Development of a dynamic building stock model for smart energy transition decision support: university campus stock case study

Vasiliki Kourgiozou[1], Salam Al-Saegh[1], Ivan Korolija[1], Mark Dowson[2], Andrew Commin[2], Rui Tang[1], Dimitrios Rovas[1], Dejan Mumovic[1]
[1]University College London, London, United Kingdom
[2] Buro Happold Ltd, London, United Kingdom

Abstract

University campuses present a unique opportunity for decarbonisation through integration of intelligence for smart-energy campuses. So far the evidence-base for smart energy campuses focuses on building-level demonstrations or archetypal approaches and the university campus stock lacks a common assessment framework to characterise and evaluate smart-energy transition pathways.

This paper presents a methodological framework that leverages automated computational methods (3DStock, SimStock) to produce building-by-building dynamic thermal models. The modelling method can benefit the evaluation of smart-energy campus and decarbonisation strategies and simulate the dynamics of complex HVAC under demand-response where data availability is more granular. Instead of using archetypal approaches to represent the heterogeneity of building stocks, this work developed an automated building-by-building stock modellng approach based on a case study. HVAC systems are also modelled based on information from Display Energy Certificates. Model calibration is performed, at stock level, against actual data from Building Monitoring Systems and operational energy performance data following the CIBSE TM63 protocol. Geometry checks showed 63% of the models were sufficiently matching actual geometry whereas energy use intensity was overestimated by around 35% across the campus in the baseline partially calibrated building models.For a typology, initial comparisons with a fully calibrated model signified lighting, cooling and heating setpoints as potential factors. A major advantage of the method is that it can be flexibly used depending on the data granularity available and therefore eliminates a significant barrier that Urban Energy Modelling presents in terms of data availabilty.

Highlights

- Automated building-by-building campus stock model.
- Stock model calibration and geometry verification.
- University campus smart energy transition framework.

Introduction

The UK's Higher and Further education sector has unique potential for reducing carbon emissions and incorporating intelligent systems. Firstly, national benchmarks suggest university campus energy consumption to be double of the energy that an open plan office consumes typically in a year (CIBSE, 2020) with intensive university building activities being the most influential electricity consumption factor (Hawkins et al., 2012). The diversity of activities, building types and ages aggregated under a single owner presents opportunity for the integration of multiple energy vectors like heat, power, electric vehicle charging etc. under a smart-energy campus system. This approach mirrors city-scale smart energy systems integration. (Guerrieri et al., 2019). Implementing intelligence to balance and optimise the system operation, communicate with the grid, enhance user experience, health and wellbeing (Kourgiozou et al., 2021). Smart energy campus transition pathways can encompass buildings, renewable energy systems (RES), distributed energy resources (DER) for multiple energy vectors and transport interventions in a systematic and holistic approach.

For a holistic approach to smart energy integration, university campus decision-makers would require a robust framework to assess transition scenarios. Characterisation and energy profiling are necessary to establish the baseline conditions. Urban energy modelling has been implemented to characterise stocks, evaluate energy efficiency, and district energy network design. As a method it can rely on less detailed top-down approaches using benchmarks, statistical archetype models or mathematical modelling. On the other hand, bottom-up simulation approaches are utilised for building energy performance modelling, evaluation of smart building interventions and renewable energy integration at the building scale. These require an in-depth knowledge of the building geometry, thermal envelope, zoning, occupancy, and systems information. Microclimate information and surrounding geospatial building context are also needed for an accurate representation of the building physics influencing the building's energy performance (Willmann et al., 2019).

The novelty of this research is that it aims to provide stakeholders with a method to use an automatic method to develop building models for stocks. Through the models they can evaluate and quantify different scenarios by integrating energy vectors, modelling scales and data granularities. The proposed decision-making framework is value-based and evidence-based as it encompasses stakeholder participation in the framework's decision hierarchy. It also implements the smart-readiness indicator (SRI) assessment method (European

Commission, 2022) by adapting it to the campus scale and uses the stock model to evaluate the impact of the SRI's smart-ready interventions. As the research is in progress, this paper focuses on this modelling approach and specifically on the method of developing a campus building stock model that can examine system interactions and is adaptable to different levels of data granularity for developing and verifying models. For that, the below objectives were fulfilled:

- To develop automated building-by-building stock models in EnergyPlus that are generated using an automated modelling method.
- To calibrate the automatically developed models by comparing against operational energy data and use hourly calibrated building energy models to understand modelling error and subsequently improve performance.
- To understand the potential opportunities and limitations of the building-by-building campus model for evaluating smart-energy transition pathways.

