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Hourly cooling demand prediction through a bottom-up model in London

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ABSTRACT

In the context of global warming, domestic cooling demand in the UK, particularly in London, is expected to rise significantly, posing challenges for an energy system traditionally focused on heating. This paper presents a high-resolutison, bottom-up model to predict hourly cooling demand in London by integrating building simulation, inventory data, and meteorological projections. The model categorizes domestic buildings into four main types and assigns different insulation levels based on building age, generating 12 distinct cooling demand profiles across London's 33 boroughs. The model forecasts a 45% increase in cooling demand by 2050, with peak electricity demand for cooling potentially doubling residential electricity usage in 2020. This study further reveals significant geographical and temporal variations and analyses the impact of increased cooling demand on London's electricity grid. The analysis of cooling duration curves highlights the low utilization of cooling equipment during non-peak periods, emphasizing the inefficiency in current systems. To mitigate peak demand, energy storage systems are proposed, with simulations suggesting that up to 50% of peak demand can be reduced, improving grid stability. The findings underscore the importance of not only accounting for future cooling demand but also optimizing equipment utilization and planning cooling infrastructure in urban areas.

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KEYWORDS
Hourly cooling demand; bottom-up prediction model; impacts of cooling operations; London's future cooling scenarios; cooling installations planning

1. Introduction

Historically, buildings in the UK have been designed to be warm and airtight, providing effective insulation during winter months. However, this approach has inadvertently led to the issue of overheating during summer (Gupta, Gregg, and Williams 2015). The recent "State of the UK Climate 2020" report reveals that the effects of global warming are already being experienced in the UK, with the average temperature between 2011 and 2020 is 1.1°C higher than the 1961–1990 average (Kendon et al. 2021). A POST note (a POST note is a research summary issued by the Parliamentary Office of Science and Technology of the UK Parliament, designed to provide scientific evidence to support policymakers.) issued by the UK Parliament states that around 20% of homes in the UK are currently overheated, even in mild summers, resulting in increased heat-related illnesses and deaths (2021). The emergence of extreme weather events undoubtedly indicates that overheating will become a widespread issue throughout the UK, posing significant health risks (2022). A majority of energy policy research has centered on space heating, while cooling has been largely overlooked within UK energy policy and research. As a result, data on cooling demand in the UK, particularly in the domestic sector, are scarce. This can be attributed to the prevalence of cooling systems primarily in commercial buildings (2021). However, in light of global warming, estimating domestic cooling demand has emerged as an indispensable area of research that warrants further attention.

Several methodologies exist for the prediction of cooling demand, paralleling the strategies used in heating demand projection. These methods can be primarily classified into two categories. The approaches are data-driven modeling and physical modeling. It is worth noting that a significant portion of heating forecasting research has been centered around physical modeling. This is due to the diverse sources of heating energy, which makes data collection a challenging task. Conversely, in regions with high cooling demand, the majority of the energy required for cooling is derived from electricity. Given the easier accessibility of electricity data, the data-driven method is more prevalently used in such regions. Economic modeling based on economic and demographic data is common in both areas. Data driven models can provide predictions with various levels of resolution, from hourly to yearly, depending on the inputted data. However, not all cases have sufficient data available for use, and physical modeling is currently an irreplaceable method of cooling prediction. Physical models can also be broadly classified into two categories. The cooling prediction of a region or country based on Cooling Degree Days (CDD) is popular. The prediction is based on the principle of heat transfer which is always used for buildings or complexes of buildings. With the effects of global warming, the impact of climate on cooling demand is a hot research area. More and more studies combined the CDD methodology with economic factors to predict cooling demand in future scenarios.

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A variety of models based on the CDD approach are the most common of the economic models. Jakubcionis et al. studied the correlation between cooling demand and meteorological conditions in the US due to insufficient European data, identified cooling indicators, and estimated the space cooling demand for European domestic buildings accordingly (Jakubcionis and Carlsson 2017). The same methodology was applied to forecast the European service sector's space cooling demand, with Jakubcionis et al. refining the estimate by classifying buildings based on usage due to the sector's increased complexity (Jakubcionis and Carlsson 2018). Falchetta et al. determined the CDD distribution by analyzing historical sub-Saharan climate and data, as well as calculating the overall energy demand from household cooling equipment use and CDD (Falchetta and Mistry 2021). Laine et al. developed a model to forecast and analyze the global demand for cooling based on socio-economic and climatic inputs under different scenarios, the core of which is the CDD method (Laine et al. 2019). Morakinyo et al. investigated the cooling demand during extreme hot weather in Hong Kong using the CDD method (Morakinyo et al. 2019). Bezerra et al. employed CDD calculations to evaluate Brazil's cooling demand by combining regional and population data and analyzed its variations under different global warming scenarios (Bezerra et al. 2021).

Physical models based on heat conservation principles are essential tools in engineering. Parameters such as outdoor temperature, indoor temperature, and building heat loss are variables that are factored into the physical model, which can influence the heat exchange between a building and its environment. Therefore, many building simulation software were developed based on physical principles which can be used to estimate the energy consumption of a building. In addition, more factors affecting the energy demand of a building have been studied. Pappaccogli et al. used the Transient Systems Simulation Program (TRNSYS) to simulate an Italian building's cooling demand, integrating the Weather Research and Forecasting/Urban (WRF/Urban) approach for enhanced meteorological data accuracy (Pappaccogli et al. 2018). Xiong et al. utilized the Designer's Simulation Toolkit (DeST) software to forecast China's future cooling demand, employing a bottom-up model that represents various climate types and dwellings through selected typical Chinese cities and buildings. Like most similar software, DeST requires meteorological data, building structures, and Heating, Ventilation, and Air Conditioning (HVAC) system operation information (Xiong et al. 2023). Cox et al. analyzed the impact of varying future weather files on the accuracy of building cooling energy demand predictions. The study found that despite coarse weather files being sufficient for annual energy demand predictions, their accuracy diminishes for daily or monthly predictions when air temperatures approach the heating or cooling balance point (Cox et al. 2015). Allegrini et al. suggested an enhancement to the building energy modeling methodology. The study measured the impact of urban radiation balance, urban heat island effect, and urban convective heat transfer coefficients on space cooling demands (Allegrini, Dorer, and Carmeliet 2012). De Rosa et al. developed a new steady state model incorporating the thermal inertia of the building envelope and monthly averaged climatic data based on the lack of accuracy of existing steady state models (De Rosa et al. 2016). The model proposed by Li et al. considered the effect of window-to-wall ratio on indoor temperature, and the model was coupled with Envi-met and TRNSYS to obtain a model with better accuracy (Li et al. 2021).

For data-driven models, whether traditional statistical models or machine learning models, historical cooling demand data are essential. These models aim to establish a mathematical correlation between inputs and outputs, necessitating a substantial data set. The cooling data could be sourced from sensors, substituted with electricity data, or derived from a physical model. However, it is evident that this methodology is not viable for present cooling estimates in many UK regions due to the scarcity of cooling data. This issue is one of the primary challenges this paper intends to address. Contrarily, the CDD-based model demands significantly less data compared to its data-driven counterpart. The advantage of this model lies in its computational efficiency and speed, making it suitable for forecasting cooling demand across large-scale regions. Nevertheless, this model is typically a steady-state one, spanning years and primarily employed to investigate future cooling scenarios in the context of climate change. As such, it is unable to study the dynamics of the cooling profile over shorter periods. On the other hand, physical models are developed based on the principles of heat balance and possess a robust capability for dynamic predictions. These models demand a more comprehensive set of environmental data. They take into account the details of the building, such as floor area, materials, cooling system, ventilation, etc. Building simulation software is the most commonly used in prediction, often yielding highly accurate predictions.

