Platform for dynamic national housing stock simulation to evaluate decarbonisation scenarios

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Abstract

National housing stock energy models have to date focussed on buildings' thermal performance to describe the energy demand of the 27 million dwellings that make up the UK housing stock. Insufficient attention has thus far been dedicated to the drivers influencing the future evolution of this demand, such as household composition, peer pressure, financial incentives, educational programs and health. In order to improve upon the understanding of these drivers, a modular platform for the dynamic simulation of the UK housing stock has been developed. This platform integrates the virtues to existing housing stock energy models, in particular their representation of the composition and attribution of the stock—albeit in reduced form, with mechanisms to explore the potential impacts of policies and strategies to decarbonise the stock.

Introduction

The UK emitted a total of 564 $MtCO_{2e}$ in 2011; this is 36% below the peak value registered in 1979 and 28% below that of 1990 (Department of Energy & Climate Change (DECC), 2013a). The domestic sector contributed 124 $MtCO_{2e}$ of the total emissions (22 %); 41% of this was caused by generation of energy in power stations and the remainder by end-use emissions. This end-use value is attributable to four key services: 54% space heating, 14% domestic hot water, 29% lighting and appliances, and 3% cooking (Department of Energy & Climate Change (DECC), 2013b).

The UK's Climate Change Act aims to reduce its 1990 emissions by 80 % by 2050 (Parliament of the United Kingdom, 2008). Led by the Committee on Climate Change, the first target (or budget) is to produce 30 % of electricity from renewable sources by 2020, to cut greenhouse gas emissions by 50 % in 2025 in comparison with 1990 levels and to achieve an 80 % reduction by 2050; these targets are established for the whole energy sector.

Notably, the aforementioned reduction of 28 % in the emissions related to 1990 was mainly caused by a supply shift from coal to natural gas; by a displacement of industrial activity (primarily to Asia), and modest improvements in the performance of the transport sector (Mallaburn and Eyre, 2014). This means that even though the reduction in this period is close to the aimed target, this has largely been achieved in the absence of structural improvements to reduce energy demands. Some of these opportunities for significant demand reduction are found in the domestic sector where, for example, their emissions have been maintained at broadly the same level as in 1990.

For this reason, a full understanding of the energy flow pathways, and factors influencing them, in dwellings is required to achieve significant reductions in their carbon intensity. However, not only the understanding of these pathways is essential (most of them related to the heat generation), but also the further knowledge on the insights of the households' properties that influence decision-making. The understanding of energy flow pathways has been central to the development of housing stock energy models (HSEM) and, consequently, in the support of programmes and policies (Swan and Ugursal, 2009; Kavgic et al., 2010) that have been, are and will be included in the national decarbonisation strategy. Yet these models have been limited by the resolution of the data and the inherent complexity in simulating, using relatively disaggregated data, the entire UK housing stock.

Despite the development of relatively sophisticated algorithms to model these energy flow pathways, there are still substantial enhancements necessary to predict the underlying drivers that affect the domestic energy system and its possible evolution; these are summarised as following:

i) The development of a solid platform of decarbonisation scenarios will be intensified not only by advancements in computational power, but also by a shift in the way data is processed, shared and published, among developers and stakeholders.

ii) Improvements in the energy efficiency of the domestic sector (envelope and appliances) are not enough to fulfil the national carbon budgets for the sector. Insights are needed in our understanding of decision-making processes to better understand the effectiveness of decarbonisation policies and strategies.

iii) Development of better quality performance metrics characterising the domestic energy sector to calibrate and validate models.

The Housing Stock Energy Hub

In order to improve the understanding of the energy flow pathways at a stock level and to gain insights in the drivers (of decision-making) that affect them (and have historically been excluded), a modular platform has developed to integrate the virtues of existing HSEMs: the Housing Stock Energy Hub (EnHub), as demonstrated in Fig. 1.

EnHub is able to use a central dataset, for example the English Housing Survey (EHS) (Department for Communities and Local Government (DCLG), 2011), and to adapt modules according to the resolution of the thermal-energy models. This is achieved by using the statistical software `R` (R Core Team, 2016) as its core and linking `Energy Plus` (Strand et al., 2000) as the main extension to perform dynamic simulation of domestic buildings. Since `Energy Plus` requires three-dimensional representations of buildings, the platform creates geometrically simplified models—similarly to the erection of façades made in the Domestic Ventilation Model (DOMVENT) (Jones et al., 2015) and Steadman's model (Steadman et al., 2009)—and populates them by performing a synthetic generation of characteristics (envelope properties, occupants and external elements). As a result, this provides the ability to derive specific metrics, such as discomfort levels per capita (and also the proportion of the stock that overheats and underheats—given appropriate descriptions of heating preferences), heat gains per floor area, disaggregated power consumption of household appliances and daily heat peaks. Thus, we have a model of both greater fidelity and utility compared with existing approaches that use simple energy balance calculations.

