DEVELOPING HIGH-RESOLUTION BOTTOM-UP BUILDING STOCK MODELS USING AERIAL IMAGES AND DYNAMIC SIMULATION

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ABSTRACT

This project aims at improve the methods currently used for the development of high-resolution (individual building level) urban models for the evaluation of energy related to space heating and cooling. This is achieved by using a dynamic simulation as calculation engine and models primarily based on publicly available satellite/aerial images. Buildings are modelled using ESP-r and represented by a single zone for a typical floor; results are multiplied by the number of floors to estimate the total energy consumption. Building geometry, fenestration and external absorptivity are derived from aerial images (no automation of this task is addressed in the paper). Results are validated using smart meter data covering 3 years of gas consumption in 8 buildings in Glasgow, Scotland, with a normalized root mean square error (NRMSE) of 28% for heating energy consumption. Future work focus on means to obtain envelope properties that can be more easily scaled up to urban level, as the current state of the art in the field relies on data from individual building surveys, which is rarely available.

INTRODUCTION

Proper understanding on the characteristics and performance of buildings within a city or country (i.e. the building stock of that region) is essential for planning purposes (Kohler et al. 2009; Coffey et al. 2009; Mata et al. 2013). This sort of work is usually conducted separately for residential (Dascalaki et al. 2016; Loga et al. 2016) and commercial buildings (Gaglia et al. 2007; Coffey et al. 2009), as they have significant differences in their properties, as well as different performance requirements (Kohler et al. 2009). The knowledge connecting relevant building properties (e.g. geometry, building materials, and systems) and performance (e.g. energy consumption, water usage) is usually referred as a building stock model. The development of building stock models poses major challenges, as they are usually required to describe thousands of buildings which have unique features and performance (Kavgic et al. 2010; Mata et al. 2014).

Building stock models are an important tool for energy policy (Csoknyai et al. 2016; Tommerup & Svendsen 2006; Loga et al. 2016). This sort of stock models have been developed for a number of regions (Uihlein & Eder 2010; European Parliament 2012; Coffey et al. 2009), using different approaches. The main approaches used are top-down and bottom-up (Dai et al. 2016; Kavgic et al. 2010). In both cases, the accuracy of a given stock model is related to the level and nature of simplifications adopted in its development. The top-down modelling approach works at an aggregated level, typically aimed at fitting the results of an arbitrary mathematical model (e.g. linear regression, principal component analysis, artificial neural networks) to historical time-series of national energy consumption or CO_2 emissions data. Such models tend to be used to investigate the inter-relationships between the energy sector and the economy at large, and could be broadly categorised as econometric top-down models (Johnston 2003). Bottom-up methods are built up from data on a hierarchy of disaggregated components that are then combined according to some estimate for their individual impact on energy usage. Often these models are seen as a way to identify the most cost-effective options to achieve given carbon reduction targets based on the best available technologies and processes. The possibility of assessing performance in alternative scenarios makes bottom-up models attractive for energy policy development, and therefore these models have been widely used in the past. However, as bottom-up models work at a disaggregated level, they require extensive databases of empirical data to support the description of each component (Shorrock & Dunster 1997).

Historically, bottom-up models for building energy policy support are based on archetype buildings. The performance of the entire building stock is obtained by extrapolating the results of archetype buildings, based on the share of each archetype in the stock. Figure 1 exemplifies results obtained with this sort of approach, in this case the archetypes were used to estimate energy saving potential for a given policy in the entire USA housing stock. This approach is straightforward, as the whole stock can be represented by few buildings (Exner et al., 2015). Validation regarding aggregated energy consumption show good agreement between modelled and measured data (Wilson et al., 2017). In spite of these advantages, archetypes has severe limitations. Firstly, the definition of archetypes involves large simplifications, as each building in the stock has unique surroundings and often has unique geometry, building components, systems and operation. Secondly, the estimation of the share represented by archetype in the entire stock is cumbersome, as it requires matching each individual building to a given archetype. Thirdly, validation is only possible using aggregated data, which may mask discrepancies that mutually cancel each other. Such mutually cancelling effect may happen: a) on stock level (e.g. an archetype shows results below measured data while another shows results above, providing good fit when the overall results are compared to aggregated metered data) or b) on archetype level (e.g. overestimation in the air infiltration rate cancelling an underestimation of building fabric thermal transmittance given an overall good agreement between results calculated and measured data). As an alternative to the use of archetypes, there is a growing body of research focused on the development of high-resolution bottom-up models, which explicitly model each building in a given area of interest.

