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The Effect of Occupants' Behaviour on the Building Performance Gap: UK Residential Case Studies

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Abstract: Studies have shown that the assumptions used to create dynamic thermal models of buildings do not reflect their actual energy use. Bridging the energy performance gap is vital in ensuring that a designed or retrofitted building meets the energy performance targets. Using thermal analysis simulation software TAS, this paper presents a simulation model of seven different UK single family houses. The results from the various models are validated by comparing the actual energy demand against the simulated consumption. The simulation results show that the heating set point has the greatest impact on the simulated energy demand. The results also demonstrate that the energy demand of the dwellings can be reduced by applying window opening schemes and by controlling the heating setpoint temperature and schedule. Plug load consumption is also considered by using plug load data of real UK households, as obtained from a longitudinal study, and calibrating the model based on average plug load contributions for the households. The results showed that, by increasing the heating set point and window opening schedules by 10% from self-reported data, and by considering an additional 12% for plug loads, the energy performance gap is reduced to less than >15% for all examined houses.

Keywords: thermal analysis simulation; performance gap; residential homes; occupant behaviour

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1. Introduction

Currently, building modelling is an essential part of building design. This is because of the increase in standards of buildings regulations [1]. Building modelling and simulation tools are used to evaluate regulatory compliance by predicting energy performance, produced and mitigated CO_2 emissions, overheating analysis, and the building's interaction with its external and internal environments [2–4].

Studies have shown that the assumptions used to create dynamic thermal models of buildings do not reflect their actual energy use [5–9]. This is known as the performance gap. Generally, it has been found that the energy performance of the actual building is higher than the energy performance of the modelled building, even when the modelled building is a reproduction of the building [10–14].

The quality of input data used to complete a thermal model has a significant effect on the accuracy of the simulated model and its outputs [15,16]. However, factors such as occupancy behaviour, plug load consumption, and weather data cannot be entirely reproduced to match real-life conditions. Furthermore, factors such as over-simplified modelling assumptions, poor energy management, and poor maintenance of building systems and components can affect the outcome of the energy performance of the building [17]. This is where the importance of conducting a thorough and accurate site survey (especially for existing buildings) plays a significant role. By spending time collecting all the necessary input data and information required, the number of modelling assumptions are reduced, and the model created can, therefore, be a closer representation of the actual building. The performance gap has been studied throughout the literature since the 1990s via projects such as PROBE (Post Occupancy Review of Buildings and their Engineering) in the UK and LEED certification investigations in the UK [18–20].

For this study, the aim is to investigate the performance gap and how it may be bridged. The study is utilising seven residential existing UK houses. Site surveys are conducted to ensure that all the modelled buildings are a reproduction of the currently existing building and all of it elements. The seven properties were specifically selected to represent typical residential houses in the UK. Dynamic simulation software TAS [21] is used to examine and compare the actual energy demand against modelled energy demand for all properties. TAS is a building modelling and simulation tool capable of performing hourly dynamic thermal simulation for new and existing buildings.

The extent of impact of occupant behaviour on energy demand is explored by using self-reported data from occupants. A record of the occupants' daily activities, such as their preferred heating set points, window opening schedule, etc., was noted so that the impact of their behaviour on energy demand can be studied and assessed as a contributing factor to the energy performance gap.

Finally, the paper will present an approach to improving modelled energy demand, based on the findings of occupant behaviour and plug load consumption, and calibrating the model. To consider plug load contribution, the monitored results of plug load consumption across 251 UK households, over the course of one year, are utilised.

2. Materials and Methods

2.1. Literature Review

The evaluation of the performance gap involves estimating the performance of a building during the design stage and comparing this to the actual measurements taken post-occupancy. This can be done by accessing energy bills or by installing monitoring systems to take hourly, daily, and monthly measurements.

Van Dronkelaar et al. found that the performance gap exists in all stages of the building life cycle [22]. They also identified the dominant factors to be related to uncertainty in modelling, occupant behaviour, and poor operational practices. Jain et al. highlighted that it is vital for studies investigating the performance gap to conduct a detailed operational performance investigation to identify and address the causes of the gap [23]. This is vital in order to separate technical causes of the performance gap (i.e., design vs. as built) from occupant behaviour related causes.

A large scale-study investigated the energy performance gap of around 200,000 dwellings [24] and found that energy-efficient dwellings, in general, consume more energy than initially predicted. The authors highlighted that, whilst simulation studies or theoretical calculations can meet the energy target reductions required by policies and targets, in real life, the actual energy reduction potential of dwellings "fails to meet most of the current energy reduction targets". This is in consonance with several other studies that have reported that the energy demand of actual dwellings is typically higher than the modelled or calculated one [25–30]. Filippidou et al. utilised a monitoring system to collect actual energy demand data on the non-profit housing sector (circa 2.1 million dwellings) [31]. Using a longitudinal analysis methodology, from 2010 to 2014, they also found that the actual energy savings of different efficiency measures were very different from the predicted savings, once again corroborating the above findings.

The design versus as-built issue can refer to discrepancies between the actual constructed building and the design of the building. This can occur due to various reasons such as negligence, uncertainty in the design, or inappropriate design aspects which cannot be applied in real-life conditions. However, it is uncommon and unusual for an entire building or a large percentage of a building to be built without adhering to the design. Johnston et al. measured whole building U-value for 25 new dwellings in the UK and found that the measured value was more than 1.6 times the estimated value [32]. Similarly, a study on several buildings in Italy measured the in situ thermal transmittance and found discrepancies, between estimated and measured, of −14% to +43% [33]. Building aspects, such as the building envelope and its performance, have a large impact on the energy performance of the building. Therefore, studies showing discrepancies between the estimated and measured performance of those aspects strongly suggest that design versus as built can be an important contributing factor to the performance gap.

Other studies have looked at whether alternative methodologies to the standard theoretical calculation can provide a better prediction of energy performance. A 2020 study, carrying out a pre/post retrofit real energy demand analysis of over 1000 buildings, found that energy performance certificates were a poor indicator of actual consumption in comparison to theoretical calculations [34].

