Cooling Demand Prediction in London Using a Physical/ML Models

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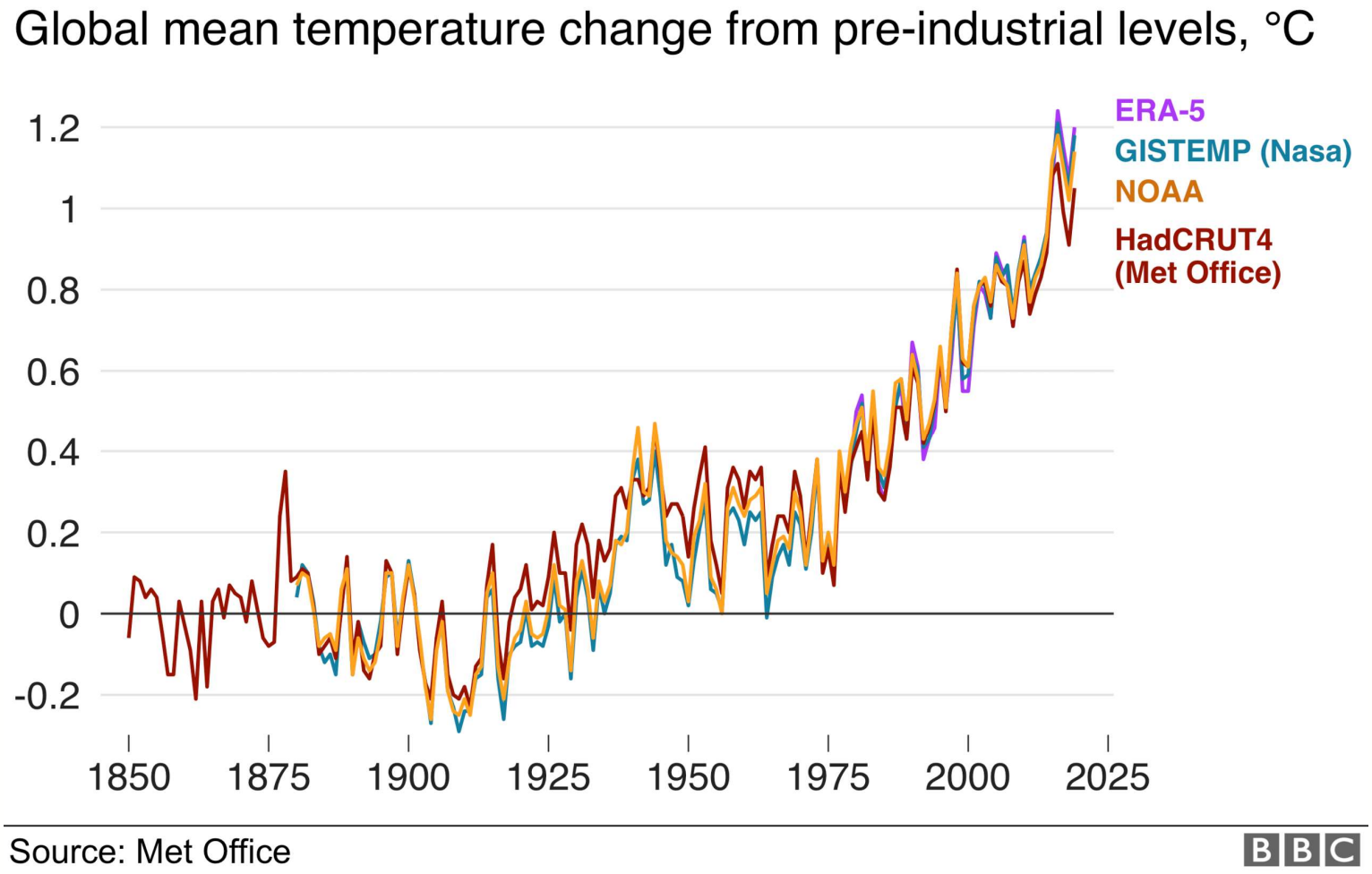
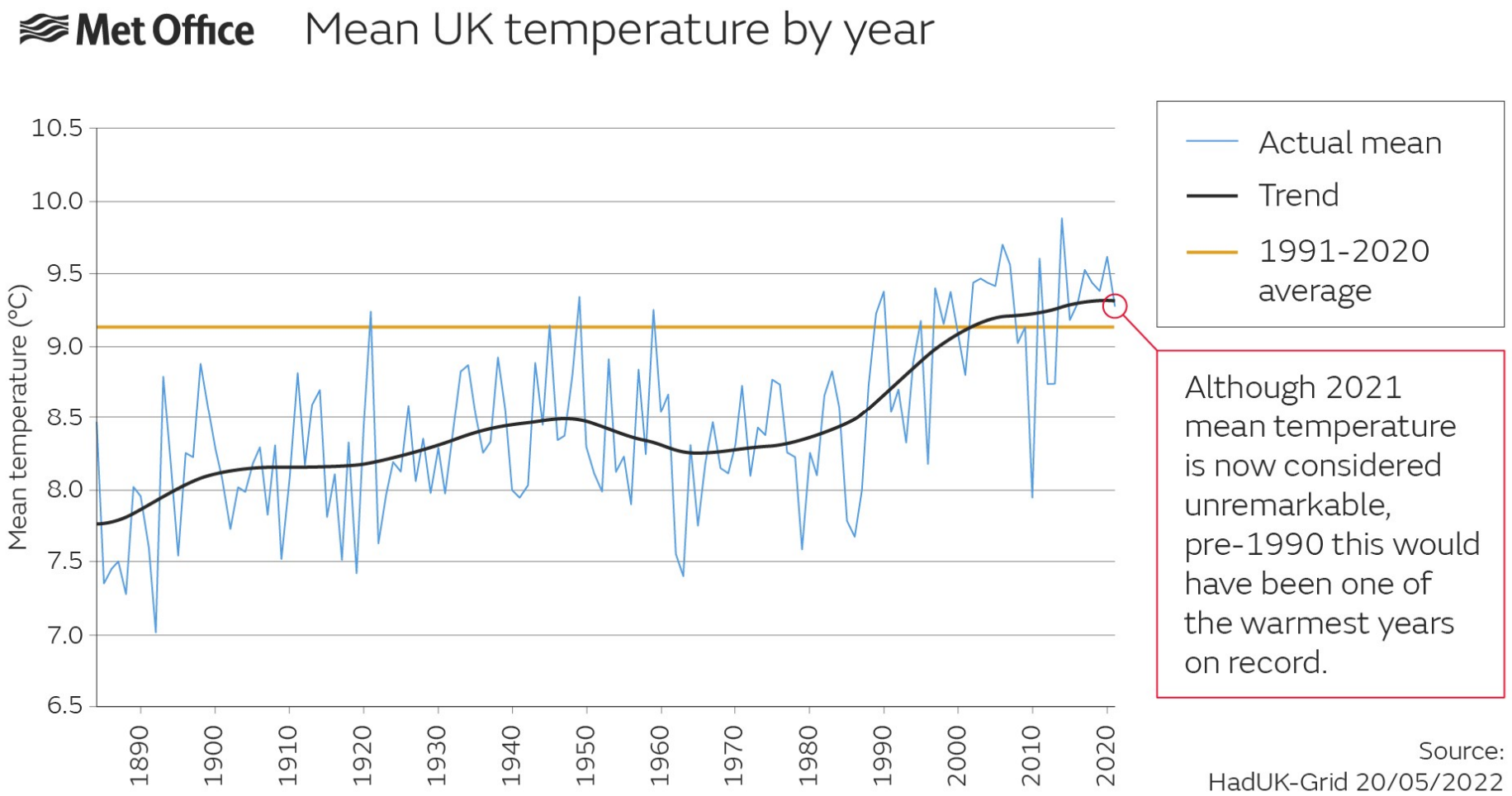
Global warming



[1]*BBC News, 2020. https://www.bbc.co.uk/news/science-environment-51111176*

[2]*Rantanen et al., 2022. The Arctic has warmed nearly four times faster than the globe since 1979. Communications Earth & Environment. https://doi.org/10.1038/s43247-022-00498-3*

