Modelling Domestic Heat Electrification

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Abstract

This paper presents a spatially referenced energy modelling framework of the domestic building stock at Low-Voltage (LV) electrical sub-station (i.e. Ridgeway New, Newcastle upon Tyne) spatial scale for area-based heat electrification project delivery. The framework brings together public open sources of data to generate hourly energy consumption (i.e. heat fuel and electricity) for spatially referenced individual buildings. The simulation model has been validated against UK Government datasets and the results are presented for the LV-area. Our results show that peak household energy demands (i.e. peak hourly ratios) are significantly higher than expected. In our discussion, we comment on the results, validation and model input limitations whilst we outlined future work.

Introduction

The United Kingdom's (UK) government ratified the Paris Agreement within the United Nations Framework Convention on Climate Change. This agreement implied pledging to work alongside other developed nations to achieve net-zero greenhouse gas emissions by 2050 (as per the 2019's agreement update). Accounting for about a fifth of all carbon dioxide emissions and a third of the UK's energy demand (National Statistics, 2020), the existing housing stock (≈ 29 million homes) is unarguably a key area for decarbonization, and low-carbon housing is the way forward. As the vast majority of the homes (≈ 80%) that will be occupied in 2050 have already been built (UKGBC, 2020), retrofitting existing stocks represents a larger opportunity for delivering low-carbon houses.

Domestic heat electrification has been identified as potential decarbonation pathway in which low carbon, decentralised generation, smart micro-grids, energy storages and electric vehicles technologies are envisaged to be mainstream (BEAMA, 2017). However, such holistic implementations will require developing a flexible and optimised energy network to cope with shifts in supply and demand as opposed to solely focusing on buildings long-term consumption. In particular, there is a need to explore solutions for buildings at the meso-level, a level of area analysis that falls between micro-level (Individual Buildings) and macro-level (City/ District) (Harrison, 2013) (van den Dobbelsteen, Broersma, & Stremke, 2012).

This research seeks to contribute to this growing area of research and highlights a strong need to develop a comprehensive energy-modelling framework to scrutinise the current building stock and assess its potential for a holistic heat electrification. The scale of study is set at the LV substation level; it is a scale large enough to identify patterns of energy consumption and supply beyond the boundaries of the single building, but small enough to address concrete solutions (Calderon et al. 2019). The central thesis of this work revolves around how to integrate smart electrically driven domestic heating in a data-driven local area-based energy planning approach, and what defines an appropriate analytical energy-modelling framework to do so?

This paper presents a spatially referenced energy modelling framework of the domestic building stock of a LV electrical sub-station (i.e. Ridgeway New) in Newcastle upon Tyne for area-based heat electrification project delivery. The framework brings together several public open sources of data to generate hourly energy consumption (i.e. heat fuel and electricity) for spatially referenced individual buildings. In this article, we first review current modelling practice to contextualise the simulation framework. The developed simulation framework (Domestic Energy Model at LV - DEM-LV-) is then presented. The results show the model validation against UK Government datasets. In the discussion section, we elaborate the challenges faced when developing this type of models and future areas of work.

Current Practice

Energy Modelling Approaches

Jebaraja & Iniyan (2006) has established, there is a vast diversity of models and software tools available in the area of urban energy systems. Some of it includes energy planning models, energy supply-demand models, forecasting models (commercial energy models, renewable energy models), and optimisation models. While the focus of the proposed research is to create a comprehensive energy supply and demand planning model, other types of energy models can be integrated while adding to the data input or adding to the resolution of the model (Swan & Ugursal, 2009) (Krstić & Teni, 2017).

Overview of selected energy models

General excellent comprehensive and systematic reviews on modelling and simulation of buildings energy systems such as (Harish & Kumar, 2016) (Hall & Buckley, 2016) have been already undertaken. However, there are significantly fewer modelling tools which are designed to produce accurate energy simulation results at high spatial and temporal resolutions needed for this study (i.e. at LV scale and hourly). Figure 2 evaluates previous energy models in order to identify their current technical shortcomings and in which directions they should be further improved to pave the path towards residential heat electrification (CitySim (Robinson, et al., 2009); Simstadt (Nouvel, et al., 2015); UBEM (Reinhart and Davila, 2016); CityBES (Hong, Chen, Lee, & Piette, 2016); CEA (Fonseca, Nguyen, Schlueter, & Marechal, 2016)).

