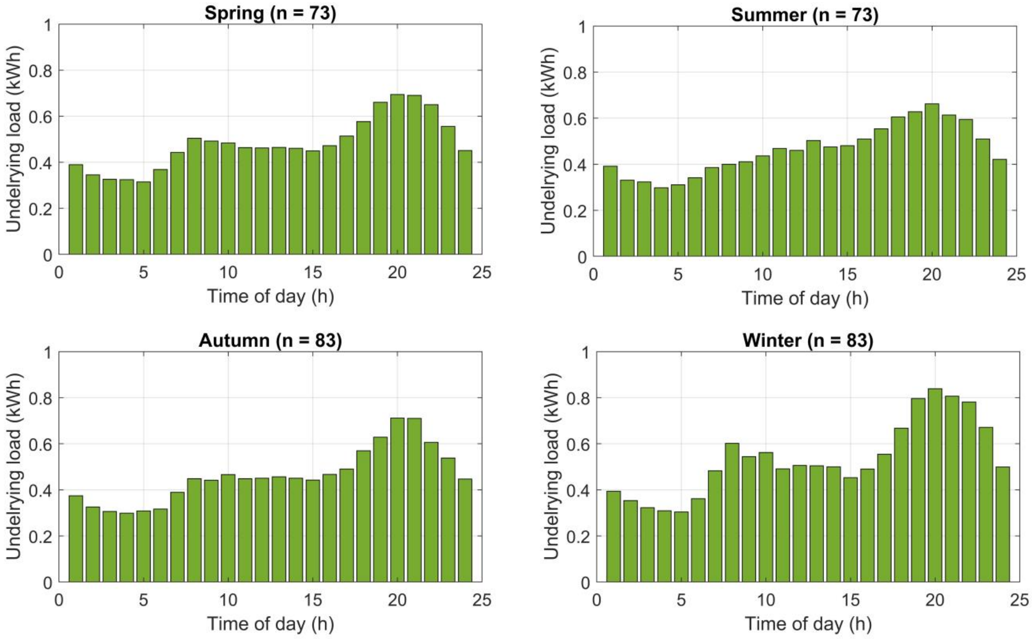

Figure E3 Underlying load of an average house per season (including both customers with and without solar)

The underlying load of customers with and without solar in Heyfield was found to be very similar; despite expectations, there was no noticeable difference between the two groups. The existence of legacy premium feed-in tariffs[a] at (a minimum of) 60c/kWh in Heyfield is believed to play a role in this pattern, as it eliminates the motivation for consuming one's own solar energy. The legacy premium feed-in tariffs currently in effect in Heyfield will expire in November 2024. It is expected that, upon the conclusion of these tariffs, there will be a shift in the incentives for the self-consumption of generated solar energy, potentially leading to alterations in electricity consumption behaviour among customers with rooftop solar PV systems.

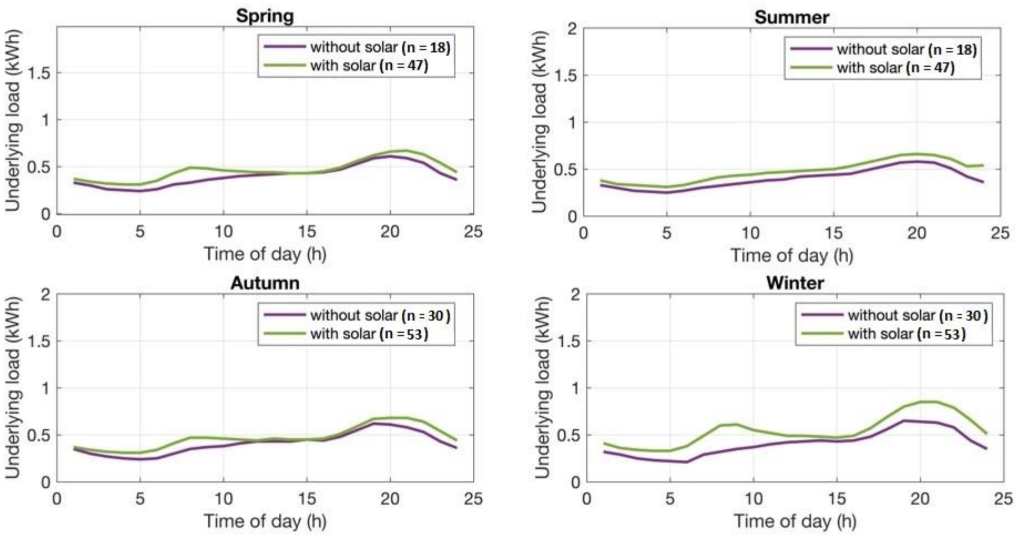

Figure E4 Underlying load profiles for customers with and without solar PV per season

[a] Premium feed-in tariffs are government-sponsored programmes aimed at encouraging the adoption of renewable energy sources, such as rooftop solar power. The objective of these tariffs is to incentivise households and businesses to invest in renewable energy systems by offering them a premium rate for the excess energy they generate and feed back into the grid.

Results – HVAC and water heating sub-loads

The typical HVAC sub-load profile derived for Heyfield (Figure E4) shows usage is highest in wintertime, but also significant in summer. Comparing the pattern of HVAC usage in summer and winter also indicates that demand for HVAC usage is lower during summer mornings compared to other times of the day, reflecting the cooler temperatures in the early hours of the day.

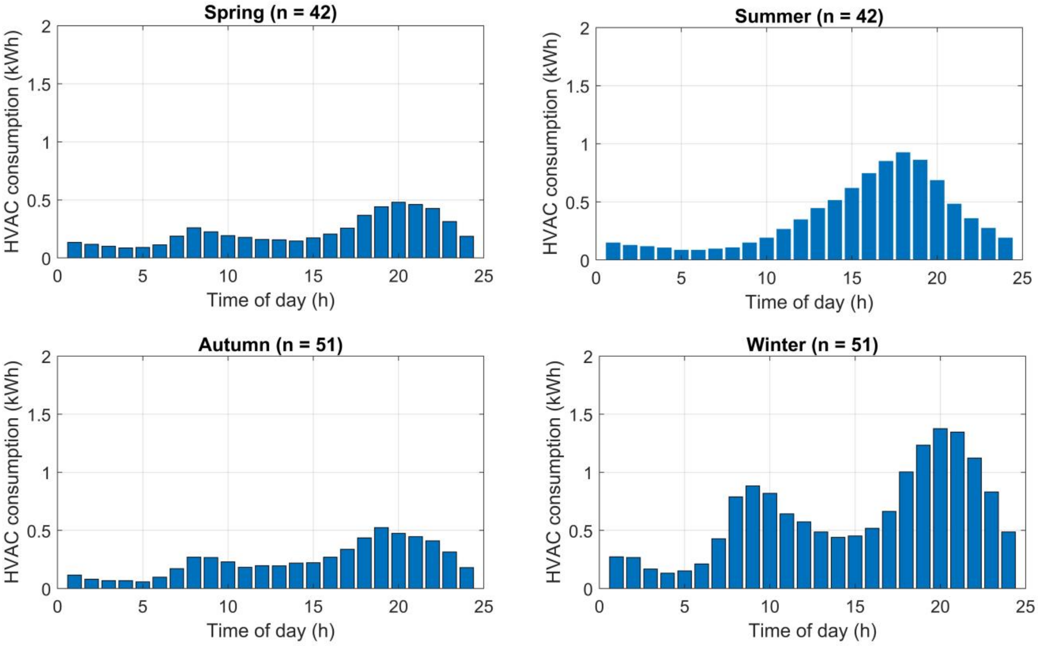

Figure E5 HVAC electricity consumption of an average house per season

Figure E5 shows the breakdown for houses with the three electric water heater types (heat pumps, standard electric elements, and electrically-boosted solar water heaters). The bar charts provide the following insights: (i) the consumption of the electric boost elements of solar hot water systems is particularly concentrated in colder autumn and winter months, and (ii) a direct comparison of the customers with heat pump water heaters and conventional electric resistance units highlights the comparable sensitivity of the consumption associated with the two water heating types to lower temperatures.

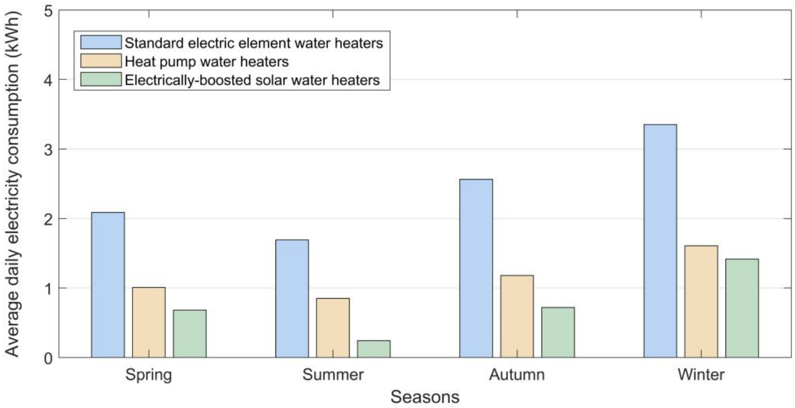

Figure E6 Average daily residential electricity consumption per season per category of hot water system

Benchmarking the typical load data to metered community loads

To verify the validity of the derived typical load profiles and ensure that they adequately represent consumption patterns in Heyfield, we benchmarked the scaled-up profiles against the actual feeder-level data. We undertook the benchmarking for the combined load of three feeders in Heyfield using the mean absolute percentage error (MAPE) metric. We needed to estimate the self-consumed solar, and therefore had to approximate the kW solar for the three feeders. We used three ways to estimate the solar penetration, with corresponding MAPE values of 40%, 30%, and 28%, respectively (lower values indicate a better fit). Figure E7 shows the comparison of the scaled-up typical load profiles to the actual feeder data for three representative months, using the method of estimating solar generation that returned the lowest MAPE value.

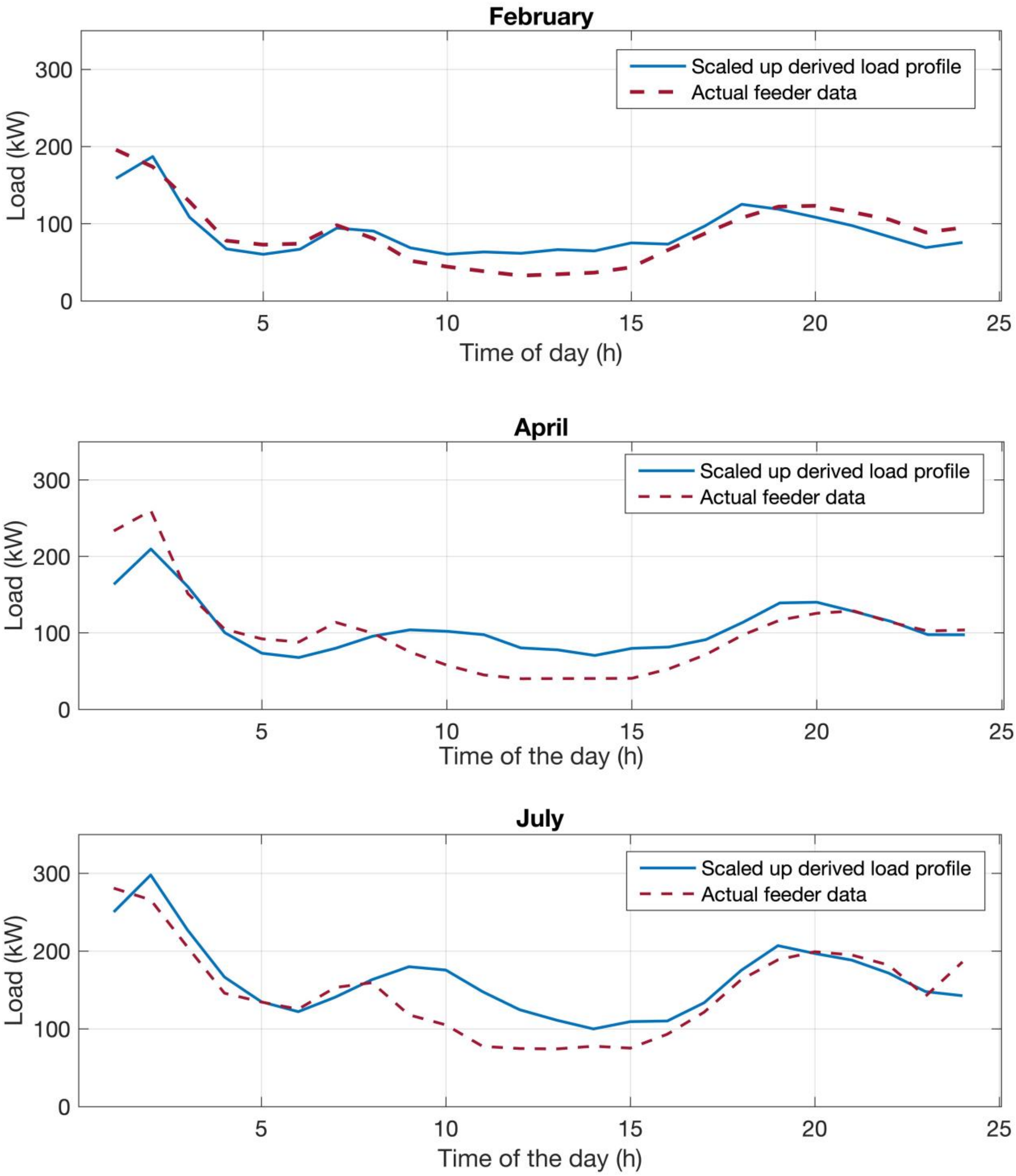

Figure E7 Scaled up derived typical load profiles benchmarked against actual feeder data for a summer month, a transition month, and a winter month – the sum of the three feeders

Discussion

The typical load and sub-load profiles derived in this study are limited by several factors including among other things: (i) no data on electric resistance heaters, (ii) potential unmonitored solar generation, (iii) and potential unmonitored HVAC or hot water systems. It is important to consider appropriate multiplier values and be cautious when extrapolating the profiles, particularly to other communities.

Despite these limitations, the profiles can provide valuable insights into electricity demand in rural regions of Australia and can support the assessment of local energy options and/or load forecasting when local data on household loads and sub-loads is not available.

The derived typical load profiles are available in an accompanying spreadsheet for download, and can be useful for a range of users, including community groups and consultants, who may not easily have access to aggregated metered data. They can be utilised for several purposes:

- *Inputs to business case analysis for local energy options:* including renewable energy, energy efficiency, and battery schemes.
- *Evaluation of demand-side management programmes:* The derived profiles can be used to evaluate the effectiveness of demand-side management programmes in reducing energy consumption.
- *Sub-loads analysis:* The profiles include the sub-loads for HVAC and various electric water heating systems, which can be used to better understand energy consumption patterns related to these loads. This can inform the development of energy-saving schemes and technologies specifically aimed at reducing energy use for HVAC and electric water heating.
- *Research insights:* The profiles can be used to gain insights into factors that influence energy consumption patterns, including the availability and use of renewable energy systems and energy-saving technologies in rural areas.

Contents

List of tables and figures

List of abbreviations

Abbreviation	Description
API	Application Programming Interface
ARENA	Australian Renewable Energy Agency
CT	Current Transformer
HVAC	Heating, Ventilation, and Air Conditioning
LPG	Liquefied Petroleum Gas
LV	Low Voltage
MEM	My Energy Marketplace
NA	Not Available
NMI	National Metering Identifier
PV	Photovoltaic
SCADA	Supervision Control and Data Acquisition
SWH	Solar water heater
WH	Water Heater

1 Introduction

The Heyfield MyTown Microgrid project is undertaking a detailed data-led microgrid and energy solutions feasibility study for the town of Heyfield (Victoria), built on a platform of deep community engagement and capacity building. Over the three-year duration, the project will develop the knowledge and tools to make it faster, easier, and cheaper for other regional communities to understand microgrids and other energy solutions for their community.

The overall aim of this report is to provide future communities who wish to develop community energy solutions but may not readily have access to data such as load profiles – necessary for undertaking the associated techno-economic feasibility analysis – with high-quality, representative, scalable load profiles, with a focus on the distinct demand characteristics of rural communities.

The MyTown Microgrid project provides a range of reports and resources, including documenting Heyfield's journey to explore a microgrid and other local energy solutions[b].

1.1 What is a typical load profile?

A load profile is a broad term that refers to electricity consumption data and represents the pattern or "shape" of electricity usage for the average customer or customer class across a specified timeframe, often a day or a year. It is in fact the measured demand in each settlement period of the electricity market[1].

The measured load becomes more representative when aggregated, with associated periods of low and high electricity consumption becoming noticeable because individual customers have chosen to do the same activities at the same time. Peak demand is driven by the degree of coincident appliance use across customers[2].

A typical load profile represents typical energy consumption patterns of a community or system. It may be derived by aggregating the loads of individual consumers – collected from a representative sample of energy monitoring devices – and then averaging them over a period of time, such as 30-minute or 1-hour intervals. The resulting profile will show the average or normal levels of energy consumption at different times of the day or week and may also include information on peak load and times of low energy usage. It may be used as a benchmark or reference point to compare actual or future load demands.

The dynamics and patterns of electricity consumption increasingly form an integral part of planning and operating renewables-rich energy systems. As the penetration of variable renewables increases, the need for advanced approaches for balancing supply and demand, for example demand-side management, does so as well. However, the real-world dynamics of power consumption are not well explored, especially on the residential level, mainly due to the lack of relevant time-series load data. Accordingly, there is a need to develop typical load profiles for use in bottom-up models, built with actual end-use electricity consumption data and end-use micro-variables such as the number of occupants or type of appliances[3].

1.2 Data used in this study

This study uses data from energy monitoring devices (Wattwatchers Auditors, see Section 2.1) to derive generalised load profiles for residential sites. These load profiles will be used for energy options analyses in Heyfield, including estimating the demand response potential of a number of key appliances, as well as the techno-economic feasibility of community batteries on selected LV feeders. The load profiles will also be made available as a resource for other communities investigating their energy options.

In a perfect world, techno-economic modelling would use data directly obtained from the actual network or community of interest[4]. However, this requires monitoring equipment, such as Wattwatchers devices, to derive load and sub-load characteristics. This may not be available, particularly in early-stage feasibility studies.

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[b] https://www.uts.edu.au/isf/explore-research/projects/mytown-microgrid-heyfield-victoria

In order to transfer generic load profiles derived for one location or end-user to another, end-user characteristics which are easy to recognise and influence energy use must be defined. These underlying parameters of load profiles can enable other communities to readily use the derived load and sub-load profiles in accordance with their situation.[c] We have therefore derived load profiles that may be adjusted based on demographics and electrical equipment ownership, including:

- Household size
- Rooftop solar PV
- Type of hot water system
- Heating system (HVAC, LPG, wood)

We have used data collected from 130 devices – 85 devices installed as part of the MyTown Microgrid project, plus 45 devices installed as part of the Wattwatchers My Energy Marketplace (MEM) project.[5] The devices are installed within a total of 96 houses[d] (out of approximately 700 houses in the town) and 16 small businesses – 107 devices on residential premises and 23 devices on commercial premises.[e]

[c] A bottom-up load profiling approach, even if highly accurate, is not normally acceptable within modelling practice and the simulation community unless it can be applied to other scenarios in a straightforward manner and used seamlessly in the mainstream energy simulation tools.
[d] Which can be broken down into 63 houses as part of the MyTown project and 33 houses as part of the MEM project.
[e] The number of devices, as well as premises and businesses, are effective as of June 2022.

2 Background – the data sources

2.1 Wattwatchers devices

The goal of Wattwatchers is to provide a platform for end-consumers of electricity to unlock energy productivity and the value of renewable energy. Wattwachers' technology enables the real-time monitoring, analysis, and control of electrical circuits, whilst providing granular monitoring, as well as low-cost and flexible data access. Figure 1 provides an overview of Wattwatchers devices.[6]

Figure 1 Wattwatchers Auditor and current transformer product range

Categorising the data collected by Wattwatchers devices as Long Energy and Short Energy, they measure power outputs from distributed energy resources, energy demand, consumption, and power quality. For the purposes of this study, we have used Long Energy data – which are captured for kWh, voltage, current, and reactive energy – and are available without time limits via the dedicated Application Programming Interface (API). For all devices, the Long Energy data commences at the time they are first installed.

2.1.1. Monitoring circuits of the devices

Each Wattwatchers device has up to 6 current transformers (represented by 6 separate channels), with each circuit used to measure either a specific appliance, the imports/exports from/to the grid, or the power output from rooftop PV systems. Up to six if the following are monitored for the properties in Heyfield:[f]

- Grid connection (always monitored)
- Solar generation (always monitored if solar is installed)
- Battery storage systems (always monitored if a solar+battery system is installed)
- Air-conditioning
- General lighting circuits
- Electric hot water
- Pool or irrigation pumps
- Oven
- Kitchen power circuits
- General power circuits

Given the presence/absence of solar generation, battery storage, and appliances such as air-conditioning, the load types monitored vary from site to site.

2.1.2. Community participation

Wattwatchers devices were installed at residential, small business and commercial sites in Heyfield between September 2020 and June 2022, with 85 devices installed from March 2021 to April 2022. A small number of installations were completed between May 2022 and July 2022, which are not included in this study because they do not provide a sufficient time series of data.

As part of the Wattwatchers ARENA My Energy Marketplace (MEM) project, 45 devices were installed at residential sites between September 2020 and December 2020. The anonymised data-sharing

[f] The installation process included capturing up to 6 of the circuit categories, as well as providing human-friendly labels, to enable the customers and the research team to identify the key appliance usage.

arrangements with the MEM project have allowed us to include this set of data in the MyTown Microgrid project. Figure 2 provides a summary of the devices and sites used in this study.

- 45 devices installed as part of the Wattwatchers My Energy Marketplacep Project: 33 houses
- 85 devices installed as part of the the Mytown Microgrid project: 63 houses and 16 businesses

Figure 2 Summary of the devices and sites used to derive load profiles

2.2 Ecologic surveys

Ecologic energy audits have been used to obtain contextual information about the device-derived energy consumption data, to provide greater insight into the underlying parameters of the load and sub-load profiles. De-identified Wattwatchers Device IDs were linked with the available de-identified Ecologic[7] survey responses to provide further detail on information such as the type of space and water heaters, size of the building, number of occupants to inform the characterisation of the load flexibility and control option, as well as to verify the contextual information derived from raw channel-level Wattwatchers data[8].

Nearly two-thirds of the Heyfield residential participants have completed the Ecologic survey. However, the MEM participants were invited but most did not respond to complete their Ecologic input. Accordingly, out of the 130 device IDs (including both residential and commercial devices), we only were able to match 86 of them to the Ecologic energy audits covering 68 linked surveys. Note that some sites have multiple devices, for example, one for the shed and one for the house, or one for the garage and one for the house.

2.3 Data confidentiality

During the registration and consent form process, participants agreed to share their anonymised energy data with the project. The research team only had access to Wattwatchers Device IDs, which are the serial number of the Wattwatchers devices, and are not considered identifying information.[g] However, to add another layer of data security, the retrieved device-level power consumption data were further anonymised by de-identifying them – removing the association between data and households. That is, the load profiles are no longer labelled by which Device ID they belong to when storing the data.

The additional data obtained from the participants' Ecologic energy questionnaire has also been made available to the research team in a de-identified format as the responses contain particularly sensitive information, such as home occupancy. As the research team did not have access to the addresses of the customers who have installed Wattwatchers devices, linking Wattwatchers Device IDs with the de-identified Ecologic responses was deemed acceptable. The information was carefully controlled throughout the analysis.

Customer data has only been used for the purposes of the MyTown Microgrid project, whilst adhering to the Wattwatchers terms and conditions[h] – accepted by the customers during the registration and consent form process.