Global warming

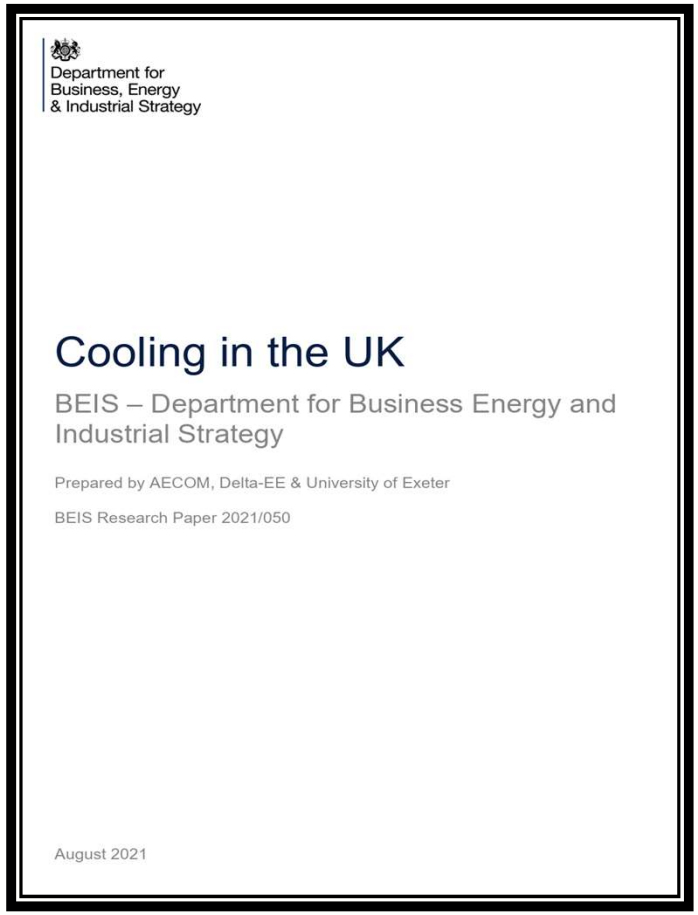


Overheating in UK buildings

- UK buildings were traditionally designed to retain heat and minimize ventilation for cold winters. This design has unintentionally caused overheating during summer months.
- A UK Parliamentary POST note reports that 20% of UK homes already overheat, even in mild summers.
- This has led to rising heat-related illnesses and deaths, especially among vulnerable populations.

Cooling Demand in the UK

- The cooling sector currently consumes around 14% of the UK's electricity.
- The cooling sector contributes around 10% of the UK's greenhouse gas emission.
- Domestic Cooling to Dominate by 2100
- The UK energy system has long prioritised heating, leaving cooling largely overlooked in policy and data.
- Cooling is so far a blind spot in UK energy policy.
- Currently, cooling is concentrated in non-domestic buildings.
- By 2100, up to 85% of cooling energy may come from homes.[1]



[1]*BEIS, 2021. Cooling in the UK: A Policy and Evidence Review. https://assets.publishing.service.gov.uk/media/614c1c75e90e077a34ed9fb7/cooling-in-uk.pdf*

Understanding Future Cooling Demand Is Crucial

- Cooling demand is electricity-driven, meaning rising use can significantly strain power generation and grid capacity, especially during hot summer peaks – heat waves.

- Forecasting future cooling demand is critical to support reliable grid operation, infrastructure planning, and efficient integration of renewables.

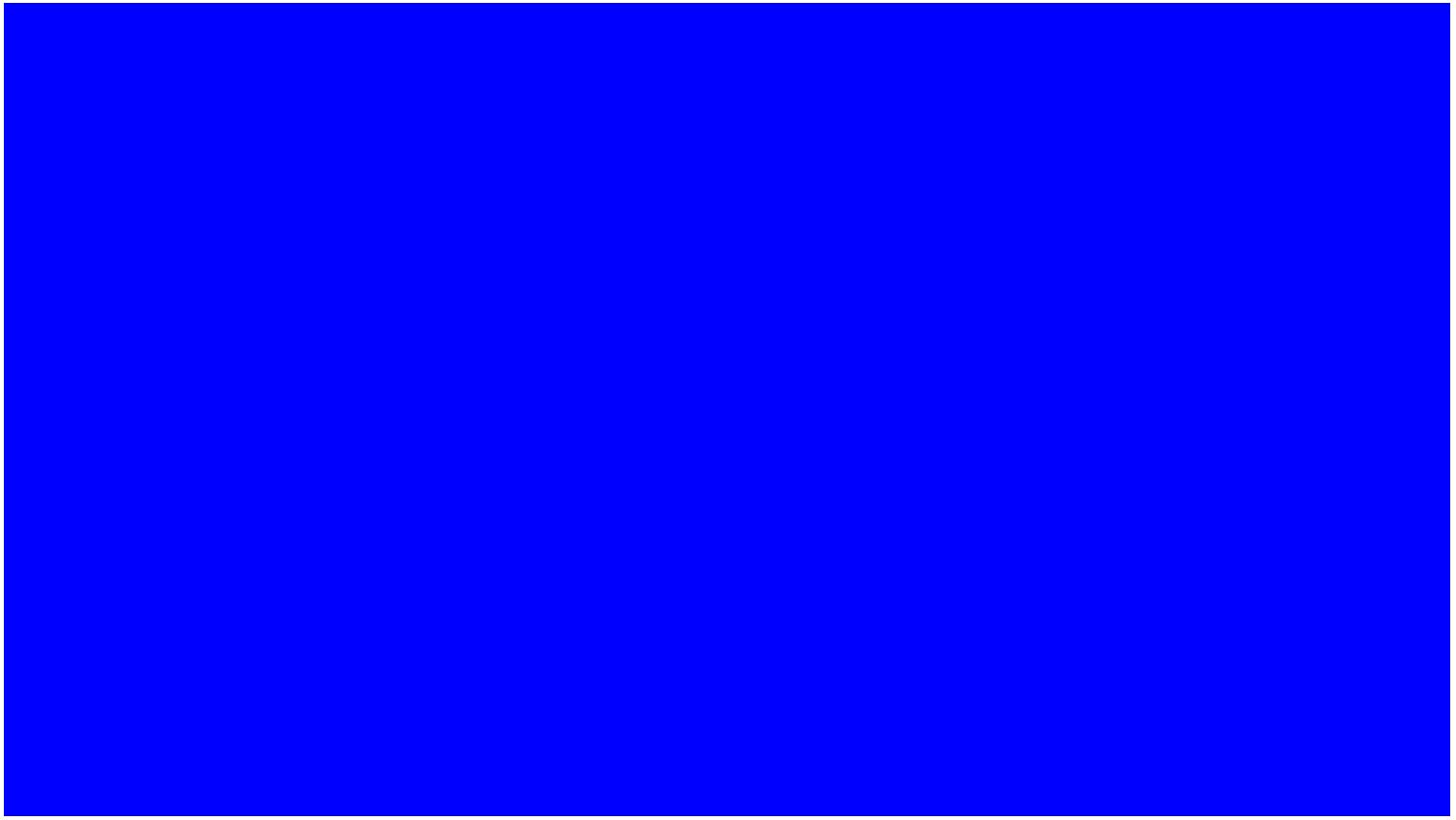
Challenges for accurate cooling demand prediction at large scale

- Lack of UK-specific domestic cooling data,
- No accurate baseline for cooling estimation
- Missing short-term, high-resolution profiles, cannot assess cooling dynamics during heatwaves
- Grid-level impacts underexplored, overlooks interaction with electricity system planning

Building Cooling Energy Prediction

Current methods for building energy prediction:

- Physical models
- Data-driven models
- Hybrid approaches



Cooling Demand Prediction

Comparison of Cooling Demand Forecasting Methods

	CDD-Based (cooling design days)	Physical Simulation	Data-Driven
Data Requirement	Low (temp, population)	Medium–High (building info)	High (cooling usage data)
Scale	Regional/National	Building/District	Flexible
Temporal Resolution	Low (seasonal–annual)	High (hourly)	High (hourly–daily)
Strength	Fast and scalable	Physics-based, dynamic	Accurate if data available
Limitation	**Cannot capture hourly dynamics**	**Input-intensive, hard to generalize**	**UK residential data lacking**

Research Aim & Objectives

Aim:
Combine physical simulation and machine learning model for cooling prediction.