The modelling method, within a smart energy transition decision-making framework, will be transformational in the way university campus stakeholders can holistically evidence decision-making that is otherwise resource-intensive and fragmented.

Methodology

The methodology for developing the campus model aims to tap into data readily available and the DEC database so that an understanding of campuses can be established with minimal data requirements. Additionally, further data layers can be inputted to the model to fine-tune based on availability and the analysis requirements. For the model development there are the major steps followed. Step 1: Use a case-study method as a reference system for data collection and analysis for the evidence-base development; Step 2: Develop an automatic building-by-building campus stock model creation process by building on existing stock modelling methods; Step 3: Use campus monthly in-use energy and calibrated building energy models for the calibration and fine-tuning of the campus simulation models.

Case study

The two main data sources for the reference university campus were the university's registry with the names, addresses and floor areas and secondly DEC certificates. The studied urban university campus comprises 216 buildings spread around a large area in London. 30 of those buildings were excluded from the study as they involved hospital and clinic activities. The building construction typologies range from Victorian terrace conversions to modern multi-tenant office buildings with seven main use types matching university building benchmarking typologies (CIBSE, 2020). These include labs (engineering, medical and chemistry), libraries, teaching, administration, and residential. 146 are available on the university's main monitoring platform and hold main utility metered data. For comparison and demonstration of the model's limitations, a recently retrofitted engineering building is presented. The building has undergone post-occupancy evaluation and an hourly calibrated dynamic thermal model is available.

Building 1 – Engineering workshop building (Lab engineering typology): A recent major retrofit (2016) of an existing building to upgrade the performance and add floor space for a total of 8887m^2 gross floor area (GFA). The building is connected to a central campus heating network, has low-carbon design elements like a ground heat exchanger, mixed-mode mechanical ventilation with heat recovery, low energy lighting and occupancy detection.

Automated campus building stock model

The model development builds upon established stock modelling methods to create an automated workflow that utilises mostly publicly available building data. This ensures it is replicable at scale and can flexibly integrate different data granularities. Additionally, different types of campuses and stocks can be modelled using this method.

Figure 1, describes how existing methods were adapted to develop a building-by-building university campus stock model. This is organised in three stages: a) the input, b) the processes, and c) the output. References to these stages are added in the corresponding methodology sub-sections in parentheses. Starting with the list of buildings to be modelled (a.1), energy modelling information is retrieved from the 3DStock method (Steadman et al., 2020) which provides a database for the UK non-domestic building stock (b.1). 3DStock, mostly from public sources, links premises to their Unique Property Reference Number (UPRN), footprint, external geometrical definition, building use, gas and electricity meters with high levels of matching success (Steadman et al., 2020). Importantly it also links to Energy Performance Certificates (EPC) and Display Energy Certificates (DEC) (c.1). In the case of qualifying higher education buildings, it also includes operational energy and building environmental system information.. The SimStock code is called (b.5) for developing the building models using the synthesised data from 3DStock (c.2). Among others, 3DStock has been used for the London Building Stock Model (LBSM) (Steadman et al., 2020) and both 3DStock and SimStock have been used for the Modelling Platform for Schools (MPS) (Schwartz et al., 2022). The final output of the method is the campus building stock model that comprises all the building-by-building energy models (c.3).

