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Developing Archetypes for Domestic Dwellings - An Irish Case Study

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Abstract

Stock modelling, based on representative archetypes, is a promising tool for exploring areas for resource and emission reductions in the residential sector. The use of archetypes developed using detailed statistical analysis (multi-linear regression analysis, clustering and descriptive statistics) rather than traditional qualitative techniques allows a more accurate representation of the overall building stock variability in terms of geometric form, constructional materials and operation. This paper presents a methodology for the development of archetypes based on information from literature and a sample of detailed energy-related housing data. The methodology involves a literature review of studies to identify the most important variables which explain energy use and regression analysis of a housing database to identify the most relevant variables associated with energy consumption. A statistical analysis of the distributions for each key variable was used to identify representative parameters. Corresponding construction details were chosen based on knowledge of housing construction details. Clustering analysis was used to identify coincident groups of parameters and construction details; this led to the identification of 13 representative archetypes.

Keywords: Stock modelling, representative archetypes, statistical analysis, residential sector.

1 Introduction

The residential sector is a significant consumer of energy in every country, and therefore a focus for energy reduction efforts [1]. The residential sector consumes approximately 30% of global primary energy [2]. Households accounted for 25 % of total energy use in the EU27 in 2007 [3], for 17% in 2003 in Canada [4], and for 33% in Spain [6]. In the UK, the residential sector accounted for 27% energy-related CO_2 emissions [5] and for 26.5% in Ireland [7].

The residential sector therefore represents an important research area for the generation of the information needed for evidence-based energy and emissions policy development for the housing stock. However, energy consumption is complex, depending on many parameters associated with building geometry, the thermal characteristics of the constructions and the way in which the building is operated. For stock modelling, an approach is needed that captures the key determinants of energy performance for the housing stock to allow technical and economic evaluation of retrofit options. Sampling actual buildings from the complete housing stock requires a large database of houses in order to ensure that a representative selection can be made that can be aggregated to determine building stock performance. An alternative is to create an archetype for each significant class of house based on statistical analysis, and then scale these according to the number of houses (or total floor area) for that archetype in order to represent the whole housing stock. If the archetypes are carefully selected, this procedure enables an evaluation of the different house types, key determinants of energy performance and economic interventions to improve energy performance to be evaluated with a reduced set of models. The approach can be applied at a national, regional or local level.

Archetypes are particularly helpful in stock aggregation, because they have the potential to support analyses of the existing stock, and, by making assumptions regarding changes in the housing stock and energy retrofit measures, they can be used to make future projections. Stock aggregation can be used to highlight areas where substantial potential exists for improvement in resource use and economic efficiency, enable quick what-if analyses, allow policy makers to optimize regulations and market incentives to achieve specific targets, and analyze how policies in one area (such as energy security or housing affordability) can affect other impacts from buildings (such as air pollution or energy demand), and develop priorities for research and development [8]. Scenarios of possible futures developed for a housing stock through use of archetypes can be used by governments and other stakeholders as a basis for strategic planning [9].

The remainder of this paper is organised as follows. Section 2 summarises the overall approaches to existing archetype classification methodologies. Based on the housing database [10] Section 3 describes the methodology used in the development of archetypes, and conclusions are drawn in Section 4.

2 Existing archetype development methodologies

The house archetype approach has been used by a number of authors to model energy and resource quantities and impacts, from a study at a regional level by Lechtenböhmer and Schüring [11] to more recent studies at urban scales by Firth et al. [12] and Shimoda et al. [13]. The emergence of many energy and resource reduction models driven by the need to support the assessment of emissions mitigation policies in the UK residential sector has been demonstrated by the BREHOMES model [14], the 40% house project [15] and the model developed by Johnston et al. (henceforth referred to as the Johnston model) [16].

