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An effective methodology to quantify cooling demand in the UK housing stock

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HIGHLIGHTS

- A methodology is presented to quantify thermal demand for common UK dwellings.
- A comprehensive range of U-values is considered to model UK houses of diverse ages.
- A model is introduced to estimate thermal load for varying thermostat settings.
- Individual and combined effects of design parameters on thermal load are assessed.
- Scarcely available cooling demand data of UK houses can be derived with the method.

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IES VE

ABSTRACT

According to the 2020 UN emissions report an increase by 3 °C of the average global temperature compared to pre-industrial levels is to be expected if no corrective measures are implemented. Alongside this, the UK Meteorological Office predicts that the UK will see a surge in both the recurrence and severity of heatwaves during summers—leading to an increased demand for space cooling. Although commercial infrastructures are likely to incorporate cooling provisions, residential properties are generally at a nascent stage to facilitate indoor cooling. Upgrading the cooling capabilities of residential dwellings would require a clear understanding of cooling demand. To this end, this paper presents a methodology to quantify cooling demand for typical UK dwellings. Following an in-depth literature review of the current UK housing stock to retrieve physical building data, a physics-based model was created using commercial building envelope modelling software. This considered building construction methods, ages, and layouts. To provide confidence in the approach, the model was verified with real data taken from a semi-detached dwelling in Loughborough, UK, and subsequently, thermal models for the most common type of dwellings were developed. Results highlight how cooling demand varies for differing dwelling types, orientations, locations, and constructions. For instance, for a typical design year, corner flats on the top floor of a 3-storey building in Cardiff, UK, with an orientation of 0° (north-facing) have the highest monthly cooling demand of 27.21 kWh and the bottom floor mid-flats have the lowest demand of 17.36 kWh. The presented methodology provides an initial framework to generate residential cooling demand data, which could be used to inform building developers, utilities, and local authorities on cooling demand peaks, overheating risks, and energy efficiency of typical UK dwellings in a warming world.

1. Introduction

The climate in the UK has mostly been temperate in the past with little demand for space cooling. However, in present times, the issue of overheating has risen to the forefront. As per the UK Meteorological Office, the UK will face warmer summers with an increase in both the recurrence and the severity of heatwaves [1]. The UK Health and Security Agency released the Heat Mortality Monitoring Report: 2022, which found that in summer 2022 there were an estimated 2985 deaths associated with heat episodes, which was the highest number in any given year [2].

From the year 1965, several phases of Building Regulations have been introduced by the UK Government to improve the thermal efficiency of buildings. These measures have been beneficial in winters when retaining heat is important. However, heat retention negatively

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Nomenclature

Abbreviations

ACH	Air changes per hour
EPW	Energy Plus Weather
MAE	Mean absolute error
TMY	Typical meteorological year
PSO	Particle swarm optimisation
RMSE	Root mean squared error

Symbols

A	Area (m^2)
k_i	Thermal conductivity (W/m-K)
Q	Heat transfer rate (W)
n	Number of data points
R	Thermal resistance (K/W)
R^2	Coefficient of determination
t_i	Thickness (m)
ΔT	Temperature difference (K)
U	U-value (W/m^2-K)
$\overline{y}$	Mean value (W)
y_i	Measured or observed value (W)
$\widehat{y}_i$	Predicted value (W)

affects dwellings during summer. For example, during the heatwave in 2022, where the ambient temperature reached over 40 °C for the first time in recorded history [3], several newly built flats in London reached internal temperatures of over 30 °C before midday [4].

As residents start to purchase and implement active mechanical cooling systems to combat overheating in dwellings, the increased electricity demand by such systems may have a knock-on effect on the distribution networks [5]. The largest energy transmission and distribution company in the UK, National Grid, conducted a study on cooling demand and released a report estimating that by 2050, cooling demand across the country will place an additional peak load of 39 GW on the network on a typical summer day [6]. Presently, the UK has a spare capacity of 76.6 GW available [7]. Therefore, under normal conditions, the increased cooling demand will occupy more than half of the current headroom. This does not include atypical days such as those during heatwaves, which could place an even larger peak load upon the networks when cooling demand would be highest.

It is worth noting that there are effective passive cooling measures that can be incorporated in dwellings to reduce their cooling demand. From [8] it was found that effective night purging techniques could reduce peak internal room temperatures in newly built houses by up to 5 °C. However, the impact of night purging in older dwellings is much less effective. In a similar note, the effect of covering the external windows, for instance with foil, may have a positive impact on reducing cooling demand. The correct adoption of passive cooling strategies may indeed lead to a significant reduction of internal temperatures, but these measures are only effective in the newer dwellings and the effect may be more muted depending on geographical location. For example, although passive cooling may be sufficient to achieve thermal comfort within dwellings located at the north of the UK even under a heatwave period, this may not be sufficient in the south of the country. In longer and more intense heatwaves, leading to significant overheating of dwellings, simple passive measures may not be sufficient to bring temperature down to safe levels.

The UK Government recently introduced Part O of the Building Regulations in 2022 [9]. The aim of this statutory guidance is to ensure that new buildings comply with the overheating risk assessment as defined by the Chartered Institute of Building Services Engineers (CIBSE) in their standard TM59 [10]. This standard, in turn, directs both architects and engineers in the UK to introduce passive cooling strategies in the design stage of a building to reduce the overheating risk. This ensures that passive measures are economically incentivised, as standard TM59 requires active cooling to be installed if simulations indicate that a building will overheat.

Whilst encouraging, the latest iteration of Building Regulations does not cover the vast majority of the existing UK housing stock. As per estimates released by the Department for Levelling Up, Housing and Communities in May 2023, there were 25.2 million dwellings in the UK as of March 2022 [11]. Combined with the annual housing supply statistics published in November 2023, 212,570 new dwellings were constructed in 2022 [12]. Assuming a similar number of new dwellings had been also developed in 2023, ~425,000 homes fall within the Building Regulations Part O. This implies that only ~1–2 % of the current UK housing stock would have factored overheating into their design.

A report in 2021 from the UK Department for Business, Energy & Industrial Strategy (BEIS) highlighted the most complete cooling demand dataset for commercial buildings available at the time [13]. While such resource is of great relevance, understanding how households and domestic buildings respond to extreme heat and how this might create greater demand for space cooling is still limited and deserves attention [14].

To bridge this gap and to combat the lack of thermal energy demand data available for the residential sector, this paper aims to provide a robust and repeatable methodology that can produce a yearly thermal energy demand dataset for different dwelling typologies within the UK as temperatures increase. Using the presented framework, custom heating and cooling scenarios can be subsequently investigated for any location, weather condition, and dwelling construction. This, in turn, may then be used to research the various effects of using differing technologies to meet cooling demand and, by combining it with long term weather forecast data, estimate the future cooling demand in any household.

Using the methodology presented in this paper, the residential cooling demand of any dwelling within the UK (or any other country) can be calculated with limited building information. This cooling demand data can then be used for a wide variety of purposes. For instance, building developers may use the information to estimate peak heating and cooling demand to size equipment to meet such demands, while utility companies could identify houses (or even pockets of dwellings) with excess energy usage to highlight potential concerns—for instance, potential overloading of distribution transformers. With the understanding that residents will begin to install active cooling devices when temperatures in homes exceed a certain threshold for extended lengths of time, the additional load on the electricity network may be estimated by considering the efficiencies of the different devices installed in households. Local authorities could also use the information to assess houses with vulnerable people at risk of overheating or community level demand during heatwaves to ensure the local energy networks can handle increased loads.

The modelling framework presented in the paper is supported by a thorough literature review on the UK housing stock, construction methods used over the last 100 years, and building plans for the most common dwelling types in the UK. The data aggregated from the review were used as inputs to develop and simulate dynamic thermal models using IES VE [15]. As a commercially licensed software widely used within the construction industry, IES VE has been validated against worldwide standards such as those from ASHRAE and CIBSE. The models were verified using real data recorded for a semi-detached house available in the existing literature [16]. This established a high degree of confidence in the modelling approach taken—leading in turn to an effective calculation of cooling demand.

2. Literature review: UK housing stock and building modelling

This section covers the literature review carried out into the relevant information required for the paper. Starting with an in-depth review of the current UK housing stock, the paper researches the age of dwellings, the historical U-values of each construction, and the most common dwelling types in the UK. The section then looks at the different modelling methodologies that can be used to help quantify the cooling demand in dwellings and the software available to simulate the demand, highlighting why physics-based modelling and the IES VE software were selected for the research.

2.1. UK housing stock

The age of most dwellings in the UK (still in regular use) spans over 100 years. Throughout this time, construction methods have been updated consistently, resulting in differing thermal efficiencies of dwellings. Fig. 1 shows results of an English housing survey conducted in 2020 by the Department for Levelling Up, Housing and Communities—indicating the age of buildings [17].

As shown in Fig. 1, most houses in the UK were constructed before 1965. This is important to note as the Building Regulations were put in place in the UK in 1965 to ensure health and safety standards of dwellings. These regulations established performance benchmarks for fire protection, egress, and building thermal efficiency [18].

The Building Regulations introduced thermal transmittance values, or U-values, which quantify the thermal efficiency of materials using a standardised methodology that allows for comparisons between different material compositions. They indicate the rate at which heat is transferred through a given material (which can be composite) [18], and the lower the U-value is, the better the insulating performance of the material will be. Conversely, a high U-value indicates a fast rate of heat transfer through the material making up the construction. Such material could be a wall, window, roof, or foundation. Interested readers are referred to [19], which provides an in-depth description of the U-value and how it is calculated. Due to maximum allowed U-values for each surface being defined in the Building Regulations, U-values of constructions can be extracted from each iteration of these documents from 1965 onwards.

Table 1 summarises the U-values for building construction components throughout the years considered in this paper. Relevant aspects around the data in the table are discussed in the next subsections.

The methodology for quantifying cooling demand presented in Section 3 of this paper does not account for the varying effects of different material compositions and, for simplicity, focuses solely upon the U-value. This is because an overall U-value provides a good metric for the heat transferred through walls and other surfaces. A detailed examination of the wall composition and its impact on the thermal demand for a building is out of the scope of this work.

2.1.1. Foundations

Pre-1965 U-values for building foundations, obtained from the Building Act of 1878, implied that a 9-in. (225 mm) thick concrete foundation should be placed on the ground unless the sub-soil is gravel or rock [20]. Based on this, pre-1930s buildings should have a foundation slab of 225 mm thick concrete.

Methods such as strip foundations were popularised in the 1940s. However, these foundations retained a concrete slab on top and do not have a large impact on the insulation properties of the material as they are used for more structural properties. The first iteration of the Building Regulations in 1965 mandated a minimum U-value for floors [18] and this has been continuously updated in subsequent years, as shown in Table 1.

2.1.2. Walls

The minimum thickness required to resist rainwater penetration in temperate climates is 315 mm for stone/brick walls [21]. Any wall that is not waterproof will have had post-processing work carried out to ensure compliance with modern Building Regulations. Therefore, the minimum thickness of walls for pre-1920s constructions is 315 mm.

After World War 1, the UK Government introduced the 'Homes for Heroes' scheme (also known as the Addison Act) to improve the living standards of the working class who took part in the war [22]. One of the key requirements was the introduction of cavity walls, which are more effective in keeping out wind and rain when compared to single-layered walls [21]. There were no significant modifications of this method until the introduction of the Building Regulations in 1965, which mandated uninsulated cavity walls and then the introduction of insulation in the 1980s. This led to improved thermal efficiency of walls throughout the years, as evidenced by the reduced U-values in Table 1 as time has passed.

2.1.3. Windows and doors

As specified in [23], new windows should last between 15 and 20 years. With many companies offering warranties for up to 25 years, most households would not have any windows older than 30–35 years. Doors also have an expected life span of 20 to 25 years for unplasticised PVC doors and 30 years for composite and timber doors [24]. Therefore, similar to windows, doors should not be older than 30–35 years.

The Building Regulations classify windows and doors in the same category for the maximum allowed U-values [18]. It is evident that the introduction of double glazing and argon-based insulation has improved the thermal efficiency of windows, as shown in Table 1.

2.1.4. Roofs

The UK Government provides grants such as the Great British

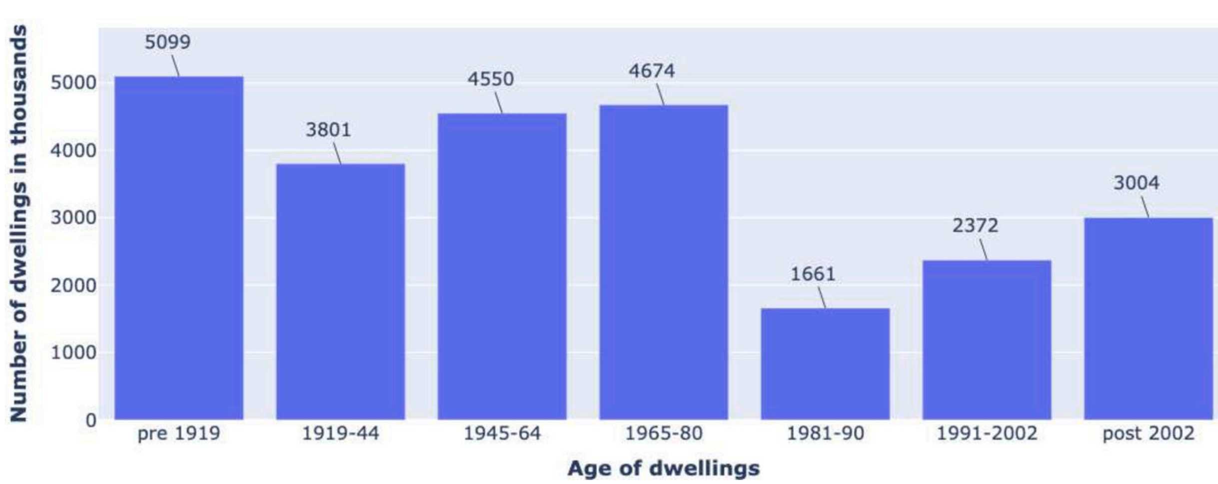


Fig. 1. Age of dwellings in England in 2020 [17].

Table 1
Summarised construction data.

Year	U-value (W/m^2-K)			
	Foundations	**Walls**	**Windows/Doors**	**Roofs**
Pre-1920	225 mm concrete slab (≈3.25)	Single layered brick /stone 315 mm (≈ 1.84)	N/A	N/A
1920	–	Uninsulated cavity walls (≈1.6)	N/A	N/A
1930	300 mm concrete slab (≈2.94)	–	N/A	N/A
1965	Thermal insulation on slab (1.2)	Uninsulated cavity walls (1.7)	N/A	Insulated roofs (1.6)
1970	–	–	Single glazed window (4.8)	–
1980	–	Insulated cavity walls (1)	–	Insulated roofs (0.68)
1990	–	Insulated cavity walls (0.6)	–	Insulated roofs (0.4)
2000	Thermal insulation on slab (0.51)	Insulated cavity walls (0.45)	Double glazed window (3.1)	Insulated roofs (0.35)
2010	Thermal insulation on slab (0.22)	Insulated cavity walls (0.3)	Low emissivity double glazed window (2.0)	Insulated roofs (0.22)
2016	Thermal insulation on slab (0.13)	Insulated cavity walls (0.18)	Double glazed low emissivity window with Argon gas filler (1.4)	Insulated roofs (0.13)
2021 onwards	Thermal insulation on slab (0.13)	Insulated cavity walls (0.18)	Double glazed low emissivity window with Argon gas filler (1.2)	Insulated roofs (0.11)

Insulation Scheme [25] to upgrade loft insulation in homes, free of charge, to reduce energy wastage. Furthermore, previous schemes such as the Green Deal [26] and other similar initiatives have been implemented. With the ease of installation and the availability of grants, most households would have upgraded their loft insulation within the last 30 years. As the Building Regulations have been in place since 1965, the vast majority of homes in the current UK housing stock will fall within this bracket.

As with other construction elements, roof insulation has improved throughout the years, leading to lower U-values for the most recent dwellings—as shown in Table 1.

2.1.5. Dwelling design selection

According to the housing survey reported in [17], which determined the percentage of dwelling types by tenure, the most common dwelling types are terraced, semi-detached, detached, bungalows, and flats. Using this information with publicly available floor plans such as those in [27], it is possible to create models of each of the aforementioned dwelling types.

2.2. Modelling approaches

There are three main approaches to modelling and calculating building thermal demand: physics-based modelling, data-driven modelling, and a combination of the two. These are briefly discussed in the following subsections.