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[g] The device number is similar to a National Metering Identifier (NMI) or a meter serial number.
[h] Available at https://mydata.energy/terms

3 Methodology

3.1 Overview

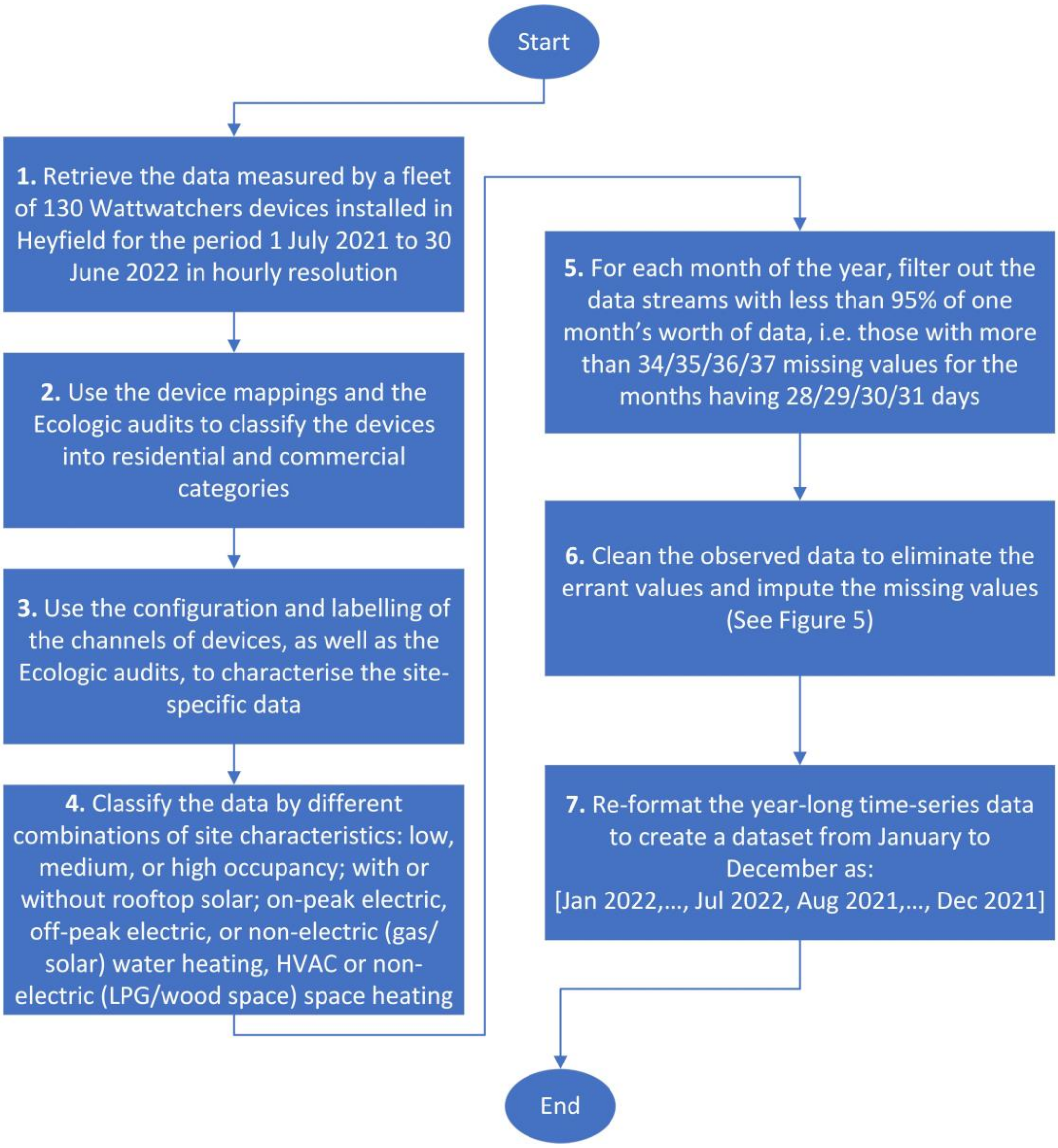


Figure 3 Flow chart of the overall method for deriving the load and sub-load profiles

In accordance with the flow chart in Figure 3, the following steps were undertaken to process the data:[i]

1. Retrieving the data measured by the fleet of 107 Wattwatchers devices installed on residential premises in Heyfield using the dedicated Jupyter Notebook[j] platform with the specific API key provided by Wattwatchers Digital Energy. The collected data was from 1 July 2021 to 30 June 2022, with an hourly data resolution.
2. Using the device mappings[k] provided by Wattwatchers, as well as the Ecologic audits (where appropriate), to classify the devices installed into residential and commercial categories.

[i] All the associated data cleansing, visualisation, and analysis processes have been carried out in MATLAB software.
[j] Wattwatchers provided a Jupyter notebook focused on downloading Long Energy data, designed to be used with Google Colab, that allows the user to save the data as a CSV file.
[k] A list of sites and devices is maintained in Heyfield MyTown Microgrid Device Mappings. To request access to this document, please log a ticket with the Wattwatchers Support team or contact the Heyfield MyTown Microgrid Project Manager for assistance.

3. Using the configuration and labelling of channels, as well as the Ecologic audits (where appropriate), to identify the characteristics of the sites of interest in terms of the household size, existence of rooftop PV, as well as the type of space heating and water heating systems. Accordingly, it is known what each year-long hourly-basis load profile is comprised of and what the associated ecological features of the de-identified sites are.
4. Classification of the data by different combinations of the listed site characteristics.
5. Selecting household-level data streams with at least 95% of the relevant month's data on a month-by-month basis. Accordingly, for a typical month with either 30 or 31 days, the maximum number of missing and/or unmeasured data points for the site to be eligible for inclusion is 36 or 37 data points[l]. The same logic holds for February, which has 28 days (29 on a leap year). The employed month-by-month eligibility assessment technique helps maximise the number of eligible devices for inclusion in each profile class, and so improves the accuracy of the load and sub-load profiles.[m]
6. Cleaning the observed data to eliminate errant values and imputing[n] the missing values; detailed instructions are given in the following for cleaning and imputing data.
7. For reasons of improved comprehensibility of the seasonality of the underlying data, the time series was shifted to create a dataset from January to December by shifting one 5-month period (August – December 2021) as follows:
    - Jan 2022,
    - Feb 2022,
    - Mar 2022,
    - Apr 2022,
    - May 2022,
    - Jun 2022,
    - Jul 2022,
    - **Aug 2021,**
    - **Sep 2021,**
    - **Oct 2021,**
    - **Nov 2021,**
    - **Dec 2021.**

3.2 Data cleaning and imputation

The following steps were undertaken for cleaning the data and imputing the missing values:

1. Searching the data for values that are below a certain threshold. This generally depends on the dataset of interest, but following the standard practice in data science, any observation that is larger than $\mu + 3\sigma$ of the dataset (where μ and σ respectively denote the mean and standard deviation of the dataset) is deemed to be an outlier[o]. To enable a fair exclusion of outliers, the comparison of the individual data points against the term $\mu + 3\sigma$ was conducted based on the population of hour-specific data points of each month for each group; for example, the population of data for the hour 3 p.m. of January for a customer segment with low occupancy, with rooftop solar PV installed, and having off-peak electric water heating and HVAC space heating.
2. Flagging the outliers (unrealistic values that are incongruous with normal observations) for removal as they are probably the result of a data measurement error and replacing them with NA (not available).
3. The missing values are then imputed using different techniques depending on the number of consecutive missing values. The single NAs[p] are imputed by taking the average of the previous hour and the subsequent hour.

[l] That is, 5% of 30 or 31 days × 24 hours.

[m] The month-by-month eligibility assessment increases the probability of considering a greater number of devices compared to whole-of-year eligibility assessment. The larger the sample size, the greater the accuracy, the greater the data analysis and computational cost. Accordingly, to maintain a sensible trade-off between cost and accuracy, a monthly sampling variable was deemed sufficient, and we did not go further, for example to week-by-week or day-by-day eligibility assessment. This led to a varying number of eligible devices per month, so the number of devices meeting the 95% data inclusion criterion should be presented as a series of up to 12 values, rather than a single value for the year.

[n] Data imputation refers to replacing missing values in a dataset by estimates based on other available information in order to allow for data analysis using standard techniques.

[o] An outlier is a data point that lies in an abnormal distance from other values in a dataset and stands out significantly from the overall pattern of values.

[p] Note that, as far as the data recorded by the device IDs used in the relevant categories within this study are concerned, all the single missing values represent the outliers. That is, no unobserved values (the data that is not recorded) were found in the Wattwatchers data retrieved if the data period is after the installation date.

4. For more than one, but fewer than 5 consecutive NAs[q], the average of the values 24 hours before and after each of the 5 missing data points are used.
5. To address greater than 5 consecutive missing values in the associated monthly-basis time series, the so-called "*last day carried forward*" technique is used, according to which the hourly data related to the same hours of the previous day are copied forward and replaced with the corresponding missing values, whilst accounting for the weekday versus weekend day effect. Note that this class of data imputation represents the devices that had not recorded a full month's worth of data for at least one month of the year at the time of data retrieval, in accordance with their installation dates.[r] An example of this scenario is a device first installed on the second day of a given month. Such a device has recorded greater than 95% of all possible data points in that month, and therefore it is eligible for inclusion, but it has certainly missed more than at least 24 consecutive hourly data points.

The main driver to consider three different means of data imputation is to maximise the accuracy of the overall process. These types of data cleaning and imputation processes are standard.

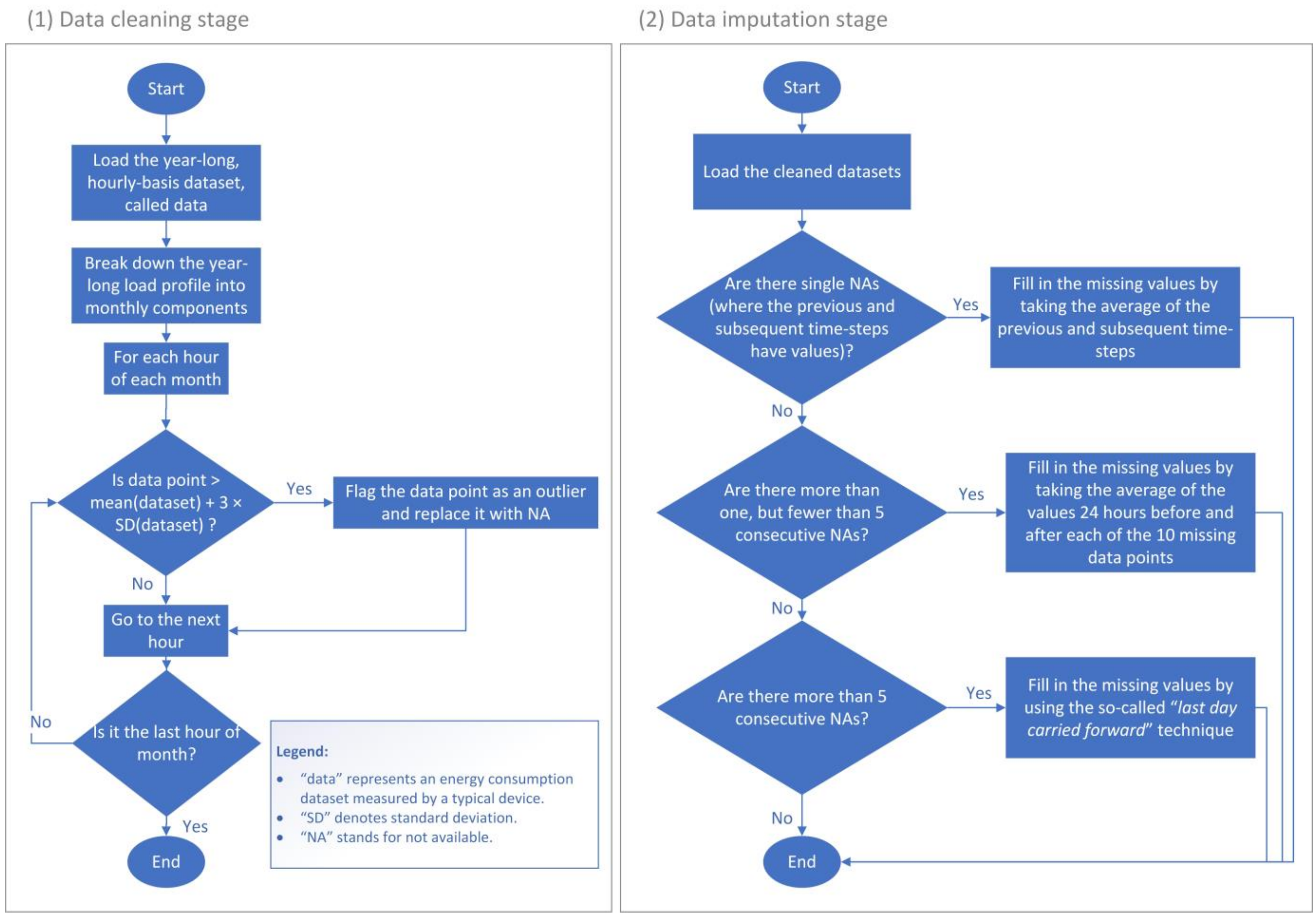


Figure 4 Sequential diagram of data cleaning and imputation techniques

3.3 Household characteristics

Residential load and sub-load profiles are derived and differentiated based on household demographics and electrical asset ownership, including household size, rooftop solar PV, type of hot water system, and type of

[q] This scenario also mainly represents the outliers.
[r] Note that as the Long Energy data is available for all devices since when the device was installed, re-defining the year-long timeframe – for which the data are retrieved – to a more recent one in the future is expected to increase the number of eligible devices for inclusion in the analysis. This is particularly because as time goes forward a greater number of recently installed devices would meet the pre-defined criterion of containing greater than 95% data points for each month of the year. However, in view of the defined project milestones and the fact that a number of outstanding device installations are ongoing (albeit small), it is necessary to use a systematic approach for device exclusions and handling missing values. Such an approach contributes to making the overall analysis more replicable for future communities.

space heating system. The defined characteristics and the possible categories are summarised in Table 1. As the categories are essentially independent, this gives a potential for 84 different load profiles.

This number (84) was too high for practical application within the project, and the numbers per occupancy category were rather low. It is also arguable that only hot water use is directly linked to occupancy. A sub-load profile was therefore derived for each of the hot water categories for a single person, and the average occupancy of 2.5 used to determine the hot water load profile for all further analysis. Initial analysis of the data showed that the patterns and trends of electricity consumption among customers with and without solar PV systems were in fact similar, with minimal variations observed. Therefore, in the interests of increasing the sample size, it was decided that differentiating the load profiles of customers with and without solar was not necessary. With these modifications, a set of 14 load profiles are derived.

Table 1 Defined characteristics for load profiles

	Number of possible values	Categories		
Rooftop solar	2	Installed	Not installed	
Hot water system	7	Electric (off-peak): (i) standard electric element, (ii) heat pump, and (iii) electric boost system of solar water heaters	Electric (on-peak): (i) standard electric element, (ii) heat pump, and (iii) electric boost for solar water heaters	Non-electric (gas or solar with gas boost)
Space heating system	2	HVAC	*LPG or wood	
Occupancy (this category is not used)	3	Low (1-2 people)	Medium (3-4 people)	High (>4 people)

* These are considered as one category from the point of view of the electrical load.

The following points should also be noted:

- Each device channel is associated with a Channel Category which is selected from a pre-defined list; there is also a Channel Label field which is set by the installer. The ‘Channel Categories’ and the ‘Channel Labels’ sometimes had to be used in combination to identify the load.[s]
- Configuration and labelling of channels were not uniform across the fleet[t] so manual checking was necessary to identify the type of electric hot water system for each channel-level dataset. In particular, manual checking was performed to distinguish standard electric element heaters from heat pumps and the electric boost elements of solar hot water systems, as well as to identify the network tariffs associated with controlled loads (via the dedicated circuit of the smart meter) – refer to Appendix C for a breakdown of the number of off-peak hot water systems on different tariffs.
- To distinguish standard electric element heaters from the heat pumps and electric boost elements of solar hot water systems, the entire relevant datasets were examined. Heat pumps were identified by their considerably lower loads (~0.85 kW to ~1.25 kW) compared to standard electric element water heaters (~2.5 kW to ~4.5 kW), while the electric boosters for solar water heaters were identified by their particularly low consumption in the summertime.
- Given the large volume of data, it was decided to use the hourly resolution to speed up data retrieval and processing.

[s] For example, an electric off-peak hot water system has in most cases been identified by the Channel Category “hot water”; if the associated Channel Label is “hot water off-peak”, this suggests that the electric hot water system is on off-peak rate. However, as the labels “hot water”, “hot water off-peak”, and “solar hot water” are set by the installer in a non-standardised way, they do not necessarily guarantee what rate they are on. Hence, it was necessary to look into the consumption patterns of hot water systems to identify the controlled loads.
[t] Due to the constraints during the installation process which was performed by a number of different installers.

- In situations where there is more than one phase of incoming energy, the relevant channels are grouped together by summing together the channels marked as groups. In the following example, Channels 0/1/2 are one group, and Channels 3/4/5 are another group:

Raw data (channels 0 – 5)					
Channel 0	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5
-1.00E-05	-0.00044	-0.00193	4.47191	4.03991	0.78506

Data after applying phase groupings	
Group 1	Group 2
-0.00238	9.29689

3.4 The data

It is worthwhile noting that the results from the Ecologic survey suggest that about 30% of the hot water demand is met by totally non-electric solutions, including gas water heating on LPG (both gas storage and instantaneous water heaters), as well as solar hot water systems with accompanying temperature controlled continuous flow gas hot water systems designed as a boost. This partly explains the difference between the total number of residential premises with all or part electric hot water systems (n = 44) and the total number of residential premises with devices data for at least one month (n = 83).

Part of the observed difference can also be attributed to the fact that the 30% share of non-electric hot water systems is calculated based predominantly on the responses of the MyTown Microgrid participants, while the devices data belong to both MyTown and MEM participants. Additionally, not all participants have completed the relevant section of the Ecologic survey, and the energy literacy levels of the participants who have completed the section and subsequent changes to their water heating systems are not known.

There is a high share of heat pump water heaters compared to the average penetration in Australia. This is due to a combination of the community's aspirations for energy efficiency, promotions made by the Community Resource Centre, and the State government's rebate programmes for Victorian households to have gas or electric hot water system upgraded to an energy efficient water heat pump at a discounted rate.Table 2 shows the number of premises associated with the various datasets for the 130 Wattwatchers devices installed in Heyfield. Note that the column "total" in the table represents the effective number of premises with Wattwatchers devices used in the employed month-by-month-basis method, whilst the number of premises associated with greater than 95% data points has also been provided as an indication of the extent to which the month-by-month procedure has increased the data for each category. Some sites have multiple devices, which explains why the sum of residential and business premises with Wattwatchers devices (n = 101) is not equal to the total of 130 devices.

There are also a number of commercial sites such as the School (4 devices), Heyfield Hall, Golf Club and Museum (all 2 devices each), as well as Wetlands Centre that did not complete the survey as the focus was on residential participants. In line with the focus on residential load profiles, the number of devices installed on commercial premises with linked Ecologic surveys is considerably lower than those on residential premises.

Table 2 Data summary – Wattwatchers devices and Ecologic audits

Data source – household characteristic	Residential		Business	
	Total	> 95% data points overall	Total	> 95% data points overall
Data obtained from Wattwatchers devices				
Device data for at least one month	83	65	18	2
PV system installed	53	42	14	2
Devices monitoring oven electricity consumption	33	26	2	0
HVAC	51	39	6	2
Off peak heat pump water heaters	22	20	0	0
Off peak standard electric element water heaters	14	12	1	0
Off-peak electric boost for solar water heaters (SWH)	8	7	0	0
Day-rate heat pump water heaters	11	10	0	0
Day-rate standard electric element water heaters	6	5	2	0
Day-rate electric boost for SWHs	4	4	0	0
Devices with linked Ecologic surveys [u]				
PV system installed	36	28	9	0
HVAC	6	4	0	0
Corresponding Ecologic survey	57	44	11	0
Gas boosted SWHs	6	4	0	0
Electric boosted SWHs	7	4	0	0
Instantaneous gas water heaters	3	1	0	0
Storage-based gas water heaters	2	1	0	0
Standard electric element water heaters	9	6	0	0
Heat pump water heaters	15	10	0	0
Wood space heating	40	33	0	0
LPG space heating	2	2	1	0
1-2 residents	27	20	N/A	N/A
3-4 residents	13	10	N/A	N/A
> 4 residents	4	3	N/A	N/A

As far as possible, the Ecologic audits were used to confirm the type of space and water heating systems, as well as the installation of solar rooftop systems. To illustrate, the hot water system sub-classes identified for each device were checked against the wider hot water system categories defined in the Ecologic questionnaire. Additionally, a number of attributes, such as the household size, were exclusively derived from the Ecologic audits, as this information is not collected during Wattwatchers device installation. Adequate floor area data was not available either from the Ecologic audits, or from the Wattwatchers information, so we were not able to use this as an adjustment.

Information on wood heating, LPG heating, gas water heaters, and number of occupants was restricted to devices with linked Ecologic audits, as this information is not collected during Wattwatchers device

[u] MyTown Microgrid project devices were installed on 63 residential premises, and 57 had linked Ecologic surveys.

installation. Also, note that data on Ecologic-derived data counts the number of premises in each category that are linked with de-identified Ecologic survey responses (this was not the case for all devices).

The reason why the total number of premises with different water heating systems (n = 42), for example, does not add up to the total number of premises with corresponding Ecologic survey (n = 57) is that not all participants have responded to the relevant question. On the other hand, the disproportionate share of HVAC systems in the devices with linked Ecologic surveys compared to the information derived from Wattwatchers devices indicates that while wood space heating is the main type of space heating, a sizeable proportion of premises additionally have HVAC systems.

Furthermore, none of the devices installed in commercial sites with linked Ecologic responses had recorded greater than 95% of the total possible data points over the pre-defined one-year timeframe.

Appendix A: Eligibility assessment of devices gives details of the process for including/ excluding device data, and the numbers that were deemed ineligible for inclusion at each stage.

3.5 Deriving typical residential profiles

After grouping, a simple average demand for each hourly period of each month for each category is created. To illustrate, summing across each hour of each month using the fractions of the population that are in each relevant monthly group, and then dividing by the corresponding population size of the monthly group gives a 24-hour-long vector of group average demand, which represents the initial typical load for the relevant month (see Figure 5).

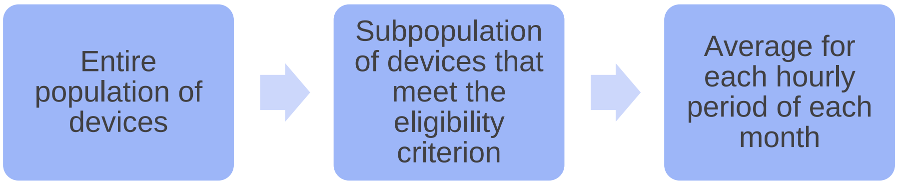


Figure 5 Overview of the grouping and averaging procedure on a month-by-month basis

3.5.1. Making average profiles more realistic

The actual load profile for a particular dwelling rarely resembles the simple average, with potentially large fluctuations between peaks and troughs. More specifically, domestic electricity load profiles are subject to a great deal of stochasticity. This is influenced by many independent variables, some of which have been accounted for directly using the pre-defined adjustments. In other words, although switching on/off some individual electrical appliances is directly influenced by the defined dwelling and occupant characteristics, other appliances may appear to be switched on and off at random.[9] To illustrate, while continuous and standby appliances tend to form a base load, electricity consumption from active appliances such as kettles and electric showers is more random. Such appliances also typically have high power requirements.

The small to an extremely small sample size of specified domestic load classes leads to low confidence intervals and margins of error around the cyclical patterns of the derived load estimates. This necessitates accounting for the associated uncertainties to improve the replicability of the typical profiles.

After calculating the simple average demand for each hourly period of the month using the fractions of the population that are in each relevant monthly group, an uncertainty characterisation layer is added to the generated profiles. To model the stochasticity of the habitual behaviour of occupants and factor in the load signatures of the local environmental condition, as well as systematically compensating for the small sets of devices that fit some criteria, the well-known first-order Markov chain technique[v] is used. Figure 6 provides an illustration of the two-state, first-order Markov model.

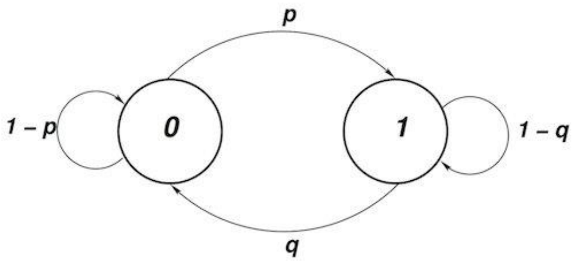


Figure 6 Illustration of the two-state, first-order Markov model[10]

Using the Markov chain modelling, a specific probability is assigned to the transition of electric water heating and HVAC systems from one discrete state (for example, ON) to another discrete state (for example, OFF). The developed Markov chain looks at the current state and the one immediately preceding it to calculate the probability of going to the next state. The power consumption of electric water heating and HVAC systems at each time step of the typical load is then calculated, which is subsequently adjusted for the probability of the relevant appliance being in the state ON/OFF. This can be mathematically expressed as:

$$P_{stoch}(t) = p_{ON} \times P_{det}(t)$$

In the equation above, $P_{stoch}(t)$ denotes the stochastic power consumption of the relevant appliance at time-step t, p_{ON} is the probability of the appliance being in the state ON, determined from the Markov chain model, and $P_{det}(t)$ is the deterministic power consumption of the appliance determined from simple averages.