Methods

The structure of EnHub takes its inspiration from the Cambridge Housing Model (CHM). CHM is also at the core of the *Energy Consumption in the UK* (Department of Energy & Climate Change (DECC), 2013b) study, which in turn is based on Building Research Establishment Domestic Energy Model (BREDEM). The dataset is derived from the EHS-2011, which comprises 14,951 dwellings, weighted to represent the 21 million houses in England. Other sources of information used for this study are the Census and the Home Energy Efficiency Database.

Figure 1 shows the steps adopted in the development of the simulation platform. The purpose of using a shell is that 1) the platform can be detached regarding the Operating System (OS) and 2) a set of low-level scripts can systematically control the process. Once the main dataset is integrated into the platform, `R` is used to manage the processing of information and to reduce the sampling size by defining the most relevant combinations found in the original dataset. Then, the reduced dataset is enriched by including the most common cases and the representative weights of each

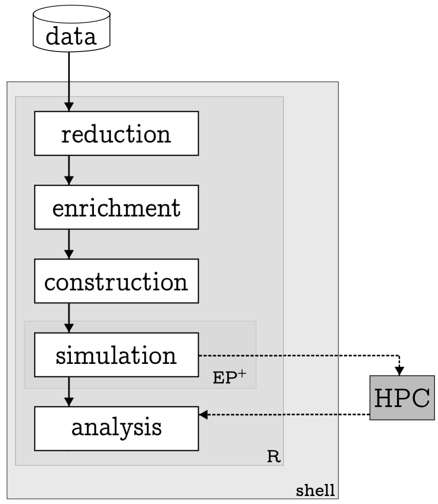


Figure 1: The EnHub Structure

combination. `R` software is also used due to its capability in programming and its ability to be controlled by either Command Language Interpreter (CLI) or Graphical User Interface (GUI). The next step uses the archetypes to create a set of volumetric models to be then passed to the `Energy Plus` engine to perform the dynamic simulation. Similarly, `Energy Plus` can be run in CLI mode or integrated into a GUI; by using the former, the integration with `R` and the shell can be performed smoothly. Lastly, the analysis derives energy performance indicators and forms preliminary results.

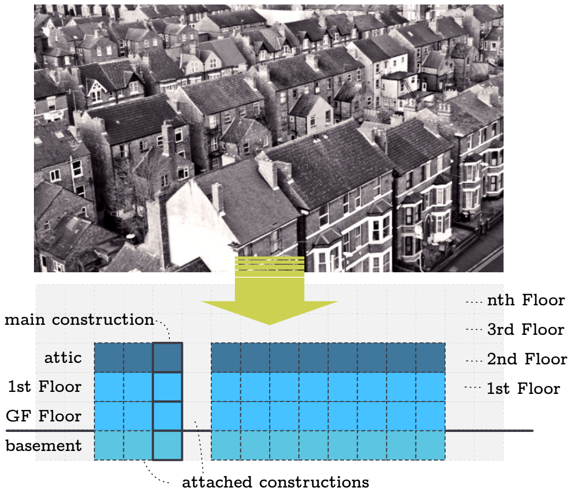
In addition, the whole process is made in a standalone mode so that each step may be detached from the flowchart, enabling the possibility to run the simulations at a different time and in a different hardware, such as the University High Performance Computing (U-HPC). By using this mode, the processing time is reduced by a factor of more than 64.

Step 1: Reduction

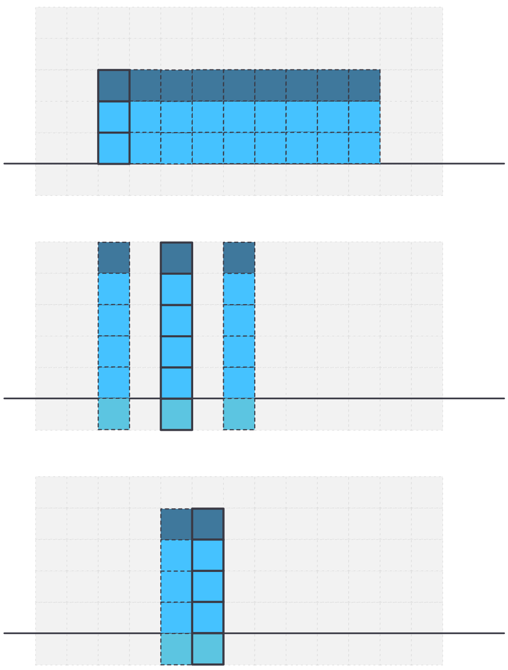
Based on the homogeneity of the housing stock typology in the UK (Sousa et al., 2016), a cuboid is conceived to potentially represent a comprehensive geometry of the stock (see Figure 2a). This cuboid accounts for the number of floors and the presence of attic, basement and attachments. By doing so, the typology is able to produce the representative residential types of the stock, such as detached houses, semi-detached, end of terrace, mid terraced, apartments and bungalows (see Figure 2b).

