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Discrepancies between theoretical and actual heating demand in Scottish modern dwellings

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Abstract: The study reports on the differences between the actual heat consumption profiles of twelve dwellings monitored for four years and their predicted heat demand profiles as calculated by the UK Government's Standard Assessment Procedure (SAP). This monitoring methodology analysed the selected homes over 4 years of occupation leading to a longitudinal study. Using descriptive statistical metrics this paper considers different groupings and normalisation methods to understand differences in heat demand. It uses this methodology to compare predicted over delivered energy over longer occupation periods. The results demonstrate that the compliance SAP model, incorrectly estimates heat demand by up to one and a half times that recorded in these dwellings. It also concludes that analysing energy consumption over time should exclude early occupation years as they suffer from occupant adjustment periods. Furthermore, by applying a heat energy factor, none of the dwellings achieve equal or better consumption levels than SAP, however flats and the low consuming group dwellings achieve closest to the predicted.

Keywords: assumed heating calculations, actual heating demand, performance gap, Scottish housing, SAP

Introduction

Heat consumption in domestic buildings is based on thermal comfort and personal hygiene regimes. Both depend on building envelope efficiency, occupant habits and behaviours and heating services. The heating services efficiency is dependent on the Coefficient of Performance (COP), fuel used and the degradation of the system over time, partially affected by poor maintenance patterns. Space heating is dependent on the building's envelope efficiency and the occupant's energy efficient habits. Number of occupants in the dwelling and also the patterns of use in cooking, showering/ bathing can greatly influence fuel used for water heating. Equally significant, are internal gains from latent heat sources, electrical appliances and solar gains influenced by building orientation and fenestration design. Household heat consumption from gas fuel accounts for the majority of the household energy (approx. 80%) and over half of the household's energy bill. (Kane et al., 2011).

Since the Energy Performance of Buildings Directive (EPBD) issued the 2010 guidelines (EU Parliament, 2010) for measurement and verification of energy consumption in buildings, a large focus has been on its calculation methodology, enforcement of minimum energy requirements and the certification process (Burman et al., 2014). In the UK the Standard Assessment Procedure (SAP) is the country's National Calculation Methodology (NCM), producing an Energy Efficient and Environmental Impact score from 1 to 100 (G to A) (Kelly et al., 2012). The SAP scores are based on dwellings heat consumption. The steady state calculation reflects the predicted performance, however recent studies indicate that actual demand can differ by two and sometimes fourfold (Menezes et al., 2012).

Results from a four year energy monitoring programme categorised by twelve different building suppliers is presented and discussed in this paper. These form part of the wider research project at the Housing Innovation Showcase (HIS) in Dunfermline, Scotland. The statistical study presents initial analysis on the differences between the predicted heat consumption (as calculated by the SAP method) of the dwellings and their delivered heat energy over a four year period. Its aim is to show the importance of longitudinal energy monitoring of buildings for determining the effects of heat energy performance gap. This paper shows the findings after statistically analysing the results using alternative clustering and normalisation methods and alternative means of comparing data. A more detailed explanation of the dwellings and their construction methods can be found in research by Bros-Williamson et al. (2016).

Methodology

The study of this housing development focused on a variety of system providers, all innovative in their fabrication, material use and assembly (off-site or on-site) (Bros-Williamson et al., 2016). A large focus was on comparing delivered heat energy since the dwellings handover in summer 2012 to winter 2016/17 against the predicted results using the SAP. The results are presented by calendar year; year 1 represents the occupied year of 2012 and so on until year 2015 which finalises in 2016. Comparison results have been obtained by taking in-home display (IHD) hourly energy consumption data, corroborated with yearly meter readings, focusing on delivered space and water heating predominantly using natural gas as a fuel.

The yearly delivered energy was analysed statistically to provide more insight into the energy consumption levels, patterns and behaviours of the households. The authors present the statistical data under well-established conventions however new ways of analysing and observing trends have been explored.