Importantly, this procedure, which adds an uncertainty characterisation layer, enables a more diversified representation of the electricity consumption patterns associated with the typical residential load profiles.

It is important to note that the overall load consumption is the sum of all the load levels over a certain period of time and will remain the same whether we use Markov Chain or any other method to create load profiles, and the total amount of energy consumed over any nominated period remains the same. However, by using Markov Chain, we can get a better understanding of how the load changes over time by modelling the probability of different load levels at different times of the day.

3.5.2. Accounting for solar

The underlying load is concealed when the resident has solar generation consumed on-site and a net metering setup[w], as is usually the case. For the load profiles derived for premises with onsite generation, the effective load was calculated by adding the solar generation measurements to the 'grid connect' load records. That is: underlying load = net-metered records (positive or negative) + solar generation records. Sub-loads are still identified based on the measurements of the dedicated channels.

3.5.3. How to avoid tiny data sets

Given the relatively small number of samples and the number of categories considered, as detailed in Table 1, the Wattwatchers sample has very few cases that would fit each category (if any at all). To avoid tiny data sets, typical loads are built up from sub-loads.

More specifically, the water heating sub-load, the space heating sub-load, and the typical underlying load excluding HVAC and water heating, were derived. Subsequently, the typical profiles per category are built up by adding the appropriate water heating profile scaled for the number of occupants (where appropriate) and the HVAC profile (where appropriate) to the relevant underlying non-(major) heating, non-water-heating profile.

[v] Markov chain is a type of Monte Carlo analysis where probability distributions determine the likelihood of a dwelling consuming a particular load.
[w] While a gross meter records all solar production as an export to the grid, a net meter only records the surplus. That is, net metering accounts the difference of excess solar power exported back to the grid and total power consumed onsite.

No material difference in the electricity usage behaviour of the customers with and without rooftop solar PV was observed[x], so it was decided to derive a single underlying load profiles for both these categories (refer to Section 4.5). The prevalence of systems with legacy feed-in tariffs of 60c/kWh in Heyfield is likely to contribute to this effect, as there is no incentive for self-consumption of solar.

The following sub-sections detail the processes of deriving the associated water heating and space heating sub-loads, as well as the underlying load excluding those sub-loads.

3.5.4. Water heating sub-load

The following steps were followed to derive the water heating sub-load profiles based on the associated Markov Chain probabilities:

1. First, two sub-load profiles for water heating – one for controlled load, one for uncontrolled – were developed based on all existing water heating sub-load profiles.
2. The two sub-load profiles were then normalised per person in accordance with Ecologic audits.
3. To maximise the number of included households and improve the statistical robustness of the derived sub-profiles, in the absence of relevant datasets linked to Ecologic surveys or where the Ecologic survey responses did not mention the number of occupants, the average household size in Victoria of 2.5 people was assumed.[11]
4. The effective sub-load profiles were then obtained by scaling back up for the actual number of people.

3.5.5. Space heating sub-load

The HVAC sub-load profile has been derived from all premises with HVAC.

3.5.6. Typical underlying load

In deriving the typical underlying load excluding HVAC and water heating in the absence of records of the demand of electric resistive heaters (because of not being on an individual circuit in the energy consumption monitoring device), two main classes can be considered to be able to isolate resistive heating load, as follows:

Dataset A: Houses with wood heating, LPG heating, or HVAC

1. For houses with solar PV, the load profile is adjusted to pre-solar load by adding back the solar generation records to the corresponding net-metered records. In other words, the -ve solar PV circuit values are converted to +ve demand, and accordingly, the 'total household load' estimates are re-built by adding back to the net-metered load to give 'gross load'.
2. The relevant actual HVAC electricity consumption is then subtracted from the overall load of the houses with HVAC.
3. Similarly, the actual water heating electricity consumption is subtracted from the overall load of the houses with electric water heating.

[x] To do this, a recognised metric to quantify the coincident power consumption between independent underlying load profiles, namely the diversity factor, is employed. First, for customers with solar, solar generation is added back to the demand net of solar. Then, to determine the diversity factor between the households with and without solar associated with the relevant hourly-basis, year-long profiles, first the maximum coincident demand and non-coincident demand were derived in hourly time steps. Then, the sum of the maximum demand of all houses with solar PV at hourly time steps are divided by the sum of the maximum demand of all houses over the course of a year. A similar process is undertaken for the houses without solar. The diversity factor varies from zero to one, where zero indicates no coincident electricity consumption between households, while a diversity factor equal to one shows strong coincidence.
A comparable diversity factor of 0.41 and 0.46 were obtained for the houses with and without solar, respectively. To compare the electricity consumption characteristics of the two major categories, the associated load factors – the ratio between the average load and the peak load – were calculated. Similarly, a load factor of 0.23
and 0.19 were obtained for the houses with and without solar, respectively. In addition, for the dwellings that are not equipped with solar PV, the mean annual underlying consumption of ~7.7 MWh is only about 12% higher than the ~6.9 MWh of those with solar PV.

4. Finally, the average load is derived, which is referred to as typical underlying load A.

Dataset B: Houses with nothing but electric resistive heating

1. For houses with solar PV, the load profile is adjusted to pre-solar load, as indicated above.
2. The relevant actual water heating electricity consumption is then subtracted from the overall load of the houses with electric resistive heating alone.
3. Finally, the average load is derived, which is referred to as typical underlying load B.

In this setting, the difference between the two average load profiles, $B - A$, is likely to represent the isolated resistive space heating load.

3.5.7. Building up the typical profile

Accordingly, for the typical load profiles per category we can build up from:

Typical underlying load + appropriate water heating profile scaled for the number of occupants + HVAC profile (where relevant). This process is depicted in Figure 7.

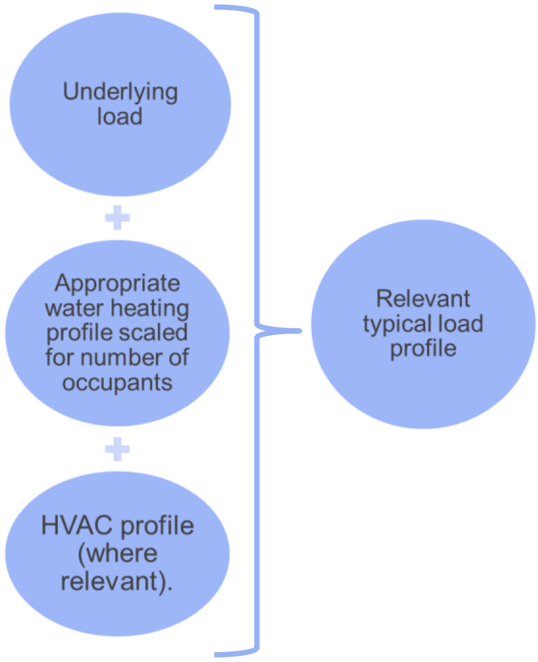


Figure 7 Process for building up the typical load profiles

3.6 Scaling up typical household sub-load and load profiles to derive a community load

To scale up the typical sub-load and load profiles to represent the power load associated with a boundary or feeder, a simple proportional scaling method is used. The method aims to produce a more accurate representation of the share of different customer types – with different electricity consumption patterns and trends – in the aggregated community-wide load profile. Rather than assuming that the base Wattwatchers device sample represents all Heyfield electricity consumption, the typical load profiles derived for various categories are scaled up using multipliers based on the data representing that category (for example, households with HVAC) from a combination of site visits and Ecologic audits.

Scaling up the typical load profiles using multipliers obtained from Ecologic and site visit data should correct for any category bias in the sample data. For example, the Ecologic survey responses have identified that 18% and 53% of dwellings have electric heating and electric water heating systems, respectively.

However, there is limited information on the percentage of off-peak and day-rate hot water systems in the Ecologic audits, so it was assumed that the same breakdown (off-peak vs day-rate) that applies to the relevant sub-category of the recruited Wattwatchers devices applies to the boundary of interest, and simply multiply the hourly mean household values for the sub-load profiles of interest by the relevant share of off-peak and day-rate consumption.

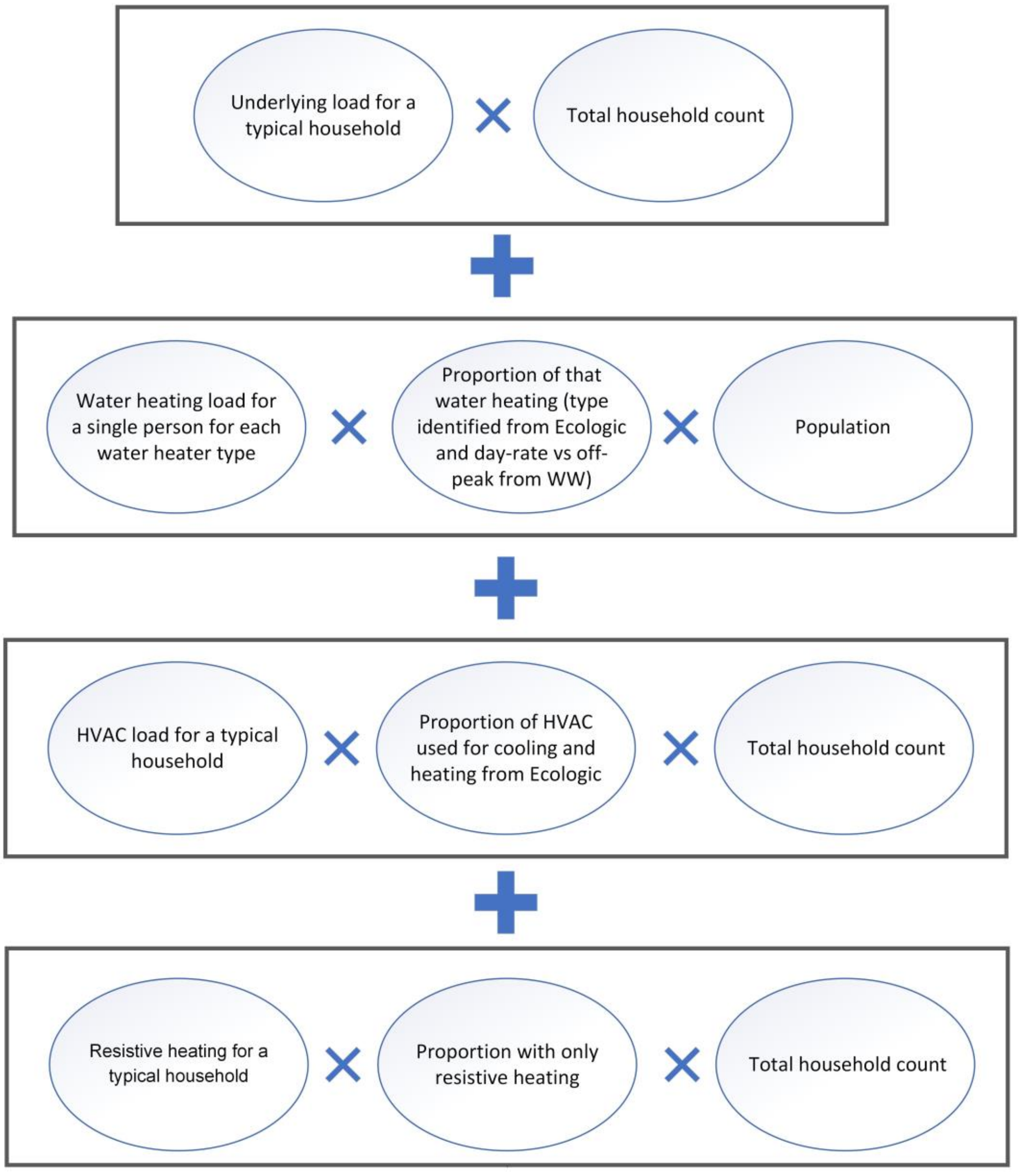


Figure 8 Illustration of the proposed method for scaling up load profiles

Similarly, given the lack of data, we assume that the same breakdown that applies to the proportion of water heating and HVAC used for cooling and heating from Ecologic audits applies to the boundary or feeder of interest.

Also note that, as illustrated in the process of deriving the underlying load, for solar PV-equipped dwellings, the total load records are adjusted to reflect gross rather than net load.[y] Furthermore, in instances where it is not feasible to isolate resistive space heating loads, these are assumed to be part of the underlying load.

[y] Accordingly, benchmarking the accuracy of the derived load profiles against real-world records would need to be conducted using gross load data. That is, if net-metered load data is available, solar generation will need to be added back to it to give gross load data. This also holds true for separately metered sub-loads on controlled load tariffs.

Figure 8 illustrates the overall method for scaling up typical household sub-load and load profiles to derive a community load.

An alternative method is presented in Appendix B: Scaling up of typical load profiles using occupancy information for scaling up typical load profiles in situations where more information on the occupancy levels of households with monitoring devices installed is available.

3.7 Legal and ethical considerations

The participants in this project have agreed to the anonymised sharing of their energy data as part of the registration and consent form process. Wattwatchers Device IDs are the serial number of the Wattwatchers devices and are not considered identifying information, as they are similar to a National Metering Identifier (NMI) or a meter serial number. However, extreme care has been taken when creating data that links the Wattwatchers Device IDs with customer addresses, names, and email addresses. In terms of reporting the data, confidentiality has been maintained by aggregating the data and referring to participants by the type of their ecologic attributes.

Participants have provided additional data through an Ecologic energy questionnaire response that contains particularly sensitive customer information (including information on home occupancy and income) that has only been made available in de-identified forms. It is considered acceptable to link the Wattwatchers Device ID with the de-identified Ecologic responses, but this information has been carefully controlled.

The following procedures are also in place for the storage of, access to and disposal of individual data, both during and at the end of the research: (i) all electronic copies are held securely in a strong password-protected way, (ii) all electronic data will be deleted on the date given below, and (iii) no hard copies are allowed.

Also, during the study, the data are stored and will be stored after the study is completed in the de-identified form. Moreover, access to non-aggregated but de-identified data is restricted to the primary researcher and immediate research team. In addition, all de-identified individual research data will be appropriately destroyed after five years on 01/01/2027.

The information and datasets obtained in this project may only be used for the purposes of the Heyfield MyTown Microgrid project. The data from the Wattwatchers devices may be used as per the Wattwatchers terms and conditions available at https://mydata.energy/terms as the customers have accepted these are part of the registration and consent form process.

4 Results

4.1 Overview

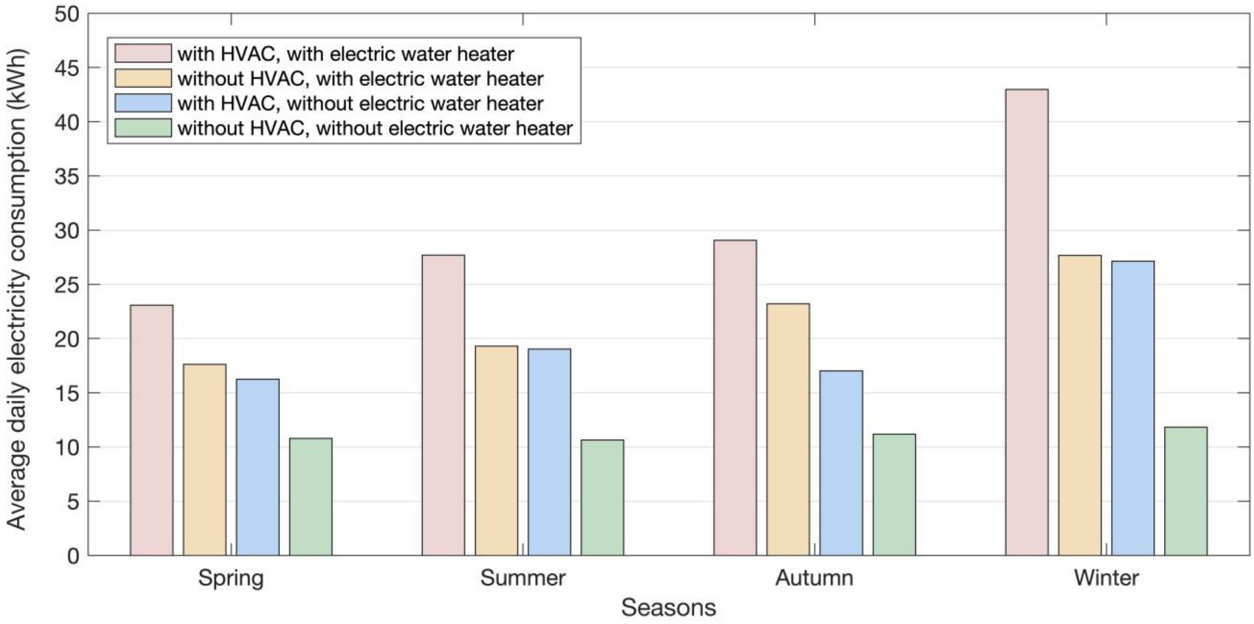


Figure 9 Average daily electricity consumption per season per category of household type (excluding electrically-boosted solar hot water systems)

Figure 9 summarises the daily average amount of electricity "average" houses in different categories consume (with and without electric hot water, with and without HVAC). All the graphs include both small and medium occupancy homes, and electric water heating refers to both controlled (off-peak) and uncontrolled (day-rate) sub-categories. The graphs exclude electrically-boosted solar hot water systems because including them would have skewed the mean seasonal values to wintertime, as the relevant data suggest that standard solar water heating systems can produce around 75% of an average household's water heating in summer, which reduces to around 25% in winter. More specifically, the bars associated with the electricity consumption of electric boost elements of SWHs would fall between the bars associated with the electricity consumption of household types with and without electric water heaters. The consumption would be closer to those with electric water heaters during the winter and closer to those without electric water heaters during the summer.

The green bars represent the load without HVAC and without hot water, which has very little seasonal variation. HVAC use is highly seasonal, with the greatest use in winter[z] (15.30 kWh, on average, for homes with and without electric water heating), falling to an average of 5.46 kWh in spring for homes with and without electric water heating.

Hot water use also shows a considerable degree of seasonality, which can be attributed to increased needs for hot water, as well as colder water temperatures and increased heat losses for tank systems in winter[12].

Figure 10 summarises the total annual electrical energy consumption per household type in MWh.

[z] For this study, the seasons are defined as: Spring – September, October, and November; Summer – December, January and February; Autumn – March, April and May; Winter – June, July and August.

Occupancy type	with HVAC, with electric water heater	without HVAC, with electric water heater	with HVAC, without electric water heater	without HVAC, without electric water heater
Medium occupancy	10.86	8.93	6.01	5.14
Low occupancy	7.21	6.11	4.77	4.19

Figure 10 Summary of the total annual electricity consumption of household types in MWh

Water heaters have the greatest effect on both the scale and seasonality of the overall residential load profile. The slight seasonality of the load without electric space and water heating can be explained by the increased need for lighting and unidentified resistive heating loads.

For greater insights into the contribution of different water heating systems to the seasonality of average daily electricity consumption, Figure 11 shows the breakdown for houses with the three electric water heater types (heat pumps, standard electric elements, and electrically-boosted SWHs), but not further sub-classified into those with and without HVAC[aa]. The bar charts are revealing in the following ways: (i) the consumption of the electric boost elements of solar hot water systems is particularly concentrated in colder autumn and winter months, as one would expect, and (ii) a direct comparison of the customers with heat pump water heaters and conventional electric resistance units highlights the comparable sensitivity of the consumption associated with the two water heating types to lower temperatures.

It should be noted that the performance and efficiency of heat pumps are highly dependent on the conditions in which they are operated. Specifically, heat pump water heaters transfer heat from the surrounding air to the water and will produce exhaust air that is cool and dry. This leads to higher heating bills in the winter months, particularly in colder climates[bb]. This is particularly so in view of the fact that heat pumps do not heat water as quickly as conventional electric resistance water heaters, particularly when recovering after a significant draw.

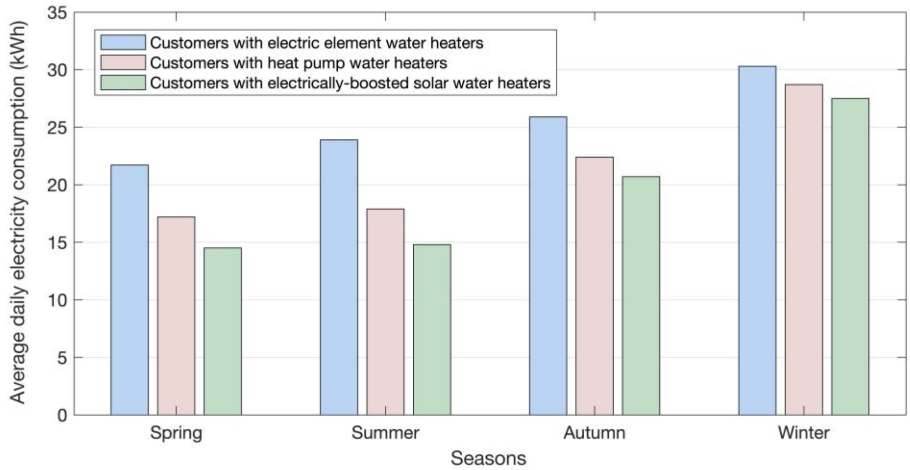


Figure 11 Average daily residential electricity consumption per season per category of hot water system

[aa] Note that the average daily consumption values for customers with heat pump water heaters and standard electric element water heaters, when combined into a single category, are equal to the corresponding average values for customers with electric water heaters shown in Figure 9, recalling that the values in Figure 9 exclude electrically-boosted solar hot water systems. In other words, Figure 9 combines the data for heat pump and standard electric element water heaters into a single category, while Figure 11 separates the data for heat pump and standard electric element water heaters.

[bb] Because the cool air from the heat pump water heater will force the heating system to work harder, paybacks for heat pump water heaters will be longer in colder climates.

4.2 Consumption by main end use

This section presents the average hourly electricity consumption per season for different household types disaggregated into the major sub-loads of HVAC and electric water heaters, as well as everything else (that is, general power or plugs, including ovens).

4.2.1 HVAC sub-load

The HVAC sub-load profile has been derived from all dwellings with HVAC (a total of 61 devices). Figure 12 shows the average hourly electricity consumption of the HVAC system of an average house per season. The numbers in the titles (n) are the total number of households used to derive the average load in each case. As one would expect, more electricity tends to be consumed by an average-sized HVAC system in both winter and summer, as compared to autumn and spring. The highest electricity consumption of HVAC systems generally happens during the evening peak hours, between 4:00 p.m. and 10:00 in the summertime and between 5 p.m. and 11:00 p.m. in the wintertime. Another important insight emerging from the seasonal HVAC sub-load profiles is the lower peak-to-average ratio (i.e., the higher load factor) in the wintertime due to the greater electricity consumption during the morning peak hours.