2.2.1. Physics-based modelling

A physics-based model is a representation of the governing laws of nature that innately embeds the concepts of time, space, causality and generalisability. These laws of nature define how physical, chemical, biological and geological processes evolve [28]. With all the known inputs, a physics-based model enables obtaining energy demand using a well-defined set of equations. In turn, there are different alternatives for simulating building energy demand within physics-based modelling. These range from lumped parameter models based on resistance-capacitance (RC) representations to more calculation-intensive options such as the finite element method (FEM).

An RC model simplifies the building model as an electrical network analogue. This simplification enables quantifying an approximate thermal demand using simple calculations. RC models vary from basic 1R1C representations (i.e. 1 resistance and 1 capacitance) to more complex scenarios, such as the 3R2C model—amenable to a more accurate temperature calculation and thus thermal demand quantification. For instance, a 3R2C model was adopted in [29] to conduct simulations for 11 dwellings over an 8-week period while reducing the root mean squared error (RMSE) to 1.03 °C between simulation results and measured values of internal temperature. An in-depth analysis of various RC models was carried out in [30] considering 8 dwellings in Exeter, UK. It was found that 2R1C models provided good estimations of heat demand for all dwellings without an increase in calculation times.

Most three-dimensional (3D) modelling software makes use of finite element analysis including FEM. For instance, FEM was used in [31] to estimate the heating and cooling demand of a residential building. The benefit of using FEM is the incorporation of more complex surface shapes within the model without overly complicating the equations required to calculate thermal demand. To achieve this, FEM splits a surface into a mesh with each node relating to a coordinate in the x, y, and z directions. The finer the mesh, the more accurate the model is but doing so also increases the computational requirement. Each node within the model is assigned a temperature and a heat flux vector. Using a set of differential equations and assuming each surface is unidirectional and the thermo-physical properties within each layer are uniform, heat transfer over time is calculated for each node including the heat flux vector at each node. More detailed information on how commercial software uses FEM to calculate the heat transfer into a building is available in [32].

Due to the lack of cooling demand data in residential buildings, physics-based modelling represents the most suitable approach to be adopted. The approach is widely used today within the construction industry as buildings in the design stages do not have any historical data.

2.2.2. Data-driven modelling

Data-driven modelling is used when there is limited or no physical data available on the building itself (only energy usage data). It utilises machine and statistical learning algorithms to build models that output the desired results [33]. In the context of this paper, historical electrical usage data, boiler information, and any other relevant information that can be obtained could be used to forecast future heating or cooling demands.

Considerable research into data-driven approaches is being carried out nowadays due to the importance of energy efficiency in buildings and the more widespread availability of sensor equipment. For instance, reference [34] reviews different data-driven models to improve energy management in buildings, such as data-driven model predictive control (MPC) and its variants.

Alternatively, work carried out in [35] used publicly available energy performance certificates (EPCs) for dwellings in the UK to estimate the annual heating demand of local communities. This information was then used to study the impact of different heating technologies—with the aim to support policy-making decisions for the UK Government to reach its decarbonisation goals in the residential heating sector and to meet the country's net-zero target.

As cooling in the UK has been largely considered superfluous, most homes have no installed active cooling measures such as air conditioning. Due to this, there is lack of available historical data that can be used, for instance, to feed a machine learning algorithm to generate a future forecast of the cooling demand in the UK. A short discussion on the adoption of forecasting methods using artificial intelligence (AI) algorithms to support cooling demand estimation is provided in Section 5.

2.2.3. Combination of data-driven and physics-based modelling

The third methodology is a combination of the approaches discussed in Sections 2.2.1 and 2.2.2. Also known as grey box models, these use historical data to calibrate simplified physical models [36].

Work reported in [37] adopted a physics-based model to calculate the energy demand in a block of residential flats. The outputs from this model were then used to train a data-driven MPC model to optimise heat use in a block of residential flats. This combined modelling approach proved effective in optimising the existing load.

Additional work carried out in [38] provides a critical review of different grey box models, with a focus upon RC models. The main task in obtaining such models is determining resistance and capacitance values either by adopting a forward approach (white box modelling) or an inverse approach. The forward approach makes use of physics-based calculations that are calibrated/fine tuned using historical data. In contrast, the inverse approach utilises historical data to provide inputs to help create a physics-based model. Methods such as the 'in-use heat balance method' [39] adopt weather data, internal gains, and heating/cooling loads to estimate the RC values of a dwelling. Using these data to then create an RC model that predicts future cooling demand is an example of an inverse approach grey box model.

The main limitation with grey box modelling is the lack of historical cooling data, thus restricting the applicability of the modelling approach. As a result, this methodology has not been applied for this work.

2.3. Modelling tools

There are well-known tools for calculating thermal demand of dwellings such as HAP, TRACE, ESP-r and IES VE [15,40–42]. However, all these software engines follow slightly differing methodologies to conduct simulations.

In general, to ensure the validity of simulation results, there are various global standards that each software package must conform to such as ASHRAE 140 & 90.1, CIBSE TM33, or ISO 5200 [43]. Depending on the standard being conformed to, the equations used to calculate thermal energy demand may vary slightly. Such variations may result in small differences between calculated outputs.

2.3.1. HAP [40]

HAP stands for Hourly Analysis Program and is a building thermal modelling software designed by the company Carrier. In the later software releases it allows 3D modelling of dwellings from floor plans to calculate the thermal demand in dwellings. It conforms to ASHRAE standards 140 and 90.1, but it does not comply with CIBSE standards. Its focus is upon HVAC load calculations and has an 'easy to learn' interface.

2.3.2. TRACE [41]

TRACE, developed by HVAC equipment manufacturer Trane, utilises a command line style system where each dwelling surface is inputted manually. However, as of writing this paper, TRACE is phasing out this approach for 3D modelling. Like HAP, TRACE has a very streamlined approach to HVAC modelling.

2.3.3. ESP-r [42]

ESP-r, developed by the University of Strathclyde and commonly used for research, is a programming-based tool geared towards Linux based on simple line-drawing. It is a free open-source software that provides high accuracy but requires an in-depth understanding of building physics to get the best results. Of all the mentioned software, it arguably has the steepest learning curve due to its complexity.

2.3.4. IES VE [15]

IES VE is widely adopted commercially in the construction industry. The software is used to calculate the thermal demand in dwellings starting from the early design stage through to the completed design. IES VE conforms to standards such as ASHRAE 140 and CIBSE TM33 [43]. This ensures a high level of confidence in both the reliability and accuracy of simulation results.

As IES VE focusses only on building modelling, it is not as heavily specified in one particular area as either HAP or TRACE. IES VE also has broader features such as more advanced modules (e.g. solar gains and thermal comfort analysis) and it is geared towards commercial use. Due to the previous attributes, the ability to create complex 3D models, and compliance with CIBSE, ASHRAE, and ISO standards, IES VE was adopted for the methodology presented in this paper.

2.4. Modelling

IES VE enables creating 3D models of all the most common house types in the UK mentioned in Section 2.1.5. An example of such a model for a terraced house developed using the software is shown in Fig. 2. Provided weather conditions are available, the model would enable quantifying the thermal demand of the dwelling.

The dwelling example in Fig. 2 shows that terraced houses have two configurations that will have differing thermal demand due to the exposed external elements. Thus, the location of the house within the terraces (middle, highlighted with a blue shading, or end, highlighted with a pink shading) needs to be accommodated within the simulations. This scenario also applies to flats, whereby the floor the flat is on (e.g. ground, middle, top) and the location within the floor (e.g. middle or end) will impact energy demand.

3. Methodology for quantifying cooling demand

3.1. Overall modelling framework

Fig. 3 provides a graphical summary of the overall modelling framework used to calculate thermal demand in buildings. Different aspects around the key steps are discussed next. The methodology begins with obtaining floor plans and images of the dwelling to be assessed. This information is then used to create 3D models of the dwelling in a suitable software. (IES VE or any other building modelling software can be adopted, as outlined in Section 2.3.) With the created model, the location of the dwelling, its orientation, and weather data are imported into the model. Corresponding U-values for each type of construction element are then incorporated into the model.

Simulations are then carried out while ensuring all variations of possible U-values are accounted for. A results file for each simulation is then created and assigned a dwelling code. Further information on how the dwelling code is created is provided in Section 3.3 (see Table 2). The file is saved and the remaining simulations are carried out. Relevant results are then extracted from the software and the saved within multiple CSV files for each dwelling, orientation, and location. This enables the results to be read easily by third party software such as Python or even read directly by the end user within MS Excel.

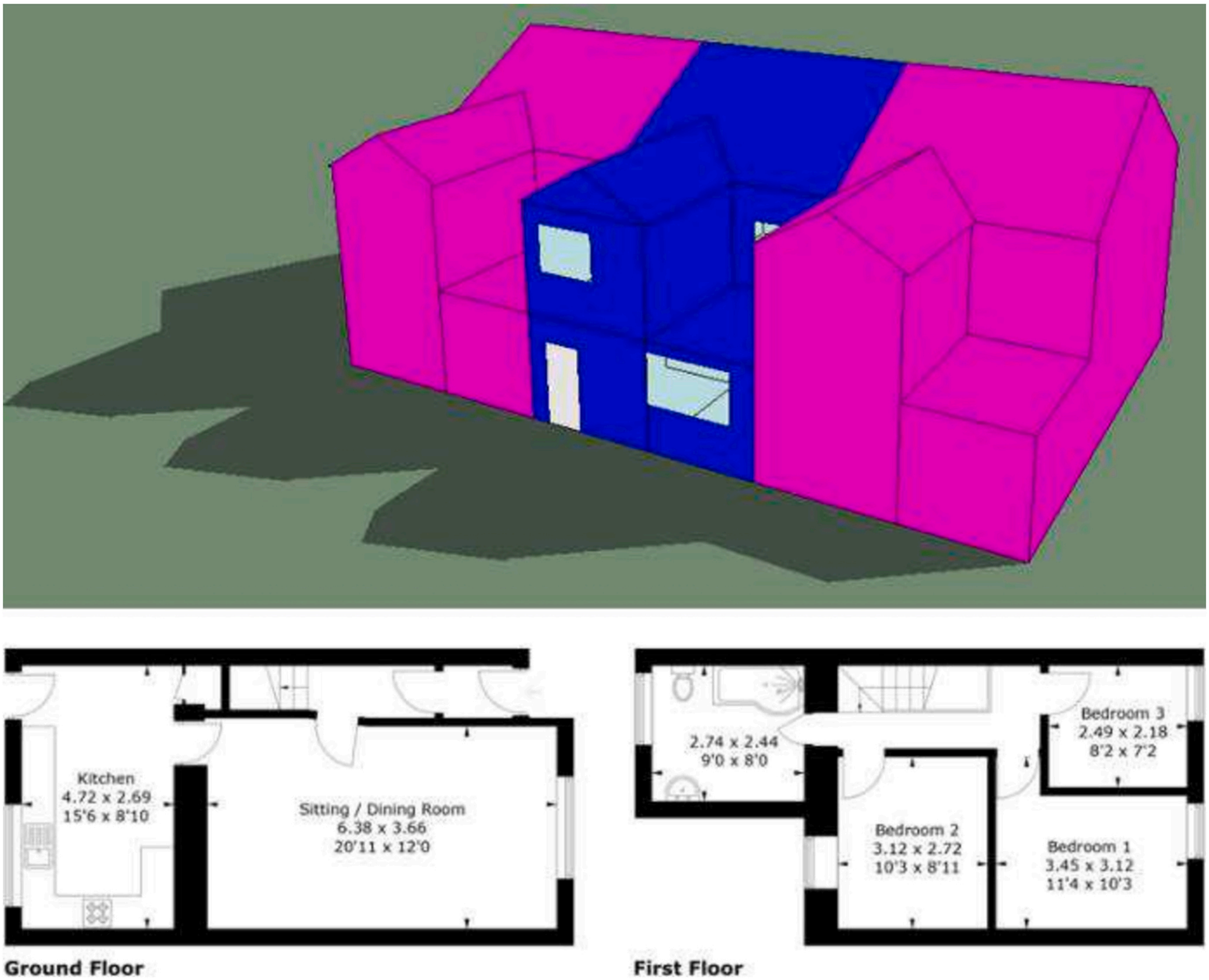


Fig. 2. Three-dimensional model of a terraced house produced in IES VE using a layout obtained from [27]. The blue shading represents the dwelling under investigation and the pink shading the adjacent buildings. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Dwelling data

3.2.1. Geographical location and building orientation

Fig. 4 shows the variability in the photovoltaic power potential across the UK [44]. The solar power directly impacts the solar radiation able to enter a dwelling, which will vary with location. Based on this, five places were selected to investigate the impact of geographical location and photovoltaic power potential on thermal demand: Cardiff, Glasgow, London, Plymouth, and Manchester. Out of the five locations considered, Plymouth has the highest photovoltaic power potential and Glasgow has the least potential.

Building orientation also impacts thermal demand. In countries within the northern hemisphere such as the UK, south-facing surfaces receive a much higher degree of solar gain than north-facing surfaces. Within IES VE, dwelling orientation is designated using a global rotation value in degrees. A north-facing dwelling is defined with an orientation of 0°. Dwellings facing east, south, and west are respectively designated with orientations of 90°, 180°, and 270°.

3.2.2. Weather data

Typical meteorological year (TMY) weather files are commonly used for buildings' weather files. These are created following the ISO 15927-4:2005 methodology [45]. A TMY file is generated using a minimum of 10 years of data, although more years are preferred. The weather files are divided into months and the daily mean is calculated using each year for the following variables: dry-bulb temperature, solar radiation, and humidity, with wind speed as a secondary parameter. Following the methodology defined in the standard, each month's variables are then ranked to determine which is the best month to use in the weather file. The selected best months are then combined into a single year. To ensure a smooth transition between each month the hourly values are then modified.

The weather files used for this paper were obtained directly from Climate One Building [46]—which provides a repository created using the methodology in [45] for thousands of global locations.

3.2.3. Thermostat controls

Indoor thermal conditions vary from household to household with the influence of diverse factors such as income levels, personal comfort levels, and geographical location. As per CIBSE Guide A, households in the UK should be designed to maintain an indoor temperature of 21 °C to 25 °C depending upon the room [19], with CIBSE TM59 requiring preventive measures such as opening windows when temperatures go above 22 °C [10]. However, warmer climate countries such as the United Arab

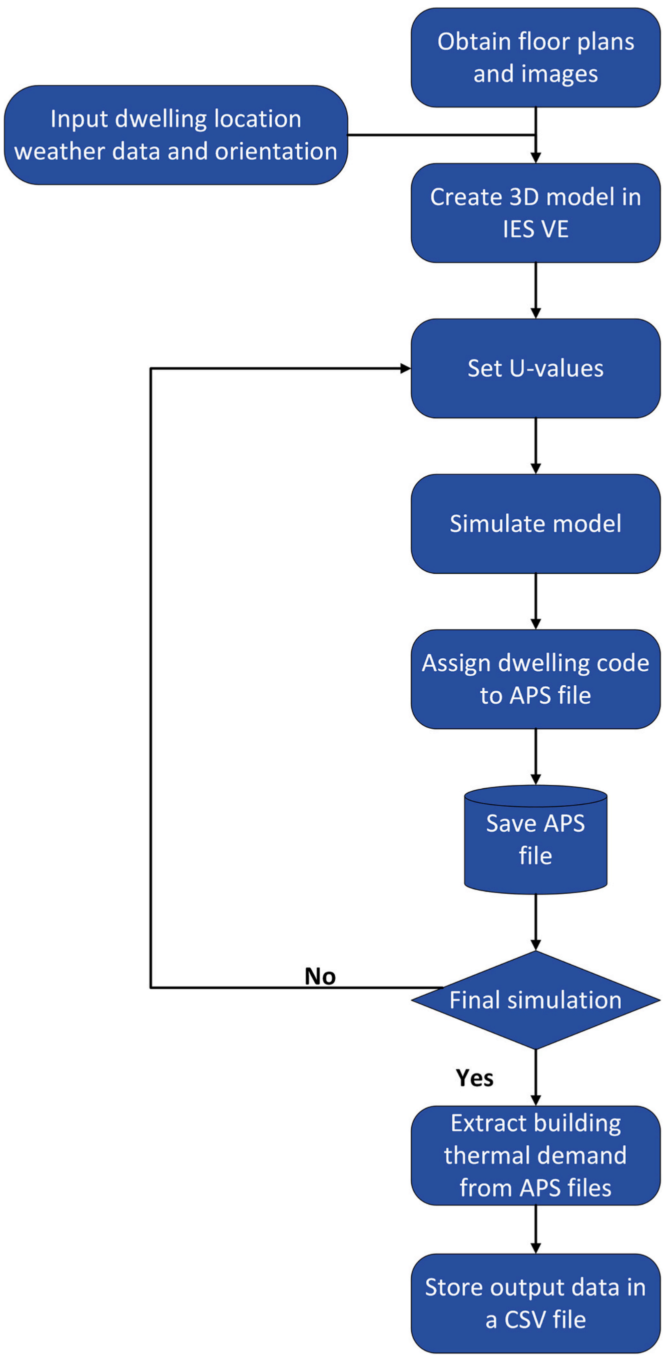


Fig. 3. Modelling framework outlining the methodology used within the paper to obtain the thermal demand of typical dwellings.