Moreover, the mechanics behind this process enable the conformation of geometrical units and the assignment of internal zones. In this case, in line with the BREDEM algorithm that represents the internal balance of energy flows, two zones are defined in the resulted archetypes, namely main zone and rest of the building.

Table 1 summarises the variables used in the reduc-



(a) Cuboid description: abstraction of a two floors mid-terraced house with attic and basement. Each block represents a zone for the **Energy Plus** format. – "Victorian Houses" Licensed under CC-BY2.0. (tinyurl.com/j8ekuvy accessed 15 March 2013)



(b) Examples of Cuboid Configurations: top - End of terrace house, middle: apartments, bottom: semidetached house with attic

Figure 2: Cuboid abstraction

tion process. The initial reduction considers the combination of the first group of variables (i.e. $C(4,1)_{flr} \cdot (C(2,1)_{bsmt} \cdot C(2,1)_{attc}) \cdot C(4,1)_{atch} = 64$). Then, in order to calibrate the resulting reduction, and particularly to include the relevance of different heating systems found in the datasets, a second group of variables is added as representative factors that shape the housing stock. These factors are identified by applying regression techniques. Not all the combinations described in Table 1 (i.e. $64 \cdot C(3,1)^3$) are found in the stock. As a result, the reduction of dwellings

Table 1: Reduction Variables

Category	Value
no. floors	GF, 1F, 2F, 3F
extra floors	basement (y/n), attic (y/n)
attachments	left, right, both, no
regions	north, central, south
heater type	gas, electric, other
built age	pre 1920, pre 1975, modern

comprises 865 units.

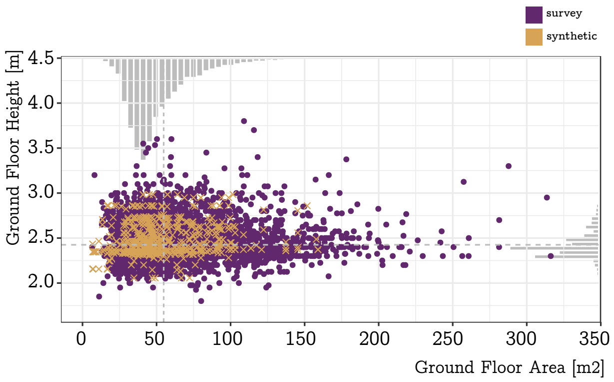
Step 2: Enrichment

To complement the reduction of units, a widespread method employed in building simulation is the development of average (or synthetic) archetypes (Natarajan et al., 2011; Ballarini et al., 2014). These archetypes usually apply predictive methods to define associations among their variables, and to provide with ranks and representative values that describe the stock. A highly developed sub-type of predictive methods includes hierarchical models (e.g. trees, additive models, neural networks) (Swan and Ugursal, 2009). They can be combined and complemented accordingly. The value of average archetypes is that they contain fit-for-purpose properties that describe the stock well.

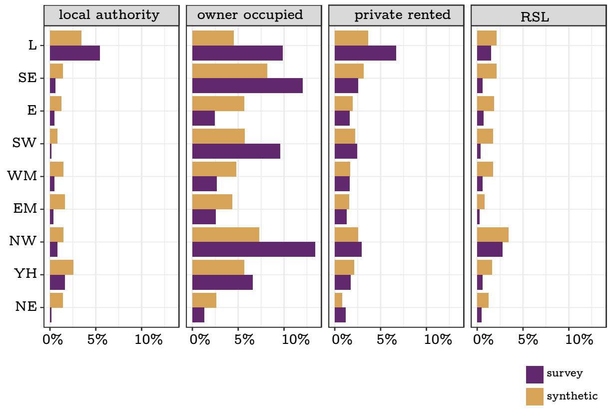
This step calibrates the reduced dataset following the next sequence: (a) use of partition trees techniques, and (b) re-weighting of the resulting archetypes. The partition trees replicate the distribution of each variable (i.e. categorical, nominal or numerical data) taking as initial reference the variables presented in Table 1. In here, each variable is iteratively derived from the predominant cases found in the EHS, so that the 865 units can represent the EHS sample (14,951) and therefore the stock total (21 million dwellings), maintaining the overall conformation of the housing stock.

Figure 3a presents a comparison between the EHS and the reduced dataset, in terms of properties provided for the ground floor space; and Figure 3b illustrates how the reduction of categorical values for the region maintains the balance after the reduction process. This figure also shows how the reduction of variables may slightly alter the variability of the original dataset; however, by applying the enrichment sequence, the dataset can still replicate the most common cases of the original dataset. Additionally, in order to measure the significance of the reductions, we apply the Kruskal-Wallis test to each of the variables. The results of this test show that 10 variables present a p-value below 0.05, which usually is a good indicator of significance for the comparison of independent tests. We then perform a One-at-a-time (OAT) Sensitivity Analysis (SA) on these variables to define the significance on the overall performance.