In previous research, the focus was on critical aspects related to urban energy systems design on a wide scale while a comprehensive domestic heat electrification model requires a smaller area of study. Taylor, et al. (2013) reported that at a small scale, a higher level of details is required. This could be translated by a high level of individual urban buildings' data input and by a more focused thermal zone analysis. While much work simulated urban buildings as single thermal zones (Nouvel, et al., 2015) (Fonseca, Nguyen, Schlueter, & Marechal, 2016), few are the ones that achieved urban buildings simulation as multi-thermal zones (Robinson, et al., 2009). Again, simulating several thermal zones rely on the abundance of accessible data. A multi-thermal zone analysis means the division of urban buildings per floors, or even more, per rooms. In a comprehensive study of the level of details required by an urban energy model, Taylor, et al. (2013) found that adding internal partitions has a significant impact on the accuracy of the model. The authors argued that possible reasons are greater thermal mass due to more internal walls, or difference in the utilisation of solar gains. Furthermore, a higher level of details means a higher simulation time-step resolution. Ultimately, hourly or even half-hourly simulation results would be beneficial to model the spatiotemporal energy pattern within local areas. Given all that has been mentioned so far, one may suppose that a satisfactory domestic heat electrification model should be situated as following within the existing modelling approaches. Of the reviewed models, only CEA model has been designed with a sufficiently high spatial resolution for the purpose of our study (i.e. micro-neighbourhood level). However, the CEA tool relies on archetypes (Fonseca, Nguyen, Schlueter, & Marechal, 2016) for building characterisation as opposed to uniquely and spatially defined (i.e. UPRN) buildings. Similarly, assigning data at individual urban building level is either not clearly specified or relies mainly on disaggregation assumptions (Robinson, et al., 2009) (Hong, Chen, Lee, & Piette, 2016).

Simulation Framework

In this section, the developed spatially and uniquely referenced (i.e. UPRN) domestic building energy modelling framework and the use data sources are presented. The presented simulation model is able to generate hourly energy consumption (i.e. heat fuel and electricity) for spatially referenced individual buildings. The simulation has been developed following Reinhart et al.'s (Davila, Reinhart, & Bemis, 2016) approach and implemented in Rhino Grasshopper. Geometrical and non-geometrical individual building level data as well as weather data are fed into Energy Plus so as to produce hourly heat fuel and electricity consumption profiles for individual buildings (see figure 1). In this paper, we use Ridgeway (New) as our case study area. Figure 4 shows one of the identified areas: Ridgeway (New). In this figure (see Figure 4), the light colour dots represent individual houses (i.e. 228 in total) associated to the LV substation (i.e. the electric tower icon).

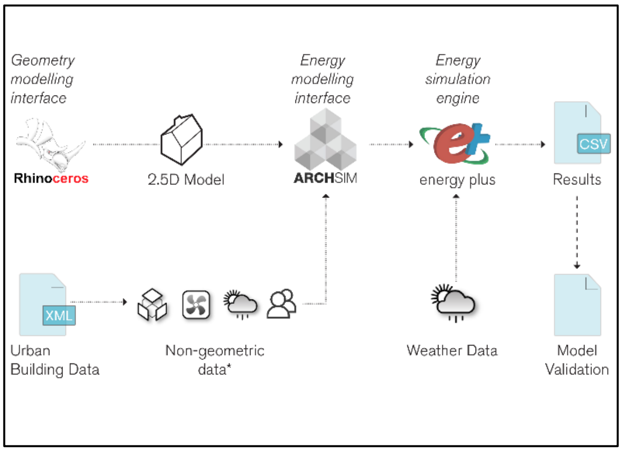

Figure 1: Simulation framework overview

The following analytical framework (see Figure.3) is structured as per the five main modelling pillars identified by (Reinhart & Davila, 2015). The five pillars are data collection, model characterisation (data preparation model), model generation (pre-simulation model), model simulation (main simulation model) and model validation (analysis model).

Data Collection

Access to data can be a significant challenge and the interactions between network operators, local government and academia can vary in different areas. In this paper, we identified open-sourced urban data required for a high-spatio temporal resolution model and balanced out the amount of urban data available and the inevitable number of assumptions made. Table 1 summarises the collected urban data by subcategories: building stock geometric data, building stock non-geometric data, and weather data.