Although the application of physical models at a city or country scale presents certain challenges, recent studies have made significant progress in addressing these issues. For instance, a recent study in the U.S. successfully developed a city-scale building simulation using physical models combined with survey data. These advancements highlighted the potential for overcoming some of the barriers in scaling physical models to larger, more complex environments. Wang et al. used EnergyPlus to simulate city-scale energy consumption under historical and future climate conditions. Instead of modeling every building in each city, they employed 40 residential and 28 commercial prototype building models developed by the Pacific Northwest National Laboratory to represent different building types, heating systems, and foundation types. Based on these 68 models, they further updated site information, design conditions to reflect specific city characteristics, extending the model to 303 cities. These updates allowed for a more accurate reflection of local climate impacts on energy use across different urban environments (Wang et al. 2023). Ma et al. simplified city buildings into 3D objects without considering structural details to facilitate large-scale simulations. The study focused on calculating the annual heat demand for buildings across 30 major U.S. cities. By using a tiled multi-city urban objects dataset and distributed data ontology, they transformed the conventional whole-city model into patch-based distributed simulations. This approach efficiently handled the interaction between urban objects and enables scalable building energy simulations (Ma et al. 2023). In recent years, studies focused on city-scale modeling and cooling demand predictions for London have been increasing. One of the larger-scale efforts was the London Building Stock Model, developed in collaboration between the London government and the University College London Energy Institute. Similar to the model proposed by Ma et al., this model provided simplified representations of every building in London and enabled rapid calculations of annual energy consumption. Although dynamic simulations are not yet supported, the model continues to be updated and improved, making it a valuable tool for energy planning and urban management (Evans, Liddiard, and Steadman 2019). Day et al. used the CDD approach to manually estimate London's cooling demand, considering the city's building stock, cooling system efficiency, and potential future scenarios. As early as 15 years ago, this method provided valuable insights into how London's cooling demand could evolve with changing climate conditions (Day, Jones, and Maidment 2009). In addition, studies on London's urban heat island effect often involved cooling demand predictions. These studies primarily focused on annual heat demand changes for the entire region under future scenarios, but lacked detailed analysis of dynamic, time-sensitive demand fluctuations. Watkins et al. found that London's urban heat island effect raises average and peak air temperatures, affecting heating and cooling demand. Their year-long measurement of hourly air temperatures at 80 locations revealed that central London is 2 K warmer than surrounding areas. Using this data in a thermal simulation model for a standard air-conditioned office building, they observed a 25% increase in cooling load and a 22% reduction in heating load. Additionally, CO2 emissions increased by 2.8% per degree of temperature rise, with the lowest emissions recorded in rural locations (Watkins et al. 2002). Kolokotroni et al. simulated a typical office building in London using an advanced thermal simulation program Integrated Environmental Solutions Virtual Environment (IESVE). Their predictions indicated that as the building's location shifts from rural to urban areas in London and from present to future years, heating loads decrease, while cooling loads and overheating hours increase (Kolokotroni et al. 2012).

It is impossible to collect all the architectural details of a country or city because they contain many details such as the construction of the building, the size, the material of the walls, the size and orientation of the windows, and so on. The study of future cooling scenarios is not sufficiently supported by large-scale steady-state models such as small-scale physical models in the context of the net-zero objective. The importance of realizing a dynamic prediction for a large-scale region in the absence of data cannot be overlooked. This not only shows the future cooling demand and scenarios but more importantly analyses the impact of the dynamic changes in cooling on the future power or energy sources. The development of a high-precision model applicable to the whole city is achieved in this paper by merging a physical model and economic data information, utilizing building simulation and collecting building inventory information. London, for instance, is used as a reference point, with building simulation employed to derive typical domestic cooling profiles. Information on the overall housing in London is provided by economic data such as stock, dwelling size, age, etc. The cooling profiles obtained from this model, which are of high resolution, can be used not only for dynamic analyses but also for future scenarios of cooling demand. The study provides a robust solution for forecasting urban cooling demand at high resolution by integrating physical with economic data. Compared to traditional city-scale prediction, this approach not only improves accuracy and resolution level. In the study, the effects of cooling operations on the power grid are examined, addressing a significant gap in UK research. Analysis methods are employed to assess both the immediate and future impacts of increased cooling demands on power demand, enhancing understanding of potential challenges.

The rest of this paper unfolds as follows: Section 2 delineates the model's methodology. Section 3 then validates the model with government data. Section 4 lays out the findings and engages in a discussion. Section 5 encapsulates the conclusions drawn from the study.

2. Methodologies

In order to effectively analyze the impact of cooling demand, it is imperative to obtain a high-resolution cooling profile. Various building energy simulation methods exist to facilitate this process. In this paper, the cooling demand is predicted using the same model utilized in the authors' previous publications (Zhang et al. 2022). The proposed building simulation model has been validated successfully using diverse data from the literature and government report. It is important to emphasize that the utilization of data from official sources is crucial to further substantiate the reliability and robustness of the model in this paper.

This paper presents a systematic approach comprising three key stages to thoroughly investigate cooling demand and its implications on energy consumption and conservation within the engineering domain. The first stage is the generation of cooling data through the utilization of a building simulation model. This step is crucial for obtaining accurate and relevant data that can be further analyzed in subsequent stages. Following the data generation, the second stage focuses on validating the reliability of the obtained results with authoritative data provided by government agencies. This step ensures the credibility and robustness of the generated results. Finally, the third stage delves into the analysis and prediction of cooling demand and its potential impact on energy consumption patterns. By employing this rigorous approach, the study aims to offer a comprehensive understanding of cooling demand, ultimately paving the way for the optimization of energy consumption and the promotion of sustainable practices in the engineering field.

2.1. Modelling

The cooling models in this paper are developed utilizing DesignBuilder, which is a reputable building energy modeling software with a calculation engine that employs EnergyPlus, a widely documented tool in the literature (Crawley et al. 2000).

In the UK, the Department for Business, Energy & Industrial Strategy (BEIS) categorizes energy end consumption into four primary sectors. These sectors encompass domestic, industry, services, and transport (For Communities and Government 2011). This classification system provides a comprehensive framework for understanding and analyzing energy consumption patterns across various aspects of society. As the service, industry and transport sectors are out of the scope of this study, only domestic buildings are investigated. Based on the building surveys in each country, domestic buildings are categorized into four categories, detached, semi-detached, terraced and flat. In this study, London is divided into 33 regions based on boroughs, as shown in Figure 1. The building stock and age vary across different regions, with insulation levels being a significant factor. For each building type, three distinct insulation levels are identified, resulting in three different classifications for each morphology (Clegg and Mancarella 2019). This approach generates 12 different hourly cooling demand profiles, derived from 12 distinct building models in each region. Data from 33 distinct regions are analyzed to obtain a comprehensive understanding of the city's cooling requirements. This involves the aggregation of 396 individual cooling profiles, which provides valuable insight into the overall cooling demand across London.

2.2. Classification and stock of buildings

In contrast to commercial buildings, where data are sparse or unclear, the information on domestic buildings in London is considerably more comprehensive. The London Government has undertaken a comprehensive survey of the city's housing stock, categorizing them into detached, semi-detached, terraced, purpose-built flats, flats in a converted/shared house, flats in a commercial building or other converted nonresidential and caravan/other mobile or temporary structure (C. & L. G. MHCLG Ministry of Housing 2023).

The data on the domestic buildings provided is broken down by each borough in London. For the purposes of this study, caravans or any other mobile or temporary structures are not included in the model. Furthermore, the three different types of flats will be collectively referred to as "Flat." As depicted in Figure 2, domestic buildings in London are categorized into four main types: detached, semi-detached, terraced, and flats. This classification aligns with the categorization used by the national government in its housing survey.

In addition to the type of housing, each borough provides thorough statistics on the age of domestic buildings, with the oldest dating back to pre-1900. In this paper, the age of buildings is re-divided according to the classification criteria, and buildings of different ages are divided into three categories as shown in Figure 3, pre-1919, 1919–1964, and 1964-present. Each age category represents a different building construction, influencing the parameter settings of the building simulation.

2.3. Meteorological data

The meteorological file serves as a crucial input for building simulations, as it establishes the climatic conditions of the simulated building's location. These conditions largely influence the building's heating or cooling demand within the building. The meteorological files utilized in this paper are endorsed for UK government compliance calculations. For 2020, actual historical weather data from Solcast is incorporated into the cooling demand prediction (2024).