It is worth drawing attention that, despite the sampling units are taken from the Lower-Super Output



(a) Ground Floor properties



(b) Regional and tenure distribution

Figure 3: Cuboid reduction. Comparison between the EHS and the reduced dataset (synthetic)

Area (SOA), these units are initially weighted to represent the whole English housing stock. Thus, the original dataset is already losing some information by using pseudo-synthetic data (Hughes et al., 2013); however, this dataset is able to define homogeneous groups of the population. Likewise, this enrichment step provides, through the average archetypes, a balanced picture of the residential stock. Yet the tuning of the dataset is constrained by the resolution of the simulation algorithms and needs to be employed with caution.

Step 3: Construction

At this point, volumetric models are generated for the reduced dataset; and semantically attributed to represent occupancy, appliance and constructional characteristics. As mentioned earlier, these are constructed to be simulated using the widely used open source software `Energy Plus`. Thus, here the platform generates typology-specific Energy Plus Input Data Files (idf) following a standard structure (Crawley and Lawrie, 2000). The main sections include: 1) identifier and timestep resolution, 2) location and simulation period, 3) associated (and unique) schedules, 4) fabric properties, 5) volumetric geometry and thermal zones, 6) internal gains and occupancy, 7) HVAC, 8) water system, and 9) outputs and performance metrics.

This step adopts an Object-Oriented Modeling (OOM) approach and deductively generates archetype properties. This is achieved by reading in a base case idf using variable flags to match the properties fields from the EHS. The base case considers a maximum amount of contiguous attachments (see Table 1), which are removed as required. We consider that this approach is a more convenient way of constructing the archetypes due to the high precision of geometric coordinates that `Energy Plus` demands. Besides, the OOM approach provides the ability to detach specific sections of the modelling process to be validated and improved independently.

In terms of the internal gains, a catalogue of appliances and heating systems is included in the base case idf. Their specifications (i.e. power, efficiency and heat gains), and corresponding fuels, are shaped according to their EHS information. Occupants are included with their associated (and theoretically) metabolic gains, and usage patterns. They can be directly linked with specific intensity values, if provided, such as energy demand per person, or floor area per capita. For all the potential elements that are affected by time-related events such as appliances, occupants, windows openings, heating systems and water fixtures, an associated schedule is defined in the idfs. The schedule profiles are made for each model applying a probabilistic function for each element. The patterns in here are shaped by the properties of each archetype such as the household composition (i.e. age, total, scholarly, income) or dwelling properties (i.e. type, construction period). This approach enables the possibility to analyse, albeit limited by the algorithms, specific behaviours on a given group of archetypes; and to emulate dynamic actions.

Also, a library of standard Energy Plus Weather (EPW) files is referenced (and identified in the idf) according to the region where the model archetype is allocated. These files are Test Reference Years (TRYs), in which each month represents the most average month in a (normally twenty year) period; the average values are then spliced together using a cubic spline method. TRYs lend themselves well to the prediction of average annual energy usage. The EPW files may include information regarding time zone, elevation, peak heating and cooling design conditions, holidays, daylight savings period, typical and extreme periods (Strand et al., 2000).

Step 4: Simulation

The simulation is carried out for an entire calendar year (and the additional preheating period) at an hourly resolution. This relatively coarse grained temporal resolution is reasonable, given that we are not explicitly modelling ventilation nor accounting for occupants' feedback at this stage; we are simply utilising infiltration and ventilation schedules, for example. Each simulation takes 30 seconds to complete using 1 core in a high-end machine. However, given that our stock is represented by 865 archetypes, to which we also wish to define and test decarbonisation scenarios—so that we perform multiple rounds of simulation—our workflow is coupled with the University of Nottingham High Performance Computing (UoN-HPC) facility, enabling the simulation of 64x models in parallel (i.e. 865·30s = 7.2hr; ∴ 64x = 7m.)

Step 5: Analysis

The derived energy performance indicators are processed in `R` so that they can be compared and stored accordingly. Some of these indicators, for example those related to comfort values, would require a high level of disaggregation to be computed in the platform. `Energy Plus` uses the comfort models described in ASHRAE-55 (Crawley and Lawrie, 2000) and is unable to account for the triggers and decision-making parameters found in houses, such as physical and mental health of occupants, and personal preferences; however, the provided resolutions of indoor temperature, humidity, infiltration and occupancy, represent initial (and fairly simplistic) guidelines for the comparison of indoor conditions amongst the model archetypes.

Each batch of simulation, encompassing the 865 archetypes, is mined and allocated making reference to the conditions of the dataset; this process is represented by the algorithm in Figure 4. For instance, the first stage (A) focuses on the data resolution, whereas the second (B) on the modelling appropriateness and the fluctuation of energy in a dynamic environment. For reasons of efficiency (and practicality), this analysis is also carried out utilising the UoN-HPC.