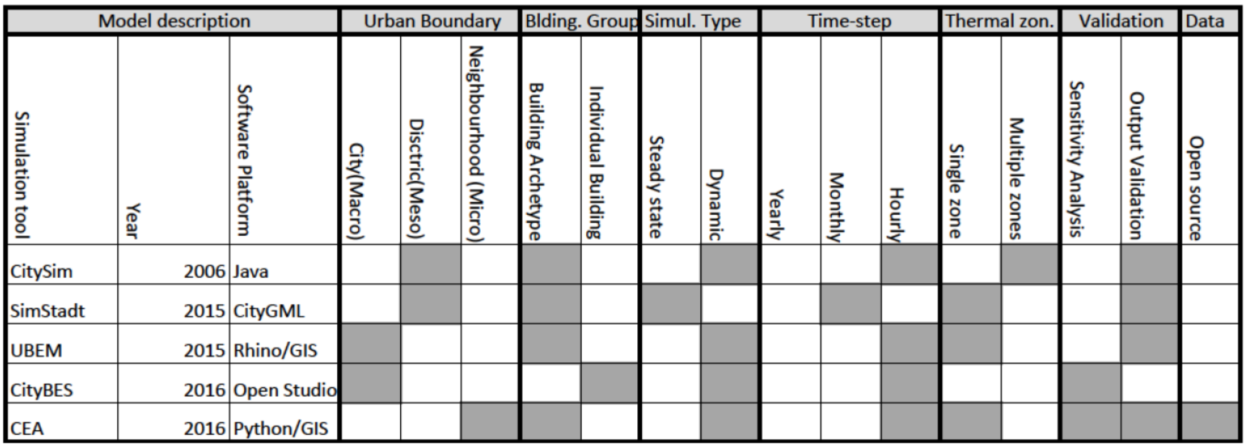

Figure 2: Urban Energy Modelling approaches review.

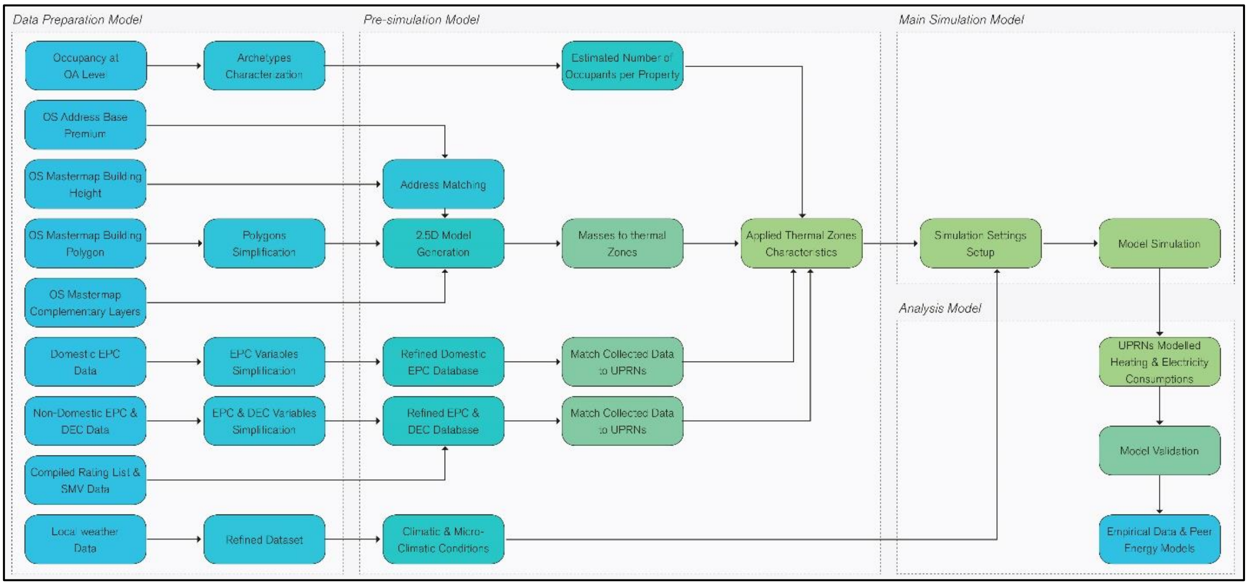

Figure 3: Urban Energy Modelling framework

Table 1: Data subcategories, input variable, sources and year

Subcategories	Model input variables	Pr
Geometrical	Building location and 2D footprint	El
	Height	O:
	UPRN, Type, Age, Total Floor area	O:
	Envelope characteristics	El
Non-Geometrical	Domestic appliances user profiles	U.
		20
	Occupancy data per household	St
	Household employment	N
Weather	Local data	PI

Figure 4: Areal and schematic view of domestic housing stock fed by one LV substation. As per real data provided by the Newcastle City Council.

Model characterisation

The domestic Housing Stock Characterisation model organises, modifies and integrates urban data from different sources into a new dataset processed as part of the pre-simulation model. The core structure of the data preparation consists of four streams of data flows.

The *first data stream* is concerned with sorting and transforming gathered necessary property database (building geometries, functions, demographics, etc.).

