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Feedback and Feedforward Mechanisms for Generating Occupant Datasets for UK School Stock Simulation Modelling.

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Abstract

National construction and energy datasets coupled with batch building performance simulation techniques have made feasible the construction of a stock building simulation model of over 16,000 schools. Although this should provide insights for targeted energy efficiency measures, discrepancies between measured and calculated performance limit predictive powers.

A case study of building simulation models of three London schools built using the stock modelling process is presented. Discrepancies in calculated performance have been demonstrated when standardised variables are assumed for schedules, setpoints and equipment over the entire stock. Feedback mechanisms are proposed as a means of recruiting school building users to facilitate future data provision.

Introduction

Motivation and methods to model school energy performance

Energy reduction measures in non-domestic buildings are a major component of the UK meeting its international commitments to climate change (IPCC, 2014) since 18% of the UK's total carbon emissions come from this sector (Carbon Trust, 2009). The education sub-sector of similar sized and function non-domestic buildings provides a rich testing ground for testing carbon reduction strategies since as public buildings generally under public ownership, fabric datasets are available and there are possibilities of implementing renovation programmes at a population level (Pereira et al., 2014).

Benchmarking (Hong et al., 2014) through Display Energy Certificates (DECs) has provided a means of informing school professionals and policy makers of the measured annual electricity and fossil fuel consumptions of their own school building relative to a benchmark (CIBSE, 2008). Although this has provided distinction between low energy but inefficient buildings and energy efficient buildings (Meier, 2004), top-down studies (Godoy-Shimizu et al., 2011) of the school stock have demonstrated that median benchmark values are changing over time.

Post Occupancy Evaluation (POE) has demonstrated discrepancies between the measured and design annual energy consumption of individual schools (Pegg, Cripps and Kolokotroni, 2007) as well as large variations in performance between energy efficient non-domestic buildings (Bordass et al., 2001) Extensive disaggregation of energy end-uses through bottom-up modelling has revealed a performance gap between original design assumptions and measured performance. Attempts have been made to disaggregate the gap in terms of model validation, data collection and external factors (De Wilde, 2014) to compare with target cases (CIBSE, 2015b) but other case studies have revealed occupant related causal factors such as a difference in heating, lighting and electrical schedules (Demanuele, Tweddell and Davies, 2010) as well as issues with building control systems (Bordass et al., 2001).

Scaling these studies up to population level stock modelling has proved challenging. However the possibility of building a school stock model of 16,000 bottom up building simulation models has recently been realised due to the development of automated functions (Evans, Liddiard and Steadman, 2017) coupled with the availability of detailed datasets (Department for Business Energy & Industrial Strategy (BEIS), 2016) and high performance computing. UCL's urban scale stock modelling tool, SimStock (Coffey et al., 2015) is such an example but in order to effectively explain performance gaps on individual members, reliable occupant datasets detailing equipment, schedules, behaviours and controls are required to populate such stock models.

Structure of research

The aim of this research is to test the effectiveness of a stock-modelling approach based on a case study of three London schools. Since the ultimate goal of this work is to feedback individual building performance as well as feeding forward aggregated insight into different sub-sectors to national and local policy makers, a distinction is made here with bottom-up studies of individual schools since the method must eventually be scalable up to cover all 22,000+ public schools in England and Wales.

The next section contains a short description of previous stock modelling efforts and current and proposed methods of accounting for different occupant schedules and setpoints within these models. The following section describes the application of the stock modelling approach to three complex London schools, comparing measured DEC consumption with simulated results and demonstrating pitfalls in the assumptions used in utilising national datasets, evident on an individual level. A final discussion section then details required additions to the

stock modelling project and outlines a framework for future research to develop and test a platform for crowdsourcing data directly from occupants and mechanisms introduced by this form of data gathering.

The role of occupant data in stock modelling

Stock modelling of non-domestic buildings

Top-down studies of the energy performance of entire urban areas or sectors have been possible for many years due to energy certification schemes such as EnergyStar and more recently the UK Display Energy Certificate (DEC) scheme (Burman, Mumovic and Kimpian, 2014; Hong et al., 2014). However building simulation modelling on an urban scale is an emerging field (Reinhart and Cerezo Davila, 2016) due to advances in computing power and methods. The advantage of the stock modelling approach is that end-use causes for underperformance are provided on a sector scale and effective policies tested (Kavgic et al., 2010).