The number of archetypes used in published research varies from as few as two to several thousand, and often data from actual buildings are used. Lechtenböhmer and Schüring [11] used only two archetypes, while admitting significant uncertainties resulting from the lack of precise statistical information of the characteristics of the EU building stock. The authors still provide rough quantifications of the potential, appropriateness and cost of relevant strategies for improving the quality of the building shells of residential buildings in the EU. Shimoda et al. [13] developed 20 dwelling types and 23 household (occupancy) types for the city of Osaka, but the results indicated that total estimated energy use is less than measured values. Forty-seven archetypes were developed by Firth et al. [12]. However, their models' annual gas consumptions for mid-terrace, semi-detached and purpose-built flats are slightly below the lower 95% confidence interval for English House Condition Survey measurements, which the authors attributed to a combination of assumptions and inaccuracies in the modelling process as well as the effects of sampling and measurement errors in English House Condition Survey itself. Three other studies, Johnston et al. [16], Shorrock et al. [14] and Boardman et al. [15]**,** employed just 2 archetypes, 1,000 archetypes and 20,000 dwelling types, respectively. Johnston projected that the UK would reach its 60% emission reduction target by 2050; however, this is disputed by another study [9], and the discrepancy may be the result of the intrinsic simplifications made in Johnston's model. Small variations are also observed between the modelled output of UKDCM [15] and BREHOMES [14] when compared to the same scenarios run in another model – the DECarb model of [9].

The present paper presents a methodology that can be used to achieve 'trade-offs' between simplifying residential dwelling stocks into characteristic archetypes and loss of resolution where the attributes of small groups of similar buildings are omitted. Multiple linear regression analysis (MLRA) is used to determine predictor variables of house energy use in order to allow a more accurate representation of the overall building stock variability in terms of geometric form, construction materials and operation. Complementary literature reviews of the different archetype bottom-up modelling techniques can be found in [1] and [17].

3 Methodology

To develop representative archetype houses, a housing database was required. In this paper, two databases have been useful in the development of archetypes – the Energy Performance Survey of Irish Housing (EPSIH) [10] and the Irish National Survey of Housing Quality (INSHQ) [18]. While the EPSIH was predominantly used in the current study, INSHQ was used to check the representativeness of the EPSIH. The EPSIH database contains data on energy use, energy rating, physical characteristics and occupancy patterns for a representative sample of 150 Irish dwellings. The INSHQ contains detailed information from a representative sample of over 40,000 householders on building characteristics, building condition and occupancy.

The broad methodology employed in this study involves the following steps:

1. Checking that the EPSIH database is representative of the Irish housing stock by comparing it with the INSHQ.
2. Using studies reported in literature to develop a full set of housing stock variables which impact energy use.

3. Conducting a statistical parametric analysis to identify and rank the key variables determining energy use which are particular to the Irish housing stock.

4. Developing representative archetypes based on the prevalence of parameters which are typically present for each key variable.

3.1 Step 1 - Representativeness of housing database

The set of common variables recorded in the EPSIH and INSHQ databases were compared in order to check the representativeness of the EPSIH database. The conclusions were that the variables of both databases demonstrate evidence of significant consistency (see Figure 1). One such example is dwelling type where the EPSIH recorded 4% more detached houses, at 50% of the existing housing stock, than the INSHQ.

3.2 Step 2 - Ranking of Household Variables

In this step an initial ranking of key independent variables is performed. A full set of variables influencing energy use as found in international literature, and as recorded in the EPSIH, were identified and tabulated based on their ranking in 17 different studies (see Table 1). The ranking approach was useful in the selection of supplementary variables in Section 3.2.1.