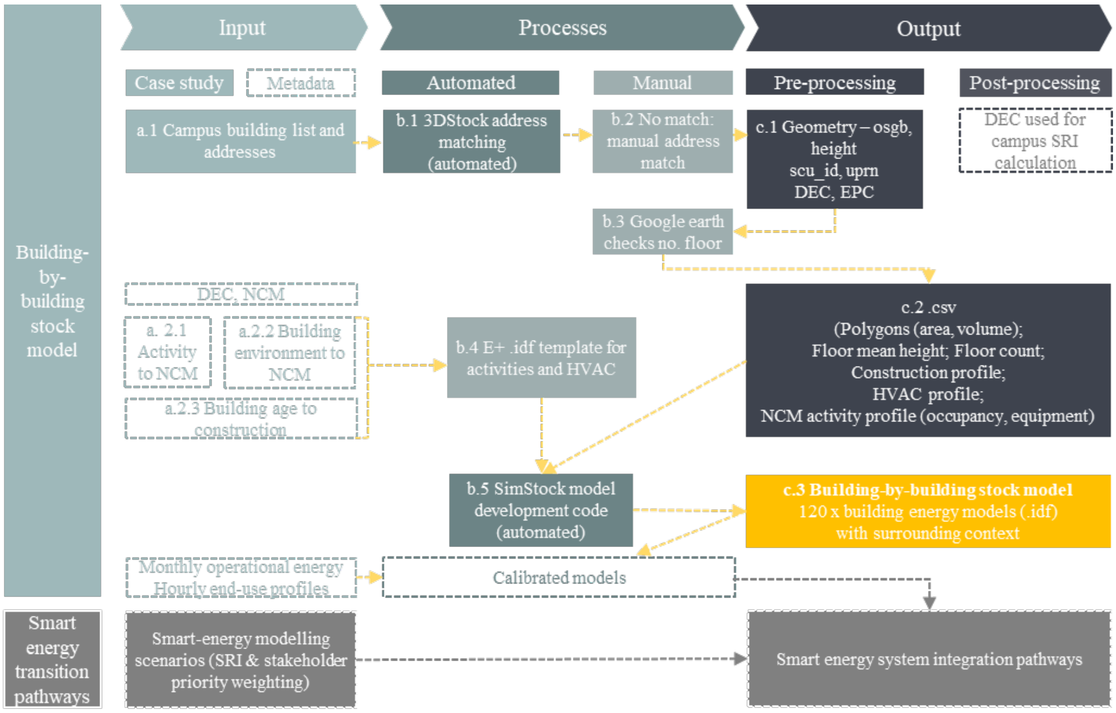

Figure 1: Building-by-building stock model development: diagram demonstrating inputs, processes, and outputs in line with overall framework. Note: Yellow arrows represent process steps for developing the campus model, grey represent processes relating to the smart energy pathway modelling beyond the scope of the paper.

Figure 1 also demonstrates the implementation of the stock model within the overall methodological framework (smart energy transition pathways).

Input

Five main categories of inputs were used to build the model: 1) building basic information, 2) premise / hereditament (VOA classification) / self-contained unit (SCU), 3) geometry, 4) activity, 5) metadata as in Table 1. The list of building names and addresses (a.1) was downloaded from the university campus's website for developing the campus-specific database through 3DStock. The method also combines data from a range of sources like the Ordnance Survey (OS), the Valuation Office Agency (VOA) and LiDar measurements to match geometry polygons to hereditaments (UARNs) and therefore SCU as described by (Steadman et al., 2020).

Table 1: Main model inputs and sources.

Input category	Input sub-category	Source
Building basic information	Building list, address	Campus website
	Building areas	3DStock; Campus monitoring platform
	Building ages	3DStock (DEC)
Self-contained unit (SCU)	SCU	3DStock (VOA)
Geometry	Polygons (3D points of building areas)	3DStock (OS & LiDar)
	Floor height, no. floors	3DStock (OS & LiDar), visual check on Google maps
Activity	Main activity	3DStock (VOA &DEC)
Metadata	Building envelope – window-to-wall ratio (wwr)	Based on previous research (Dong et al., 2020)
	Model building constructions (U-values)	3DStock (DEC), rdSAP2012 (BRE, 2012)
	Activity profiles (occupancy and people metabolic rates, equipment loads, illuminance levels)	3DStock (DEC), NCM
	HVAC system	3DStock (DEC) & NCM

Additionally, several metadata sources were used to assign further properties to the building energy models. Firstly, for typical construction thermal properties (a.2.3), the rdSAP methodology (BRE, 2012) was used as it provides typical U-value assumptions for different age bands, see Table 2. For the glazing ratio per façade a study that surveyed London Schools has been used as the source (Dong et al., 2020), see Table 3. Moreover, the National Calculation Methodology provides standard assumptions for activity (a.2.1) and HVAC profiles (a.2.2) for the calculation of EPC certificates. These standard profiles were used as input to the building models for each building usage category, see Table 4. Typical HVAC systems were selected including gas boilers, chillers and air-handling units to represent those building environments with standard system characteristics from NCM.

Table 2: Campus stock model thermal building element properties using rdSAP 2012 grouped by DEC age data.

DEC building age categories	rdSAP age bands	Campus stock model age bands	Wall U-values (W/m²K)	Roof U-values (W/m²K)	Floor U-values (W/m²K)	Glazing U-values (W/m²K)
Pre-world war I (Pre 1914)	A. Before 1900, B. 1900-1929	Pre 1914	1.7	2.3	1.5	4.8
Inter war (1918-1939)	B. 1900-1929, C. 1930-1949	1918-1939	1.7	2.3	1.5	4.8
Post-war regeneration and expansion (1945-1980)	C, D, E, F: 1930-1982	1945-1980	1.35	1.5	1.4	4.8
Modern (Post-1980)	G, H. I, J, K, L: 1983-2012	Post-1980	0.4	0.4	0.94	3.1

Table 3: Window-to-wall ratio per model age band (Schwartz et al., 2022).