The analysis begins by justifying the use of typical grouping and identifier methods. Convention in this area of research selects the use of archetypes of dwellings to obtain groups within the sample. As a result of the small sample size and the varied archetype, it was intended to observe the data differently. The mean (average) delivered heat demand results over the 4 years of monitoring against the heating predicted SAP results are plotted over monitored years, first by archetype followed by consumption grouping converted into Z scores and analysing variables in a K-means cluster analysis (MacQueen, 1967), with one iteration to establish groups. The results effectively divided the sample into three groups; 'low energy consumer', 'medium energy consumer' and 'high energy consumer'' relative to the yearly energy delivered within the group.

The paper proceeds to identify the best normalisation factor. Most energy related studies will use delivered energy over a set period, normalised by the heated floor space of the building (kWh/m^2/yr). However, in this paper the data is compared by using other conditions such as yearly energy demand per volume (kWh/m^3), number of people (kWh/ppl) and predicted over actual energy consumption (kWh/kWh) (Stinson, 2015). The Coefficient of Variation (CV), as a percentage, was used as an indicator to describe which normalisation condition was a best fit for the data. The lower the percentage CV, the closer each individual data point is to the group mean. This would suggest that the mean is a good representation of the whole data set of that sample.

Following this, the paper proceeds by statistically displaying results with a mixed-design analysis of variance (ANOVA) comparing the significant interaction between archetypes and the three groups K-means method using Z scores during the 4 years of the study.

To conclude, the paper summarises all the methods and compares the predicted against delivered heat energy demand referred to as the heat energy factor (HEF). A HEF of 0 indicates the household consumed equal to its predicted result (SAP), results >0 show higher consumption and <0 show lower consumption than the predicted SAP. The HEF is presented as archetypes (n=4) and consumption levels (n=3).

Pre-analysis of data

Most appropriate identifier

Four years energy consumption data and many of the household's characteristics have been considered to identify the most appropriate grouping for the sample (n=12).

Typically an archetype classification is used, in this sample there are (n=12), flats (n=2), Bungalow semi-detached (n=2), house semi-detached (n=7) and house mid-terrace (n=1). The flats belong to the denominated four-in-a-block configuration with a separate main entrance.

The mean delivered heat energy and its corresponding mean SAP result by each archetype is plotted per monitored year, shown in Figure 1. The mean SAP results are noticeably lower than any year of the mean delivered heat energy by each archetype ranging from the 3,000kWh/year and 4,500kWh/year. The mean results for each monitored year of consumption are closely grouped. In order to interpret the yearly spread and amount of variability relative to the mean, the CV was calculated. Flats CV = 3%; Bungalow semi-detached CV = 8%; House semi-detached CV = 4%. A CV for the House mid-terrace could not be calculated because of the small sample size. The level of variation within the archetypes is considerably low, signifying it is a good descriptor for the samples energy consumption.

A second clustering method was applied which considered key variables of the household, including the dwellings floor area, volume, number of occupant adults (>16 years of age), number of occupant children (<16 years of age), the SAP results and the yearly delivered heat energy. This data was converted to Z scores and analysed as variables in a K-means cluster analysis creating the three consumer groups; 1. 'low energy consumer', 2. 'medium energy consumer' and 3. 'high energy consumer'. Figure 2 shows how these compare over the 4 years. The clustering analysis combinations are shown in Table 1 below.