Such an approach is based on the ability to form geometric inputs based on comprehensive floorspace taxation databases and 3D polygon datasets (Evans, Liddiard and Steadman, 2017). Another requirement is that the fabric of all the buildings being investigated can be generalised by a set of archetypes representing different construction ages and types and climate zones (Monteiro et al., 2017) as a trade-off between accuracy and model complexity. Standardised templates for input data are required (Cerezo Davila, Reinhart and Bemis, 2016) to ensure consistency between buildings of different age and function.

The choice of weather file used for calculating stock modelling heating loads depends on the aims of the stock model. If the aim is to generate an average design year, a Typical Meteorological Year (TMY) can be used for the appropriate degree day region; actual recorded weather should be used, where possible, when a comparison to measured data such as DEC annual consumption is required. However if neighbouring buildings have annual data recorded over different timeframes, adjustments will have to be made (Hong, 2015).

Although a more comprehensive list of stock modelling projects is given elsewhere (Reinhart and Cerezo Davila, 2016), Table 1 gives some examples of urban scale modelling - largely identification and remedying underperforming sub-sectors using Energy Use Intensities (EUI). Most of these are district scale rather than sets of buildings of the same sector so involve aggregating data from neighbouring buildings rather than comparison between peer buildings of the same sector. However, as alluded to in the Introduction, oversight of schedules, setpoints and equipment are also required at the district scale to distinguish between energy inefficiency and high energy usage (Meier, 2004), although sector-level also requires normalising the effect of weather when comparing buildings in different regions.

Gathering of occupant data for stock modelling

For gathering these vital occupant datasets, the International Energy Agency Annex 66 (Yan et al., 2017) has developed a framework integrating behavioural modelling and building simulation including truthfulness, management and ethics as well as how and what data is collected. Previous data gathering efforts for bottom-up studies have focussed on two main areas: in situ monitoring (Menezes et al., 2012) and survey based (Dasgupta, Prodromou and Mumovic, 2012) or a mixture.

Table 1: Summary of selected stock modelling methods containing description of role of occupant data

Institution	Reference	Scope of study	Objectives of model	Occupant input data source
MIT (Boston, USA)	(Cerezo Davila, Reinhart and Bemis, 2016)	102,439 polygons representing 98% of residential and non-domestic built floor area in Boston	Providing a basis for demand-response intervention studies at a city scale such as the manipulation of thermostat settings on a large scale	Statistical methods used to upscale metered data to entire urban scale model
EPFL (Lausanne, Switzerland)	(Haldi and Robinson, 2011)	Using CitySim stock modelling software to represent stochastic models of window and blinds opening on a shoebox model	To demonstrate behavioural diversity- inter-occupant spread more significant than within a single occupant Ultimately -decision support for energy policy makers to minimise net use of energy	Data recorded from single office spaces in a research building in EPFL. Multiple simulations run based on derived probability distributions of presence, window and blind opening.
BEST (Milan, Italy)	(Caputo, Costa and Ferrari, 2013)	All residential and commercial buildings in Milan	Support to energy planners, administrators and public utilities by demonstrating the pros and cons of new local /national buildings legislation	Standard occupancy patterns assumed from Swiss Standards for Energy and Building Technology
Osaka University (Osaka, Japan)	(Shimoda et al., 2004)	1,128,000 households in Osaka City using 55 household types (family structures)	Evaluating the effectiveness of insulation and appliance standards and investigating the effect of the urban heat island	Occupant schedules from national time use survey defined for 55 households, scaled up by census data

A potential gap has been defined (Cerezo Davila, Reinhart and Bemis, 2016) in generating hourly usage profiles in the absence of in situ data, which is not always available from utility companies. Post Occupancy Evaluation (POE) has been used effectively to gain insight into bottom-up school energy consumption from school building users (Pegg, Cripps and Kolokotroni, 2007). However the cost and time constraints of specialist personnel and equipment to survey and monitor sample buildings has limited such studies to small samples.