Table 2
Assigning U-values to each type of dwelling construction.

	X—	-X–	–X-	—X
	Walls	**Foundations**	**Roof**	**Windows**
1	0.18	0.13	0.11	1.2
2	0.3	0.22	0.13	1.4
3	0.45	0.51	0.22	2
4	0.6	1.2	0.35	3.1
5	1	2.94	0.4	–
6	1.7	3.25	–	–
7	1.84	–	–	–

Emirates recommend maintaining indoor temperatures to 24 °C ± 1.5 °C [47]. Such stark differences show how thermal conditions may vary depending on the country.

In this paper, the internal temperature was set to 21 °C as per UK building design. However, it is possible to assess personal preference and its effect on energy demand for the modelled dwellings. This idea is illustrated in Section 3.3.

3.3. Modelling assumptions

Table 1 summarises the construction data for the UK housing stock according to Building Regulations. From the table, there are 6 foundation types, 8 wall types, 5 window types, and 7 roof types. This implies there are 1680 possible combinations for a dwelling considering these construction elements. As highlighted in Section 2.1.5, 5 types of dwellings are considered in this paper: bungalows, detached houses, flats, semi-detached houses, and terraced houses. Considering 4 different orientations for each location as discussed in Section 3.2.1 (north-facing -0°-, east-facing -90°-, south-facing -180°-, and west-facing -270°-), this accounts for a total of 6720 building configurations per geographical location (i.e. Cardiff, Glasgow, London, Plymouth, and Manchester) and 184,800 overall for all type of dwellings and their variations (e.g. terraced houses and flats).

Quantifying thermal demand for any configuration would require a computational simulation taking ~1 min to run without considering pre- and post-processing times. This is equivalent to 112 h of total simulation time for a single dwelling and geographical location. Combined with all the dwellings and locations, the simulations would take over a year to complete, which is not practical. It is desirable to eliminate the least likely scenarios to reduce computation time. The process for achieving this is explained next.

As per the housing surveys report 2021–2022, 87 % of homes in England have installed double-glazed windows [17]—leaving 13 % of homes with single glazing. However, as shown in Table 1, single-glazed windows could not be installed in new homes or have been replaced in older buildings since 2000. Alternative solutions to double glazing are available such as secondary glazing, which consists of installing a separate discrete window between the external window and the room. This provision allows listed buildings with single glazing to meet energy performance requirements for UK households. A study into the thermal performance of secondary glazing was conducted in [48], where it was concluded that secondary glazing provides the same level of thermal resistance as double-glazed windows. Thus, single-glazed windows may be removed from the modelling process as they can no longer be installed.

Grants such as the Green Deal Home Improvement Fund, Home Upgrade Grant in England, Nest in Wales, and Warmer Homes in Scotland offered monetary support to improve loft insulation in UK households [26,49]. These schemes have been consolidated with the Great British Insulation Scheme, which provides funding for the insulation of roofs and other surfaces within dwellings (e.g. floors and walls) [25]. It can be thus assumed that most dwellings will have had their loft insulation upgraded within the last 20 years and older loft insulation values may be removed.

Furthermore, for dwellings constructed in the 1920s, U-values for uninsulated cavity walls were approximated to be 1.6 W/m^2-K. With the introduction of the Building Regulations in 1965, the maximum allowed U-value was 1.7 W/m^2-K [18]. As the 1965 standard provides a higher and thus more conservative value, it can be adopted for modelling purposes.

Using the previous considerations the amount of required simulations was reduced. To provide clarity into the simulation cases and their results, a unique building code was assigned for each possible dwelling. For example, building code ‘1111’ refers to a dwelling constructed using the most thermally efficient walls, foundations, roofs, and windows—in that specific order. The lowest U-values in Table 1 correspond to this

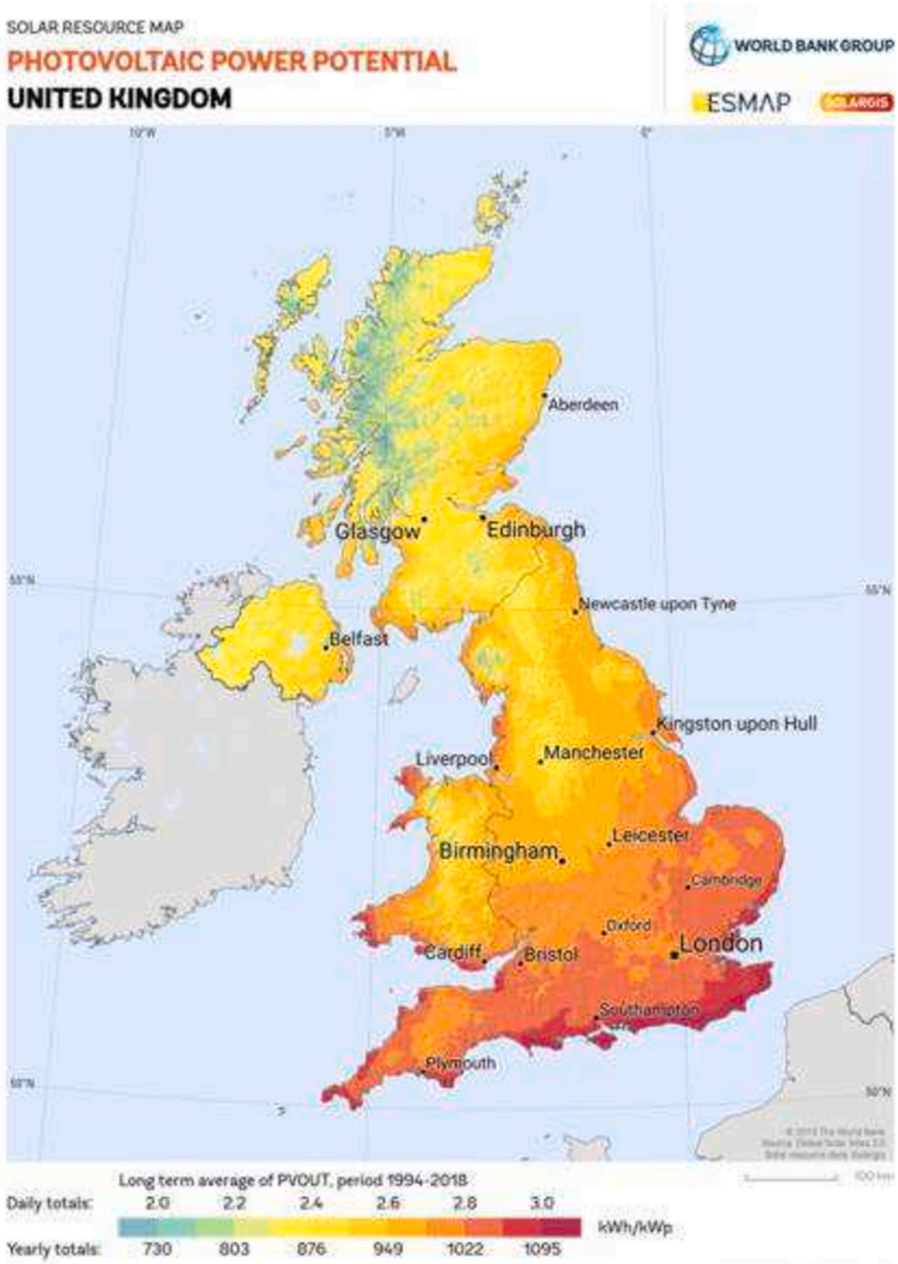


Fig. 4. Photovoltaic power potential in the UK [44].

example. Following the same approach for other entries in Table 1, unique building codes indicating the surface U-values for each construction are shown in Table 2.

For simplicity, semi-detached houses, terraced houses, and flats, which have a shared surface with an adjacent dwelling will assume that the adjacent dwelling will be an unconditioned space.

Note: For this paper, the internal heat gains (including building occupancy) have been so far ignored and set to zero. This was done because all internal gains are considered as positive and, thus, can be added after conducting any simulation. This simplified approach enabled providing a baseline for cooling demand estimation where other relevant aspects not depending on the building fabric or weather conditions can be easily integrated, such as personal preferences. To showcase the validity of incorporating internal heat gains to simulation results and assess their effect on the cooling demand of a dwelling, an additional case study was conducted. This is showcased in Section 4.6.

3.4. *Cooling demand calculation considering thermostat preference*

As highlighted in Section 3.2.3, it is possible to assess personal thermostat preference and its effect on energy demand. This was done in this paper by considering the change in energy demand as a constant value for each house typology shown in Table 2 (i.e. a dwelling with its own unique set of constructions as outlined earlier). Subtracting a set value from the energy demand would simulate a reduction in the internal temperature settings and adding the same value would represent an increase in the thermostat temperature.

The previous idea is illustrated in Fig. 5, which shows the behaviour of an insulated detached house with varying thermostat temperatures enabled by 4 different simulations. The house is north-facing (orientation of 0°), located in Cardiff, with a building code '3244' as per Table 2. Results are shown for a one-week period of a typical design year, where thermal demand refers to the energy required to maintain the internal temperature at 21 °C. Positive values represent heat demand and

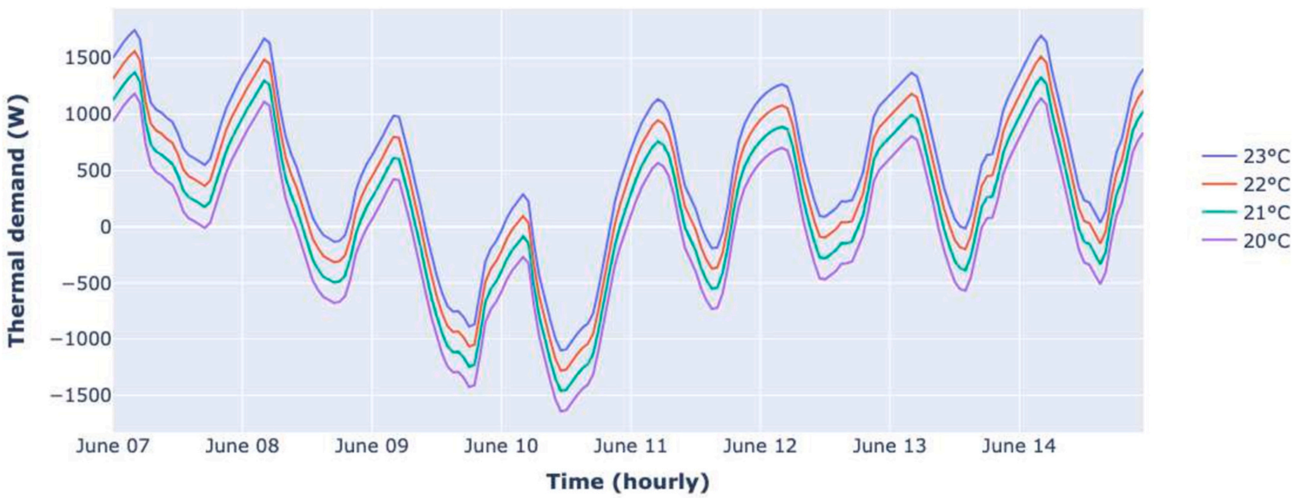


Fig. 5. Comparison of hourly thermal demand with different thermostat temperatures for a typical design year. Detached house in Cardiff at orientation 0° (i.e. north-facing) with a building code '3244'.

negative values cooling demand. It is apparent that a change in thermostat temperature induces a constant change in hourly energy demand. For this case, the increase or decrease in hourly energy demand is by approximately 160 W/°C. This value is scalable: a rise in temperature by 0.1 °C increases heating demand hourly by ~16 W in winter and reduces the cooling demand in summer by the same amount. Similarly, a reduction of 0.1 °C decreases the heating demand in winter and increases the cooling demand in summer hourly by ~16 W.

The difference in hourly energy demand shown by the example in Fig. 5, however, is unique for any two temperature set points. Obtaining this difference from a reference scenario (e.g. for 21 °C) with respect to a different thermostat setting would require duplicating the computational effort, as additional simulations must be performed again with a new temperature set point. To illustrate this idea, a range of building constructions for a detached house was simulated in IES VE for two different thermostat settings (in this case 21 °C and 22 °C for simplicity). The selected construction combinations were randomised to cover an even distribution of the overall U-values, including the best and worst-case thermal efficiency scenarios as per the unique reference building codes provided in Table 2 (codes '1111' and '7654'). The difference between the energy demands was then calculated, with results shown in Table 3. It is evident that the energy efficiency of a building, in this case for a detached house, has a profound effect on the difference in energy demand between two thermostat settings, which increases when the U-values are larger.

An alternative method was developed to assess the impact of varying thermostat set points on the difference in thermal demand without having to conduct a simulation for each set point temperature. To this end, it was assumed that the U-value for each external surface has a similar effect on the overall demand, but its surface area adjusts the weighting of the effect. For example, since windows have the smallest surface area for most dwellings, they thus have the lowest impact on the overall demand.

Table 3
Effect of thermostat changes by 1 °C in energy demand for detached constructions.

Dwelling code	Difference in hourly energy demand (W)
1111	92
2122	108
3244	161
4124	167
4612	293
5433	237
5643	342
6534	402
7212	259
7654	431

A correlation coefficient of the data points comparing the weighted U-values to the calculated energy demand due to a change in the thermostat setting by 1 °C was first obtained. To achieve the desired output result, in this case a correlation coefficient value of 1, particle swarm optimisation (PSO) was used to heuristically adjust the U-value's weighting for each relevant surface. Interested readers are referred to [50] for additional details on PSO. With this approach, the following linear equation was obtained:

$$y = 81.27x + 43.82 \tag{1}$$

where y represents the change in hourly thermal demand [W] due to a change in thermostat settings by 1 °C and x represents the total weighted U-value. Eq. (1) is useful to predict the effect of changing the thermostat temperature on the difference in energy demand between set points.

For each dwelling, its U-values were given a unique weight determined using PSO. For instance, the optimised weights for a detached house were obtained as 1.19 for walls, 0.54 for foundations, 0.62 for roofs, and 0.21 for windows. From Table 2, considering the U-values for the window, wall, foundation, and roof with the best thermal efficiency, the adjusted U-value is calculated as

$$\begin{aligned} x &= (0.18 \times 1.19) + (0.13 \times 0.54) + (0.11 \times 0.62) + (1.2 \times 0.21) \\ &= 0.60\ \mathrm{W/m^2 - K} \end{aligned} \tag{2}$$

Substituting $x = 0.60$ W/m^2-K into (1), the change in hourly energy demand due to adjusting the thermostat temperature by 1 °C for a detached house is obtained as

$$y = 81.27(0.60) + 43.82 = 92.6\ \mathrm{W} \tag{3}$$

The result given by (3), when compared to the difference in hourly energy demand for a detached house in Table 3 (92 W), shows that the approximation method exemplified by (1)–(3) can be used as a prediction tool as it leads to a value within an acceptable range. This (constant) change in energy demand can be thus easily determined for each scenario without conducting several simulations.

Determining the minimum number of simulations for achieving an accurate change in energy demand involved conducting multiple simulations across a range of different overall building U-values. For the examples in Table 3, the approximation method was initially applied to 2 simulation scenarios for the detached house (using U-values for the best and worst scenarios, with dwelling codes '1111' and '7654' in

Table 2). The number of simulations was increased by one at a time to find an acceptable degree of accuracy. The overall percentage error dropped to 1.79 % with 10 simulations, which provided a maximum error of 18 W. The simulated results plotted alongside the predicted results are shown in Fig. 6.

