CoolDown Work Package 2: Modelling the building stock, cooling use and demand response analysis across the ENWL network

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Executive Summary

This report presents the development and application of a modelling method to predict cooling demand and demand response (DR) potential at secondary substation level across the ENWL licence area as part of the CoolDown innovation project led by ENWL.

In the Discovery phase, a proof-of-concept was tested on two substations, where each building connected to the substation was modelled individually. Cooling adoption was predicted, and demand response was implemented, with outputs presented as aggregated half-hourly electrical loads for each substation.

The Alpha phase further developed this initial work in three main ways:

1. Refining the model to incorporate electricity demand diversity, more sophisticated predictions of cooling uptake, and insights on cooling schedules from other CoolDown work packages.
2. Scaling up the analysis to predict DR across thousands of substations in the ENWL region.
3. Localising the analysis by using regional predictions of future weather, not available during the Discovery phase.

The output from the Alpha phase is a set of predictions of cooling uptake for 2030, 2040 and 2050 compared to current levels (represented by the year 2023), and of cooling DR potential for summers in 2030, 2040, and 2050. These predictions are made for each of the 2,438 ENWL secondary substations with good quality monitored data. The modelling workflow applied is based on open-source data and software, meaning it can be applied to any network area with geolocated service point data available by secondary substation.

This analysis shows estimations of hourly cooling demand and peak shaving potential using the ENWL region, which could also be produced using the same method for any other region with adequate substation monitoring.

The approach involved detailed modelling of building stocks connected to 20 representative substations and using the results to predict cooling demand response potential across the ENWL network.

Results showed that climate change significantly affects the number of buildings that overheat, with 39% predicted to overheat by 2050, up from 9% in 2023. Active cooling is expected to increase in prevalence, with 30% of buildings cooled by 2050, up from 5% in 2023. By 2050, all substations modelled had cooling demand, peaking in the daytime for non-domestic buildings and in the evening for domestic buildings, with peak hourly cooling ranging between 100-300kW for most substations.

The effect of cooling DR on peak electrical load at the substation is highly dependent on the assumptions used to model DR and how cooling demand aggregates across buildings. If demand peaks last much longer than DR events, DR tends to provide short-term relief at the expense of a higher peak later on. Conversely, if the length of demand peaks is similar to the length of DR events, DR can successfully mitigate peaks. It was possible to flatten the domestic evening cooling peak without creating a substantial new peak, although the acceptability of this is unclear given householders' preference to cool their bedrooms before sleep.

In conclusion, the method presented allows prediction of hourly cooling demand and demand response potential for all of a DNO's LV substations with good quality monitored data. The findings highlight the significant impact of climate change on building overheating and the increasing prevalence of active cooling, as well as the technical feasibility of using DR to manage peak cooling demand.

Introduction

In this work package we have developed a modelling method to predict cooling demand and demand response (DR) potential at secondary substation level across the ENWL region.

In the Discovery phase we provided a proof-of-concept, tested on two substations, in which each building connected to the substation was modelled individually, cooling adoption was predicted, and demand response implemented. The outputs presented were aggregated half hourly electrical loads for each substation.

The Alpha phase has further developed this initial work in three main ways:

- **Refining the model** to incorporate electricity demand diversity, more sophisticated predictions of cooling uptake, and recent insights on cooling schedules;
- **Scaling up** the analysis to predict demand response across thousands of substations in the ENWL region.
- **Localising** the analysis by using regional predictions of future weather, not available during Discovery Phase

The output from the Alpha phase is a set of predictions of cooling uptake for 2030, 2040 and 2050 compared to current levels (represented by the year 2023), and of cooling DR potential for summers in 2030, 2040, and 2050. These predictions are made for each of the 2,438 ENWL secondary substations with good quality monitored data. The modelling workflow applied is based on open-source data and software, meaning that it can be applied to *any network area* for which geolocated service point data is available by secondary substation. In this report we show, using the ENWL region, estimations of hourly cooling demand and peak shaving potential, which could also be produced using the same method for any other region for which adequate substation monitoring exists.

Approach

This phase of the project modelled the building stocks connected to 20 representative substations in detail and used the results to predict cooling demand response potential across the ENWL network. There were 8 main steps:

1. Classifying ENWL substations into 20 archetypes (and selecting the most representative from each archetype)
2. Processing and cleaning of building stock data
3. Defining cooling uptake and other assumptions
4. Incorporating of time diversity in schedules
5. Completing first model runs to assess overheating risk without cooling
6. Completing second model runs which predicted cooling demand
7. Completing third model runs to predict cooling DR potential
8. Scaling up from 20 substations to 2,438

These steps are explained in more detail below.

1. Classifying ENWL substations into 20 archetypes (and selecting the most representative from each archetype)

It is too computationally- and time-intensive to model hourly electricity demand for every building in the ENWL region for each of the output years, therefore 20 substations were selected which represented the

diversity of load profiles and building types across the region, and the results scaled up to the rest of the region.
The 20 substations were selected by firstly performing cluster analysis on a large group (~2000) of substations with monitored timeseries data available for summer 2023, based on features of their electrical load and the type of areas they serve. Appendix 1 contains the set of features used for the cluster analysis and how they were selected using dimensionality reduction technologies. Once 20 clusters had been identified, the "medoid" (the most central substation in each cluster) was selected as the archetypal substation for that cluster. In this way, the 20 archetypal substations can be taken, between them, to represent the ENWL region. An example of an archetypal substation is shown in Figure 1.

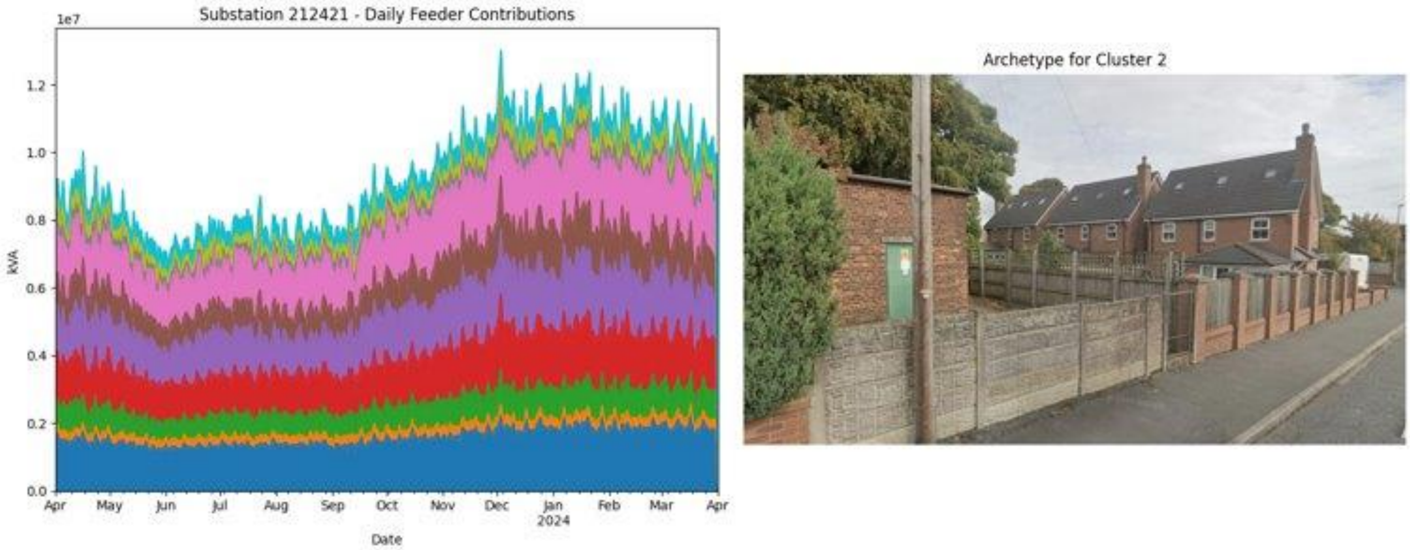

Figure 1. Example of archetypal substation. Left: Electrical load data for one year: different colours indicate contributions from different feeders. Right: Typical buildings served by this substation, illustrating that each archetypal cluster tends to be associated with a certain building type (or in some cases mix of building types).

