Optimization of computational time for Urban Building Energy Modelling, through generalizing the Building Footprint. A case study in London, UK.

Apostolopoulou Athanasia*[1], Boyd S. Doreen[1], Calderon Carlos[2], Cavazzi Stefano[3], Wilson Robin[1] and Jimenez-Bescos Carlos[4]

[1]University of Nottingham, Nottingham, UK
[2]Newcastle University, Newcastle, UK
[3]Ordnance Survey, Southampton, UK
[4]University of Derby, Derby, UK

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Summary

The reconfiguration of everyday human activities is considered necessary to tackle the challenge of climate change. Building stock is one of the major contributors to urban energy consumption and targeting its energy performance through upgrade could help policy makers to reach the energy reduction goals. Given the rapidity of climate change, Urban Building Energy Modelling (UBEM) is needed. However, gathering the essential data for UBEM is a challenge, and the simplification of its process has become one-way solution. This study focuses on the Level of Generalization (LoG) of the building footprint (individual, local, district), that is needed. Preliminary results show the higher the LoG, the higher the underestimation of energy demand.

KEYWORDS: Urban Building Energy Modelling (UBEM), Data Requirements, OS MasterMap, Building Footprint, Computational Time

1. Introduction

1.1. Climate Change

The reconfiguration of human activities in everyday routine is considered necessary in order to tackle the challenge of climate change and ensure global future prosperity (European Environment Agency (EEA), 2020). Without taking the Greenhouse Gas (GHG) emissions into consideration, the limitation of the temperature rise becomes unachievable (Intergovernmental Panel on Climate Change (IPCC), 2021), while the world's temperature could escalate by 2.5 to 4.5 °C by 2100 (NASA, no date). However, several studies have found that during the 1970s and 2000s, the amount of greenhouse gases increased by 70% (Younger *et al.*, 2008).

1.2. The role of Building Stock

According to the International Energy Agency (IEA) and the U.S. Energy Information Administration (EIA), the proportion of GHG emissions from buildings is 28%–30% and the highest of all built environment sectors (Energy Information Administration (EIA), no date; International Energy Agency (IEA), no date). Particularly for the UK, the percentage of CO2 emissions attributable to solely dwellings is equivalent to 23% of all UK carbon emissions (Bonfield, 2016; Gupta and Gregg, 2018).
Accounting for the urbanization, urban regions are responsible for 67-76% of the world's energy consumption and 71-76% of its energy related GHG emissions (Wang, Han and de Vries, 2020). Therefore, buildings are one of the major contributors to urban energy consumption and targeting to their energy performance upgrade could help city planners to reach their energy reduction goals (Mohammadiziazi and Bilec, 2019; Tardioli *et al.*, 2020).

*laxaa46@nottingham.ac.uk

1.3. The Ally: Urban Building Energy Modelling

Building energy modeling at the individual level is not feasible given the rapidity of climate change. Since energy conservation measures should be applied severely as a first step, decision makers might identify the most energy inefficient areas by modeling the energy performance of buildings at the city scale. Therefore, Urban Building Energy Modeling (UBEM) is essential for achieving these goals, whether they focus on reducing climate change or adapting the building stock to future climate.

Since many of the necessary input data are missing, acquiring them has become a significant challenge for energy analyzers. On the other hand, UBEM has to deal with the fact that its approaches often use extremely large datasets, which indicates computational problems, particularly when comprehensive building stock information is needed for an entire city. For that reason, this paper focuses on the data requirements, and more specifically, to the geometric input parameters. In other words, the research aim is to investigate the Level of Generalization that is needed, regarding the building footprint of an area, for the optimization of the computational time, as it is a big challenge when dealing with urban scales and its big datasets.