The choice of weather data can also have a considerable impact on the performance gap. The Chartered Institute of Building Services Engineer's (CIBSE) weather files are typically utilised within the UK's construction industry for simulating and examining buildings. Two types of weather files are provided by CIBSE, known as the 'Test Reference Year' (TRY) and the 'Design Summer Year' (DSY). Using 14 different locations around the UK, CIBSE gathered 30 years of real weather data, including data regarding: dry bulb temperature (°C); wet bulb temperature (°C); atmospheric pressure (hPa); global solar irradiation (W·h/m^2); diffuse solar irradiation (W·h/m^2); cloud cover (oktas); wind speed (knots); wind direction (degrees clockwise from North. The weather files consider the effect of climate change and are the best data sets that can be currently used in simulation studies [35,36]. Despite the level of improvement in current weather data in comparison to previous years, the weather data used for the simulation should, ideally, replicate the microclimate of the building. However, this is challenging to achieve and can lead to the variation between simulated and actual energy demand.

Some researchers have claimed that the energy performance gap can be mainly explained by occupant behaviour [37–39]. Yet, there continues to be a lack of widely available occupant data to fully confirm the influence of occupant behaviour on energy demand. This is because most studies that investigated this have used pre-occupancy data, as opposed to post-occupancy data, due to the time-consuming and intrusive nature of carrying out such monitoring. However, to improve simulation models and set realistic energy targets and recommendations, it is vital that actual occupant behaviour is investigated and understood.

The specific ways in which occupant behaviour can potentially influence energy demand include number of heating hours, set-point temperature, as well as how frequently hot water, lighting, and appliances are being used. Guerra-Santin found that even using a radiator for different number of hours in different rooms around a dwelling can lead to a variation in the actual energy demand [40]. For example, the variance for the living room is 8.8%, and for the bathroom, it is 5.9%. Gerdes et al. discussed how the number of people per household has a significant influence on the energy used for DHW [41]. Meanwhile, a larger number of household occupants leads to a decrease in the energy demand per person (but overall higher energy demand) [42]. As time and technology change, studies have recorded a change in the mix of energy use within households. For example, energy use for cooking has continually decreased over the past few years, while energy use from electrical appliances has increased significantly.

Studies that did not explore pre- or post-occupant behaviour have focussed on occupant characteristics instead. Two different studies in England have confirmed that there is a positive correlation between household income and actual energy demand. Brom et al. highlighted that the effectiveness of renovations is dependent on occupant type [43]. Using a longitudinal methodology and investigating nearly 90,000 renovated dwelling with pre and post renovation data, they found the occupants with a high income save more energy than occupants with low income; dwellings with employed occupants benefit more from improved building installations than dwellings occupied by unemployed occupants.

Consequently, deep renovations often save less energy than predicted (even if they are the most effective at reducing consumption).

Based on the review of the above literature, it is clear that there are multiple contributing factors to the performance gap, and that it is an issue that requires a far more comprehensive, coordinated approach that combines model validation and verification, improved data collection for predictions, better forecasting, and change of industry practice.

2.2. Case Studies

Seven different residential properties are examined in this section. Properties 'A1–A2' are located Bracknell, Berkshire, England. Meanwhile, properties 'A3–A7' are all located in the London Borough of Hillingdon (the westernmost of the London borough councils) (Figure 1). The properties were selected based on several criteria: design, build year, location, and occupant availability. Properties 'A3–A7' are built in the period of 1929 to 1939, and the other two properties are built post-1930s but pre-1990s. As for the background information regarding these residential buildings, the building regulations at the time of the construction of these houses were quite different and were well below today's building standard. The houses (A1–A7) taken understudy are detached, semi-detached, terraced, detached, end of terrace, mid-terrace, and end of terrace, respectively, and the number of occupants varies in each dwelling, as provided in Table 1. However, they are interviewed, and data is recorded. Only 14% of the UK population currently live in a flat or maisonette; although it should be noted that, within London, 43% of Londoners live in a flat [44].

The homeowner(s) were all willing to be interviewed. They provided details of their daily activities, such as their preferred heating set points, window opening schedule, etc., so the impact of occupant behaviour on energy demand can be studied to assess the extent to which it is potentially a contributing factor to the energy performance gap.

It is important to include more than one case study for this investigation to gain an accurate insight into which factors affect the performance gap and to what extent their influence can be on this. Furthermore, it will be very interesting to compare the initial energy demand of houses with a similar size and occupancy rate. Table 1 shows a summary of the details for the various houses and a summary for the heating and window opening schedule.

Table 1. Summary of case study and modelling process.

Typical Block Characteristic								
Element/System		**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
Type		Detached	Semi-detached	Terraced	Detached	End of terrace	Mid-terrace	End of terrace
Building fabric	Type	Solid wall; original build; cavity wall	Solid wall; original build; cavity wall	Solid wall; original build; cavity wall	Solid wall	Solid wall; original build; cavity wall	Solid wall	Solid wall; original build; cavity wall
Total No. of occupants		4	2	3	1	2	3	1
Wall (calculated area weighted average u-values) [1]	u-value (W/m^2K)	0.32	0.35	0.33	0.30	0.32	0.35	0.32
Roof (calculated area weighted average u-values)	Type	Gable roof	Pyramid hip roof	Gable roof	Gable roof & shed roof	Gable/hip roof	Saltbox/gable roof	Hip roof
	u-value (W/m^2K)	0.30	0.30	0.31	0.33	0.32	0.31	0.30