For the projections into 2050, the Typical Meteorological Year (TMY) weather file provided by the Chartered Institution of Building Services Engineers (CIBSE) was used for the analysis (2023). It provides an hourly weather data of London in 2050. The variables of the meteorological include dry-bulb temp, wet-bulb temp, atmospheric pressure, relative humidity, global

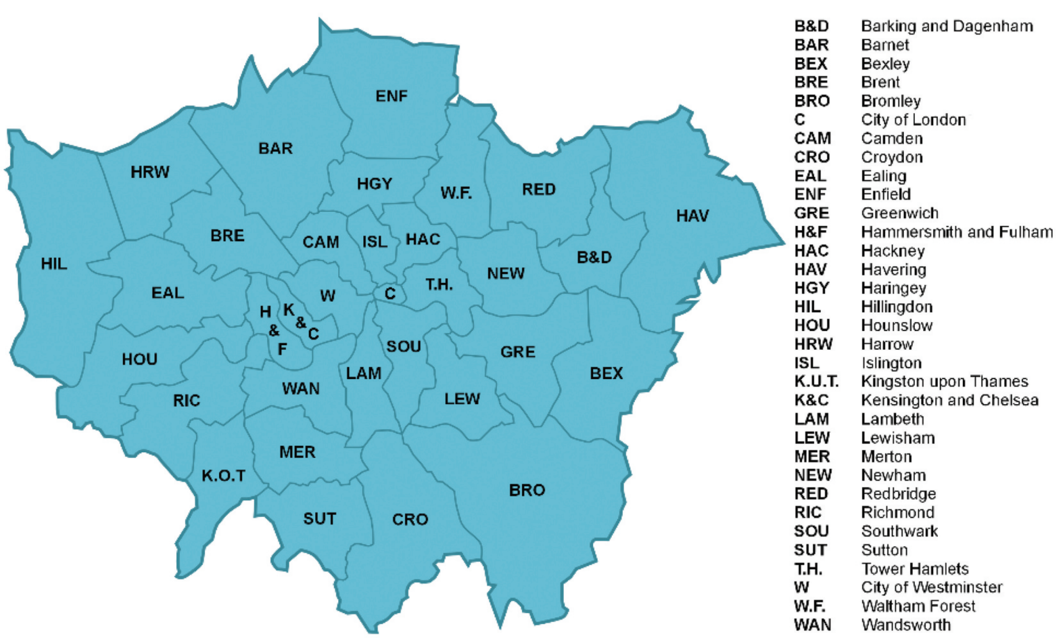

Figure 1. London borough map (Wikimedia commons contributors 2023b).

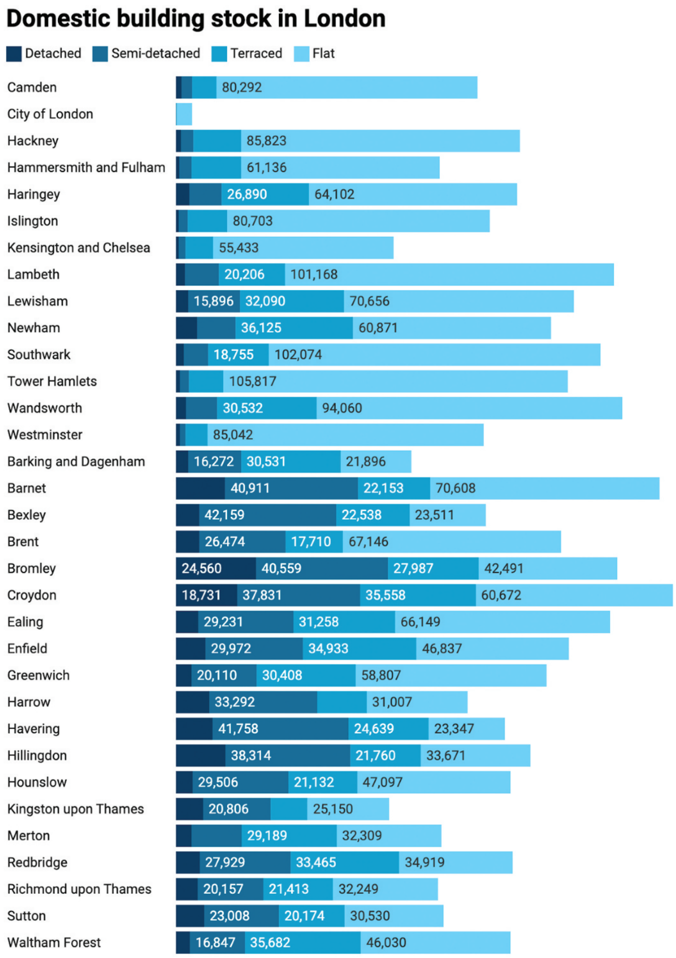

Figure 2. London domestic building stock (C. & L. G. MHCLG Ministry of Housing 2023).

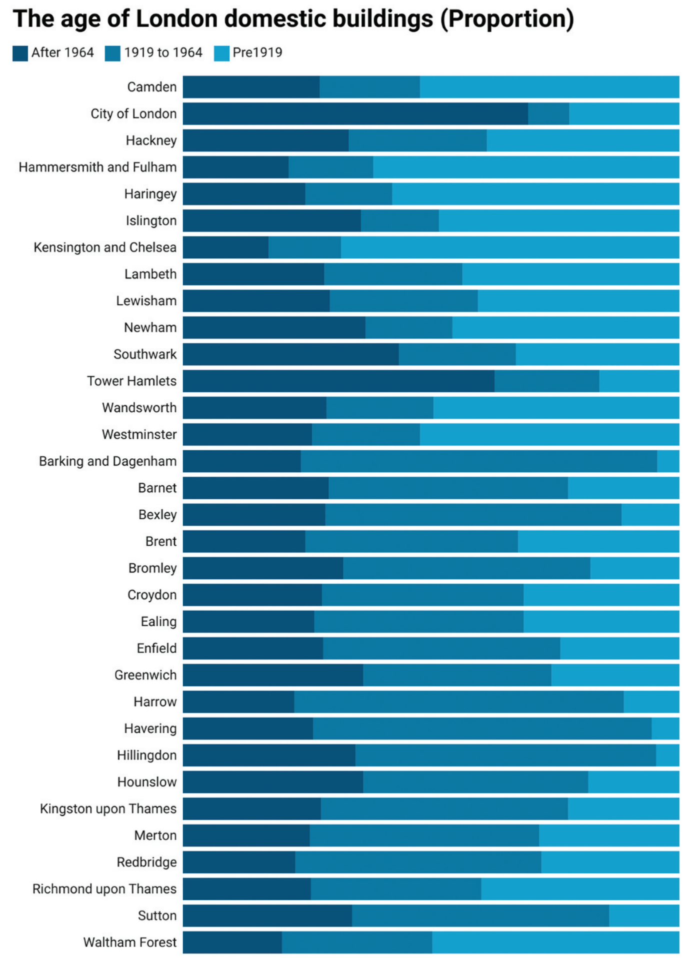

Figure 3. The age of London domestic building.

Horizontal Irradiance, direct Normal Irradiance, diffuse Horizontal Irradiance, wind speed and wind direction. The TMY file is derived from the monthly averages of the preceding 10 or 30 years, selected from the corresponding data for each month of a year that closely matches the 10- or 30-year average. The Met Office relies on TMY data and global warming to predict the weather in 2050, implying that the 2050 weather file incorporates global warming effects but neglects extreme weather conditions. Some of the weather data used in the model is given in Figure 4. It is noteworthy to mention that July is typically regarded as the peak month for cooling demand.

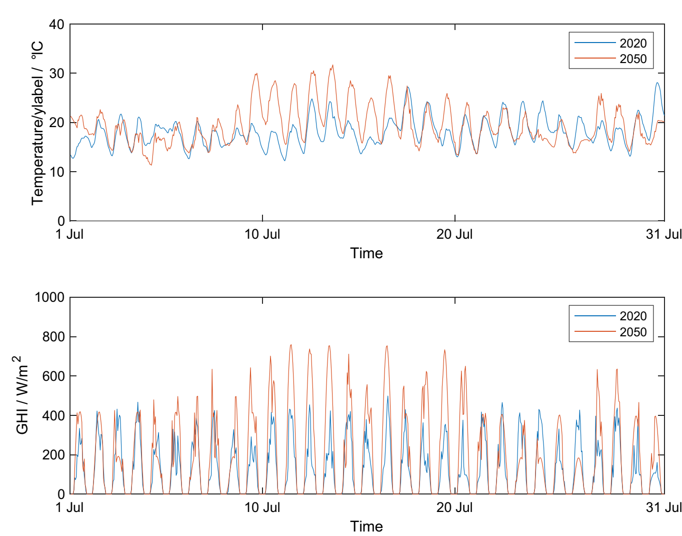

Figure 4. Comparison of partial meteorological data for July 2020 and July 2050.