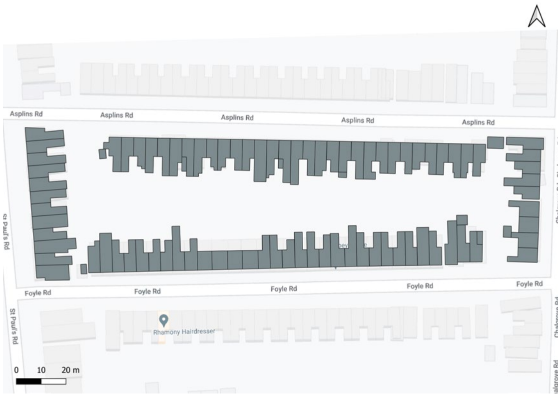
2. Methodological Approach

For the investigation of the appropriateness of the generalized building model, the following datasets have been used (**Table 1**). Firstly, with Python through Jupyter Notebook the building typology has been constructed, depending on the building type, age and construction materials, and two columns have been created, one for the construction materials and a second one for the mechanical building parameters, called "Construction Set" and "Program Type", accordingly.

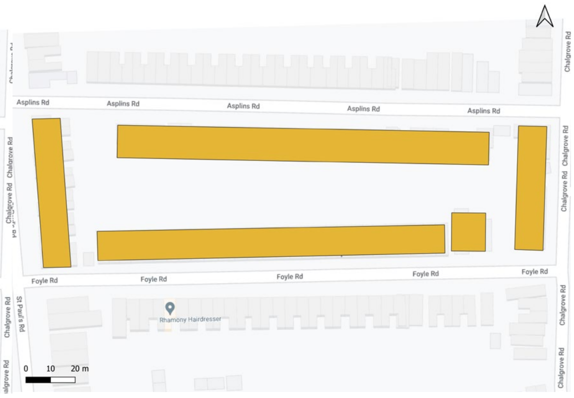
Table 1 Datasets

Dataset	Provider	Source	Format
OS MasterMap Topography layer	Ordnance Survey	Digimap, EDINA	GPKG
OS MasterMap Building Height attribute	Ordnance Survey	Digimap, EDINA	CSV
Colouring London	Colouring CITIES	https://colouringlondon.org/	CSV
OS Features API (Local Buildings layer)	Ordnance Survey	OS Data Hub	API
OS Features API (District Buildings layer)	Ordnance Survey	OS Data Hub	API
Statistical GIS Boundary Files for London	GREATER LONDON AUTHORITY	https://data.london.gov.uk/dataset/statistical-gis-boundary-files-london	SHP
OS Boundary Line	Ordnance Survey	Digimap, EDINA	SHP

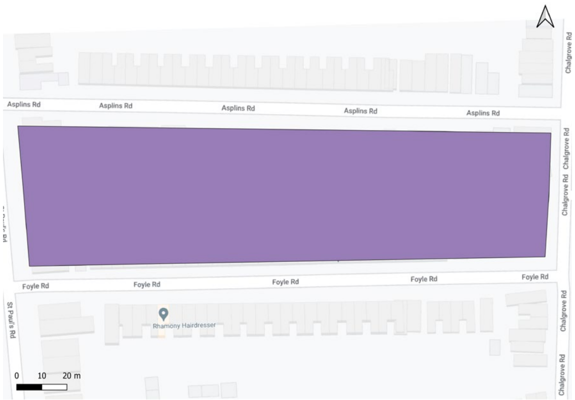
After creating the building typology, in borough scale, it has been imported to QGIS software, with the OS Features API for the local and district building scale. Then, the specific building block for the case study, depending on the fullness of the building scale dataset, has been chosen. After that, all three scales of datasets have been clipped to the building block level and a few buildings at Level of Generalization 1 (LoG1) dataset without information have been assumed to have same attributes with their neighbors, in order to have a full building block. Hence, the LoG2 and LoG3 datasets, have been clipped to the AOI (**Figure 1**). Finally, with Rhino-Grasshopper, an energy model has been constructed, where all three LoGs datasets have run one at a time, in order to compare the results and investigate the necessity of the individual building footprint in UBEM. **Figure 2** shows the methodological diagram.