The limitation of this process is that not all of ENWL's low voltage substations have monitored data, and of those which do, only a subset have data for the period used for the cluster analysis. It is not known whether the 2,438 substations used as inputs to the cluster analysis are representative of the wider set of existing ENWL substations for which monitored data is not available. This is further explored in Step 8 of the Approach.

2. Processing and cleaning of building stock data

A detailed model of the existing building stock served by each substation was created using UCL's 3DStock model to link together multiple databases. Network data in the form of geolocated service points was provided by ENWL for the 20 substations. A spatial join was used to combine these points with Ordnance Survey Address Base data containing Unique Property Reference Numbers (UPRNs) and building height and footprint data. This data was then combined with data from the Valuation Office Agency (VOA) property tax data to identify cases where multiple premises share a building or single premises cover more than one building. This ensures a higher fidelity representation of the building stock and means that different activities can be assigned on a floor-by-floor basis. Since building energy consumption is closely linked to the activities which are undertaken within them, VOA data was also used to identify the use of each premises [1]. Finally, domestic and non-domestic Energy Performance Certificate (EPC) data was linked to individual premises using UPRNs, providing additional data on building fabric, condition as well as heating and cooling systems.

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The limitation of this approach is that EPC data is only available for around 50% of premises. Consequently, a clustering approach was used to impute missing data: the strength of the relationship between all the data points (height, age, etc.) was assessed using the Pearson correlation coefficient [2] and highly correlated fields were discarded so that the clustering was not biased. K-prototypes clustering [3] was used to separate the data into distinct clusters. This is a machine learning method which can accommodate continuous data (for example, numerical values for energy performance rating and categorical data like age bands). The in-cluster variance was then measured as a function of the number of clusters. A value of n=7 clusters of building characteristics was found to give a relatively low variance, while increasing the number of clusters beyond 7 gave only minor further improvements. Typical values for each data field were then extracted from these clusters, cross-referenced with EPC ratings and used to construct 7 construction archetype profiles. The result was that buildings without EPC data had their data estimated from similar buildings.
Note that new buildings, built between now and 2050, were not in scope of this work, since step 1 of the approach relies on electricity demand data from buildings which already exist.

3. Defining cooling uptake and other assumptions

In this section we describe how cooling uptake was predicted for the years 2023, 2030, 2040 and 2050. Throughout this report, the year 2023 is taken to represent the current situation, as this was the most recent year that weather data and substation load data were available.
Various methods of predicting cooling uptake have been used in previous literature, including using data from abroad [4], extrapolation of current UK market trends [4], and linking cooling uptake to outdoor temperature [1][5].
In the Discovery phase, uptake of active cooling systems was directly linked to buildings shown by the dynamic simulations to overheat. This led to a very high percentage of buildings adopting cooling (note also that in the Discovery phase, the Manchester weather files had not yet been made available so London files were used, resulting in higher outdoor temperatures).
In the Alpha phase, the overheating assessment was retained (see Step 5), but an additional assumption was introduced: that only a proportion of overheated buildings would adopt cooling. The proportion was taken to vary over time using an S-curve, frequently used in the literature to represent diffusion of new technologies, including air conditioning. S-curves (another name for the cumulative logistic function) have three parameters, broadly representing the time at which uptake ramps up, the steepness of the increase, and the value at which uptake plateaus. These values, which are all unknown, were discussed amongst the project partners and the agreed scenarios are shown in Figure 2. Note that Figure 2 does not predict the percentage of buildings which install cooling over time, but the percentage of *overheated* buildings which do so. Note also that buildings which already have cooling in 2023 are also excluded from Figure 2.

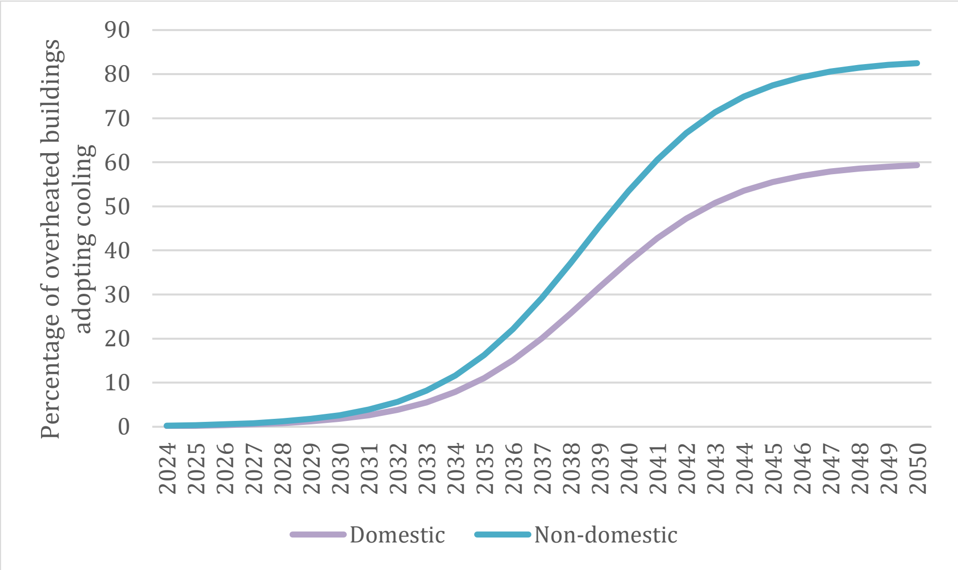

Figure 2. Cooling uptake scenarios for domestic and non-domestic buildings. Y-axis is percentage of overheated buildings which adopt cooling. This does not include buildings which already have cooling in 2023.

Cooling technology assumptions were retained from the Discovery phase[1], except an extra step to size cooling capacity in buildings in order to limit how quickly cooling is deployed in the dynamic thermal simulations (see Appendix 3 for these sizing assumptions). EPC data was used to identify buildings which already have cooling installed. The Discovery Phase report (10103019 | ENA Innovation Portal) contains more detail on how this information was processed.

Weather conditions for 2023, 2030, 2040 and 2050 were modelled using Design Summer Year (DSY) files. These represent a year with an atypically warm summer, based on the latest UK Meteorological Office's probabilistic projections for future climate (UKCP18). The climate change scenario modelled is based on Representative Concentration Pathway 2.6 [6], representing a best estimate global average temperature rise of 1.6°C by 2100 compared to the pre- industrial period. Weather files for the Manchester area, taken in this project to represent the ENWL region, were created from this scenario by the University of Exeter.

This climate change scenario corresponds to the "low" path in Figure 3, produced by the IPCC [7].

[1] 10103019 | ENA Innovation Portal

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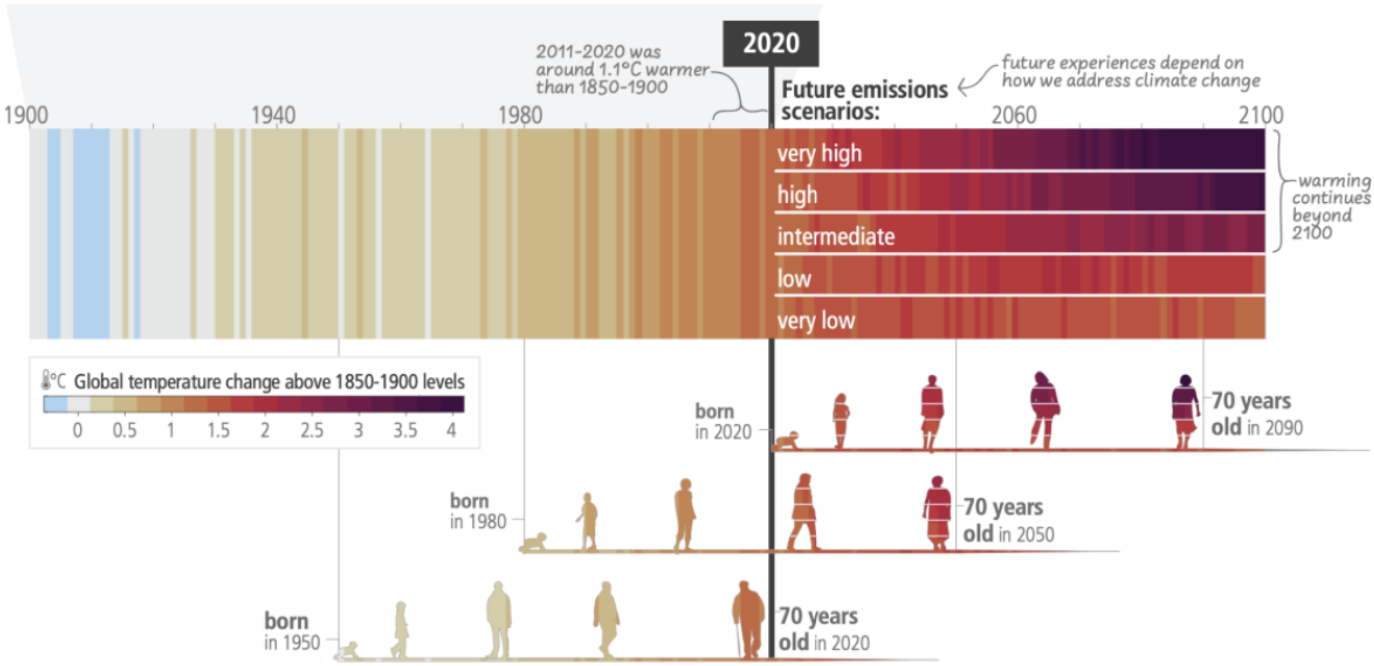