As shown by Fig. 6, the presented methodology provides a linear relationship to predict the energy demand of a building at varying thermostat temperature set points. To test the prediction performance, a random detached construction was selected (dwelling code '6534'). The predictive model determined that the constant hourly energy demand increase (or decrease) would be 403 W, which was close to the simulated difference of 402 W using IES VE (see Table 3).

The energy demand for a dwelling will be affected by additional heat gains from equipment loads (e.g. TVs, cookers, laptops), occupants, and lighting. In addition, the energy from these heat sources may fluctuate considerably between dwellings. Creating a standard internal thermal load for each case is thus not practical. However, these loads will always be positive and can be defined at a later stage to be applied to the simulated data. This way, it is possible to assess custom scenarios to account for varying schedules (e.g. indoor activities in the evening or night hours).

3.5. Verification of the modelling approach

Results provided in reference [16] were borrowed to verify the modelling methodology presented in the previous sections. In the reference, a pair of semi-detached households (termed East and West houses for simplicity), shown in Fig. 7, was investigated. Alongside building properties and plans, internal temperatures and external weather conditions were measured and recorded over a 3-week period. Internal gains were induced electrically using a heating fan on a set schedule to mimic occupancy in the dwellings. With windows in the control dwelling (East house) kept closed at all times, internal and external temperatures were monitored at 1-min intervals.

IES VE was used to develop 3D models of the buildings in [16] and their surrounding area following the plans and the detailed construction properties given. A screenshot of the dwellings modelled in IES VE is shown in Fig. 8. Using the data recorded by the weather station for the period of time investigated in the reference, the weather files were manually updated to match the external prevailing conditions.

IES VE can read multiple weather file types, with Energy Plus Weather (EPW) being the most standardised format. EPW files are widely available online and can be easily customised as needed by converting them to CSV files. Using the recorded data, the CSV files were modified (adjusting the solar radiation, temperature, wind, precipitation, cloud cover, and humidity values) before being reconverted back to EPW files.

The thermal mass of furniture may have a significant impact on the local indoor humidity and thermal comfort of dwellings [51]. This is because the furniture absorbs heat from the air and solar radiation (if near a window) and slowly releases the heat back into the room much slower than compared to the air. Whilst the dwellings in [16] were considered mostly empty, it is unknown how much furniture was there. Therefore, using IES VE's Furniture Mass Factor (set to 1), a thermal mass was assigned within the rooms and accounted for the effects of the additional thermal mass.

Internal gains from sources such as the occupant, equipment, and lighting loads were replicated using a heating element with a scheduled control system. This way, IES VE was able to incorporate the loads matching the installed system.

In [16], a blower door test was carried out to determine the ventilation rates. The external openings (windows, doors, and fireplaces) were sealed to prevent the leakage of air and a fan was placed at the entrance. By inducing a pressure difference of 50 Pa (either by blowing air in or out of the building), the air flow rate on the fan required to maintain the pressure difference between the external air and indoors was thus the ventilation rate at a pressure of 50 Pa. This was converted to air changes per hour (ACH) by dividing it by the volume of the dwelling.

Following the test, the ACH at 50 Pa was 15.3 for the West house and 15.6 for the East house. However, as stated in [52], the pressure differential between outdoors and indoors is closer to 7.3 Pa. Since the measured ACHs in [16] were much higher than the natural ventilation rates, these values had to be scaled down for model verification in IES VE. The commonly accepted method to scale ACH is by dividing the measured value by values between 10 and 30. Using the East house as a reference, simulations were carried out in IES VE using different values, starting with 0.78 ACH (15.6/20), 0.52 ACH (15.6/30), and a lower value of 0.35 ACH. From these simulations, it was found that the lowest value (0.35 ACH) provided the most accurate results. This is consistent with the UK Building Regulations Part F [53], which states that less airtight dwellings can be assumed to have an infiltration rate of 0.15 ACH. As the buildings under investigation in [16] were constructed in the 1930s, an ACH of 0.35, higher than the less airtight dwellings from nowadays, was used for simulations.

Whilst both dwellings were simulated in IES VE, only the control house (East house) was used in the verification as the opening and closing of windows were not simulated. The simulated indoor temperatures, alongside the measured temperatures in [16] for the rooms that were monitored, are shown in Fig. 9.

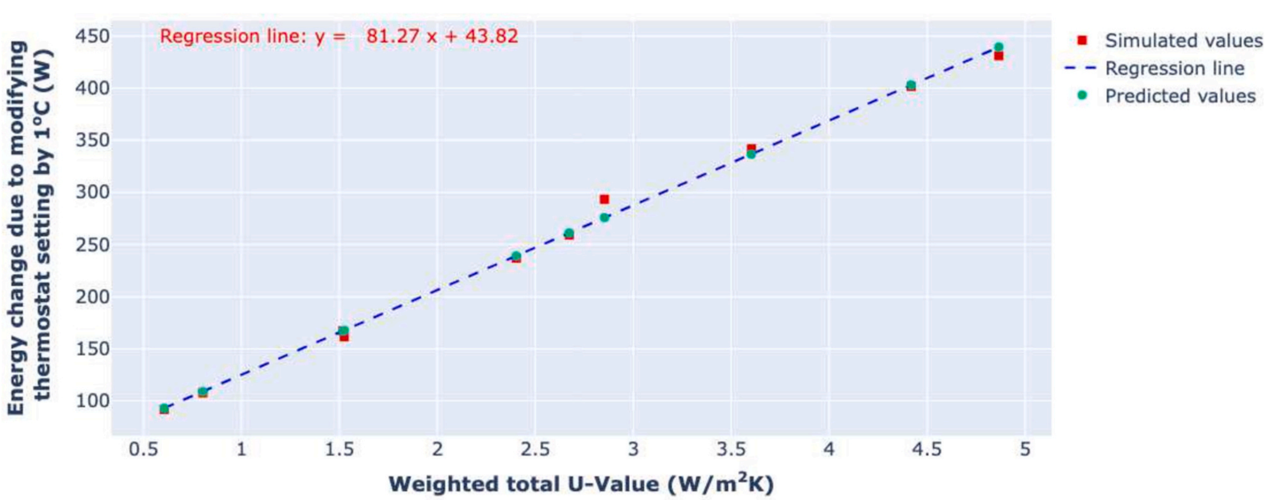


Fig. 6. Variation of hourly thermal demand for a detached house in Cardiff at orientation 0° (i.e. north-facing) for different weighted total U-values.

(a) (b)

Fig. 7. Houses adopted from [16] to verify the numerical model in IES VE: (a) front view; (b) rear view.

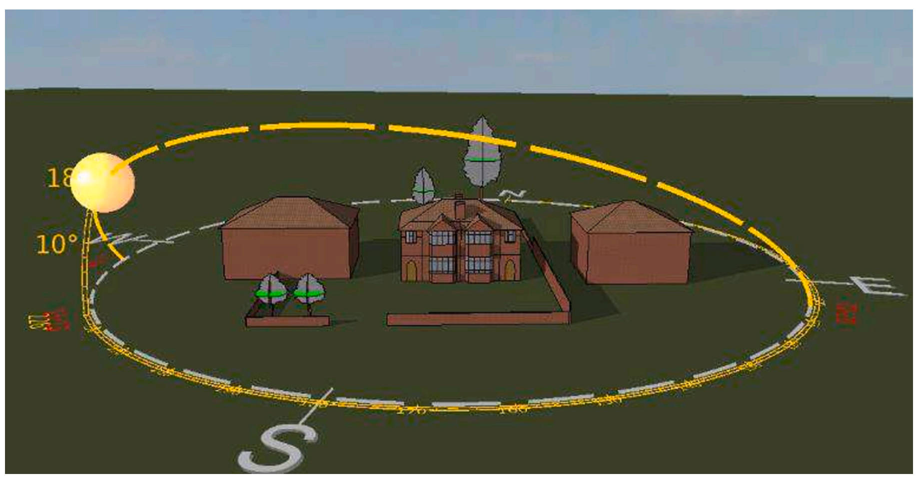


Fig. 8. Houses in [16] modelled in IES VE.

As shown in Fig. 9, the results obtained with IES VE closely resemble the measured data in [16]. To further confirm this, three calculations were carried out to determine the accuracy of the model, namely coefficient of determination (R^2), RMSE, and mean absolute error (MAE). For a more detailed description on their calculation methods and definitions, the interested readers are referred to [54]. The results for these metrics are shown in Table 4.

An average R^2 value of 0.87 for the house was obtained, which indicates a reasonable agreement of the simulated results with the experimental data. The average MAE between the simulated and experimental results was 1.34 °C and the RMSE was 1.62 °C.

Due to the limitations in both the model and the measured data, an exact match was not expected. For example, the amount of furniture in the dwelling was not stated and was therefore assumed. The ventilation rates provided in [16] were not accurate due to the adopted estimation of ACH. In addition, a time-step size of 10 min was used in IES VE, while the reporting interval for results presented in [16] was hourly. Due to the discrepancies in the simulated and measured data, along with the metrics in Table 4 and the visual representation in Fig. 9 showing reasonable agreement, IES VE was considered a suitable tool for calculating thermal demand in buildings.

4. Results and discussion

Using the methodology presented in Section 3, the thermal demand for the five different dwellings (i.e. bungalows, detached houses, flats, semi-detached houses, and terraced houses) across the five considered geographical locations (i.e. Cardiff, Glasgow, London, Plymouth, and Manchester) was obtained for a typical design year. A simulation time-step of 1 h was used in IES VE to quantify the hourly energy demand.

The most relevant results are discussed in the next subsections. Unless indicated otherwise, positive values of thermal demand represent heat demand and negative values cooling demand. To support the discussion, Fig. 10(a) shows the external temperature for each location during a week of June of the design year, while Fig. 10(b) does this for the whole month of June.

4.1. Cooling demand variations of different property types at a similar location

To assess how cooling demand changes for a fixed location depending on the type of dwelling, thermal demand was quantified for the investigated dwelling types in Cardiff while keeping other key attributes the same. For a more insightful comparison, a week in June of the design year was chosen (blue trace in Fig. 10(a)). All dwellings were considered to have the highest thermal efficiency (i.e. building code ‘1111’) and an orientation of 0° (north-facing). Results are shown in Fig. 11.

As shown by the traces in Fig. 11, the detached house (solid red trace) consistently exhibits both the highest cooling demand and highest heat demand throughout the week. This can be attributed to this type of dwelling having the largest external wall surface area among all house

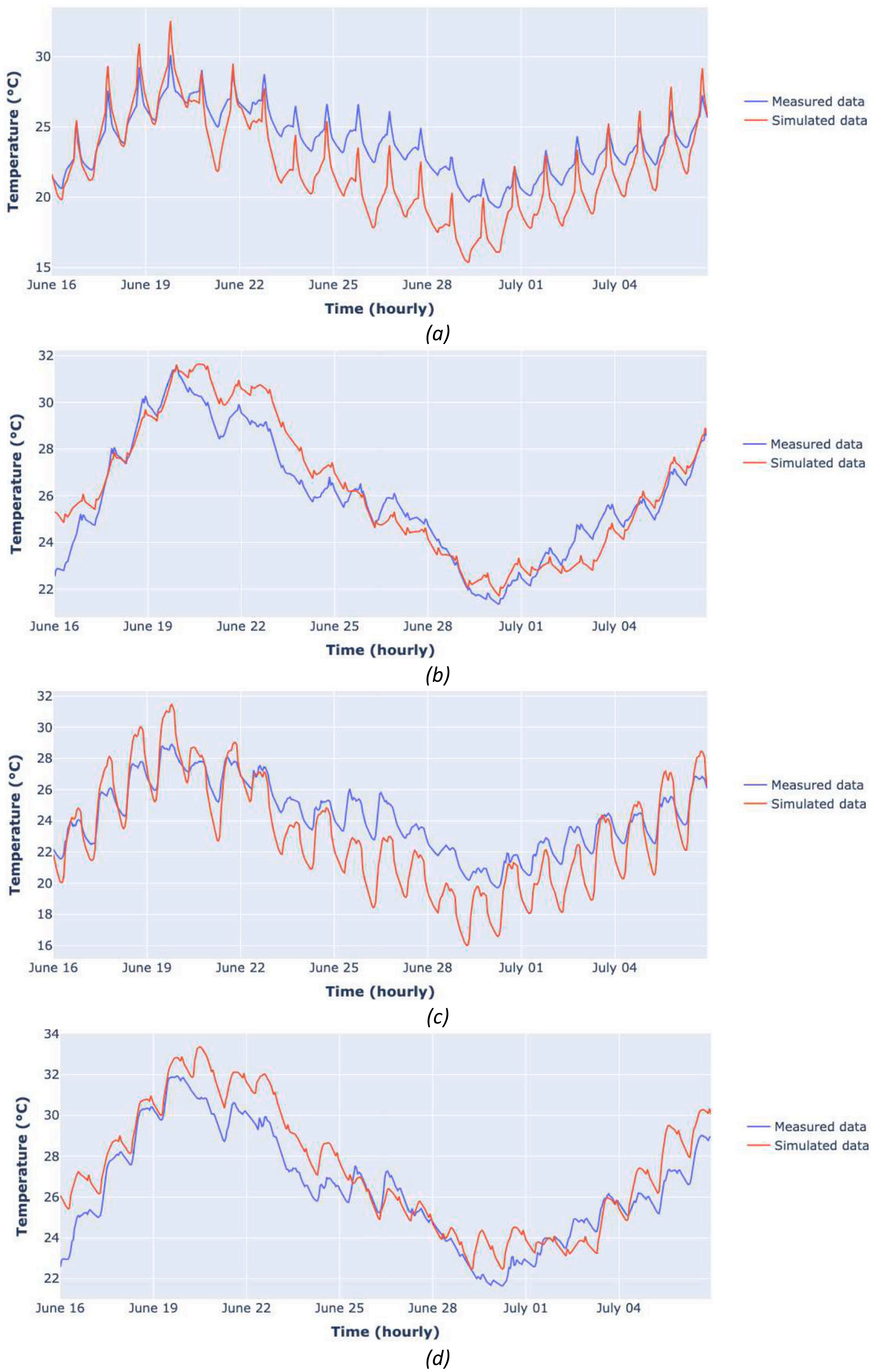


Fig. 9. Comparison of internal room temperatures using IES VE with measured values reported in [16]: (a) kitchen; (b) rear bedroom; (c) living room; (d) front bedroom.

Table 4
Accuracy metrics for the simulated and measured results.

	East house				
	Living room	Kitchen	Front bedroom	Rear bedroom	Single bedroom
R^2	0.87	0.84	0.90	0.91	0.85
MAE [°C]	1.68	1.99	1.10	0.73	1.22
RMSE [°C]	2.01	2.37	1.32	0.90	1.49

types. In contrast, the flat has the smallest external wall surface area, leading to the lowest heating and cooling demands (green trace). However, the location of a flat within a building may impact its cooling demand, so this type of dwelling is explored separately and in more detail in Section 4.2.

Indoor heat gain due to conduction through walls has a higher impact on cooling demand than heat gains through windows. This is evidenced by the bungalow, which has the second largest external wall area and second smallest total window area, leading to the second highest cooling demand (blue trace in Fig. 11) of all types of dwellings during the week under assessment.

4.2. Cooling demand variations for flats

As highlighted in Section 4.1, the position of a flat within a building has an impact on its cooling demand. This is shown in Fig. 12, where the total monthly cooling demand in June for flats located in Cardiff is shown. Fig. 12(a) shows results for flats with the highest thermal efficiency (building code ‘1111’), while Fig. 12(b) for the lowest energy efficiency (building code ‘7654’). As in Section 4.1, it was assumed that the external wall is north-facing (orientation of 0°).

For either the highest or lowest thermal efficiency, the flat with the lowest cooling requirement is the ground floor (bottom) flat within the centre of the building (dark blue bar, both figures). This is due to a ground cooling effect applied to the foundations, where the model uses a ground temperature of 13 °C year-round [32]. When the indoor air temperature rises above this level, the ground cools the building.