Platform to Evaluate Decarbonisation Scenarios

Definition of Scenarios

The sequence described in Figure 1 to evaluate the effectiveness of a set of scenarios conceived to minimise the $CO2$ emissions due to the national housing stock energy demand. To this end, we explore two perspectives, adapted from national policies (Shorrock et al., 2005; Foda et al., 2014) and figures (Department of Energy & Climate Change (DECC), 2013b), to study the energy performance of the stock: (i) *perfect uptake*, where the properties in dwellings (i.e. fabric components and appliances) are upgraded to the most efficient values regardless of the current conditions; and (ii) *conditional uptake*, where the upgrade is conditioned to the fulfilment of some properties—most of them related to households—which act as triggers in the adoption of efficient technologies. These scenarios, summarised in Table 3, are allocated in a systematic way and include a large spectrum of variations in the properties fed into the model.

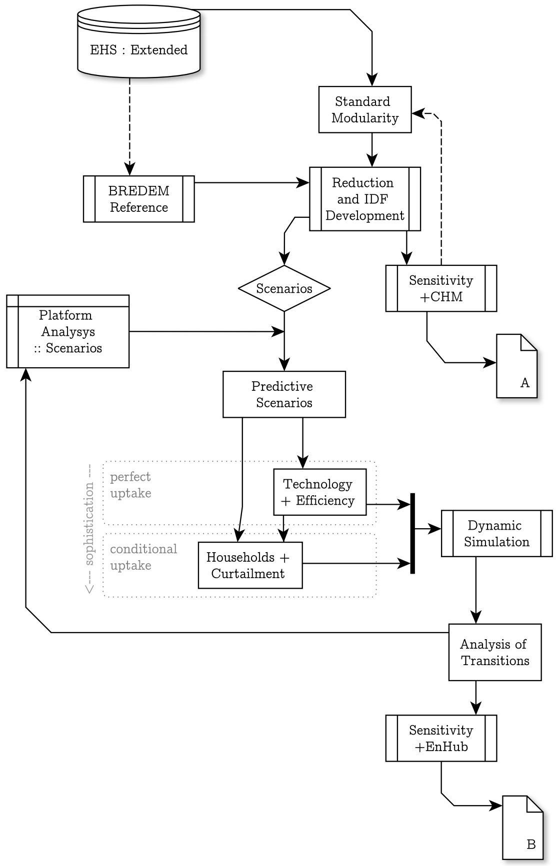


Figure 4: Simulation and analysis flowchart: development of scenarios

In addition to these perspectives, we test an additional (and iterative) scenario where we study different occupancy profiles and patterns of use. This scenario aims to evaluate the range of variation in the total energy demand due to households' energy use. This is possible by assigning multiple profiles based on their corresponding probabilistic distribution so that the values are constrained by the conditions of each archetype. Although the overall objective is to evaluate the decrease in the energy demand, this is not necessarily the case and, due to different patterns of occupancy and use, a significant increase in the energy demand may be expected. Nevertheless, this scenario provides certainty in the development of HSEMs by defining a fluctuation range due to patterns of use.

Figure 4 shows the SAs applied on both inputs and the resulting scenarios. The findings of SAs are relevant for tracking errors and assumptions in the inputs, for narrowing strategic changes in the housing stock and for improving the development of domestic stock models (Calleja Rodríguez et al., 2013). By employing an OOM approach, each component can be independently evaluated with specific inputs. In this way, it can be identified whether the resolution of the model lacks in the provided (or available) data or

Table 2: Opted scenarios for perfect and conditional uptakes

.	Upgrade	Description	Current Status
A: perfect uptake			
A01	**Solid wall insulation**	Add maximum insulation for each wall material	Non-insulated: 47%; semi-upgraded: 21%; efficient 32%
A02	**Loft insulation**	Add maximum insulation for each loft construction (i.e. top up 120-270 mm)	Non-insulated: 45%; semi-upgraded: 35%; efficient 20%
A03	**Double glazing**	Upgrade to the most efficient glazing technology in the market (i.e. double and triple glaze)	Non-efficient windows: 45%; semi-upgraded: 35%; efficient 20%
A04	**Cylinder insulation**	Upgrade to the maximum volume of insulation on the cylinder (i.e. more than 150 mm)	Non-insulated:15%; below 50mm: 50%; efficient:35%
A05	**Draught proofing**	Reduce the infiltration and ventilation values to the minimum existing assumptions	Below permitted: 65%; efficient: 35%
A06	**Low energy lights**	Upgrade of lightings efficiency (i.e. 100% of light devices using CFL or LED technology)	Non-efficient lighting: 35%; semi-upgraded: 50%; efficient 15%
A07	**Improved electrical appliances**	Upgrade of appliances' efficiency (i.e. lower power demand)	Non-efficient appliances: 50%; semi-upgraded: 45%; efficient 5%
B: conditional uptake			
B01	**Solid wall insulation**	Transition from lowest levels to efficient ones, including from medium levels if not in FP and if considerable heat gains above mean. Only 60% of A01 fulfil the requirements	
B02	**Loft insulation**	Transition from lowest levels to efficient ones, including from medium levels if not in FP and if considerable heat gains above mean. Only 45% of A02 fulfil the requirements	
B03	**Double glazing**	Transition from lowest levels to efficient ones, including from medium levels if not in Fuel Poverty (FP) and if considerable heat gains above mean. Only 56% of A03 fulfil the requirements	
B04	**Cylinder insulation**	Transition from lowest levels to efficient ones, including from medium levels if not in FP and if considerable heat gains above mean. Only 46% of A04 fulfil the requirements	
B05	**Draught proofing**	Transition if the heat gains are above the mean. Only 33% of A05 fulfil the requirements	
B06	**Low energy lights**	Transition from lowest levels to efficient ones, including from medium levels if not in FP and if considerable heat gains above mean. Only 40% of A06 fulfil the requirements.	
B07	**Improved electrical appliances**	Transition from lowest levels to efficient ones, including from medium levels if not in FP and if considerable heat gains above mean. This represents: 40% of the SA07 upgrade.	
AB8	**User Behaviour**	Test different assumptions on occupancy and energy use intensity (EUI)	