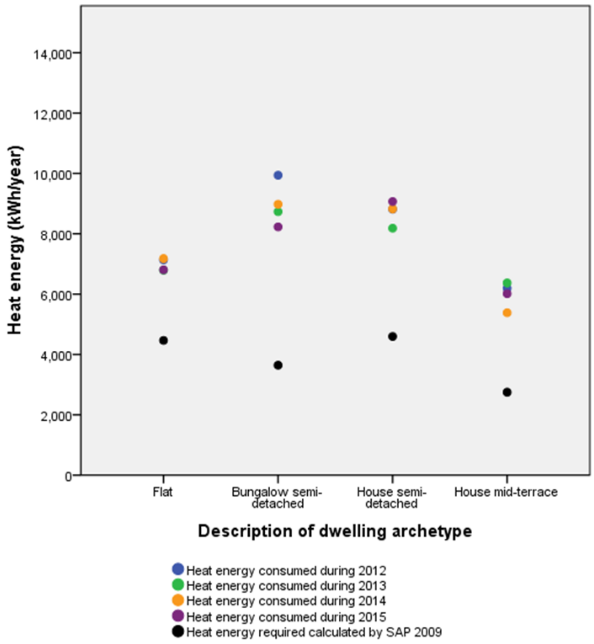

Figure 1. Heat energy by archetype

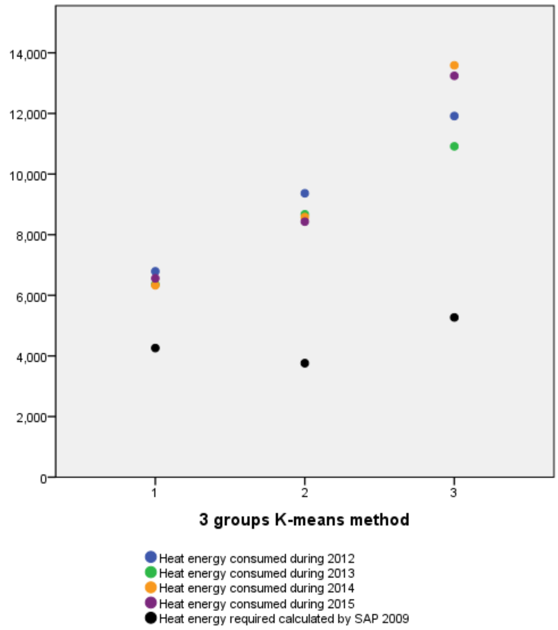

Figure 2. Heat energy by variables clustering

Table 1. Spread of sample group by archetype and variables clustering

	Energy consumer groupings [group]		
Archetypes (n total = 12)	**Low [1]**	**Medium [2]**	**High [3]**
Flats (n=2)	1	1	
Bungalows semi-detached (n=2)		2	
House semi-detached (n=7)	4	1	2
House mid-terrace (n=1)	1		

Analysing the yearly delivered heat energy demand with an on-way ANOVA (analysis of variance) showed that the differences in mean heat energy demand for each archetype was not statistically significant for any of the 4 years ($p > .05$). However, when the sample are split into their associated groups determined by k-means clustering the differences in mean heat energy demand are statistically significant for each individual year ($p < .05$).

Similar to the observed results in Figure 1; the mean results for each monitored year of consumption are closely grouped. Low energy consumer (n=6) CV = 3%; medium energy consumer (n=4) CV = 5%; high energy consumer (n=2) CV = 10%. The level of variation within the group is also considerably low, signifying that identifying the sample by the household's variables i.e. grouping using K-Means method is also a good descriptor for the samples energy consumption. The lower energy consumers are clustered around a mean of 6,500kWh/ year, medium energy consumers mean of 9,000kWh/year whereas the high energy consumers a mean of 12,000kWh/ year.

Most appropriate normalisation factor

Other authors investigating the performance gap in buildings have conventionally used a normalisation factor of delivered energy for every meter squared of heated floor space (m^2).

Results presented in Table 2 show that by normalising the heat energy consumption data by the volume of insulated space (kWh/m^3) provided the lowest CV for the sample data. Normalising the heat consumption data by floor area (kWh/m^2) or energy without normalisation provide the next lowest CV. Normalising the heat energy consumption by number of people (ppl) provided the highest CV, perhaps signifying that the weighting of people on a 1 to 1 ratio is insufficient to account for the complexities of heat consumption behaviour by households with very young and/or elderly occupants. Normalising the heat energy data by the SAP result (kWh/kWh) returned a high CV value meaning it is not the best for this sample (Stinson, 2015).