Table 1. *Cont.*

Typical Block Characteristic								
Element/System		**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
Floor (calculated area weighted average u-values)	Type	Concrete	Concrete	Timber	Concrete	Timber	Timber	Concrete
	u-value (W/m^2K)	0.57	0.54	0.57	0.65	0.54	0.60	0.57
Windows (calculated area weighted average u-values)	Type	Double glazing (air-filled)	Double glazing (air-filled)	Double glazing (air-filled)	Double glazing (air-filled)	Double glazing (air-filled)	Double glazing (air-filled)	Double glazing (air-filled)
	u-value (W/m^2K)	2.80	2.80	2.90	2.45	2.45	2.95	2.80
Cooling		No cooling system						
Heating	Fuel	Natural Gas						
	Temperature Set Point	19 °C	17 °C	16 °C	18 °C	21 °C	22 °C	20 °C
	Heating Capacity	2—3 kW						
	Working temperature	60—80 °C						
	Heating distribution	Central heating radiators						
	Schedule	20:00—6:00	23:00—7:00	23:00—5:00	23:30—3:00	18:30—5:00	17:00—6:00	21:00—5:30
Domestic Hot Water (DHW)	Type	Conventional gas boiler system	Conventional gas boiler system	Combi boiler	Conventional gas boiler system	Combi boiler	Conventional gas boiler system	Conventional gas boiler system
	Temperature	45—52 °C						
	Average daily consumption	130—140 litres per person per day						
Ventilation	Type	Passive/Natural						
	Schedule	8:30–18:00	8:00–15:30	13:00–15:00	12:00–14:30	8:00–16:00	14:00–17:00	17:30–19:00
Zone—occupancy levels, people density, lux level	NCM constructions database—v5.2.tcd	Bedroom—0.094 person/m^2, 100 lux Toilet—0.1188 person/m^2, 200 lux Reception—0.105 person/m^2, 200 lux Hall—0.183 person/m^2, 300 lux Food prep/ kitchen—0.108 person/m^2, 500 lux Eat/Drink area—0.2 person/m^2, 150 lux Circulation—0.115 person/m^2, 100 lux Store—0.11 person/m^2, 50 lux Laundry—0.12 person/m^2, 300 lux						
Air permeability		5–10 $m^3/h/m^2$ at 0 Pa						
Infiltration		0.500 ACH						
Lighting Efficiency		5.2 W/m^2 per 100 lux						
Fuel Source		Natural Gas—CO_2 Factor—0.216 Kg/kWh						
		Grid Electricity—CO_2 Factor—0.519 Kg/kWh						
Weather data		DSY (CIBSE) for London. Includes: dry bulb temperature (°C); wet bulb temperature (°C); atmospheric pressure (hPa); global solar irradiation (W·h/m^2); diffuse solar irradiation (W·h/m^2); cloud cover (oktas); wind speed (knots); wind direction (degrees clockwise from North); and Present Weather Code.						

[1] refers to brickwork and blockwork constructions (walling is of masonry construction and tied with stainless steel ties to an outer leaf of block/brick).

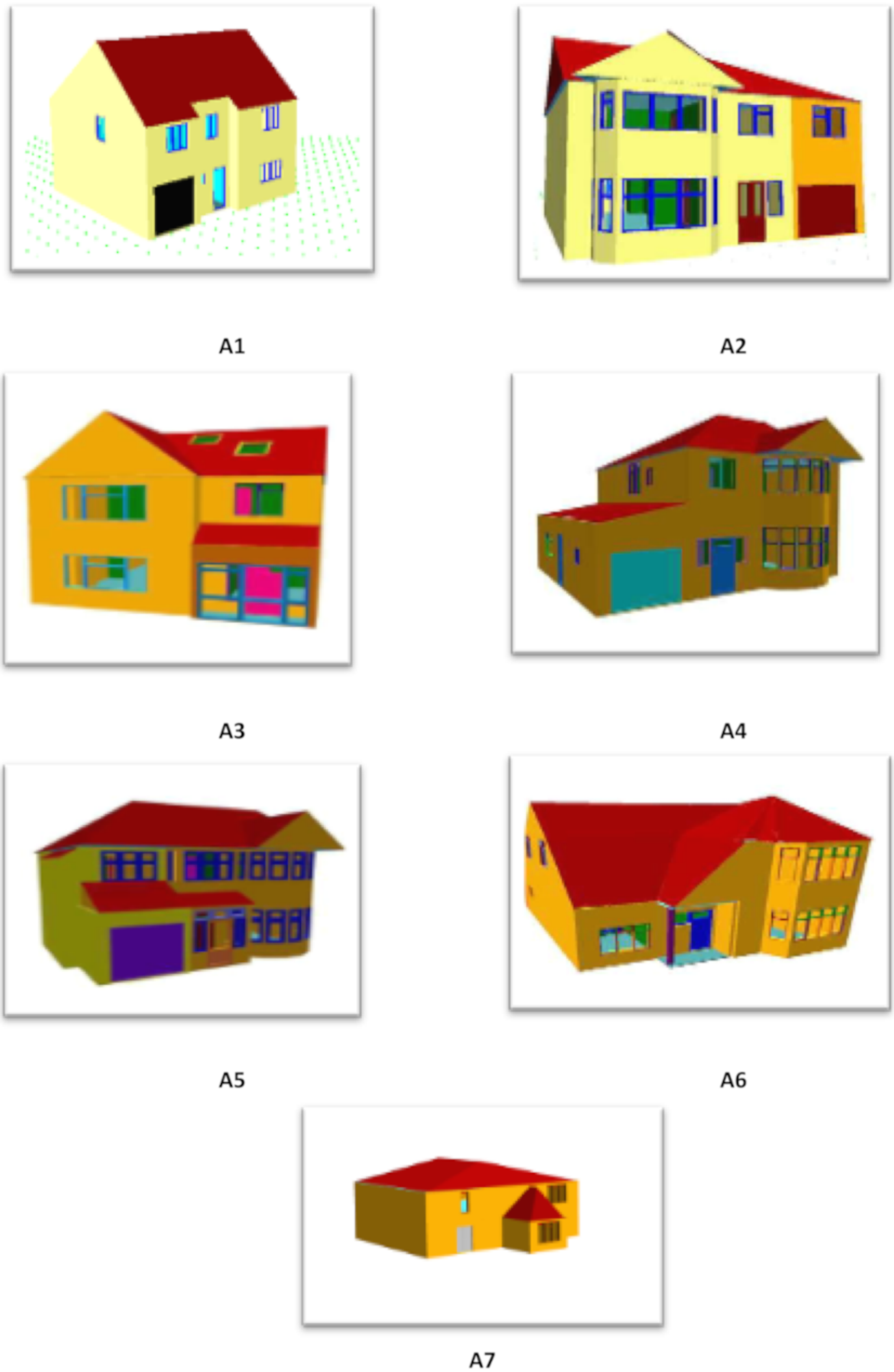


Figure 1. 3D Models of the seven houses (See Table 1).