2.4. Building simulation

As depicted in Figure 5, the building fabric under consideration comprises detached, semi-detached, terraced, and flat structures. Various parameters are taken into account during the modeling process, with the most fundamental being the material and thickness of the building envelope. While the study does not extensively delve into the complex building materials found in the London area, it utilizes a U-value to represent these materials. The U-value signifies the rate of heat transfer across the structure, otherwise known as the heat transfer rate. It provides a measure of an insulator's impact on a building's thermal performance, which can be determined by calculating the thermal resistance of all the materials constituting the building elements (Baker 2011; Loga, Stein, and Diefenbach 2016). Apart from external walls, other U-values to be considered in the model include the roof, ground floor, and glazing. As government-issued building

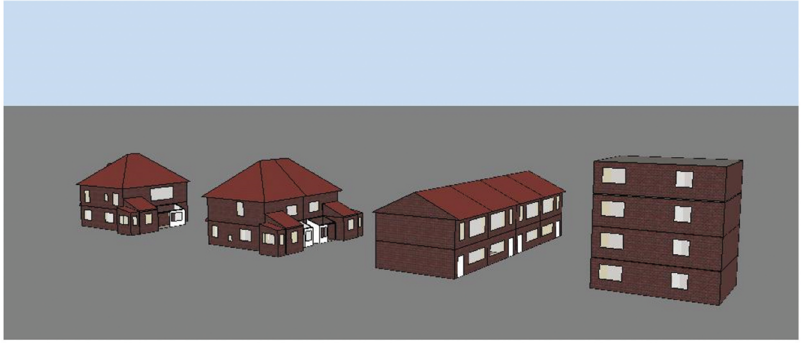

Figure 5. Models of domestic buildings in DesignBuilder.

Table 1. The setting U-value of different parts in the buildings (Clegg and Mancarella 2019).

	External wall	Roof W/m^2	Glazing	Ground floor
1964-now	0.43	0.15	2.7	0.25
1919–1964	1.5	0.75	3.3	0.84
Pre1919	2.1	2.5	6.2	1.1

regulations can differ at each stage, a significant number of buildings in London exhibit varying standards and constructions. Consequently, buildings' insulation levels are categorized into three classes based on the building's age. The U-values for each class are specified in Table 1. The solar radiation (G-value) for all windows is set at 0.69 without the consideration of window's orientation (Clegg and Mancarella 2019).

The cooling demand within a building is not only influenced by the structure itself but also by the internal heat gain. The detailed parameters such as radiation from appliances and luminaires, as well as personnel activity, could not be precisely set due to the absence of comprehensive data and monitoring. The occupancy density for the building is set to 0.0196 people per square meter. The appliances are not considered in the model. Furthermore, a comprehensive HVAC system inclusive of equipment and piping can be designed in the model, though this study primarily utilizes a simplified HVAC model. The cooling setpoint is established at 24°C and cooling set back temperature is 28°C for each space in the building. When a threshold above 28°C, the building's cooling system would be activated for the whole spaces in the buildings. The cooling system will stop when the room temperature reaches to 24°C. The schedule of cooling system during the day will be on at 10am in the morning and stop at 3pm.

In this paper, it is presumed that all buildings in London possess efficient ventilation systems as there is no valid information to provide details of ventilation in London buildings and this assumption provides the most idealized prediction of cooling demand. Thus, both natural and mechanical ventilation are inherently available in the model. However, it is worth noting that this may not all buildings have efficient ventilation systems. The architectural design of a building may inherently restrict ventilation. Moreover, safety reasons in various areas further curtail the availability of natural ventilation. This is often achieved by implementing measures such as keeping the windows closed. These factors are not addressed in this study. Consequently, the results derived from this study can be viewed as the minimum cooling demand in London under the given weather conditions.

3. Model comparison

As previously stated, the model discussed in this paper has undergone validation checks for accuracy in past research (Zhang et al. 2022). To further enhance the dependability of this model, the model will be validated again when applied to cooling forecasts. Data pertaining to cooling in the UK, particularly domestic data, are notably limited. The lack of domestic cooling demand data in the government's public archives adds complexity to the model's validation process. Unlike the validation method for heat demand, which compares the overall annual demand against the government's publicly available energy consumption data for space heating, the approach in this paper contrasts the average peak month cooling demand per square meter of the building which is provided by the London government. This alternate validation and cross-validation methodology augment the model's reliability.

The London Government has mandated a suggested cooling demand benchmark, providing benchmarks for two distinct calculation methods (2015). The first method is based on the Standard Assessment Procedure (SAP), a UK government-proposed standardized calculation of residential cooling demand across the UK. While this calculation provides a fair reference, it is static, primarily focusing on temperature effects while excluding other factors. Despite this, it is widely regarded as a reliable and accurate standard. The second benchmark improves upon the limitations of the SAP and is specifically tailored for the London area. This benchmark considers the building's dynamic balance and the cooling demand in various scenarios, which is the new Proposed Benchmark (PB) in the report.

Table 2 presents the mean cooling demand for each type of building, per square meter, over the summer months (June, July, and August) according to the model utilized in this study. It indicates that detached buildings require the least cooling,

Table 2. Average (for June, July and August) cooling demand per square meter in different buildings.

$kWh/m/^{m2}$	After 1964	1919 to 1964	Pre1919	Average
Detached	1.23	0.73	0.66	0.88
Semi-Detached	1.22	0.78	0.73	0.91
Terraced	1.20	0.82	0.75	0.93
Flat	1.48	1.36	1.11	1.32

while flats necessitate the most. A correlation is observed between building density and cooling demand, with less dense buildings having lower cooling requirements. The building density means the number of buildings per unit area without regard to the number of people living in the buildings. Furthermore, older buildings tend to have lower cooling demands than newer ones due to the superior insulation performance of modern structures. An examination of the mean values for the four building types reveals that the figures for the three types are similar, with flats being slightly higher.

Table 3 provides the acceptable cooling demand range for flats and duplexes as per the SAP and BP standards and it concludes standards categorize buildings into two classes the "poor external conditions" and "good external conditions." The "good" category refers to the cooling demand of buildings under optimal conditions, while "poor" represents the cooling demand under extreme conditions. Since the classification of buildings in this study differs from these standards, detached, semi-detached, and terraced houses are categorized as duplexes. A comparison of Tables 2 and 3 reveals that the average values for all building types align with these standards, with slight deviations for post-1964 detached, semi-detached, and terraced houses, and pre-1919 flats. These variations primarily stem from differences in construction methods and materials used in this study compared to those in the government report. The structures highlighted in the governmental report are specifically selected, characterized by their fixed structures and representative of quintessential London residences. Contrarily, the buildings examined in this study are more encompassing, aligning with and reflecting the broader spectrum of London's architectural landscape. Hence, these discrepancies fall within acceptable margins.

Due to the lack of detailed statistical data, conducting a comprehensive quantitative analysis of the model results presents significant challenges. In this study, the adopted approach involves calculating the median values of PB and SAP scores, which are then compared against the average values derived from four different building types. This method provides a baseline for evaluating the model's accuracy and consistency in predicting heating demand across varying scenarios. The percentage difference between the SAP value (1.4) and the flat average (1.32) is approximately 5.71%, while the difference between the PB value (1.8) and the flat average is 26.67%. For detached buildings, the percentage difference between the SAP value (0.755) and the detached average (0.88) is −16.56%, and between the PB value (0.775) and the detached average is −13.55%, indicating both SAP and PB are lower than the average. Similarly, for semi-detached buildings, the percentage differences between SAP (0.755) and PB (0.775) with the semi-detached average (0.91) are −20.53% and −17.42%, respectively. For terraced buildings, the percentage differences are −23.18% for SAP and −20.00% for PB when compared to the terraced average (0.93).

Table 3. Suggested average cooling demand per square meter from SAP and PB.

$kWh/mm/^2$	SAP good	SAP poor	PB good	PB poor
Duplex	0.57	0.94	0.45	1.10
Flat	1.29	1.51	1.27	2.33

4. Results

The findings of this research are organized into three primary sections. The initial section provides an intuitive understanding of the cooling demand in London for the years 2020 and 2050. It offers a comparative study of the geographic variations in annual cooling demand across London's 33 boroughs and employs daily demand curves to analyze the temporal spread of the demand throughout the year. The subsequent section delves into the implications on electricity demand if the cooling demand is entirely satisfied in 2020, and it further explores the practicability of addressing this cooling electricity demand via energy storage solutions. The final section scrutinizes the cooling demand under varying scenarios, in the framework of a net-zero emissions scenario in 2050. It also considers the necessary installed capacity and annual plant usage to fulfil this demand.