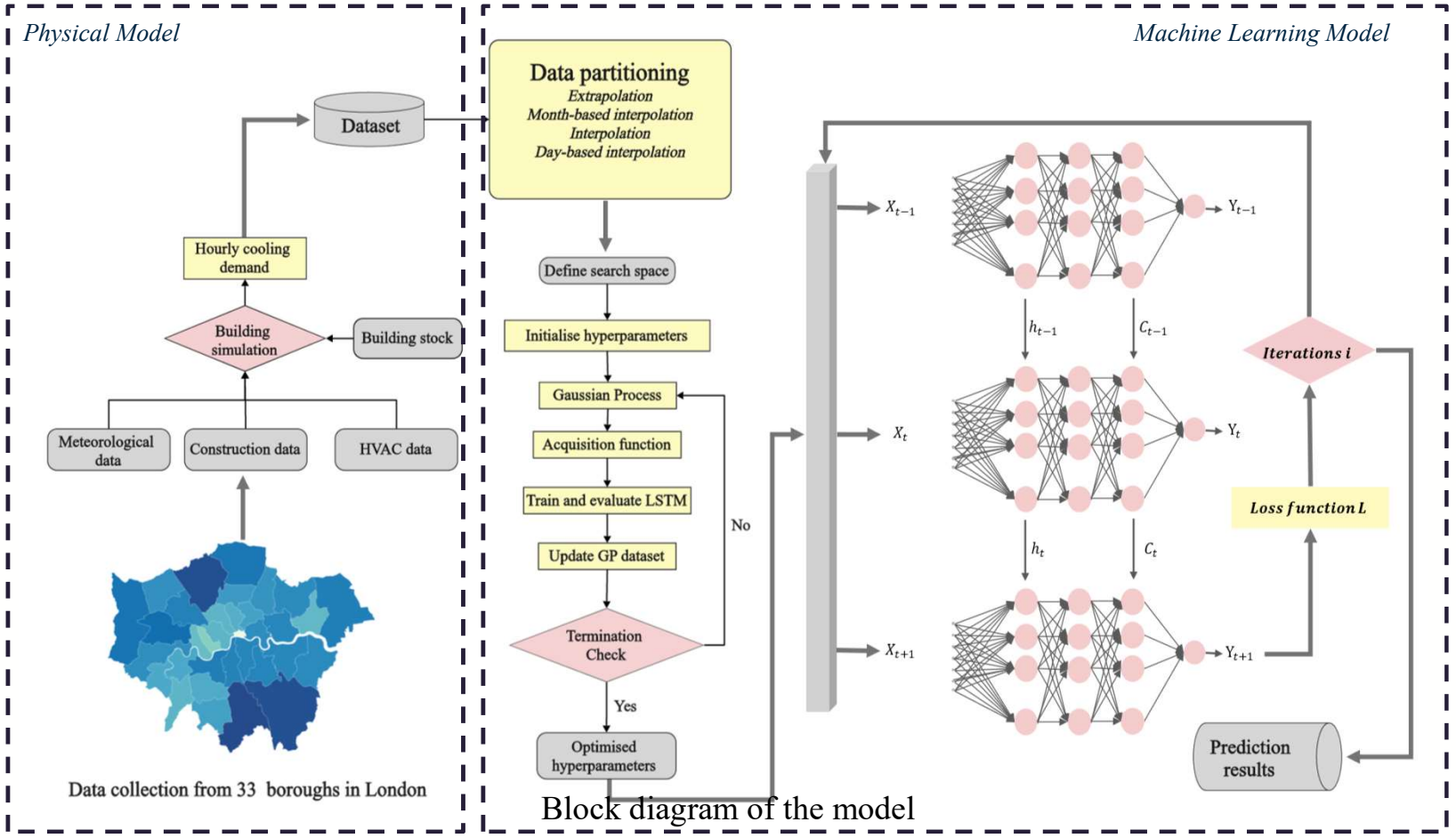
Objectives:

1. Physical simulation provides high-resolution, realistic cooling demand profiles, solving the data scarcity problem.

2. Machine learning models (LSTM/GRU) are trained on these synthetic profiles to enable fast, flexible, and generalisable prediction.

3. This hybrid approach combines accuracy, scalability, and practicality, and allows for forecasting across future climate scenarios.

Our Cooling Demand Prediction Framework



Block diagram of the model

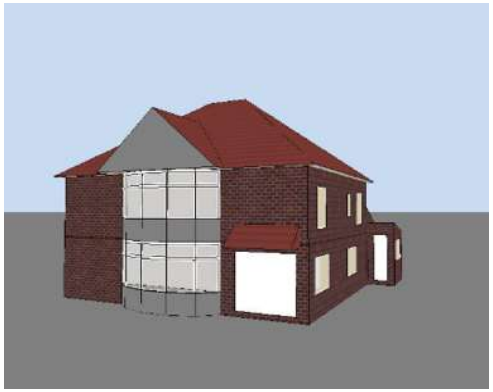
Zhang, M., Li, Z., & Yu, Z. (2024). Machine Learning-based Regional Cooling Demand Prediction with Optimized Dataset Partitioning. Energy and Buildings, 301, 113734. https://doi.org/10.1016/j.enbuild.2024.113734

Physical Model- Building Simulation

DesignBuilder

Domestic buildings are divided into four categories:

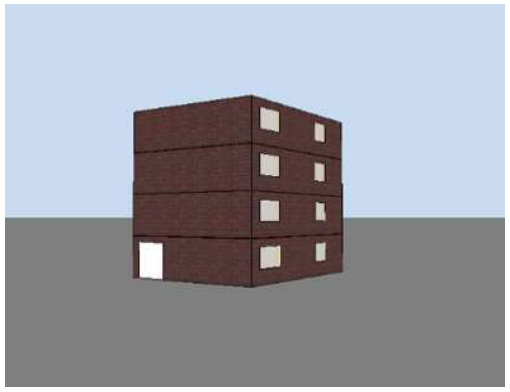
- Detached
- Semi-detached
- Terraced
- Flat



Detached

Terraced

Semi-Detached



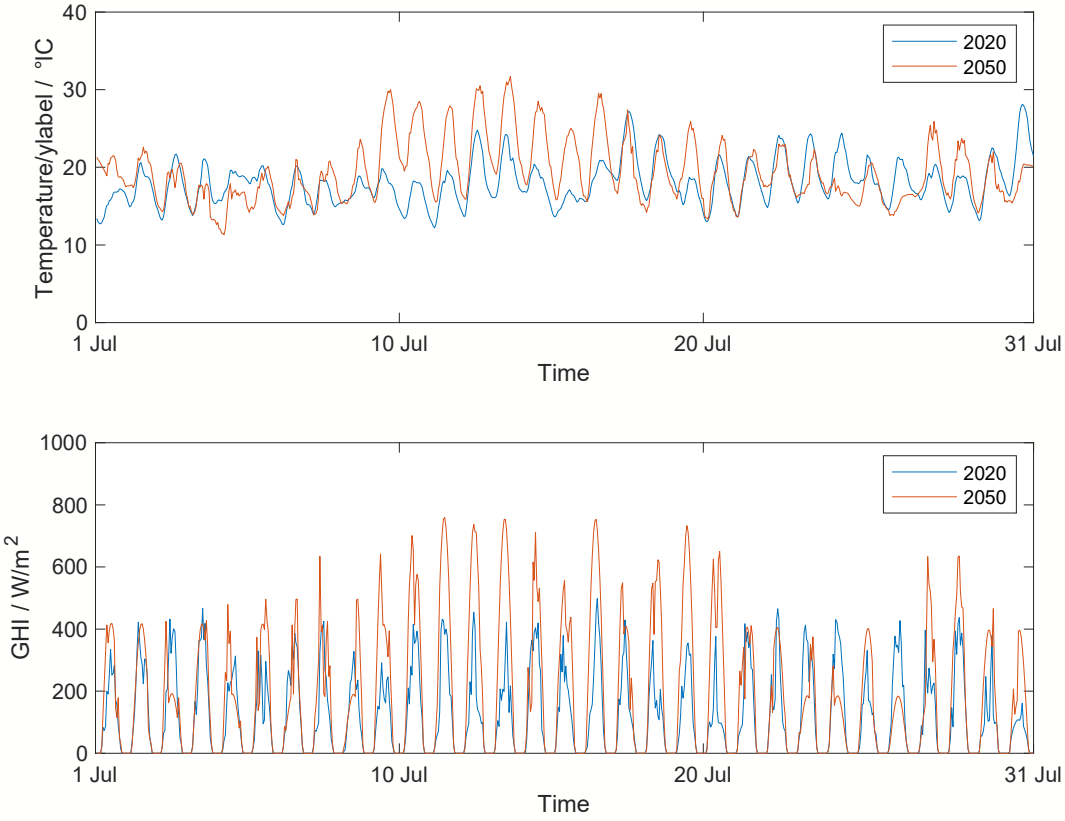
Department

Meng Zhang, Si Chen, Yaxing Ren, Zhibin Yu & James Yu (17 Jan 2025): Hourly cooling demand prediction through a bottom-up model in London, International Journal of Green Energy, DOI: 10.1080/15435075.2025.2452220

