Enhanced System Planning Project

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DRAFT REPORT

Title:	**WP1.1 Technical modelling of electrification of heating (and cooling) profiles**
Document ID:	Task 1: Literature review
Date:	1st April 2023
Prepared For:	Centre for New Energy Technologies (C4NET)
Lead Researcher:	Prof Pierluigi Mancarella Department of Electrical and Electronic Engineering The University of Melbourne
Research Team:	Antonella De Corato, Sleiman Mhanna Department of Electrical and Electronic Engineering The University of Melbourne
Contact:	Prof Pierluigi Mancarella pierluigi.mancarella@unimelb.edu.au

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Table of Contents

Abbreviations and Acronyms

ABS	Australian Bureau of Statistics
AEMO	Australian Energy Market Operator
ASHP	Air-Source Heat Pump
CDD	Cooling Degree Days
COP	Coefficient of Performance
DER	Distributed Energy Resources
DHW	Domestic Hot Water
DNSP	Distribution Network Service Provider
DR	Demand Response
EHP	Electric Heat Pump
ETT	Electro-Thermal Technologies
GSHP	Ground Source Heat Pump
HDD	Heating Degree Days
HEC	Household Energy Consumption
HVAC	Heating, Ventilation and Air Conditioning
LGA	Local Government Area
LV	Low Voltage
MV	Medium Voltage
NN	Neural Network

Executive summary

As the need for whole-energy system decarbonization becomes more urgent, the building sector, particularly in urban areas, is currently in the spotlight as it is responsible of a significant share of greenhouse gases (GHG) emissions, mostly coming from heating and cooling energy requirements, as well as domestic hot water (DHW) consumption [1] [1].

Different pathways have been proposed and explored to decarbonize the building sector, including direct electrification of heating/cooling (e.g., through heat pumps) and the replacement (including blending) of fossil-fuels with renewable gases, i.e., “green” hydrogen, leading to links and interaction between different energy infrastructures [3] (e.g., electricity and gas).

Hence, it is crucial to assess how these changes in the heating (and cooling) sector would impact on the energy business and infrastructure, for example in terms of networks’ adequacy and potential reinforcements/investments requirements and quantifying the value of demand side flexibility that can potentially be accessed. In fact, the possibly “peakier” thermal demand may effectively be “hidden” by the storage embedded in buildings’ thermal mass and, potentially, by the heating (cooling) distribution system (e.g., underfloor water pipes in hydronic heating systems), and with the existence of hot water storage tanks. This could be unveiled and captured only at higher time resolution (e.g., sub-hourly).

For instance, the absence of an emitter system in the case of a switch to electro-thermal technologies such as air-to-air heat pumps, where heat (cooling) is directly supplied to the indoor environment, would result in a decreased buildings’ storage capacity, potentially leading to a more intermittent and peaky electricity consumption profile. Moreover, occupants’ presence and preferences in terms of temperature setpoints (and tolerance on comfort levels) along with the actual indoor environment temperature changes, may further accentuate this intermittency as these aspects also condition the actual operation and control of different technologies. Furthermore, the variety of heating (cooling) units’ operation modes, e.g., electric heat pumps equipped with a variable-speed compressor enabling a modulable heating/cooling generation compared to an ON-OFF mode, as well as the impact of external factors such as external source temperature (i.e., air for ASHP, water for water-source heat pumps) on the device performance also constitute modelling challenges. Additionally, the co-existence and operational complementarity of different technologies are other aspects that should be accounted for in the modelling. For example, a combination of reversible heat pump and a gas boiler acting as an “auxiliary heater” in a hybrid heat pump system may act as an alternative solution to help smooth consumption peaks seen by the electricity network as well as prevent heat pump oversizing. This may be achieved by deploying the reversible heat pump to meet space cooling as well as space heating demand during more “normal” operating conditions, complemented by the auxiliary boiler to cover for the remainder space heating demand in extreme weather conditions.

Thus, the required modelling framework should incorporate all the relevant demand drivers and capture, at **different aggregation levels**, their *diversity* and *coincidence* with an adequate time granularity to be able to realistically estimate *electrified* buildings’ heating (and cooling) energy requirements.

[1] Heat is also required for cooking activities. However, it only accounted for ~5% of the total residential energy demand in Australia.

This report provides the findings of a comprehensive literature review conducted on existing studies and academic and commercial tools in Australia and worldwide developed for estimating heating and cooling energy requirements profile within and across many buildings.

In this respect, to estimate the thermal energy requirements of the building sector at different aggregation levels independently from prior historical energy consumption information, while also understanding the physical components' inherent flexibility (e.g., buildings' envelope, technologies' operation) with high spatial and temporal granularity, a physics-based bottom-up modelling approach is regarded, compared to a top-down method, as more suitable in the context of this project. After identifying some of the key drivers of the thermal demand, including location and weather conditions, buildings' envelope construction materials and equivalent thermal properties, buildings' internal conditions and installed technologies type, it emerged that bottom-up tools and models currently available in the literature to estimate thermal energy requirements of the Australian building sector are not adequate. A comparative summary of the features of the surveyed bottom-up models and tools is provided in Table 1.

As highligthed in Table 2, these models, apart from [22][2], do not include an accurate and realistic modelling of the whole-building system thermal inertia3 associated not only with the building envelope, but also its interactions with hot water tanks and heating and cooling distribution system (e.g., emitters). As a result, they are not able to realistically capture the impact of such interactions on the heating (and cooling) unit's control and operation. Moreover, the accuracy the different technologies are modelled with, is sometimes limited as performance dependency on external factors, such as external source temperature (e.g., air, water) or input energy vector is not considered. Similarly, apart from the models in [20] and [22], for a given household size (i.e., total occupants number), the time-dependency of the number of *active* occupants and its effects on energy consumption is disregarded. Additionally, the co-existence and operational complementarity of different technologies and applications, e.g., using the same heating unit to provide both space heating and domestic hot water (i.e., hydronic systems), or already-installed gas boiler operated as auxiliary heater in hybrid heat pump systems under extreme weather conditions, are not explored. Finally, some of the surveyed models do not separate dwelling's energy services demand and energy vector consumption and cannot readily capture the effects of switching energy services between input energy vectors under different technological penetration scenarios.
Indeed, the development of an accurate physics-based bottom-up model with all the above-mentioned features, specifically developed for the Australian building sector, including residential and small commercial buildings, represents the next step of this project.

[2] However, this was originally developed for the UK.
[3] Also affected by the adopted time resolution.

Table 1. Summary of physics-based bottom-up thermal energy demand models.