3.3 Step 3 - Statistical analysis

A total of 23 variables were selected for the multiple linear regression analysis that was performed. The approach adopted in selecting these variables was to include all variables in the housing database that will ordinarily contribute to prediction of house energy use [19] while only one out of any two or more variables with a high bivariate correlation was used in the analysis [20], resulting in a total of 23 variables. For example there are high bivariate correlations between house volume, floor area and window area. While the three variables were used in turn for the initial MLRA, house volume resulted in the highest coefficient of determination (R^2), so it was chosen for the final MLRA. The 23 variables selected for the final MLRA include: Wall U-values (W/m^{2}K), Roof U -values (W/m^{2}K), Floor U -values (W/m^{2}K), Window U -values (W/m^{2}K), Air Change Rate (ac/h), Internal Temperature (^{o}C), House Volume (m^3), Heating System Efficiency (%), Dwelling Type, Temperature controls (Basic control/Thermostatic radiator valve/Full-time temperature zone control), Number of Occupants, DHW Cylinder Insulation Thickness (mm), Cylinder Size (litre), Pipe-work Insulation (mm), Previous upgrades (upgrades/no-upgrades), Electricity Tariff rate (day/night/standard), Draughts (persistent draughts/some draughts when high winds/no draughts even when high winds), Humidity (typically damp/occasionally damp/typically dry), Immersion Heater Weekly Frequency, Electric shower weekly frequency, Electric water heater frequency, Typical Weekly Occupancy Pattern (heating season) (low/medium/high) and Number of Storeys.

To identify the importance of the above variables in Irish housing, MLRA was undertaken using a statistical computer package (SPSS) [19]. All 23 variables were regressed as independent variables against Total Energy Use. It should be noted that Total Energy Use in this instance is the sum of fuel and electricity purchased (in kWh) for the purposes of space and water heating, lighting and appliances.

3.3.1 Results of the statistical analysis

The results of the linear regression indicate a coefficient of determination (R^2) of .391 (see Table 2), indicating that 39.1% of the variance in household Total Energy Use is described by the model. Four of the variables are significant at the 1 and 5% levels; indicating a confidence that these variables influence the dependent variable, Total Energy Use. Variables which are significant at this level include: Typical Weekly Occupancy Pattern (heating season) (low/medium/high), Internal Temperature (^{o}C), Air Change Rate (ac/h) and Immersion Heater Weekly Frequency. Table 2 gives the results of MLRA model; column headings are explained below.

- Unstandardised Regression Coefficient (B) – gives the change in the dependent variable (Total Energy Use) due to a change of one unit of a predictor variable. The relationship between Air Change Rate (ac/h) and Total Energy Use indicates the greatest strength with an un-standardised coefficient of 150.5 (i.e. significantly different from 0; for every unit increase in house air change rate there is an increase of 150.5kWh/m^2.yr in house energy use) showing that Air Change Rate (ac/h) contributes significantly to the estimation of Total Energy Use. This is followed by un-standardised coefficients for Internal Temperature (^{o}C) of 71kWh/m^2.yr, Typical Heating Season Weekly Occupancy Pattern of 40.3kWh/m^2.yr, and Immersion Heater Weekly Frequency of 1.3kWh/m^2.yr. The high unstandardised coefficient for air change rate can be explained as most of the sample houses indicate significant air tightness. For example, Sinnott and Dyer [21], report on the air permeability of the existing Irish housing, and found the pre-1975, 1980's and 2008 dwellings to be 7.5m^3/hr/m^2, 9.45m^3/hr/m^2 and 10.45m^3/hr/m^2, respectively, and that new dwellings cannot be automatically be assumed more air-tight than older buildings. Similarly, the high unstandardised coefficient for internal temperature can attributed to the presence of sample houses with high heating energy. For example, one such example is a $47m^2$ floor area house running on a peat-fired Back-Boiler with main heat source seasonal (SEDBUK) efficiency of 50% and $709.4kWh/m^2.yr$ heating energy.

- Standardised Coefficient (Beta) – indicates which independent variables have the greatest effect on the dependent variable, since the variables have different measurement units subject to certain data quality assumptions. Internal Temperature (^oC) is the most significant in predicting Total Energy Use with a standardised coefficient of 0 .243, followed by Typical Heating Season Weekly Occupancy Pattern (heating season) of 0.233, Air Change Rate (ac/h) of 0.211 and Immersion Heater Weekly Frequency of 0.172.
- Significance level of a predictor variable quantifies the probability that the relationship identified between Total Energy Use and the independent variables is chance. A significance threshold of 5% was chosen.