Ordnance Survey (OS) EDINA Digimap data include buildings' geometry polygons which were then simplified in order to provide the base for extrusion of the 2.5D model. The Building footprint Geographic Information System (GIS) shape file attributes are limited to basic geometric information such as building height, building TOpographic IDentifier (TOID), and postcode. For an inclusive modelling, secondary OS data might be found but is not limited to, land use, power network, streets, and topographical data.

AddressBase Premium (ABP) dataset gives the most up to date, accurate information about addresses, properties and land areas where services are provided (O.S. 2018). In order to enrich the EDINA GIS data, the ABP layer attributes were merged with the initial polygons layer. TOID information and Unique Property Reference Number(s) (UPRNs) were used as a common ground to match both datasets into one large Comma-Separated Values (CSV) file. The task was achieved using QGIS 2.18 and Microsoft Excel.

The *second data stream* scrutinises open sourced EPC data and extracts necessary individual building data, identified by their UPRNs. Namely, data about domestic building envelope conditions and energy systems. These data were then sorted out in an excel sheet and used as an input for the simulation model.

Building fabric (wall, roof and floor) EPC options were narrowed down to categories as such: Walls (Solid wall, cavity wall with no insulation and insulated wall), Floors and roof (insulated and non-insulated). Similarly, the following categories were identified for the glazing system (single, double and triple glazing). Then, a typical envelope U-value was assigned respectively (Designing Building Wiki, 2020). G-value was assigned as a constant for all type of glazing. Although a typical glazing to wall ratio was assigned initially to the whole building stock, whenever available the glazing ratio was refined to match the total property glazed area identified in the EPC.
The main heating fuel and system(s) were identified from the EPC data as well. Example systems include Boiler system with radiators, warm air system and room heater. Similarly, for Domestic Hot Water (DHW), options were identified with central heating, dedicated boiler or electric immersion heater. For each of the systems a system efficiency was assigned accordingly. Note that only gas heating fuel options were considered for this study.

The *third data stream* relates to household characteristics. To estimate the household count and the occupancy behaviour, socio-demographic information was gathered, at an Output Area (OA)/ postcode level, from several open-source data (SC, 2018) (ONS, 2018), then joined, aggregated and assigned per UPRN. Additionally, below are some of the model input assumptions made:

- Zone loads. Whenever occupant number is not available an estimated people density figure (person/m^2) was assigned (Palmer and Cooper 2013).
- The heating setpoint schedule was set to 18:00 to 06:00 or 24 hours based on the employment status, and household occupation collected data.
- Domestic appliances use profiles was set for all domestic dwellings as per (Palmer and Cooper 2013). A constant equipment power density (W/m^2) and a lighting power density (W/m^2) was assigned.
- DHW demand was assigned per capita per UPRN (m^3/hour/person) as per (Chmielewska et al. 2017).

Finally, the *fourth data stream* is the simulation weather data. To adequately consider local weather conditions, a Typical Reference Year (TRY) climate data for Newcastle Upon Tyne was used (PROMETHEUS, 2011) Future work might entail microclimatic data simulation which can be simulated using ENVI-met software recently added as a plug-in to Rhino-Grasshopper.

Model generation

The resulting dataset from the first data stream in model characterisation was fed into a generic algorithm in Grasshoper/Rhino to generate the 2.5D massing (i.e. flat roof models) all identifiable by their UPRNs (see Fig. 5). Subsequently, the non-energy consuming UPRNs were zoned out the study and 228 thermal zones were identified out of the 248 domestic dwellings in Ridgeway (New).

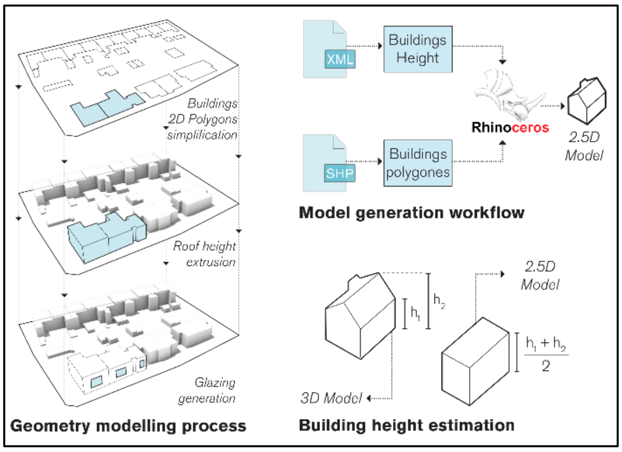

Figure 5: 2.5D model: building's height

Geometry validation

"Ground-truthing" of the selected area was carried out to empirically test building geometry and property data matching procedure. Common geometry parameters (i.e. total floor area and building height) can be found in the EDINA Digimap and the ABP datasets. After these two datasets were brought together, only 0.02% (6 out of 228) of the buildings had a mismatch of geometry data. These were then crossed checked on Google Earth Pro (2018), and an estimate of the mistaken building heights is drawn. Subsequently, Google Street View® was used to spot whether building classifications correspond to the 'truth' on the ground. A random selection of entries was manually revisited to verify the automatically generated base model. Parameters checked include window to wall ratios, property types and buildings' heights.