For individual findings to be scaled up to regional level, the high intensity, manpower and costs of data gathering has necessitated the use of statistical methods (Hawkins et al., 2012) and neural networks (Hong et al., 2014) to derive occupant datasets based on acceptable ranges derived from observation. Unfortunately this may reduce the causal determination powers of the model by removing dependence on building physics. Conversely accruing real data by simply shifting the onus to the building user leads to unreliable or sporadic data due to lack of expertise and motivation on the part of the participants or even lack of control (Menezes et al., 2012).

Crowdsourcing (Zhao and Qinghua, 2014) has previously been proposed (Robertson, Mumovic and Hong, 2015) to bridge this enthusiasm and knowledge gap in recruiting school building users to assist in stock modelling, While data gathering through an online platform has been trialled previously through Carbonbuzz (Dasgupta, Prodromou and Mumovic, 2012) to highlight discrepancies between peer buildings as well as between operational and asset performance, these efforts have been targetted at building professionals responsible for designing buildings rather than users responsible for operating buildings.

Implicit in ensuring the quality of data gathered through non-experts is the need to provide feedback to participants reviewing, updating and correcting data to ensure knowledge and satisfaction are being provided as compensation. While tailored feedback (Abrahamse et al., 2007) has previously been demonstrated as a means of informing hundreds of households individually of energy performance measures it has not yet been used to encourage the provision of accurate heating, lighting and equipment schedules and setpoints or to aggregate local and national data within the same platform. Sourcing data direct from building users who have influence over heating, lighting and equipment controls means that aggregated outputs from modelling are a closer representation of reality. National and local policymakers can then be better informed of the potential upsides and downsides of policy instruments while designing key benchmarks which can be measured over the whole stock due to the consistency within the stock model.

Another advantage of engaging building users directly through the data gathering process is that confirmation of comfort and successful provision of building services can be acquired concurrently. Testing the trade-off between comfort and emissions reduction requires connecting the outputs of building users to the aggregated reduction targets of policy makers. Similarly, Human Computer Interaction (HCI) (Bleil de Souza and Tucker, 2016) has also been demonstrated to enhance understanding of the outputs of building simulation for design engineers by automating the simulation process to give feedback in real time, allowing access to libraries of building data and facilitating comparison between cases.

The next section presents a case study demonstrating the importance of individualised occupant datasets in the school setting and the format of data which can be fed back.

Criticality of occupant data: a case study of three complex school campuses

Input data construction and modelling method

In order to test the veracity of using a stock modelling approach to produce calculated EUIs to compare with measured data used in producing the DEC, three complex school campuses in north London consisting of multiple buildings of different ages ranging from Victorian to post-2005 design and technology extensions were modelled.

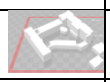
	School 1	School 2	School 3 Main Build	School 3 Upper
3D				
Floor DEC (m^2)	7940	7209	4878	4765
Electricity (kWh/m^2)	56	59	33	73
Heat (kWh/m^2)	243	91	114	86

Figure 1: Description of three Camden school campuses

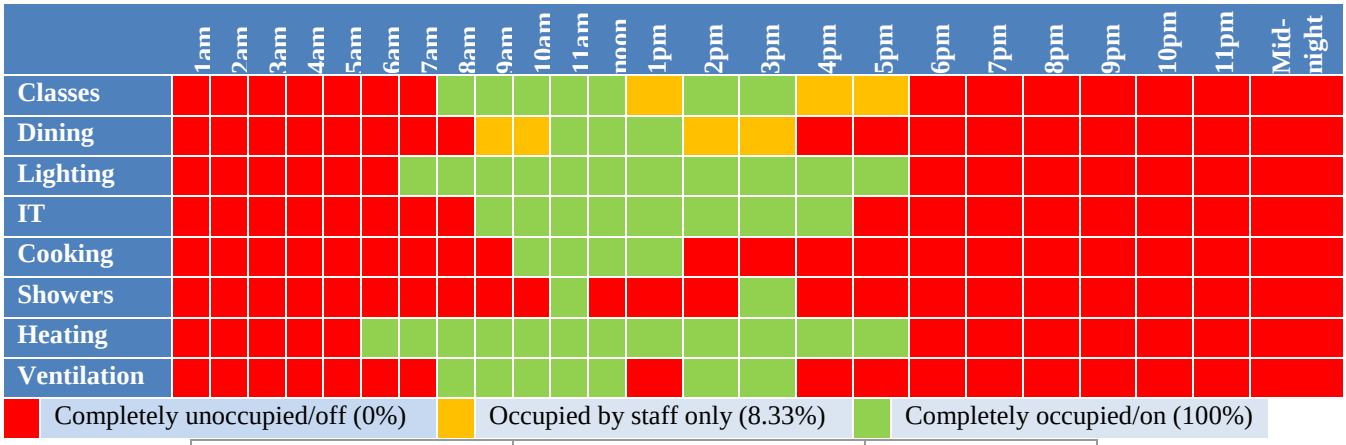
The geometrical models for the three schools, 1, 2 and 3 are shown in Figure 1 together with DEC derived floorspace and annual measured EUI data. School 3 has 2 DECs corresponding to main building and upper school. Input data sets were constructed under four categories:

- Weather – IWEC file measured at Gatwick representing a typical year based on 1983-2001 data
- Built form:
    - Geometry - a series of polygons were constructed using 3DStock functions (Evans, Liddiard and Steadman, 2017) with LIDAR derived Ordnance Survey (OS) coordinates and heights.
    - Filtering – polygons constituting <2% of volume were removed. DEC floorspace was compared to total polygon floorspace.
    - Glazing - glazing ratios were calculated using automatable area measuring methods based on images gathered by site visits/Google Streetview.
- Fabric
    - Archetypes – have been defined in an earlier paper (Bull et al., 2014) to which an extra modern archetype has been added based on the design of the 2005-built Design and

Technology studios on the site of School 1 (Haverstock Architects, 2006)

- Building age – derived using historical maps – possibility of automating this process for more than 22,000 schools

Table 2: Occupant schedules and variables as defined by literature and expected school function



Parameter	Unit	Setting
Heat generated by seated, active occupant	W	120, 250
Thermostat heating set point (Gym/Arts, class)	degC	17, 20
Thermostat Cooling Set Point	degC	25
Infiltration rate (pre-2005, modern)	air ch/hour	0.7, 0.2
Ventilation rate	l/s/person	8
Power of lighting strip (pre-2005), LED (modern)	lumen/W	60, 100
Power of active computer	W/computer	300
Cooking facilities	kWh/meal	1.5

- Occupant schedules, setpoints and equipment –Table 2 demonstrates typical parameters required as inputs for the building simulation. Since the objective of this study is to determine the relative power of each of the above datasets to influence overall consumption when provided deterministically to a stock modelling process, single values are used first based on literature and then tested in the sensitivity analysis. This data comes from a variety of sources including industry standards (CIBSE, 2015), educational regulations (UK Parliament, 1999) and other studies of wattage of equipment (Mudie et al., 2014)

Input data files (.idf) were created for EnergyPlus V8.7 based on LIDAR derived geometry using the 3D stock method (Evans, Liddiard and Steadman, 2017). Fabric and occupant variables, stored in a separate database were pre-processed and automatically added to the .idf file. A simulation was run with the .idf file and IWEC weather file calculating heat and electricity loads at hourly intervals for an entire year.

Results

For School 1, the floorspace indicated by the DEC was 7940 m^2, whereas total floorspace from polygons was calculated to be 15015 m^2. Since it is not possible to determine whether the floorspace figure is wrong or whether the DEC only applies to parts of the building, School 1 was removed from consideration, whilst noting the importance of cross-checking floorspace and which parts of premises a DEC applies to when stock modelling thousands of schools.

Comparison between measured DEC data and calculated end-use usage revealed that for the three remaining DECs (1 for School 2 and 2 for School 3), calculated space heating usage was between 50-150% higher than fossil fuel consumption indicated by the DEC. This difference is even more marked given that water heating for catering and showers which has been separated out from calculated space heating could be included in the fossil fuel consumption measurements. Figure 2 show a typical comparison with three calculated cases, explained in the following section. The remainder of annual consumption allocated to IT, lighting, cooking and showers is within 20% of the measured annual figure for electricity.