in the adopted algorithm. Not only we measure the potential of improvements at stock level, but also provide information to describe the transition processes.

Evaluation of the Scenarios

The results indicate that carbon emissions are highly sensitive to housing insulation levels (21.5%). However, our stratified approach reveals that this improvement is not necessarily the most likely scenario to be applied at a national scale, due to its cost; particularly in relation to hard-to-treat properties. Conversely, reducing infiltration and draughts is a sound strategy, despite a relatively limited reduction on emissions (5%). Initial investigations suggest that occupants' behaviours may also have significant repercussion in reducing future emissions. We identify a variation of $\pm$ 7% in the energy demand. To sum up, Figure 5a shows that the most successful scenario is A01, followed by A02, A05, A07, A03, A04 and A06. This is further explored in the OAT test for each of the affected properties (the outcome A in Figure 4).

For example, by comparing the first scenario for the two stages (i.e. A01 and B01), we found that even though the technical outcome of the former is significant, at least compared to the variation against the baseline, when some conditions are added into the transition process such as income status or partial implementation, the final outcome is considerably different. Figure 5b shows that houses with older constructions have the major potential to improve fabric conditions, but once the constrains are included, the potential of improvement is similar among the typologies. Also, we identified that the implementation of such a scenario is usually convenient for old and large constructions, because of the noticeable differences in the fabric properties, but sometimes (under a realistic scenario) the spaces and zones within these type of buildings have been re-adapted and are not susceptible to be modified any more. This is the case of lofts, for example, that have been designated for storage, which makes the energy-related measures difficult to be implemented.

The scenarios A06 and B06 show that lighting has the advantage of being a low cost upgrade with a fairly quick return of investment. However, due to this cost and perhaps due to imperceptible changes in the indoors conditions by their occupants, this measure has not been very effective, at least not when the uptake remains on the households' decision-making. Similar conditions are found in the A07 and B07 scenarios. In fact, we can mention that developing a model to demonstrate reduction on the electricity demand of more efficient appliances may be redundant; nevertheless, what is relevant for the platform is the ability to link models that account for ownership and detailed use of appliances. Figure 5c exemplifies that the adoption of measures can also have a significant impact on the indoor conditions, which may also be more significant in the decision-making process rather than purely a reduction in the yearly energy demand. Finally, other relevant groups with significant poten-

Table 3: Scenarios Results: Perfect Uptake

	gov-ref	BASE	A01	A02	A03	A04	A05	A06	A07	ALL
Energy Demand [ktoe]	33.0	31.4	24.8	30.0	30.8	31.0	29.9	31.3	30.5	24.5
Int Temperature [°C]	17.60	17.10	+ 0.30	+ 0.74	+ 0.78	+ 0.05	+ 1.12	+ 0.76	+ 0.56	0.25
Emissions [tCO2/hh]	4.5	6.5	78.9%	98.4%	99.8%	100.0%	95.2%	100.7%	92.0%	73.0%
Energy per area [kWh / sqm]	208	202	166	198	200	200	192	198	198	154

Table 4: Scenarios Results: Conditional Uptake

	gov-ref	BASE	B01	B02	B03	B04	B05	B06	B07	BLL
Energy Demand [ktoe]	33.0	31.4	28.8	31.1	31.1	31.2	30.4	31.3	30.6	28.7
Internal Temperature [°C]	17.60	17.10	+ 0.18	+ 0.45	+ 0.43	+ 0.02	+ 0.37	+ 0.3	+ 0.36	0.39
Emissions [tCO2/hh]	4.5	6.5	91.6%	98.9%	99.9%	100.0%	96.8%	100.4%	94.0%	90.5%
Energy per area [kWh / sqm]	208	202	187	199	201	201	195	199	199	185

tial to perform further studies are those dwellings where gas is the predominant fuel used. Consequently, measures affecting gas-based systems are meant to have a sounder impact across the stock in the overall energy fluctuation (i.e. space heating, water heating and cooking).