Model simulation

Taking as input detailed building information from the described data streams, the simulation model is able to generate hourly energy consumption at a high spatial resolution, one of individual buildings entries.

Results

The simulation outputs comprise of four estimated energy uses: space heating, electrical equipment loads, lighting loads, and DHW, which were then grouped as the following. Heat fuel represents space heating and DHW, whereas electricity represents lighting and electrical appliances. For validation purposes, the simulated energy outputs were compared with empirical data provided by the National Energy Efficiency Data Framework (NEED) (BEIS, 2019). The NEED data provides energy consumptions by both house type and by floor area band by each UK local authority.

Validation

In general, the simulation recorded output provides confidence in the model's calculation, with an averaged error percentage of 12%. This is broken down as follows: 10% for electricity consumption and 14% for heat fuel consumption (see Table 2). Whereas, the validation results compare well with NEED, the simulated figures appear to always being lower than the NEED reference.

Table 2: Median annual heat fuel and electricity consumption comparison.

House Type	DEM-LV (kWh)	NEED (kWh)	Difference (%)
Heat Fuel	10,966	12,740	-14
Electricity	2,411	2,689	-10

Floor area bands-based comparison

To compare results on a floor area band basis with equal weighting, it is appropriate to consider a uniform range of floor areas to comply with NEED data categorisation. The simulated building stock within Ridgeway (New) neighbourhood were aggregated per NEED floor area bands as such: 50 or less, 51 to 100, 101 to 150, 151 to 200 and over 200 m2. Energy consumption results per floor area band, were then averaged and compared with NEED data energy estimates (see Tables 3 and 4). The number of dwellings by area-band within the 228 dwellings sample is also shown in the below tables.

Table 3: Electricity consumption comparison by floor area bands in kWh between NEED and present work

Floor Band (m^2)	DEM-LV (kWh)	NEED (kWh)	Difference (%)	Simulated Sample (Dwellings)
50 or less	1,182	1,936	-39	7
51 to 100	2,230	2,508	-12	193
101 to 150	3,321	3,118	6	22
150 to 200	5,947	3,959	54	3
Over 200	6,740	5,103	32	3

Table 4: Heat fuel consumption comparison by floor area bands in kWh between NEED and present work

Floor Band (m^2)	DEM-LV (kWh)	NEED (kWh)	Difference (%)	Simulated Sample (Dwellings)
50 or less	6,255	7,547	-18	7
51 to 100	11,296	11,408	-1	193
101 to 150	13,928	16.252	-15	22
150 to 200	14,207	22,841	-38	3
Over 200	24,050	29,956	-20	3

House type-based comparison

To compare results on a property type basis with equal weighting, it is appropriate to consider similar categorisation as NEED data. The simulated building stock within Ridgeway (New) neighbourhood were aggregated per property type as such: Detached, semi-detached, end-terrace, mid-terrace, bungalow, converted flat, and purpose-built flat. The last three categories do not exist within the Ridgway New neighbourhood, thus were excluded in the comparison analysis. Energy consumption results were then averaged per property type and compared with NEED data energy (see Tables 5 and 6). The number of dwellings by house-type within the 228 dwellings sample is also shown in the below tables.

Table 5: Electricity consumption comparison by house type in kWh between NEED and present work

House Type	DEM-LV (kWh)	NEED (kWh)	Difference (%)	Simulated Sample (Dwellings)
Detached	3,685	3,599	2	22
Semi-Detached	2,220	2,996	-26	86
End-Terrace	2,334	2,762	-16	35
Mid-Terrace	2,307	2,847	-19	85

Table 6: Heat fuel consumption comparison by house type in kWh between NEED and present work

House Type	DEM-LV (kWh)	NEED (kWh)	Difference (%)	Simulated Sample (Dwellings)
Detached	13,390	17,843	-25	22
Semi-Detached	11,862	15,248	-23	86
End-Terrace	9,337	12,251	-24	35
Mid-Terrace	9,275	12,521	-26	85

Fuel and electricity domestic building stock profiles

The modelling framework results are presented at the LV-area scale but results at archetype and individual building scales can also be obtained (Aoun and Calderon, 2020).