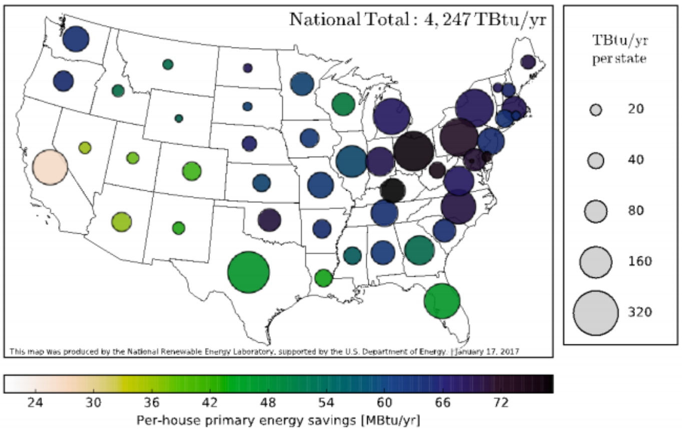

Figure 1: Example of aggregate and average primary energy savings based on stock model results bottom-up stock model using archetypes (Wilson et al., 2017)

An example of high-resolution bottom-up model is the SUNSHINE project which demonstrated the development of stock models from GIS data on building level as shown in Figure 2 (Bloem et al. 2015). This project was one of the pioneers in this field, and used simplified energy models to calculate energy performance certificates for the building stock (asset rating, not actual energy consumption). Another example of high-res bottom-up model is City Building Energy Saver (CityBES) which focuses on energy modelling and analysis of a city's building stock to support district or city-scale efficiency programs as shown in Figure 3 (Hong et al. 2016). CityBES relies on satellite images to derive building perimeter and adopts several assumptions to create energy simulation models for every building in the stock (in particular, floors are modelled as in a core and shell approach, with one thermal zone per facade). Several other initiatives in the same direction have been reported in the literature. The development of high-res bottom-up stock models has not been validated against metered data neither for CityBES nor SUNSHINE (Chen et al. 2017; Chen & Hong 2018; Bloem et al. 2015). Moreover, information on building facade (fenestration and absorptivity) were assumed based on typical data rather than modelled considering the particularities of each building.

Figure 2: Example of heating demand per building in the SUNSHINE project (Bloem et al. 2015)

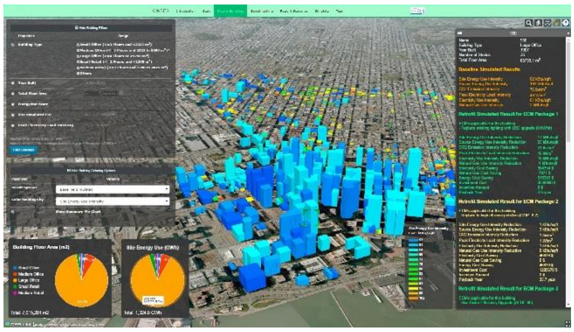

Figure 3: Screenshot of CityBES, showing colour-coded simulated site energy use intensity (Chen et al. 2017)

This paper describes a bottom-up method for high-resolution stock modelling based on aerial/satellite images and building energy simulation. The main innovative aspects of this work are: a) the use of aerial imaging to obtain information regarding building fenestration and solar absorptivity of facades, removing assumptions in this area adopted in previous works (Chen et al. 2017), b) the use of a single zone to model the entire floor which largely simplifies the modelling workflow, and c) the validation of results for 8 commercial buildings, based on 3 years of gas consumption data. The work described in this paper is not focused on the automation of the modelling process (heavily addressed by CityBES), on satellite/aerial image processing (also a field with extensive research already published e.g. Colomina et al., 2014 and Jin et al., 2005) and on frameworks for integration of simulation in the urban si (e.g. Remmen et al., 2018).