Physical Model-Important Inputs

1. Weather Files: Weather files for London 2020 and 2050 are available.

- Historical data of 2020
- 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.
- It provides an hourly weather data of London in 2050.



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Physical Model-Important Inputs

2. **Building Construction Data**: There are three sets of construction data based on different insulation levels

	External wall	Roof	Glazing	Ground floor
	W/m^2			
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

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Physical Model-Important Inputs

3. **Cooling Schedules**: Different heating modes can be used for the demand prediction.

	Periods	States
10 hours schedule	00:00 - 06:00	0.5
	06:00 - 9:00	1
	9:00 - 15:00	0.5
	15:00 - 22:00	1
	22:00 - 24:00	0.5
11 hours schedule	00:00 - 07:00	0.5
	07:00 – 12:00	1
	12:00 - 17:00	0.5
	17:00 - 23:00	1
	23:00 - 24:00	0.5

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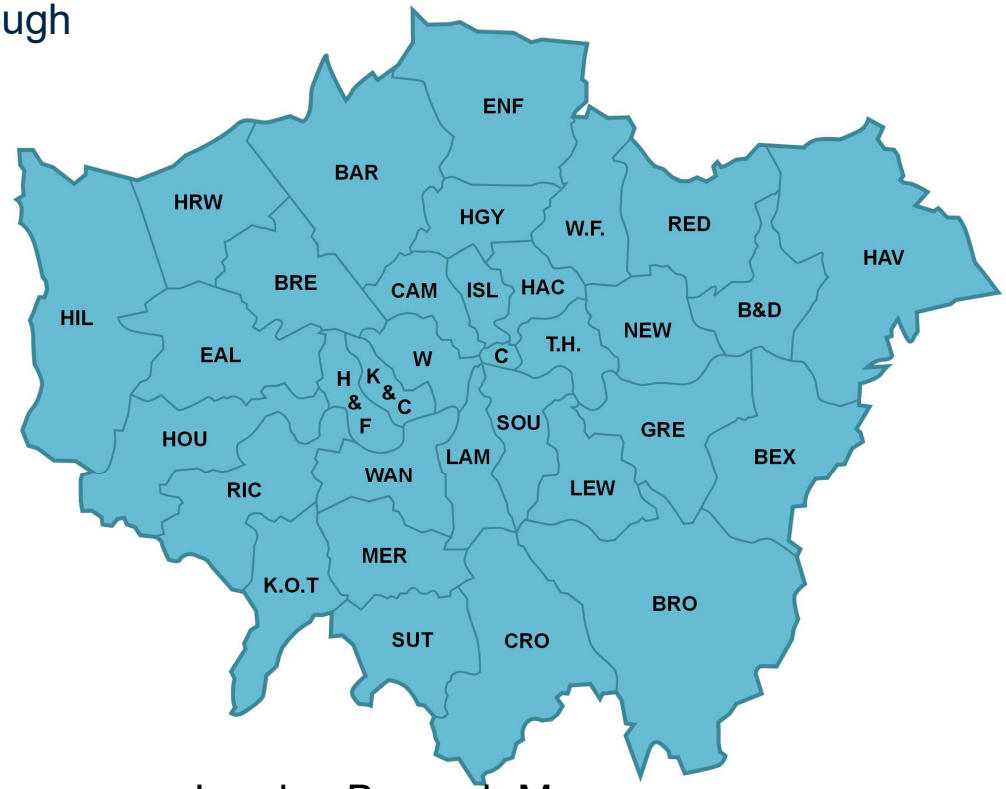
Physical Model-Building Stock in London

In this study, London is divided into 33 regions based on borough



London Borough Map

B&D	Barking and Dagenham
BAR	Barnet
BEX	Bexley
BRE	Brent
BRO	Bromley
C	City of London
CAM	Camden
CRO	Croydon
EAL	Ealing
ENF	Enfield
GRE	Greenwich
H&F	Hammersmith and Fulham
HAC	Hackney
HAV	Havering
HGY	Haringey
HIL	Hillingdon
HOU	Hounslow
HRW	Harrow
ISL	Islington
K.U.T.	Kingston upon Thames
K&C	Kensington and Chelsea
LAM	Lambeth
LEW	Lewisham
MER	Merton
NEW	Newham
RED	Redbridge
RIC	Richmond
SOU	Southwark
SUT	Sutton
T.H.	Tower Hamlets
W	City of Westminster
W.F.	Waltham Forest
WAN	Wandsworth

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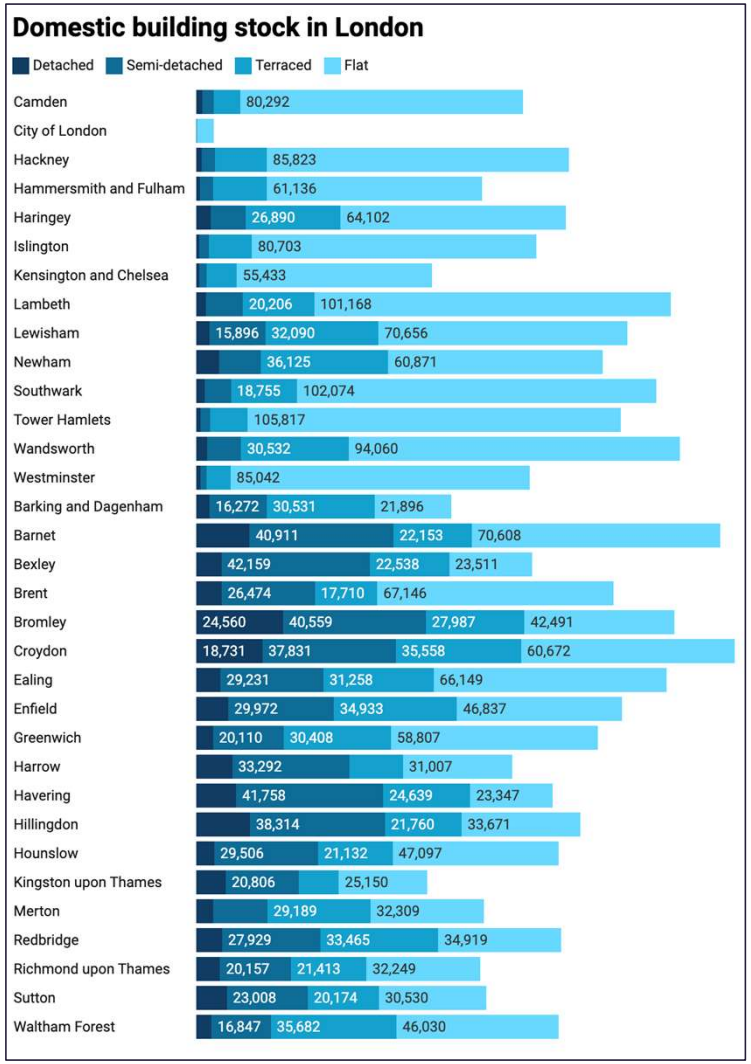
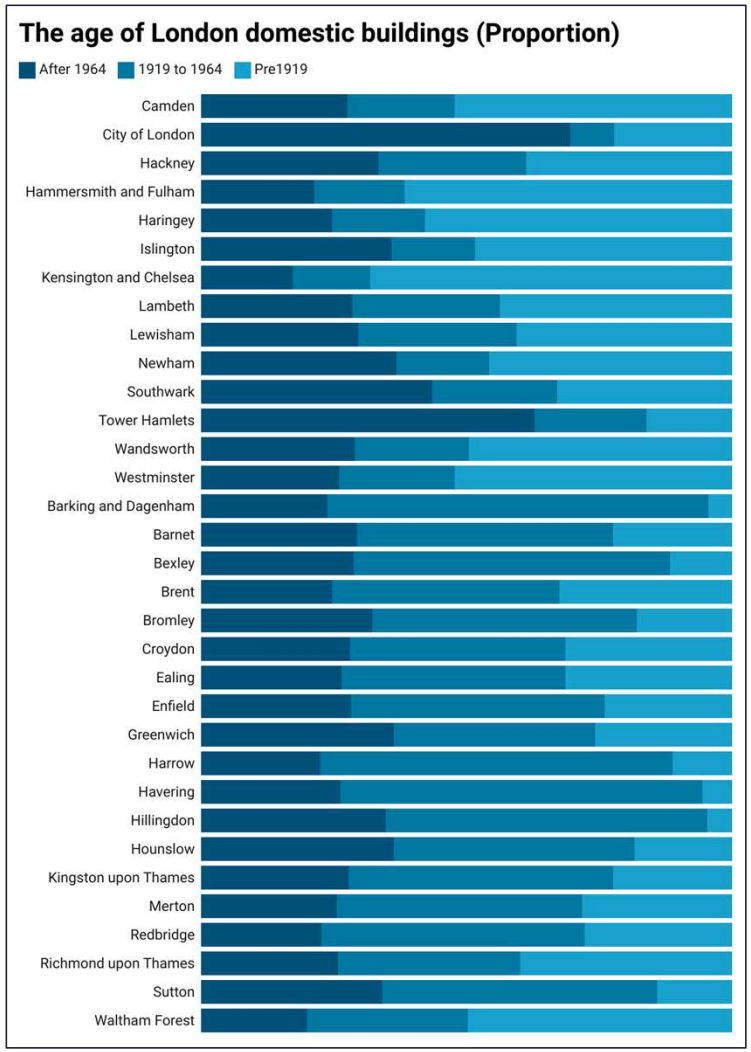
Physical Model-Building Stock in London