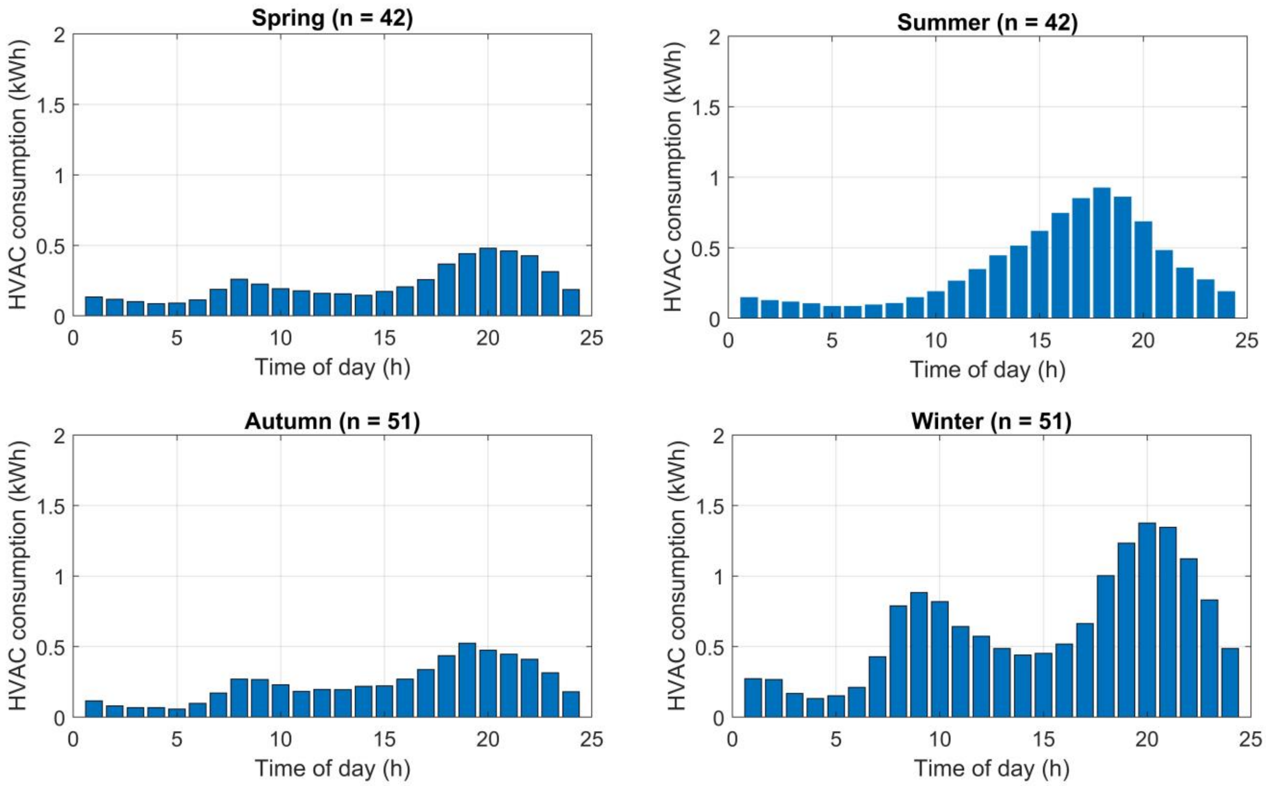


Figure 12 HVAC electricity consumption of an average house per season

Furthermore, Figure 13 deals with the 10th and 90th percentiles of the collected HVAC data[cc], to illustrate the variability of the HVAC consumption pattern across the recruited cohort of HVAC systems. Importantly, as the associated variability patterns indicate, the 90th percentile of the relevant data could be more than double the average values, whereas the 10th percentile could be as low as half of the corresponding average values. This observation can be probably explained by using HVAC data associated with all occupancy categories to achieve an adequate level of statistical representativeness. Additionally, given the observation that some

[cc] It is worth illustrating that where the 90th percentile of the load data at a certain hour of a certain season is equal to x kWh, this indicates that only 10% of all the data points in that sub-set (consisting of all the relevant houses and all days of the relevant season at that hour) are greater than x kWh. For example, let we have10,000 data points for 4 p.m. of summer, and the 90th percentile of those data points is equal to 4 kWh, this means that 4 kWh is the 9,000th highest ranked data point (10,000 data points $\times$ 0.9) – and 1,000 data points are higher than 4 kWh – amongst all the relevant houses and all days of the relevant season.

households in the low occupancy category are associated with greater HVAC consumption compared to those in the medium occupancy category, even if more data points were available, it would have still been plausible to take the average over the entire fleet – particularly in view of the unidentified share of wood and HVAC heating for households that might have both.

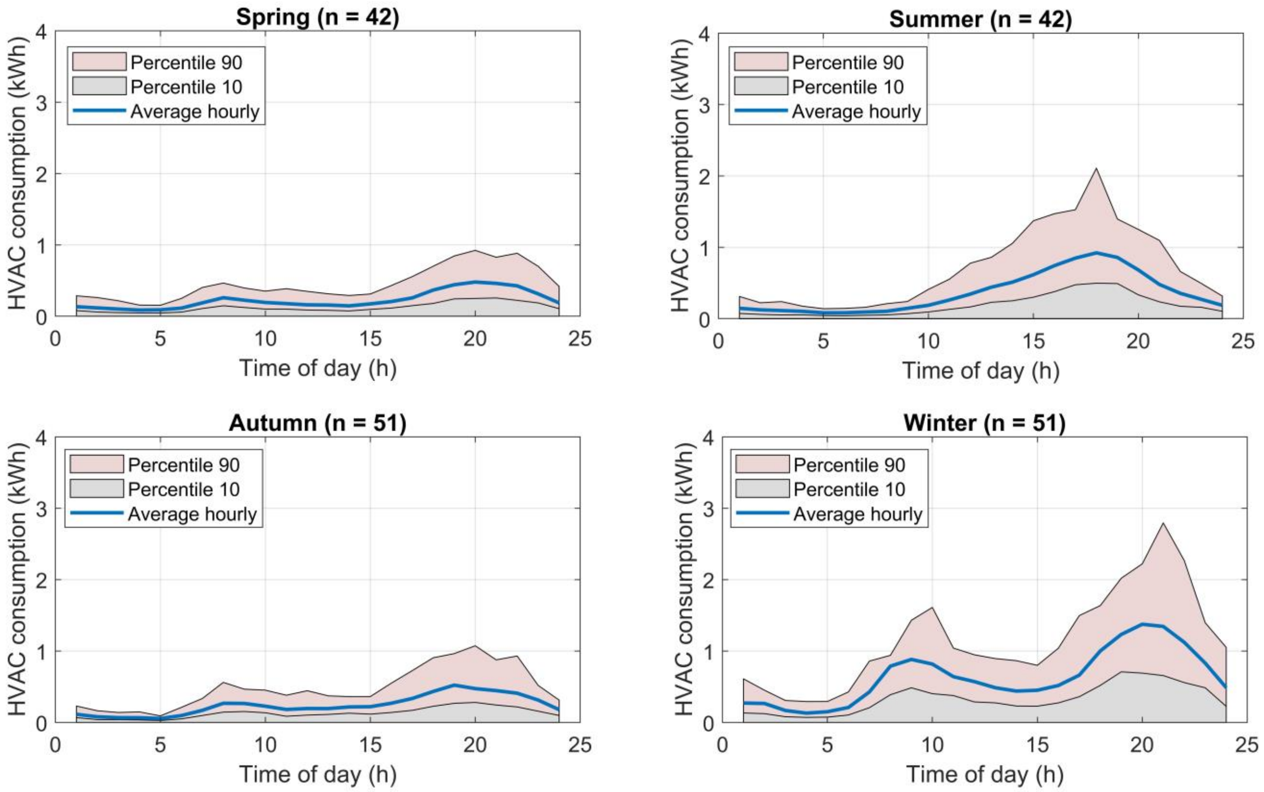


Figure 13 Illustration of the variability of the HVAC consumption across the associated fleet

4.2.2 Electric water heater sub-load

As described above, for the purposes of this study, the electric water heating systems are broadly classified into (i) standard electric hot water cylinders which include an electrical heating element, (ii) heat pumps, and (iii) electric boost for solar hot water systems.

Following the per-occupant scaling approach (Section 3.5.4), this sub-section provides the seasonal average hourly electricity consumption of the three system types broken down into off-peak and day-rate sub-classes.

Determining which type of water heater and whether it is controlled

Note that we were still limited by the households who have completed the Ecologic surveys and stated both the number of occupants and the type of water heaters. Controlling the hot water load is carried out using an advanced internal two-element "smart meter" where the second element applies to a dedicated circuit that is switched by AusNet Services, and that is required to be separately measured as the off-peak load.[13] Three relevant residential tariff structures, namely NAST13, NAST14, and NAST15 are available for the controlled loads:

- NAST13: 11:00 p.m. to 7:00 a.m. Monday to Sunday
- NAST14: 11:00 p.m. to 7:00 a.m. and 1:00 p.m. to 4:00 p.m. Monday to Sunday
- NAST15: 6 or 8 hours between 8:00 p.m. and 8 a.m. Monday to Sunday

To identify whether a hot water system is on a controlled load or not, a combination of Ecologic audit surveys (where available) and checking out the patterns of recorded data was used. Given the lack of readily available data on the actual tariff classes for the controlled loads, we had to manually check the associated patterns of electricity consumption to identify the tariff. In doing so, we considered the tariffs NAST13 and NAST15 as one category, and the tariff NAST14 as the other. This is because the tariffs NAST13 and NAST15 are virtually the same, and no electricity consumption from controlled water heating loads was found to occur in the period 8 p.m. to 10 p.m. or at 8 a.m. in the sample of dwellings studied.

4.2.3 Different water heating loads compared

Figure 14 compares the average daily electricity consumption per season of the hot water system types studied on a per-occupant basis. The results depicted in the figure indicate that standard electric element hot water systems are the most energy-intensive option for providing hot water. Heat pump hot water systems have a much lower energy consumption, approximately 50% less than that of standard electric element systems, on average. This is due to the fact that heat pump systems use a small amount of electricity to transfer heat from the air, rather than generating heat through resistance. The data in the figure also illustrate that the energy consumption of electrically boosted SWHs is comparable to that of heat pump hot water systems in winter but is particularly low in summer due to the abundance of solar energy available.

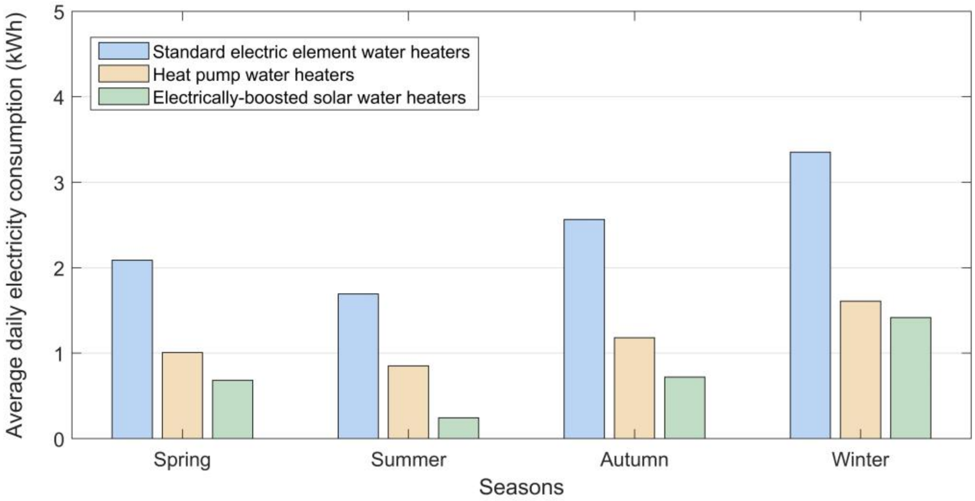


Figure 14 Average daily electricity consumption of hot water (per occupant) by type and season

Table 3 provides a comparative summary of the per-occupant total annual electricity consumption of the three electric water heating types with a breakdown of the systems on continuous electric supply and existing controlled load tariffs – under the assumption that the devices not linked to Ecologic responses with stated number of occupants are associated with an average occupancy of 2.5 people. The table indicates that the estimated total annual electricity consumption values derived from the average values of the studied samples are nearly the same for the controlled and the corresponding uncontrolled categories of all three electric hot water systems, despite the extremely small sample size in some categories. The results also suggest that heat pumps and electric boost elements of solar hot water systems consume comparable total annual electricity per occupant, both of which are found to use 60% less energy, on average, compared to conventional resistive electric element systems.

The results suggest that there is no major difference in consumption driven by the tariffs, and that households exhibit similar levels of total energy consumption for water heating over a given period regardless of their tariff. This indicates that the consumption of energy is driven more by the habits of households, rather than the tariffs they are on[dd].

[dd] The minor observed differences in consumption between different tariffs could be explained by sample noise, or could be a result of slightly higher losses because the water is heated overnight, rather than in response to demand.

Table 3 Per-occupant annual electricity consumption of various hot water systems by tariff

Network tariff	**Type of hot water system**		
	Electric boost of solar hot water systems	Standard resistive electric element systems	Heat pumps
Continuous supply (day-rate)	275 kWh	829 kWh	330 kWh
Night-rate controlled load (NAST13 or NAST15)	304 kWh	873 kWh	361 kWh
Night-rate controlled load with afternoon heating boost (NAST14)	N/A	N/A	322 kWh

It is also noteworthy that the comparability of the total annual hot water consumption values for the controlled and uncontrolled variants of the same hot water category indicates that almost all the samples included in the uncontrolled category meet the system size eligibility conditions that are common for connecting electric storage hot water systems (usually greater than 100 litres) for connection to controlled load tariffs.

Appendix C: Hot water system profiles presents and provides an in-depth discussion of the load profiles associated with various hot water systems types on different tariffs.

4.3 Typical underlying load excluding HVAC and hot water

The typical underlying load excluding HVAC and electric hot water components in Figure 15 represents the average hourly consumption pattern of the underlying load of an average house per season, which illustrates the different times of the day when the total electricity consumption is the highest, particularly in the evening peak hours. The figure reveals a modest degree of variability (see morning and evening peaks) throughout the year, although much more pronounced in the winter evening, which can be attributed to the lighting use. Note that lighting use is concentrated in winter due to fewer daylight hours.

It is also noteworthy that given that only two Ecologic responses indicated houses with nothing but electric resistive heating, it was not possible to isolate the demand of electric resistive heaters, and it is combined with other underlying loads. However, given the high share of non-electric heating appliances used for space heating and that only two houses have nothing but electric resistive heaters, it is not inconceivable that electric-resistance heating in theory constitutes only a relatively small fraction of the overall load. This is particularly true in view of the considerable uptake of heat pumps in Heyfield. Collectively, the aforementioned observations indicate that it is probably not unreasonable to assume that the isolation of the electricity consumption from electric resistive heaters would not have made a material difference to the derived underlying load profiles.

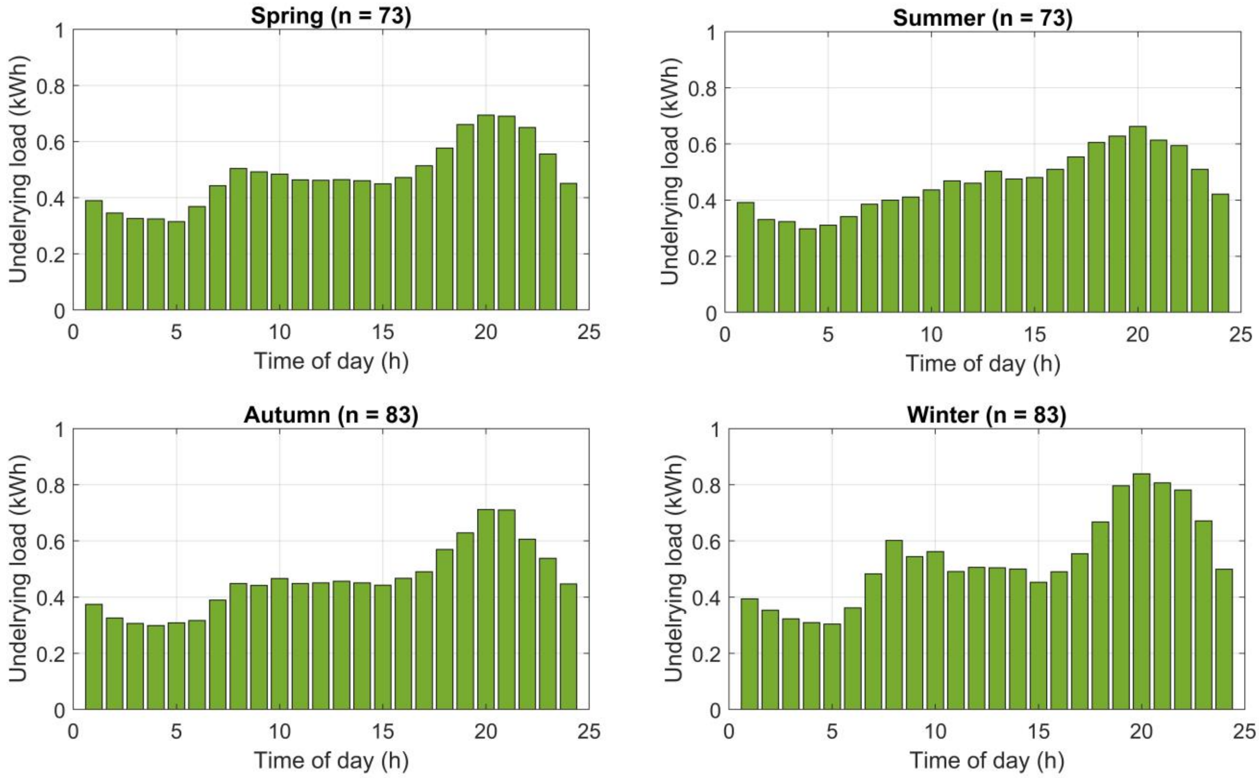


Figure 15 Underlying load of an average house per season

Also, Figure 16 shows the 10th and 90th percentiles of the collected and processed underlying load data to illustrate the variability of the underlying consumption pattern across the monitored houses. Again, note that this study has focused on averaging the underlying load across the entire cohorts of houses for reasons of improved sample representativeness and energy usage variations, but the most household size-sensitive sub-load, namely electric hot water, is derived on a per-person basis.

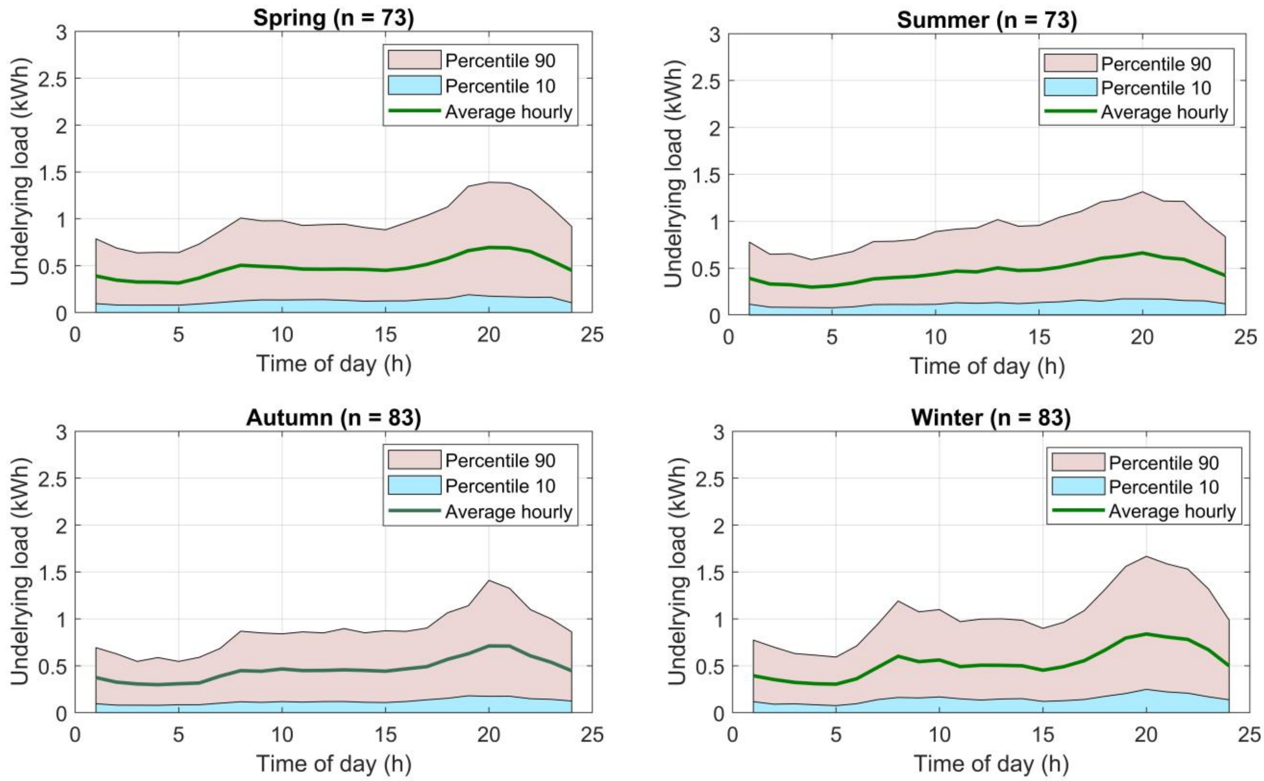


Figure 16 Illustration of the variability of the underlying load across the monitored houses

4.4 Comparison of households with and without solar PV

To show why it was decided not to select two meta-classes of customers with and without solar, the following process is followed to separate the underlying load of houses with and without solar PV:

1. Separate houses into houses those with and without rooftop solar PV
2. For houses with solar PV, adjust so it is pre-solar load
3. Subtract the actual HVAC Profile from ones with HVAC
4. Subtract the actual electric water heating profile (where appropriate)
5. Derive the average load separately for houses with and without solar

Accordingly, Figure 17 compares the derived underlying load profiles for the two meta-classes of customers with and without solar PV per season. As the figure indicates, for the PV-equipped dwellings, the underlying profile does not tend to be particularly biased towards solar generation times, thereby supporting the decision of not splitting the entire cohort into those with solar and those without.

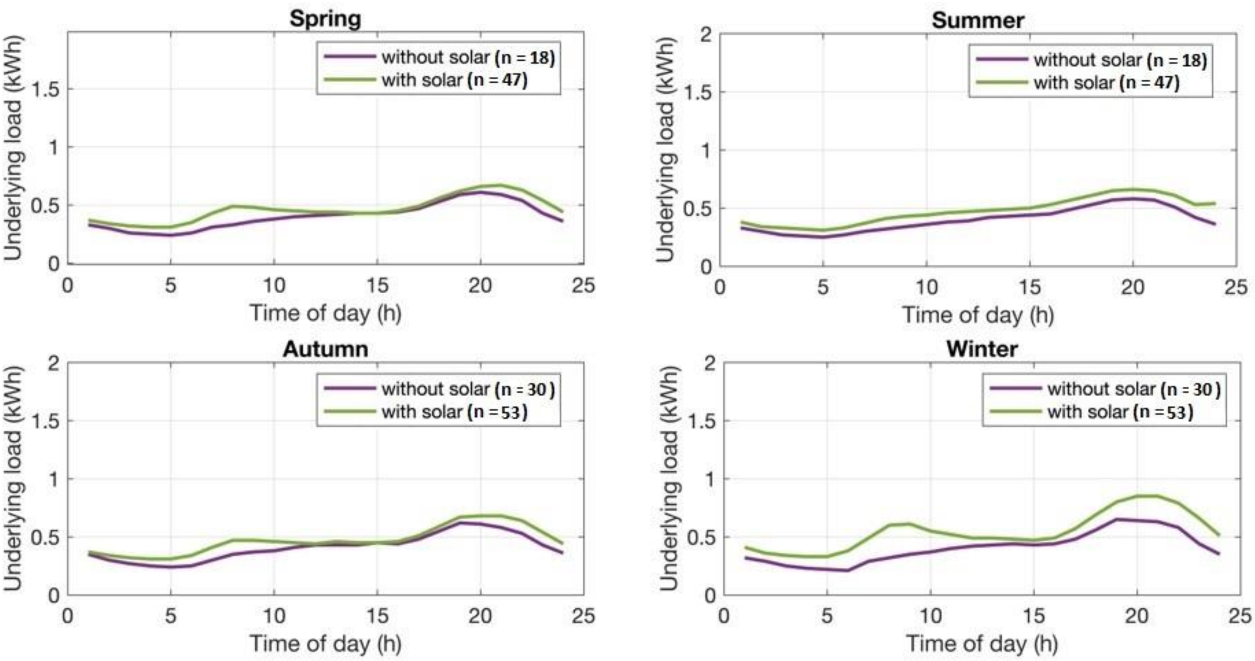


Figure 17 Underlying load profiles for customers with and without solar PV per season

4.5 Rooftop solar PV generation

Figure 18 provides a bar chart representing the average daily electricity generation by rooftop solar PV systems per season for all the 61 PV-equipped dwellings, including those with linked Ecologic surveys and those without.

While the associated self-consumption components of households with rooftop solar PV are accounted for in the associated load profiling processes, generating the average town-wide residential gross PV generation profile was deemed to be particularly useful for planned future analyses, including the analysis of a front-of-the-meter community battery on one of the residential LV feeders. Recall that because no drastic changes were observed in either the overall load shape or the total annual consumption of households with and without solar (as long as they are in the same category in terms of occupancy), it was decided to add the solar PV generation records of PV-equipped dwellings to the corresponding net-metered electricity consumption records without considering separate load profiles for houses with and without rooftop solar PV.

Furthermore, due to the lack of readily available data on floor area (and in turn, roof area), as well as the observation that not all households with a higher occupancy have larger-sized rooftop PV systems, it was decided to take the average of solar generations over all dwellings with installed PV. Accordingly, the typical solar generation data can be easily used for future stakeholder analyses where the load and sub-load profiles produced in this study are present.