Campus stock model age bands	Window-to-wall ratio
Pre 1914	33%
1918-1939	35%
1945-1980	38%
Post-1980	30%

Table 4: DEC building environment and campus model HVAC types.

DEC building environment categories	HVAC type
Heating and mechanical ventilation (Air conditioning)	HVAC 1: Heating, cooling, and mechanical ventilation system
Heating and natural ventilation (Air conditioning)	HVAC 2: Heating, cooling, and natural ventilation system
Heating and mechanical ventilation	HVAC 3: Heating and mechanical ventilation system
Heating and natural ventilation	HVAC 4: Heating system and natural ventilation

Processes & outputs

The process of developing the campus building models starts with matching the campus addressees to the 3DStock SCU database. From 216 building names, 172 were automatically matched to a SCU_id (b.1). Further 10 buildings were matched manually using the full address instead of just the postcode. In total 120 buildings were modelled and included in the study, by streamlining names referring to parts of buildings that for the purposes of this modelling could be integrated to one and 30 buildings excluded from the study as hospitals and clinics were beyond the research scope (b.2, b.3).

The matched campus buildings and the corresponding 3DStock SCU_ids with the data associated to them are extracted to a .csv file for input into SimStock (c.2). The data includes the polygons corresponding to each building, the mean object height that represents the mean height per floor, the activity, age and building environment. Additionally, SimStock requires a definition of all the modelling parameters in .idf format (b.4). The.csv and .idf template files are called in the SimStock code to create the models (c.3). These include thermal zones defined per floor and the surrounding buildings acting as shading elements.

Stock model calibration

For the calibration of the models, the guidelines from CIBSE TM63 *Operational performance: Building Performance modelling* (Jain et al., 2020) have been used. The guide addresses single-building measurement and verification practices; however, it was considered that the method can be tailored for the purposes of the stock model as outlined in Figure 2. The first calibration step is to replace the Typical Meteorological Year (TMY) weather file with a weather file that is specific to the location and the calibration year. Monthly operational energy data were used to calibrate the baseline. For that, the guidance suggests that the NMBE (normalised mean bias error) which represents the average error between the measured and simulated values normalised by the mean of the measured values should be within ±5% and the Cv(RMSE) (coefficient of variation of the root square mean error) which is derived by normalising the root mean square error by the mean of measured values should be below 15%. Monthly main utility usage was used as the calibration interval. Monthly totals are considered to provide sufficient resolution for establishing the campus's energy demands and evaluate energy efficiency interventions. Importantly, seasonal usage and generation patterns can be derived to balance demand and supply under smart energy scenarios including energy storage and EV capacity planning. A limitation of the model is that it can require hourly calibration where hourly or half-hourly resolution is required, for example for flexibility scenarios, forecasting and technical system operation that respond to grid signals

The model can be used to demonstrate the comparative impact of different interventions based on the assumed building specifications and the subsequent baseline conditions estimated for the campus. In the next steps of the research, typical hourly end-use consumption profiles will be developed to further fine-tune each typology for the experience-based part of the method and compare with actual building performance. Finally, model energy predictions and the "Building 1" actual performance data arecompared to benchmarks to assess the potential discrepancies that could be attributed to the performance gap instead of modelling error.

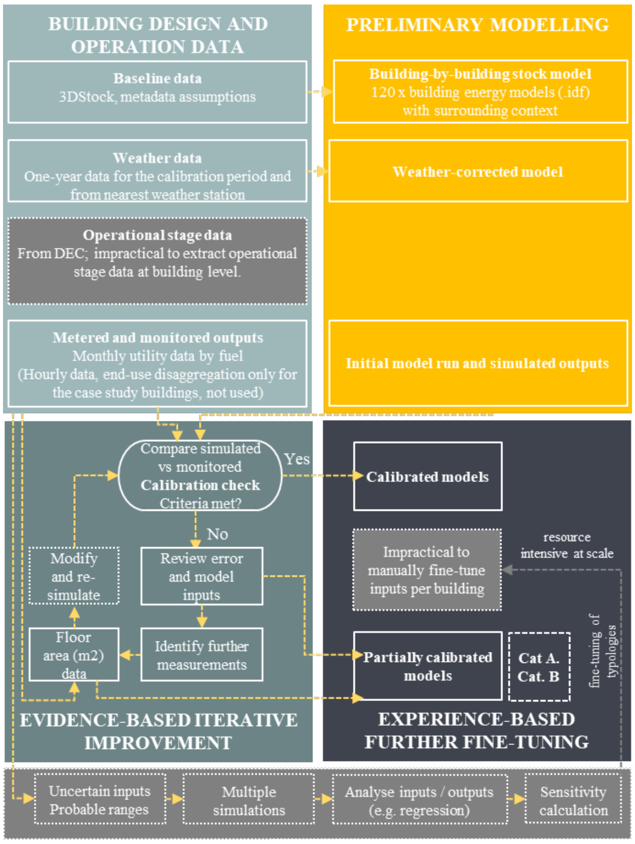

Figure 2: Calibration workflow adapted from CIBSE TM63 (Jain et al., 2020). *In grey, TM63 processes that were considered impractical at scale and altered.*

Results analysis & discussion

The paper results and discussion are organised in the categories presented in the Figure 2 workflow diagram.