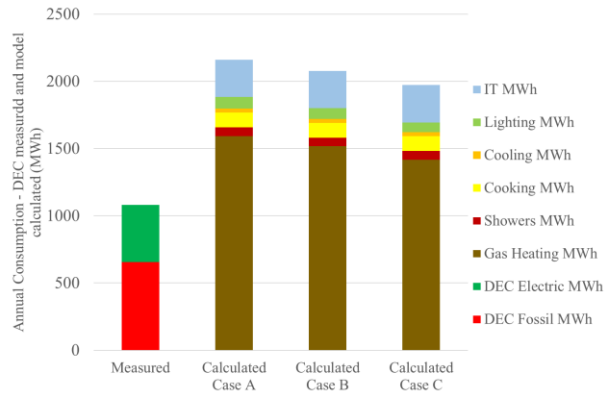


Figure 2: DEC Measured vs. calculated end-use annual consumption in MWh for single school (School 2)

Some variation between measured and calculated consumption is expected due to differences in building constructions and model replication as part of the performance gap acknowledged in the Introduction. A sensitivity analysis was carried out, qualitatively reviewing the possible flexibility of the four input data types as well as quantifying the impact on calculated annual consumption based on perceived flexibility.

- Weather - Since DEC data is measured over a precise time frame indicated on the certificate, there is scope to vary the exact temperature from the "typical year" IWEC file by up to around 2 degC either side based on monthly averages from 2015 and 2016 compared to the IWEC monthly average. In addition the urban heat island effect may mean that temperatures close to the centre of London are higher by around 2-3 degC. Therefore two additional cases were run representing slightly hotter (2 degC added to all temperatures) and much hotter (4 degC) conditions, accounting for different times and locations from where IWEC was recorded.
- Built form - small differences were found between polygons and reality where curved roofs were not accounted for, external walkways were incorrectly interpreted as being part of the thermal envelope or the polygon consisted of two sections of different ages. These mismatches are impossible to identify and correct automatically through a stock modelling process since they would require specialised interrogations of the polygons formed within 3D stock as demonstrated in the next section. Glazing is one area where built form can be misinterpreted so two extreme cases of 0% and 63% glazed were run to demonstrate the range.
- Fabric - As shown in Figure 2, three cases were created for each school representing increasing complexity of fabric modelling:
    - Case A: A single archetype was used across the entire campus based on the age of oldest building with school activities (cooking, gym, art, computing, etc) spread homogeneously throughout.
    - Case B: Different archetypes and activities were allocated to individual polygons based on publicly available data.
    - Case C: Splitting of polygons to account for extensions of different ages and subsequent allocation of activities.
- Occupant setpoints - Simplistic ideal heating loads have been used in EnergyPlus in conjunction with minimum and maximum setpoints and schedules. Classrooms and gyms are heated to different temperatures but no further distinction between heating zones (ie corridors, offices, toilets and classrooms) takes place. A single heating setpoint is over-simplistic since areas of each school will be heated to different extents but could also be a proxy for increasing the space which is considered to be unheated corridor from the conservative starting assumption that all indoor space is heated to the standards specified for classrooms in Table 1. A minimum setpoint of around 16 degC could be interpreted as a rough method of accounting for around half the "classroom" space in the model being unheated space.

Figure 3 shows the relative effects of the four sensitivity variables relative to the measured DEC fossil fuel consumption. It can be seen that temperature and heating setpoints are the most significant factors which can be altered to provide the magnitude of change required to approximate measured annual fossil fuel consumption.

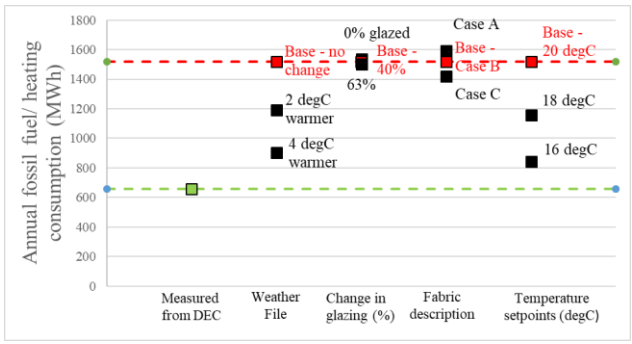


Figure 3: Sensitivity analysis on weather, glazing, fabric cases and temperature setpoints (Base Case- School 2, Case B, 20 degC heating)

Having demonstrated that standardised heating setpoints provide insufficient detail on an individual level for school stock modelling, the remainder of this paper discusses future work acquiring more robust datasets of occupant schedules, setpoints and equipment and how design of feedback mechanisms may facilitate this.