2.3. Modelling Details

The methodology applied in this paper is split into four main phases:

Actual site data: this phase involves conducting a site visit to collect AutoCAD plans (i.e., floor plans), information regarding the actual building construction, systems, and plant details, as described above. This allows the creation of a model that reproduces the current state of the building. In addition, the actual monthly and annual energy demand is collected for the latest year, and the previous two years, for comparison and validation. The latest year is utilised for comparison to the modelled energy demand. The previous two years are used if an anomalous energy profile appears (e.g., during a cold spell in May that leads to unusually high energy demand). In the case of an anomaly, the average of the previous two years is taken. Furthermore, data survey questions were recorded, such as typical window opening schedule and typical heating set point, as shown in Tables 2 and 3.

Table 2. Summary of factors investigated for contributing to the performance gap.

Factor	Unit	Parameter
Heating set point	°C	+4 °C from current set point
Heating schedule	hrs/day	+4 h from current schedule
Window opening schedule	hrs/day	+4 h from current schedule
Plug Load consumption	%	TBD [1] based on findings [2]

[1] To be determined. [2] See Tables 3 and 4.

Table 3. Summary of average plug load consumption results for UK households.

Average Annual Consumption (kWh)	
Appliance Type	
Refrigerator	162
Fridge-freezer	427
Washing machine	166
Washer dryer	243
Dish washer	294
Clothes dryer	394
Oven	290
Cooker	317
Hob	226
Microwave	56
Kettle	167
TV	658
Audiovisual site [1]	465
Computer site [2]	240

Source: Survey results of 251 monitored UK households over 1 year (Intertek Report, 2012). [1] Audio-visual site includes products typically used around RV sets, i.e., DVD players, recorders, VCR, set top boxes, games consoles, home cinema amplifiers, and speakers. [2] Computer site includes all computer products that were typically switched on whenever a desktop PC or laptop was used, i.e., screen, printer, etc.

TAS software: the site data that is collected from the first phase is used to build a holistic baseline model on TAS. The typical energy use in a building (heating, cooling, ventilation, lighting, and DHW) needs to refer the indoor environmental parameters. The standard zones that are applied within the model (where applicable) are bedrooms, hallway, bathroom/water closet, living room, kitchen, and garage.

When populating the TAS Building Data (TBD) file, such as filling out typical constructions of the building envelope, it is ensured that they represent the building's constructions, building fabric, glazing, and year of construction. Once this is done, the building's systems are specifically and individually designed within TAS systems utility to replicate the current HVAC systems/plants. Refer to ref. [45] for full details on the simulation process, including the air permeability, which should range of 5–10 $m^3/h/m^2$ at 50 Pa. However, for the purpose of research, air permeability of each house is to be taken as 6.0 $m^3/h/m^2$ at 50 Pa. Similarly, for the ventilation purposes, airtight constructions mean that adequate ventilation is necessary for maintaining a high level of indoor air quality, along with preventing air leakage and overheating. Since the residential buildings are built in from 1929 to 1939, and the other two properties are built post-1930s but pre-1990s, the dominant ventilation is the natural ventilation, with windows opening as the main source of ventilation.

CIBSE Weather Data: the CIBSE weather datasets are based on a 30-year timeline and it is generally recommended that, where possible, the weather file selected should be in close proximity to the location of the case study being examined. TAS and other simulation software recommend that the existing pre-selected 'typical years' weather files that are within 20–30 miles (30–50 km) of the case study will most closely match the long-term climatic temperature, solar radiation, and other relevant variables. The relevant weather file selected for carrying out the analysis is the Test Reference Year (TRY). This is selected because the Design Summer Year (DSY) weather file is suitable for overheating analysis. Meanwhile, the Test Reference Year (TRY) is suitable for "energy analysis and for compliance with the UK Building Regulations (Part L)".

Simulation: finally, the model is simulated after all the details have been inputted and the U-values, energy demand, carbon emissions etc., are all calculated and generated by TAS. The energy demand figures obtained from utility bills are then compared to the modelled energy demand of each building and the percentage error/difference is calculated to validate the model.

Table 4. Summary of average load contribution for various load types and UK households.

Load Contribution Average (%)	
Load type	All days
Cold appliances	16.2%
Cooking	13.8%
Audiovisual	14.4%
Computer site	6.1%
Washing/drying	13.6%
other	3.7%

2.4. Investigated Factors

Three factors have been initially selected—namely, the heating set point, heating schedule, and window opening schedule to investigate the impact of occupant behaviour on energy demand. For each of the factors selected, the established parameter is that the set point or schedule will be increased by 4 °C or 4 h, and this will be done in 1 °C or 1-h increments on TAS. The effect of the '1 point' increase on energy demand is examined, and the percentage difference between this and the actual energy demand is compared. Table 2 is showing the summary of the factors that are investigated.

As discussed in the literature review, plug load consumption is one of the factors that have been overlooked across the literature as a contributor to the performance gap. Typically, a longitudinal study of at least 6 months is required to effectively investigate this. Therefore, for this study, the monitored survey results of real-life plug load consumption across 251 UK households over the course of one year are utilised to calibrate the model and include plug load contribution [46]. Tables 3 and 4 are showing the summary of the main appliance types and their annual consumption, as well as the average plug load contribution across UK households for various load types such as cooking, computer, and audiovisual loads. Using the survey results, it is established that real-life plug load contribution is estimated at a 12% average increase or approximately 580 kWh annual plug loads. However, to validate this, three scenarios will be explored initially to investigate whether this 12% can be used as a standard value in reducing the performance gap (see Tables 3 and 4 for further detail).

3. Results

3.1. Baseline Model Validation Results

Figure 2 is showing a comparison of the modelled energy demand versus the actual energy demand (as obtained from energy bills). It is interesting to observe that a 3 °C in set internal temperature between house A6 and A1 led to a difference of less than 1440 kWh or 4% difference in their annual energy demand. Meanwhile, a 6 °C difference between house A3 and A6 led to a substantial 55% difference in their annual energy demand. This strongly suggests that heating set point, and occupant interaction with heating set point, can be a leading cause for the performance gap.