4.1. Cooling demand in 2020 and 2050

The prediction results presented in Figure 6 provides a comprehensive view of the annual cooling demand across the 33 London boroughs for the years 2020 and 2050. The cooling demand, measured in Gigawatt hours (GWh), is projected to increase in all boroughs by 2050, with an overall estimated growth of approximately 45% for London. The borough of Croydon presents the highest cooling demand for both years, with a demand of 42.17 GWh in 2020, expected to rise to 59.31 GWh in 2050, marking an increase of 40.6%. This is primarily due to the high domestic building stock in Croydon, the highest among the London boroughs. Conversely, the City of London exhibits the lowest cooling demand, with 1.06 GWh in 2020, projected to increase to 1.61 GWh in 2050, an increase of 51.9%.

In 2020, the cooling demand of Inner London is 310.18 GWh and is projected to increase to 468.37 GWh by 2050. On the other hand, Outer London, which is significantly larger in area, has a higher cooling demand of 548.63 GWh in 2020, which is expected to rise to 776.58 GWh by 2050. The larger cooling demand in Outer London is primarily due to its greater area, which spans 1253 square kilometers, compared

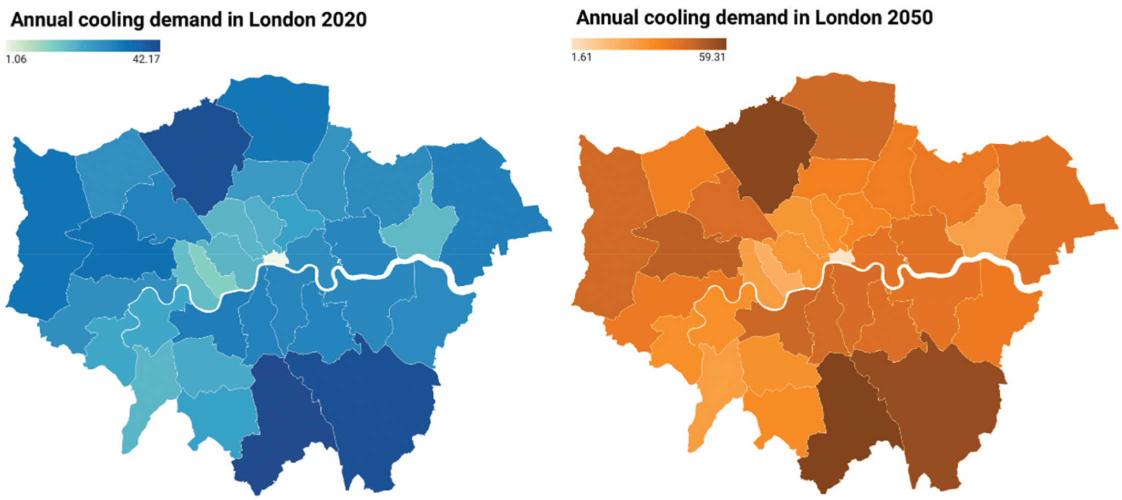

Figure 6. Annual cooling demand for domestic by London boroughs in (a) 2020; (b)2050.

to Inner London's 318.6 square kilometers. This means that Outer London has more buildings that need to be cooled, thus requiring more energy. The number of inhabitants in Inner London is recorded to be approximately 3.4 million. In contrast, Outer London boasts a larger population, with an estimated count of around 5.4 million. Interestingly, despite Inner London's higher population density compared to Outer London, its per capita cooling demand is lower. This implies that residents of Outer London experience a higher degree of comfort during the summer months compared to those residing in Inner London. This difference is attributed to the variance in dwelling types in these areas, which will be explored in further detail in the subsequent sections of this paper.

As depicted in Figure 7, the total daily cooling demands for London for the years 2020 and 2050 are illustrated. The figure shows extreme weather in August 2020, with peak cooling demand reaching 100GWh. This can be attributed to the extreme heat experienced in the summer of 2020, while the TMY file for 2050 is used for comparison. The TMY files used past 10- or 30-year averages to predict 2050 weather, incorporating global warming effects but not extreme weather conditions. The cooling season in London initiates in May and concludes by October, a duration notably shorter than the heating period. The annual cooling demand for 2020 was recorded as 858.81 GWh, with the maximum daily cooling demand peaking at 105.7 GWh. This peak day accounts for 12.3% of the annual cooling demand, a remarkably high proportion, indicating a concentrated pressure on the grid on this particular day. In the year 2020, the climatic conditions in London during the month of July were notably milder compared to the preceding month of June and the following month of August. The average temperature recorded in July closely mirrored that of May. Moreover, the absence of

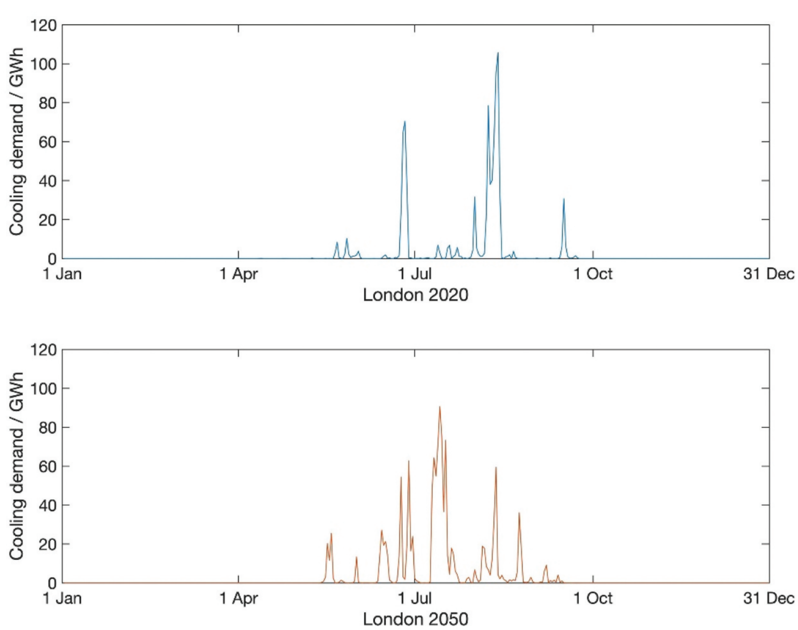

Figure 7. Comparison of total daily cooling demand in London in 2020 and 2050.

any extreme weather patterns resulted in the nonoccurrence of a peak in cooling during this month. The cooling demand in 2020 was predominantly concentrated in the months of June and August, correlating with numerous instances of extreme heat events. The cooling demand curve for 2050 aligns more closely with the typical cooling demand scenario. As temperatures escalate throughout the year, the cooling demand follows a similar upward trend, reaching its zenith in July, after which the demand gradually diminishes as temperatures recede.

Comparing the cooling demand in 2020 and 2050, it is evident that although the total cooling demand in 2050 exceeds that of 2020, the peak demand is smaller in 2050. Despite a higher peak in 2020, the number of days with a cooling demand exceeding 20 GWh is significantly higher in 2050. The model takes into account the effects of global warming but not the extreme weather events. Therefore, if the frequent occurrence of extreme weather events is factored in, the pressure on future cooling demand could potentially exceed the projections made in this study.

4.2. Impact of cooling demand on electricity supply

While comprehensive yearly data on London's electricity use across various sectors are accessible, the city lacks detailed hourly data. Given that London's population comprises 13% of the entire UK populace, it is reasonable to infer that its electricity consumption contributes significantly to the overall UK electricity demand. Therefore, the annual electricity demand in London is broken down approximately into hourly demand based on the available hourly electricity demand in the UK. Although this methodology may not be entirely precise, it provides a useful estimate of London's hourly electricity usage, which is expected to reflect the city's electricity profile in 2020. London's total domestic electricity consumption for 2020 was 13,113.9 GWh. It is often challenging to achieve a more detailed breakdown of electricity data, particularly when attributing consumption to specific appliances within buildings. Under this definition, no further distinction is made between cooling and non-cooling demands in domestic electricity consumption. According to government reports, cooling accounts for a very small proportion of electricity demand. The 2021 English Housing Survey Energy Report highlighted that air conditioning is used by only 2% of households in the UK (Ministry of housing Online), and a 2019 report indicated that active cooling systems are present in less than 3% of UK housing stock (English housing survey 2023).