Figure 3. IPCC illustration of different climate change scenarios. CoolDown has used 'low' emission scenario due to consistency with previous UK cooling projects

4. Incorporating time diversity in schedules

Building stock models often assume that all buildings of a certain type (e.g. shops) carry out their activities at the same time. The Discovery phase of CoolDown used one time schedule per building type, using standard schedules as defined in the National Calculation Methodology (NCM) for nondomestic buildings [8] and CIBSE TM59 for domestic buildings [9].

However, when working on problems related to peak electricity demand, it is important to capture demand diversity [10]. That is, even if many buildings of the same type (e.g. homes) are connected to a single substation, their energy using activities will not all occur at the same time. Since this project is focussed on the effect of cooling on peak electricity demand, it is especially important to characterise *cooling* demand diversity well.

Whilst heating demand diversity has been well characterised [11], no measured data was found on cooling demand diversity in the UK. Therefore two modelling approaches were used:

- For domestic cooling schedules and diversity, the findings from CoolDown WP4 were used as a starting point. In this work package survey responses were provided by households with air conditioning regarding when they use it. Since respondents were given a certain time window (e.g. "night") and could respond "I always use AC", "I sometimes use AC", etc, these responses were transformed into probabilities that AC was used at a given time in a given building, and used to stochastically generate cooling schedules for each building.
- For nondomestic cooling, cooling schedules were linked to occupancy schedules taken from NCM. However, to incorporate diversity, the start time and end time of the occupancy and cooling were drawn randomly from a uniform distribution of possible times spanning a couple of hours before and

after the times set out in NCM. In this way the schedules were “spread out” across buildings of the same type.

5. Completing first model runs to assess overheating risk without cooling

Modelling was undertaken using SimStock, an automatic modelling platform developed by UCL which is used to translate the building stock data described in Step 2 into input files for EnergyPlus. EnergyPlus is a widely used, open-source dynamic simulation engine developed by the US Department of the Environment which allows the energy flows to be calculated on a sub-hourly basis, taking account of the building fabric, local context and internal loads and activities.

For this project, each premises was modelled at an hourly timestep with realistic schedules for occupancy and equipment internal heat gains, incorporating diversity as mentioned in Step 4. In buildings without cooling, windows were assumed to open once the temperature reached 22˚C, in accordance with the national overheating calculation methodology [12]. In buildings with cooling, windows were assumed to be closed.

Indoor overheating is defined using a nationally agreed set of criteria [12]; this is explained fully in Appendix 1. In summary, three tests are applied to each zone of a building, related to the “operative temperature”, which is the mean of the indoor air temperature and radiant (ie indoor-facing surface) temperature. If a zone (here, a floor) fails two out of the three tests it is technically defined as overheating. Note that the feeling of being overheated is also related to other factors, such as relative humidity, air speed and clothing levels as well as psychological factors, however the technical definition is deliberately kept simple.

The output of this step is a binary indicator of whether overheating occurs in every building connected to each substation, for 2023, 2030, 2040 and 2050.

6. Completing second model runs to predict cooling demand

For those buildings shown in Step 5 to overheat, a random proportion were given active cooling systems as defined by the logistic functions set out in Step 3.

Dynamic simulations were run again for all buildings, this time including this cooling uptake, as well as the demand diversity described in Step 4. The model gives as an output cooling load in thermal Watts, which is then divided by the assumed technological efficiency of the cooling system to give a cooling load in electrical Watts.

The assumed cooling efficiency was kept constant at 540%, based on analysis commissioned by BEIS [13] which is in turn extrapolated from an International Energy Agency report on the future of cooling [14]. Cooling efficiency is complex to model in detail. In general it is likely to increase a small amount between now and 2050, however the introduction of DR (ie more ramping up and down) and the increased prevalence of higher outdoor temperatures may decrease it, therefore a simple assumption of constant efficiency was used. Furthermore, under this simple assumption, no differentiation is made between systems installed in domestic, small non-domestic and large non-domestic buildings. The aforementioned BEIS analysis [13] assumed that domestic properties are more likely to install portable systems in the near future and transition to fixed systems as the climate warms. Since portable systems only cool a small space, and the model used in CoolDown applies cooling to whole floors, it was not possible to model portable cooling. However, its efficiency is roughly half that of fixed systems and, it is expected to be installed in only some spaces per floor, therefore the resulting electricity consumption is likely to be similar to that of fixed systems[2]. A cooling set point of 21°C was assumed throughout where AC was installed, in line with the findings from CoolDown WP4.

Cooling electrical loads per building were then aggregated to substation level. The output of this step is hourly cooling electrical loads per substation (as well as total electrical load, ie. Including all other uses of electricity apart from cooling).

7. Completing third model runs to predict DR potential

The potential for load shedding from space cooling was investigated by simulating demand response in buildings. In the Discovery phase, this was implemented by altering the air temperature setpoints in all the buildings up to 26°C for periods where substation load is high, based on previous literature exploring thermal comfort during cooling demand response in other countries [15].

This approach was refined in the Alpha phase. CoolDown WP5 confirmed that air temperature setpoint changes for a certain period was an appropriate method of implementing DR. The trigger for DR events in non-domestic buildings was outdoor temperature: the 95th percentile for the daily maximum outdoor temperature in Manchester in Summer 2023, which was 26.5˚C. In domestic buildings, it was found that cooling load peaks in the evening (see Results section), so as well as the outdoor temperature trigger, an extra condition was set that domestic DR events could only take place at 6pm-9pm, in order to capture the time of peak load.
The duration of demand response events was set to 120 minutes in domestic contexts and 60 minutes in nondomestic. The latter was based on real offerings and experience of the Flexibility Service Provider in the project team, whose experience to date has been that events lasting longer than 60 minutes become less acceptable to building occupants. In the domestic context, clothing and activities are likely to differ from the non domestic context so events may be longer: this is a hypothesis which could be tested in a future phase of CoolDown.
After a DR event, a recovery period of 60 minutes was allowed before another DR event was allowed to take place. In homes, two DR events were allowed per day, and in nondomestic buildings, three events.

From the results of Steps 6 and 7, hourly electricity load profiles aggregated from building level to substation level were produced, which could be compared before and after DR was implemented, for each of the 20 substations modelled.

8. Scaling up from 20 substations to wider ENWL region

The final step of the method involved making inferences beyond the 20 substations modelled in detail. This was possible because the 20 archetypal substations were originally derived as cluster medoids from a wider set of 2,438 substations with complete monitoring data for a summer period. Each substation in the 2,438 can be represented by its cluster medoid, the archetypal substation.

[2] Fixed cooling systems in homes consist of air conditioning and reversible air-to-air heat pumps, which are the same technology and therefore have the same efficiency in cooling mode. Other possible technologies exist such as ground-to-water heat pumps providing passive cooling; however, these are likely to be rare compared to air-to-air systems (see CoolDown Work Package 5).