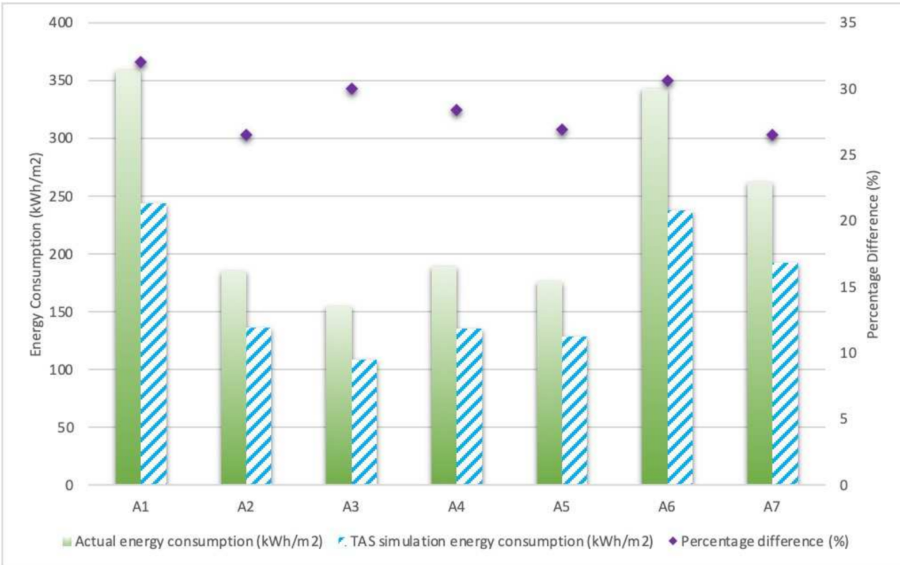


Figure 2. Comparison of the modelled energy demand versus the actual energy demand and the percentage difference.

In terms of the percentage difference between actual and modelled energy demand, all the houses had a difference within the range of 27% to 32%. This corroborates the idea within the literature that there may be common factors which lead to this performance gap between actual and simulated energy demand. In other words, there are certain (potentially behavioural) factors for which TAS does not account, thereby leading to this difference.

Looking at the heating consumption differences shown in Figure 3, a similar trend is observed. Once again, House A1 presented that largest difference between actual and modelled consumption with a 36% gap. However, as the lowest percentage gap obtained is 27%, this suggests that there are other major factors still contributing to the overall energy demand gap.

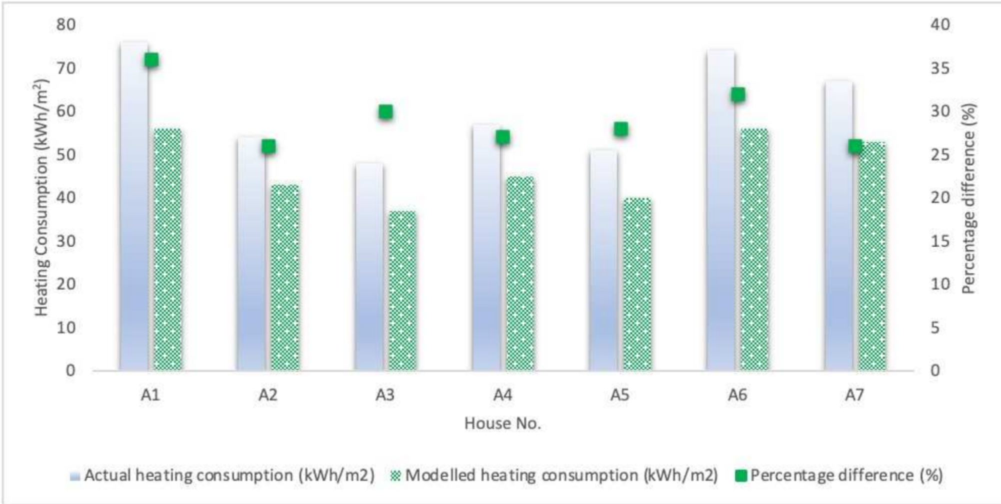


Figure 3. Comparison of the modelled heating consumption versus the actual heating consumption and the percentage difference.

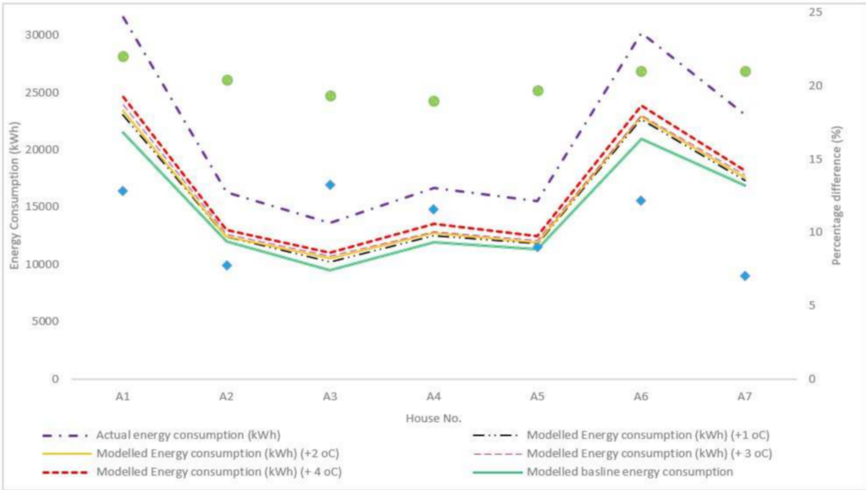
3.2. Performance Gap Investigation and Model Calibration Results

Figure 4a–c is showing the actual energy demand against the TAS energy demand for the various altered factors.