Reference	Spatial granularity (Scale)	Temporal granularity	Occupancy patterns	Building physical properties	Technologies operational characteristics	Aggregation method	Weather-dependency	Country	Included (thermal) energy services	Building stock
[17]	Building-level	Monthly	Only number of occupants but no time-resolved occupancy profiles	Yes, simplified	Fixed, with differentiation between Summer and Winter	NA	Yes	UK	Space heating and cooling, DHW, cooking	Residential
[18]	Building-level	Sub-hourly	User-defined	Yes, detailed	Detailed, sub-components included.	NA	Yes	USA	Space heating and cooling, DHW, cooking	Residential and small commercial
[20]	Building-level to district-level	Hourly	Yes, considering difference in number of occupants	Yes (EnergyPlus)	Average efficiency	Archetypes	Yes	Switzerland	Space heating and cooling, DHW	Residential
[21]	Building-level to city-level	Hourly	Yes, with no differentiation by number of occupants	Yes (DOE2-eQUEST)	Default efficiency	Archetypes	Yes	Australia (City of Melbourne)	Space heating and cooling, DHW	Residential and small commercial
[22]	Building-level up to region-level	Sub-hourly	Yes, considering difference in number of occupants and reflective of location-specific population's behavior	Yes (4 nodes electrical analogue approach)	EHP COP modelled as function of indoor and outdoor temperature, defrost cycles included.	Archetypes	Yes	UK	Space heating and cooling, DHW, cooking	Residential
[26]	Building-level up to region-level	Hourly	Yes, with no differentiation by number of occupants	Yes (EnergyPlus)	EHP COP modelled as function of outdoor temperature	Archetypes	Yes	Texas (USA)	Space heating and cooling	Residential
[29]	Building-level	Hourly	Yes, with no differentiation by number of occupants	Yes (Frequency response model)	Average efficiency	NA	Yes	Australia	Space heating and cooling	Residential
[34], [37]	Building-level up to Country-level	Yearly. Hourly resolution available at aggregated level only.	Yes, with no differentiation by number of occupants	Yes (using [25])	Average efficiency	Stock model of residential appliances coupled with archetypes	Yes	Australia	Space heating and cooling, DHW, cooking	Residential
[39]	Building-level up to Country-level	Hourly. Daily for DHW.	Yes, with no differentiation by number of occupants	Yes (using [25])	Average efficiency	Archetypes	Yes	Australia	Space heating and cooling, DHW	Residential

Table 2. Summary of the capabilities and modelling features of bottom-up models and tools currently available in the literature.

Reference\Feature	Interactions between building envelope and heating/cooling distribution system's thermal storage and DHW tanks	Time-dependency of number of *active* occupants	Technology performance dependency on external factors	Co-existence and operational complementarity of different technologies and applications	Separation of dwelling's energy services demand and consumption
[17]	×	×	×	×	✓
[18]	×	×	✓	×	✓
[20]	×	✓	×	×	×
[21]	×	×	×	×	×
[22]	✓	✓	✓	✓	✓
[26]	×	×	✓	×	×
[29]	×	×	×	×	×
[34], [37]	×	×	×	×	✓
[39]	×	×	×	×	✓

1 Background

As the need for whole-energy system decarbonization becomes more urgent, the building sector, particularly in urban areas, is currently in the spotlight as it is responsible of a significant share of greenhouse gases (GHG) emissions. It is in fact accountable for 17.5% of GHG emissions (10.9% for residential and 6.6% for commercial), mostly coming from space conditioning (heating and cooling) energy requirements, as well as domestic hot water (DHW) [1] consumption[4]. In Australia, space heating and DHW accounted for 40% and 23%, respectively, of the total residential energy demand in 2014 [2].

With the mass adoption of localised renewable energy generators and distributed energy resources (DER), different pathways have been proposed and explored to decarbonize the building sector. These include direct electrification of heating/cooling (e.g., through heat pumps) along with the replacement (including blending) of fossil-fuels with renewable gases, i.e., "green" hydrogen, potentially establishing links and interaction between different energy infrastructures [3] (e.g., electricity and gas) as the heat fulfilled by one network may be supplied by the other.

Hence, it is crucial to assess the effect of these changes in the heating (and cooling) sector on the energy business and infrastructure, e.g., by informing on networks' adequacy and potential reinforcements/investments required and quantifying the value of potential demand side flexibility that can be accessed, useful for example for demand aggregators.

When moving from transmission to distribution level, because of the variability in buildings' characteristics as well as customers' behaviour and energy usage, the diversity has a less smoothing effect on the aggregated demand profile which could then impact on its peaks. This could also be further exacerbated by the high seasonality (weather sensitivity) of the thermal demand, which also shows a comparatively lower diversity (compared to electricity) [4].

In fact, the storage intrinsically available in buildings' thermal mass and potentially from heating/cooling system's emitter (e.g., radiator panel or underfloor water pipes in hydronic heating systems) as well as the existence of hot water storage tanks, effectively hides the possibly "peakier" thermal demand, which could only be captured at higher time resolution (e.g., sub-hourly).

For instance, the switch to electro-thermal technologies such as air-to-air heat pumps, where heat (cooling) is directly supplied to the indoor environment without an emitter system, would eliminate this further heat transfer step, thus resulting in a decreased buildings' storage capacity and unveiling a peaky and more intermittent electricity consumption profile. This intermittency also comes, and may be further accentuated, by the actual operation and control of different technologies. In fact, the heating (cooling) system operation is dictated by occupants' presence and preferences in terms of temperature setpoints (and tolerance on comfort levels) along with the actual building response, in terms of indoor environment temperature changes, to the thermal energy provision. Aspects like the variety of heating (cooling) units' operation modes and controls, such as ON-OFF or modulable heating/cooling generation (e.g., single vs variable-speed compressor electric heat pumps), or the possible performance dependency on external factors, such as external source temperature (e.g., air, water), may represent an additional modelling challenge. Nonetheless, the co-existence and complementarity of different technologies, for example determined by extreme weather

[4] Heat is also required for cooking activities. However, it only accounted for ~5% of the total residential energy demand in Australia.

conditions or price signals, should be taken into consideration in the modelling. Indeed, there may be cases where hybrid heat pump systems, which consist of a combination of reversible heat pump and a gas boiler acting as an "auxiliary heater", represent a plausible option that could help smooth such peaks seen by the electricity network as well as avoid heat pump oversizing. In this respect, the reversible heat pump can be deployed to meet space cooling as well as space heating demand during more "normal" operating conditions while the auxiliary boiler can be exploited to help meet the remainder space heating demand in extreme weather conditions (e.g., during very cold days in Winter) along with DHW load. This calls for a modelling framework that allows to realistically estimate *electrified* buildings' heating (and cooling) energy requirements while identifying all the relevant demand drivers and capturing, at **different aggregation levels**, their *diversity* and *coincidence* with an adequate time granularity.

In this context, two main modelling approaches can be distinguished, namely top-down and bottom-up, whose main features will be discussed in the following sections.

2 Buildings' thermal energy demand modelling approach

Buildings' energy consumption models aim to quantify the energy requirements for specific end-uses as function of input parameters. Depending on the input information type, model focus and purpose as well as calculation/simulation techniques, two main modelling approaches can be identified: top-down and bottom-up [5]-[6]. An overview of these modelling techniques is provided in the following sections.