Results

Results of overheating analysis

The effect of climate change on the number of buildings which overheat according to the national definition is illustrated in Figure 4 for two example substations. These substations are used throughout the results to illustrate different phenomena, and were selected as #165743 mostly serves domestic buildings while #450954 serves a mix of domestic and non-domestic buildings.
Figure 4 shows the percentage of overheated buildings increasing from 2030 to 2050.Not all buildings overheat by 2050. It must be noted that the climate change scenarios used to model future weather are likely to underestimate the outdoor temperature so this is likely to be a lower bound on the number of overheated buildings and other studies. For example, the recent Overheating Risk in England and Wales analysis published by the Department for Environment, Food and Rural Affairs, also uses an alternative high emissions scenario [14].
The substation with more non-domestic buildings shows a higher proportion of overheated buildings at all points in time; this is likely due to higher "internal gains" in non-domestic buildings, i.e. heat generated from appliances and occupants; it may also be due to the construction of the buildings e.g. single glazed windows in some shops.

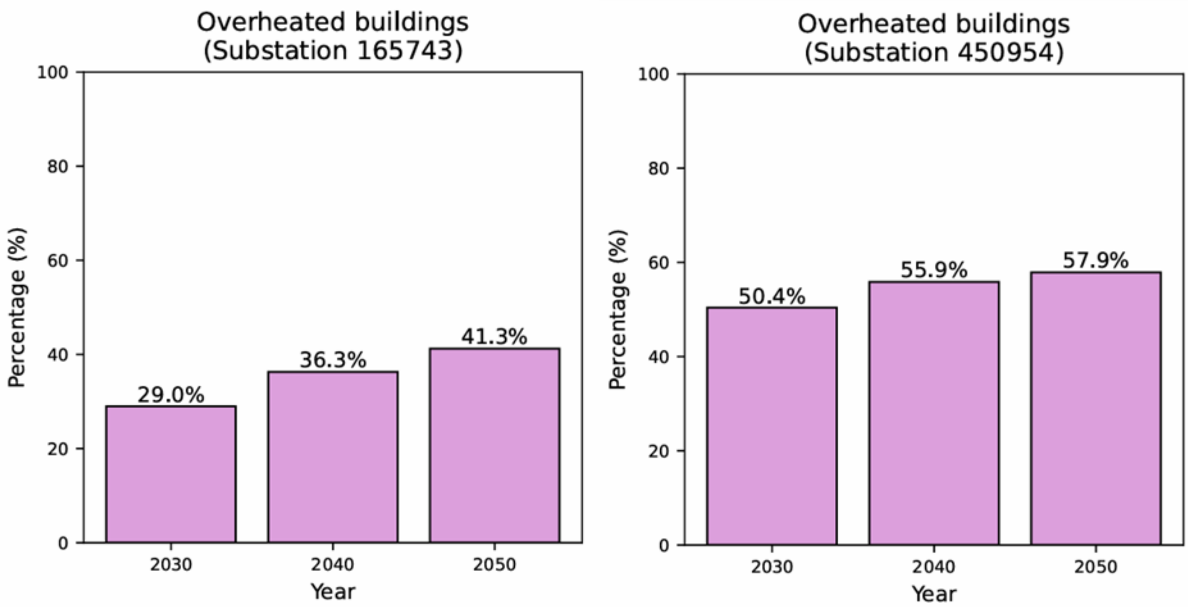

Figure 4. Illustration of overheating increasing over time for two example ENWL substations. Left: a substation dominated by domestic buildings. Right: a substation serving a mix of domestic and non-domestic buildings.

Results of cooling uptake predictions

Predicted cooling uptake is shown in Figure 5 for the same two example substations as above. It can be seen from comparing the right (non-domestic dominated) to the left (domestic dominated) plots that cooling adoption is anticipated to be faster in areas with more non-domestic buildings.

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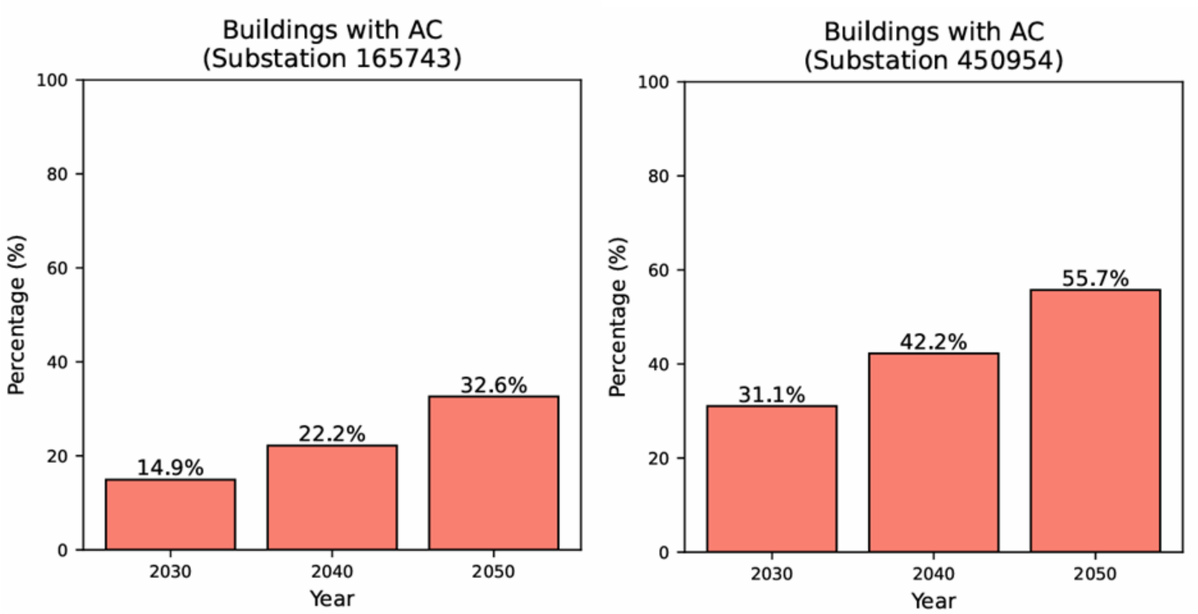

Figure 5. Predicted proportion of buildings with cooling installed, over time, for two example ENWL substations. Left: a substation dominated by domestic buildings. Right: a substation serving a mix of domestic and non-domestic buildings.

Results of cooling demand response modelling for 20 substations

Figure 6 illustrates, for the example substation introduced above dominated by domestic buildings, the hourly load from cooling and other building loads in 2050[3], before and after implementing cooling DR. The top plot shows that by this year, cooling is predicted to add a significant load to the substation, and to exacerbate the existing summer evening peak. This is due to its common use as household members are trying to cool their bedrooms ready to sleep. Cooling use also extends into the night, although the overall peak is lower by this point.

The bottom plot shows that when DR is implemented at the time of this new evening peak, it is possible to significantly flatten the peak, without causing additional peaks later on in the night.

[3] Not including electric vehicles or the use of heat pumps to heat hot water.