It has been mentioned previously that, 60.9% of the variation in house energy use is not explained by the model. This is not surprising because occupancy behaviour, for which data were not available, will have a significant impact on the main energy use. Occupancy is ignored in the analysis because long-term average occupancy is best applied for stock modelling purposes and the houses are occupied by many different types of users (young couples, families with young children, families with teenagers, older couples, pensioners etc.) over their lifespans. Furthermore, some data exhibited evidence of weak interactions among two or more variables, possibly due to the upgrade of individual building elements over the years so that, for example, wall, window and roof U-values were not clustered. In some situations, it may be impossible to establish if an outlying point is bad data as outliers may be a result of random variation or indicate something scientifically interesting [22]. For example, when buildings are renovated, it is expected that wall and roof U-values will comply with the current building regulations. So it is would be expected to see some clustering between those variables. Furthermore, while [23] found that the levels of cavity-wall insulation in Ireland were at 42% in 1998 and remained static over the period 1996–2001, the levels of roof insulation were significantly better, with almost four-fifths of the stock possessing this energy efficiency measure, mainly a result of the State-funded attic-insulation scheme of the 1980s [24]. It should also be noted that the present study found that roof U-values were in closer compliance with current building regulations than wall U-values.

3.3.2 Final list of key household variables (explanatory variables)

In the previous section the four key variables impacting house energy use were determined based on a multiple linear regression analysis of the EPSIH database. In this section, these variables are adjusted and combined with other information to determine the final list of variables required in the formation of archetypes. The final list of household key variables obtained from MLRA was streamlined to remove behavioural variables and those with very small effects. It was then supplemented with variables which are undisputedly important based on literature/or theory as outlined below:

Although four variables were found to be significant at the 5% threshold in the MLRA (see above), Internal Temperature (^{o}C), Typical Weekly Occupancy Pattern (Heating Season) (low/medium/high) and Immersion Heater Weekly Frequency were excluded since the final archetypes will operate under average, long-term temperatures and occupancy. These variables are ones that are determined by the behaviour of occupants, and for the stock modelling objectives of this study occupant-related variables are standardised. Thus, only one key variable was selected from the results of the regression analysis, namely Air Change Rate (ac/h).

As one key variable selected from the results of the regression analysis is not sufficient to provide the necessary parameter inputs to adequately define representative archetypes and perform energy analysis, it was therefore, important to obtain supplementary variables. Eight supplementary variables were obtained from the ranking of key variables in Table 1 and are justified as follows:

i. Wall, Roof, Floor and Window U-values were selected based on their importance in determining energy consumption, as reported in the literature (see Table 1).
ii. Similarly, Dwelling Type was chosen based on the literature review (see Table 1), and in particular as it is a major determinant of energy for space heating whilst also determining the number of exposed walls and the average floor area (both of which influence the dwelling heat loss) [12]. For example, it is possible to have a terrace and detached house with the same values for all the parameters, such as U-values, air change rate, and so on, but they would have very different energy consumptions because of the difference in the number/area of external walls.
iii. Heating System Efficiency (%) was selected based on the ranking of variables in Table 1, and in particular as the primary energy use for operating a building depends mainly on the processes in the energy supply systems for electricity and heat [25]. It should be noted that

primary energy refers to the total energy required to provide the end user with delivered energy, including energy losses due to transformation and delivery.

iv. DHW Cylinder Insulation Thickness (mm) was selected because heat losses can be significant due to inadequate insulation.

v. Floor Area (m^2) has been selected based on literature, and in particular as it is more commonly used for housing energy analysis than house volume.