The corner flat at the ground floor similarly retains the cooling effect but has a larger external wall area, which therefore increases its cooling demand (red bar, both figures). Without the cooling effect, for the newest and most efficient buildings, shown in Fig. 12(a), the middle-floor (green and purple bars) and top-floor flats (orange and teal bars) exhibit higher levels of cooling demand. However, the difference between the top and middle floors is minimal as the thermal efficiency of

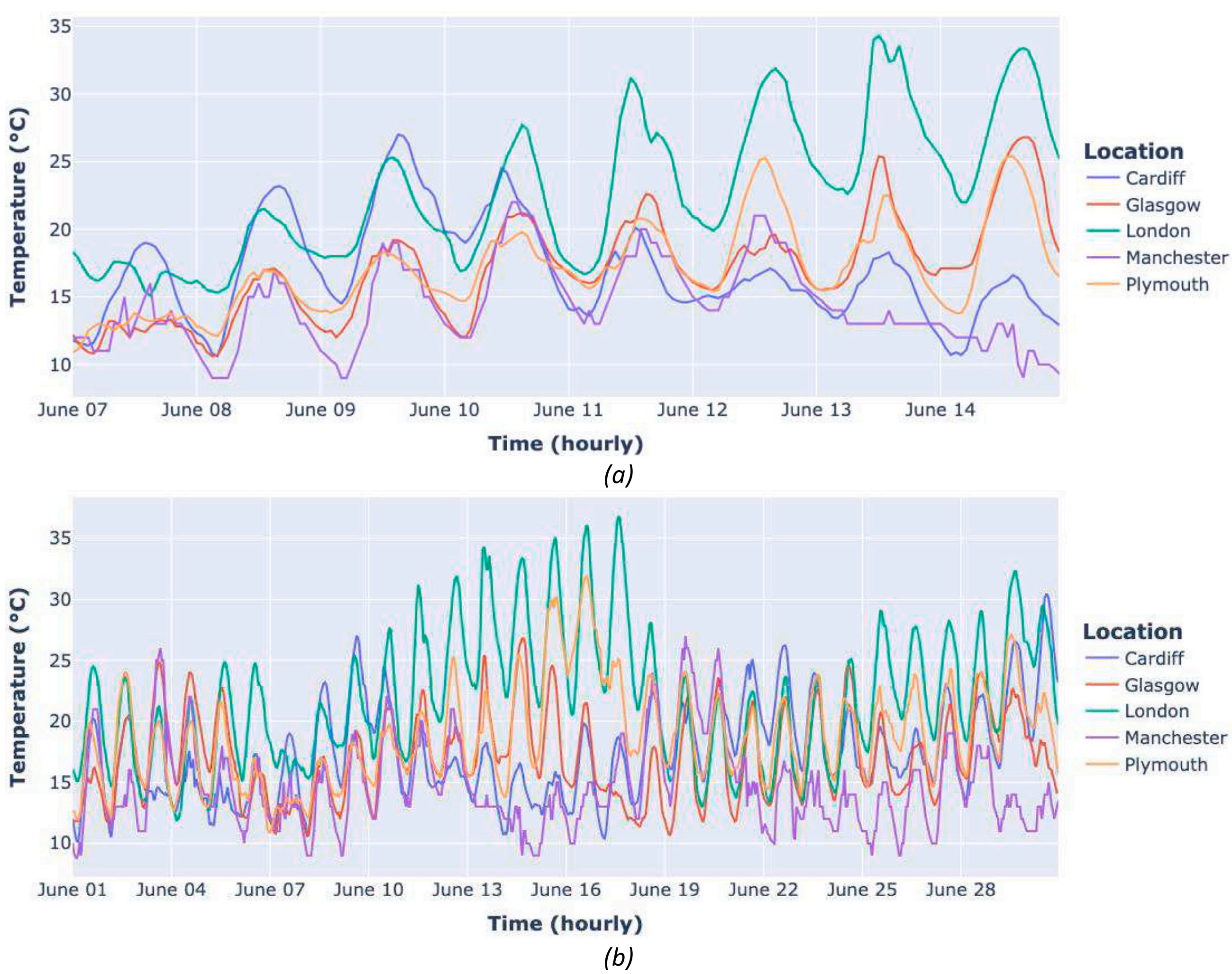


Fig. 10. External dry bulb temperature for the geographical locations under investigation: (a) Week in June; (b) whole month of June.

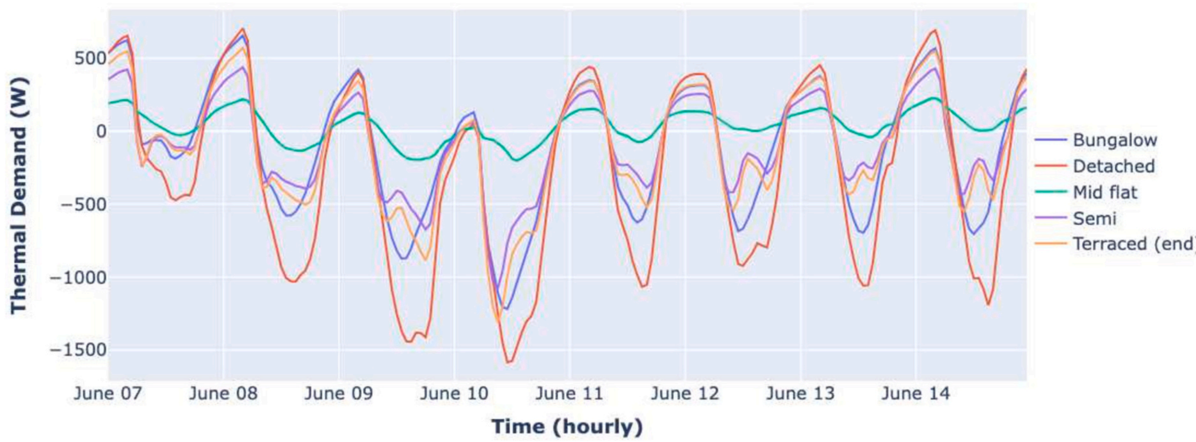


Fig. 11. Hourly cooling demand for each dwelling type in Cardiff with the highest thermal efficiency (building code '1111') and orientation of 0°.

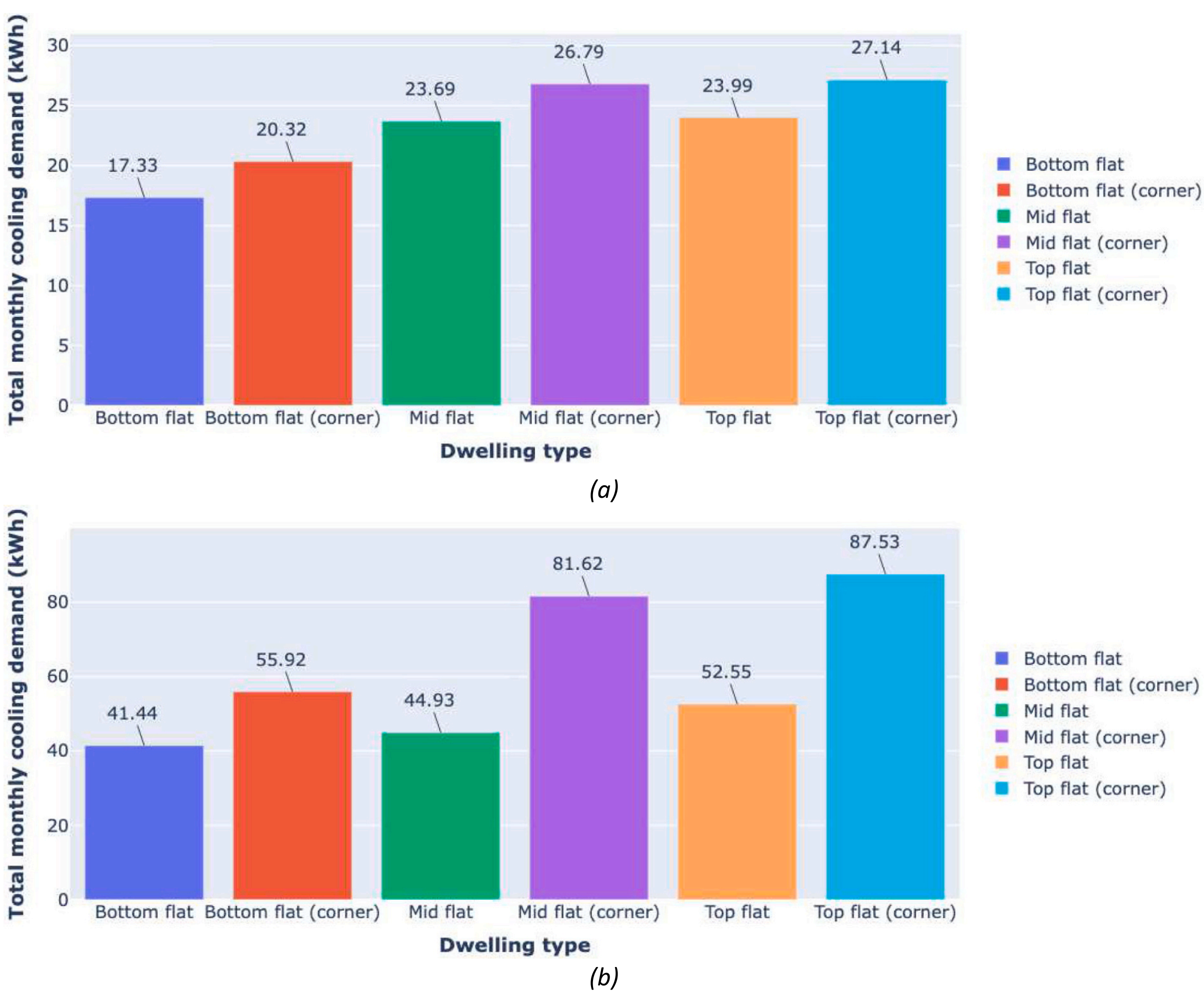


Fig. 12. Total monthly cooling demand in June for all flat types (north-facing external wall, orientation of 0°). Flats with: (a) highest thermal efficiency (building code '1111'), (b) lowest efficiency (building code '7654').

the roof prevents additional heat from entering the flats. In contrast, for the least thermal efficient flats, shown in Fig. 12(b), the difference between cooling demand between flats at top and middle floors is more pronounced.

When modifying the flat orientation so that the external wall is east-facing (orientation of 90°), there are significant effects on the total monthly cooling demand. This is shown in Fig. 13 for the most and least thermally efficient constructions. The first notable difference is the overall increase in cooling demand across all flat variations. This is attributed to solar radiation directly impacting windows throughout the day. Compared to Fig. 12, when windows are on the north-facing wall, there is no direct sunlight on them. Furthermore, for the more efficient flats (code '1111', Fig. 13(a)), the position of the flat within the building has a negligible effect on the total cooling demand. This was expected, as

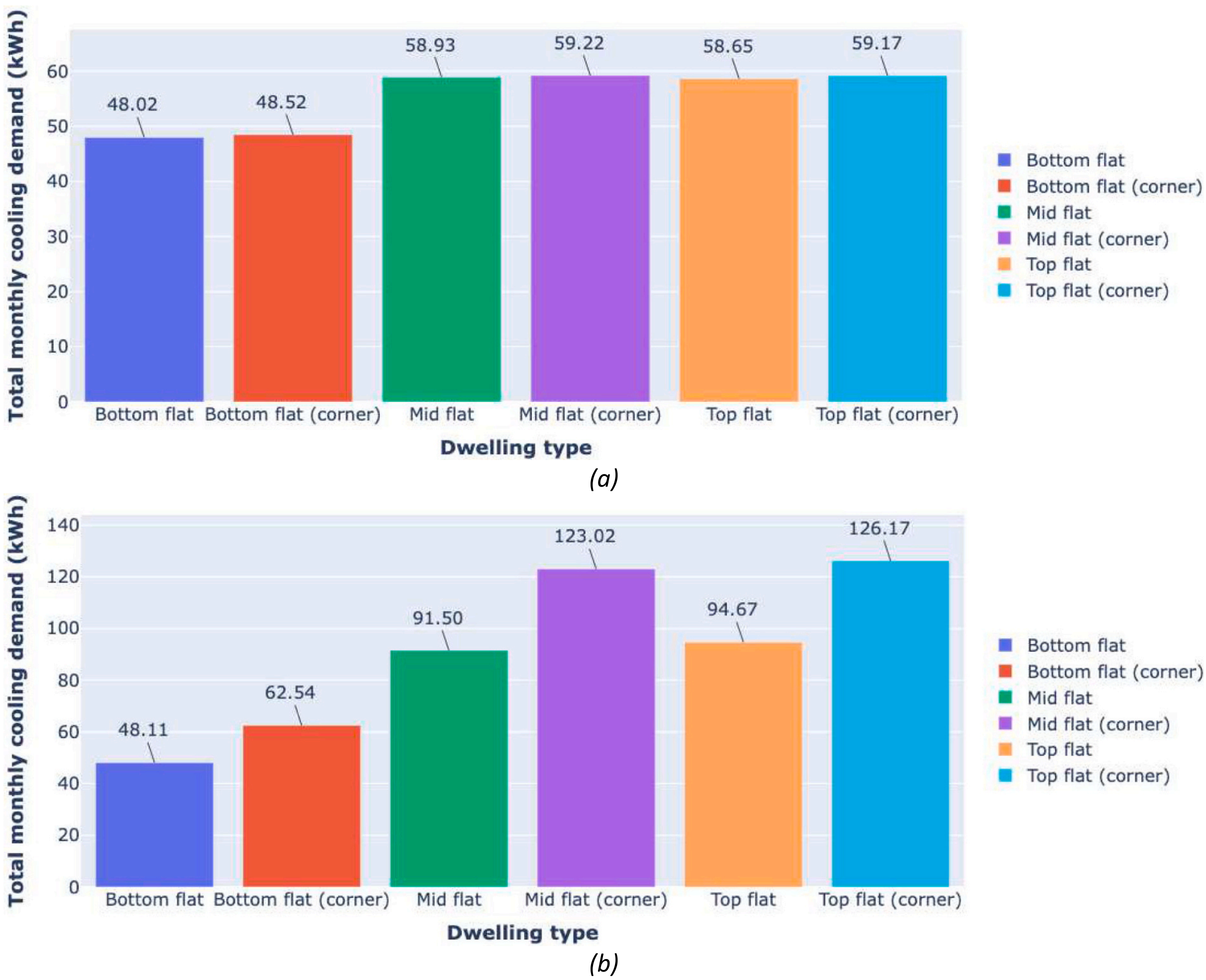


Fig. 13. Total monthly cooling demand in June for all flat types (east-facing external wall, orientation of 90°). Flats with: (a) highest thermal efficiency (building code '1111'), (b) lowest efficiency (building code '7654').

the solar gain has the largest effect on the thermal demand of the dwelling.

4.3. Cooling demand variation based on orientation

Orientation is another attribute which may affect cooling demand. Since flats located at an intermediate storey within a building have a single external wall/window facing one direction, the orientation of this type of the dwelling has the starkest impact on the cooling demand.

To explore this in more detail, Fig. 14 shows the thermal demand for a middle-floor flat in Cardiff during a week of June of the design year. Results are shown for dwellings with the highest thermal efficiency (building code '1111') in Fig. 14(a) and for the lowest thermal efficiency (building code '7654') in Fig. 14(b).

As observed in both subfigures, orientation of the dwelling has a large impact on the peak cooling demand alongside the time in which the peak occurs—regardless of the flat's overall thermal efficiency. For example, east-facing flats (orientation of 90°) experience peak demand in the morning, but west-facing flats (270°) in the evening instead. However, the south-facing flats (180°) exhibit peak demand at midday due to the consistent level of solar gains throughout the day. Furthermore, thermal efficiency, whilst having a significant effect on the magnitude of the cooling demand, does not affect the just discussed pattern. This is consistent in both Figs. 14(a) and 14(b).

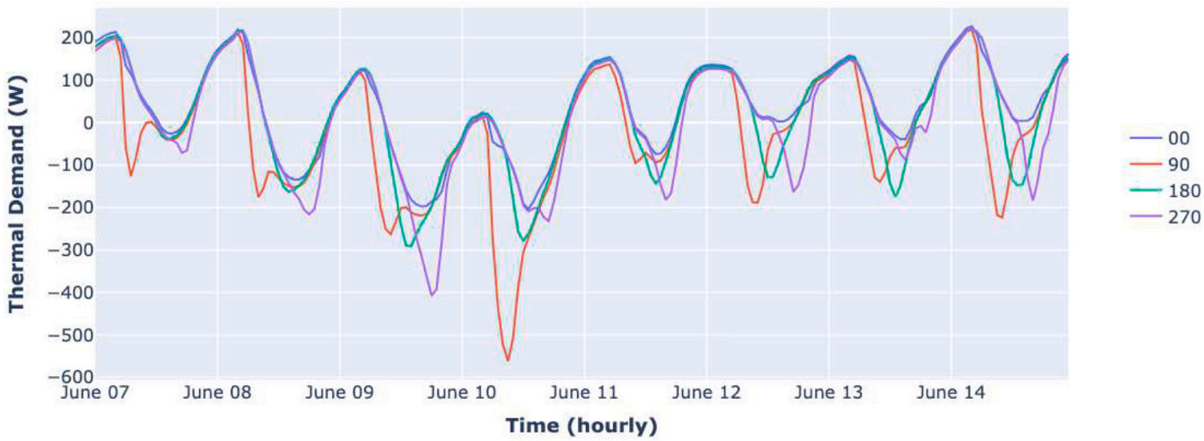
4.4. Detached houses

The overall thermal efficiency of a dwelling has a significant impact on both its heating and cooling demands. From the different types of dwellings under consideration, a detached house represents the worst case scenario given the amount of surfaces exposed to the environment. Fig. 15 shows the thermal demand for a detached house in Cardiff during a week of June of the design year. Results for a range of thermal efficiencies of the construction materials are shown.