Metering and operational data results

In total the campus's central monitoring platform holds 146 separate building entities that amounts to 454,642m^2 GFA. The campus has three categories of consumption meters: fuel and heat, electricity, and water. 35 buildings are missing space heating, and 18 buildings are missing electricity data for the selected year 2019. The non-empty meters are mostly manually updated, although automated meter readings (AMR) are available for some buildings. The distribution of meters per building was compared against the modelled number of floors per building in-lieu of other data. Figure 3, Figure 4 demonstrate a low-level of disaggregation available in the main monitoring platform. More than 50% of buildings have less than three utility meters connected to the monitoring platform, even though more than 50% of buildings have five to six floors. This suggests that utility level meters are mostly available at main incomer level and that disaggregation per floor is widely unavailable on the platform. Gap analysis was performed to the operational measured data using statistically valid techniques as described in (EVO, 2022). Table 5 demonstrates the yearly normalised energy consumption for the measured operational energy per fuel.

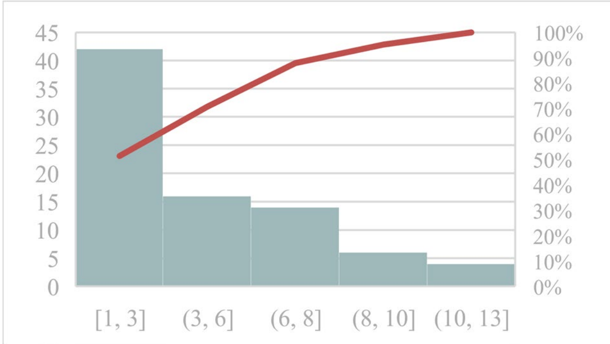

Figure 3: Number of total electrical and fuel and heat meters per building and cumulative frequency curve.

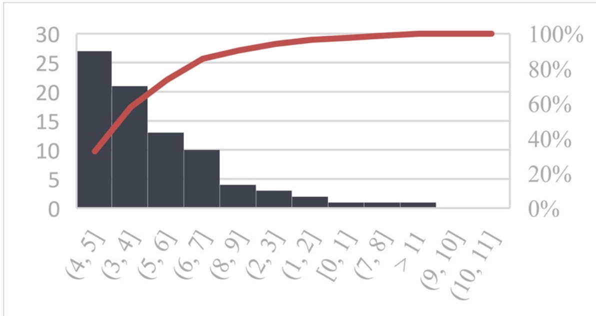

Figure 4: Number of modelled floors per building and cumulative frequency of floor numbers.

Simple linear regression analysis was performed using the 2019 monthly heating degree-days to estimate monthly, area normalised space heating consumption. For electricity, hot water and the 'gas other' category, normalised monthly averages were calculated instead to fill in the data gaps. The estimated missing data were filled via interpolation and are labelled as 'interpolated' in Table 5.

Table 5:Campus energy use intensity: Measured energy use presented for raw consumption data and estimated consumption to account for missing data and simulated energy

	Measured–raw (kWh/m2)	**Measured–interpolated (kWh/m2)**	**Simulated (kWh/m2) 2019 actual weather file**
Fuel and heat (Gas)	118.5	126.1	110.5
Electricity	187.4	204.3	123.9

Initial model development

The 120 models were simulated in EnergyPlus^{TM} using the TMY and 2019 actual weather data from the closest to the campus weather station (DesignBuilder, 2022). Monthly total energy results were obtained for the two main utility sources: electricity and gas facility. The comparison of results is illustrated in Table 5 in the columns labelled as 'simulated' and in Figure 5.

Campus model calibration

For the baseline model monthly data statistical checks, the following results were calculated as shown in Table 6.

The calculations for the campus's aggregated statistical checks were performed by aggregating the monthly energy consumption for all buildings.