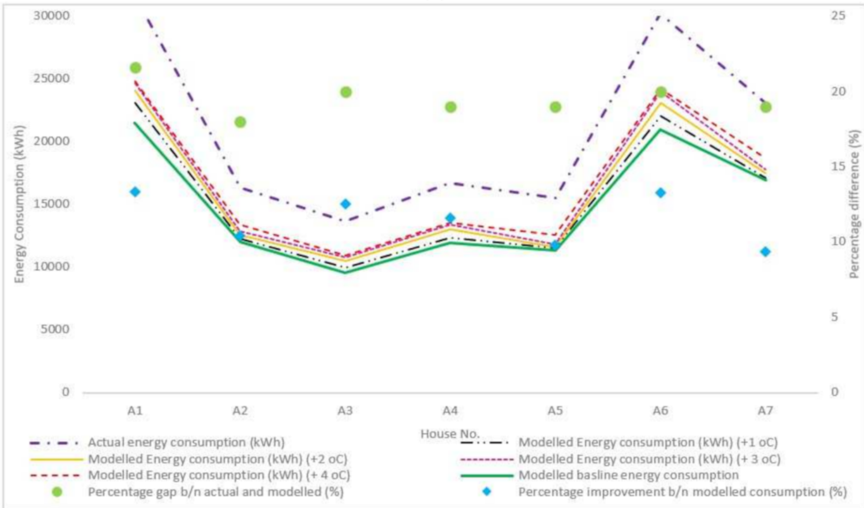
For the altered heating set point shown in Figure 4a, the results show that a 1 °C increase leads to a 5% improvement in the performance gap between actual and simulated energy demand for house A1. Meanwhile, a 4 °C increase leads to a 13% improvement. In other words, the performance gap between simulated and actual energy demand for house A1, after a 4 °C increase in the heating set point, decreased from 32% to 22%. A similar trend is observed for all houses. The percentage decrease, for all the houses with the heating set point +4 °C, is in the range of 19–22%. Between the baseline simulation and the altered simulations there is an average improvement of 10% for all houses. What this suggests is that, although the heating set point plays a significant role in affecting the energy demand, there are additional factors that still need to be considered because the percentage gap was still more than 15%.

Looking at the results with the altered heating schedule shown in Figure 4b, the effect this has on decreasing the performance gap is like the effect of altering the heating set point. For example, once again looking at house A1, a 1 h increase leads to an identical 5% improvement in the performance gap between actual and simulated energy demand for the house. The 4 h increase leads to a 13% improvement. The percentage decrease for all the houses with the heating schedule +4 h is in the range of 18–20%. Between the baseline simulation and these simulations, there is an average improvement of 9% for all houses.

Finally, looking at the effect the window opening schedule has on the simulated energy demand, there is a larger gap between the actual and simulated consumption, as shown in Figure 4c. For house A1, a 1 h increase leads to a 3% improvement in the performance gap between actual and simulated energy demand for the house. Between the baseline simulation and the altered simulations, there is 12% improvement for house A1 and an average 10% for all houses. The 4 h increase leads to an 11% improvement from the baseline performance gap (i.e., a 23% percentage gap). This 23% gap is once again significantly higher than the actual energy demand, although it does represent an improvement from the baseline modelled scenario.



(**a**)



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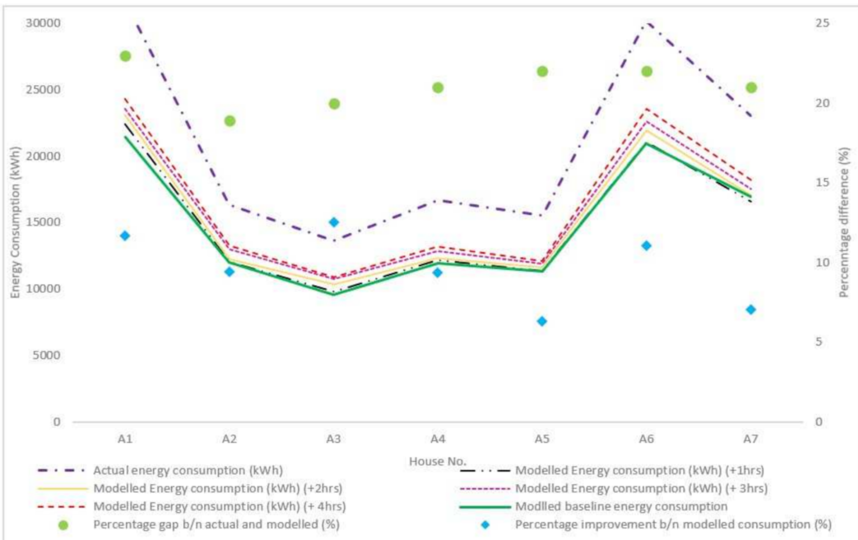


(**c**)

Figure 4. Modelled performance versus actual, with altered heating set point, and heating and window opening schedule (**a**) altered heating set point, (**b**) altered heating schedule, and (**c**) altered window opening schedule.

In general, despite altering the heating and window opening schedule, as well as heating set point, the performance gap was not reduced adequately and an average performance gap of 22% remains. Although this 22% presents an improvement from the initial >30% gap, it is substantial and continues to have a negative effect on the validity of the model and thereby, the reliability of the outcomes. The results above suggest that the heating set point should be increased by a 2 °C, and the heating and window opening schedule should be increased by +2 h from the self-reported data. This will ensure that any anomalous behaviour due to sudden changes in temperature etc., is taken into consideration by the simulated model. The next phase of analysis will now focus on calibrating the model to help bridge the remaining gap by updating the input parameters. Table 5 is showing the updated input parameters with plug loads now also taken into consideration. Three scenarios are created, and finally, the model is adjusted based on the findings (see Table 6), as discussed earlier.

Table 5. Updated input parameters.