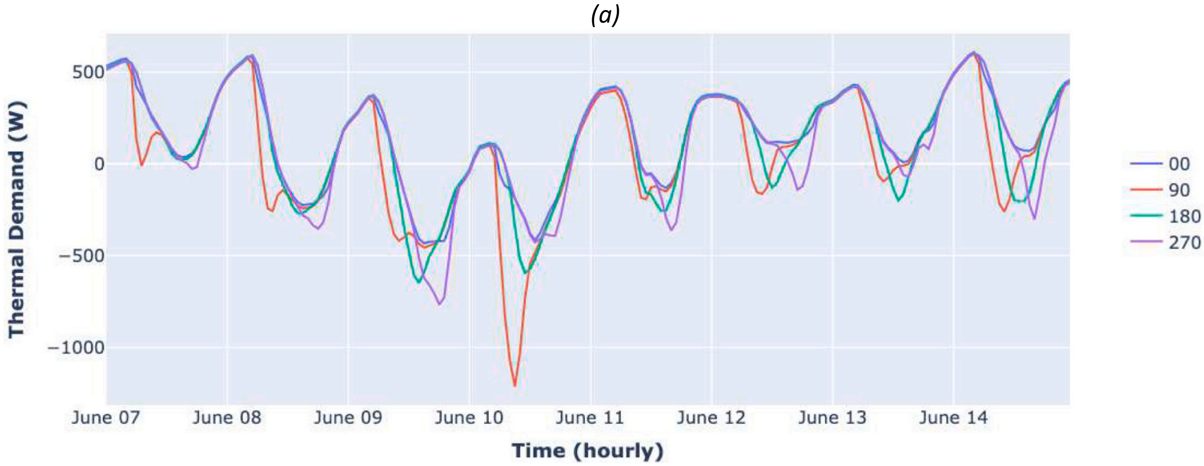
Fig. 15 shows that heat demand for less efficient detached houses (building codes '7654' and '5553', purple and green traces) is much higher than for newer builds (building codes '1111' and '3332', blue and red traces). There are multiple days with a cooling demand of approximately 1000 W for newer dwellings with building codes '1111' (blue trace) and '3332' (red trace), but no cooling demand at all for older dwellings with building codes '5553' (green trace) and '7654' (purple trace).

Although cooling demand tends to be lower for the least efficient dwellings, these exhibit pronounced peak demands. This is a relevant result, as on hotter days, cooling demand for the least efficient dwellings will outstrip the most efficient ones—indicating that older constructions will be more severely affected during heatwaves when outdoor temperatures substantially increase.

For a detached house, modifying windows may have a larger impact on heating demand than cooling demand. This effect is explored in Fig. 16. In this case, the construction materials for walls, foundation, and roof for a detached house in Cardiff (north-facing) were assumed highly



(a)



(b)

Fig. 14. Effects of external wall orientation on the hourly cooling demand for a middle-floor flat in Cardiff. Flat with the (a) highest thermal efficiency (building code '1111'), (b) lowest thermal efficiency (building code '7654').

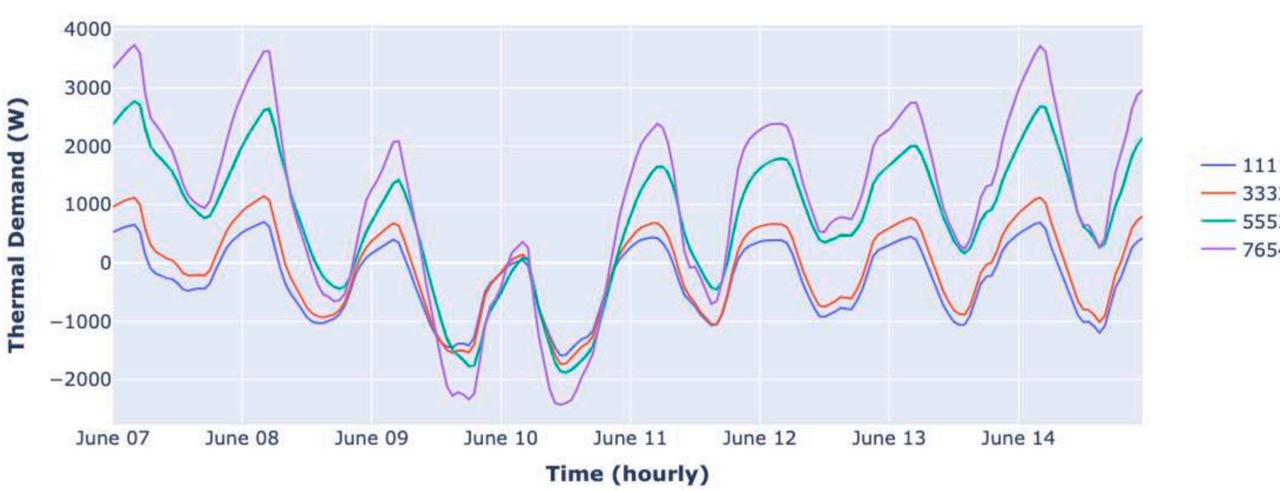


Fig. 15. Effects of thermal efficiency on the hourly cooling demand for a detached house in Cardiff oriented at 0° (north-facing).

thermally efficient but the type of window was varied.

As observed in Fig. 16, the pronounced effect on heat demand may be attributed to the lower thermal efficiency of the windows at night. Since solar gains are zero during night time, heat escapes the building faster. From the figure, windows with a low thermal efficiency (e.g. older double-glazed windows, building code '1114') will reduce cooling demand—except for clear days where solar gains are higher. Thus, radiation entering the detached house adds more heat than is lost through windows with low thermal efficiency.

However, because there are windows on multiple sides of a detached house, the effects of orientation are more muted when compared to those on flats having windows only on a single wall (which are examined in Section 4.3, Fig. 14). To examine this in more detail, Fig. 17 shows the effect of orientation on a detached house in Cardiff during a week in

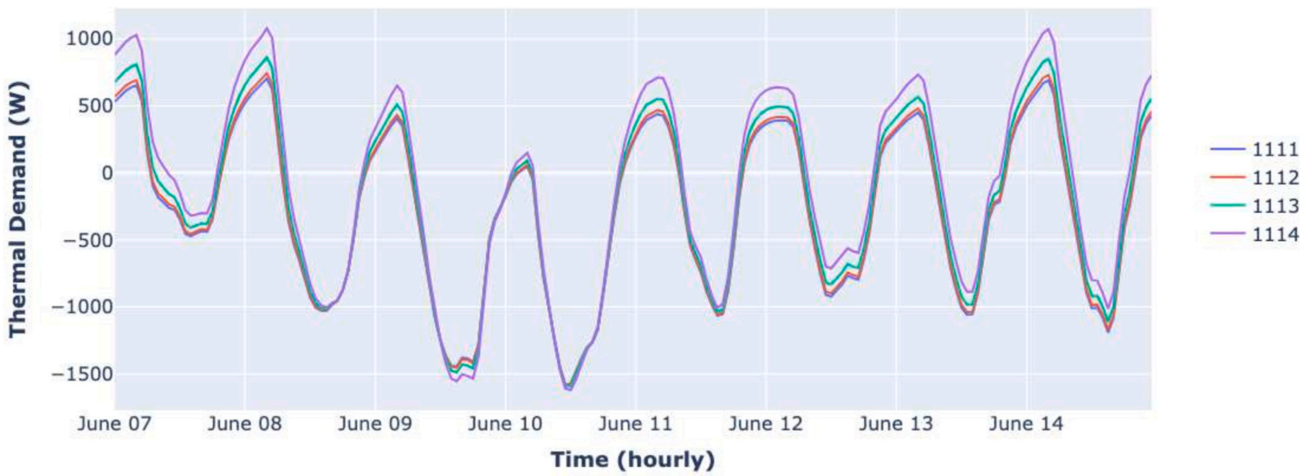


Fig. 16. Effects of window construction on the hourly cooling demand for a detached house in Cardiff oriented at 0° (north-facing).

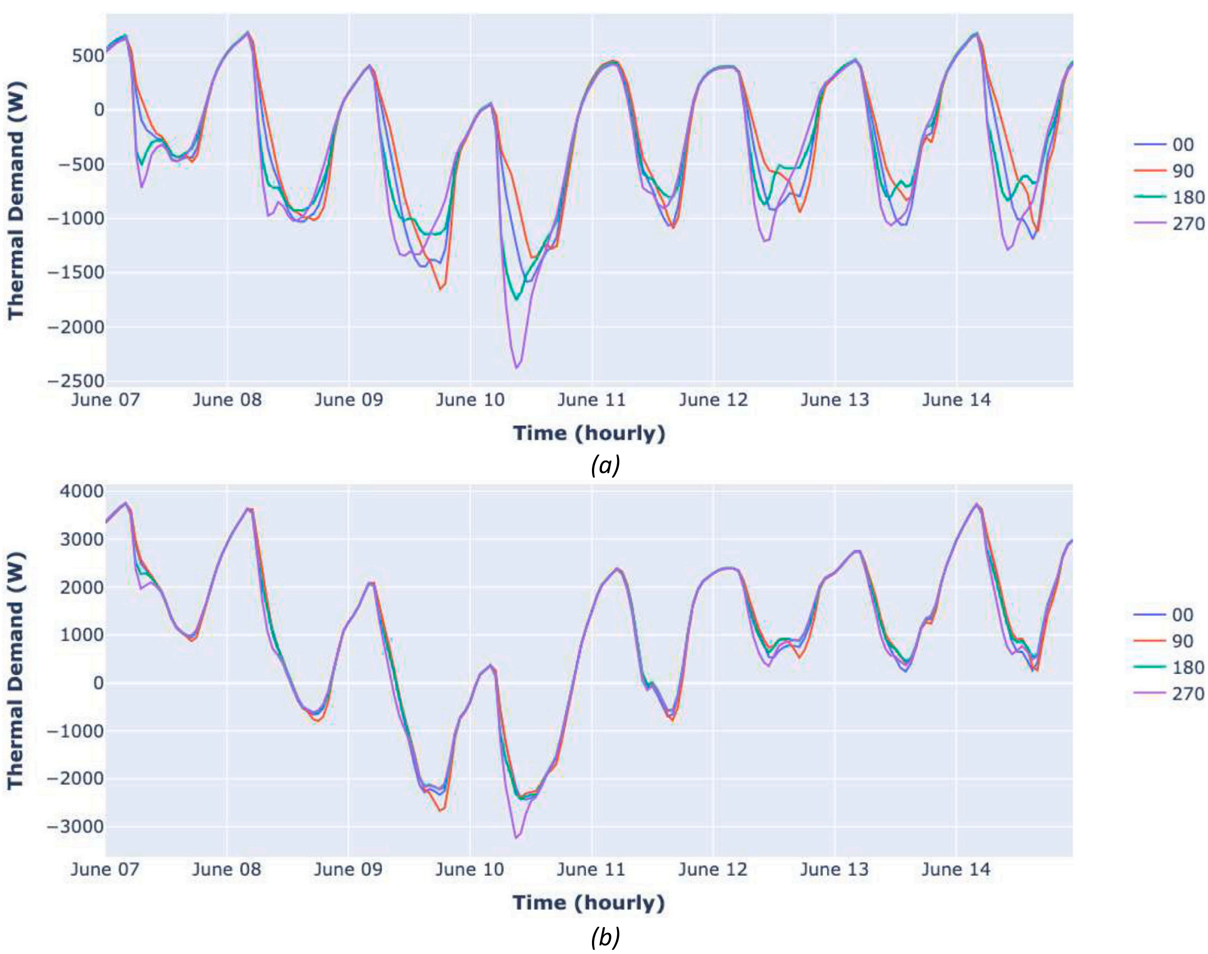


Fig. 17. Effects of orientation on the hourly cooling demand for a detached house in Cardiff. Dwelling with the (a) highest thermal efficiency (building code '1111'); (b) lowest thermal efficiency (building code '7654').

June of the design year. Fig. 17(a) shows results for construction elements with the highest thermal efficiency (building code '1111'), while Fig. 17(b) for the lowest thermal efficiency (building code '7654').

As observed in Fig. 17(a), whilst there is an impact on cooling demand peaks and times due to orientation, similar to those previously discussed for flats, these peaks are not as sharp—although the magnitudes are significantly higher for the detached house. However, as shown in Fig. 17(b), the impact of orientation decreases for detached houses with low overall thermal efficiency. This could be due to the increased heat gains entering the building through the other surfaces diluting the effects of solar gains entering the dwelling through the windows.

4.5. Cooling demand variation based on geographical location

As inferred from Fig. 4, cooling demand for a given property will be heavily influenced by geographical location. To examine this in more detail, the annual cooling demand for the design year was quantified for a highly thermally efficient north-facing detached house in the five geographical locations being assessed. Since the heating season is considered to occur between October to March/April [55], it was assumed in this paper that the cooling season lasts from May to September. (Cooling demand outside these limits could be potentially met with passive measures such as opening windows, but this is not further explored in this paper.) Results are shown in Fig. 18.

Cooling demand for the detached house in the southern locations is higher than for a dwelling in the northern cities, which was anticipated. However, a higher cooling demand for the house in Plymouth compared to that in London would have been expected (and similarly for Manchester and Glasgow) based on the photovoltaic power potential map shown in Fig. 4. This is explained by differences in the data to create the weather files for each location (see Section 3.2.2 for further details on how the weather files are created). For instance, the design year weather files created for Glasgow and Manchester indicate that on average Glasgow is warmer than Manchester based on the years selected to create the files. This is supported by Table 5, which shows the mean outdoor temperature for the cooling season for the weather file of each location. The values shown in Table 5 are consistent with the results shown in Fig. 18.

From the results presented so far in this section, it can be concluded that the conduction gains outweigh the effects of solar gains. However, reducing the thermal efficiency of a dwelling may have a significant effect on the yearly cooling demand. Fig. 19 shows the annual cooling demand for a detached house as in Fig. 18, but now with the least efficient construction materials (building code '7654'). The significant difference in temperature between London and Plymouth increases the cooling demand from one location to the other. Cooling demand for Manchester in this case is higher than for Glasgow—showing that the relationship between cooling demand and solar radiation is sensitive to the thermal efficiency of the dwelling. In other words, the effect of solar radiation on cooling demand reduces as the thermal efficiency of the dwelling increases.

When comparing Figs. 18 and 19, whilst the other locations all see a decrease in yearly cooling demand when thermal efficiency is reduced (i.e. from building code '1111' to '7654'), cooling demand in London shows a marked increase. This could be caused by the higher temperatures not allowing the building to purge the excess heat in the evenings/nights and, therefore, maintaining a more consistent cooling demand over the cooling season. To verify this, further studies into sustained heatwave scenarios could be conducted to determine if this effect applies across all the different dwellings and cities—however, carrying out these studies falls out of the scope of this paper.

Table 5
Mean outdoor air temperature for each weather file.

Location	Mean outdoor air temperature (°C)
Cardiff	16.7
Glasgow	15.5
London	20.2
Manchester	14.6
Plymouth	17.8

Other dwelling types (i.e. bungalows, semi-detached, and terraced houses) exhibit similar results as those presented so far in this section. Therefore, these have not been included in the paper.

4.6. A study on the effects of internal gains on cooling demand

A simple case study was carried out using a ground floor flat as this represents the simplest household model. The dwelling is located in Cardiff, with a building code '1111' (highest efficiency) and a 0° orientation. Simulations were carried out when no internal heat gains are considered and once internal gains are incorporated. The internal gains consist of 2 people producing 90 W of heat between 8 am and 6 pm, and a continuous lighting load of 2 W/m^2. (**Note**: Cooling demand for different types of flats with a building code '1111' located in Cardiff and 0° orientation, including a ground floor flat without considering internal heat gains, was assessed in Section 4.2. In those results, shown in Fig. 11 (a), only the total monthly cooling demand was presented.) The considered internal heat gains for the flat are shown in Fig. 20.