Discussion

Inevitably, the perfect uptake is convenient for the trade-off between energy demand and cost, which is consequently affected when some conditions (on both households and dwellings) are included. This suggests that the more detailed conditions, particularly on the households' characteristics, the more constrained adoption of improvements; however, on the other hand, these constraints aim to further develop a tangible and amenable platform for testing energy-related measures and decarbonisation strategies in the housing stock. Without an understanding of the underlying drivers affecting the uptake by households of energy-related improvements, we are unable to effectively understand the trade-offs between energy demand and costs and thus to prioritise decarbonisation policies and strategies.

The study of scenarios is being useful in that it enables us to quickly and conveniently explore the limits of what it is possible to achieve with a policy or strategy that is targeting a particular measure, or a combination of measures. The testing of scenarios relating to conditional uptake let us understand the implication of constraints in the uptake of renovation measures.

For example, insulation of walls and lofts reduces heating demand and this reduction is significant at the stock level. But such a reduction can be counteracted if the occupants a) increase their comfort expectations, and/or b) increase the use (and ownership) of appliances. Both phenomena have been commonly described as rebound effects. Similarly, by altering the indoor conditions with respect to infiltration and ventilation levels, the heating demand can be diminished; however, if we consider the occupants' responses, the indoor conditions can be counter-productive because the reduction or the absence of air exchange may directly harm occupants' health.

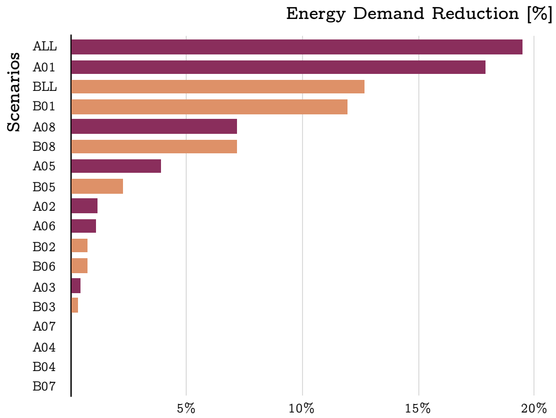
Conclusion

We have developed a new open-access modular platform for the dynamic simulation of the UK housing stock, with a view to evaluating the effectiveness of national decarbonisation strategies; not only to explore the possible implications from perfect or assumed uptake of strategies, but also of their likely uptake in response to specific policy drivers, accounting for the dynamic performance of the buildings comprising this stock. In this way (and data permitting) we have a platform that enables the interplay between energy, comfort and fuel poverty to be systematically explored as well as the effectiveness of strategies to bring about changes in investment and day-to-day operational behaviours and the technologies destined to support these changes. This is essential in the formulation of robust decarbonisation policies and strategies and will be the focus of a future paper, extending the present study.

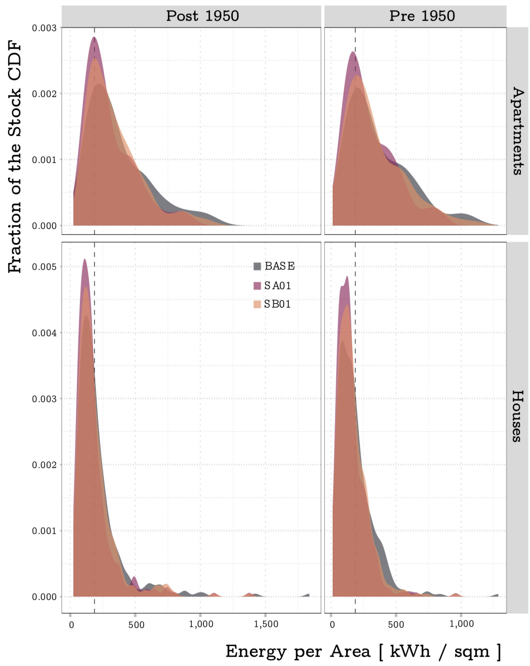
But to achieve its potential, this platform needs to be accompanied by substantial changes in the way data is computed (i.e. collected, processed and shared): if we measure with accuracy, we can correct with certainty. In agreement with previous research (Mata et al. (2013); Hamilton et al. (2016)), we suggest that platforms that put emphasis on data resolution should be used to evaluate the relative impacts of different scenarios, rather than as a means for making absolute predictions; although improved data will enable uncertainties in predictions to be far better quantified.