The topic of cooling methods and the suitability of different types of cooling equipment for various buildings is expansive and beyond the scope of this section. However, it is worth noting that the Energy Efficiency Ratio (EER) of different cooling equipment can vary significantly. For the purposes of this study, the average EER of 3 is assumed for such cooling equipment (Andrade, Restrepo, and Tibaquirá 2021; Zhou et al. 2022). The red curve in Figure 8 represents the predicted electricity consumption required to fully meet all cooling demand, whereas the blue curve reflects the actual electricity consumption, indicating that the cooling demand is not fully

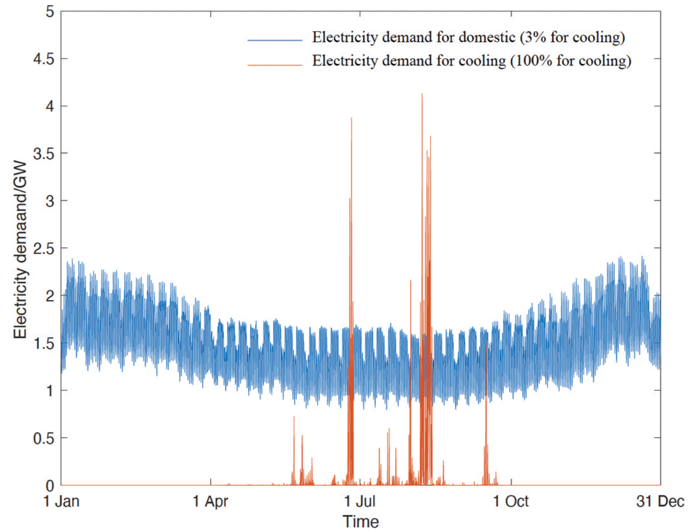

Figure 8. Comparison of domestic electricity demand and cooling electricity demand in London 2020. (EER = 3)

satisfied in reality. According to the reference provided, less than 3% of households in the UK are currently equipped with active cooling systems. Consequently, the total domestic electricity demand shown by the blue curve includes only up to 3% of cooling demand, while the red curve represents the total cooling demand. This explains why the predicted cooling demand (red curve) significantly exceeds the actual domestic electricity consumption (blue curve) during the summer months. The peak electricity demand for cooling (red curve) soars to 4.12GW, more than double the domestic electricity demand (blue curve) at the same time. London's summer domestic electricity demand (blue curve) hovers around 1.4GW, with the electricity demand for cooling (red curve) exceeding 1.4GW for 66 h dispersed over 18 days. For instance, in 2020, to meet all cooling needs, the London region would have required an additional 4GW of installed capacity of new generation to avoid power shortages during peak cooling periods.

Figure 9 examines the day of maximum cooling demand in London. In Figure 9(a), a comparison is made between the domestic electricity demand of London and the total electricity demand with cooling. The electricity demand throughout this day, when no cooling needs are addressed, maintains a nearly steady pattern and stays below 1.5GW. The demand gradually escalates from 6 a.m. until approximately 9 a.m., maintaining stability thereafter without any significant peaks. However, once the cooling demand is factored in, the electricity usage curve exhibits two distinct peaks – one in the morning from 7 to 10 am and another in the evening from 6 to 10 pm. This pattern is typical for domestic buildings, where cooling demand typically arises during periods of human activity, i.e., mornings and evenings. The morning peak reaches up to 4GW, and the evening peak is up to 5GW.

Addressing this segment of the electricity demand could involve grid upgrades or the implementation of an energy storage system. The latter is a potential solution to the challenges posed by the high variability of cooling energy demand. Figure 9(b) explores the potential of using energy storage, such as batteries, to manage peak electricity

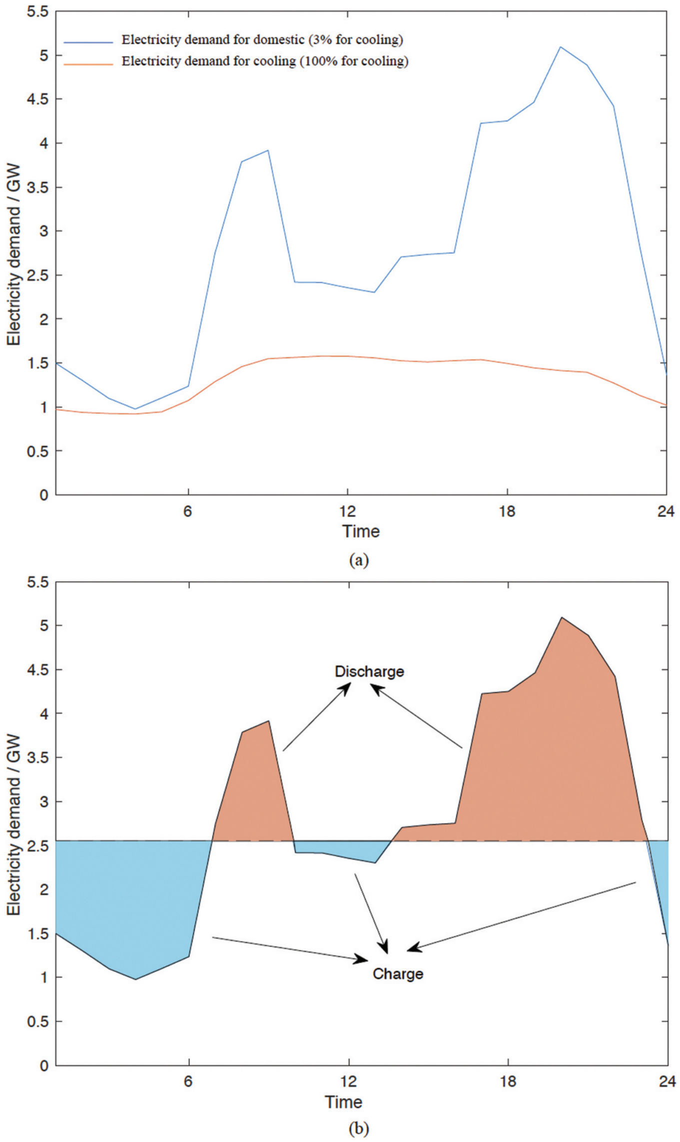

Figure 9. (a) Electricity profile of peak day in 2020; (b) storage demand for peak day in 2020.

consumption. Energy storage can be initiated during off-peak periods, storing surplus energy, possibly from renewable sources. Then, releasing the stored energy during peak periods can help alleviate the impact on power generation and enhance the utilization of renewable energy sources. The figure suggests that to halve the peak and maintain it near 2.51GW, an energy storage capacity of approximately 26.8GWh is required. This translates to a per-household storage requirement of about 18.8 kWh. Given that 26.8GWh of energy storage corresponds to the day of maximum cooling demand, it indicates that 26.8GWh of energy storage could entirely address the peak power demand caused by cooling needs in 2020. According to Figure 6, even though the total cooling demand in 2050 is expected to be higher than in 2020, the peak demand is projected to be about 14% lower. Moreover, with the anticipated widespread adoption of renewable energy by 2050, the corresponding energy storage systems will also have evolved significantly. Therefore, the application of energy storage to regulate the surge in demand induced by cooling is not just a practical solution, but also a sustainable alternative.

Beyond the realm of batteries, an array of diverse energy storage methods exists, each characterized by distinct dimensions and uses. The focus of this paper predominantly lies on the capacity of these energy storage systems in regulating the surge in electricity demand instigated by cooling requirements, thereby refraining from an in-depth analysis of the technical intricacies of such systems.

In the analysis of the electricity profile of a day in a year, Figure 10 presents a boxplot that illustrates the domestic electricity consumption patterns throughout various hours in the year 2020 in London. Each hourly data point is represented by 365 individual measurements, each corresponding to a -different day of the year, and their distribution within a -single hour is visualized in the boxplot. The boxplot's