As shown in Fig. 20, all heat gains are positive as there are no elements removing heat from within the dwelling, The occupancy gains (shown with a red trace) are only active when scheduled and the lighting load (blue trace) is a constant value. The total internal gains (green trace) is the sum total of the two loads. This load profile can be either integrated directly into the simulation or, alternatively, can be added to the simulation results for empty dwellings to obtain the total cooling demand for the building. The internal load profile has been simplified as, in reality, heat gains may be highly variable depending on activity levels of the occupants, differing equipment, and lighting schedules. This simplification has been done to demonstrate in a simple way the effect of internal gains in cooling demand without overcomplicating the analysis,

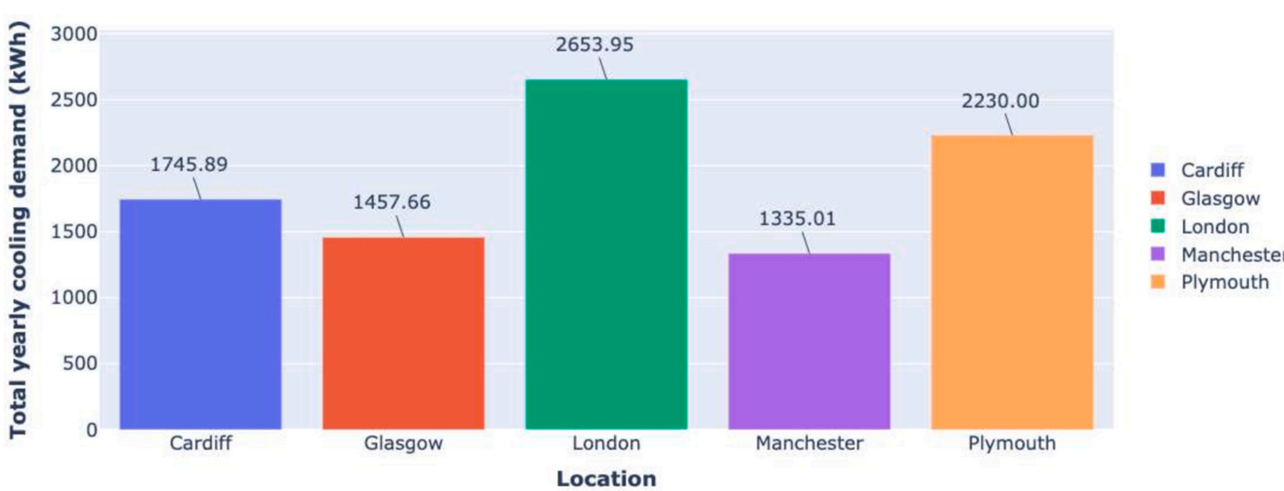


Fig. 18. Total yearly cooling demand for a north-facing (orientation of 0°), highly thermally efficient (building code '1111') detached house at different locations in the UK.

Fig. 19. Total yearly cooling demand for a north-facing (orientation of 0°), lowly thermally efficient (building code '7654') detached house at different locations in the UK.

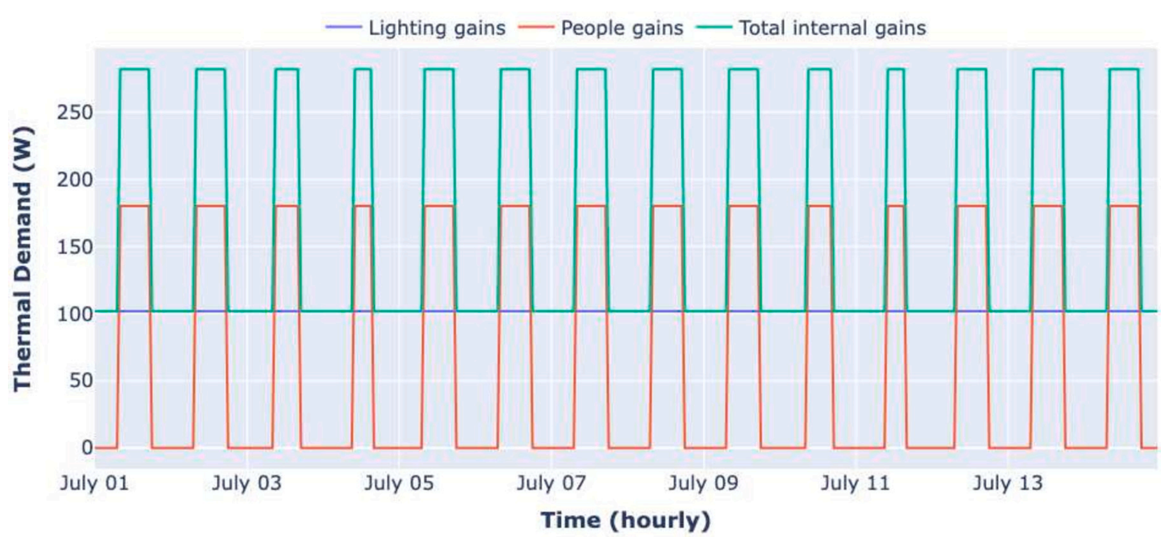


Fig. 20. Internal heat gains for a ground floor flat.

thus restricting computational burden.

Simulation results are shown in Fig. 21. The blue trace shows the baseline thermal demand in the dwelling without any internal loads—equivalent to the existing load profiles shown in previous results in Section 4. The red trace instead shows the simulation results once the internal loads are incorporated into the model. The green trace shows results when the internal gains are incorporated via post processing (adding the total internal heat gains to the results shown with the blue trace). This exercise was conducted to show that either approach for assessing the effect of internal heat gains on cooling demand as discussed in the previous paragraph renders similar results.

Based on the results presented in Fig. 21, whilst not matching perfectly, adding all the internal gains after running the simulations shows negligible difference when compared to incorporating internal loads into the model before running the simulations. Due to the high efficiency of the flat, whilst empty there are very few external gains either exiting or entering the building (see blue trace). Therefore, the internal gains, which are based on the number of people and equipment in the dwelling, have a large impact on the cooling demand as they are applied directly to the internal atmosphere and not muted by highly efficient materials. Repeating the same simulation for a less thermally efficient flat (building code '7654') in the same location and with a same orientation leads to the results shown in Fig. 22.

As shown in Fig. 22, and compared to the results shown in Fig. 21, the internal heat gains have less of an impact on the thermal demand in older dwellings. For both simulation cases though, either considering the additional thermal loads as part of the simulation (red trace) or adding them as a separate load profile following simulations of an 'empty' dwelling (green trace) provides very similar results.

Following the same methodology but with 2 W/m^2 for the lighting load and this time using 5 people at 90 W each for a fixed period of time to cater for occupancy heat gains, additional simulations were conducted for a detached house in Cardiff, north-facing. Results for both a new dwelling (building code '1111') and an old one (building code '7654') are shown in Fig. 23.

Compared to the results presented in Section 4.4 which did not account for internal heat gains, internal loads for the highly thermally efficient detached house, shown in Fig. 23(b), have less of an overall impact on the thermal demand than those in the highly thermally efficient dwelling, as shown in Fig. 23(a). This could be because the additional sources of heat gains from other sources (solar gains, conduction gains) dilute the impact of the smaller internal heat gains used. The blue

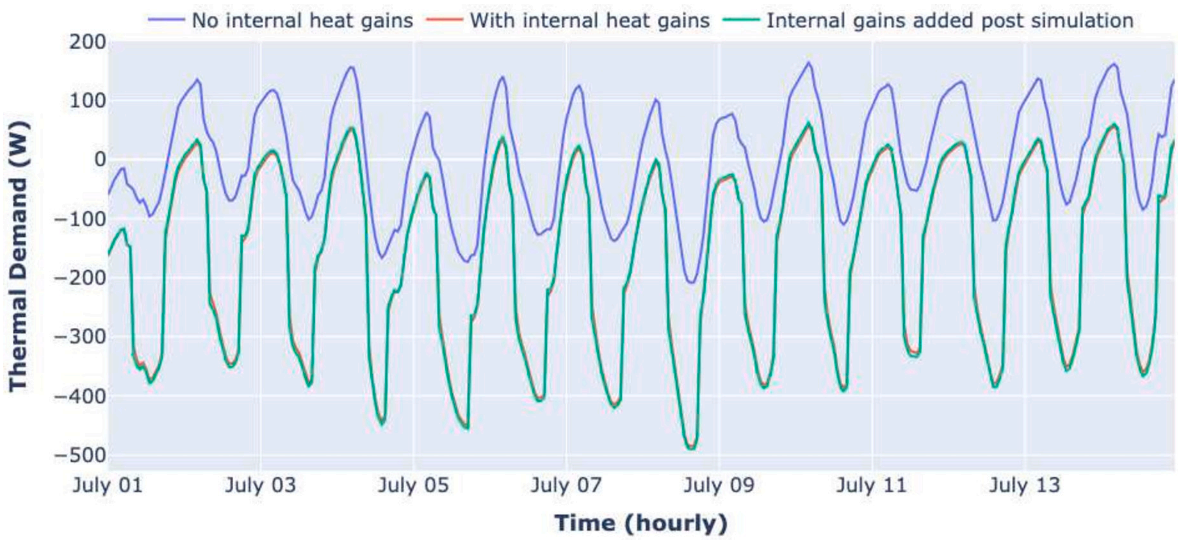


Fig. 21. Effect of internal heat gains in the cooling demand of a ground floor flat in Cardiff with the highest thermal efficiency (building code '1111') and orientation of 0°.

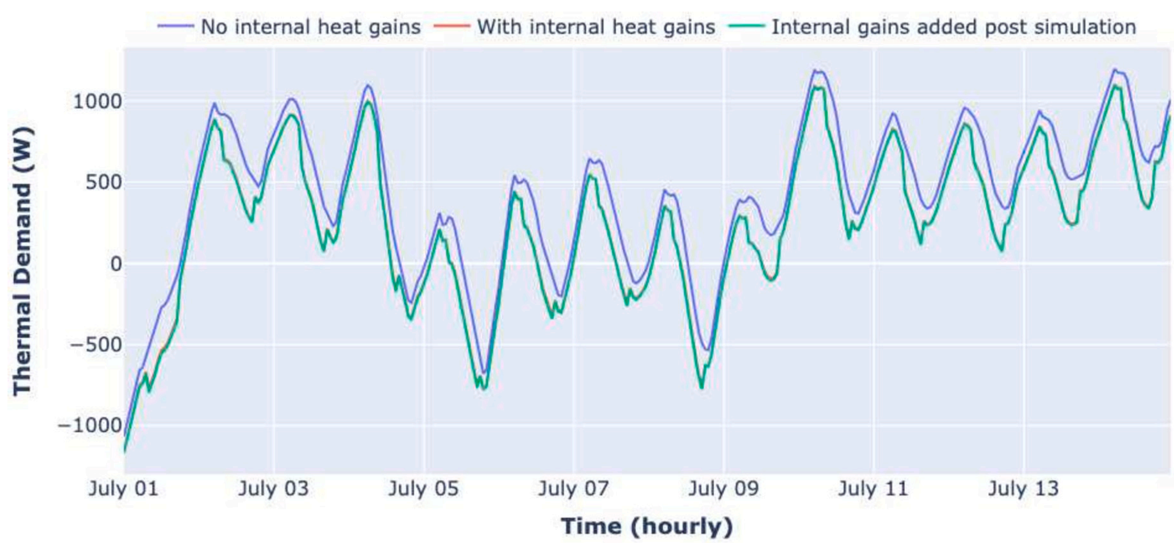


Fig. 22. Effect of internal heat gains in the cooling demand of a ground floor flat in Cardiff with the lowest thermal efficiency (building code '7654') and orientation of 0°.

traces, corresponding to the case without considering heat gains, are similar to those presented in Fig. 15 also with a blue trace for the highest thermal efficiency house and with a purple trace for the least thermal efficient house. Similar conclusions can be also drawn for different types of dwellings, although this is not explicitly shown in the paper with additional simulation results to prevent it from becoming too long.

With the presented approach in this section, it is possible to assess the potential cooling demand in a dwelling considering buildings' usage, number of people living in the dwelling, or equipment installed in the premises.

5. Discussion on the limitations of the methodology

Whilst the methodology presented in this paper provides an accurate estimation of cooling demand in UK households, there are some limitations within the scope of the work.

Although an overall U-value provides a good metric for heat transfer through walls (and other surfaces) in a dwelling, the wall composition will have an impact on its thermal demand. In [56], the effects of thermal mass on building energy consumption were investigated. It was reported that thermal mass is not only poorly quantified in the existing literature, but also that a higher thermal mass is less desired in dwellings located at warmer climates and thus exhibiting considerable cooling demand. The thermal mass of the materials that make up the wall can absorb heat and release it slowly into the building, reducing peak demand in a building for both heating and cooling. As highlighted by the beginning of Section 2.1, a comprehensive assessment of wall composition and how this affects thermal demand is not accounted by the methodology here presented.

The thermal load on dwellings may be realistically met by adopting passive strategies which have not been considered by the methodology. During heatwaves, for instance, various methods such as closing blinds, opening windows at night to purge the heat, and implementing shading on the windows to block solar radiation can reduce cooling demand. However, when active cooling measures are being implemented, the likelihood of passive methods being used is decreased.

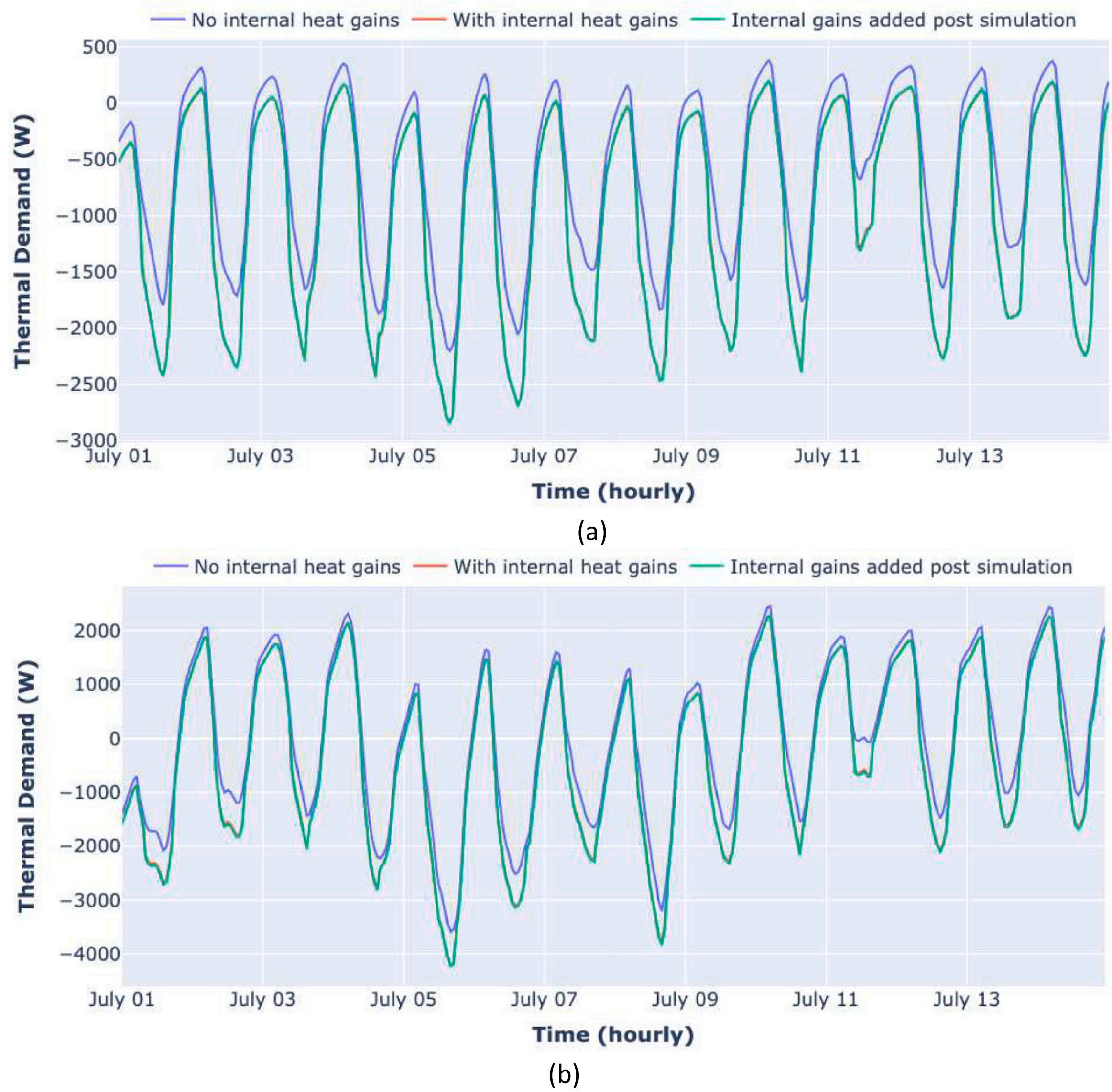


Fig. 23. Effect of internal heat gains in the cooling demand of a detached house in Cardiff oriented at 0° with: (a) the highest thermal efficiency (building code '1111'); (b) the lowest thermal efficiency (building code '7654').