- This approach generates 12 different hourly cooling demand profiles.
- Data from 33 distinct regions are analyzed.
- This involves the aggregation of 396 individual cooling profiles





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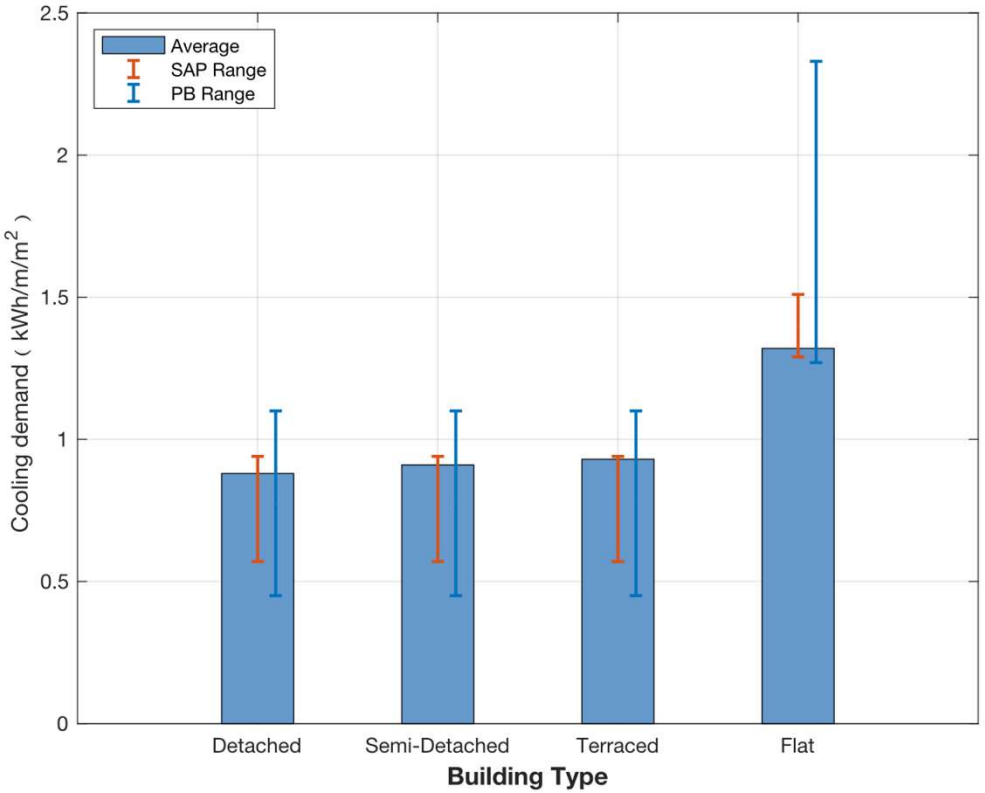
Physical Model-Validation



Indicator

SAP – Standard Assessment Procedure

UK's official method for assessing the energy performance of residential buildings

PB – Proposed Benchmark

A London-specific dynamic benchmark introduced by the Greater London Authority

No direct UK domestic cooling data available for validation. Used London Government benchmarks: Simulated average June–August cooling demand (kWh/m²) falls within both SAP and PB accepted ranges

Confirms model reliability for generating training data

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- The cooling demand in 2050 is projected to increase approximately by 45% for London compared with 2020.
- In 2020, the cooling demand of Inner London is 310.18 GWh and is projected to increase to 468.37 GWh by 2050.
- Outer London has a higher cooling demand of 548.63 GWh in 2020, which is expected to rise to 776.58 GWh by 2050.

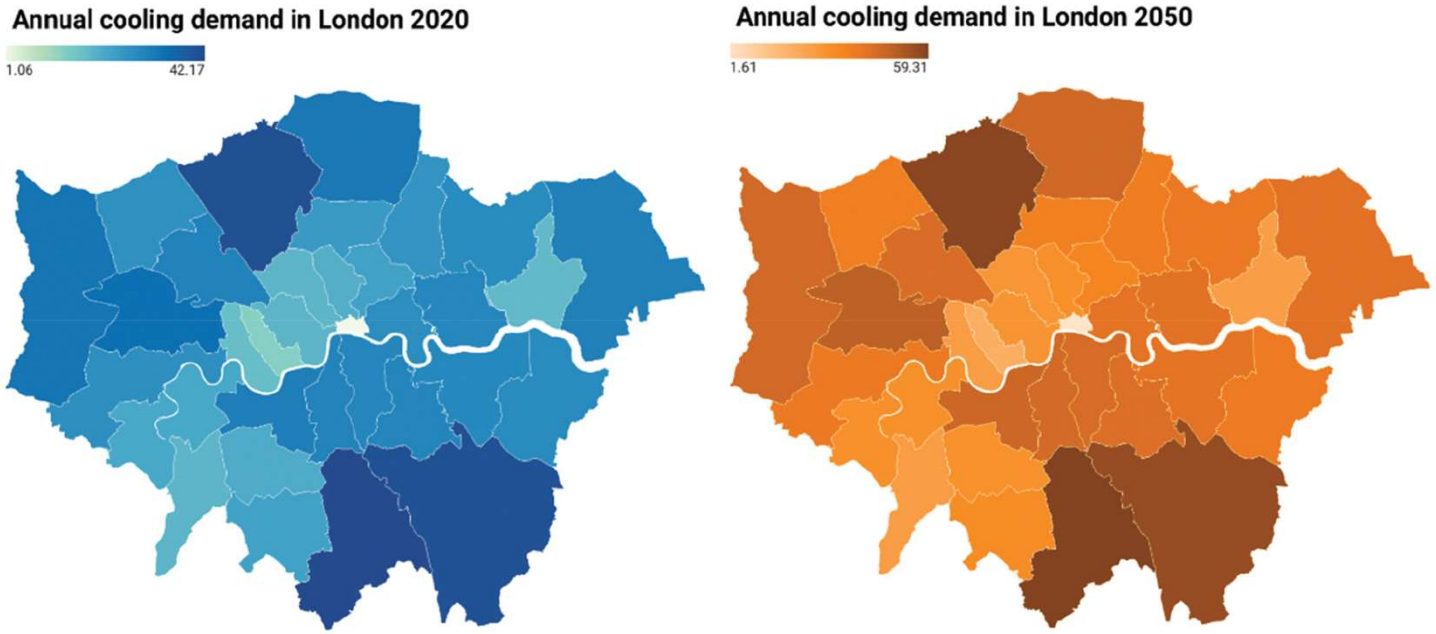

Figure 6. Annual cooling demand for domestic by London boroughs in (a) 2020; (b)2050.