With the selection of eight supplementary variables above, the final list in the development of archetypes in Step 4 below represents nine. These include the one key variable obtained from the MLRA and the eight supplementary variables obtained above - Wall U value (W/m^2K), Roof U value (W/m^2K), Floor U value (W/m^2K), Window U-values, Air Change Rate (ac/h), Heating System Efficiency (%), Dwelling Type, Floor Area (m^2), DHW Cylinder Insulation Thickness (mm). This number was considered sufficient as the variables were considered most important based on Table 1, and in particular as they have been individually justified above.

3.4 Step 4 - Archetype development

Once the full set of key determinants of Total Energy Use has been identified, a set of archetypes could be developed. The following characteristics were used to differentiate the archetypes.

1. Those features that are significant in establishing how house energy use might change according to the building regulations due to the time of construction (e.g. differences in age) [8] – Wall U-value (W/m^2K), Roof U-value (W/m^2K), Window U –values (W/m^2K), Floor U-value (W/m^2K), Air Change Rate (ac/h), Floor Area (m^2), Heating System Efficiency (%), Dwelling Type and DHW Cylinder Insulation Thickness (mm).

2. Characteristics of construction detail or construction type – Wall construction types: cavity wall (timber walls are considered to be included in the cavity wall category), and single-leaf wall (hollow block walls are considered to be included in this category); Roof insulation types: ceiling insulation, and rafter insulation; Floor construction types: solid floor and suspended timber floor; and Window insulation types: single glazing, double glazing and low-e glazing. It should be noted that construction detail has been considered important because two dwellings with the same dwelling type may not necessarily have the same construction detail, and hence differing impacts on house energy use (e.g. single solid wall versus cavity wall).

The above selections generated a matrix that allowed for 81 categories (i.e. the product of 9 key variables of energy use and 9 building construction types and which can be described as house archetypes. However, in order to comply with the primary aim of the study, and in particular as a large number of archetypes would make description, stock analysis, and the assessment of new scenarios difficult [26], the number of archetypes were significantly reduced using the following three principal techniques:

1. *Using frequency histograms to choose parameters which are representative of the key variables:* Using the data in the EPSIH database, frequency histograms were generated in order to identify concentrations of particular values, thus allowing representative values ("typical values") to be chosen. In order to ensure that the representative values represent well-defined centres of the distributions, the approach adopted was to choose: (1) modes of symmetric distributions of key variables; and (2) means or medians or modes of skewed

(non-symmetric) distributions (depending on the summary and characteristics of the dataset of the individual distributions) of key variables. Here mode is the preferred central value since it will be representative of a common construction type; mean and median may yield values which are not. Figures 2 and 3 are histograms of wall and roof U-values from the EPSIH database. Figure 2 shows a bimodal mixture of 2 normal distributions with wall U-values clustering around two peak values from which representative values were chosen. The first mode is between 0.375 and 0.5 W/m^{2}K. The second mode is between 1.5 and 1.625 W/m^{2}K. Figure 3 represents a skewed distribution, and the mode is at or near the left tail of the data and so it appears not to be a good representative of the centre of the distribution. Having considered the three metrics of mean, median and mode in regard to summarising and characterising the dataset, the mean was considered to serve well as the representative value ("typical value"), and is between 0.33 and 0.46 W/m^{2}K. The chosen representative values for these two variables are:

a. Wall U-value: between 0.375 and 0.5 W/m^{2}K; and between 1.5 and 1.625 W/m^{2}K.
b. Roof U-value: between 0.33 and 0.46 W/m^{2}K.

2. *Using representative parameters and knowledge of construction details/building regulations to choose representative construction details:* Using the above chosen representative U-values for Wall and Roof U-values and based on knowledge of construction details/building regulations, representative construction details were chosen as follows:

a. 0.375 and 0.5 W/m^{2}K: full fill cavity wall with 100mm mineral wool insulation and partial fill cavity wall with 75mm mineral wool insulation; and 1.5 and 1.625 W/m^{2}K: un-insulated cavity wall.

b. 0.33 and 0.46 W/m^{2}K: roof with 120mm mineral wool insulation between the joists or 150mm mineral wool insulation between the rafters and 75mm mineral wool insulation between the joists or 100mm mineral wool insulation between the rafters.