Both criteria are not met for electricity at campus level, which showed higher error levels compared to heating energy (gas). The heating energy criterion for the Cv(RMSE) exceed the limit of 15% by 27.2% and complies with the NMBE criterion at -0.51%. This signifies that the campus's space heating energy consumption is better represented via the automated model development method and subsequently the inputs relating to space heating like the building fabric specification and heating system appear to be more typical of the actual conditions compared to the electricity consumption modelling prediction that is based on the NCM inputs and is largely dependent on the building floor area. Furthermore, the guideline addresses single building measurement and verification methods and therefore the building level calculations are also presented in Figure 5 for comparison.

Table 6: Initial campus aggregated building-by-building model statistical compliance checks using the (Jain et al., 2020) *compliance targets for whole-building calibrated simulations.*

	All buildings		Category A	
	Fuel and heat (gas)	**Electricity**	**Fuel and heat (gas)**	**Electricity**
Cv(RMSE campus, %	42.2	35.1	23.0	36.8
NMBE campus, %	-0.1	0.6	19.6	55.3
Percentage error, campus monthly average	37.9	38.3	25.5	35.5
Percentage error, campus annual	-6.9	50.3	16.4	35.6

On average, the Cv(RMSE) coefficient for heating energy was calculated at around 94% across all buildings and for electricity at 80%. The NMBE value for heating energy was on average around -24% and -21% for electricity.

Figure 6, demonstrates the percentage error between the actual and simulated consumption totals per month. For electricity it is observed that there is on average a 39% underestimation of electricity usage in the model that needs to be rectified. For space heating, it is observed however that the discrepancy is mostly happening in the non-winter months (March-October) with the highest discrepancy observed in the summer months. A reason for this can be attributed to the performance gap as heating systems by design are expected to operate less during the summer months. In the model this is reflected by the NCM HVAC operation profiles and heating setpoint and setback temperatures that will be investigated in the next research steps. Additionally, the current model assumes that all technical systems follow the occupancy profiles to operate. Higher operational energy use can potentially be attributed to longer system operation times. Further testing, as part of the smart energy scenario modelling will investigate extended usage profiles.

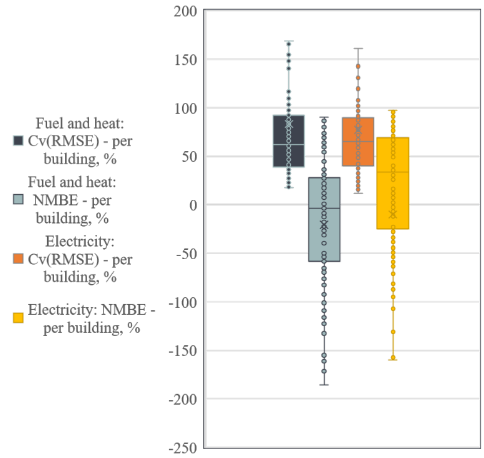

Figure 5: Box and whisker plot of the statistical checks Cv(RMSE) and NMBE calculated per building for the initial model. The outliers were excluded from the plot.

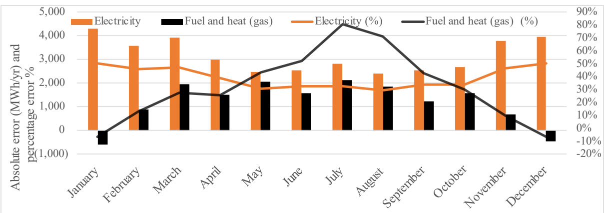

Figure 6: Monthly percentage error between actual and modelled electricity and fuel consumption. Total electricity represents the aggregated electrical consumption at utility level.

Further to the statistical tests, a traffic-light evaluation system was developed to assess the geometry generation quality of the method. This involved assessing the match of the model footprint to the actual footprint per building mathematically and visually on Google maps and via the DesignBuilder Software.. For the scale of the model, the total of the modelled buildings was visually checked to verify the match of geometry and areas. For larger stocks, a sample of buildings could be used instead. The campus models were split into five categories based on the matching between the actual and automatically generated model floor areas as in Table 7. For this campus, 63% of the buildings modelled were considered a good match to the actual buildings and can be used as the baseline for further fine-tuning and analysis. For 9% of them, pro-rating energy consumption by the number of floors is considered an appropriate measure to adjust to actual conditions. For 28% of the buildings further checks could potentially demonstrate address and SCU_id mismatches as university building naming does not always match the building address naming. Table 6 shows that the statistical calibration checks for the category A subset marked an improvement in accuracy with regards to space heating as all checks (with the exception of NBME that increased by 19.7%) were closer to the limiting values. For electricity, however, the checks remained similar to the campus aggregated calculations. A potential reason could be the underestimation of electricity in the model, as described earlier. Better geometry representation, however, can result in more accurate space heating predictions that is inherently linked to the building form.