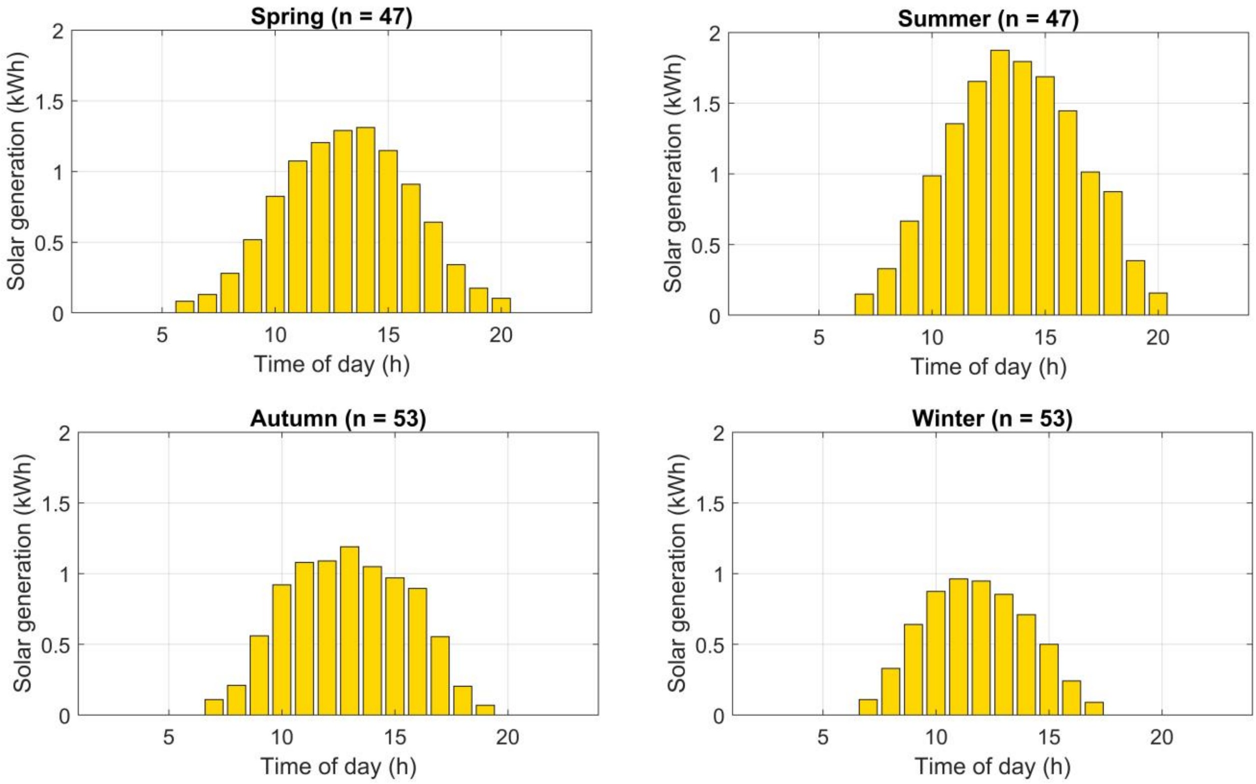


Figure 18 Solar generation of an average PV-equipped house per season

It is also worth mentioning that, as far as the data from Wattwatchers devices are concerned, the average size of the residential rooftop solar PV system is ~4 kW_p the total annual generation of an average house was found to be ~5.7 MWh/year. Note that, given the associated tilt variations, and also due to the fact that average values in Figure 18 represent the same hours of the month[ee], the peak solar generation displayed is not around 4 kWh. More specifically, Figure 19 shows the 10th and 90th percentiles of the collected data, to illustrate the variability of the generation pattern across the fleet of residential PV systems.

[ee] Note that solar generation does not reach its peak capacity at all days of the summer season.

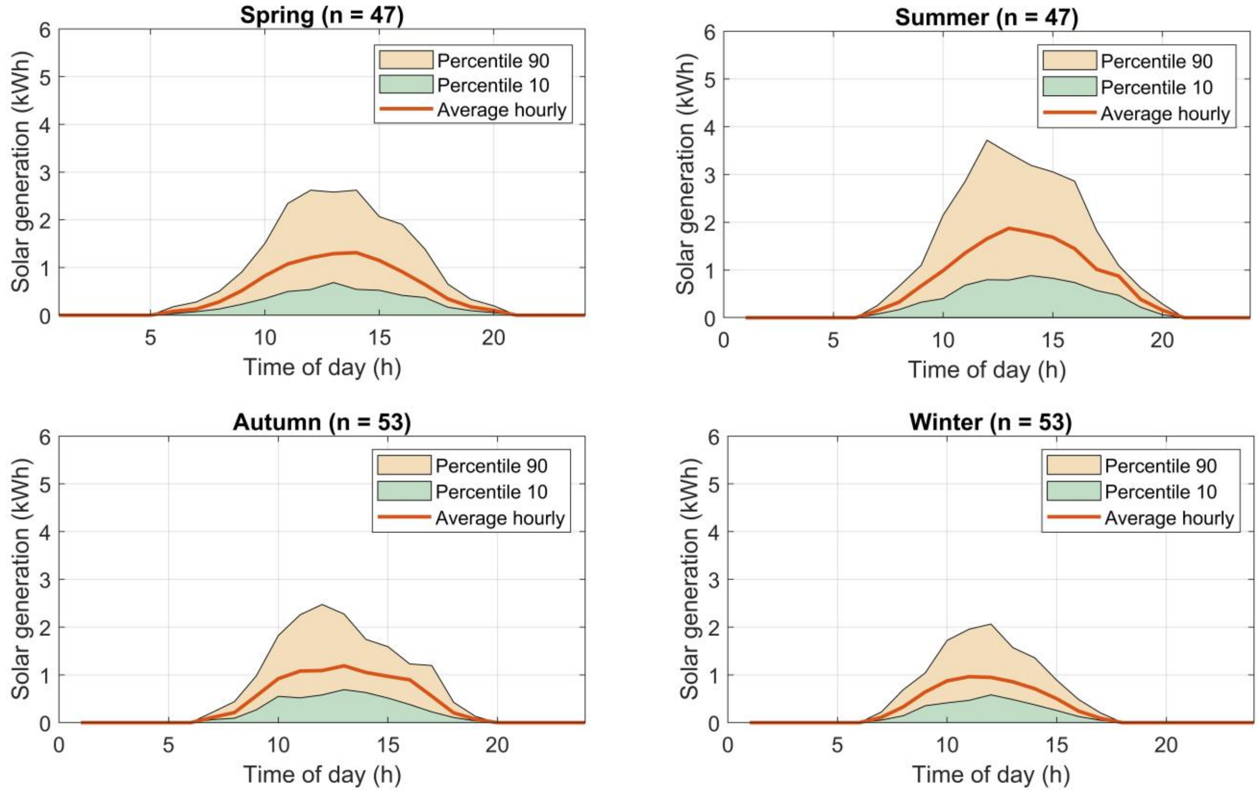
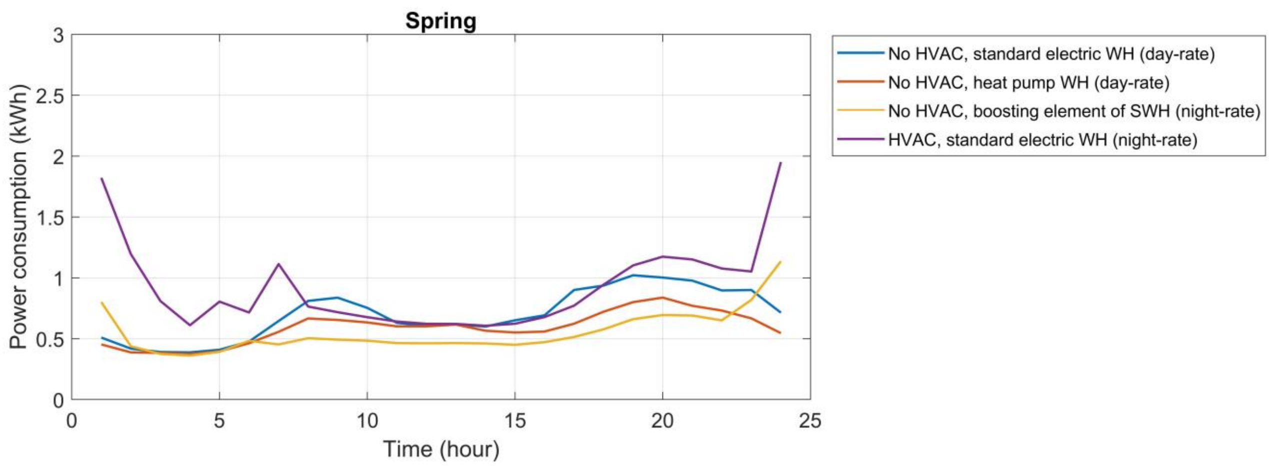


Figure 19 Illustration of the variability of the solar PV generation across the associated fleet

4.6 Typical residential load profiles

In accordance with the approach explained in Section 3.5.7, typical residential load profiles were built up for various adjustments in terms of having HVAC or not and the type of water heater. Note that the typical load profiles are scaled for an average household size of 2.5 people. Also note that given that the underlying load, as well as electric water heater and HVAC consumption components, are derived from varying numbers of datasets, the typical overall load profiles are not associated with unique numbers of underlying datasets/ households. Accordingly, Figure 20 shows the super-imposed typical load profiles per season for the most contrasted combinations of HVAC and electric hot water system ownership.

Appendix D: Numeric values of derived load and sub-load profiles provides the numeric values of typical load profiles derived for various customer categories defined, as well as the numeric values of sub-load and underlying load profiles derived.



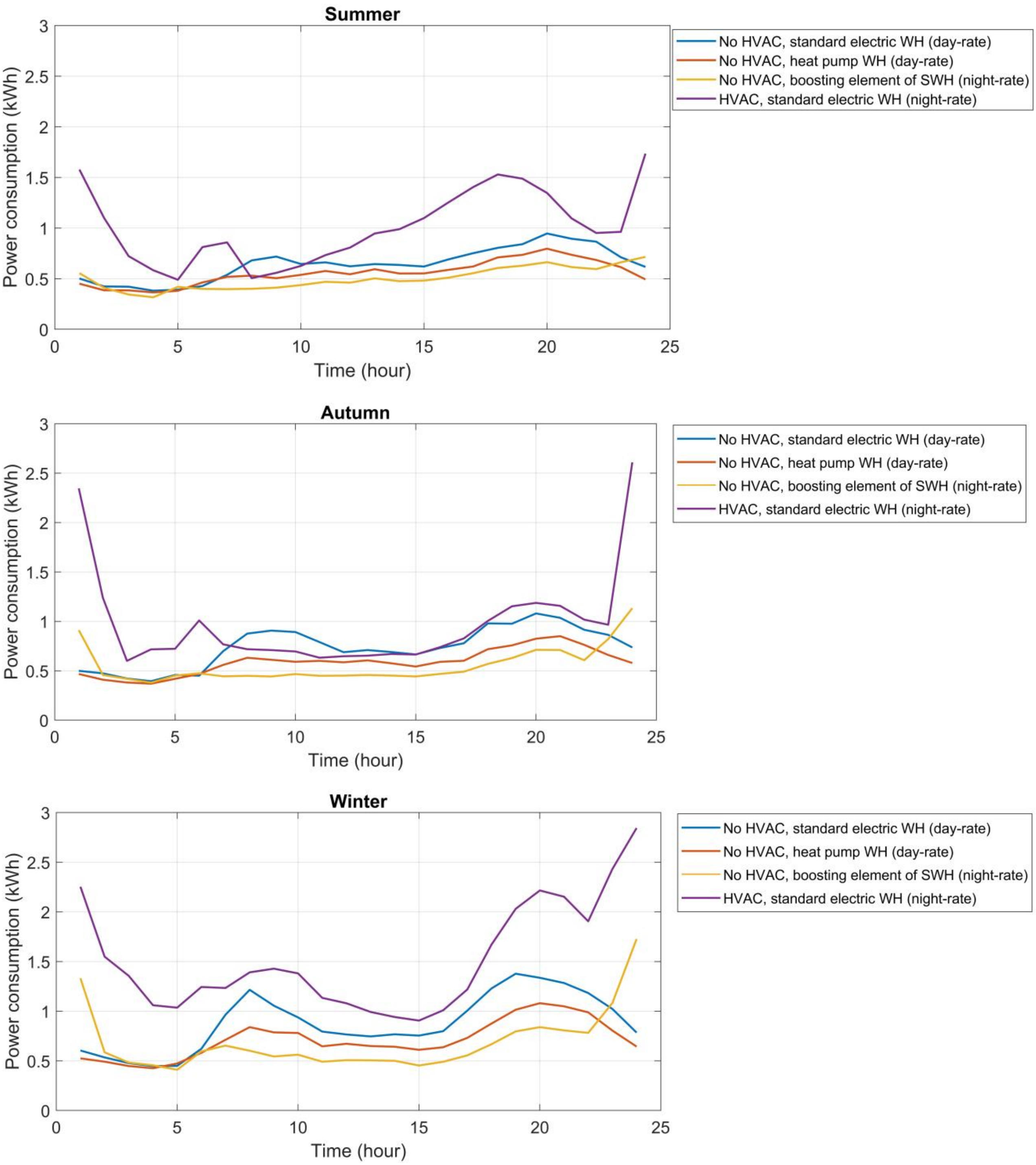


Figure 20 Selected typical load profiles per season

4.7 Scaling up typical load and sub-load profiles

This section compares the load derived from scaling up typical profiles to the actual metered data from smart meters, to see if this is a reasonable approach and can be used in Heyfield and potentially in other communities.

In accordance with the multiplier-based scaling up approach explained in Section 3.6[ff], we wished to compare the scaled up typical load and sub-load profiles with actual metered data for the whole of Heyfield

[ff] Underlying load x total households (N) + Water heating load for a single person for each type x proportion of that water heating x population + HVAC x proportion of HVAC x N.

(754 occupied houses). However, smart meter data separated into residential and commercial customers was only available for three feeders, so we had to benchmark against a smaller number of homes.

AusNet Services provided us with aggregated smart meter data for residential customers for three feeders in Boundary 3. They provided the data split into the following items:

- "main_load", which is the meter readings for loads other than controlled load added together
- "controlled load", which is all the controlled load meter readings added together
- "to_grid", which is all the export solar readings added together

At a feeder level, determining the underlying load also requires adding in any feeder-level solar exports, as those will reduce the net load on the feeder. The underlying load is, therefore, calculated as:

Underlying load = [net load on feeder] + [self-consumption of solar] + [solar exports to grid]

We did this for the three feeders and added the resulting values together on an hourly basis.

On the other hand, the derived typical loads are what is underlying, that is, including whatever load is being met by self-consumption of solar, so:

Underlying load = [main load] + [controlled load] + [solar self-consumption]

We, therefore, had to approximate the kW solar for the three feeders, in order to calculate the self-consumption. We did this in three ways, as follows:

- *Derive kW solar from metered export:* We knew the average export from the typical households with solar profiles. We divided the metered export from the aggregated smart meter data for the three feeders to determine the number of systems that are exporting based on typical size, and used the typical size from the fleet of Wattwatchers devices. This resulted in an estimated 184.7 kW solar for the three feeders combined.
- *Calculate kW from the number of homes:* In this method, we multiplied the total number of houses by the average size of residential PV systems and the average penetration of solar in Heyfield from site inspections. This resulted in an estimated 160.3 kW solar for the three feeders combined.
- *Determine kW from the solar penetration on the residential feeder (feeder #18):* This feeder has no commercial customers. It has 107 residential customers, and 31 customers with solar with a total solar capacity of 88.53 kW. This corresponds to a penetration of 29% of homes, with each having 2.86 kW. We assumed this penetration for the other two feeders. This resulted in an estimated 152.6 kW solar for the three feeders combined.

We estimate there are a total of 184 occupied homes on the three feeders of interest. There were 230 customers recorded for the three feeders (that is, 230 metered supplies), but we estimated that 10% were unoccupied[gg,14], and another 10% resulted from multiple meters at the same premises[hh].

[gg] The 2021 Census reveals that about 10% of Australia's private dwellings were unoccupied on the night of the Census for various reasons, such as homes owned by people currently living overseas, homes are being renovated, homes being sold as vacant possessions, holiday homes, and so forth. These get included in AusNet number of houses even if they are de-energised. They might also be "between tenants", that is, energised but have very low consumption.

[hh] According to the on-site investigations and communications with AusNet Services, the customer numbers recorded for the three feeders of interest may be 10% too high due to the presence of multiple meters at some premises. This could result in an overestimation of the number of occupied homes. This argument is supported by our following observation: We estimate that there are 735 occupied homes in Boundary 3. However, there are 1,148 energised NMIs. This difference may be accounted for by multiple meters, with some of the difference also accounted for by business customers.

Then, following the proposed approach in Section 3.6, we scaled up the derived typical sub-load and underlying load profiles for the estimated 184 effective residential customers. We used the simplifying assumption that the feeders are perfectly typical, that is, we used the average penetration of sub-loads (HVAC ownership, for example) for Boundary 3, as we did not have information specific to the feeders. These multipliers were based on a mixture of site visits and survey data.

Following the observation that the houses with and without rooftop solar PV are not associated with materially different load profiles (see Section 4.5), it was decided to undertake the aggregation without splitting the houses into those with and without solar.

To benchmark the accuracy of the scaled-up typical load profiles against the corresponding actual feeder-level data, we used the mean absolute percentage error (MAPE) metric, which is the standard metric for load profile benchmarking purposes. The MAPE metric represents the arithmetic average of the ratio between the absolute error in approximation and the actual demand in $n = 8760$ intervals, as follows:

$$MAPE = \frac{\sum_{i=1}^{8760} \left|\frac{E(i)}{M(i)}\right|}{n} \times 100$$

where $E(i)$ is the absolute error in forecasts and $M(i)$ is the measured feeder-level demand data.

The MAPE values obtained when estimating kW solar for the three feeders from the three methods defined above were found to be 40%, 30%, and 28%, respectively. This indicates that the estimated solar generation is a key influence on the calculation of load, which is unsurprising.

Figure 21 shows the scaled-up typical load profiles for the three feeders of interest and the corresponding sum of actual feeder data for three representative months – when using the solar generation estimation method that gives the lowest MAPE value (method 3). Refer to Appendix E: Comparison of scaled up derived load profile and actual feeder data for the comparison of all months. It can be seen that solar generation hours are the least well-performing hours in terms of matching up, which can be largely explained by the significant role of estimated solar generation and the associated inaccuracies.

While the uncertainties associated with scaling up should be considered, the derived load and sub-load profiles provide valuable insight into electricity demand in rural regions of Australia and can inform predictions for the future.

It would be prudent for users to try and find community-appropriate multipliers when scaling up from the profiles, as these play a significant role in minimising the margin of error[ii] in the confidence interval[jj] – in line with setting future expectations of electricity demand across other regions of Australia. One of the variables (amount of solar installed) could potentially be estimated directly by communities wishing to estimate their loads, which would remove a source of error, as would gaining reasonably accurate multipliers on penetrations of HVAC or different types of water heating.

[ii] The margin of error is a measure of the precision of an estimate, and it is typically expressed as a percentage or a decimal. It is affected by several factors such as sample size, population variability and level of confidence. To minimise the margin of error, one can increase the sample size, decrease the level of confidence, or reduce population variability.

[jj] A confidence interval is a range of values that is likely to contain the true value of a population parameter with a certain level of confidence, usually expressed as a percentage (e.g. 95%).

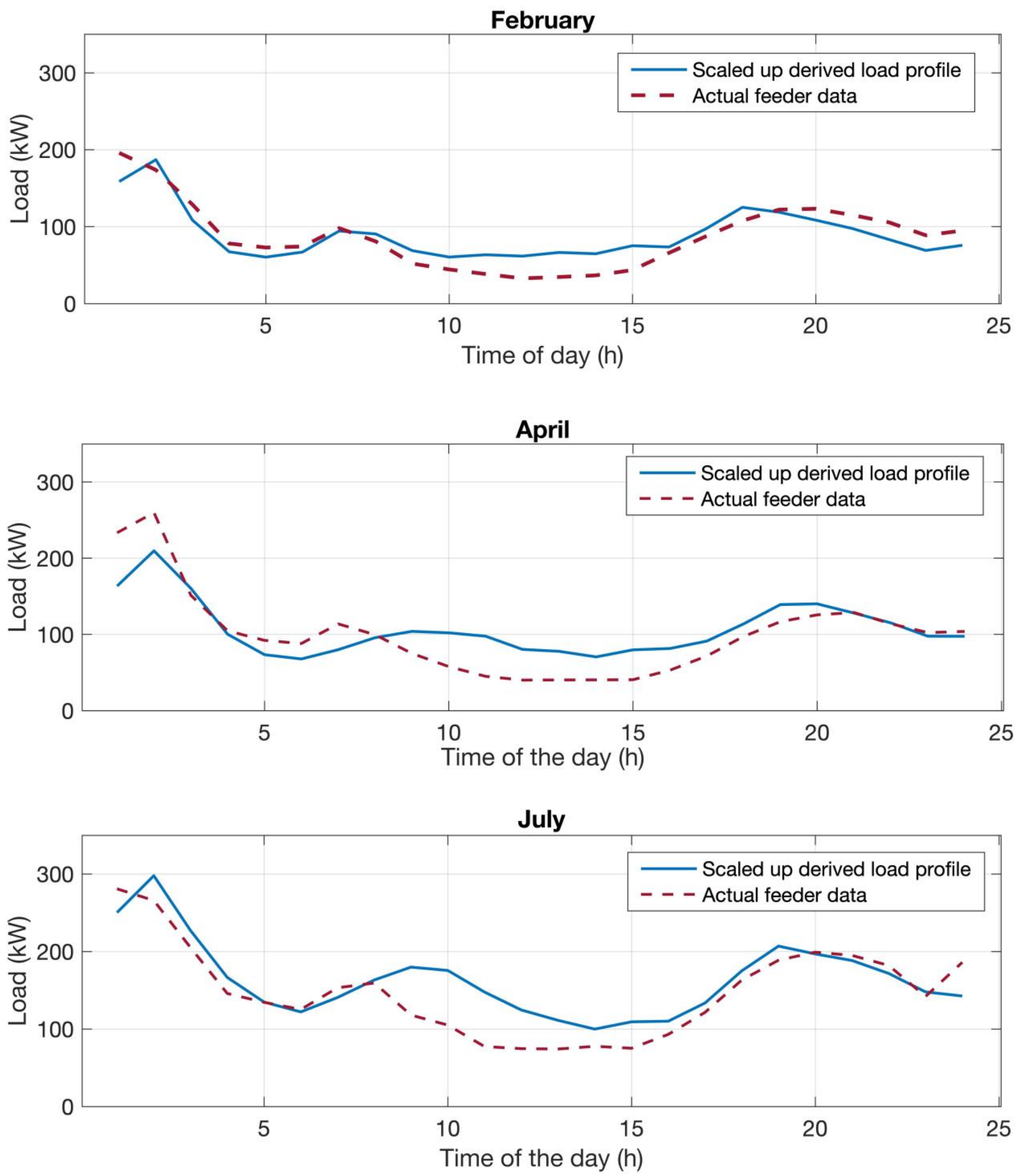


Figure 21 Scaled up derived typical load profiles benchmarked against actual feeder data by month
Data shown for a summer month, a transition month, and a winter month; the sum of the three feeders of interest

5 Limitations

The load and sub-load profiles derived in this study are specific to rural communities in Australia and cannot be directly applied to urban or suburban areas. Rural communities may have less diversity in load profile than urban areas as most residents have similar building types, equipment and appliances, and energy consumption patterns may be more similar[kk]. While this study provides statistically robust insights into the residential energy consumption patterns in rural areas, the load profiles derived from this study are limited by several factors, namely:

- No actual data on electric resistance heaters was available given the absence of a dedicated circuit in the property switchboards. This causes particular uncertainty in some cases where reverse-cycle air conditioners were switched off in late evening hours of wintertime, indicating that either a separate unmeasured HVAC system or an electric-resistance heater may be used. However, electric-resistance heating is thought to constitute only a relatively small portion of the overall load.
- Due to the electrical arrangements at some sites, or the fact that some customers may have had solar installed after the Wattwatchers device was installed, it is possible not all solar generation is directly monitored. In this situation, while the grid channels will still monitor all of the excess solar generation being exported to the grid, total solar generation is not available. While not a frequent occurrence, this introduces some uncertainty in the solar PV generation records.
- If a configuration change is made to correct an installation issue, such as incorrect phase assignment, reversed current transformer (CT) or CT ratio change, then the change only impacts the data from that point forward, as Wattwatchers does not change historical data for individual devices. While not typical, this may also cause some uncertainty around the historical records.
- There could be situations where a CT may be reversed or a channel has been incorrectly labelled and manual data checking has failed to identify the error, although this has been mitigated by the Wattwatchers team inspecting the data to identify major issues.
- Although generally unlikely, it is possible that an HVAC system or electric hot water system is not allocated a specific circuit, and hence is not monitored separately. While such sources of error in deriving the underlying load cannot be ruled out, the positive impact of increasing the sample size – and not limiting the analysis to those linked to Ecologic surveys with identified space heating type – is expected to outweigh the potential inaccuracies imposed.
- Despite significant efforts to avoid it, misallocation of hot water systems to off-peak tariffs cannot be entirely ruled out. For example, provided that units have manual override boost switches, it is technically possible that a solar hot water system with an electric boost element is misallocated to the NAST14 tariff simply because the customer presses the dedicated 'boost' button during the same time period in which the controlled load tariff is applied.