METHODOLOGY

The dynamic building simulation software ESP-r is used to model intermediate floors of a selection of University of Strathclyde buildings to evaluate whether dynamic modelling can achieve accurate results when compared to measured data. The simplest means of modelling a building is to approximate it as a single thermal zone. It is important to bear in mind that the purpose of building simulation is not to exactly represent the building physically but rather to provide a mathematical description of the factors that will affect final energy consumption. Buildings with two floors and less have been excluded from the study as they would be inaccurately simulated due to ground floor and roof properties.

The research addressed 8 buildings of the campus of the University of Strathclyde, Glasgow, Scotland. Buildings comprise a mix of office space, research and teaching areas. These buildings were built at several points of the last century, using a variety of technologies and were subject to different degrees of renovations and maintenance over the years. Detailed information about them can be found at Byres (2016).

Aerial images of each building (e.g. Google, 2016) were used to estimate the shape of the building and glazed area in each façade. Figure 4 shows this process for the building B, where the richness of images currently available can be observed. In particular, it is possible to see each individual façade of any building in areas with this sort of image resolution. The data was used to develop energy simulation models using ESP-r, where each building was represented by a single thermal zone for a typical floor. The energy consumption of the whole building was calculated by multiplying results by the number of floors (also obtained from the aerial images). Figure 5 shows the geometry of the 8 models used to represent the building addressed in this research, demonstrating the range of complexity that can be tackled using the proposed approach. Aerial images were also used to identify the type of finishing material of each façade. The absorptivity and emissivity data was imposed in the model based on the material identified.

The focus of this work is on the relation between data on images and the accuracy achieved in the energy calculations, not on image processing per se. Therefore, there was no attempt in this paper to automate such image processing and all data extraction was made by the direct analysis of images by the researchers. This allows the evaluation of the accuracy of the proposed approach, before expending considerable resources in the automation of the process.

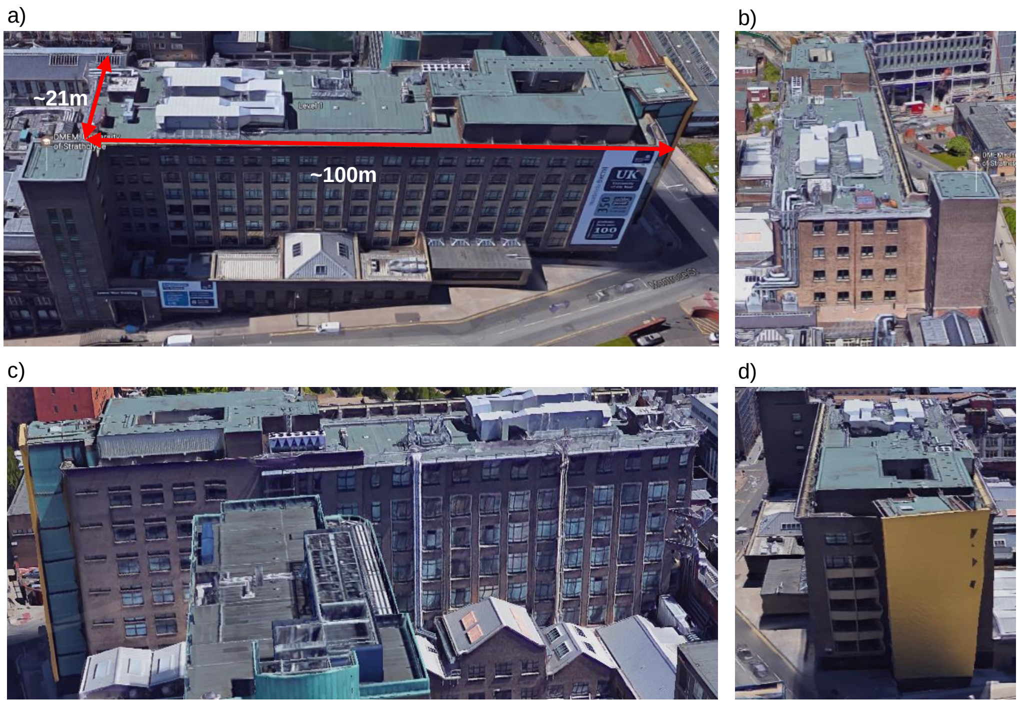

Figure 4: Aerial images of James Weir Building a) eastern façade b) south façade c) western façade d) north façade