Table 2. CV values for normalisation factors applied to heat energy

	2012	2013	2014	2015	4 year average
kWh	26%	23%	33%	31%	27%
kWh/m²	26%	24%	32%	31%	27%
kWh/ppl	35%	33%	38%	35%	34%
kWh/m³	25%	23%	31%	27%	25%
kWh/kWh	33%	33%	33%	35%	32%

Results

Longitudinal comparison of energy demand

The yearly delivered energy was analysed to provide a clearer understanding of how energy was consumed identifying trends linked to occupant behaviour.

The data in Figure 3 shows that the semi-detached houses, flats and semi-detached bungalows decreased their consumption between year 1 and 2 with a small increase in year 3. The mid-terrace house increases in year 2, then decreases in year 3. The mid-terrace houses increase demand in year 4 meeting demand of year 3 and 4. The heat energy demand profile for the flats is of similar magnitude to that of the house mid-terrace. Also, the profile of the bungalow semi-detached is similar to that of the houses semi-detached.

Results from a mixed-design ANOVA tests suggest that the delivered heat energy levels for each year are similar between the 4 archetypes. These showed that the level of heat consumed over the first 4 years of occupation are not statistically different within the 4 archetypes category $F(9,24) = 0.608$ $p>.05$. Investigating this interaction further, contrasts were performed comparing each year of heat energy consumed to year 1 across the 4 archetypes. These showed non-significant ($p>.05$) differences when comparing the archetypes heat energy consumption for year 2 to year 1 $F(3,8) = 0.472$. Year 3 to year 1 $F(3,8) = 0.265$. Year 4 to year 1 $F(3,8) = 1.121$.

Figure 4 shows the heat energy demand profiles for each energy level type based on the K-means cluster analysis. The ANOVA results using the heat energy demand as grouped by the K-means clusters shows that there is a significant ($p<.05$) difference in means over the years and the grouping type, $F(6,27) = 2.90$.