Energy management in homes has not been incorporated within the scope of work either. With the introduction of smart controllers, residents will only activate heating and cooling as needed or on set schedules. This will have a large impact on the thermal load, but this has not been considered in this paper.

Furthermore, although the knock-on implications that increasing cooling demand may have upon the local electricity networks has been mentioned, a detailed study on those effects falls out of the scope of work for this paper. Potential future work can be done in a number of fronts to get a better understanding of the impact of increasing cooling demand on electrical power systems, such as: a) looking into the varying effects of different electricity-driven technologies to meet the demand for local communities; b) assess the extent of which supplying cooling will affect peak electricity demand and its implication on network reinforcements; c) detailed network analysis to assess the impacts of cooling demand on distribution and primary substations; d) investigating the potential for flexibility provision to the electrical power system by integrating passive and active cooling techniques and thermal energy storage.

With regards to the software adopted to model the different dwellings, IES VE implements a fixed ventilation rate. In practice, ventilation rates vary constantly based on the weather conditions and the effect of users opening and closing doors and windows. Whilst their impact on thermal demand may not be significant, ventilation rates will likely have an effect. This aspect requires further investigation.

Additionally, the insulation among older buildings may degrade over the years due to water damage or other types of damage. This is not factored into the methodology. However, it is possible to simulate a degraded insulation by using more conservative U-values than would be expected from the building age.

The methodology assumes there is no degradation of the surfaces and buildings are constructed to the standards of the time. However, some constructed dwellings do not reach the set standards and this cannot be incorporated into the model. Therefore, whilst accounting for surface degradation or lack of standard compliance falls beyond the scope of work, choosing a higher U-value setting for buildings that do not meet the expected standards could be done to cater for such uncertainties.

By simplifying the methodology to not include any internal heat gains and reducing the complexity of the model, simulation times are reduced drastically (as mentioned in Section 3.3). Using this approach, post-processing can be done in a simple and quick way depending upon the required scenarios. Having said that, as shown in Section 4.6, incorporating internal heat gains into the simulation scenarios can be done in an effective way.

As mentioned previously in the paper, the use of AI and machine learning has not been considered in this work due to the lack of cooling demand data available for residential dwellings in the UK. However, advancements in computational power and AI research have led many researchers to integrate AI, machine learning, and deep learning to various applications. This is something that falls out of the scope of this paper, but application examples from other fields of research, such as in [57], can be incorporated into the methodology here presented to look into predicting future cooling demand using forecast data.

Integrating lessons learnt from load forecasting in electrical power systems can also be explored within the context of cooling demand forecasting. For instance, reference [58] adopted convolutional neural networks (CNN) and support vector regression to forecast short term future electricity demand based on weather forecast data. Reference [59] applied a hybrid CNN-based long short-term memory (LSTM) model to predict the hourly heating load for a district heating plant over 48-h and 72-h periods. A similar approach was followed in [60], where transfer learning was incorporated to estimate room temperatures using smart thermostat data.

While deep learning requires historical data, the insights gained from research reported in the references discussed in the previous paragraph demonstrate the potential that CNNs and other machine learning methods have, combined with weather forecast data, to effectively estimate the thermal demand for buildings.

6. Conclusions

This paper provides a methodology to quantify cooling demand for the most common dwelling types in the UK housing stock. To ensure coverage of the majority of existing buildings, an in-depth literature review was carried out to find the ages, typical dwelling types, and construction methods used throughout the previous century.

The methodology enables determining the thermal demand of any building with only minimal knowledge (e.g. when any renovations were last carried out and the current age of the building). It also accounts for the impact on energy demand due to variable thermostat settings through a regression model developed on the simulation outputs. This allows adopting preferred settings of users whilst showcasing the impact of the set points on household energy expenses. The methodology is comprehensive as differing dwelling types, orientations, locations, and constructions may be accounted for when quantifying thermal demand.

The approach was deployed in a case study involving dwellings located in five cities in the UK that experience distinct weather conditions. Results suggest that dwellings in northern locations have a much lower cooling demand than those in the southern locations, as expected. For example, considering the most thermally efficient walls, foundations, roofs, and windows (i.e. building code '1111'), a detached house in Glasgow has a yearly cooling demand of 1458 KWh, while a similar home in Plymouth exhibits a cooling demand of 2230 kWh. This difference in cooling demand for the same type of dwelling is accentuated upon lower thermal efficiencies in the building fabric (e.g. building code '7654'), where the cooler climates and lower outdoor temperatures decrease cooling demand significantly (Glasgow, 479 kWh) but only slightly in the warmer climates (Plymouth, 2035 kWh).

Overall, the results presented in the paper demonstrate the utility of the modelling methodology in identifying and quantifying the variations in cooling demand across different UK dwelling types and locations and for different times of the year within the same dwelling. This is of value for various end-users. For example, developers and urban planners may use the estimated heating and cooling demand to determine the impact this demand has in a local area and ensure that local networks can handle it. Utility companies can use the data to get an estimated thermal demand for any dwelling within their network and use that to identify any anomalous energy usage. Local authorities can benefit from the modelling methodology to help highlight potential at risk locations for vulnerable people where active cooling may be needed. In a similar manner, policy makers may use key results obtained with the modelling tool to estimate when users could potentially install active cooling measures, alongside studying the the impact of varying technologies used to meet the thermal demand on the electrical network, and introduce restrictions on the most environmentally harmful or inefficient technologies.

The methodology presented in this paper constitutes a tool which could be expanded to consider other geographical locations beyond the UK to understand cooling demand peaks, overheating risks, and energy efficiency of typical dwellings in a warming world.

CRediT authorship contribution statement

Lloyd Corcoran: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pranaynil Saikia:** Writing – review & editing, Methodology, Formal analysis. **Carlos E. Ugalde-Loo:** Writing – review & editing, Methodology, Conceptualization, Resources, Supervision, Project administration, Funding acquisition. **Muditha Abeysekera:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A – IES VE settings

This appendix highlights some relevant IES VE settings used in the modelling. This is to provide a glimpse of the software simulation platform and support the interested readers in replicating the modelling work carried out in the paper.

As shown in Fig. A1, each of the rooms within the dwelling has been assigned both a space type and sub-type. This consists in assigning a 'Building Space' room type which simply states that the room needs to be incorporated into the simulation. Assigning other variables such as the 'Adjacent Building' space type does not run any of the room thermal calculations and only retains the geometry in the 3D model to provide shading for the rooms being modelled. Space sub-types have been set to 'void' for the roof space which implies that there is no heating or cooling applied to the room. The 'Room' sub-types ensure that any settings for the thermostat temperatures and internal gains are incorporated into the model for the rooms.

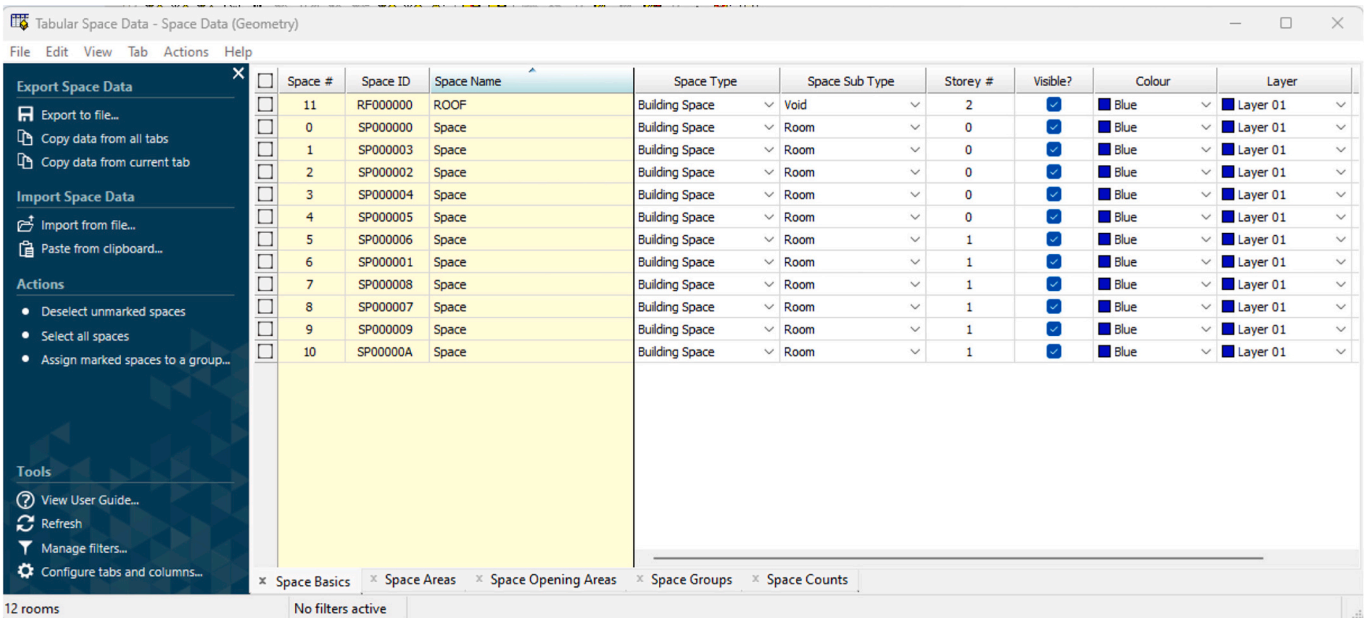

Fig. A1. Screenshot showing the space and subspace settings for each room in a given dwelling.

Fig. A2 illustrates the basic simulation settings used to run the simulations. The 'Results file' is the name of the output file. Enabling the SunCast link runs the model using the variable solar radiation data incorporating the shading effect of surrounding dwellings, forestry, and walls. 'MacroFlo', 'ApacheHVAC' and 'RadianceIES' are additional modules that can be incorporated into the model. Lastly the 'Simulation' box shown on the right-hand side sets the time period the simulation runs for, the desired time-steps for the simulation, and the reporting interval (i.e. the output time steps for the information). The preconditioning period accounts for the heat storage capacity of the dwelling.

Fig. A3 shows the detailed simulation settings for each room. For this specific example shown, as additional detailed information is not required for any of the rooms, none are selected. As a result, the basic simulations are run for each room. If more information such as the specific solar radiation data or surface temperatures is required, the room should be highlighted and the relevant outputs must be selected.

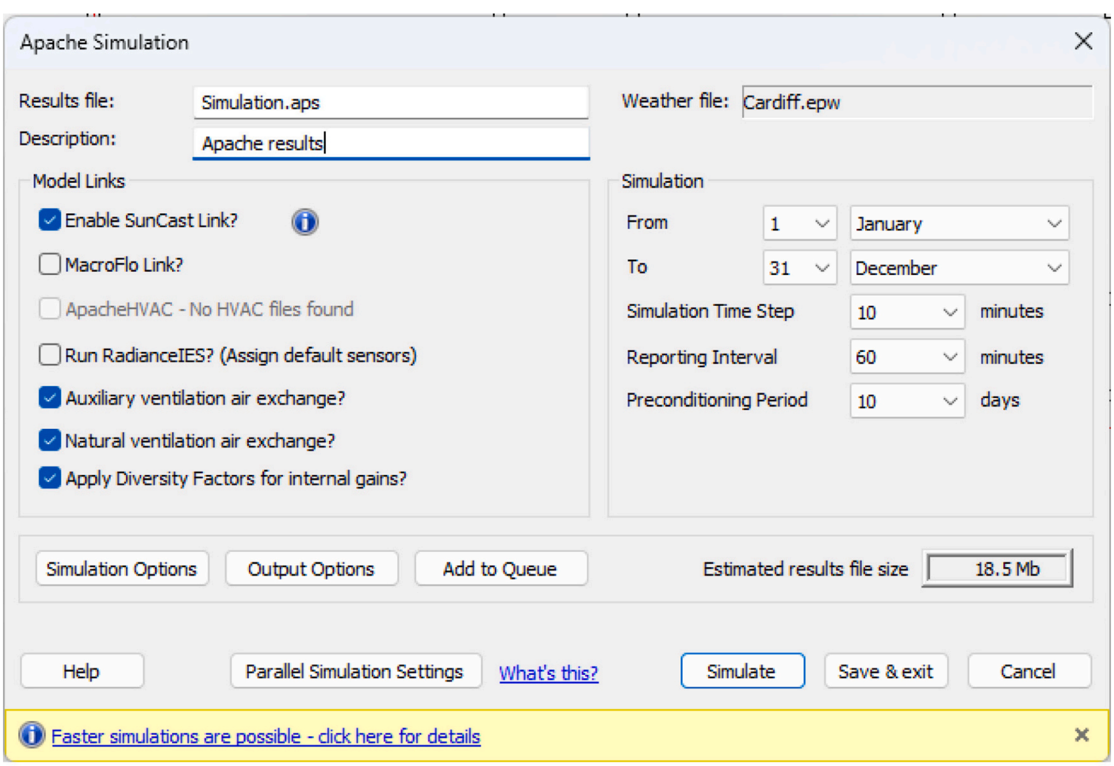

Fig. A2. Screenshot of the simulation settings used to run the model.

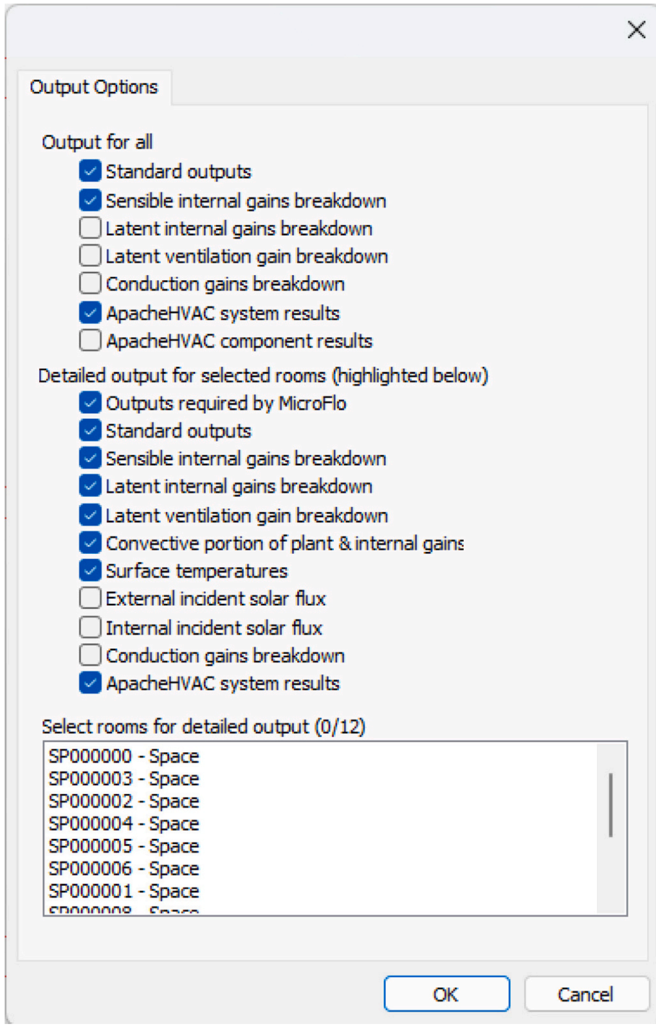

Fig. A3. Screenshot showing the detailed simulation settings for each room within a dwelling.

Data availability

Data will be made available on request.

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