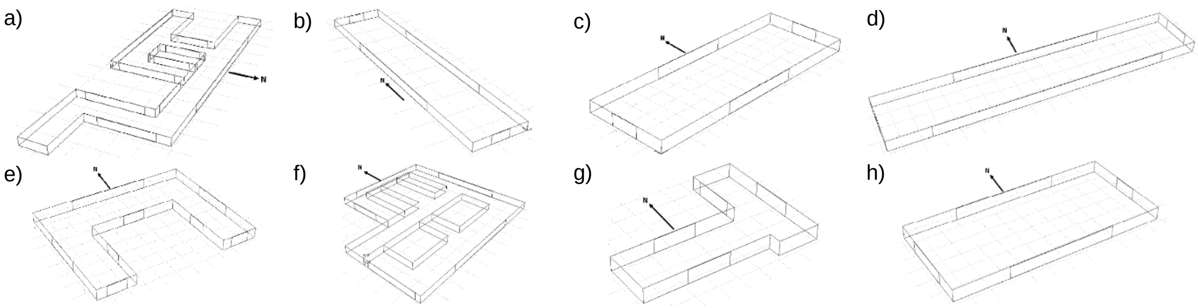

Figure 5: Wireframe view of each floor of University of Strathclyde buildings a) to h) as modelled as a single zone

Simulations were carried out using a typical weather file for Glasgow complied by CIBSE using historical data. Data from survey for the production of Energy Performance Certificates (EPC) was available for all buildings and it was used in the development of the simulation models. These data was combined, whenever necessary, by defaults and recommended values adopted in the calculation of EPC using the software SBEM which is the official calculation method for legal compliance in the UK (BRE / AECOM 2011). **Error! Reference source not found.** shows data available regarding U-values of walls for Building B. The thicknesses and properties for the external wall, ceiling/floor and window glazing was estimated based on this values and can be found in **Error! Reference source not found.**.

Table 1: Fabric information on building "B"

Fabric Element	U-value (W.m^{-2}.K^{-1})	Description
External Walls	1	Cavity brick to 1966, '75, '82 building regulations
Internal Walls	1.69	Plaster – block – plaster
Window Glazing	2	Double glazed metal frame to 2002 building regulations
External Doors	2.2	Entrance and personnel doors
Internal Ceiling/Floor	2.28	Ceiling and floor are equivalent. Ceiling tiles – slab - carpet

Table 2: Thermophysical properties for single zone construction of building "B"

Layer	Material	Thickness (cm)	Thermal Conductivity (W.m^{-2}.K^{-1})	Density (kg.m^{-3})	Specific Heat Capacity (J.kg^{-1}.K^{-1})	Absorptivity	Emissivity
External Wall, U-value = 0.95 W.m^{-2}.K^{-1}, Thickness = 46cm							
1	Brick	20	0.77	1700	1000	0.7	0.9
2	Air	2	0	0	0	N/A	N/A
3	Mineral fibre	2	0.04	105	1800	N/A	N/A
4	Medium weight concrete block	20	0.86	1970	840	N/A	N/A
5	Light plaster	2	0.16	600	1000	0.5	0.91
Ceiling/Floor, U-value = 2.29 W.m^{-2}.K^{-1}, Thickness = 20cm							
1	Ceiling tile (white gypboard)	2	0.19	950	840	0.85	0.9
2	Medium weight concrete slab	17	0.86	1970	840	N/A	N/A
3	Cellular rub underlay	0.5	0.1	400	1360	N/A	N/A
4	Carpet (synthetic)	0.5	0.06	186	1360	0.22	0.91
Window Glazing, U-value = 2.81 W.m^{-2}.K^{-1}, Thickness = 2.4cm							
1	Glass plate	0.6	0.76	2710	8373	0.05	0.83
2	Air	1.2	0	0	0	N/A	N/A
3	Glass plate	0.6	0.76	2710	8373	0.05	0.83