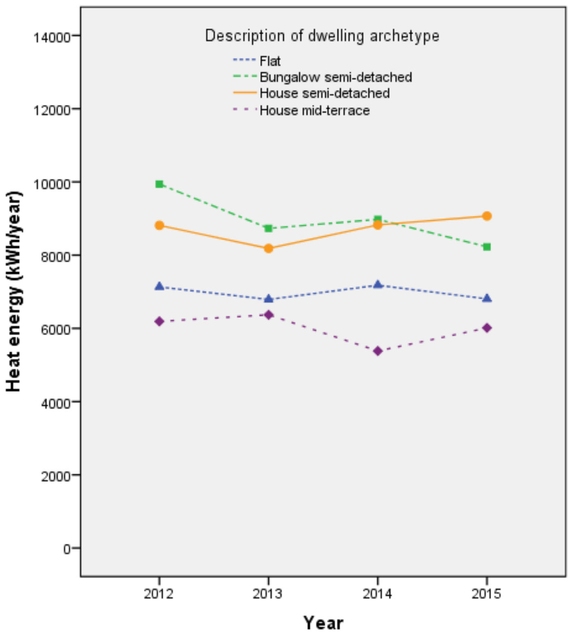

Figure 3. Delivered heat energy by archetype

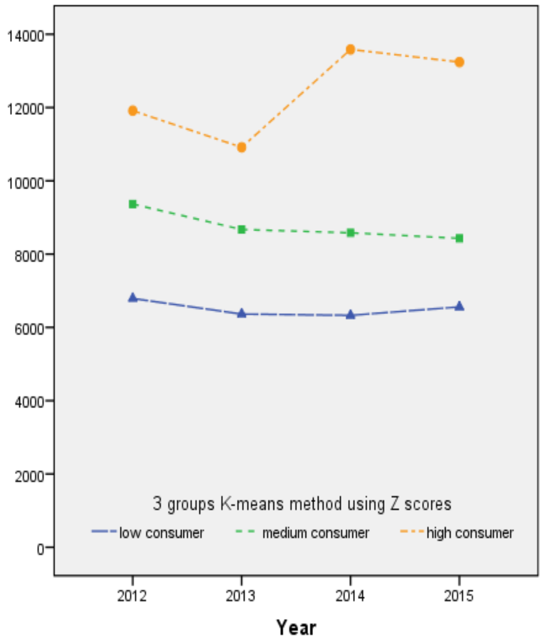

Figure 4. Delivered heat energy between the 3 groups

Investigating this further, comparing each year of delivered heat energy demand to year 1 across the 3 groups revealed a non-significant (p>.05) interaction when comparing the 3 groups delivered heat energy for year 2 to year 1 $F(2,9) = 0.258$. Year 3 to year 1 $F(2,9) = 3.038$. Year 4 to year 1 $F(2,9) = 2.255$. The group of lower and medium heat energy consuming households lowered their heat energy consumption year on year after year 1.

The data presented provides evidence to support the theory that the heat energy demand for year 1 is different from the subsequent years and that that yearly heat energy demand data are statistically significant from heat energy consumed in year 1. Dependent paired samples T-test shows the highest consumption was in year 1 (M = 8502, SE = 634) compared to any of the other of the 3 years (year 2: M = 7892, SE = 534), (year 3: M = 8289, SE = 800), (year 4: M = 8297, se = 752). The difference between year 1 and year 2 delivered heat energy was found to be statistically significant $t(11)=2.23$, $p<.05$, r=0.9. The differences between other years to the previous year were found not to be statistically significant (p>.05).

Predicted against actual energy demand

The heat energy factor (HEF) with the sample grouped by archetype is presented in Figure 5 and Figure 6 where the sample is grouped by consumption level. The dashed line indicates a HEF of 0 or the mean SAP score thus less of a performance gap between the groups. The results show that none of the groups align to a HEF of 0 but flats and low energy consumers are the closest. Figure 7 shows all the analysed dwellings delivered heat demand performance is compared against SAP as a percentage above the predicted annual heat energy demand.