References

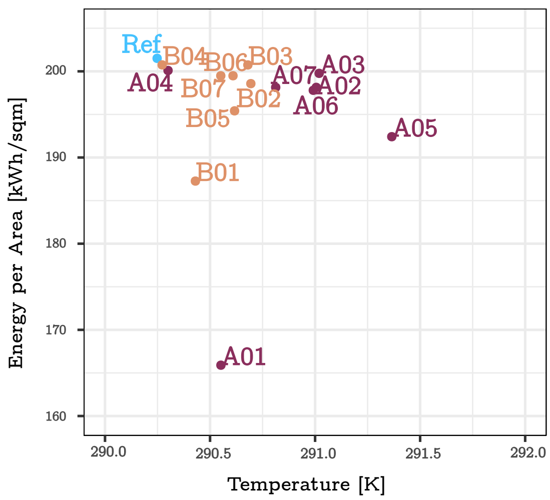
Ballarini, I., S. P. Corgnati, and V. Corrado (2014). Use of reference buildings to assess the energy saving potentials of the residential building stock: The experience of TABULA project. *Energy Policy 68*,



(a) Reduction of energy demand among the scenarios



(b) Energy inensity by type and age



(c) Indoor Energy Indices

Figure 5: Energy Performance Metrics

273–284.

Calleja Rodríguez, G., A. Carrillo Andrés, F. Domínguez Muñoz, J. M. Cejudo López, and Y. Zhang (2013, dec). Uncertainties and sensitivity analysis in building energy simulation using macroparameters. *Energy and Buildings 67*, 79–87.

Crawley, B. D. B. and L. K. Lawrie (2000). EnergyPlus : Energy Simulation Program. *Ashrae 42*(4), 49–56.

Department for Communities and Local Government (DCLG) (2011). English Housing Survey : Housing Stock Data. Technical report, Colchester, Essex.

Department of Energy & Climate Change (DECC) (2013a). *Digest of United Kingdom Energy Statistics 2013*. London: Crown Copyright.

Department of Energy & Climate Change (DECC) (2013b). Energy Consumption in the United Kingdom (ECUK). Technical Report July, Department of Energy and Climate Change, London.

Foda, E., D. Allinson, K. J. Lomas, and D. Loveday (2014). Using Uk Green Deal Assessment Data Of A Stock Of Dwellings To Run A Batch Of Building Energy Models. In *Building Simulation and Optimization Conference*, Number Xml.

Hamilton, I. G., A. J. Summerfield, D. Shipworth, J. P. Steadman, T. Oreszczyn, and R. J. Lowe (2016). Energy efficiency uptake and energy savings in English houses: a cohort study. *Energy and Buildings online*, 259–276.

Hughes, M., J. Palmer, V. Cheng, and D. Shipworth (2013, apr). Sensitivity and uncertainty analysis of England's housing energy model. *Building Research & Information 41*(2), 156–167.

Jones, B., P. Das, Z. Chalabi, M. Davies, I. Hamilton, R. Lowe, A. Mavrogianni, D. Robinson, and J. Taylor (2015). Assessing uncertainty in housing stock infiltration rates and associated heat loss: English and UK case studies. *Building and Environment 92*, 644–656.

Kavgic, M., A. Mavrogianni, D. Mumovic, A. J. Summerfield, Z. Stevanovic, and M. Djurovic-Petrovic (2010). A review of bottom-up building stock models for energy consumption in the residential sector. *Building and Environment 45*(7), 1683–1697.

Mallaburn, P. S. and N. Eyre (2014). Lessons from energy efficiency policy and programmes in the UK from 1973 to 2013. *Energy Efficiency 7*(1), 23–41.

Mata, É., A. S. Kalagasidis, and F. Johnsson (2013). A modelling strategy for energy, carbon, and cost assessments of building stocks. *Energy and Buildings 56*, 100–108.

Natarajan, S., J. Padget, and L. Elliott (2011). Modelling UK domestic energy and carbon emissions: an agent-based approach. *Energy and Buildings 43*(10), 2602–2612.

Parliament of the United Kingdom (2008). Climate Change Act 2008. Technical report.

R Core Team (2016). R: A Language and Environment for Statistical Computing.

Shorrock, L. D., J. Henderson, and J. Utley (2005). *Reducing carbon emissions from the UK housing stock*. BRE Press.

Sousa, G., B. M. Jones, P. A. Mirzaei, and D. Robinson (2016). A review and critique of UK housing stock energy models, modelling approaches and data sources.

Steadman, P., S. Evans, and M. Batty (2009). Wall area, volume and plan depth in the building stock. *Building Research & Information 37*(5-6), 455–467.

Strand, R. K., D. B. Crawley, C. O. Pedersen, R. J. Liesen, L. K. Lawrie, F. C. Winkelmann, W. F. Buhl, Y. J. Huang, and D. E. Fisher (2000). EnergyPlus : A New-Generation Energy Analysis and Load Calculation Engine for Building Design Introduction : What is EnergyPlus ? In *ACSA Technology Conference*, Volume 2. NREL.

Swan, L. G. and V. I. Ugursal (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.