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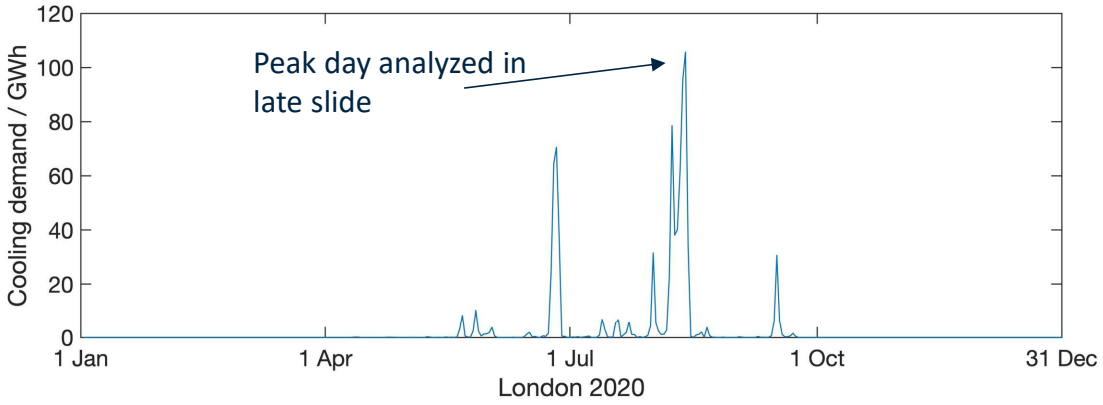
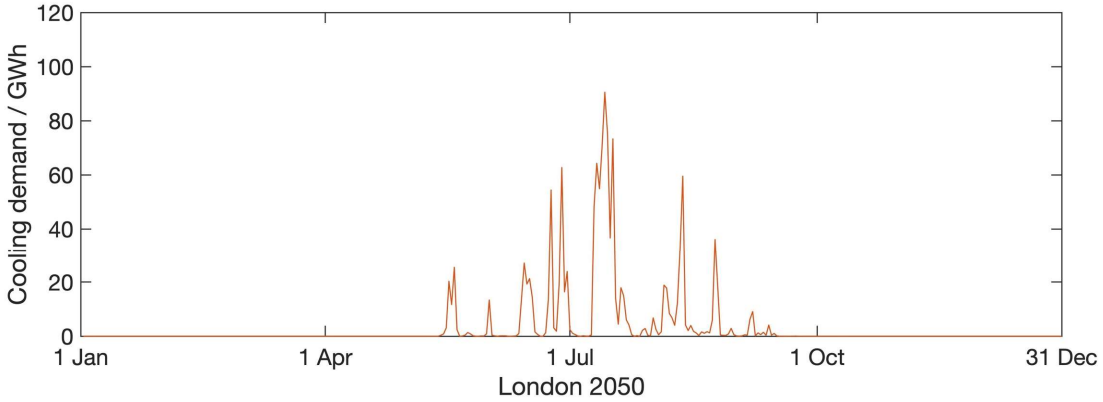
Comparison of total daily cooling demand in London in 2020 and 2050

- The annual cooling demand for 2020 was recorded as 858.81 GWh
- The maximum daily cooling demand peaking at 105.7 GWh due to heat wave.
- This peak day accounts for 12.3% of the annual cooling demand due to heat wave.
- Indicating a concentrated pressure on the grid due to heat waves.





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Comparison of domestic electricity demand and cooling electricity demand in London 2020 (COP=3)

- Active cooling systems are present in less than 3% of UK housing stock (English housing survey 2023).
- The total domestic electricity demand shown by the blue curve, and it includes only around 3% of cooling demand during summer.
- The red curve represents the total cooling demand calculated in 2020, if it is all met by air-conditioning systems.
- With the electricity demand for cooling (red curve) exceeding 1.4GW for 66 h dispersed over 18 days
- To meet all cooling needs, the London region would have required an additional 4GW of installed capacity of new generation

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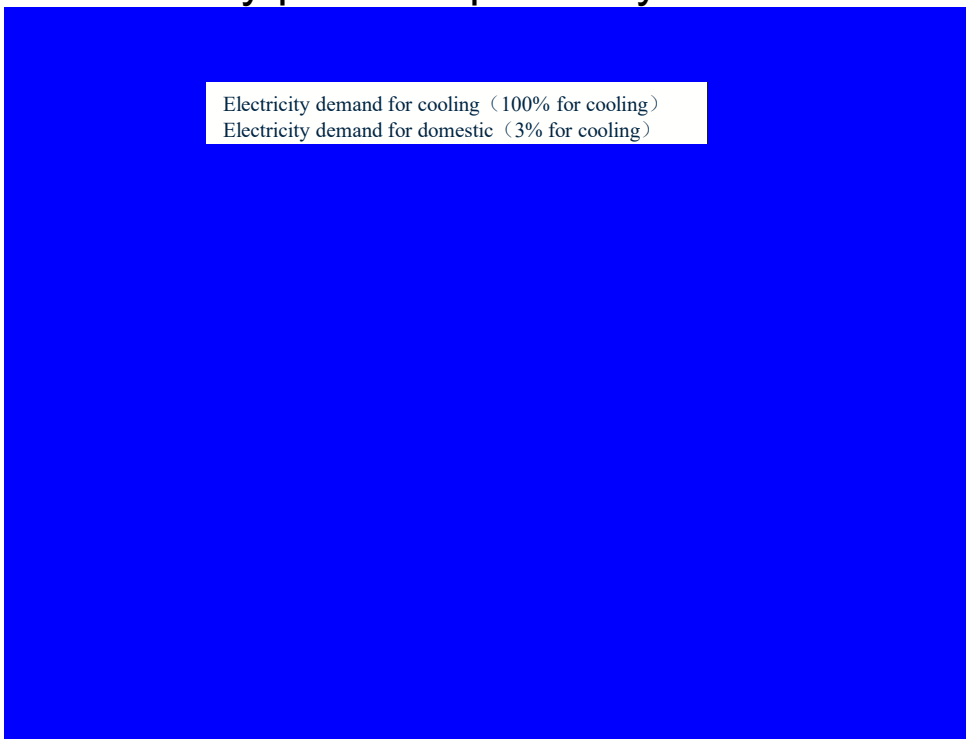
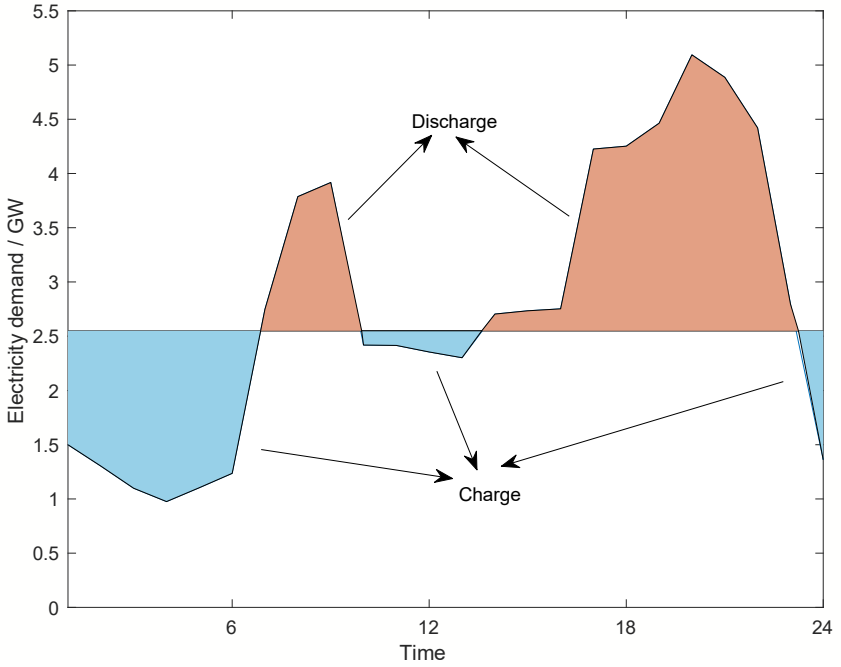
Electricity profile of peak day in 2020