2.1 Top-down modelling approach

A top-down modelling approach considers a group of buildings as a single entity and the estimation of the energy consumption of the aggregate is derived by regressing historic energy consumption as function of top-level drivers/variables including macroeconomic indicators, e.g., gross domestic product, energy price, and general weather conditions, population, housing construction/demolition rates, and estimates of appliance ownership and number of units.

Such approach is currently deployed by AEMO for electricity (and gas) demand forecasting [7]. Specifically, the drivers can be split into two different types, namely structural drivers, which can be estimated based on past trends, such as population, economic growth, electricity price, technology adoption, and random drivers, which can be modelled as probability distributions, such as weather-driven coincident customer behaviour, weather-driven embedded generation output. A regression model is developed considering the historical daily (monthly) consumption of the residential loads, temperature measures, namely cooling/heating degree days[5] (CDD/HDD), non-working days and shocks leading to structural breaks such as COVID. This is then used to calculate the daily (monthly) average consumption split between base load, cooling and heating load per connection, then scaled up by the (forecast) number of connections.

The same modelling technique has been adopted in [8]. This work introduces a methodology for generating hourly electrified urban heating load profiles (space heating, water heating and cooking) from historical data, requiring daily electricity demand, hourly ambient temperature, and annual fuel consumption. The model was applied to Australia for different climate zones and considers different building end-uses (i.e., residential, and different sub-categories of commercial buildings). With respect to space heating, the model relies on the concept of heating degree days, assuming that the amount of heat required is proportional to the difference between the daily average ambient temperature and the heating base temperature. Then, daily heating demand is allocated to the different hours based on daily distribution curves which follow the average air-conditioning load profiles obtained from Typical House Energy Use survey by CSIRO [9] for residential buildings. However, the consumption may differ by buildings' thermal performance, also considering the diversity in occupancy patterns. Nonetheless, such differentiation by building type/construction material and thermal performance is not captured. As such, this model cannot realistically model the effect of changes in the building stock, for example improvements in the buildings' thermal performance, nor the impact of the penetration of different technologies as only electric heat pumps are modelled. In fact, it is assumed that all fossil gas and liquefied petroleum gas usage in residential and commercial buildings are replaced by heat pumps (for both space heating and DHW) and cooking appliances powered with electricity. However, there is no clear

[5] They are estimated as the difference between air temperature and a critical temperature considered to be a threshold temperature for heating or cooling appliance use.

information provided on the percentages assumed by building types in different areas, how many of these are electricity-only and how many are connected to the gas network both for SH and DHW provision. The same modelling approach is adopted for DHW and cooking, where the allocation of DHW demand is based on daily/seasonal factors obtained from a study conducted in South Australia [10]. However, these profiles are not differentiated by number of occupants, particularly important in residential buildings.

Therefore, the conclusions drawn with respect to electricity load increase and peak demand are not realistic or exhaustively justified.

Generally, the main feature of the top-down approach is that the energy consumption of the housing sector is "attributed" rather than calculated, based on statistics and an estimate of the total residential sector energy consumption, thus the differences among individual buildings or end-uses are not accounted for. Therefore, such modelling approach does not require detailed input information about the different technologies or buildings' characteristics, which makes it relatively simple to implement.

Nonetheless, this lack of details, e.g., with respect to the different technologies and their operational characteristics, construction materials, control strategies, does not allow to capture the effects of each individual end-use energy demand on the energy infrastructure and suggest key areas for potential improvements/interactions. Moreover, this modelling approach heavily relies on historical data and, given that socio-economic and physical conditions tend to change over time due to, for example, technology breakthrough and climate change, its accuracy may decrease as greater deviations from the "status quo" occur.

2.2 Bottom-up modelling approach

A bottom-up modelling approach focuses on each individual building (or group of buildings) and calculates the energy consumption for each end-uses based on a more detailed level of information, which are then used to extrapolate the (estimated) energy consumption to regional and national levels based on the representative weight of the modelled sample. This approach can be further categorized into two types: statistical and physics-based/engineering methods.

2.2.1 Statistical method

Similar to a top-down approach but at a more disaggregated level, a statistical bottom-up method still relies on historical data. Building's energy consumption can be attributed to each end-uses via three main techniques: regression analysis, conditional demand analysis, and neural network analysis.

+ Regression techniques deploy regression analysis to evaluate the coefficients of the model associated to each input parameter considered to be affecting building's energy consumption. For example, in [11] the energy billing data was regressed onto a non-weather sensitive constant parameter and a weather-dependent coefficient associated with heating degree days to examine the weather and non-weather sensitive components of building's energy consumption. Similarly, the authors in [12] developed a demand simulation model considering socio-technical parameters including technological improvements, population and occupancy behavior changes to study the DR potential of a high uptake of heat pumps in the UK.
+ The conditional demand analysis (CDA) relies on regression analysis based on the presence of end-use appliances. In particular, the total dwelling energy consumption

is regressed onto the list of appliances belonging to the specific dwelling (indicated as binary or count variable). This technique only requires information on appliance ownership data combined with energy use data, potentially obtained via surveys or utility billing records. Additional household socio-economic variables and behavior can also be incorporated, such as in [13]. Nonetheless, to produce reliable results and depending on the number of variables, a large amount of data from hundreds/thousands of buildings may be required.

+ The neural network (NN) analysis makes use of hidden layers made up of “neurons” to mimic the interconnectivity among the output and the different inputs, where each neuron is characterized by a bias term and weights coefficients (with no physical significance), adjusted to minimize error of the model. For instance, this technique was adopted in [14] to estimate the heating and cooling load of residential buildings, taking account of surface area, wall area, roof area, overall height, orientation, glazing area, glazing area distribution and relative compactness as model inputs. Similarly, NNs were used to estimate the energy use of appliances, lighting, and cooling [15], as well as space heating and domestic water heating energy consumption [16] in Canadian residential buildings.

2.2.2 Physics-based method

The physics-based method directly calculates the energy consumption by end-use by solely relying on weather conditions (e.g., temperature, wind, and solar radiation), and detailed information on physical characteristics of individual buildings, taking account of their geometry, envelope fabric/construction materials and thermal properties, indoor temperature setpoints and occupancy schedules as well as technologies’ operational characteristics and power ratings.

As the physics of the end-uses are captured, this approach does not require historical energy consumption data (unless for calibration/validation) and allows for the modelling of new technologies for which historical data does not exist. However, it does require the knowledge of a large number of physical parameters for building’s characterization at such high-level of detail and, given the uncertainty/(potential) low accuracy of the input data, such models need to be calibrated before being applied for final energy modeling. Additionally, this modelling approach allows for a relatively high temporal resolution (daily, hourly, and/or sub-hourly) which is fundamental to properly capture consumption peaks which would otherwise be smoothened over a wider timeframe.