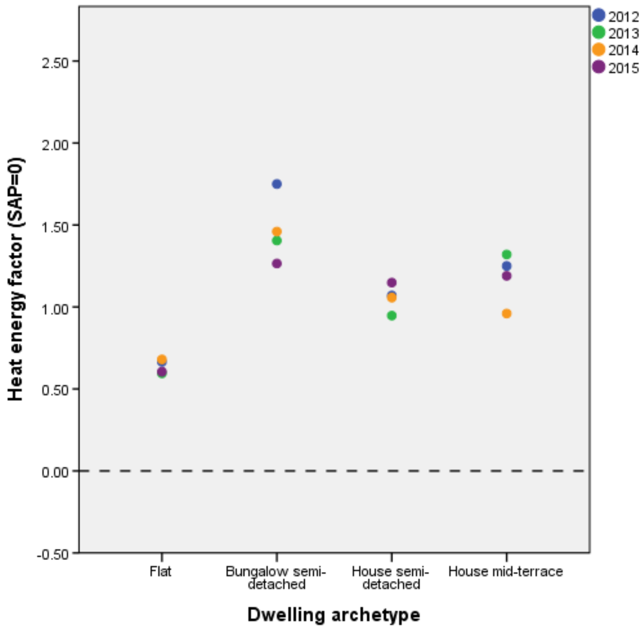

Figure 5. Energy factor by archetype

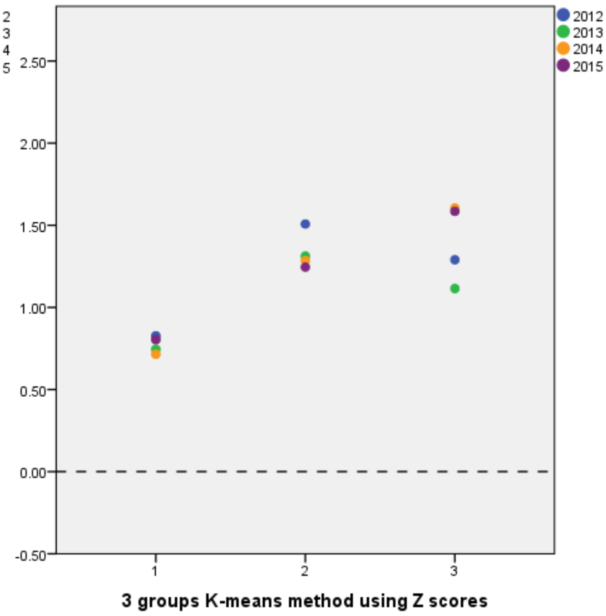

Figure 6. Energy factor by consumption groups

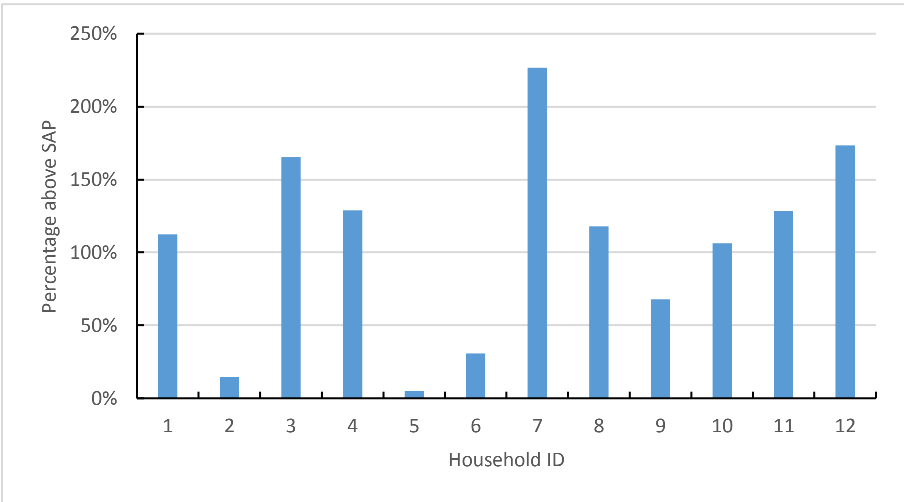

Figure 7. Average of 4 years delivered heat energy compared to SAP

Conclusion

Using descriptive statistics, this paper investigates the use of conventional and un-conventional methods for evidencing the impacts between predicted energy and actual delivered energy of a sample of twelve homes in Dunfermline, Fife.

The conventional use of clustering by archetype has been analysed, as well as proposing a different descriptor of energy demand by grouping low, medium and high energy consumer homes. Both were statistically convenient, however energy groupings evidences the gap in performance clearer over longer periods. In the same way, the normalisation methods used for analysing and benchmarking energy demand. Most will use conventional kWh/m^2/yr, however this paper uses volume, people and SAP results. Lower confidence of variation (CV) results show that normalising by volume is better than conventional methods.

Finally, results comparing delivered energy over time against the predicted revealed a non-significant ($p>.05$) interaction. This was evident when comparing year 1 against other years, revealing that early occupation years give little evidence of the actual energy consumption with a preference for ≥3 years of occupation. Furthermore, analysis of the individual household's delivered heat energy showed that the dwelling built with conventional methods and technology, obtained a HEF close to 0 thus performing similarly to the predicted, as shown in Figure 7 as household 5. This observation could lead to concluding that the steady-state compliance tools for predicting energy are better suited to conventional dwellings and possibly not suited to alternative construction types with new technology. It also raises concerns over alternative heating technology, not used suitably by occupants leading to increased energy.

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