Table 7: Stock model automatically generated geometry evaluation represented via traffic light system

Category	Geometry match
A (52%)	**Good**, good total floor area match. Likely to represent actual geometry to a sufficient level.
B (11%)	**Acceptable**, acceptable floor area discrepancy but likely to have a good footprint match. Small geometry irregularity is possible across floors.
C (9%)	**Medium**, actual floor area matches the model footprint. Include in further analysis, adjustment to the final energy consumption required.
D (28%)	**Low**, big discrepancy in floor areas with smaller discrepancy in footprints. Unlikely that the automatic match is representative. Possibly error in SCU_id and polygon match. Campus building naming mismatch to address names that can be verified manually.
E (11%)	**Poor**, Missing data (e.g. SCU_id not found) or large area discrepancy.

Model comparisons – post-occupancy and modelled performance

Finally, model comparisons were undertaken between the automated building-by-building method and the actual performance for Building 1. It was observed that the modelled energy performance largely exceeded that of the actual building as derived from a post-occupancy evaluation study. However, the building has recently undergone building energy retrofit which was not captured by the earlier version of the DEC database used for the model development and classed the building under the 1945-1980 age category. Based on the pre-refurbishment DEC, the building consumed 179 kWh/m^2/h which was verified with metered data and more than 600 kWh/m^2/h for heat that could not be verified. However, based on the CIBSE benchmarking tool, typical practice fossil fuel consumption per year is 131 kWh/m^2/year for engineering type buildings while CIBSE TM46 states 240 kWh/m^2/year. Utility totals and end-use disaggregation is illustrated in Figure 7. The simulated, the metered and the Building Energy Efficiency Survey (BEES) energy intensities are compared for major end-uses like space heating and hot water, lighting, cooling and small power and auxiliary energy. The largest discrepancy is shown for lighting and cooling energy, followed by space heating where the automated method has over predicted consumption. The building selected for comparison demonstrates the importance of the building age as a parameter in the model development.

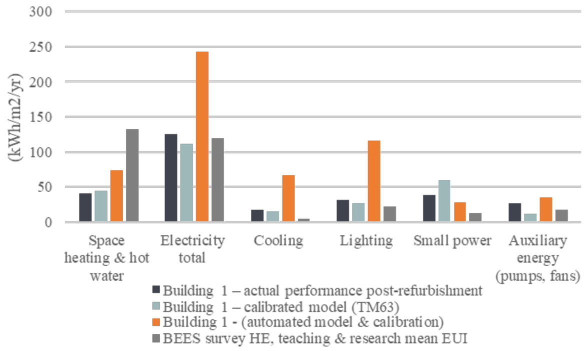

Figure 7: Comparison of annual energy (kWh/m2/yr) between actual (post-refurbishment), detailed model with TM63 calibration and automatic model calibration. Total electricity represents the aggregated electrical consumption at utility level.

Limitations and further work

To make the most of the building-by-building models developed as part of this research it is necessary to understand that its main capabilities lie in diagnosing energy demand and evaluating the comparative impact of different energy efficiency and smart-ready interventions for decarbonisation and smart energy integration pathways. The SRI offers different levels of functionality that are progressively more responsive to short-term system variation. Through ongoing work the limitations of the campus model will be established. This includes the level of smart-ready functionality improvements that can be addressed via the automatically calibrated models and where more detailed hourly calibration is required for accurate modelling of such interventions. Even so, the building-by-building model can evaluate smart-energy interventions based on the assumed characteristics assigned to the model. Therefore, it provides comparative conclusions for the effectiveness of decarbonisation and smart-ready services and the overall impact on the SRI calculations for the campus. As part of the wider research aims, the models developed will be utilised for:

- Scenario modelling for decarbonisation and smart-energy integration. Scenarios are based on the EPBD SRI assessment carried out and stakeholder multi-criteria decision-analysis. The method of this research also aims to apply advanced simulation methods (Energy Management Systems (EMS)) to introduce further smart energy system nodes and services to the stock model.
- Finally, a user-interface for spatial representation and pathway visulisation could be developed as part of the stakeholder engagement of the research and contribution to the industry.

Conclusion

This paper presents the approach towards developing a modelling framework for a university campus stock building-by-building model. The aim is to overcome the barriers of developing detailed dynamic thermal models at scale or the oversimplification that can be associated with archetype-based approaches. The proposed framework aims to leverage the untapped decarbonisation potential of higher education campuses by integrating the three largest carbon-emitting sectors – buildings, transport, and the power sector into a multi-vector energy approach.