Figure 6 shows the average heat fuel and electricity energy consumption for all the 228 domestic dwellings in Ridgway (New) with a winter (January) heat peak of 1,828 kWh and a thorough of 177 kWh in August. Electricity consumption has a flatter profile with winter (January) peak of 323 kWh and a thorough of 109 kWh in August. As understanding peak energy consumption is critical for heat electrification planning in Ridgeway (New), the rest of our analysis focuses on January (peak month) at hourly temporal resolutions. Figure 7 shows average hourly electricity and heat fuel consumptions throughout the month of January for all 228 dwellings in Ridgeway (New) with heat peak of 2,538 kWh between 22:00 and 6:00 hours and an electricity peak of 0.970 kWh between 17:00 and 20:00 hours.

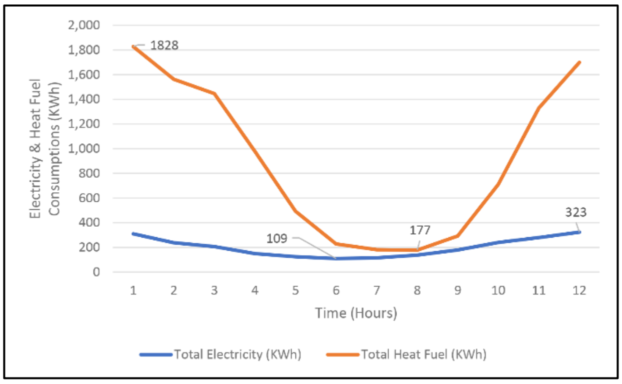

Figure 6: LV area monthly average total electricity and heat fuel consumption in kWh

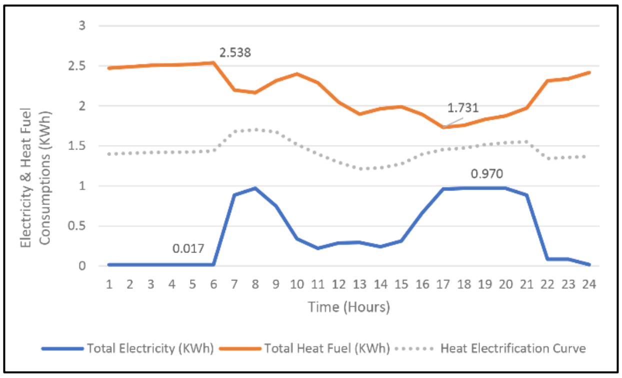

Figure 7: LV area January hourly average total electricity and heat fuel consumption in kWh

Discussion

Validation and results

In general, as shown in Table 2, the results compare favourably with NEED but simulated figures always being lower than the NEED reference. This is expected as the overarching purpose of NEED is to monitor progress on energy efficiency improvement measures to the UK housing stock and it will be biased towards houses with insulation upgrades (i.e. having a high energy consumption). Thus, NEED estimations should be higher.

Furthermore, a significant proportion (69%) of the estimated housing stock has a floor area band of 51m^2 to 100m^2. For this segment, our heat fuel and electricity validation results show higher alignment with NEED data, -1% and -12% respectively (see Tables 3 & 4). There are however some caveats. A significant increase in the percentage of error was observed in the floor area bands classification for both electricity and heat fuel consumptions. High percentages of errors ((Simulated Figures - NEED data) / NEED data) were observed at bands 50 m^2 or less (-17% for heat fuel, -39% for electricity), 151 to 200 m^2 (-38% for heat fuel, 54% for electricity) and over 200 m^2 (-20% for heat fuel, 32% for electricity). The results mismatch could be explained by the few numbers of the estimated domestic houses (i.e. sample) which fall under this category. For instance, out of the 228 houses, 7 fall under the 50 m^2 or less category, 3 fall under the 151-200 m^2, and another 3 fall under the over 200 m^2 category. Whereas for NEED data, 11,932 falls under the 50 m^2 or less category, 5,464 fall under the 151 to 200 m^2, and 2,082 fall under the over 200 m^2. The high error ranges can be argued that they are due to our samples being small and also with local characteristics not fully captured in a national survey such as NEED.

The results suggest that urban energy prediction accuracy can be increased significantly by using disaggregated data at building level. The reported error range validated at an aggregate buildings scale varied in between 7 to 66% when based on archetypes (Reinhart & Davila, 2015). However, the presented work error range is between 1 to 26% when based on individual building data. Thus, suggesting that validation results should be further inspected at an aggregate and individual building scale.