Discussion and future research

The need for and format of occupant feedback

The previous section demonstrated that setpoints and even floorspace of the annual consumption covered by the DEC can provide significant uncertainty for individual school buildings within a school stock model. Scope for correcting or generating these datasets should be accounted for within the stock model framework in order

for correct information to be fedforward to policy makers. The current scope for UCL's stock modelling platform SimStock is detailed below in Figure 4**Error! Reference source not found.**. Under "other data", individualised schedule, setpoint and equipment datasets will be required to complement the built form ("3D stock") and fabric ("16000/22000 School Database"). In addition there is a need to define how this data can be aggregated and categorised ("Analysis Module" in Figure 4) to track progress towards CO2 reduction targets to national and local policy makers.

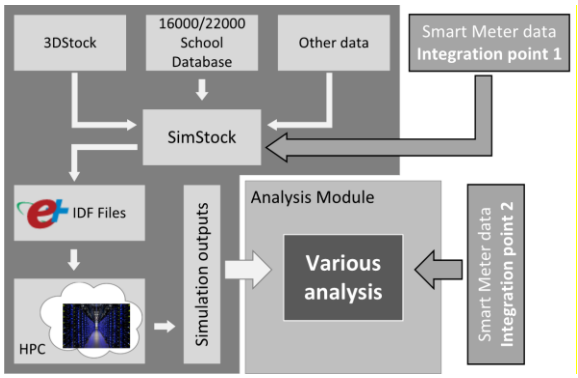


Figure 4: Current SimStock framework

The previous section demonstrated that for individual building performance to be determined accurately and aggregated in the stock modelling process, there is evidence that this data will need to be obtained actively rather than extrapolating model inputs from elsewhere. Since building users themselves are responsible for defining this dataset, by definition this data needs to be sourced directly from building users, who may lack the initial motivation and knowledge to accurately provide this information.

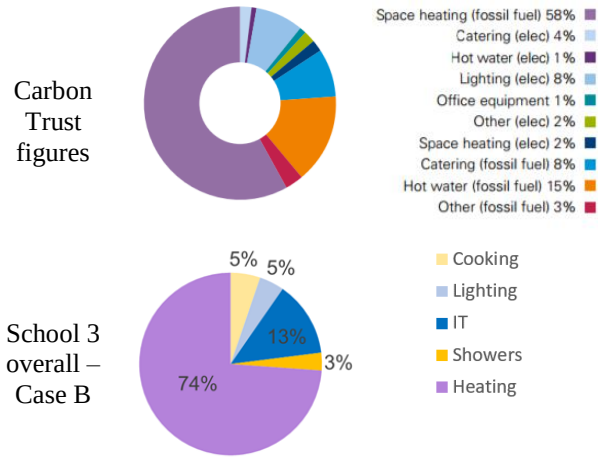


Figure 5: Comparison of simulation with literature breakdown of energy uses (Carbon Trust, 2012)

Comparisons with peers or national benchmarks are possible through stock modelling; while DECs provide overall comparisons, modelling output allows different energy end-uses to be disaggregated and compared. Figure 5 demonstrates such a comparison between a case study schools and Carbon Trust figures (Carbon Trust, 2012) for a "typical school", demonstrating overprediction of heating requirements and IT relative to literature figures. Such comparison could demonstrate to individual schools where significant operating costs could be being incurred in relation to other schools (feedback) and also conversely demonstrate nationally where false assumptions are being made about the use of energy in schools.

Future work developing a platform to test feedback and feedforward mechanisms

The previous section discussed tailoring feedback towards different school users within a national school stock model. However the format and usability of aggregated data to national and local policy makers, or feedforward mechanism, is also critical to the success of the stock modelling platform as a decision making tool. The following research questions will require consideration.