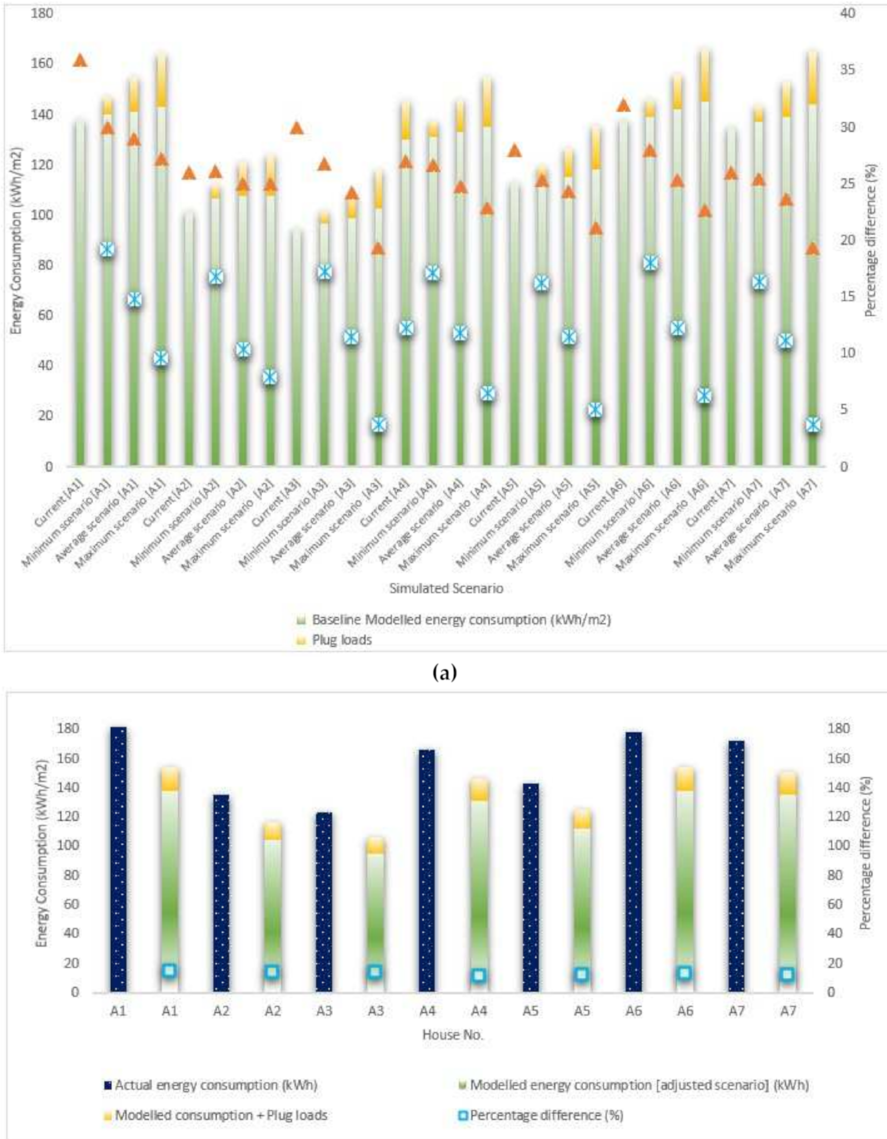
Model	Details	Unregulated Energy Use
Original system model	Energy model dynamically simulated via customised TBD file and Tas systems utility.	Dynamic heating set point and heating and window opening schedules are considered based on obtained self-reported data. Plug loads are not considered.
System model + minimum scenario	Energy model simulated via customised TBD file and Tas systems utility.	Dynamic heating set point and heating and window opening schedules are considered with a conservative increase of 5% for plug loads
System model + average scenario	Energy model dynamically simulated via customised TBD file and Tas systems utility.	Dynamic heating set point and heating and window opening schedules are considered with a moderate increase of 10% for plug loads
System model + maximum scenario	Energy model dynamically simulated via customised TBD file and Tas systems utility.	Dynamic heating set point and heating and window opening schedules are considered with an ultimate increase of 20% for plug loads

Table 6. Final adjusted system model.

Model	Details	Unregulated Energy Use
Adjusted system model	Energy model dynamically simulated via customised TBD file and Tas systems utility.	Dynamic heating set point and heating and window opening schedules are considered with a 12% increase for plug loads

Figure 5a is showing the calibrated model performance of the three scenarios against actual performance. The results display the baseline model results and the difference when the plug loads are considered. In addition to this, the figure also shows the initial percentage difference and the new percentage difference with the plug loads. Looking at Figure a, it is immediately observed that the percentage difference with plug loads taken into consideration for all scenarios is significantly lower than the initially obtained gap between actual and modelled energy demand. The minimum, average, and maximum scenarios for all properties led to an average decrease of 18%, 13%, and 7% in the performance gap. With just a 5% consideration for plug loads, the model immediately improved by more than 10% in terms of the percentage difference between modelled and actual consumption. The 10% consideration contributed to an improvement of 14%, and the 20% consideration resulted in an 18% improvement. Based on these findings, the final adjusted scenario includes a

12% consideration for plug loads, as shown in Table 6. The quantitative representation of Table 6 is shown in Figure 5. Figure 5b shows the results for the final adjusted scenario and established that the 12% consideration is sufficient, as all properties now have a percentage gap of less than 15%. House A1 still has the highest percentage gap of exactly 15%. For properties A2–A7 the performance gap was very closely matched between 12–13% for all properties.



(**a**)

(**b**)

Figure 5. Updated model performance with plug load consideration against actual performance. (**a**) calibrated model performance of the three scenarios with plug loads considered and updated percentage difference (**b**) adjusted final model performance with updated percentage difference and actual energy consumption.

4. Discussion

In the analysis, the actual energy demand of the investigated properties was used as a baseline for comparison against the modelled energy demand. Despite certain houses being comparable in size and the number of occupants, their energy demand varies greatly. This difference can be attributed to occupant behaviour. For instance, the three occupiers of house A3 maintain a set internal temperature of 16 °C most of the year. This comfort level might be at the low end for many people, but the outcome can be seen directly in terms of the yearly energy demand. On the other hand, for the three occupiers of house A6, the opposite scenario holds true; their usual temperature setting is around 22 °C, which is equally reflected in the annual energy demand.

As mentioned in the results section, House A1 presented the largest difference between actual and modelled consumption with a 36% gap. Although the heating set point of House A1 is not the highest, the property has largest number of occupants in comparison to the other properties. This, therefore, indicates that having more occupants in a dwelling is likely to cause an increase in the energy and heating consumption, which cannot be directly translated to the simulated model. Looking at the heating performance gap for houses A2, A4, A5, and A7, the same conclusion is drawn. These four properties are the only properties with just one or two occupants, and for the heating and energy demand, these properties have the smallest performance gap between actual and modelled consumption.

As a result of this apparent gap in all the modelled houses, the next step in the investigation involved altering heating set point and heating and window opening schedule to see the extent of their impact on energy demand.

Considering the results derived from Figure 4 in general, for all the factors investigated, as the behaviour is increased from the 'real-life' typical hourly schedule or set point on TAS, the performance gap is decreased. This suggests that the software underestimates the effect activities, such as heating set point and schedule have on energy demand.