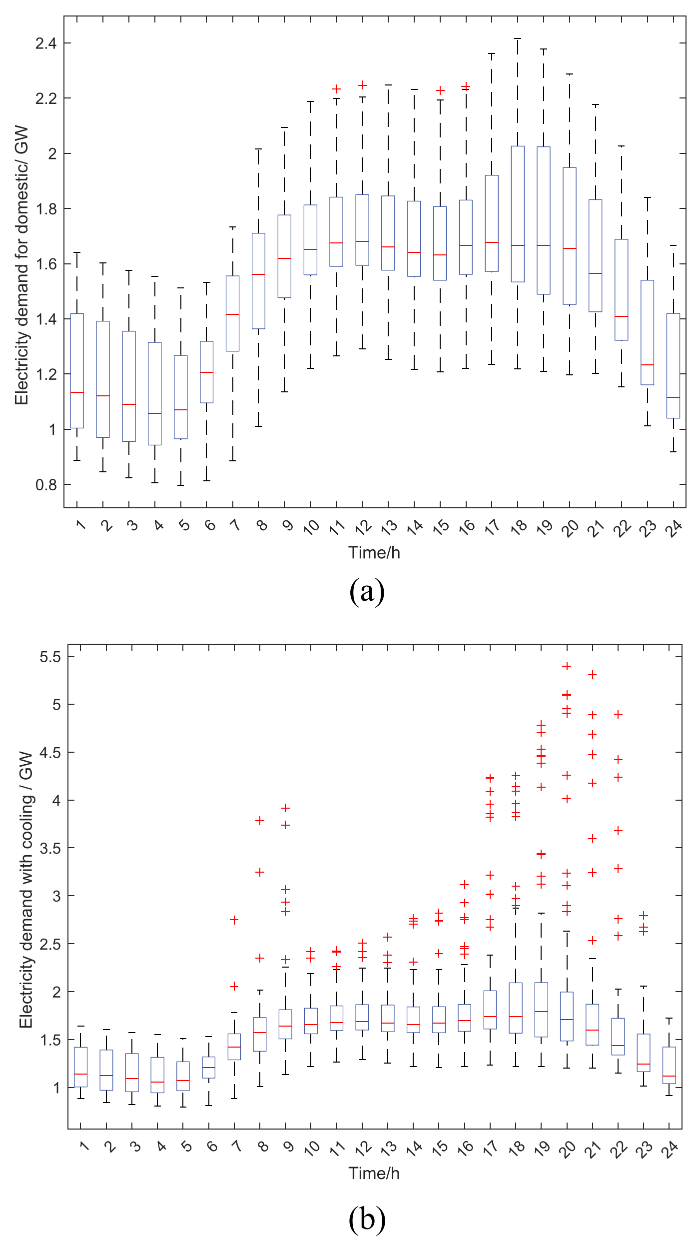

Figure 10. (a) Boxplot of the electricity demand in 2020; (b) boxplot of total electricity demand with cooling demand in 2020.

structure is as follows: the "red line" within the box signifies the median (Q2), the lower boundary of the box indicates the first quartile (Q1), and the upper boundary represents the third quartile (Q3). The boxplot's "whiskers" are denoted by "-' symbols, with the formula for the upper whisker being q3 + w × (q3 − q1) and the lower whisker being q1 − w × (q3 − q1). These whiskers roughly encapsulate the maximum and minimum values. In instances where the values within the data set surpass the boundaries set by the upper and lower whiskers, they are denoted by red '+" symbols and are identified as outliers. The outliers reflect values at the extremes conditions, while in most cases the value is between the whiskers.

The boxplot illustrated in Figure 10(a) delineates the pattern of electricity demand for domestic buildings in London throughout the year 2020. The demand profile generally corresponds to conventional working hours, registering its nadir at 5 am each day. As the day progresses, electricity consumption escalates steadily, stabilizing around 11 am. Post 4 pm, the consumption trajectory continues to climb, culminating in a daily apex around 7 pm. This escalation is primarily attributable to amplified demand for lighting and increased utilization of other electrical home appliances.

In contrast, Figure 10(b) portrays the boxplot of the aggregate electricity demand, inclusive of cooling. Both graphs display a similar 24-h electricity consumption pattern, peaking at 7 pm and bottoming out at 5 am. A notable distinction between Figure 10(a,b) is the significant number of "+" symbols observed beyond the cap in Figure 10(b). The outliers in Figure 10(b) predominantly transpire between the hours of 5–7 am and 5–10 pm, corresponding to periods of heightened residential activity. This signifies that the amalgamated demand for electricity and cooling remains largely unvarying throughout the year. However, the emergence of a substantial number of outliers indicates that on specific days, the electricity demand considerably surpasses the typical range for that time slot, potentially doubling in some instances. It not only impacts London's total electricity demand during the summer but also influences the demand profile's shape, resulting in a steep peak. While this does not affect London's electricity demand for the majority of the year, it imposes a significant strain on the grid for brief periods.

4.3. Comparison of different cooling scenarios in 2050

As illustrated in Figure 11, the cooling demand for various types of residences in Inner and Outer London for the year 2050 varies significantly. In Inner London, the highest demand for cooling is seen in flats, requiring 350GWh, followed by terraced houses with a demand of 110GWh. Semi-detached and detached houses show a lower demand for cooling, requiring 40GWh and 15GWh, respectively. The peak demands for these four types of buildings are represented in Table 4, showing values of 0.14GW, 0.31GW, 1.02GWh, and 3.45GW,

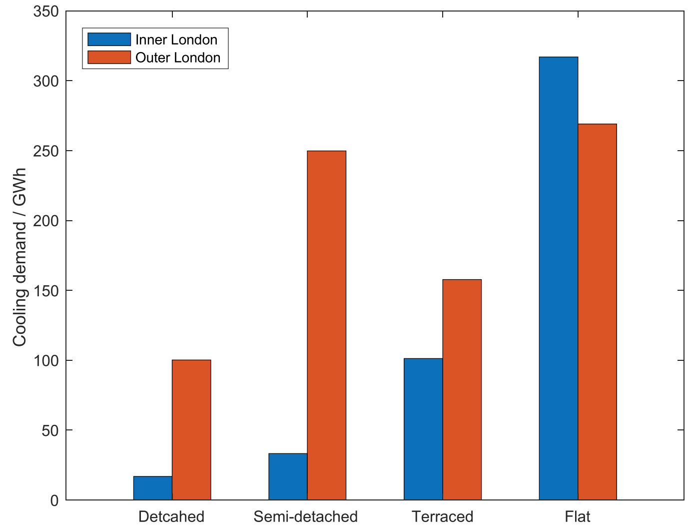

Figure 11. Annual cooling demand of different domestic buildings in London in 2050.

respectively. This higher demand in Inner London can be attributed to the higher number of commercial buildings present. The prevalence of commercial buildings in Inner London also leads to a lesser number of detached dwellings compared to flats. In Outer London, flats continue to demonstrate the highest cooling demand at 280GWh, peaking at 2.88GW. Semi-detached houses follow closely with a cooling demand of 250GWh, similar to that of flats, peaking at 2.3GW. The cooling demand for terraced and detached houses in Outer London is recorded at 150GWh and 100GWh, with peak demands of 1.66GW and 0.85GW respectively. Even though flats in Outer London continue to have the highest cooling demand, their contribution to the total regional demand has decreased.

Upon comparing Inner and Outer London, it is observed that, except for flats, the cooling demand for the other three types of buildings in Inner London is significantly less than in Outer London. Flats in Inner London, however, show a marginally higher cooling demand than those in Outer London. It is important to note that Outer London's larger geographical area allows for more detached homes, while Inner London's smaller area and higher population density result in a predominance of flats. As discussed in section 4.1, the population density is not considered in the simulation. However, the per capita cooling demand in Inner London is higher, primarily because flats require more cooling. Consequently, for Inner London, along with managing the electricity demand for cooling, the comfort of future domestic building occupants should be given more consideration.

For a more comprehensive understanding of the cooling demand characteristics in London by 2050, Inner London was used as a case study. Figure 12(a) presents a duration curve for four representative buildings. The x-axis of the diagram

Table 4. Peak demand for different domestic buildings in London.

Peak demand/GW	Detached	Semi-detached	Terraced	Flat
Inner London	0.14	0.31	1.02	3.45
Outer London	0.85	2.30	1.66	2.88

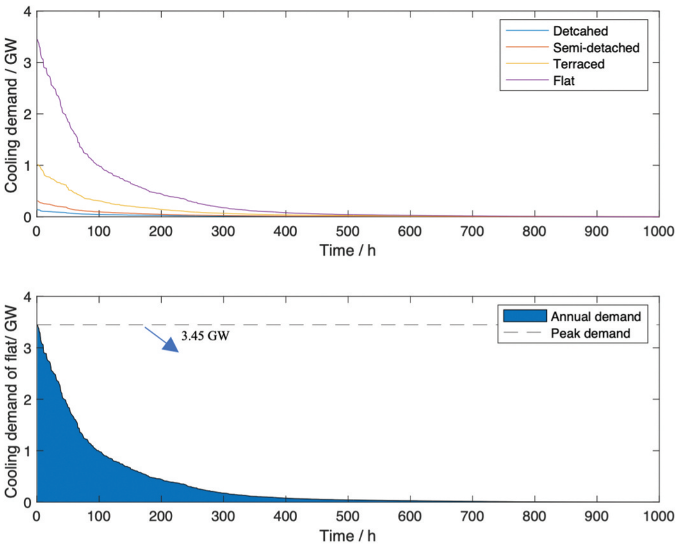

Figure 12. (a) Duration curve of cooling demand for domestic buildings in inner London in 2050. (b) Duration curve of cooling demand for Flat in inner London in 2050.

represents time in hours, while the y-axis denotes the cooling demand of the four buildings in 2050, ordered from the highest to the lowest value. The duration curve suggests a substantial fluctuation in load across different periods, indicating that the cooling equipment's output varies dramatically throughout the year. Extremely high cooling demand increases the need for cooling equipment in the summer months. Hence, the duration curve can be instrumental in examining the correlation between cooling demand and capacity utilization, providing a foundation for planning the cooling plant's installed capacity. Figure 12(b) is the duration curve of flats in Inner London, comparing the annual cooling demand with the total energy that can be supplied by full load operation. The blue segment of the figure represents the annual cooling demand, while the blank space beneath the dotted line signifies the wasted output of the unit at full load. The peak demand is 3.45GW. The figure suggests that if cooling equipment is installed to cater to peak demand, the equipment utilization rate is remarkably low.