One of the most widely used physics-based models is the Building Research Establishment's Domestic Energy Model (BREDEM) [17] in the UK which estimates the *monthly* fuel consumption for various end-uses of a dwelling based on its characteristics (e.g., number of occupants, installed appliances, building’s thermal characteristics). Another popular physics-based model is EnergyPlus [18], which builds on DOE2 model [19], and simulates building’s energy consumption by end-use (e.g., lights, HVAC systems, etc.) taking account of building’s features including its envelope, geometry, glazing, occupancy schedule, weather-related parameters as well as the dynamics (and thermodynamics) of different heating and cooling systems and controls.

In the process of extrapolating the demand profiles to higher aggregation levels (e.g., district, city, regional level), one of the major drawback of such modelling approach lies in the high number of buildings to be simulated, accompanied by a lack of detailed information for each and every building. Therefore, instead of simulating the entire building stock, this is performed for a limited set of "representative" buildings. In this respect, two techniques can be identified, namely archetype and sample techniques. The archetype technique broadly classifies the housing stock according to categories, based for instance on construction year, size, building type, thermal characteristics etc., based on housing surveys and available data. On the other hand, the sample technique refers to the use of actual sample house data and, since the variety of buildings within a specific area can be substantial, a large database of representative buildings may be required.

Eventually, the energy consumption estimates at higher aggregation levels is extrapoled via scaling up the results considering the number of buildings which fit in the specific archetype/sample category to represent the true building stock in a given area, as done for example in [20]-[21].

3 Buildings' thermal energy demand models: Literature review

In the context of this project, given the features of both top-down and bottom-up modelling approaches outlined in the previous sections, a physics-based bottom-up modelling approach is deemed more suitable since it allows to estimate the electrified thermal energy requirements of the building sector at different aggregation levels while capturing the flexibility inherent in the physical components (e.g., buildings' envelope, technologies' operation) at high spatial and temporal granularity without any prior historical energy consumption information.

Therefore, in this section the focus will be on relevant physics-based bottom-up models and tools currently available in the literature, discussing their merits and limitations with respect to the factors identified as (some of) the main drivers of the aggregated buildings' thermal energy requirements.

3.1 Typical drivers of buildings' heating (and cooling) energy demand

Multiple factors play a role in the aggregated buildings' heating and cooling energy requirements, both structural and random[6], including location and weather conditions, buildings' envelope thermal characteristics and occupants' number and their behavior. For instance, a strong correlation exists between thermal loads and:

+ Outdoor temperature, as it may determine the need for turning on the heater/cooler (i.e., heating/cooling degree days) while also potentially impacting the operating performance of some technologies such as electric heat pumps.
+ Solar radiation, which represents an additional (indirect) heating source, thus reducing the need for heating in Winter while increasing the demand for cooling in Summer. Moreover, solar radiation directly influences electricity generation from rooftop solar PV which can in turn be used to (partially) meet the electrified heating demand.
+ Building's intrinsic storage associated with envelope construction materials and equivalent thermal properties, which define its ability to resist heat flow (i.e., thermal resistance) and to absorb, store and release heat (i.e., thermal mass/capacity), with the latter being a measure of its thermal inertia and flexibility. In fact, buildings with high thermal resistance will be less prone to let heat (cold) enter from the outdoor environment in Summer (Winter), thus requiring a lower amount of energy to cool down/warm up the indoor environment. Similarly, a high thermal mass allows to smooth out the extreme temperatures during the day by alternately storing and releasing heat [22]. This inherent flexibility in buildings' physics can help decouple energy7 use and demand and be exploited to further integrate RES at distribution level where networks are experiencing in some cases reverse flows, overloading of lines and overvoltage issues [23] leading to energy shifting and peak shaving opportunities as part of demand response schemes [24]. Nonetheless, such flexibility may also be coupled with the thermal inertia and storage availability associated with the heating system, which includes not only the heating (cooling) unit(s), but also the emitter (e.g., water flowing in underfloor pipes or radiator panels) and possibly a buffer in hydronic systems. However, when this additional storage is removed by the adoption of ETT

[6] Structural drivers can be estimated based on past trends and expert judgement, but which cannot be assigned a probability, for example population, technology adoption (e.g., PV, EV, ESS). Random drivers can be modelled as probability distributions, for example weather-driven coincident customer behaviour [7].

[7] It can be electricity under an electrification scenario, or any other energy vector adopted to meet the heat demand.

such as air-to-air EHP, the smoothness of the electricity demand profile decreases, and the peaks are directly transferred onto the electricity network. These peaks need to be captured with an adequate time resolution to assess their impact on the network (e.g., 10 min resolution for voltage studies) and infrastructure (e.g., from 10-30 min for transformer overloading, up to 1 min for peaking generation capacity requirements).

+ Building's internal conditions, including:

  - Appliances' ownership.
  - Occupants' preferences (e.g., indoor target temperature).
  - Occupants' number, occupancy pattern and energy behavior, which is in turn influenced by building's end-use (e.g., residential, commercial) as well as the specific time of the day, that is whether the occupant is sleeping, or is at home or at work, specific day of the week (i.e., weekdays, public holidays, and weekends) and specific month of the year. Incentives (e.g., time-of-use or real-time pricing) as well as government policies/regulations may also drive occupants' energy attitude.
  - Occupants' activity profile (e.g., cooking, washing, showering) as the energy consumption of some appliances may affect the energy consumption of others. For example, the heat released during the cooking activity (as energy lost) can help reduce space heating energy requirements.
  - Installed technology size, operation, and controls. Indeed, a major challenge is posed by the variety of heating (cooling) units' operation modes, such as ON-OFF or modulable heating/cooling generation (e.g., single vs variable-speed compressor electric heat pumps) along with the possible performance dependency on external factors, such as external source temperatures as well as input energy vector. Indeed, the work in [22] demonstrated how, for the same building's thermal demand, the resulting energy vector demand profile (i.e., electricity and gas) will differ depending on the specific characteristics of the technology adopted.
  - Installed technology type, that is direct energy "converter"[8] or storage. For example, the total DHW *volumetric* demand depends on the total number of building's occupants, and when they are likely to be active doing activities like showering/bathing, laundry, etc. Therefore, the actual DHW volumetric consumption profile would appear as a sequence of many peaks occurring over limited time windows[9] throughout the day. In this respect, two main types of system exist for heating water, namely instantaneous and storage-based [25]. While in the former case water is heated as required, thus directly reflecting these peaks onto the electricity consumption profile, the latter entails an insulated tank where water is stored and kept hot which allows the corresponding energy requirements to be smoothened.
  - Co-existence and operational complementarity of different technologies, which can potentially help alleviate the stress on the electricity network in terms of reduced peaks, particularly during extreme weather conditions. For example, previously installed gas boiler can still be operated as auxiliary heater, in hybrid heat pump systems, to help provide the additional space heating

[8] That is a technology that consumes energy from a specific energy vector and directly "transforms" it into heating/cooling, for example an EHP which consumes electricity to provide heating services.