(a) LoG1 (Individual Building Level)



(b) LoG2 (Local Building Level)



(c) LoG3 (District Building Level)

Figure 1 Level of Generalization – Residential Building Block in Haringey borough.

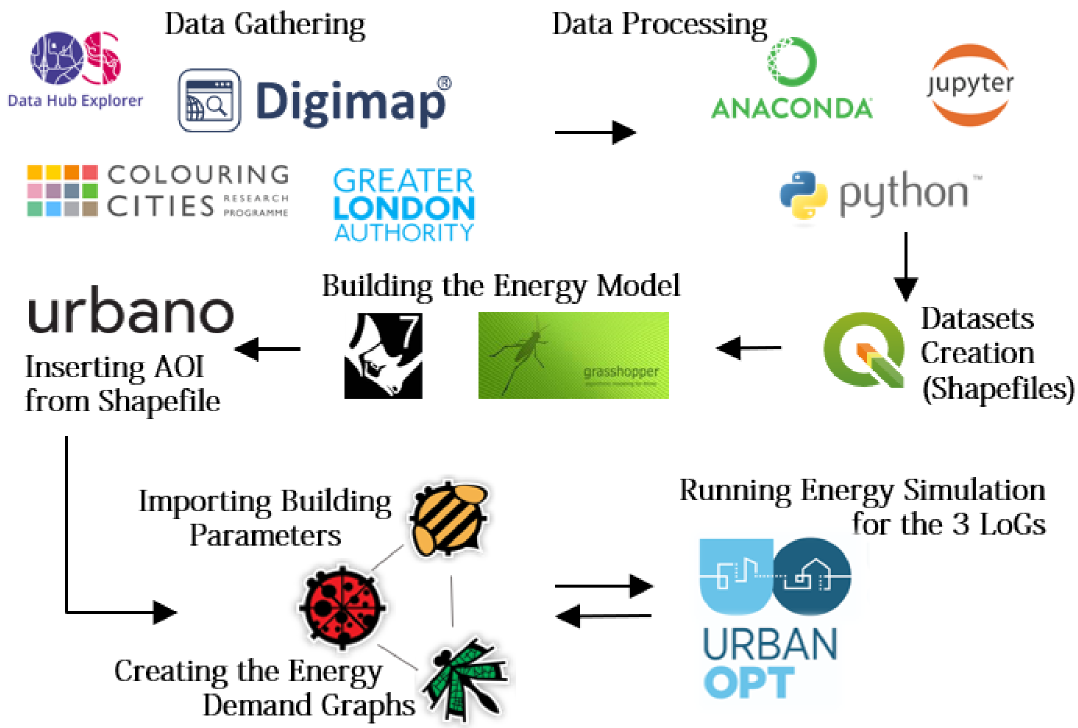


Figure 2 Methodological Diagram.

3. Results

3.1. Area of Interest (AOI)

According to the housing zone areas of London and the availability of specific building attributes in Colouring London dataset, Haringey borough has been chosen. Haringey borough is a residential area of 2,960 hectares consisting of 109,412 dwellings (London Councils, no date). Particularly, the case study building block is the one created from St Paul's Rd, Asplins Rd, Chalgrove Rd and Foyle Rd, illustrated in **Figure 1**.

3.2. Energy Demand Graphs

Before running the energy models, due to homogeneity at the program type and construction type of the dwellings at LoG1 dataset, the dwellings with lack of data have been assumed to be similar to their neighbours. For the local building footprint scale dataset, an average height, program type and construction set has been taken for each local building, as well as with the district building footprint scale. After that, the three shapefiles were imported into Rhino (**Figure 3**) and the results obtained are presented below (**Figure 4**).