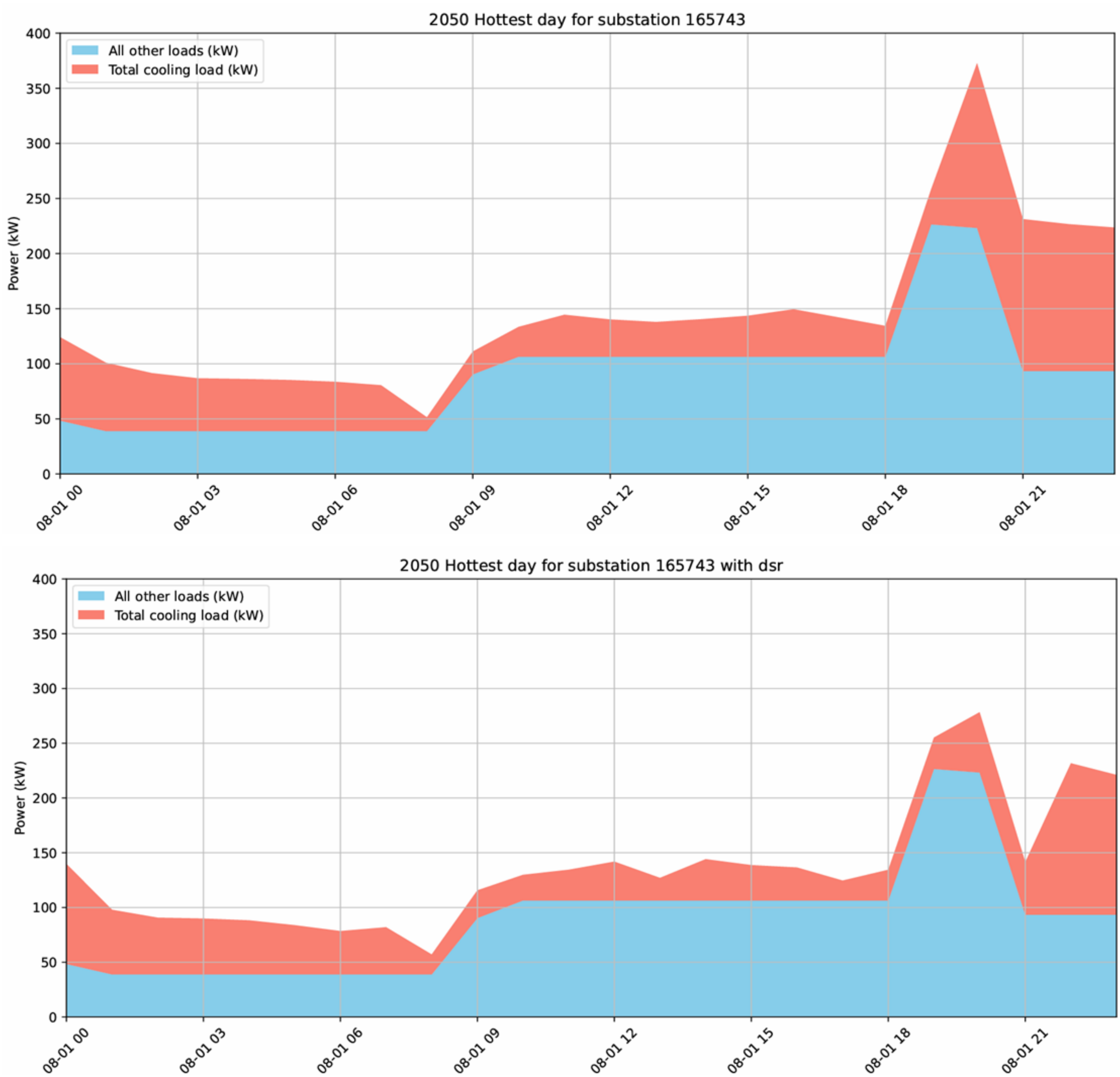

Figure 6. Hourly load profile before (top plot) and after (bottom plot) cooling DR is carried out, for an example substation serving mostly domestic buildings

Figure 7 illustrates the effect of DR on the second example substation introduced above, which has some nondomestic buildings connected to it. In nondomestic buildings, the cooling load ramps up in the morning and remains high for 5-6 hours until the early evening. This is different to the domestic load which is highest in the evening and is at its highest for only a couple of hours.

When nondomestic buildings participate in DR, using events which only last one hour (see Step 7 in the Approach), this has the effect of temporarily reducing demand, but then increasing it afterwards during the 'recovery period' in which DR is not allowed to take place, in some cases to a higher level than would occur if no DR had been carried out. This cycle then repeats, leading to the 'spiky' plot in Figure 7.

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This behaviour is a consequence of the DR period being significantly shorter than the period of peak demand, and also of DR being carried out in all the nondomestic buildings at once.
Conversely, in the evening the domestic peak load is reduced by DR without causing new peaks, in the same as was illustrated for the previous substation in Figure 6.

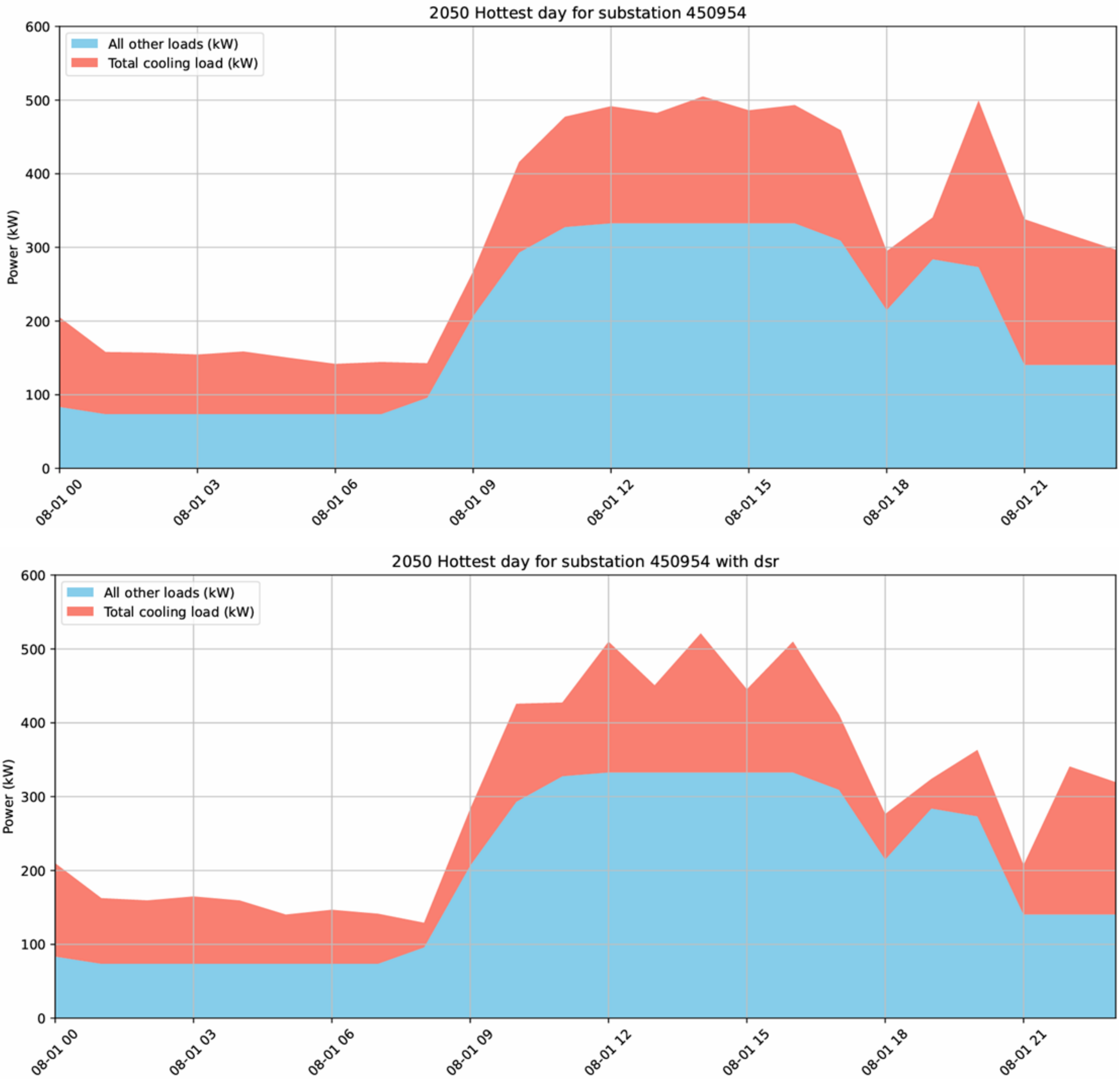

Figure 7. Hourly electricity load profile before (top plot) and after (bottom plot) DR is carried out, for an example substation serving a mix of domestic and nondomestic buildings.

Results of scaling up across ENWL region

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Using the mapping between archetypal substation cluster medoids and all other substations within their cluster described in Step 8 of the approach, it is possible to quickly generate results for the 2,438 ENWL substations for which monitored data was provided to UCL.