The paper discusses the steps taken to build the university campus's building-by-building energy models. Additionally, the calibration and model geometry evaluation results are presented. Calibration was based on monthly metered energy data derived from the campuses main monitoring platform. Statistical checks appropriate for whole-building energy model calibration were used. The calculation was used to assess campus compliance by aggregating the monthly consumption for all buildings and also looked at the per building calculations on an average basis which was considered less conclusive. To evaluate geometry,building and model floor areas and footprints were used. Verification was undertaken through visual inspection on Google Earth. Although the campus statistical checks were in exceedance of the building level targets, it is considered that an accurate geometrical representation of the buildings is a more appropriate measure of accuracy at scale. Uncertainty in the inputs can therefore be addressed by scenario modelling and comparisons between the model predictions and more granular actual data per typology. For the geometry match categories A and B, the models can be considered partially already. The case study campus,based on main utility meters and heating degree day linear regression, in 2019 the campus's energy use intensity for space heating was 125 kWh/m^2/year compated to the 112-219 kWh/m^2 CIBSE benchmark range for different types of higher education buildings (CIBSE, 2020). Electricity was estimated at 187 kWh/m^2/year that was on average 38% higher that the actual electricity usage. To conclude, 63% of the automatically developed models were considered a good match to the actual buildings in terms of geometry and can be used as the baseline for further analysis.

Acknowledgement

This work was supported by the UCL and Engineering Physical Sciences Research Council (EPSRC) DTP CASE, sponsored by EPSRC and Buro Happold Limited as the industrial sponsor.

References

BRE. (2012). *Appendix S: Reduced Data SAP for existing dwellings*.

CIBSE. (2020). *CIBSE - Digital Tools - The Energy Benchmarking Tool (Beta Version)*. https://www.cibse.org/knowledge/digital-tools/the-energy-benchmarking-tool-(beta-version)

DesignBuilder. (2022). *Weather and Climate Data for Building Performance Simulation*. https://designbuilder.co.uk/cahelp/Content/About.htm

Dong, J., Schwartz, Y., Korolija, I., Mavrogianni, A., & Mumovic, D. (2020). London School Building Stock Model for Cognitive Performance Assessment. *Proceedings from BSO-V 2020 5th Building Simulation and Optimisation Virtual Conference*.

European Commission. (2022). *SRI implementation tools*. https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/smart-readiness-indicator/sri-implementation-tools_en

Guerrieri, M., La Gennusa, M., Peri, G., Rizzo, G., Scaccianoce, G., Gennusa, M. La, Peri, G., Rizzo, G., & Scaccianoce, G. (2019). University campuses as small-scale models of cities: Quantitative assessment of a low carbon transition path. *Renewable and Sustainable Energy Reviews*, *113*, 109263. https://doi.org/https://doi.org/10.1016/j.rser.2019.109263

Hawkins, D., Hong, S. M., Raslan, R., Mumovic, D., & Hanna, S. (2012). Determinants of energy use in UK higher education buildings using statistical and artificial neural network methods. *International Journal of Sustainable Built Environment*, *1*(1), 50–63. https://doi.org/10.1016/j.ijsbe.2012.05.002

Jain, N., Burman, E., Mumovic, D., & Davies, M. (2020). *TM63: Operational performance: Building performance modelling and calibration for evaluation of energy in-use*. https://www.cibse.org/knowledge/knowledge-items/detail?id=a0q3Y00000I0imxQAB

Kourgiozou, V., Commin, A., Dowson, M., Rovas, D., & Mumovic, D. (2021). Scalable pathways to net zero carbon in the UK higher education sector: A systematic review of smart energy systems in university campuses. *Renewable and Sustainable Energy Reviews*, *147*, 111234. https://doi.org/10.1016/j.rser.2021.111234

Schwartz, Y., Korolija, I., Godoy-Shimizu, D., Hong, S. M., Dong, J., Grassie, D., Mavrogianni, A., & Mumovic, D. (2022). Modelling platform for schools (MPS): The development of an automated One-By-One framework for the generation of dynamic thermal simulation models of schools. *Energy and Buildings*, *254*, 111566. https://doi.org/10.1016/j.enbuild.2021.111566

Steadman, P., Evans, S., Liddiard, R., Godoy-Shimizu, D., Ruyssevelt, P., & Humphrey, D. (2020). Building stock energy modelling in the UK: the 3DStock method and the London Building Stock Model. *Buildings and Cities*, *1*(1), 100–119. https://doi.org/10.5334/bc.52

Willmann, A., Katscher, L., Leiser, T., & Voelker, C. (2019). A Comparison of Bottom-up and Top-down Modelling Approaches in Urban Energy Simulation for the Assessment of City District Data Models. *Proc. from BS2019 16th International Conferene and Exhibition*, 3303–3310. https://doi.org/10.26868/25222708.2019.210424