Casual gains are a significant source of heat in office and teaching spaces (Randall McMullan 2007). Radiation and convection from people, lighting and small power and IT equipment can act to significantly reduce the heating load and/or increase cooling requirements (Clarke 2001). The lighting and IT equipment exist to serve the needs of the occupants and so it was further assumed that their respective heat gains would be in keeping with the occupancy schedule which was set from 09:00 to 17:00 only on weekdays (Herrando et al. 2016; Menezes et al. 2012). According to the ASHRAE (American Society for Heating, Refrigerating and Air-conditioning Engineers) Fundamentals Handbook 2001, the average sensible heat gain for an adult working in an office is 70W and the latent is 60W (Ashrae Standard 2001). Lighting can take up a significant portion of a building's overall energy use, rising as high as 40% of the total in some office buildings (Jenkins & Newborough 2007). The casual gains from lighting was defined as in the information provided from EPC surveys. For the purpose of this project, it is assumed that every person has their own desktop computer with monitor and also that there are two laser printers present in each floor. Table 3 displays the values for computers, monitors and laser printers which is the average value when in operation and in energy saving mode. Some information on the systems was also provided from the survey which is displayed in Table 4 for Building B, as an example, based on data from EPC survey and EPC calculation assumptions. Temperature set-point is assumed to be 19^{o}C, as advised in the EPC calculation documentation.

Table 3: Casual heat gain from office equipment in building "B"

Equipment	Continuous Use Heat Gain (W)	Continuous Use Heat Gain Density (W.m^{-2})	Idle Use Heat Gain (W)	Idle Use Heat Gain Density (W.m^{-2})
Computer	65	0.031	25	0.012
Monitor	70	0.033	0	0
Printer	550	0.262	125	0.05

Table 4: Mechanical Systems information in building "B"

System	Function	System Area (m^2)	Weekday Start	Weekday End	Weekend/ Holiday Start	Weekend/ Holiday End
2	Heating	3384	06:00	18:00	Off	Off
15	Heating	1563	06:00	18:00	Off	Off
19	Local Ventilation and Heating	876	06:00	18:00	Off	Off

ESP-r allows for ventilation and infiltration of air to either be modelled as a mechanical system with periodic operation or an air mass flow can be imposed upon the building and/or zone. The average value of 4AC.hr^{-1} was chosen for the Building B model, which is equivalent 10L.s^{-1} per person and includes both mechanical and natural ventilation. Mechanical ventilation is only required when people are present and so the value of 4AC.hr^{-1} was only imposed for the hours between 09:00 - 17:00 on weekdays. The remaining times were all subject to natural infiltration which was set at 1AC.hr^{-1}, which is quoted as a typical air infiltration allowance by (CIBSE Guide 1999). The overall efficiency of the heating system was estimated in 85%.

Smart meter data regarding gas consumption for each building was adopted. Original data comprised both space heating and hot water, and the fraction of each component was estimated based on water energy consumption of the building. Measured data for 3 years was used to calculate the average energy consumption for each building, which was then compared to simulation results. Discrepancies between measured and simulation results were used to calculate the mean bias error (MBE), root-mean squared error (RMSE), and normalized root mean squared error (NRMSE). Simulation result for space heating were analysed in terms of kWh.m^{-2}.year^{-1}, where the area of the building was estimated based on the shape and number of floors.

RESULTS ANALYSIS AND DISCUSSION

Figure 6 shows a comparison between dynamic simulation results against measured data.

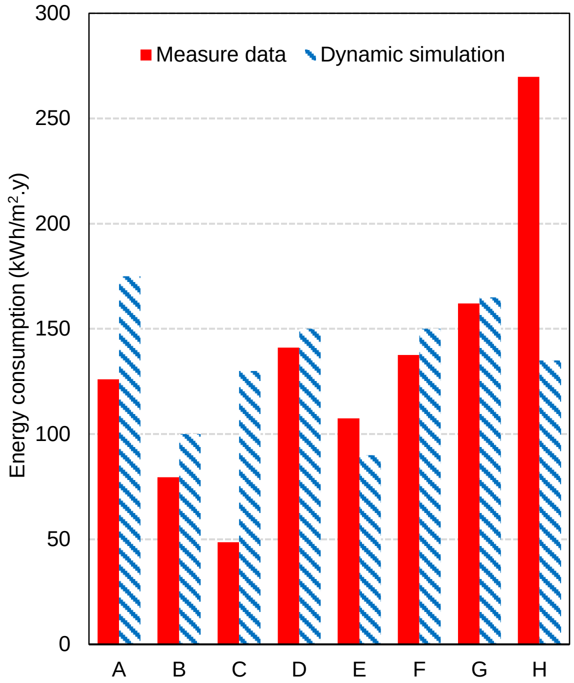

Figure 6: Comparison between dynamic simulation and actual energy consumption for University of Strathclyde buildings