Overall, the proportion of overheated buildings is predicted to be 39% by 2050, and the proportion of buildings with cooling installed is 30%, as shown in Figure 8. For context, the current (2023) proportion of overheated buildings and cooled buildings are estimated to be 9% and 5% respectively.

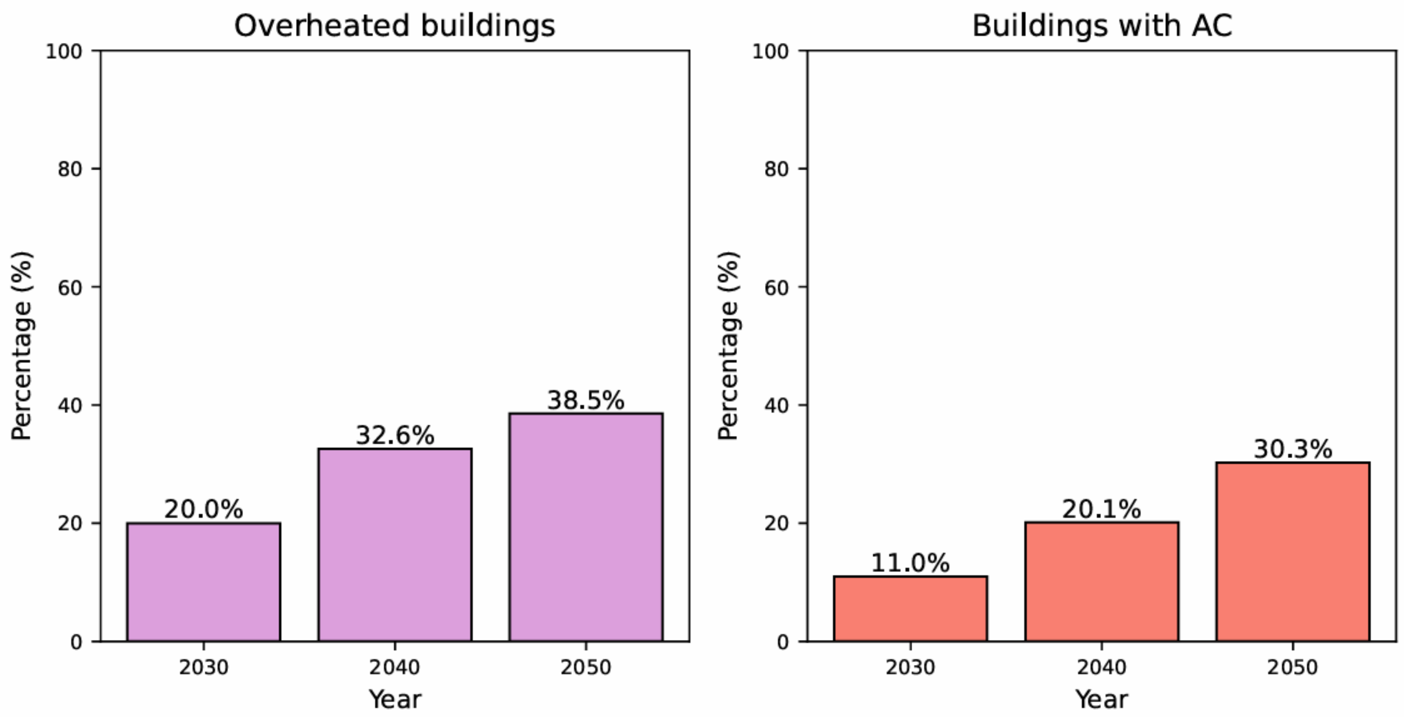

Figure 8. Predicted proportion of buildings which overheat in future years, and predicted proportion of buildings with cooling installed, across 2,438 ENWL substations.

Two effects drive an increase in cooling demand over time: cooling being installed in more buildings, and hotter summers leading to existing cooling plant delivering more cooling.
Figure 9 shows peak hourly cooling demand from 2023 to 2050. In the top plot this is shown as a map of one dot per substation. Note that white dots represent substations with no cooling demand. It can be seen that at present (represented by the year 2023), some substations have no cooling demand, however by 2050, all substations have cooling demand. The bottom shot shows the same information in histogram form – note that this only includes substations with cooling demand. By 2050, the majority of substations experience peak cooling demands of around 100-300 kW.

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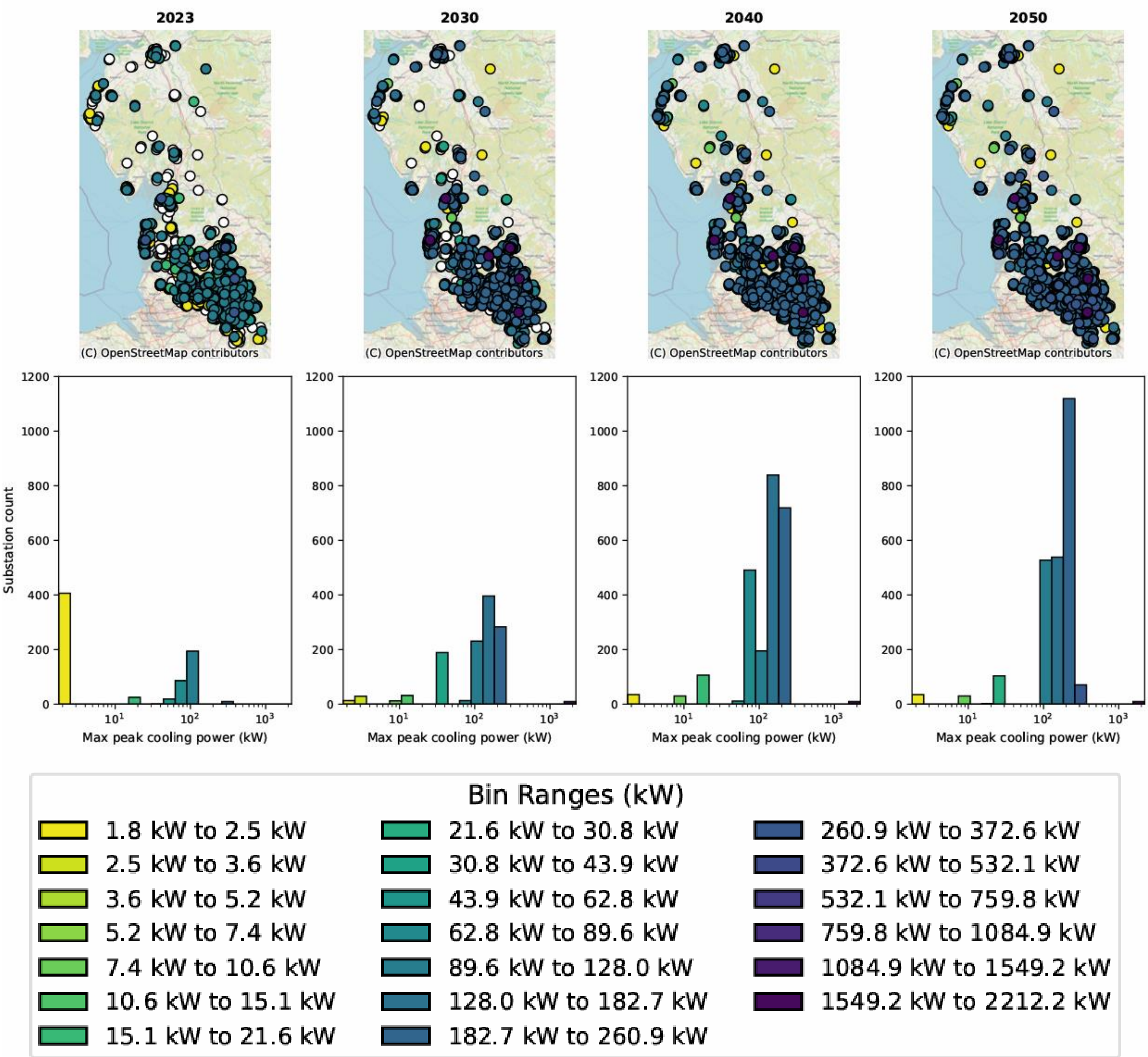

Figure 9. Two visualisations of peak hourly cooling demand in 2,438 ENWL substations.