Feedback from school building users:

- What motivational drivers such as the cost of school energy as the second largest expense after salary (Pereira et al., 2014) can be used to encourage engagement of school users with the review, updating and correction of their school's data?
- What level of detail and interaction of simulation outputs could educate school users with the knowledge required to improve the quality of provided data?
- Is it additionally possible to influence potential improvements in the operation of school buildings through tailored feedback?

Feedforward to policy makers:

- What are the key performance metrics and sub-sectors required by local and national policymakers from aggregated data?
- What range of policies or school measures (Smith, Mumovic and Curtis, 2013) require testing by policy makers?

A future research project by this paper's authors will involve the development of a crowdsourcing platform as detailed in Figure 6 to answer the questions posed above. To inform the design of feedback and feedforward mechanisms, engagement with the following key stakeholders would be required through workshops and testing:

1. National policy makers - defining progress towards emissions targets and prioritising sub-sectors of the stock to target energy measures on.
2. Local authorities - determining the allocation of financial (such as Salix funding) and bulk project managing resources
3. Individual school building users - to tailor feedback mechanisms which can suitably inform and motivate different school building users to provide accurate datasets.

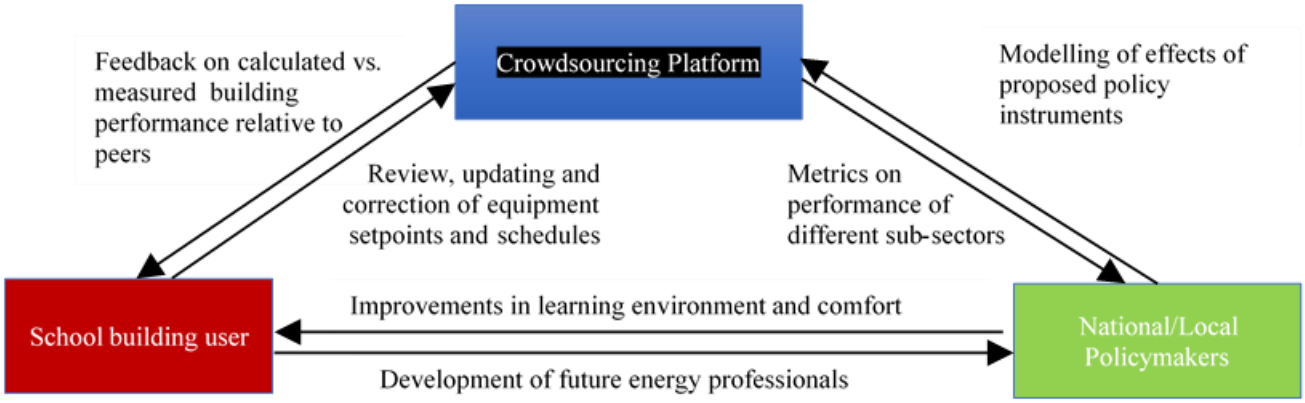


Figure 6: Crowdsourcing platform with feedback and feedforward mechanisms to key stakeholders

Engagement between building simulation and school design professionals has been previously demonstrated for the purposes of carbon reduction (Smith, Mumovic and Curtis, 2013). However as the case study demonstrated, simulating thousands of buildings still requires inputs on an individual level, which requires the building user as a key stakeholder.

Conclusions

The effectiveness of the school stock modelling process has been investigated in the above case study of three schools based on available weather, built form, fabric and occupant datasets. The study has demonstrated that details of heating, lighting and equipment schedules and setpoints at an individual level are essential to building simulation models which predict end-use energy usage.

While other stock modelling methods detailed in Table 1 have required occupant datasets, these have generally been generated from case studies or reference data and scaled up through statistical or machine learning methods. The only potential source of insight into actual rather than design usage on an individual building basis across the stock without sampling through cost and time intensive post occupancy evaluations are the building users themselves. In addition quality control of existing datasets is required as with DEC floorspace in School 1.

Crowdsourcing this data directly from building users may provide a potential method of creating occupant schedule, setpoint and equipment datasets. However, future work will require testing of the design of motivation and information feedback to the building user. The effectiveness of such a platform will additionally require monitoring incremental improvements to the accuracy of simulation models generated relative to measured data as well as the quality of aggregated output to be fed forward to national and local policymakers for progress tracking and decision making.

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