[9] For example, average shower duration in Australia is ~7 min [40].

requirements during extremely cold days in Winter, which would only occur on a limited number of instances, instead of oversizing the heat pump.

Moreover, for a specific area, the knowledge of total number of buildings, buildings proportion by selected attributes, e.g., type, number of occupants, thermal performance, appliances, and DER penetration levels, is fundamental.

3.2 Physics-based bottom-up models for aggregated thermal energy demand profiles

Different models have been proposed in the literature to estimate the aggregated electrified thermal energy consumption of the building sector and assess the impact of the adoption of different technologies on the energy infrastructure.

3.2.1 International bottom-up models for aggregated thermal energy demand profiles

From an international perspective, the authors in [26] adopted a bottom-up approach to study the effects of electrification of space heating by replacing all natural gas and other fossil-fuel furnaces with reversible air-source electric heat pumps[10] in the Texas residential sector in terms of energy requirements, peak power demand, and grid capacity utilization. Specifically, the ResStock tool, which samples location-specific buildings' parameters to construct thousands of representative archetypes, is combined with the physics-based tool EnergyPlus. Based on the information provided by the U.S. Census American Community Survey and other geospatial data sources, the ResStock tool estimates the number of buildings corresponding to each weather file location so that the impact of location-specific weather conditions could be considered. To simulate diversified residential heating behavior, the study used sampling probability distributions of cooling and heating setpoints, setpoint offsets, and setpoint offset periods. Nonetheless, only space heating and cooling demand was modelled while the effects of changes in domestic hot water provision were ignored.

The combination of statistics data and EnergyPlus tool was also adopted in [20] where a bottom-up archetype-based methodology was applied to estimate the residential building stock's hourly energy demand for multiple services including heating, domestic hot water, cooling and electricity of a district in Switzerland. In particular, the model can analyse retrofit measures (e.g., envelopes, roof, new DER/heating systems,…) and how these would impact on the energy demand. The tool EnergyPlus represents the simulation core as it generates *hourly* energy demand profiles of individual buildings considering building material, its geometry, location-specific weather information, etc., as well as internal conditions, in terms of occupants' number and presence, activities and indoor environment preferences (e.g., temperature setpoints). In this respect, each individual building is assigned different values of the stochastic parameters such as nominal floor area per person, termostat settings, installed appliances/lighting capacity, sampled from their respective probability distributions. Domestic hot water consumption is also estimated based on probability distribution. Each building is also assigned to a different occupancy profile, generated by applying random variations to the standard-based ones[11].

[10] ASHP COP was modelled as function of outdoor temperature.

[11] Starting from standard-based typical daily schedules for occupancy/appliance usage, diversity is introduced by applying a "vertical" and an "horizontal" variability. With the former, for each hour a random perturbation is applied around its nominal value (by a certain %), to mimic a different number of people in the building; within the latter, the 24 hours are divided into N blocks and within each block the nominal values are shuffled with each other.

An archetypical modelling approach was also adopted in [21] where a bottom-up methodology was proposed to estimate energy consumption profiles for both residential and commercial buildings at city level. The identified archetypes were simulated through the DOE2-eQUEST software which estimates building's energy consumption by end-use including heating, cooling, domestic hot water, and lighting. A set of different occupancy schedules were obtained by combining standard daily presence profiles on weekdays and weekends (holiday) as defined by the ASHRAE 90.1 [27] with traffic profile. Aggregated profiles were obtained based on the number of buildings and the floor area of each building type in each city area. The model was then applied to evaluate the flexibility potential from HVAC control of buildings in the City of Melbourne, considering building's thermal inertia, time of the day, weather conditions, heating system operation and occupants' presence and comfort.

To this point, the models presented above are technology-specific, e.g., EHP for heating purposes. However, direct electrification through electro-thermal technologies (ETT) like EHP is only one of the pathways being proposed and a model that captures the effects of switching energy services between input energy vectors (e.g., electricity, hydrogen) by clearly separating dwelling energy services demand and consumption in a multi-energy context is fundamental to assess different decarbonization scenarios. Moreover, the technologies modelling details and time granularity adopted may not be appropriate to realistically capture the electrified heating (and cooling) demand profiles. In fact, while "virtual" storage associated with the building envelope is accounted for, the effects of existing ''physical'' storage[12] in buildings, such as hot water tanks and heat storage in heat emitters, are overlooked. Nonetheless, this modelling element is crucial when assessing the shift from natural gas to electricity.

In this respect, a high-resolution spatially-resolved multi-energy domestic demand profiles, including space heating and DHW, as well as cooking and electrical appliances, was developed in [22], which considers the full potential for thermal storage in the heating system and building elements. Unlike the works mentioned above which deploy black box tools, such as EnergyPlus/eQuest, to simulate buildings' energy consumption, the building model is described using the electrical analogue approach, made up of four nodes and characterised by node thermal capacitances and thermal resistances, whose values depend on the construction materials' thermal properties and buildings' geometry. The system is then perturbed by the outdoor environment temperature evolution as well as by energy fluxes related to solar radiation, cooking, ventilation and occupant metabolism, the latter being dependent on dwelling occupancy. In this respect, while in previous works occupancy profiles were obtained from predefined standards, thus not being reflective of location-specific population's behavior, the work in [22] adopts the model developed by Richardson et al. in [28]. Specifically, the model in [28] is capable of generating realistic occupancy data for UK households, considering surveyed time-use data describing what people do and when, accounting for differences between weekdays and weekends as well as different households size (i.e., total number of occupants). Another important feature of the model is its high granularity as it can operate at one minute time resolution and is thus able to capture the relevant intertemporal dependencies and interactions, including ETT performance and controls and whole building heating (cooling) system inertia, considering not only hot water tanks and building fabric but also heat storage in heat emitters. Finally, similarly to previous works, aggregated dwellings' energy profile is determined based on building stock's statistics.

[12] Particularly when exploring demand response potential from ETT.

Nonetheless, the model was specifically built, calibrated and validated for the UK building sector and corresponding parameters for Australian buildings (in each state) are needed to apply the model to this study.

3.2.2 Australian bottom-up models for aggregated thermal energy demand profiles

In the context of the Australian building sector, the Nationwide House Energy Rating Scheme (NatHERS) software was first developed by CSIRO to calculate hourly heating and cooling energy requirements for residential buildings and, based on the totals over a year, star ratings were assigned with star bands being set by each state or territory jurisdiction [29]. The software could model single storey detached houses, and only up to four zones could be described by the user, namely living, bedrooms, other conditioned[13], and unconditioned. Moreover, the available building elements (walls, floors, etc.) were limited to a fixed list and the ventilation model is not very accurate as it did not account for wind direction, opening sizes and locations.