While the limitations outlined above should be considered, the derived load and sub-load profiles provide valuable insight into electricity demand in rural regions of Australia. Nonetheless, it would be prudent for users to take into consideration appropriate multiplier values when extrapolating the profiles, as these play a significant role in minimising the margin of error[ll] in the confidence interval[mm] – in line with setting wider and future expectations of electricity demand across other regions of Australia.

[kk] Diversity here refers to variation in the pattern of electricity consumption across different types of customers, and can be caused by different types of buildings or equipment, as well as different activities and behaviours of the customers.

[ll] The margin of error is a measure of the precision of an estimate, and it is typically expressed as a percentage or a decimal. It is affected by several factors such as sample size, population variability and level of confidence. To minimise the margin of error, one can increase the sample size, decrease the level of confidence, or reduce population variability.

[mm] A confidence interval is a range of values that is likely to contain the true value of a population parameter with a certain level of confidence, usually expressed as a percentage (e.g. 95%).

6 Conclusion and next steps

This analysis aimed to derive typical residential profiles for various categories based on household demographics and electrical asset ownership – including household size, rooftop solar PV, type of hot water system, and type of space heating system – in accordance with data recorded by Wattwatchers devices, with a focus on the distinct demand characteristics of rural communities. Load profiles at a disaggregated (single load) level, particularly hot water systems and air conditioning devices, are derived which can be useful in the planned analysis of load flexibility, which is widely recognised as an enabler of the community battery local energy solution. A load flexibility study is planned study for Heyfield as part of the analysis of local energy solutions.

Some conclusions can be drawn from this load analysis study:

- The residential Wattwatchers sample in Heyfield comprises more heat pump water heaters and HVAC systems than we would expect for the community from which they were drawn mainly due to the community's energy efficiency aspirations. Therefore, care must be taken in extrapolating the derived typical load and sub-load profiles to similar rural communities.

- We have also shown that it is possible to proportionally upscale small samples to produce local electricity load profiles. However, to ensure the robustness of the results, the sample needs to reflect the entire population and adequately represent sub-groups of households – such as those with different electric water heating systems and tariffs.

- In terms of total electricity usage per occupant for water heating, a typical heat pump water heater was found to be able to use 60% less energy (on average) than a standard electric hot water system. Also, electrically boosted solar hot water systems are also found to be associated with total annual electricity consumption values comparable to heat pumps. The energy required for heat pumps is also quite flat throughout the year compared to solar boosting where much of the consumption is attributable to colder winter months.

- The total annual consumption of controlled and uncontrolled sub-categories of the electric hot water systems are nearly the same, which can be probably explained by the size of houses, and in turn, the size of storage hot water systems in Heyfield.

- As the associated variability patterns indicate, the individual HVAC and hot water systems used for deriving the typical sub-load profiles can be more than double the average values or as low as half of the corresponding average values.

- The underlying loads associated with the customers with and without rooftop solar PV systems are not materially different – neither in terms of shape nor total consumption. While it should be in the interest of customers with solar to use as much of the solar power as possible as it is being produced (that is, changing consumption habits to coincide with when the sun is shining), the reason why it has not been the case is probably that the households are not home for the majority of daylight hours. Accordingly, to make the most of their solar systems when they are not home, the occupants are recommended to use the delay start option to run their dishwashers and washing machines around midday (peak sun hours).

Appendix A: Eligibility assessment of devices

Figure 22 provides an overview of the eligibility assessment process of devices, with details of the number of devices for various ineligibility factors.

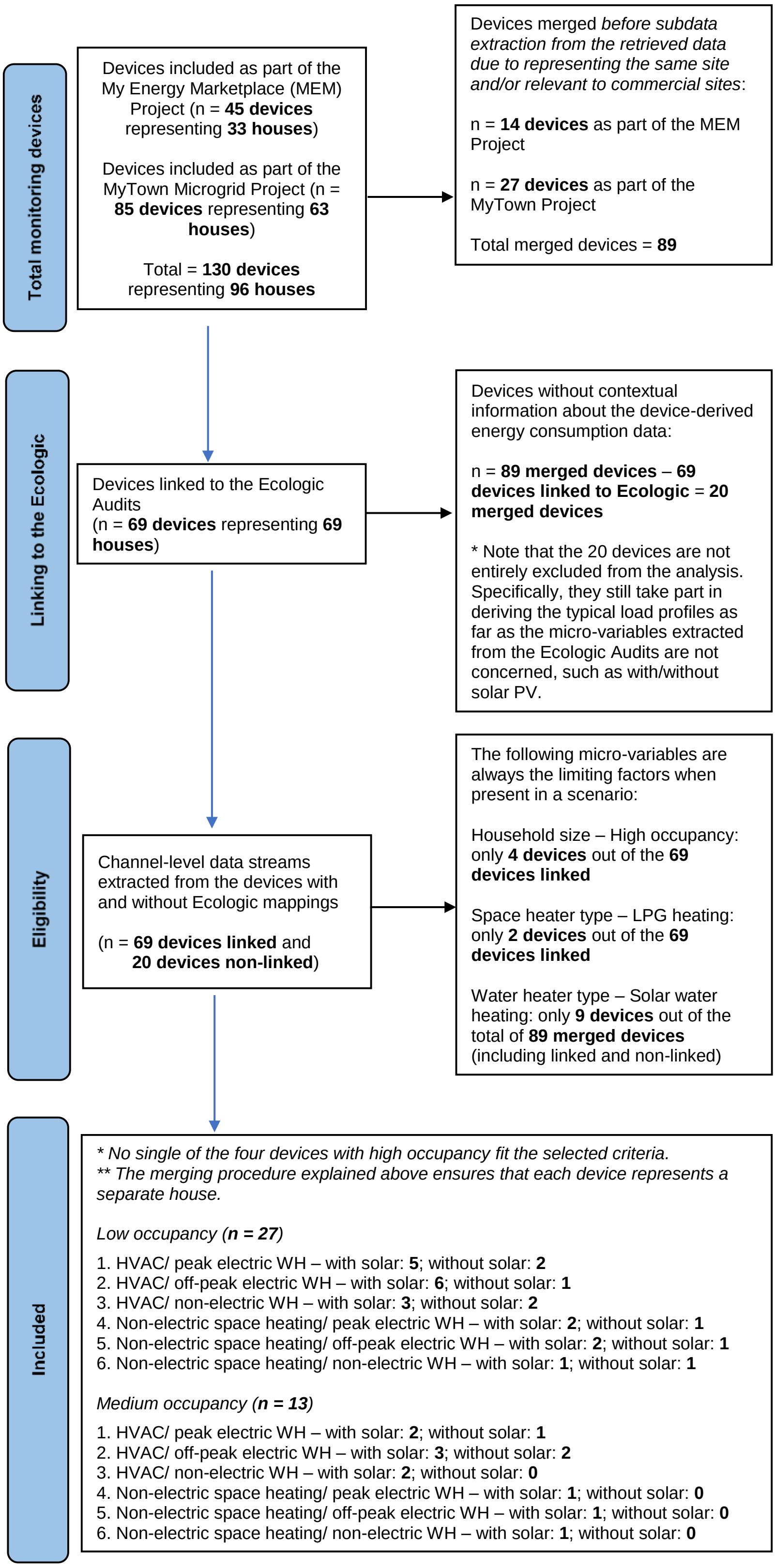


Figure 22 Initial number of device IDs that fit the selected criteria

Appendix B: Scaling up of typical load profiles using occupancy information

To derive community-level load profiles, the typical load profiles can also be multiplied by the number of houses that fit within each household occupancy category in the boundary and the estimates of electric water and space heating prevalence from Ecologic audits, in accordance with Table 4. Also, given the lack of data, we can assume that the same breakdown that applies to the household occupancy from Ecologic audits applies to the boundary of interest (61% low occupancy, 30% medium occupancy, 9% high occupancy).

However, in the cases where only a very small number of device IDs fit a category (for example, 4 device IDs fit the high occupancy criterion in this study), it is suggested to ignore them for consistency reasons[nn]. Accordingly, the household percentages associated with other occupancies (in this case, low and medium occupancies) could be increased by the same proportion – to retain the relationship between them – such that they sum up to 1.

The proportional scaling up process described above would need assigning appropriate percentage values to different load categories[oo], as illustrated in Table 4, for example, based on the data from this study.

Table 4 Percentage contribution of each load category to the overall load demand

Load category	Percentage
Low occupancy	
Premises with HVAC and controlled hot water (including heat pumps, standard electric element, solar hot water with off-peak boost)	4% (2.5% heat pumps, 0.9% standard electric elements, 0.6% electric-boosted solar hot water)
Premises with HVAC and uncontrolled hot water	5% (3.1% heat pumps, 1.1% standard electric elements, 0.8% electric-boosted solar hot water)
Premises with HVAC and non-electric hot water	11%
Premises without HVAC and controlled hot water (including heat pumps, standard electric element, solar hot water with off-peak boost)	10% (6.3% heat pumps, 2.2% standard electric elements, 1.5% electric-boosted solar hot water)
Premises without HVAC and uncontrolled hot water	11% (6.9% heat pumps, 2.4% standard electric elements, 1.7% electric-boosted solar hot water)
Premises without HVAC and non-electric hot water	26%
Sub-total	67%
Medium occupancy	
Premises with HVAC and controlled hot water (including heat pumps, standard electric element, solar hot water with off-peak boost)	2% (1.3% heat pumps, 0.4% standard electric elements, 0.3% electric-boosted solar hot water)
Premises with HVAC and uncontrolled hot water	2% (1.3% heat pumps, 0.4% standard electric elements, 0.3% electric-boosted solar hot water)

[nn] Clearly, the very small sample size of a certain occupancy type would led to significant uncertainty in the estimates of (non-) electric hot water and (non-) space heating systems.

[oo] Given the significant dependency of hot water consumption to the household size, we have normalised the relevant data to per-person consumption, remembering that where an electric hot water dataset is not linked to an Ecologic response with stated number of occupants, it is assumed to be associated with an average household size of 2.5 people. Also given the pre-defined ranges of low occupancy (1 to 2 people) and medium occupancy (3 to 4 people), the per-occupant hot water sub-loads are multiplied by the mean household sizes of 1.5 and 3.5 respectively during the scaling up of the relevant typical load profiles that have electric hot water sub-loads.

Load category	Percentage
Premises with HVAC and non-electric hot water	6%
Premises without HVAC and controlled hot water (including heat pumps, standard electric element, solar hot water with off-peak boost)	5% (3.1% heat pumps, 1.1% standard electric elements, 0.8% electric-boosted solar hot water)
Premises without HVAC and uncontrolled hot water	6% (3.8% heat pumps, 1.3% standard electric elements, 0.9% electric-boosted solar hot water)
Premises without HVAC and non-electric hot water	12%
Sub-total	33%
Total	100%

Appendix C: Hot water system profiles

This appendix presents and discusses the load profiles derived for various hot water systems types on different tariffs.

Electrically boosted solar hot water

Figure 23 shows the seasonal per-occupant average hourly electricity consumption profiles for uncontrolled electric boost elements of solar hot water systems. Although the samples used in this study have too few cases of the uncontrolled electrically-boosted solar hot water system to make the derived seasonal sub-load profiles representative, they confirm that solar boosting requires considerably more energy in the colder months.

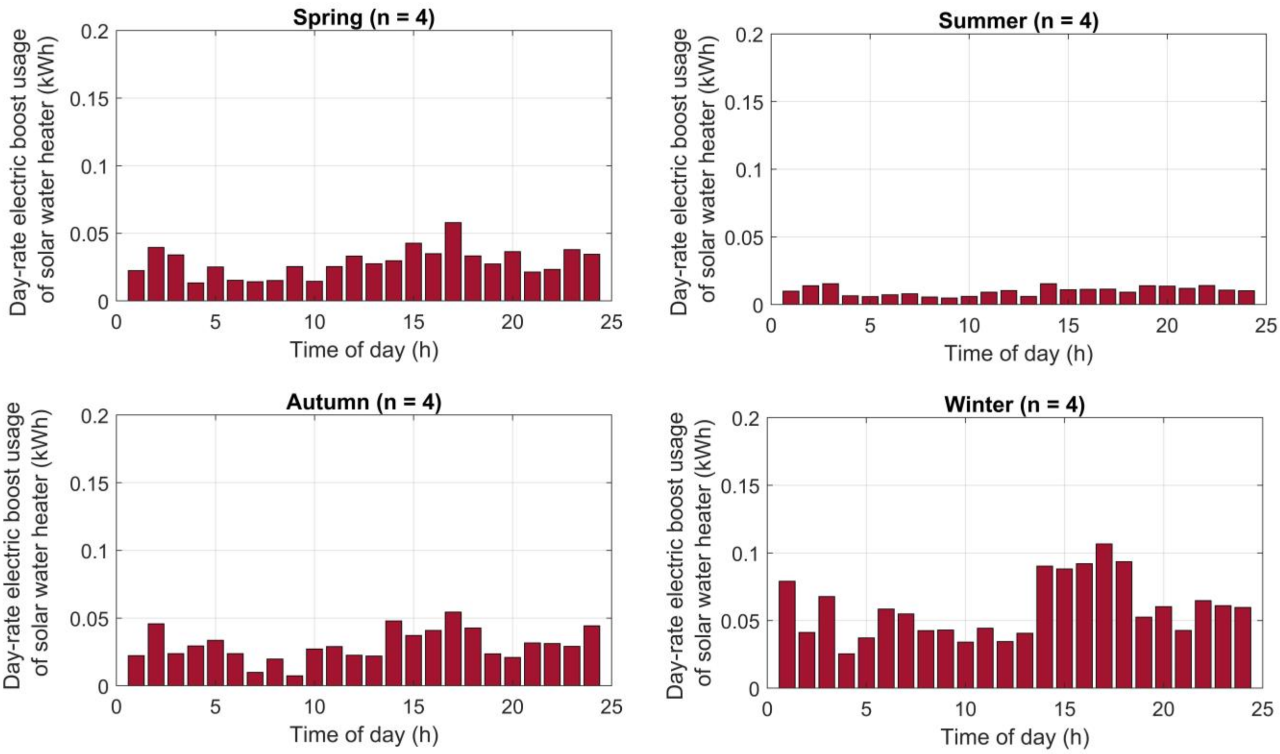


Figure 23 Average hourly electricity consumption uncontrolled electric boost elements SHW (per-occupant)

Also, as evidenced in the summary of Wattwatchers data, most of the electrically boosted solar hot water systems are on night-rate controlled load tariffs. Specifically, out of the total of 7 dwellings with electrically boosted solar hot water systems, 5 of them are connected to controlled load tariffs NAST 13 and NAST15. In the absence of other data sources, unfortunately, it is not possible to give a breakdown of the number of boosting elements connected to each of the above two controlled load tariffs. Accordingly, Figure 24 displays the seasonal per-occupant average hourly electricity consumption profiles for electric boost elements of solar hot water systems that are connected to night-rate controlled load tariffs.

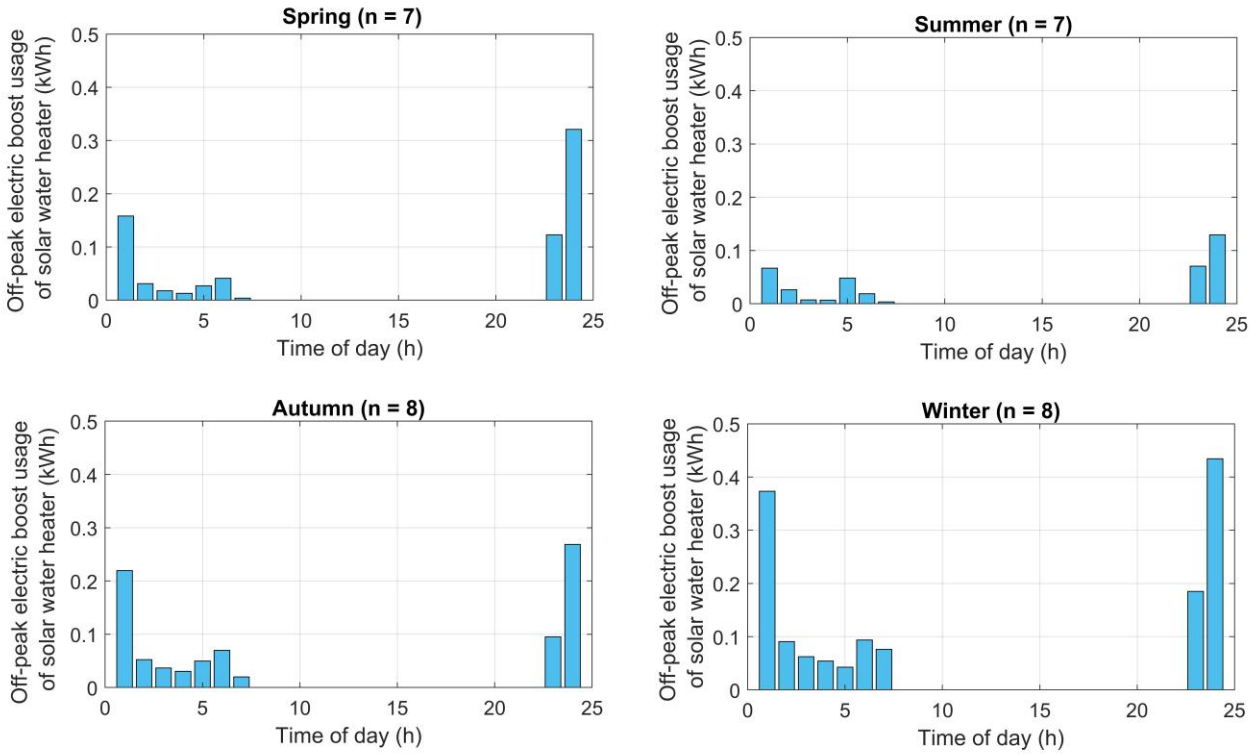


Figure 24 Average hourly electricity consumption controlled electric boost elements SHW (per-occupant)

Conventional resistive hot water systems

Figure 25 shows the seasonal average hourly electricity consumption profiles for standard electric element hot water systems on continuous electricity supply tariffs on a per-occupant basis. As the figure shows, autumn and winter constitute generally higher electricity consumption than spring and summer. The morning and evening peaks in winter portray up to 300 Wh per occupant on average. The morning and evening peaks in other seasons are similarly almost the same at about 200 Wh per occupant in spring and autumn, and 150 Wh per occupant in summer. It is also noteworthy that generally, where smart meters with load control capability are available, electric storage hot water systems that are on continuous electricity supply tariffs represent those with smaller storage tank sizes making them ineligible for controlled load tariffs.

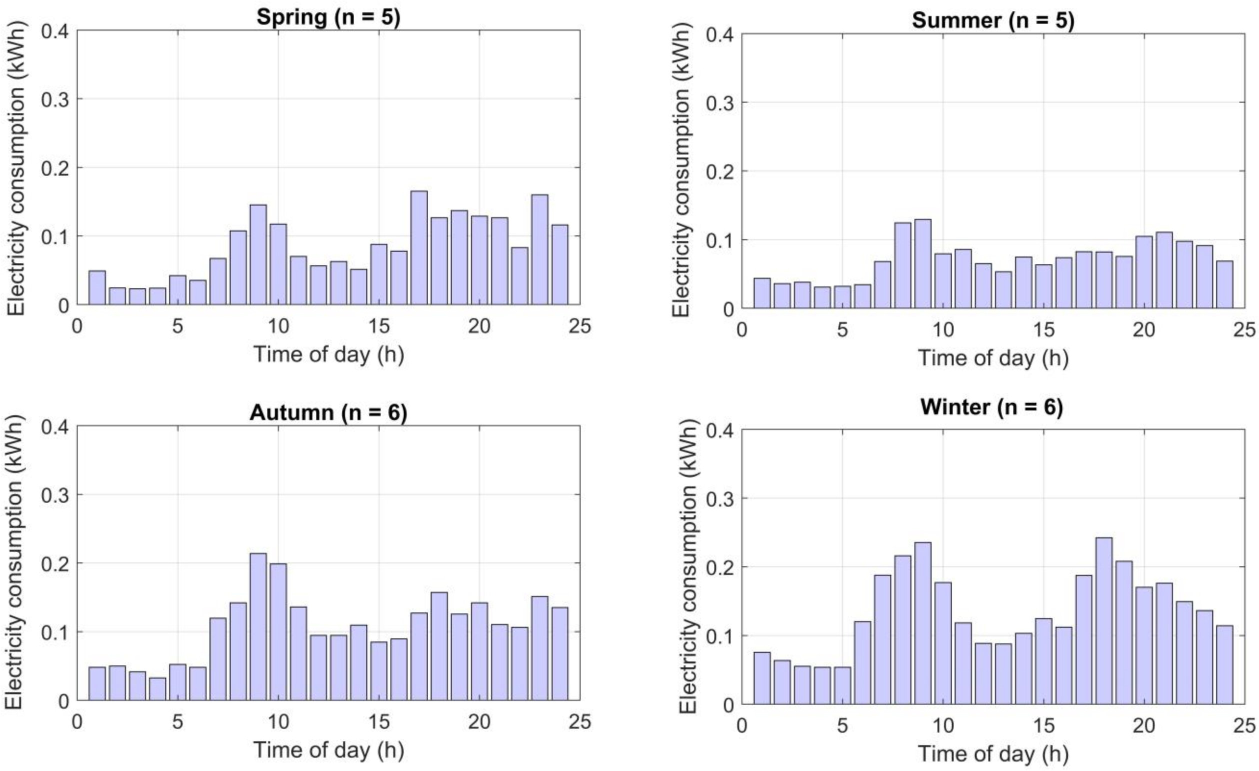


Figure 25 Average hourly electricity consumption uncontrolled standard electric hot water (per-occupant)

Also, Figure 26 depicts the derived seasonal average hourly sub-load profiles for the standard electric element water heaters connected to night-rate tariffs (NAST13 and NAST15) on a per-occupant basis. As far as the data from the studied samples are concerned, no standard electric element water was found to be connected to the night-rate controlled load tariff with an afternoon heating boost period (NAST14). As before, the number of households with night-rate controlled load tariffs broken down into the tariffs NAST13 and NAST15 was deemed secondary for the goal of showing the distinctions between night-rate controlled load tariffs and the night-rate controlled load tariff with an afternoon heating boost period. Furthermore, the relevant seasonal sub-load profiles derived indicate that they are characterised by a higher electricity consumption in the early hours of the associated night-time period, and a comparatively much lower consumption from 2:00 a.m. onwards in the defined controlled load period, particularly in spring, summer, and autumn. An observation that holds true for all the seasons in the controlled electric boost elements of solar hot water heaters, as can be seen in Figure 26.