In Figure 6 and Figure 7 it was shown that cooling demand response can decrease peak aggregated electricity load under certain conditions, and can increase the load in other cases. The modelling implied that if the length of the DR event is similar to the length of the demand peak, DR can reduce the peak without creating new peaks. This was observed in domestic dominated substations. If the length of the DR event is shorter than the length of the demand peak, DR can temporarily reduce the peak but then cause a snapback which causes an overall increase in the peak.

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The effect of the demand response intervention across 2,438 ENWL substations is shown in

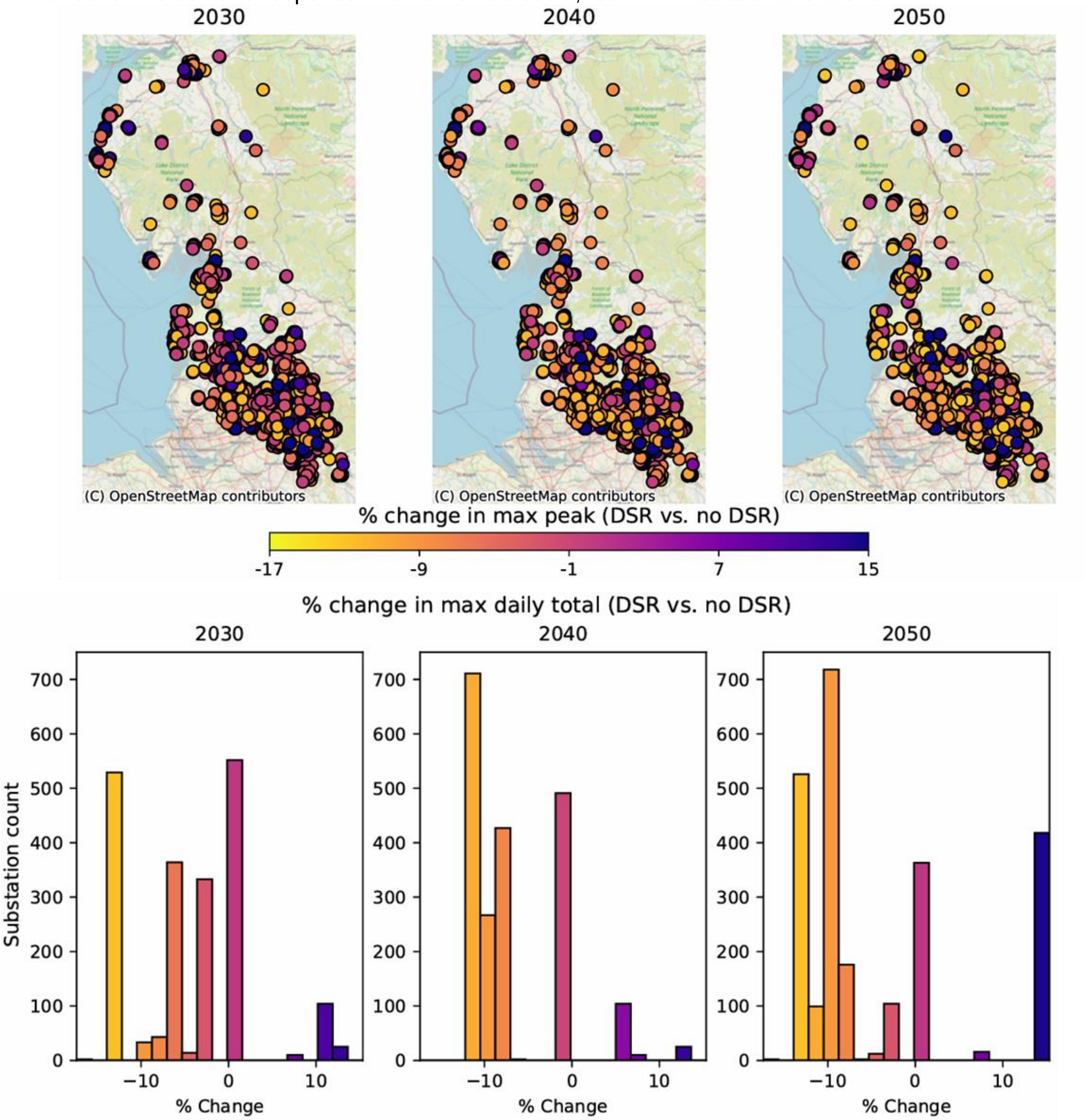

Figure 10. Most substations experience a decrease in peak load as a result of demand response. This is likely to be because the specific intervention modelled here was shown to work best in domestic dominated substations, which are prevalent in the 2,438 ENWL substations used in the analysis.

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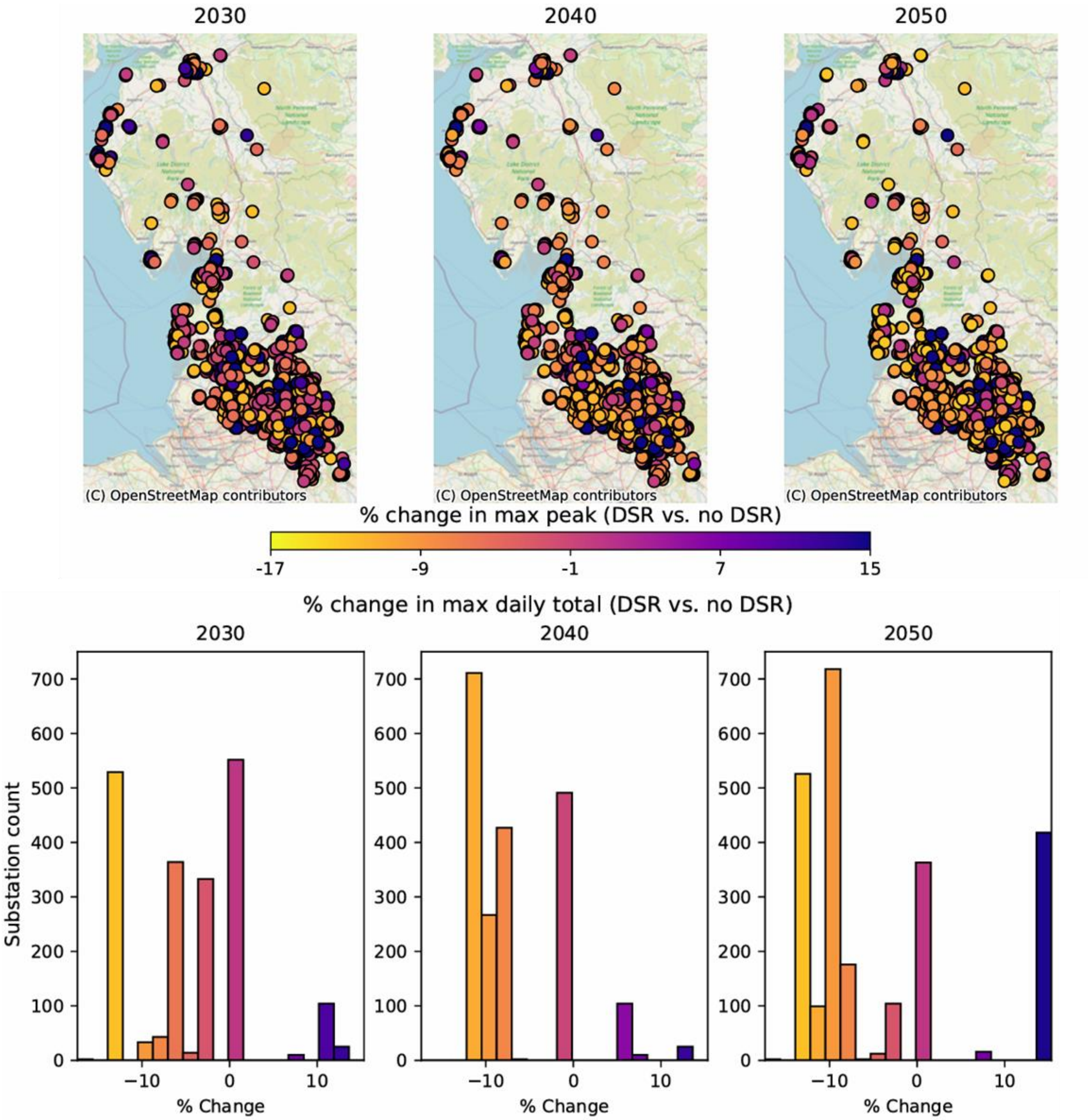

Figure 10. Change in peak hourly cooling demand due to DR, for each substation in the ENWL region.