Therefore, the AccuRate software [30] represents an improved version of NatHERS. In fact, it couples a frequency response building thermal model [31] and an improved multi-zone ventilation model [32] where the flow rates through openings (indoors-outdoors, or between zones) are then used, together with the temperatures of the incoming air flows, to calculate the effect on the temperature of each zone. Among the many improvements, the software allows the user to build new constructions and to modify existing ones based on a comprehensive fixed list of materials, including insulations and air gaps, and it can describe up to 99 zones. Moreover, the user can change the thermal settings, including heating and cooling schedules and thermostat settings, to consider occupants' behavior and occupancy patterns.

This tool was deployed in different studies. For instance, the Department of Industry, Science, Energy and Resources commissioned an update of the Residential Baseline Study (RBS) conducted in 2008 [33], with the objective to develop a model of energy consumption for all categories of residential appliances/equipment (and projection until 2030) as well as potential residential electricity peak demand during extreme weather events [34]. The RBS model is a bottom-up engineering model as it calculates the *yearly* energy consumption for each end-use (e.g., space conditioning, water heating, cooking, etc.) and by fuel at the household level and then aggregates these consumptions on a jurisdictional basis (state/territory/country) and by relevant climate zone where applicable. The approach estimates the energy use at the appliance level (Unit Energy Consumption, UEC) and then aggregates the energy use across all appliances and households to get the total energy use. First of all, the model builds on a stock model of all residential appliances, which collects data on the equipment characteristics of the products sold in every year, e.g., the average size, power, and efficiency, and usage patterns and user behavior regarding all appliance use. With respect to space conditioning equipment, the usage depends on factors such as the locality, weather, building thermal efficiency, equipment type and occupant usage behaviours. The approach adopted for this specific appliance category calculates the UEC considering information on usage behavior. Information was available on the operating hours of space conditioning equipment across different types of equipment and States in Australia, for example from the Australian Bureau of Statistics Household Energy Consumption survey (ABS HEC 2014) [35]. Then, these estimates are adjusted in accordance with the outcomes from thermal modelling depending

[13] i.e., heated and/or cooled space.

on building shell efficiency changes. In particular, the software AccuRate developed by CSIRO [30] was used to assess the building shell efficiency and estimate the heating and cooling energy requirements in different climate zones, given its specific design, construction, orientation and specified internal thermal comfort conditions and *predefined* occupancy. Also in this piece of work an archetype approach was adopted to estimate the aggregate energy demand, and in particular the “average” dwelling for each identified category was analyzed [36]. Nevertheless, the hourly energy consumption and peak demand were not explicitly described. This gap was covered with the RBS 2021 [37] over the period from 2000 to 2040. Compared to the study performed in 2015, the RBS 2021 includes average (hourly) power demand by time of use for weekdays and weekend, and for summer, winter and shoulder seasons including summer and winter peak demand, as well as annual weather data linked to energy use such as annual CDD and HDD. In particular, the relationship between the weather variables and hours of use of space conditioning products is a user-defined input and affects the annual energy consumption by space conditioning in the State. To estimate the time-of-use profiles14 of each end-use product, the Annual Energy Consumption (AEC) of each product for a specific operation mode (e.g., stand-by) and for each region is proportioned to each typical day type (by season and week/end day), following default proportions, and then allocated over the 24-hour period in a day. However, these proportions are not differentiated over the many buildings within the area of interest and the resulting profiles, especially for those appliances whose energy consumption is highly related to residents’ behavior, cannot realistically capture the diversity and coincidence of multi-energy demand profiles.

By combining AccuRate engine with modules for energy consumption for lighting, water heating and other household appliances within the Australian Zer-Emission House (AusZEH) tool [38], the authors in [39] developed a physics based bottom-up model to estimate, with an hourly resolution, the annual housing stock multi-energy services energy consumption at different aggregation levels (Census Collection District, Statistical Local Area, city, state, nation). The model adopts an archetypical approach as a limited set of ‘‘prototype’’ dwellings that represent categories of houses identified in the housing stock are simulated using AusZEH tool to assess energy requirements for space heating and cooling (via AccuRate engine), water heating, lighting and other household appliances. While space heating and cooling energy requirement profile is determined with an hourly resolution considering building construction materials and their thermal characteristics, equipment and appliances, local climates and occupancy patterns, energy consumption for hot water, lighting and other appliances are calculated on a daily basis considering their average consumption based on the time (hours) spent in active, standby and off modes. In fact, although the models accounts for the total number of occupants, they do not capture “when” each occupant is active in households with more than one occupant. Indeed, only seven predefined occupancy profiles were considered in the models, identified in accordance with the ABS Time Use Survey, and only reflect a “single person” occupancy.

Finally, with respect to the existing models for the Australian building sector, the existing interactions among the different end-uses, e.g., heat gains form cooking activities which impact the space conditioning energy requirements, are not captured as well as the impact of and temporal interdependency of existing storage elements. A summary of the characteristics of the physics-based bottom-up models surveyed and described above is provided in Table 1 below. Then, Table 2 highlights the available models’ capabilities and the potential to include

[14] Proportion of annual energy consumed by the product in a given period (1 hour).

and capture the effects of the main typical drivers of buildings' heating and cooling energy consumption profiles listed above.

Table 1. Summary of physics-based bottom-up thermal energy demand models.

Reference	Spatial granularity (Scale)	Temporal granularity	Occupancy patterns	Building physical properties	Technologies operational characteristics	Aggregation method	Weather-dependency	Country	Included (thermal) energy services	Building stock
[17]	Building-level	Monthly	Only number of occupants but no time-resolved occupancy profiles	Yes, simplified	Fixed, with differentiation between Summer and Winter	NA	Yes	UK	Space heating and cooling, DHW, cooking	Residential
[18]	Building-level	Sub-hourly	User-defined	Yes, detailed	Detailed, sub-components included.	NA	Yes	USA	Space heating and cooling, DHW, cooking	Residential and small commercial
[20]	Building-level to district-level	Hourly	Yes, considering difference in number of occupants	Yes (EnergyPlus)	Average efficiency	Archetypes	Yes	Switzerland	Space heating and cooling, DHW	Residential
[21]	Building-level to city-level	Hourly	Yes, with no differentiation by number of occupants	Yes (DOE2-eQUEST)	Default efficiency	Archetypes	Yes	Australia (City of Melbourne)	Space heating and cooling, DHW	Residential and small commercial
[22]	Building-level up to region-level	Sub-hourly	Yes, considering difference in number of occupants and reflective of location-specific population's behavior	Yes (4 nodes electrical analogue approach)	EHP COP modelled as function of indoor and outdoor temperature, defrost cycles included.	Archetypes	Yes	UK	Space heating and cooling, DHW, cooking	Residential
[26]	Building-level up to region-level	Hourly	Yes, with no differentiation by number of occupants	Yes (EnergyPlus)	EHP COP modelled as function of outdoor temperature	Archetypes	Yes	Texas (USA)	Space heating and cooling	Residential
[29]	Building-level	Hourly	Yes, with no differentiation by number of occupants	Yes (Frequency response model)	Average efficiency	NA	Yes	Australia	Space heating and cooling	Residential
[34], [37]	Building-level up to Country-level	Yearly. Hourly resolution available at aggregated level only.	Yes, with no differentiation by number of occupants	Yes (using [25])	Average efficiency	Stock model of residential appliances coupled with archetypes	Yes	Australia	Space heating and cooling, DHW, cooking	Residential
[39]	Building-level up to Country-level	Hourly. Daily for DHW.	Yes, with no differentiation by number of occupants	Yes (using [25])	Average efficiency	Archetypes	Yes	Australia	Space heating and cooling, DHW	Residential

Table 2. Summary of the capabilities and modelling features of bottom-up models and tools currently available in the literature.