Table 5 delineates the necessary installed capacity to cater to varying peak scenarios in London by 2050, including the annual cooling demand fulfilled and the equipment utilization rate. When the entire peak demand is satisfied, the cooling equipment's installed capacity is 12.52GW, which addresses the annual cooling demand. However, the equipment's usage rate is a mere 1.13%. If the peak demand is only 80% satisfied, the installed capacity can be decreased to 10.02 GW. This capacity meets 1231 GWh of the annual cooling demand, approximately 98.88% of the total yearly demand. Consequently, the cooling equipment's usage rate increases from 1.13% to 1.4%. When only 50% of the peak demand is satisfied, the installed capacity demand is approximately 6.26 GW. This satisfies 1099 GWh of the yearly refrigeration demand, which constitutes 88.27% of the total annual cooling demand. The equipment's usage rate then rises from 1.4% to 2%.

Table 5. Cooling demand and utilization of facilities under different peak conditions.

Peak demand/GW	Capacity/GW	Annual demand/GWh	Unitization
100%	12.52	1245	1.13%
80%	10.02	1231	1.40%
50%	6.26	1099	2.0%

These comparisons illustrate that the majority of the annual cooling demand can be met without necessarily meeting the year's cooling peaks, indicating that weather extremes are relatively rare and can be disregarded when considering cooling equipment installation. This approach could potentially lead to cost reduction and increased equipment utilization. However, regardless of how much the installed capacity is reduced, the cooling equipment's usage rate remains significantly low. Therefore, exploring ways to improve equipment usage rates is a topic worthy of further discussion. For instance, the employment of reversible heat pumps, which provides cooling in summer and heating in winter, could be considered.

Table 6 provides a succinct discussion of the potential installed capacity of various equipment and the achievable cooling peaks to meet different levels of annual heat demand. The focus is on three prevalent types of active cooling equipment: reversible heat pumps, chillers, and traditional AC units (air conditioner units for cooling only). The choice of these cooling apparatuses is guided by proven technological reliability, effective active cooling, and commonplace usage in residential settings.

Reversible heat pumps are a technology that aligns with net-zero objectives and is suitable for detached homes, given the space they necessitate for installation. For larger housing complexes, chiller units could be a viable option due to their superior cooling efficacy and broader coverage. Currently, there are no specific Building Regulations in the UK for home air conditioning systems. Residents in restricted or protected areas should follow the standard rules that apply to any home improvement work. AC units are suggested for scenarios where reversible heat pumps and chillers may not be suitable. Based on the proportions of the pre 1919 domestic buildings and the official publication from UK Government in 2020 "A guide to air conditioning inspections in buildings," it is postulated that 80% of detached and semi-detached homes can accommodate reversible heat pumps and 80% of flats and terraces can install AC units. The remaining 20% are AC units, assuming that the EER of the cooling equipment is 3

Table 6. Peak demand and installed capacity (electricity) of cooling equipment for different cooling demand scenarios.

Annual demand/GWh	Peak demand/GW	Reversible HP/GW	Chiller/GW	AC units/GW
100%	12.52	0.96	2.40	0.84
80%	9.07	0.69	1.78	0.61
50%	4.31	0.35	0.84	0.30

(C. & L. G. MHCLG Ministry of Housing 2023; H. & C. M. of H. C. & L. G). Table 6 outlines the installed capacity requirements for each cooling equipment type under different scenarios.

Assuming that 100% of the annual cooling demand is satisfied, the peak cooling is likewise fulfilled. Under this condition, the installed capacity of the reversible heat pump, chiller, and AC units is approximately 0.96 GW, 2.4 GW, and 0.84 GW, respectively. If 80% of the annual cooling demand is met, the installed capacity of the reversible heat pump, chiller, and AC units is 0.69 GW, 1.78 GW, and 0.61 GW, respectively. This provides a maximum power output of 9.07 GW, which is 72.44% of the peak. If only half of the annual cooling demand is met, the installed capacity of all three cooling equipment types is nearly halved compared to a scenario where 80% of the annual demand is met. However, this only satisfies 34.43% of the peak demand, indicating insufficient cooling for the majority of hot summer days.

Table 6 offers an estimated installed capacity for different scenarios. However, if an optimal installed capacity is sought, factors such as equipment costs, operational costs, equipment utilization, and environmental comfort must also be considered. This introduces a complex optimization problem worthy of further research, which is beyond the scope of this paper.

5. Conclusion

In this paper, a bottom-up approach is used to build a model of cooling demand through building simulation, which can be used to obtain the hourly cooling demand on a city scale. London is used as a representative example, with the city being segmented into 33 zones based on its administrative layout. Each zone's domestic buildings are further categorized into 12 types, allowing for an in-depth analysis of the cooling demand either regionally or in totality. This model serves to fill the gaps in the UK's incomplete cooling data, particularly in the domestic sector which has been largely overlooked in UK policy.

The study predicts a 45% increase in London's cooling demand from 2020 to 2050. This is attributed to the forecasted rise in average temperatures by 2050. If the cooling demand in 2020 is fully met, the peak electricity used for cooling would double the residential electricity usage. Although such variations would minimally affect the annual electricity consumption, they could potentially lead to instability during the summer and add pressure on the power grid operations. The study's conclusions emphasize the integration of energy storage systems as a strategy to manage the anticipated increase in summer cooling demand and to improve the efficiency of renewable energy use. The analysis of cooling demand duration curves, particularly for flats in Inner London, reveals significant variances in equipment output throughout the year, thereby highlighting the necessity of accurately aligning the cooling plant's installed capacity with the varying demand. Although the research indicates that a substantial portion of the annual cooling demand can be met without fully catering to peak demand scenarios, the persistently low utilization rates of cooling equipment point toward a need for optimization. The deployment of reversible heat pumps, offering dual functionality for heating and cooling, presents a promising solution to enhance the usage rate of installed capacities. This integrated approach not only promises cost savings but also aligns with the objective of maximizing energy efficiency and operational effectiveness of cooling installations.

However, the classification of domestic buildings in the model is not sufficiently detailed. While common domestic types are included, the model lacks detailed insulation level settings based on building age, which could affect the accuracy of energy demand estimations. This is particularly relevant as newer buildings tend to have better insulation. Furthermore, several key assumptions, such as the exclusion of population growth and its potential impact on future cooling demand, limit the model's ability to fully capture long-term trends. Additionally, the model does not account for economic factors that could influence building renovations, technological advancements, or changes in energy efficiency policies over time. Future work will focus on incorporating more detailed building data, particularly insulation levels based on age, to improve the model's accuracy. Furthermore, dynamic factors like population growth and economic influences should be considered to better capture long-term trends in cooling demand.

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Abbreviations

POST	Parliamentary Office of Science and Technology
CDD	Cooling Degree Days
TRNSYS	Transient Systems Simulation Program
DeST	Designer's Simulation Toolkit
HVAC	Heating, Ventilation, and Air Conditioning
BEIS	Department for Business Energy & Industrial Strategy
WRF	Weather Research and Forecasting
IESVE	Integrated Environmental Solutions Virtual Environment
CIBSE	Chartered Institution of Building Services Engineers
TMY	Typical Meteorological Year
SAP	Standard Assessment Procedure
PB	Proposed Benchmark
EER	Energy Efficiency Ratio
GWh	Gigawatt Hour
AC	Air Conditioner

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