Conclusions

In this report, a method was presented which allowed prediction of hourly cooling demand and demand response potential for all of a DNO's LV substations which have good quality monitored data. Using this method and analysing the results, it was found that:

- Climate change has a significant effect on the number of buildings which overheat from now until 2050, by which our model predicts that 39% of buildings overheat.
- Active cooling was predicted to increase in prevalence; our scenarios led to 30% of buildings being cooled by 2050.
- By 2050 all substations we modelled had cooling demand, which tended to peak in the daytime for non-domestic buildings and in the evening for domestic buildings. Peak hourly cooling ranged between 100-300 kW for most substations.
- The effect of cooling DR on peak electrical load at the substation is very dependent on the assumptions used to model DR as well as how cooling demand aggregates across buildings.
- If demand peaks last much longer than DR events, the way that DR is carried out in this study tends to provide a short term DR at the expense of a higher peak later on
- If the length of demand peaks is similar to the length of DR events, then DR can successfully mitigate peaks
- Due to the above, it was possible from a technical perspective to flatten the domestic evening cooling peak without creating a substantial new peak. However the acceptability of this is unclear given the findings in WP4 that this is specifically the time that householders aim to cool their bedrooms before going to sleep.

References

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Appendix 1: set of features used to cluster ENWL low voltage substations

Table 1 shows the whole set of metrics explored to assess which best differentiate substations into groups.

Table 1. Clustering attributes used on substation data.

Core load metrics	Total kVAh
	Mean kVa
	Median kVa
	Peak kVa
	Coefficient of variation of kVa
Variability and load patterns	Peak to average ratio
	Weekday to weekend ratio
	Summer to winter ratio
	Autocorrelation
	Day to night ratio
Additional context	Number of feeders
	Local climate zone (LCZ)

Figure 11 shows that some of the metrics in Table 1 are highly correlated.

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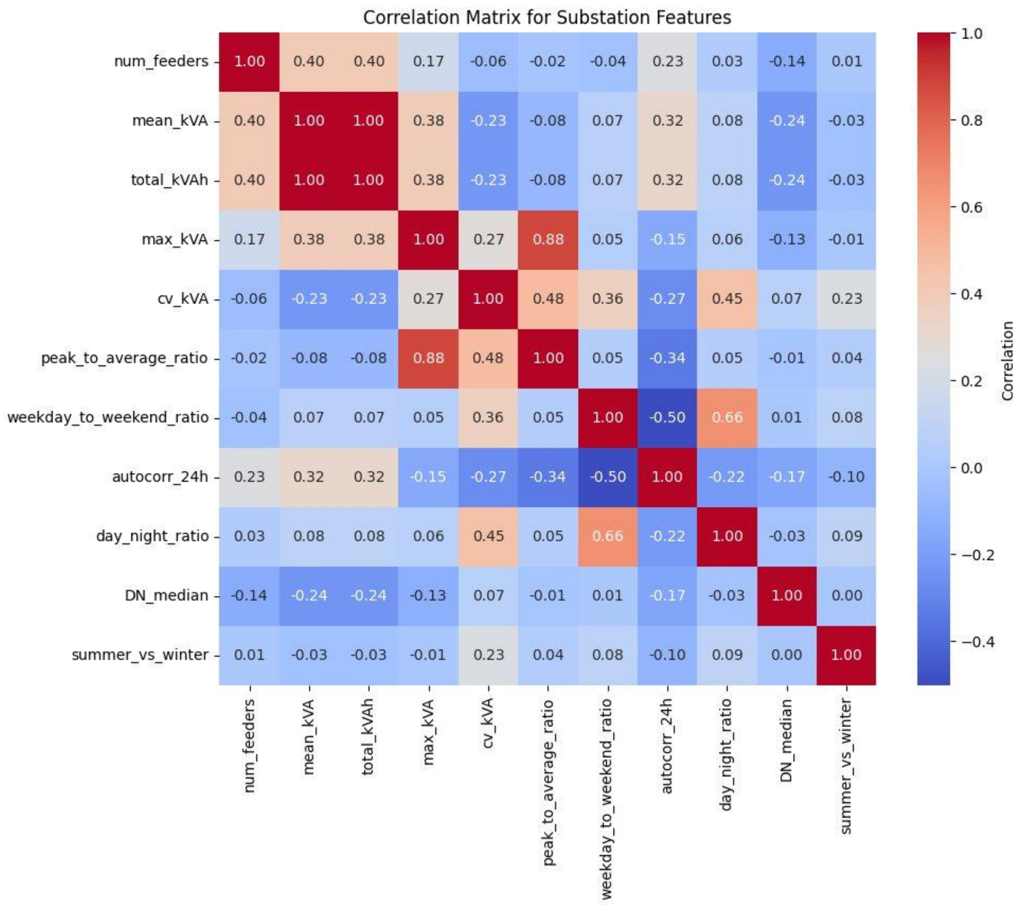

Figure 11. Correlation matrix for substation features.

Given the high correlation between some features, it was possible to reduce the number of inputs to the clustering via Principal Components Analysis. While this gives a reduced set of features, it is not simply a subset of the list of features in Table 1; the principle components each combine multiple of the original features.

Appendix 2: definition of overheating in buildings

The Chartered Institution of Building Services Engineering (CIBSE) sets out three criteria, of which two must be met in order that a building does not overheat. Otherwise put, if a building fails two or more criteria then it overheats.

Criterion	Explanation
T_{op} should not exceed T_{max} by more than 1 degree for more than 3% of occupied hours during the months of May to September.	This criterion is about the **duration** of overheating: the number of hours over summer that the indoor temperature exceeds a certain threshold
T_{op} should not exceed T_{max} by more than 6 degree-hours per day	This criterion is about the **level** and **duration** of overheating within single days
T_{op} should never exceed T_{max} by more than 4 degrees	This criterion is about the **level** of overheating: it limits the maximum indoor temperature

Where:
T_{op} is the mean of the air temperature and the radiant temperature;

T_{max} is a temperature threshold defined using the outdoor temperature as follows:

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$T_{max} = 0.33\ T_{rm} + 21.8$

T_{rm} is a weighted running mean of the outdoor temperature (T_{od}), most heavily weighted for most recent days:

$T_{rm} = (T_{od-1} + 0.8\ T_{od-2} + 0.6\ T_{od-3} + 0.5\ T_{od}-4 + 0.4\ T_{od-5} + 0.3\ T_{od-6} + 0.2\ T_{od-7})/3.8$

Appendix 3: Sizing rules used for cooling plant in buildings

In domestic buildings, cooling plant in each zone (i.e. floor) was 3.5 kWth (thermal). This is based on current available products.
In nondomestic buildings, the cooling plant size was defined as 138 Watts per m2 floor area. This was calculated from real installations in the nondomestic EPC database by performing linear regression on a subset of buildings in the Manchester area.

Appendix 4: List of abbreviations

AC – Air Conditioning

BEIS – former UK government Department for Business, Energy and Industrial Strategy

CIBSE – Chartered Institution of Building Services Engineers

CSNOW – Climate Services for a Net Zero World

DR – Demand Side Response

DNO – Distribution Network Operator

DSY – Design Summer Year

ENWL – Electricity North West Limited

EPC – Energy Performance Certificate

IPPC – International Panel on Climate Change

LCZ – Local Climate Zone

LV – Low voltage

kVa, kVah: Kilovolt-amps, Kilovolt-amp hours

kW, MW – Kilowatt, MegaWatt

kWth –Thermal Kilowatt, i.e. Kilowatt of coolth

NCM – National Calculation Methodology

RCP – Reference Climate Pathway

SEER – Seasonal Energy Efficiency Ratio

UCL – University College London

UKCP – UK Climate Projections

UPRN – Unique Property Reference Number

VOA – Valuation Office Agency

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