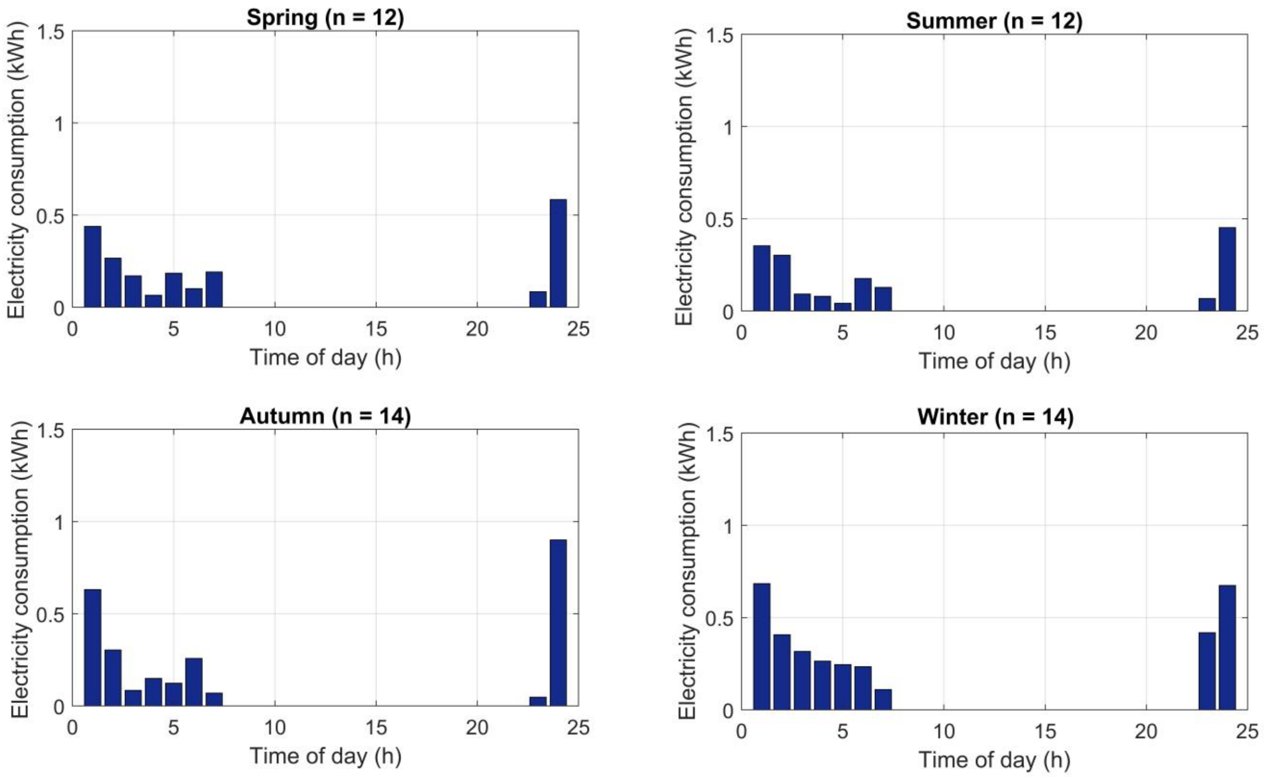


Figure 26 Average hourly electricity consumption controlled standard electric hot water (per-occupant)

Heat pump water heaters

Figure 27 shows the seasonal average hourly electricity consumption profiles for day-rate heat pump water heaters on a per-occupant basis. As can be inferred from the derived seasonal sub-load profiles, compared to the counterpart profiles for standard electric element water heaters and electric boost elements of solar hot water systems, the energy required for heat pumps is associated with considerably less sharp morning and evening peak periods throughout the year. This is mainly because, depending on hot water usage and weather conditions, heat pump water heaters run continuously for between 2 and 4 hours per day – though the pump running for 6 straight hours during the coldest nights is not unusual.

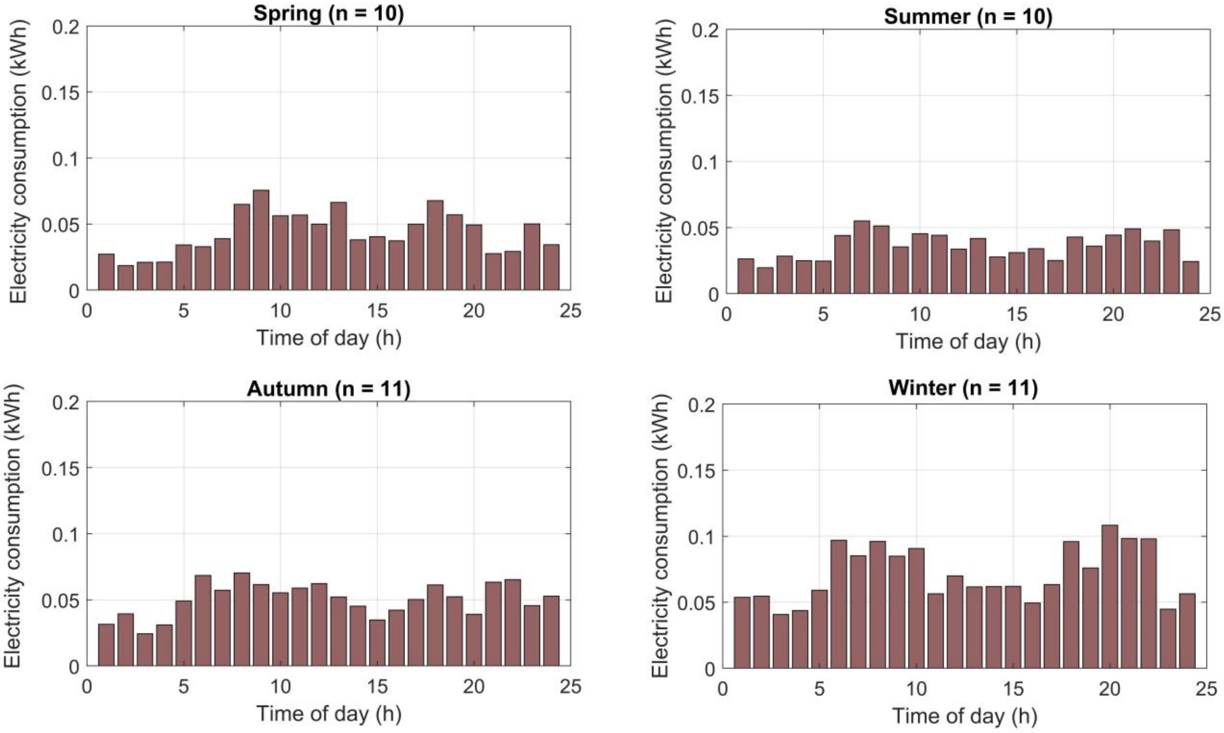


Figure 27 Average hourly electricity consumption uncontrolled heat pump hot water systems (per-occupant)

Unlike the other two electric water heating systems, from the patterns of electricity consumption, it has been found that controlled heat pump water heaters can be connected to night-rate tariffs (NAST13 and NAST15) or night-rate tariffs with afternoon heating boosts (NAST14). Accordingly, Figure 28 and Figure 29 respectively display the average hourly electricity consumption per season for controlled heat pump water heaters on night-rate tariffs and night-rate tariffs with afternoon heating boost. A direct comparison of the two sub-load profiles of interest indicates that the estimated values of total consumption for the two classes are nearly the same – about 1.5 kWh per day per occupant on average in spring, 1.2 kWh in summer, 1.6 kWh in autumn, and 2.3 kWh in winter.

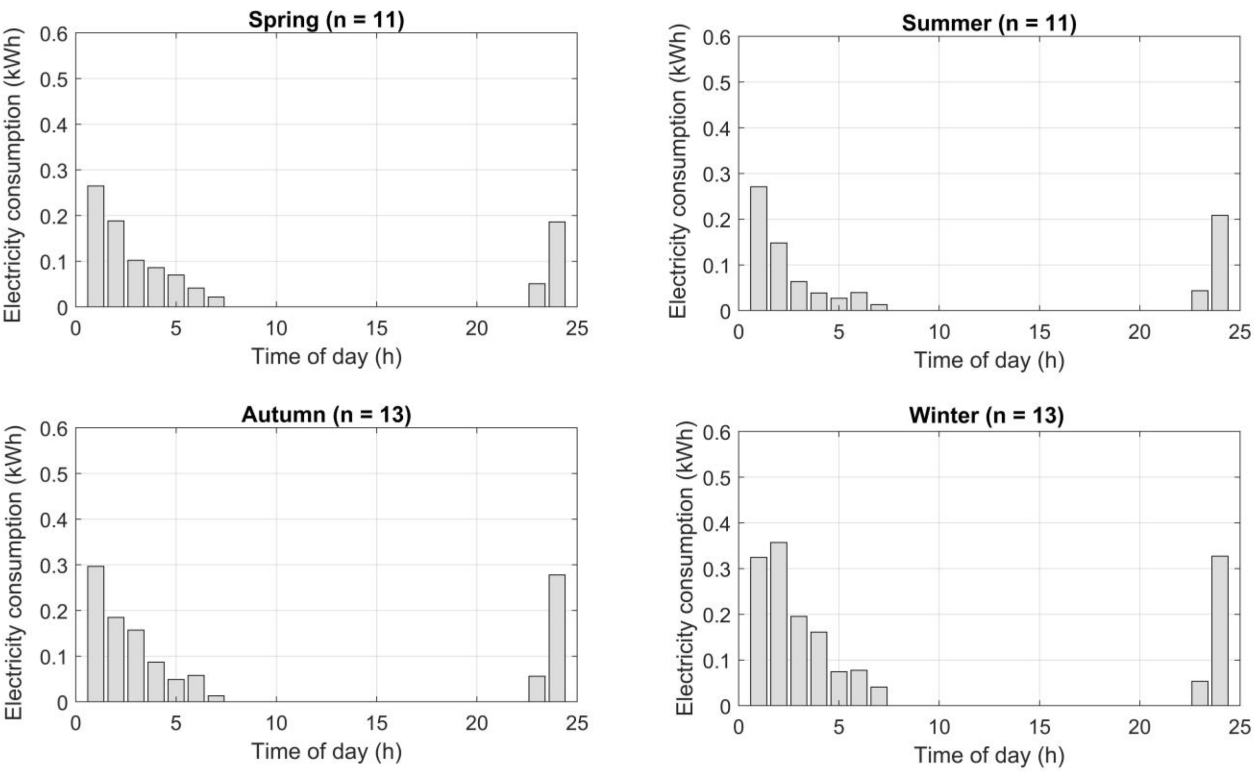


Figure 28 Average hourly electricity consumption heat pump hot water (night-rate tariffs, per-occupant)

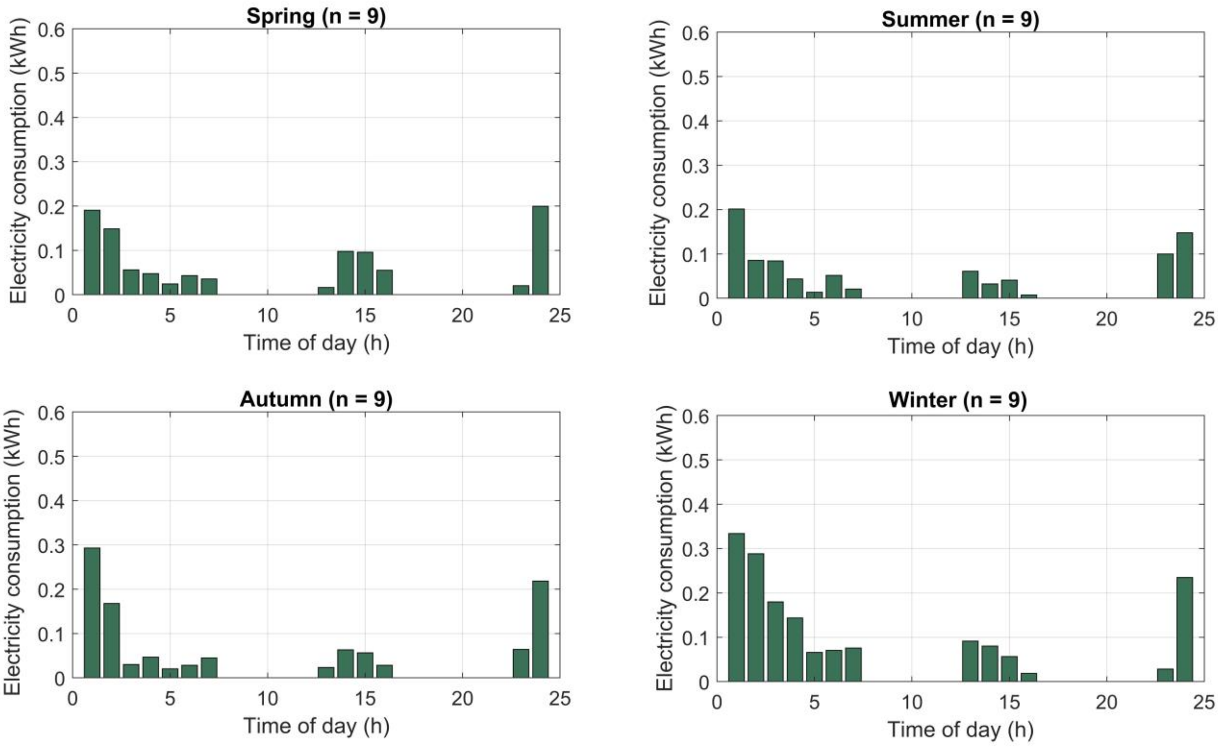


Figure 29 Average hourly electricity consumption heat pump hot water (night-rate & afternoon boost, per-occupant)

Again, note that only some of the heat pump water heaters are connected to the controlled load tariff that has an afternoon heating boost period. As far as the evidence from the samples investigated in this study is concerned, this is likely to indicate that the consideration of connecting the hot water system to a better-controlled load tariff is usually made – regardless of whether it’s a decision of the customer or the retailer, or a joint decision – when upgrading the water heating systems to heat pump hot water systems.

Appendix D: Numeric values of derived load and sub-load profiles

This appendix and the accompanying spreadsheet 'Derived seasonal profiles' provide numeric values of derived typical load profiles and associated sub-load profiles. for the typical underlying load, typical hot water, and HVAC sub-loads, as well as typical solar generation on a seasonal mean daily (24-h) basis. The typical load profiles derived for 16 customer categories are presented in Table 5, Table 6, Table 7, and Table 8 respectively for spring, summer, autumn, and winter.

Table 5 Numeric values of typical load profiles for spring

Hour	Customer category															
	No HVAC, no electric WH	HVAC, no electric WH	HVAC, standard WH (day-rate)	HVAC, standard WH (night-rate)	No HVAC, standard WH (day-rate)	No HVAC, standard WH (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, heat pump WH (day-rate)	HVAC, heat pump WH (night-rate)	HVAC, heat pump WH (night-rate with afternoon boost)	No HVAC, heat pump WH (day-rate)	No HVAC, heat pump WH (night-rate)	No HVAC, heat pump WH (night-rate with afternoon boost)
00:00	0.39	0.52	0.64	1.82	0.51	1.69	0.58	0.93	0.44	0.80	0.45	0.71	0.61	0.55	0.85	0.74
01:00	0.35	0.46	0.54	1.19	0.42	1.08	0.55	0.55	0.44	0.44	0.39	0.63	0.52	0.48	0.74	0.63
02:00	0.33	0.43	0.49	0.81	0.39	0.71	0.52	0.48	0.42	0.37	0.38	0.47	0.40	0.46	0.57	0.50
03:00	0.32	0.41	0.47	0.61	0.39	0.52	0.44	0.45	0.36	0.36	0.37	0.44	0.38	0.44	0.52	0.47
04:00	0.32	0.41	0.50	0.80	0.41	0.71	0.46	0.48	0.37	0.39	0.40	0.39	0.34	0.45	0.48	0.43
05:00	0.37	0.48	0.59	0.72	0.48	0.60	0.53	0.60	0.41	0.48	0.46	0.43	0.43	0.53	0.55	0.54
06:00	0.44	0.63	0.83	1.11	0.65	0.93	0.67	0.64	0.48	0.45	0.56	0.48	0.49	0.69	0.66	0.68
07:00	0.50	0.76	1.07	0.76	0.81	0.50	0.80	0.76	0.54	0.50	0.67	0.50	0.50	0.85	0.76	0.76
08:00	0.49	0.72	1.06	0.72	0.84	0.49	0.77	0.72	0.55	0.49	0.65	0.49	0.49	0.80	0.72	0.72
09:00	0.48	0.68	0.95	0.68	0.75	0.48	0.72	0.68	0.52	0.48	0.63	0.48	0.48	0.75	0.68	0.68
10:00	0.46	0.64	0.81	0.64	0.63	0.46	0.70	0.64	0.53	0.46	0.60	0.46	0.46	0.71	0.64	0.64
11:00	0.46	0.62	0.77	0.62	0.61	0.46	0.71	0.62	0.55	0.46	0.60	0.46	0.46	0.69	0.62	0.62
12:00	0.46	0.62	0.78	0.62	0.62	0.46	0.68	0.62	0.53	0.46	0.62	0.46	0.48	0.70	0.62	0.64
13:00	0.46	0.61	0.75	0.61	0.60	0.46	0.69	0.61	0.54	0.46	0.57	0.46	0.59	0.66	0.61	0.74
14:00	0.45	0.62	0.82	0.62	0.65	0.45	0.73	0.62	0.56	0.45	0.55	0.45	0.57	0.67	0.62	0.74
15:00	0.47	0.68	0.90	0.68	0.69	0.47	0.76	0.68	0.55	0.47	0.56	0.47	0.54	0.72	0.68	0.74
16:00	0.51	0.77	1.16	0.77	0.90	0.51	0.90	0.77	0.64	0.51	0.62	0.51	0.51	0.83	0.77	0.77
17:00	0.58	0.94	1.30	0.94	0.94	0.58	1.02	0.94	0.65	0.58	0.72	0.58	0.58	1.02	0.94	0.94
18:00	0.66	1.10	1.46	1.10	1.02	0.66	1.17	1.10	0.73	0.66	0.80	0.66	0.66	1.17	1.10	1.10
19:00	0.69	1.17	1.48	1.17	1.00	0.69	1.28	1.17	0.80	0.69	0.84	0.69	0.69	1.24	1.17	1.17
20:00	0.69	1.15	1.44	1.15	0.98	0.69	1.21	1.15	0.75	0.69	0.77	0.69	0.69	1.19	1.15	1.15
21:00	0.65	1.08	1.32	1.08	0.90	0.65	1.14	1.08	0.71	0.65	0.73	0.65	0.65	1.12	1.08	1.08
22:00	0.56	0.87	1.21	1.05	0.90	0.74	0.95	1.13	0.64	0.82	0.67	0.61	0.58	0.92	0.92	0.89
23:00	0.45	0.64	0.90	1.95	0.71	1.76	0.73	1.32	0.55	1.14	0.55	0.66	0.73	0.68	0.85	0.91

Table 6 Numeric values of typical load profiles for summer

Hour	Customer category														
	No HVAC, no electric WH	HVAC, no electric WH	HVAC, standard WH (day-rate)	HVAC, standard WH (night-rate)	No HVAC, standard WH (day-rate)	No HVAC, standard WH (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, heat pump WH (day-rate)	HVAC, heat pump WH (night-rate)	HVAC, heat pump WH (night-rate with afternoon boost)	No HVAC, heat pump WH (day-rate)	No HVAC, heat pump WH (night-rate)	No HVAC, heat pump WH (night-rate with afternoon boost)
00:00	0.39	0.54	0.65	1.58	0.50	1.43	0.56	0.70	0.41	0.55	0.45	0.73	0.62	0.57	0.88	0.76
01:00	0.33	0.46	0.55	1.10	0.42	0.97	0.50	0.54	0.37	0.41	0.38	0.52	0.45	0.48	0.65	0.57
02:00	0.32	0.44	0.54	0.72	0.42	0.61	0.47	0.46	0.36	0.34	0.38	0.40	0.41	0.47	0.52	0.53
03:00	0.30	0.40	0.49	0.58	0.38	0.48	0.42	0.42	0.32	0.32	0.36	0.35	0.36	0.44	0.45	0.46
04:00	0.31	0.39	0.47	0.49	0.39	0.40	0.41	0.50	0.33	0.42	0.38	0.34	0.33	0.43	0.43	0.41
05:00	0.34	0.43	0.51	0.81	0.43	0.73	0.45	0.48	0.36	0.40	0.46	0.39	0.41	0.49	0.47	0.50
06:00	0.39	0.48	0.63	0.86	0.54	0.76	0.50	0.49	0.40	0.40	0.52	0.40	0.41	0.55	0.50	0.51
07:00	0.40	0.50	0.78	0.50	0.68	0.40	0.52	0.50	0.41	0.40	0.53	0.40	0.40	0.57	0.50	0.50
08:00	0.41	0.56	0.86	0.56	0.72	0.41	0.57	0.56	0.42	0.41	0.50	0.41	0.41	0.60	0.56	0.56
09:00	0.44	0.63	0.83	0.63	0.64	0.44	0.64	0.63	0.45	0.44	0.54	0.44	0.44	0.68	0.63	0.63
10:00	0.47	0.73	0.92	0.73	0.66	0.47	0.75	0.73	0.49	0.47	0.58	0.47	0.47	0.79	0.73	0.73
11:00	0.46	0.81	0.97	0.81	0.62	0.46	0.83	0.81	0.49	0.46	0.54	0.46	0.46	0.85	0.81	0.81
12:00	0.50	0.95	1.09	0.95	0.64	0.50	0.96	0.95	0.52	0.50	0.59	0.50	0.57	0.99	0.95	1.01
13:00	0.48	0.99	1.15	0.99	0.64	0.48	1.03	0.99	0.52	0.48	0.55	0.48	0.52	1.03	0.99	1.03
14:00	0.48	1.10	1.24	1.10	0.62	0.48	1.12	1.10	0.51	0.48	0.55	0.48	0.53	1.13	1.10	1.14
15:00	0.51	1.25	1.43	1.25	0.69	0.51	1.28	1.25	0.54	0.51	0.59	0.51	0.52	1.29	1.25	1.26
16:00	0.55	1.40	1.60	1.40	0.75	0.55	1.43	1.40	0.58	0.55	0.62	0.55	0.55	1.44	1.40	1.40
17:00	0.61	1.53	1.73	1.53	0.80	0.61	1.55	1.53	0.63	0.61	0.71	0.61	0.61	1.58	1.53	1.53
18:00	0.63	1.49	1.70	1.49	0.84	0.63	1.53	1.49	0.67	0.63	0.73	0.63	0.63	1.54	1.49	1.49
19:00	0.66	1.35	1.63	1.35	0.95	0.66	1.39	1.35	0.70	0.66	0.80	0.66	0.66	1.41	1.35	1.35
20:00	0.61	1.10	1.38	1.10	0.89	0.61	1.12	1.10	0.64	0.61	0.74	0.61	0.61	1.16	1.10	1.10
21:00	0.59	0.95	1.22	0.95	0.87	0.59	0.98	0.95	0.63	0.59	0.68	0.59	0.59	1.00	0.95	0.95
22:00	0.51	0.78	0.98	0.96	0.71	0.69	0.80	0.93	0.53	0.66	0.61	0.56	0.62	0.83	0.83	0.89
23:00	0.42	0.61	0.80	1.73	0.62	1.55	0.64	0.90	0.45	0.71	0.49	0.72	0.64	0.65	0.90	0.82