As early as 1950, a study by Dick et al. [47] created the first energy-related behavioural study, and it was identified that there appears to be a strong seasonal pattern in the occupant's opening windows habits, which was corroborated by another study later on [48]. Another early study by Rea et al. pointed out that disregarding occupant interaction with solar shading, by analysing window blind use, leads to an overestimation of energy savings [49]. This suggests an alternative explanation: although occupants have provided details of their 'typical' heating set point or schedule, this does not mean it is followed faithfully in the same way that the software would project. Factors such as thermal comfort play a significant role in occupant behaviour. Even if an occupant knows that, in general, they keep their house at a set temperature, on a particularly cold day or week or several weeks, this 'typical' behavioural pattern will change without much thought. Whilst this will be reflected in the operational energy use, it cannot be translated to the software. The same can be said during a heatwave and the effect it has on a window opening schedule.

This is corroborated by several studies focussing on the actual daily monitoring of occupants in residential buildings, which conclude that "occupancy and interactions with building devices are highly dependent on time" [50,51]. Furthermore, studies have shown that, whilst occupant behaviour can be influenced by objective factors such as climate, air velocity, temperature, noise, accessibility to control building features, time, and activity type (all of which can be monitored and measured), it can also be influenced by subjective factors such as the perception of comfort, expectations, gender, age, values, and social interaction. These factors may also be influenced by additional external features, such as politics, economics, and culture [52–55].

In terms of modelled energy demand, TAS accounts for heating, cooling, ventilation, lighting, and DHW energy uses, the remaining unaccounted energy uses are catering and plug load consumption. There are benchmarks available for catering energy use in commercial buildings. However, the same cannot be said for residential buildings. According to the European Commission, cooking devices typically require 6%+ of the energy used by households [56]. This is in consonance with the results obtained earlier from the survey that is used to account for load contribution within this study. Despite altering the heating set point and heating and window opening schedule, an average performance gap of 22% remained. Hence, it was vital that plug loads are also taken into consideration. Based on this, three scenarios were created for plug load consideration to calibrate the model by selecting the optimal adjusted plug load consideration based on the findings. The heating set points of any buildings are liable to change and are directly impacted by the future of the climate change in the locality [57].

House A1 (with the largest number of occupants) seemed to benefit the most from taking into consideration plug loads consumption. Houses A4–A7 experienced a performance gap of $\leq$5% with the maximum scenario. Meanwhile, house A1 remained at 10% even with the maximum scenario. Thus, indicating that increasing the plug load consideration any further will not offer additional contributions and is an unnecessary overstatement. Once again, this is in consonance with the findings from the monitoring survey results, which suggest that on average plug loads contribute to 12% of annual energy demand. Consequently, the final adjusted scenario includes a 12% consideration for plug loads. With the adjusted scenario the simulations were re-run, and finally, a performance gap of $\leq$15% was achieved for all properties.

It is incredibly challenging to develop a model that will mimic real-life behaviours unless long-term monitoring of those behaviours is conducted. This study shows that, by utilising such data and combining it with simulation modelling, a greater level of accuracy can be achieved, and we can bridge the gap between modelled and actual consumption. In addition to this, when it comes to discussion of occupants and their interactions with the building, a social science perspective should be considered and combined with the results to aid in the understanding of the limitations and challenges of accurately predicting occupant behaviour.

There are many challenges that arise when engaging occupants in reducing plug load energy use. The first of those challenges is educating building owners, property managers, and occupants on the significance of plug energy use, in relation to whole-building energy demand, and the opportunity that exists in saving energy by controlling plug loads. However, even if stakeholders understand the importance of reducing their plug load use, the next challenge is to encourage building occupants to take action and control their plug load usage. This is something outside the control of designers, engineers, and researchers. Hence, the best next action is to work on increasing our understanding of occupant behaviour so we can better predict. In the future, this would mean working on coupling machine learning and artificial intelligence to work on improving our existing assumptions and, therefore, bridge the gap between modelled and actual consumption.

5. Conclusions

Bridging the energy performance gap is vital in ensuring that a designed or retrofitted building meets the energy performance targets that are set at the beginning of the project. This paper presented a simulation model of seven different residential UK buildings. The model is initially simulated to reproduce the current state of the buildings and the self-reported occupant behaviour, such as the window opening schedules and thermostat setpoint temperature and schedule, to see what the impact on energy demand, due to different occupants' behaviours, can be. The results from the various models are validated by comparing the actual energy demand (as obtained from energy bills) with the simulated.

The simulation results showed that the heating set point has the greatest impact on the simulated energy demand out of the other investigated factors. The results also demonstrate that the energy demand of the dwellings can be reduced by appropriately applying window opening schemes and by controlling the heating setpoint temperature and schedule.

Although the investigated factors attempt to account for the reasons behind the performance gap, it is demonstrated that a direct comparison of predicted versus measured annual energy use is difficult. This is largely caused by uncertainties in the available data that are very difficult to model and propagate in energy simulations. For example, the self-reported data, whilst it can be considered a modest representation of an occupant's behaviour, will never be able to wholly replicate it.

Furthermore, plug loads can also play a significant role in affecting the energy demand. Using plug load data of real UK households, as obtained from a longitudinal study the results, showed that, by increasing the heating set point and heating and window opening schedules by 10% from self-reported data and also by considering an additional 12%

increase for plug loads, the energy performance gap is reduced to less than 15% for all examined houses.

The above highlights that future research efforts should not only focus on improving the quality of simulation software and other technological focusses but also on improving our understanding from a research perspective on occupant behaviour. Typically, simulation studies include many assumptions, especially when it comes to occupant behaviour, and reference data is used. By gathering adequate data on occupant behaviour and occupant interaction with buildings we can build better models that represent a true to life version of the existing buildings. This, in turn, will work to contribute to the reduction in the performance gap. Essentially, a coordinated approach is needed to better understand, and eventually bridge, the energy performance gap. Finally, it must be noted that the energy demand is only one performance aspect of a building's performance. Once predicted and actual energy use are matched, further work will be needed to address performance gaps in areas such as thermal comfort and indoor air quality.

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