Model Spatiotemporal Resolution

With the monthly energy figures, the electricity consumption is keeping more or less the same trend throughout the year with an average of 200 kWh (see Figure 6). However, electricity demands variations were observed at a higher temporal granulate with hourly data provided (see Figure 7). Thus, we see as an indication that this type of models would even benefit further from higher temporal resolution (e.g. down to half-hour simulation steps).

In regards to heat fuel demands, monthly profiles indicate a peak demand in January, and the hourly profiles looks at the use profile shaping up daily peaks. In the provided figure heat fuel was peeking up night time from 22:00 to 06:00 and this is linked to the assumption made the heating setpoint profile activated between 18:00 and 06:00 for all employed occupants.

The peaks and troughs in heat demand, both within a day (see Figure 7) and across the seasons (see Figure 6), are far greater than the variations in electrical demand. January LV area energy figures shows that the heat fuel demand has five times greater peak when compared to what is expected from a national study (McLean et al. 2016). These bumpy peaks make the energy supply more volatile so that a back-up storage system will be necessary for reliability of supply. The proposed modelling framework will enable to assess, for example, the following scenarios separately or combined:

- A higher penetration of electrical heating which may help balancing out the demands and smoothing out the energy consumption curves throughout the year, month or day.
- Peak shaving solutions and load shape altering mechanisms which include measures such as thermal storage, demand response, and time-of-use tariffs.

Model Input limitations

The largest remaining limitation is due to tightly restricted access to measured building energy use as well as generally insufficient knowledge of the thermal properties of buildings which in this framework where depicted from individual building's EPC data.

The inaccuracy in the recorded simulation output might be the result of the following model input limitations:

- Opting for a 2.5D extrusion model due to the restricted access to Light Detection and Ranging (LiDAR) data at the time of the study. More sophisticated 3D models can be obtained by accessing LiDAR data from EDINA Digimap.
- Urban buildings have been simulated as singular thermal zones. Whereas, the study could benefit from a more comprehensive zoning of buildings per floor level or even per floorplans as explained in the current practice section.
- Assumptions made such as a constant energy use profiles and heating system efficiency, envelope insulation simplified figures, and constant estimated infiltration rates based on the construction age.
- Individual building's occupant behaviour, in most of the instances, was derived from the available postcode level data which will have a direct effect on the pattern of use (Bacher & Paone, 2018).

Model next steps

Future work should look at the association between variables in the model in detail and further validate individual building simulated data against measured data (i.e. energy bills). Relevant model variables include building characteristics (building height, type, size, and age), urban attributes (terrain topography, urban massing and context shading) and occupant characteristics (total occupants, household size, worker density, weekly working hours, and employment status and jobs).
Furthermore, future research should aim to improve the integration of the power network within urban buildings energy modelling and explore a higher model temporal resolution (e.g. half-hour simulation steps).

Conclusion

This paper has presented a spatially referenced energy modelling framework of the domestic building stock at Low-Voltage (LV) electrical sub-station (i.e. Ridgeway New, Newcastle upon Tyne) spatial scale for area-based heat electrification project delivery. Our results have shown that peak household energy demands (i.e. peak hourly ratios) are significantly higher than expected. However, validation and model input limitations should be addressed so as to develop the next generation of models.

References

Aoun, J., Calderon, C. (2020). Data-Driven Local Area Energy Framework for Modelling Domestic Heat Electrification. In: 2020 Building Performance Analysis Conference & SimBuild. 2020, Chicago, IL. In Press

Bacher, J.-P. & Paone, A. (2018). The Impact of Building Occupant Behavior on Energy Efficiency and Methods to Influence It: A Review of the State of the Art. *Energies, 11(4),* 953–972.

BEAMA. (2017). *Electrification By Design.* London: BEAMA. Retrieved from http://www.beama.org.uk

BEIS. 2019. “National Energy Efficiency Data Framework (NEED).” Technical Report, BEIS. (accessed 11th December 2019).

Bigg, T. (2017). Sustainable development in the UK – an issue for party manifestos? London: IIED International Institute for Environment and development.

Calderon, C., Underwood, C., Jialiang, Yi., Mcloughlin, A.,and Williams, B.. 2019. 'An areabased modelling approach for planning heating electrification.' *Energy Policy 131* (aug): 262–280.