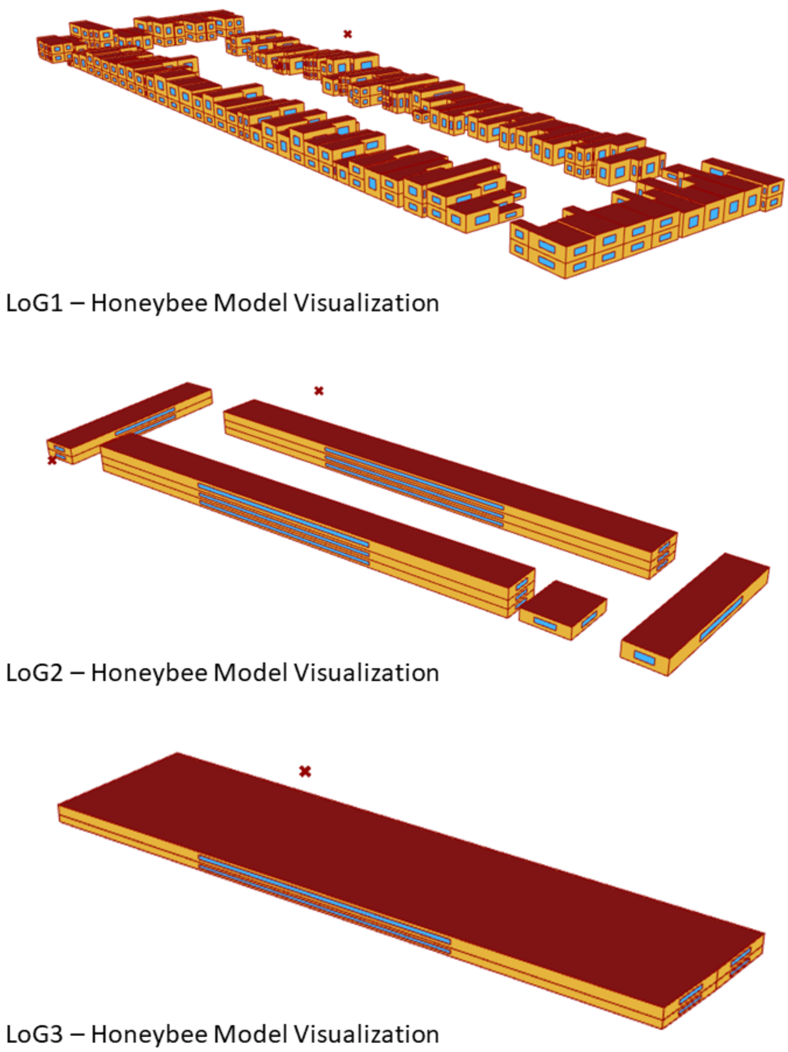


Figure 3 Honeybee Model Visualization from Rhino-Grasshopper at all LoGs

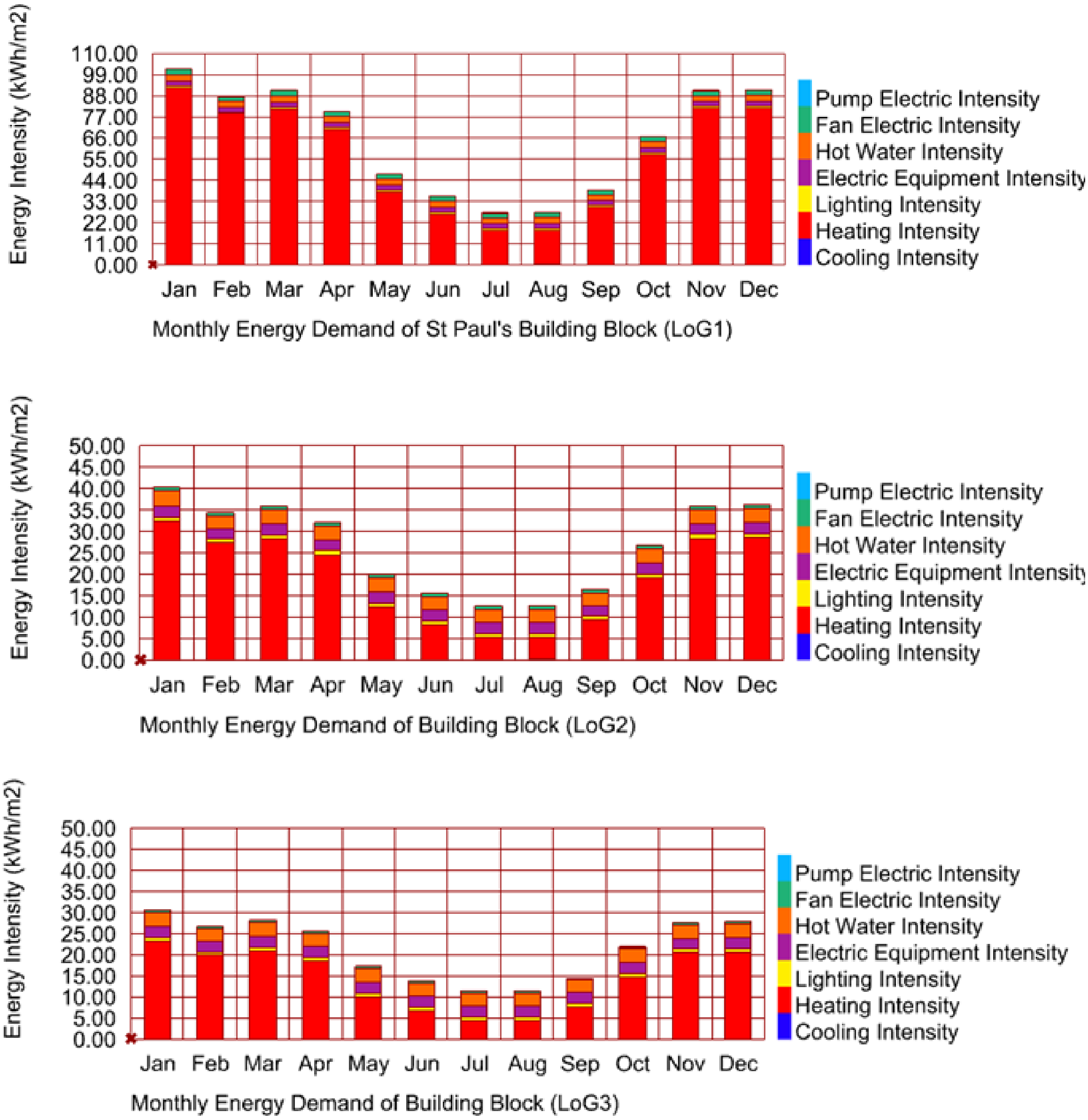


Figure 3 Monthly Energy Demand of Haringey Building Block at all LoGs

The graphs demonstrate that the generalization of the building footprints underestimates the energy demand by up to 50% less than the LoG1 building footprints.

4. Discussion & Conclusions

The data challenges that occur through UBEM process, such as data availability and computational time, make its simplification essential. This experiment has made an effort for the generalization of the individual building footprint to the local and district building footprint scale, aiming for the optimization of the UBEM computational time. The results have shown that generalization leads to an underestimation of the modelled energy demand. However, the next step for the project is to validate the exact values of the energy demand, as during this experiment a comparison from LoG1 to LoG3 has been implemented. Therefore, a different AOI could be chosen depending on the "Colouring London" energy performance column. Finally, further research should be done regarding the variety of the building type and building age and their combination, as the case study building block is homogeneous, as well as for the validation of the energy model.

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References

Bonfield, P. (2016) Each Home Counts: An Independent Review of Consumer Advice, Protection, Standards and Enforcement for Energy Efficiency and Renewable Energy. London.

Energy Information Administration (EIA) (no date) International Energy Outlook 2017. Available at: https://www.eia.gov/outlooks/archive/ieo17/ (Accessed: 13 January 2022).