Reference\Feature	Interactions between building envelope and heating/cooling distribution system's thermal storage and DHW tanks	Time-dependency of number of *active* occupants	Technology performance dependency on external factors	Co-existence and operational complementarity of different technologies and applications	Separation of dwelling's energy services demand and consumption
[17]	×	×	×	×	✓
[18]	×	×	✓	×	✓
[20]	×	✓	×	×	×
[21]	×	×	×	×	×
[22]	✓	✓	✓	✓	✓
[26]	×	×	✓	×	×
[29]	×	×	×	×	×
[34], [37]	×	×	×	×	✓
[39]	×	×	×	×	✓

4 Final insights and overview of proposed modelling framework

From the literature review, and highlighted in Table 2, it emerged that tools and models currently available to estimate thermal energy requirements of the Australian building sector are not adequate for the puroposes of realistically analyzing the impact of "energy and power shifting" in the heating (and cooling) sector on the energy network and infrastructure and quantifying the flexibility, e.g., for demand response applications, available from electro-thermal technologies, building's heating (cooling) system and its envelope.

Therefore, to fill the identified gaps, a physics-based bottom-up model, specifically developed for the Australian building sector, including residential and small commercial buildings, will be developed in the next stages of the project. Specifically, the model simultaneously:

+ Models building's construction material and thermal inertia;
+ Considers location-specific occupancy patterns and activity profiles for households of different sizes;
+ Allows for high temporal granularity (hourly, sub-hourly) of multi-energy thermal demand profiles for heating, cooling, DHW, cooking;
+ Includes an accurate and realistic modelling of heating (and cooling) technologies' operational characteristics and controls to realistically incorporate the variety of operation modes along with the possible performance dependency on external factors, such as external source temperature (e.g., air, water) as well as input energy vector.
+ Accurately represents the whole-building system thermal inertia, coming from the ''virtual'' storage in the building envelope element, and the ''physical'' storage associated with hot water tanks as well as heat storage in heat emitters and captures their relevant intertemporal dependencies and interactions.
+ Considers the relevant time resolution to properly capture the peaks of the electrified thermal demand profiles arising from energy vector (and technology) shitfing;
+ Clearly separates dwelling energy services demand and consumption in a multi-energy context thus capturing the effects of switching energy services between input energy vectors while not being restricted to a technology-specific analysis, but rather incorporating the co-existence and operational complementarity of different technologies such as in hybrid heat pump systems.

In the process of aggregating the thermal demand profiles of individual buildings, to overcome the limitations posed from the lack of detailed information for each and every building in the area under analysis, an archetypical modelling approach will be deployed. Specifically, a limited set of "sample"/"prototype" buildings representing classes of houses in the housing stock classified according to different criteria, e.g., to dwelling type, insulation level/construction year, size, etc., will be simulated and then combined and "weighed" to represent the true building stock in the area(s) of interest. Finally, for a given technology portfolio and penetration levels, the thermal demand profiles are mapped to the corresponding energy vector.

With a focus on post 2030 period, the famework relies on projections of future building sector conditions, including population growth, buildings' construction activities and thermal performance (e.g., building envelope retrofit measures following changes in buildings' construction code requirements), technological developments (e.g., appliances uptake, efficiency improvements) as well as future climate scenarios.

An overview of the proposed buildings' heating (and cooling) energy demand profile modelling framework is reported in Figure 1.

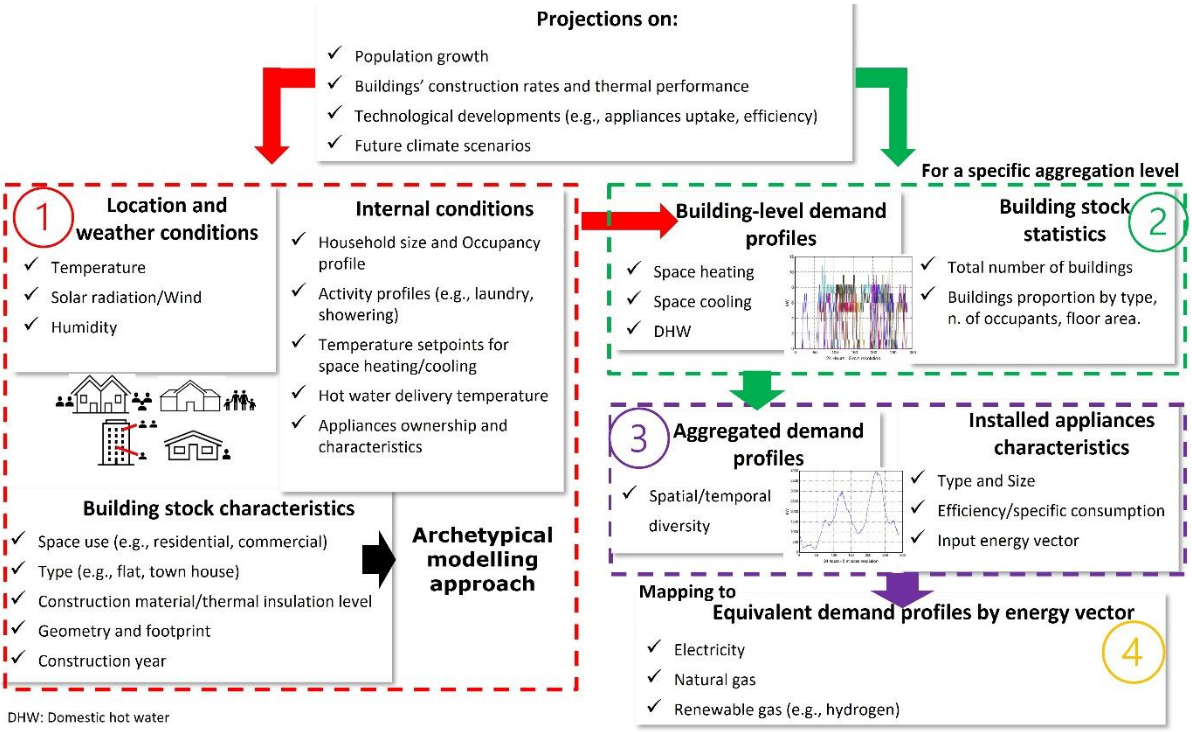

Figure 1. Proposed buildings' heating (and cooling) energy demand profile modelling framework.