Table 7 Numeric values of typical load profiles for autumn

Hour	Customer category															
	No HVAC, no electric WH	HVAC, no electric WH	HVAC, standard WH (day-rate)	HVAC, standard WH (night-rate)	No HVAC, standard WH (day-rate)	No HVAC, standard WH (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, heat pump WH (day-rate)	HVAC, heat pump WH (night-rate)	HVAC, heat pump WH (night-rate with afternoon boost)	No HVAC, heat pump WH (day-rate)	No HVAC, heat pump WH (night-rate)	No HVAC, heat pump WH (night-rate with afternoon boost)
00:00	0.37	0.49	0.61	2.35	0.50	2.23	0.55	1.02	0.44	0.91	0.47	0.76	0.81	0.54	0.87	0.92
01:00	0.33	0.41	0.55	1.24	0.47	1.16	0.50	0.54	0.42	0.46	0.41	0.60	0.56	0.45	0.68	0.64
02:00	0.31	0.37	0.49	0.60	0.42	0.53	0.45	0.49	0.38	0.42	0.38	0.52	0.35	0.41	0.59	0.41
03:00	0.30	0.37	0.46	0.72	0.39	0.65	0.43	0.45	0.37	0.38	0.37	0.43	0.35	0.40	0.49	0.42
04:00	0.31	0.37	0.51	0.72	0.46	0.67	0.44	0.51	0.38	0.45	0.42	0.38	0.34	0.42	0.44	0.39
05:00	0.32	0.41	0.55	1.01	0.45	0.91	0.47	0.57	0.37	0.47	0.47	0.40	0.35	0.49	0.49	0.45
06:00	0.39	0.56	0.87	0.77	0.70	0.60	0.59	0.61	0.42	0.44	0.56	0.41	0.46	0.65	0.58	0.63
07:00	0.45	0.72	1.15	0.72	0.88	0.45	0.77	0.72	0.50	0.45	0.63	0.45	0.45	0.81	0.72	0.72
08:00	0.44	0.71	1.17	0.71	0.91	0.44	0.73	0.71	0.46	0.44	0.61	0.44	0.44	0.79	0.71	0.71
09:00	0.47	0.70	1.12	0.70	0.89	0.47	0.76	0.70	0.53	0.47	0.59	0.47	0.47	0.76	0.70	0.70
10:00	0.45	0.63	0.97	0.63	0.79	0.45	0.71	0.63	0.52	0.45	0.60	0.45	0.45	0.71	0.63	0.63
11:00	0.45	0.65	0.88	0.65	0.69	0.45	0.70	0.65	0.50	0.45	0.59	0.45	0.45	0.71	0.65	0.65
12:00	0.46	0.65	0.90	0.65	0.71	0.46	0.71	0.65	0.52	0.46	0.60	0.46	0.48	0.73	0.65	0.68
13:00	0.45	0.67	0.91	0.67	0.69	0.45	0.80	0.67	0.58	0.45	0.57	0.45	0.53	0.73	0.67	0.75
14:00	0.44	0.66	0.89	0.66	0.66	0.44	0.77	0.66	0.55	0.44	0.54	0.44	0.51	0.71	0.66	0.73
15:00	0.47	0.74	1.00	0.74	0.73	0.47	0.86	0.74	0.59	0.47	0.59	0.47	0.51	0.80	0.74	0.78
16:00	0.49	0.83	1.11	0.83	0.78	0.49	0.95	0.83	0.61	0.49	0.60	0.49	0.49	0.88	0.83	0.83
17:00	0.57	1.00	1.41	1.00	0.98	0.57	1.11	1.00	0.67	0.57	0.72	0.57	0.57	1.08	1.00	1.00
18:00	0.63	1.15	1.50	1.15	0.98	0.63	1.21	1.15	0.69	0.63	0.76	0.63	0.63	1.22	1.15	1.15
19:00	0.71	1.19	1.55	1.19	1.08	0.71	1.25	1.19	0.77	0.71	0.82	0.71	0.71	1.24	1.19	1.19
20:00	0.71	1.16	1.48	1.16	1.04	0.71	1.23	1.16	0.78	0.71	0.85	0.71	0.71	1.23	1.16	1.16
21:00	0.61	1.02	1.33	1.02	0.91	0.61	1.09	1.02	0.68	0.61	0.76	0.61	0.61	1.10	1.02	1.02
22:00	0.54	0.85	1.18	0.97	0.86	0.65	0.93	1.14	0.62	0.82	0.66	0.60	0.62	0.91	0.91	0.93
23:00	0.45	0.63	0.92	2.61	0.74	2.43	0.74	1.31	0.56	1.13	0.58	0.74	0.80	0.69	0.92	0.98

Table 8 Numeric values of typical load profiles for winter

Hour	Customer category															
	No HVAC, no electric WH	HVAC, no electric WH	HVAC, standard WH (day-rate)	HVAC, standard WH (night-rate)	No HVAC, standard WH (day-rate)	No HVAC, standard WH (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, solar boost (day-rate)	HVAC, solar boost (night-rate)	HVAC, heat pump WH (day-rate)	HVAC, heat pump WH (night-rate)	HVAC, heat pump WH (night-rate with afternoon boost)	No HVAC, heat pump WH (day-rate)	No HVAC, heat pump WH (night-rate)	No HVAC, heat pump WH (night-rate with afternoon boost)
00:00	0.39	0.67	0.88	2.25	0.60	1.98	0.84	1.60	0.57	1.33	0.52	0.85	0.80	0.73	1.12	1.07
01:00	0.35	0.62	0.80	1.55	0.53	1.28	0.73	0.85	0.47	0.59	0.49	0.86	0.72	0.69	1.13	0.99
02:00	0.32	0.49	0.65	1.35	0.48	1.19	0.64	0.65	0.47	0.48	0.45	0.59	0.60	0.55	0.76	0.77
03:00	0.31	0.44	0.58	1.06	0.45	0.93	0.51	0.59	0.38	0.46	0.43	0.52	0.50	0.50	0.65	0.63
04:00	0.30	0.46	0.60	1.04	0.45	0.88	0.56	0.56	0.41	0.41	0.47	0.40	0.40	0.54	0.56	0.55
05:00	0.36	0.57	0.83	1.24	0.62	1.03	0.73	0.81	0.52	0.59	0.58	0.45	0.44	0.68	0.66	0.65
06:00	0.48	0.91	1.39	1.23	0.96	0.80	1.04	1.08	0.61	0.65	0.71	0.53	0.58	1.03	0.96	1.01
07:00	0.60	1.39	2.00	1.39	1.21	0.60	1.50	1.39	0.71	0.60	0.84	0.60	0.60	1.51	1.39	1.39
08:00	0.54	1.43	1.94	1.43	1.05	0.54	1.54	1.43	0.66	0.54	0.79	0.54	0.54	1.55	1.43	1.43
09:00	0.56	1.38	1.76	1.38	0.94	0.56	1.46	1.38	0.64	0.56	0.78	0.56	0.56	1.49	1.38	1.38
10:00	0.49	1.13	1.44	1.13	0.79	0.49	1.24	1.13	0.60	0.49	0.65	0.49	0.49	1.21	1.13	1.13
11:00	0.51	1.08	1.34	1.08	0.77	0.51	1.16	1.08	0.59	0.51	0.67	0.51	0.51	1.16	1.08	1.08
12:00	0.50	0.99	1.23	0.99	0.75	0.50	1.08	0.99	0.59	0.50	0.65	0.50	0.61	1.06	0.99	1.10
13:00	0.50	0.94	1.21	0.94	0.77	0.50	1.19	0.94	0.75	0.50	0.64	0.50	0.59	1.01	0.94	1.03
14:00	0.45	0.90	1.21	0.90	0.75	0.45	1.11	0.90	0.65	0.45	0.61	0.45	0.52	0.98	0.90	0.98
15:00	0.49	1.01	1.32	1.01	0.80	0.49	1.22	1.01	0.70	0.49	0.64	0.49	0.52	1.08	1.01	1.04
16:00	0.55	1.22	1.67	1.22	1.01	0.55	1.50	1.22	0.83	0.55	0.73	0.55	0.55	1.31	1.22	1.22
17:00	0.67	1.67	2.23	1.67	1.23	0.67	1.90	1.67	0.90	0.67	0.88	0.67	0.67	1.77	1.67	1.67
18:00	0.80	2.03	2.61	2.03	1.38	0.80	2.19	2.03	0.95	0.80	1.01	0.80	0.80	2.14	2.03	2.03
19:00	0.84	2.21	2.71	2.21	1.34	0.84	2.40	2.21	1.02	0.84	1.08	0.84	0.84	2.34	2.21	2.21
20:00	0.81	2.15	2.63	2.15	1.28	0.81	2.26	2.15	0.91	0.81	1.05	0.81	0.81	2.27	2.15	2.15
21:00	0.78	1.90	2.31	1.90	1.18	0.78	2.05	1.90	0.93	0.78	0.99	0.78	0.78	2.01	1.90	1.90
22:00	0.67	1.50	1.85	2.43	1.02	1.60	1.63	1.91	0.80	1.08	0.80	0.74	0.71	1.57	1.57	1.54
23:00	0.50	0.99	1.27	2.84	0.78	2.36	1.16	2.21	0.67	1.73	0.64	0.91	0.80	1.06	1.39	1.29

Typical sub-load and underlying load profiles

The numeric values of the derived sub-load and underlying load profiles are presented in the tables below.

Table 9 Numeric values of typical heat pump (day-rate) loads (WHs, per-occupant basis)

Heat pump hot water systems (day-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.03	0.03	0.03	0.05
01:00	0.02	0.02	0.04	0.05
02:00	0.02	0.03	0.02	0.04
03:00	0.02	0.02	0.03	0.04
04:00	0.03	0.02	0.05	0.06
05:00	0.03	0.04	0.07	0.10
06:00	0.04	0.06	0.06	0.09
07:00	0.06	0.05	0.07	0.10
08:00	0.08	0.04	0.06	0.08
09:00	0.06	0.05	0.06	0.09
10:00	0.06	0.04	0.06	0.06
11:00	0.05	0.03	0.06	0.07
12:00	0.07	0.04	0.05	0.06
13:00	0.04	0.03	0.05	0.06
14:00	0.04	0.03	0.03	0.06
15:00	0.04	0.03	0.04	0.05
16:00	0.05	0.03	0.05	0.06
17:00	0.07	0.04	0.06	0.10
18:00	0.06	0.04	0.05	0.08
19:00	0.05	0.04	0.04	0.11
20:00	0.03	0.05	0.06	0.10
21:00	0.03	0.04	0.07	0.10
22:00	0.05	0.05	0.05	0.04
23:00	0.03	0.02	0.05	0.06

Table 10 Numeric values of typical heat pump (night-rate) loads (WH, per-occupant basis)

Heat pump hot water systems (night-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.19	0.21	0.28	0.33
01:00	0.26	0.27	0.30	0.32
02:00	0.19	0.15	0.19	0.36
03:00	0.10	0.06	0.16	0.20
04:00	0.09	0.04	0.09	0.16
05:00	0.07	0.03	0.05	0.07
06:00	0.04	0.04	0.06	0.08
07:00	0.02	0.01	0.01	0.04
08:00	0	0	0	0
09:00	0	0	0	0
10:00	0	0	0	0
11:00	0	0	0	0
12:00	0	0	0	0
13:00	0	0	0	0
14:00	0	0	0	0

Heat pump hot water systems (night-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
15:00	0	0	0	0
16:00	0	0	0	0
17:00	0	0	0	0
18:00	0	0	0	0
19:00	0	0	0	0
20:00	0	0	0	0
21:00	0	0	0	0
22:00	0	0	0	0
23:00	0.05	0.04	0.06	0.05

Table 11 Numeric values of typical heat pump (night-rate/ afternoon) loads (WH, per-occupant basis)

Heat pump hot water systems (night-rate/ afternoon)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.20	0.15	0.22	0.23
01:00	0.19	0.20	0.29	0.33
02:00	0.15	0.09	0.17	0.29
03:00	0.06	0.08	0.03	0.18
04:00	0.05	0.04	0.05	0.14
05:00	0.02	0.01	0.02	0.07
06:00	0.04	0.05	0.03	0.07
07:00	0.04	0.02	0.04	0.08
08:00	0	0	0	0
09:00	0	0	0	0
10:00	0	0	0	0
11:00	0	0	0	0
12:00	0	0	0	0
13:00	0.02	0.06	0.02	0.09
14:00	0.10	0.03	0.06	0.08
15:00	0.10	0.04	0.06	0.06
16:00	0.06	0.01	0.03	0.02
17:00	0	0	0	0
18:00	0	0	0	0
19:00	0	0	0	0
20:00	0	0	0	0
21:00	0	0	0	0
22:00	0	0	0	0
23:00	0.02	0.10	0.06	0.03

Table 12 Numeric values of typical standard electric element (day-rate) (WHs, per-occupant basis)

Standard element hot water systems (day-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.05	0.04	0.05	0.08
01:00	0.02	0.04	0.05	0.06
02:00	0.02	0.03	0.04	0.06
03:00	0.02	0.03	0.03	0.05

Standard element hot water systems (day-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
04:00	0.04	0.03	0.05	0.05
05:00	0.04	0.07	0.05	0.12
06:00	0.07	0.12	0.12	0.19
07:00	0.11	0.13	0.14	0.22
08:00	0.15	0.08	0.21	0.24
09:00	0.12	0.09	0.20	0.18
10:00	0.07	0.07	0.14	0.12
11:00	0.06	0.05	0.09	0.09
12:00	0.06	0.07	0.09	0.09
13:00	0.05	0.06	0.11	0.10
14:00	0.09	0.07	0.08	0.12
15:00	0.08	0.08	0.09	0.11
16:00	0.17	0.08	0.13	0.19
17:00	0.13	0.08	0.16	0.24
18:00	0.14	0.10	0.13	0.21
19:00	0.13	0.11	0.14	0.17
20:00	0.13	0.10	0.11	0.18
21:00	0.08	0.09	0.11	0.15
22:00	0.16	0.07	0.15	0.14
23:00	0.12	0.04	0.14	0.11

Table 13 Numeric values of typical standard electric element (night-rate) loads (WHs, per-occupant basis)

Standard element hot water systems (night-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.58	0.45	0.90	0.67
01:00	0.44	0.35	0.63	0.68
02:00	0.27	0.30	0.30	0.41
03:00	0.17	0.09	0.08	0.32
04:00	0.07	0.08	0.15	0.26
05:00	0.19	0.04	0.12	0.25
06:00	0.10	0.18	0.26	0.23
07:00	0.19	0.13	0.07	0.11
08:00	0.00	0	0.00	0.00
09:00	0.00	0	0.00	0.00
10:00	0.00	0	0.00	0.00
11:00	0.00	0	0.00	0.00
12:00	0.00	0	0.00	0.00
13:00	0.00	0	0.00	0.00
14:00	0.00	0	0.00	0.00
15:00	0.00	0	0.00	0.00
16:00	0.00	0	0.00	0.00
17:00	0.00	0	0.00	0.00
18:00	0.00	0	0.00	0.00
19:00	0.00	0	0.00	0.00
20:00	0.00	0	0.00	0.00
21:00	0.00	0	0.00	0.00
22:00	0.00	0	0.00	0.00

Standard element hot water systems (night-rate)				
Hour	Season			
	Spring	Summer	Autumn	Winter
23:00	0.08	0.07	0.05	0.42

Table 14 Numeric values of typical electrically-boosted (day-rate) SWHs (Whs, per-occupant basis)

Electrically-boosted solar hot water systems (day-rate)				
Hour	Season			
	Spring	Summer	Autumn	Winter
00:00	0.02	0.01	0.02	0.08
01:00	0.04	0.01	0.05	0.04
02:00	0.03	0.02	0.02	0.07
03:00	0.01	0.01	0.03	0.03
04:00	0.03	0.01	0.03	0.04
05:00	0.02	0.01	0.02	0.06
06:00	0.01	0.01	0.01	0.05
07:00	0.02	0.01	0.02	0.04
08:00	0.03	0.00	0.01	0.04
09:00	0.01	0.01	0.03	0.03
10:00	0.03	0.01	0.03	0.04
11:00	0.03	0.01	0.02	0.03
12:00	0.03	0.01	0.02	0.04
13:00	0.03	0.02	0.05	0.09
14:00	0.04	0.01	0.04	0.09
15:00	0.03	0.01	0.04	0.09
16:00	0.06	0.01	0.05	0.11
17:00	0.03	0.01	0.04	0.09
18:00	0.03	0.01	0.02	0.05
19:00	0.04	0.01	0.02	0.06
20:00	0.02	0.01	0.03	0.04
21:00	0.02	0.01	0.03	0.06
22:00	0.04	0.01	0.03	0.06
23:00	0.03	0.01	0.04	0.06

Table 15 Numeric values of typical electrically-boosted (night-rate) SWHs (WHs, per-occupant basis)

Electrically-boosted solar hot water systems (night-rate)				
Hour	Season			
	Spring	Summer	Autumn	Winter
00:00	0.32	0.13	0.27	0.43
01:00	0.16	0.07	0.22	0.37
02:00	0.03	0.03	0.05	0.09
03:00	0.02	0.01	0.04	0.06
04:00	0.01	0.01	0.03	0.05
05:00	0.03	0.05	0.05	0.04
06:00	0.04	0.02	0.07	0.09
07:00	0.00	0.00	0.02	0.08
08:00	0.00	0.00	0.00	0.00
09:00	0.00	0.00	0.00	0.00
10:00	0.00	0.00	0.00	0.00
11:00	0.00	0.00	0.00	0.00

Electrically-boosted solar hot water systems (night-rate)				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
12:00	0.00	0.00	0.00	0.00
13:00	0.00	0.00	0.00	0.00
14:00	0.00	0.00	0.00	0.00
15:00	0.00	0.00	0.00	0.00
16:00	0.00	0.00	0.00	0.00
17:00	0.00	0.00	0.00	0.00
18:00	0.00	0.00	0.00	0.00
19:00	0.00	0.00	0.00	0.00
20:00	0.00	0.00	0.00	0.00
21:00	0.00	0.00	0.00	0.00
22:00	0.00	0.00	0.00	0.00
23:00	0.12	0.07	0.10	0.19

Table 16 Numeric values of HVAC system loads (WHs, per-household basis)

HVAC				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.13	0.15	0.12	0.27
01:00	0.12	0.13	0.08	0.27
02:00	0.10	0.12	0.07	0.17
03:00	0.09	0.10	0.07	0.13
04:00	0.09	0.08	0.06	0.15
05:00	0.11	0.08	0.10	0.21
06:00	0.19	0.09	0.17	0.43
07:00	0.26	0.10	0.27	0.79
08:00	0.22	0.15	0.27	0.88
09:00	0.19	0.19	0.23	0.82
10:00	0.18	0.26	0.18	0.64
11:00	0.16	0.35	0.20	0.57
12:00	0.16	0.44	0.20	0.49
13:00	0.15	0.51	0.22	0.44
14:00	0.17	0.62	0.22	0.45
15:00	0.21	0.74	0.27	0.52
16:00	0.26	0.85	0.34	0.66
17:00	0.37	0.92	0.44	1.00
18:00	0.44	0.86	0.52	1.23
19:00	0.48	0.68	0.47	1.38
20:00	0.46	0.48	0.45	1.35
21:00	0.43	0.36	0.41	1.12
22:00	0.31	0.27	0.31	0.83
23:00	0.19	0.19	0.18	0.49

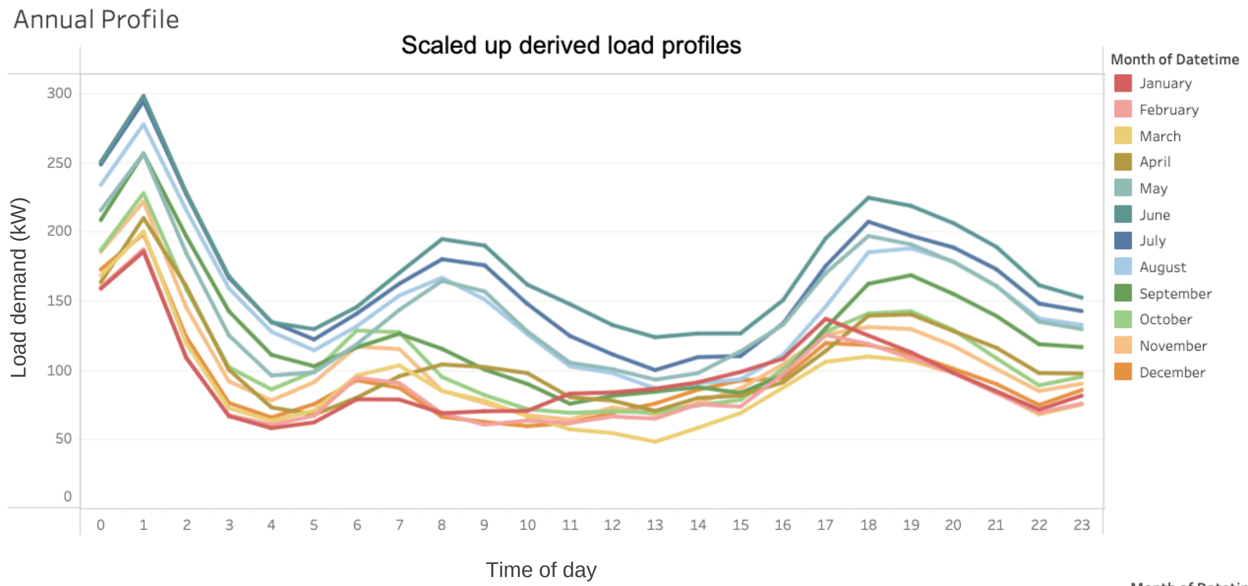
Table 17 Numeric values of underlying load per season (WHs, per-household basis)

Underlying load				
Hour	**Season**			
	Spring	Summer	Autumn	Winter
00:00	0.39	0.39	0.37	0.39
01:00	0.35	0.33	0.33	0.35
02:00	0.33	0.32	0.31	0.32
03:00	0.32	0.30	0.30	0.31
04:00	0.32	0.31	0.31	0.30
05:00	0.37	0.34	0.32	0.36
06:00	0.44	0.39	0.39	0.48
07:00	0.50	0.40	0.45	0.60
08:00	0.49	0.41	0.44	0.54
09:00	0.48	0.44	0.47	0.56
10:00	0.46	0.47	0.45	0.49
11:00	0.46	0.46	0.45	0.51
12:00	0.46	0.50	0.46	0.50
13:00	0.46	0.48	0.45	0.50
14:00	0.45	0.48	0.44	0.45
15:00	0.47	0.51	0.47	0.49
16:00	0.51	0.55	0.49	0.55
17:00	0.58	0.61	0.57	0.67
18:00	0.66	0.63	0.63	0.80
19:00	0.69	0.66	0.71	0.84
20:00	0.69	0.61	0.71	0.81
21:00	0.65	0.59	0.61	0.78
22:00	0.56	0.51	0.54	0.67
23:00	0.45	0.42	0.45	0.50

Appendix E: Comparison of scaled up derived load profile and actual feeder data

Figure 30 shows the scaled-up typical load profiles in a bottom-up manner for the three feeders of interest and the corresponding sum of actual feeder data over all months. It can be seen that solar generation hours display a lower degree of accuracy compared to other time periods across all months, which can be explained by the significant role of estimated solar generation in the associated inaccuracies.

The observed load profiles for the three feeders of interest revealed that some months in both summer and winter seasons exhibited poor performance in terms of matching up on the corresponding solar generation hours. However, the analysis did not provide sufficient evidence to support any definitive conclusions regarding whether the overall match-up between the derived load profiles and actual data at solar generation hours is better in summer or winter. Further research is, therefore, needed to gain a more comprehensive understanding of the underlying factors that may contribute to the observed discrepancies and to evaluate the potential impact of seasonal variations on the accuracy of load profiles.



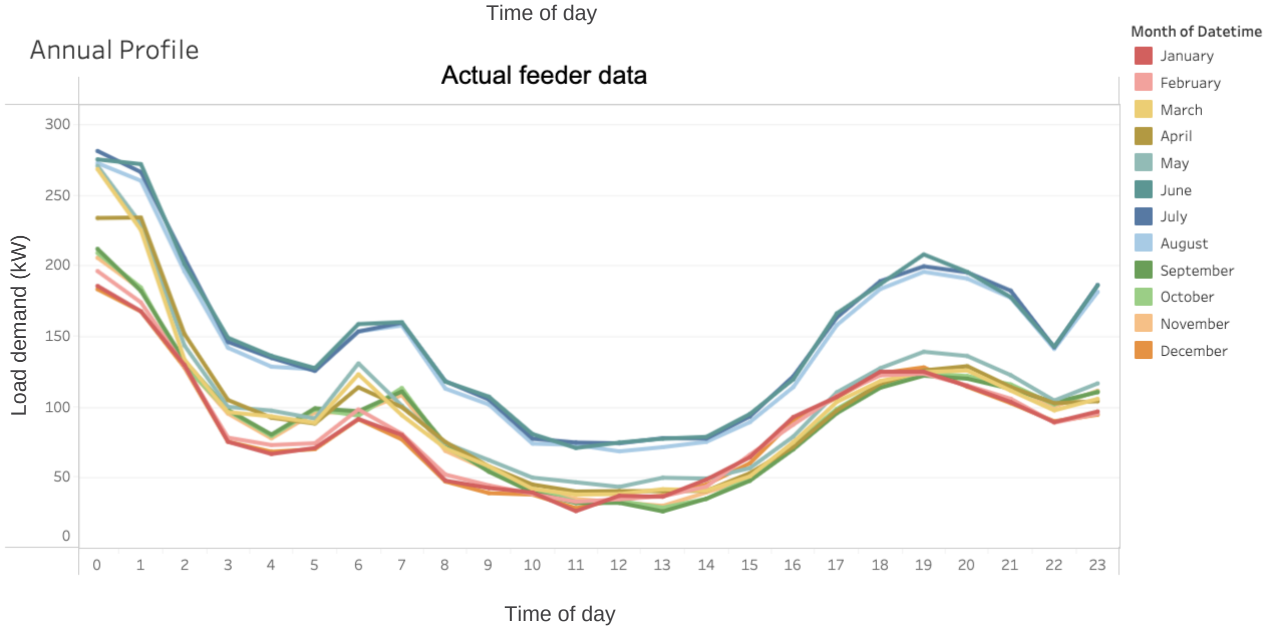


Figure 30 Scaled up derived typical load profiles benchmarked against actual feeder data over all months The sum of the three feeders of interest.

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