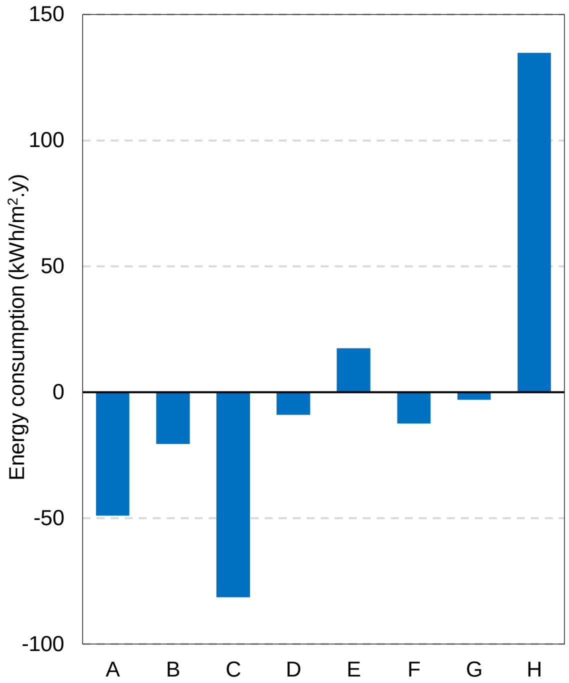

Figure 7: Error in energy consumption using dynamic simulation for University of Strathclyde buildings

In five buildings in Figure 6 (B, D, E, F, G), results show a remarkable agreement considering the level of simplification adopted in the modelling. Results for buildings A, C and H show larger discrepancies. Further investigation in these buildings revels that discrepancies in the results are consistent with particularities of these buildings that could not be captured by method adopted in the development of the models. These particularities can be classified in two groups: geometry and usage. In one of the cases, a large inner atrium is present in the building, however this atrium is not visible from the outside and was not modelled. These particularity regarding the geometry of the building led to the modelling of large office areas (with their corresponding energy consumption) when in fact there is a large void in the building interior. In the other two cases, particularities related to the level of internal gains and heating set-points/schedules was the cause for the lack of agreement between measurements and simulations. This shows the limitation of the proposed method regarding the modelling of buildings with:

a) a particularly intensive energy use (high internal gains and reduced energy for heating), b) high use of gas for processes (cooking, experiments), c) unusual heating schedules (e.g. 24-hours operation) and d) unusual heating set-points (higher set-points to offset low mean radiant temperature in buildings with high thermal mass or low insulation levels).

Considering the 8 buildings as the stock, the dynamic simulation gives a MBE of 3 kWh/m^{-2}y, i.e. simulations do not consistently under or overestimate the consumption, with deviation between measurements and simulations in both directions. The RMSE is 19 kWh.m^{-2}y (NRMSE of 28%.), which gives, assuming a normal distribution, a confidence interval of ± 38 kWh.m^{-2}y for the simulated results (confidence level of 95%,). This is a high value considering that the measured performance goes from 50 to 270 kWh.m^{-2}y, however it is clear from Figure 7 that in most cases the error is lower, and the size of the confidence interval is stretched due to the outliers discussed in the paragraph above.

CONCLUSIONS

The main objective of this study is to improve current practice for energy in building stock modelling by using dynamic simulation and compare it with actual meter readings. Based on the results presented in this paper the following conclusions can be drawn:

- Results indicate that a single-zone approach, and geometry derived from images/satellite images can provide reasonably accurate values for space heating energy consumption.
- These results support the adoption of bottom-up high-resolution modelling, by validating this approach with long-term monitored data for 8 commercial buildings. Predictions have a confidence interval of ± 38 kWh.m^{-2}y for space heating energy consumption.

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