Storage demand for peak day in 2020



Storage-Based Mitigation

- To halve the peak to ~2.51 GW, required storage: ~26.8 GWh;
- Equivalent to ~18.8 kWh per household;
- This storage could fully absorb peak cooling load for the entire day

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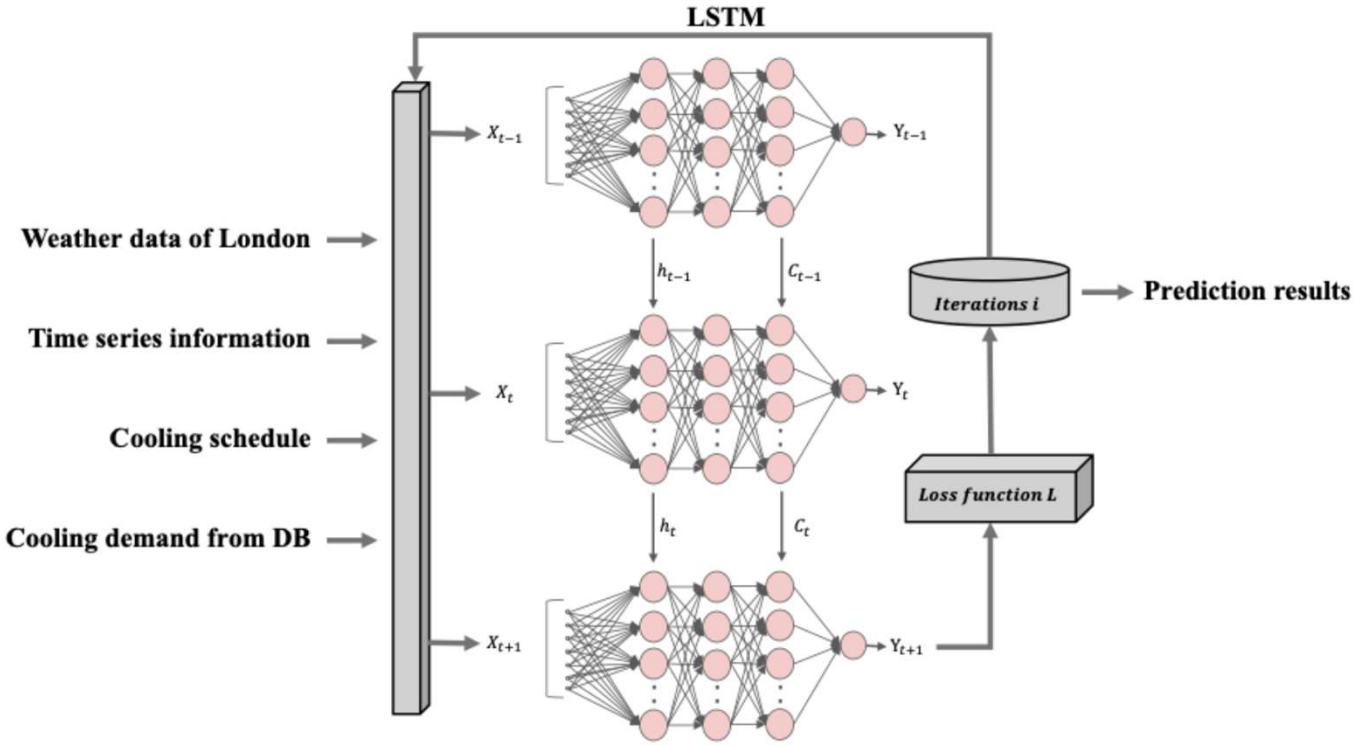
Machine Learning Model-Topology



- LSTM/GRU models use only meteorological data and time of day to predict London's total cooling demand.
- The models were trained on 2020 summer weather data, with an 80/20 train-test split based on simulation-generated demand.

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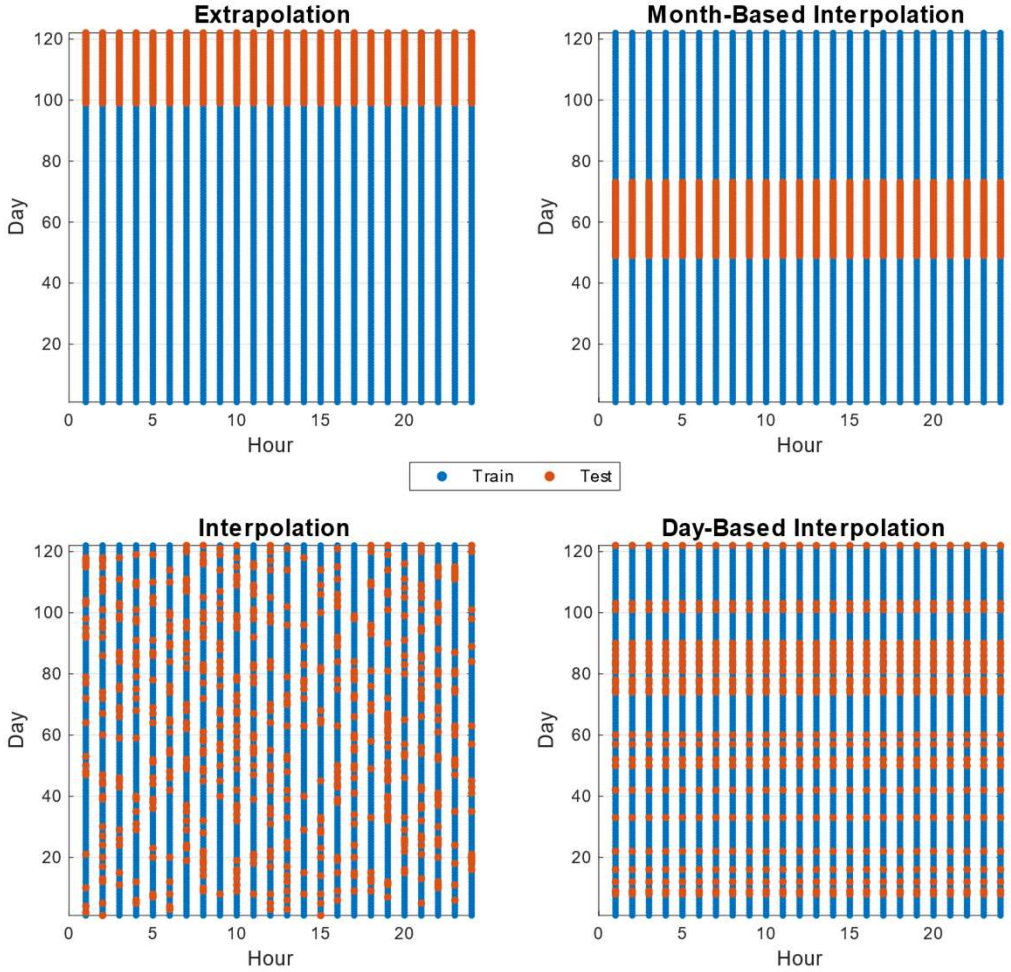
Data Partitioning



Four data partitioning strategies were used

Extrapolation:
Train on the first 80% of data, test on the last 20% (chronological split)

Month-based Interpolation:
Select one continuous block (20%) as test set, remaining used for training

Global Interpolation:
Randomly select 20% of all data points for testing (shuffles entire time series)

Day-based Interpolation:
Randomly select 20% of full days as test set; time sequence within each day preserved