Chmielewska, A., Zgrzywa, M. S., & Danielewicz, J. (2017). Domestic hot water consumption in multiapartment buildings. EDP Sciences.
Davila, C. C., Reinhart, C. F., & Bemis, J. L. (2016). Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets. *Energy, 117*, 237-250.
Designing Building Wiki. (2020, July 13). *U-values*. Retrieved from Designing Building Wiki: https://www.designingbuildings.co.uk/wiki/
EDINA. 2018. “Digimap.” Technical Report, The University of Edinburgh, 2018. Available at: https://digimap.edina.ac.uk/.
Fonseca, J. A., Nguyen, T.-A., Schlueter, A., & Marechal, F. (2016). City Energy Analyst (CEA): Integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts. *Energy and Buildings, 113*, 202-226.
Google Earth Pro. (2018). *Download Google Earth Pro for PC, Mac, or Linux*. Retrieved from https://www.google.com/earth/download
Hall, L. M., & Buckley, A. R. (2016). A review of energy systems models in the UK: Prevelant usage and categorisation. *Applied Energy, 169*, 607-628.
Harish, V., & Kumar, A. (2016). A review on modeling and simulation of building energy systems. *Renewable and Sustainable Energy Reviews, 56*, 1272–1292.
Harrison, F. (2013). *The Hidden Potential of Sustainable Neighborhoods: Lessons from Low-Carbon Communities* (illustrated, reprint ed., Vol. 27). California: Island Press.
Hong, T., Chen, Y., Lee, S. H., & Piette, M. A. (2016). CityBES: A Web-based Platform to Support City-Scale Building Energy Efficiency. San Francisco: Research Gate.
Jebaraja, S. & Iniyan, S., 2006. A review of energy models. *Renewable and Sustainable Energy Reviews, 10(4)*, p. 281–311.
Krstić , H., & Teni, M. (2017). Review of Methods for Buildings Energy Performance Modelling. IOP Conference Series: Materials Science and Engineering.
McLean, K., R. Sansom, T.Watson, and R. Gross. 2016. 'Managing Heat System Decarbonisation. Comparing the impacts and costs of tranisitons in heat infrasctructure.' Technical Report, Imperial College London. Centre for Energy Policy and Technology.
MHCLG. 2108. “Energy Performance of Buildings Data: England and Wales.” Technical Report, Ministry of Housing, Communities & Local Government (MHCLG). Available at: https://epc.opendatacommunities.org/.
National Statistics. (2020). *2019 UK greenhouse gas emissions, provisional figures.* Department for Business, Energy & Industrial Strategy.
Nouvel, R., Brassel, K. H., Duminil, E., Coors, V., Eicker, U., & Robinson, D. (2015). *Simstadt, A New Workflow-Driven Urban Energy Simulation Platform for CityGML Models.* Lausanne, Switzerland: CISBAT 2015.
ONS. 2018. “Nomis Official Labour Market Statistics. Postcode Headcounts and Household Estimates - 2011 Census.” Technical Report, Office for National Statistics (ONS). Available at: https://www.nomisweb.co.uk/census/2011/.
OS. 2018. “AddressBase Premium.” Technical Report, Ordance Survey (OS). Available at: https://www.ordnancesurvey.co.uk/business-andgovernment/ products/addressbase-premium.html.
Palmer, J., and I. Cooper. 2013. “United Kingdom housing energy fact file.” Technical Report, Department of energy and climate change (DECC).
PROMETHEUS. 2011. PROMETHEUS. Centre for Energy and Environment. University of Exeter.
Reinhart, C. F., & Davila, C. C. (2015). Urban building energy modeling-A review of nascent field. *Building and Environment, 97*, 196-202.
Robinson, D., Haldi, F., Kämpf, J., Leroux, P., Perez, D., Rasheed, A., & Wilke, U. (2009). Citysim: comprehensive micro-simulation of resource flows for sustainable urban planning. Glasgow, Scotland: Eleventh International IBPSA Conference - Building Simulation.
SC. 2018. “Street Check.” Technical Report, Street Check (SC). Available at: https://www.streetcheck.co.uk/.
Swan, L. G., & Ugursal, V. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews, 13*(8), 1819-1835.
Taylor, S., Allinson, D., Firth, S., & Lomas, K. (2013). Dynamic Energy Modelling of UK Housing: Evaluation of Alternative Approaches. *Proceedings of the 13th International Conference of the International Building performance Simulation Association* (pp. 745-751). Chambéry, France: IBPSA.
UKGBC. (2020). *UKGBC’s vision for a sustainable built environment is one that mitigates and adapts to climate change.* Retrieved from UKGBC Website: https://www.ukgbc.org/climate-change/
Van den Dobbelsteen, A., Broersma, S., & Stremke, S. (2012). Energy Potential Mapping for Energy-Producing Neighborhoods. *International Journal of Sustainable Building Technology and Urban Development, 2*(2), 170-176. Retrieved from https://www.researchgate.net/publication/233451136_Energy_Potential_Mapping_for_Energy-Producing_Neighborhoods