References

[1] https://ourworldindata.org/emissions-by-sector

[2] Australian Energy Council, "Australia's Energy Future: 55 by 35 Electrification & Heat",Discussion Paper Series, 2022.

[3] L.J.Reedman, M.S. Chew, J. Gordon, W. Sue, T.S. Brinsmead, J.A. Hayward, and L. Havas, "Multi-sector energy modelling", CSIRO, Australia, 2021.

[4] S. Heinen, P. Mancarella, C. O'Dwyer, and M. O'Malley, "Heat electrification: The latest research in Europe," IEEE Power Energy Mag., vol. 16, no. 4, pp. 69–78, 2018.

[5] L. G. Swan, V. Ismet Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques", Renewable and Sustainable Energy Reviews, Volume 13, Issue 8, 2009, Pages 1819-1835.

[6] W. Li, Y. Zhou, K. Cetin, J. Eom, Y. Wang, G. Chen, X. Zhang, "Modeling urban building energy use: A review of modeling approaches and procedures", Energy, Volume 141, 2017, Pages 2445-2457.

[7] AEMO, "Forecasting Approach –Electricity Demand Forecasting Methodology", August 2022.

[8] C. Cheng, "*A pathway to decarbonized energy*", Doctoral thesis, Australian National University, 2023.

[9] CSIRO. Typical House Energy Use n.d. https://ahd.csiro.au/other-data/typical-house-energy-use/

[10] D. Whaley, R. Liddle, L. Mudge, E. Harmer, W. Saman, "Residential Water Heater Baseline Data Study-

Final Report", 2014.

[11] E. Hirst, R. Goeltz, D. White, "Determination of household energy using 'fingerprints' from energy billing data", Energy Research 1986;10(4):393–405.

[12] S. Eggimann, J. W. Hall, N. Eyre, "A high-resolution spatio-temporal energy demand simulation to explore the potential of heating demand side management with large-scale heat pump diffusion", Applied Energy, 2019.

[13] M. Papineau, K. Yassin, G. Newsham, and S. Brice, "Conditional demand analysis as a tool to evaluate energy policy options on the path to grid decarbonization", Renewable and Sustainable Energy Reviews, 2021.

[14] G. Zhou, H. Moayedi, M. Bahiraei, Z. Lyu, "Employing artificial bee colony and particle swarm techniques for optimizing a neural network in prediction of heating and cooling loads of residential buildings", Journal of Cleaner Production, 2020.

[15] M. Aydinalp, V. Ismet Ugursal, A.S. Fung, "Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks", Applied Energy, 2002.

[16] M. Aydinalp, V. Ismet Ugursal, A.S. Fung, "Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks", Applied Energy, 2004.

[17] J. Henderson, and J. Hart, "BREDEM 2012, A technical description of the BRE Domestic Energy Model", 2012.

[18] Department of Energy. EnergyPlus. 2016. https://energy.gov/eere/buildings/downloads/energyplus-0.

[19] N. Doe, J. Hirsch. Overview of DOE-2.2. 1998. Camarillo, CA.

[20] D. Wang, J. Landolt, G. Mavromatidis, K. Orehounig, J. Carmeliet, "CESAR: A bottom-up building stock modelling tool for Switzerland to address sustainable energy transformation strategies", Energy and Buildings, Volume 169, 2018, Pages 9-26.

[21] Q. Gao, M. Demoulin, H. Wang, S. Riaz and P. Mancarella, "Flexibility Characterisation from Thermal Inertia of Buildings at City Level: A Bottom-up Approach," 2020 55th International Universities Power Engineering Conference (UPEC), Turin, Italy, 2020.

[22] N. Good, L. Zhang, A. Navarro-Espinosa, and P. Mancarella, "High resolution modelling of multi-energy domestic demand profiles," Appl. Energy, vol. 137, pp. 193–210, 2015.

[23] A. Navarro-Espinosa, N. Good, L. Zhang, P. Mancarella and L. F. Ochoa, "EHP in low voltage networks: Understanding the effects of heat emitters and room temperatures," 2015 IEEE Eindhoven PowerTech, Eindhoven, Netherlands, 2015, pp. 1-5.

[24] L. Zhang, N. Good, P. Mancarella, “Building-to-grid flexibility: Modelling and assessment metrics for residential demand response from heat pump aggregations”, Applied Energy, Vol. 233–234, 2019, Pages 709-723.

[25] https://www.energyrating.gov.au/products/water-heaters

[26] P. R. White, J. D. Rhodes, E.J.H. Wilson, M. E. Webber Walker, “Quantifying the impact of residential space heating electrification on the Texas electric grid”, Applied Energy, 2021.

[27] ASHRAE, “ASHRAE 90.1–2013: Energy Standard for Buildings Except Low-Rise Residential Buildings, American Society of Heating,” Atlanta, 2013.

[28] I. Richardson, M. Thomson, and D. Infield, “A high-resolution domestic building occupancy model for energy demand simulations,” Energy Build., vol. 40, no. 8, pp. 1560–1566, 2008.

[29] A. Delsante, “Is the new generation of building energy rating software up to the task? - A review of AccuRate”, CSIRO Manufacturing and Infrastructure Technology, Paper presented at ABCB Conference ‘Building Australia’s Future 2005’, Surfers Paradise, 11-15 September 2005.

[30] https://ahd.csiro.au/about/software/

[31] P.J. Walsh, A. E. Delsante,”Calculation of the thermal behaviour of multi-zone buildings”, Energy and Buildings, 5:231–42, 1983.

[32] Z. Ren, D. Chen, “Enhanced air flow modelling for AccuRate – A nationwide house energy rating tool in Australia”, Building and Environment, 45: 1276-1286, 2010.

[33] Department of the Environment, Water, Heritage and the Arts, “Energy Use in the Australian Residential Sector 1986-2020”, 2008.

[34] EnergyConsult, “Residential Energy Baseline Study: Australia”, August 2015.

[35] https://www.abs.gov.au

[36] EnergyConsult, “Residential Energy Baseline Study: Technical Appendix”, August 2015.

[37] EnergyConsult, “RBS2.0 Methodology Report”, September 2020.

[38] Z. Ren, G. Foliente, W. Chan, D. Chen and M. Syme, “AusZEH Design: Software for low-emission and zero-emission house design in Australia”, Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association, Sydney, 14-16 November.

[39] Z. Ren, P. Paevere, C. McNamara, “A local-community-level physically-based model of end-use energy consumption by Australian housing stock”, Energy Policy, 2012.

[40] https://www.mdba.gov.au/sites/default/files/water-volumes-teacher-notes.pdf