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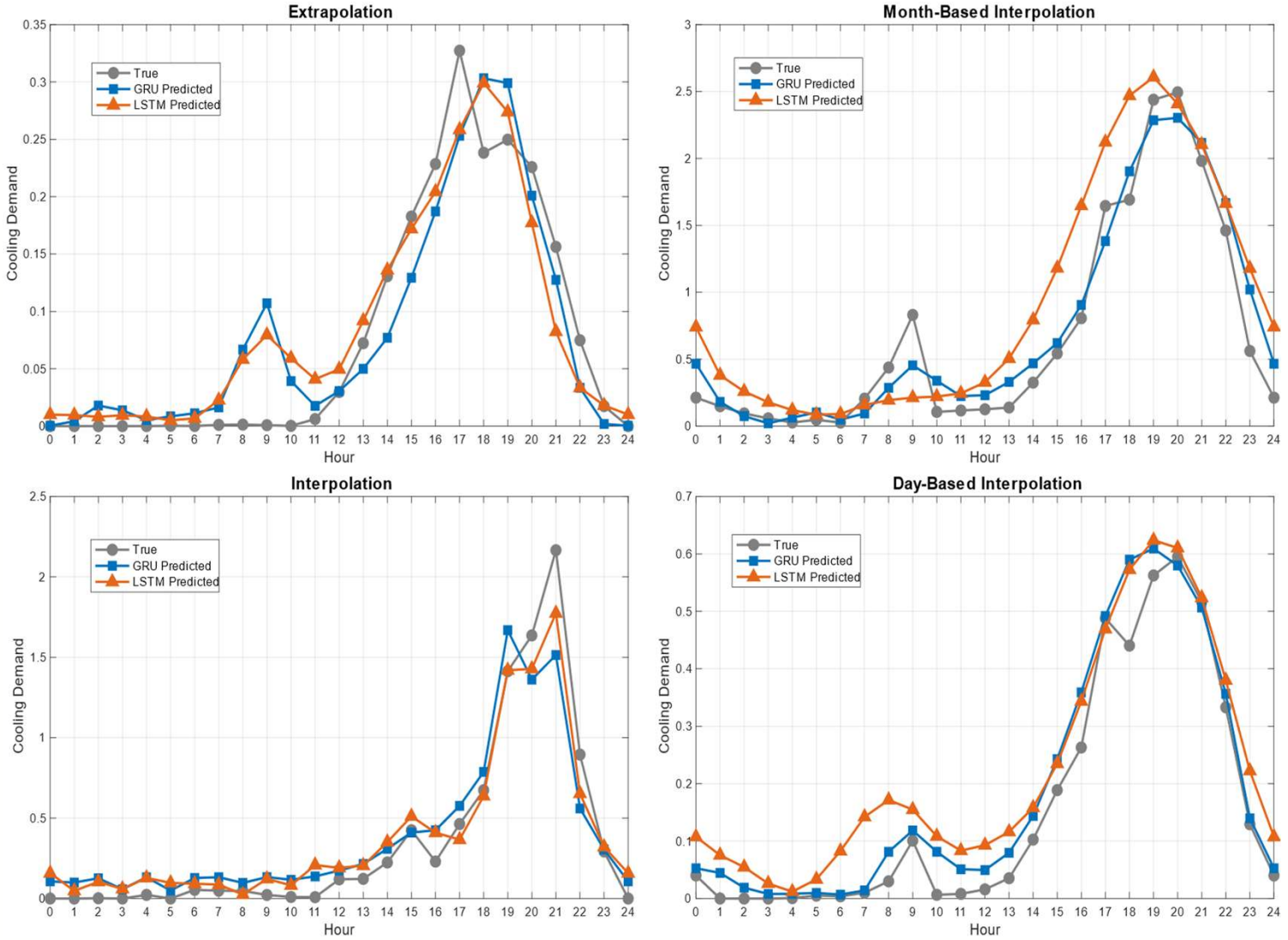
Average hourly cooling demand prediction of test dataset

GRU: Gated Recurrent Unit

LSTM: Long-Short Term Memory

True: physical model prediction

- The results show good agreement
- Next step to apply the ANN model to different area – ongoing work



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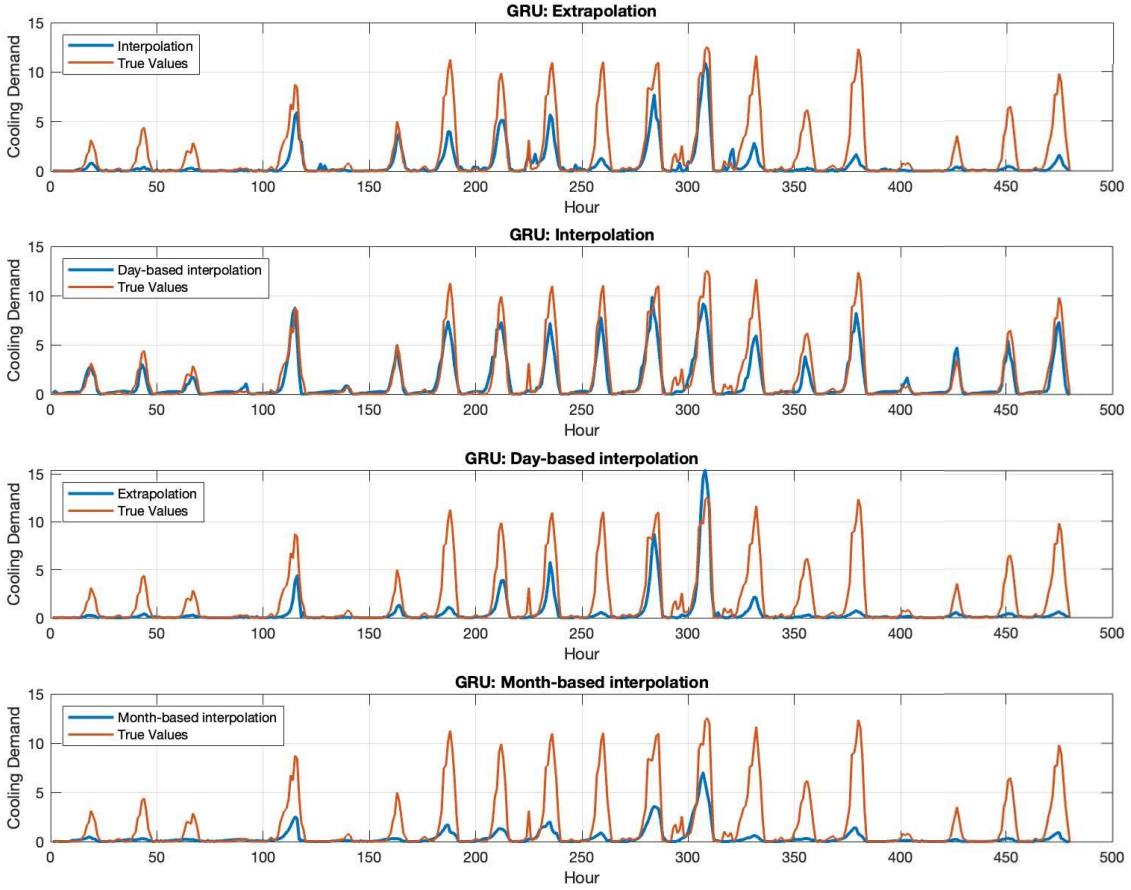
The performance of different GRU models in predicting peak cooling demand in 2050



GRU	RMSE	MAE
Extrapolation	5.411%	1.988%
Interpolation	6.556%	3.559%
Day-based interpolation	6.027%	2.054%
Month-based interpolation	6.881%	2.446%
LSTM	**RMSE**	**MAE**
Extrapolation	5.984%	2.088%
Interpolation	15.679%	6.923%
Day-based interpolation	6.107%	2.309%
Month-based interpolation	5.706%	2.655%

Performance of LSTM and GRU models in prediction of 2050 cooling demand

Conclusion

- A cooling demand model was built **using building simulation and ML,** covering all 33 zones in London.
- Cooling demand is expected to increase by **45% from 2020 to 2050**, potentially **doubling peak** residential electricity usage.
- Findings highlight the need for **storage integration and reversible heat pumps** to handle peak loads and improve equipment utilisation.
- Machine learning models strained on simulation data, combined with **day-based interpolation and Bayesian optimisation**, achieved high accuracy and generalisation.

Thank you for listening!

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