European Environment Agency (EEA) (2020) Europe's state of the environment 2020: change of direction urgently needed to face climate change challenges, reverse degradation and ensure future prosperity — European Environment Agency. Available at: https://www.eea.europa.eu/highlights/soer2020-europes-environment-state-and-outlook-report (Accessed: 10 January 2022).

Gupta, R. and Gregg, M. (2018) 'Targeting and modelling urban energy retrofits using a city-scale energy mapping approach', Journal of Cleaner Production, 174, pp. 401–412. Available at: https://doi.org/10.1016/j.jclepro.2017.10.262.

Intergovernmental Panel on Climate Change (IPCC) (2021) 'Climate change widespread, rapid, and intensifying – IPCC — IPCC', 9 August. Available at: https://www.ipcc.ch/2021/08/09/ar6-wg1-20210809-pr/ (Accessed: 10 January 2022).

International Energy Agency (IEA) (no date) Tracking Buildings 2020 – Analysis, IEA. Available at: https://www.iea.org/reports/tracking-buildings-2020 (Accessed: 13 January 2022).

London Councils (no date) London Borough of Haringey. Available at: https://directory.londoncouncils.gov.uk/directory/haringey/ (Accessed: 18 January 2023).

Mohammadiziazi, R. and Bilec, M.M. (2019) 'Developing a framework for urban building life cycle energy map with a focus on rapid visual inspection and image processing', Procedia CIRP, 80, pp. 464–469. Available at: https://doi.org/10.1016/j.procir.2019.01.048.

NASA (no date) Is it too late to prevent climate change?, Climate Change: Vital Signs of the Planet. Available at: https://climate.nasa.gov/faq/16/is-it-too-late-to-prevent-climate-change (Accessed: 10 January 2022).

Tardioli, G. et al. (2020) 'A methodology for calibration of building energy models at district scale using clustering and surrogate techniques', Energy and Buildings, 226, p. 110309. Available at: https://doi.org/10.1016/j.enbuild.2020.110309.

Wang, G., Han, Q. and de Vries, B. (2020) 'A geographic carbon emission estimating framework on the city scale', Journal of Cleaner Production, 244, p. 118793. Available at: https://doi.org/10.1016/j.jclepro.2019.118793.

Younger, M. et al. (2008) 'The Built Environment, Climate Change, and Health', American Journal of Preventive Medicine, 35(5), pp. 517–526. Available at: https://doi.org/10.1016/j.amepre.2008.08.017.

Biographies

Athanasia Apostolopoulou: Athanasia Apostolopoulou is a PhD researcher in Geospatial Systems CDT, at Nottingham Geospatial Institute. Her PhD project is funded by Ordnance Survey. Her research interests lie at the intersection of geospatial science and building energy modelling for smart cities and sustainable environments.

Doreen Boyd: Doreen Boyd is Professor of Earth Observation with research interests is in using cutting-edge geospatial data science on standard and novel data streams. The principal data stream is that captured by remote sensing systems. Applications cut across a range of UN SDGs attracting over £10 million in research funding.

Carlos Calderon: Carlos Calderon is a senior lecturer in the School of Architecture at Newcastle University. His research interests lie at the intersection of the built environment and computation around three main areas: energy and carbon modelling in buildings, communities, and cities; smart materials and environments; and intelligent systems and digital design.

Stefano Cavazzi: Stefano Cavazzi is a Principal Innovation and Research Scientist at Ordnance Survey where he leads the development of GIS and geomatics research programmes.

Robin Wilson: Robin Wilson is an Associate Professor, in Faculty of Engineering at University of Nottingham. He is a is a member of the Human Factors Research Group.

Carlos Jimenez-Bescos: Carlos Jimenez-Bescos is a lecturer in University of Derby. His research interests lie at the architecture, built environment and human thermal comfort in that.