3. *Creating scatter-plots based on the datasets of the pairs of the individual variables and identifying coincident (clustered) values from the resulting cluster points.* In typical building regulations, values are specified for various fabric elements and heating systems. However, when building regulations are reviewed, it is expected that the U-values of the walls and roof of the sample follow the wall and roof U-values of the building regulations being introduced. So it is expected to see some clustering between those variables. Therefore, in this procedure, variables that are expected to be correlated were paired and scatter plots were generated for each of these pairs using their distribution data as recorded in the EPSIH. Their clusters in the scatter-plots were then identified (i.e. as circled in Figure 4). As shown there are three clusters of data points from which archetype parameters representative of a combination of building construction details were chosen for combined roof and wall construction details. Cluster "A" represents the following values (Roof U value, Wall U value): (0.17, 0.25), (0.33, 0.25), (0.17, 0.375), (0.33, 0.375), (0.33, 0.5) and (0.46, 0.5) W/m^{2}K; Cluster "B" represents (0.33, 1.5), (0.33, 1.625), (0.46, 1.625) and (0.46, 1.75) W/m^{2}K; and Cluster "C" is represented by (0.33, 2.0) W/m^{2}K.

Archetype development: The above identified key variables, and clusters of construction details served as a basis for defining archetypes. In order to maintain the main purpose of simplification in stock aggregation as well as minimise number of archetypes, the approach adopted was to combine cluster values into parameters as much as possible based on the chosen representative values in the frequency histograms (see technique 1 above).

The final parameters of roof and wall construction details in the development of archetypes are as follows:

1. Cluster "A"

- All values of cluster "A" above were aggregated to (Roof U value, Wall U value): (0.33, 0.375), (0.33, 0.5), (0.46, 0.5) W/m^{2}K.

2. Cluster "B"

- All values of cluster "B" were aggregated to: (0.46, 1.625) W/m^{2}K.

The above procedure was repeated for all the remaining paired variables in succession. Thus, the archetype parameters were chosen for: Dwelling Type Class; Wall Construction Type; Roof Construction Type; Floor Construction Type; Window Type; Air Change Rate; Heating System Efficiency; DHW Cylinder Insulation; and Floor Area. With the above procedures a total of 13 representative archetype houses have been developed using 9 classes of construction detail (construction type) and statistical categories of 9 key variables of energy use.

Table 3 illustrates the final archetypes identified in this study. For each of the thirteen archetypes the parameters for all nine key variables are shown together with a description of the characteristic construction details corresponding to these parameters. The thirteen archetypes were representative of 98 dwellings in the sample of 150 (or 65% of the sample).

4 Conclusions

This paper develops a methodology for characterising residential dwelling stocks into archetypes and implements it using Irish data. The methodology involves a literature review of studies to identify the most important variables which explain energy use in domestic dwellings and a representative sample of household data to identify which of these variables are most relevant to explaining the energy use of the housing stock in question. It should be noted that in the case presented in this study only one significant building-related parameter was identified from the housing database. Nevertheless, it is believed that this is likely to be due to deficiencies in the database, and that this step is worth including in other archetype development studies. A statistical analysis of the distributions for each key variable was used to identify representative parameters and corresponding construction details based on a knowledge of housing construction details and thermal characteristics for the sample. Clustering analysis was used to identify coincident groups of parameters and construction details; this led to the identification of 13 representative archetypes.

The study indicates that archetypes can be developed based on: the identification of key variables from literature and sample of statistical analysis; a parametric analysis of these variables based on the central values of their distributions; and then determining parameter combinations based on cluster analysis. Using this approach and applying it to an Irish case study, it was found that the 13 archetypes developed were representative of 65% of the population of the existing Irish housing stock. This number should be sufficient to guide policy on energy retrofits. Although some smaller groups of house types are not included, the number of resulting archetypes is manageable for testing upgrade strategies.

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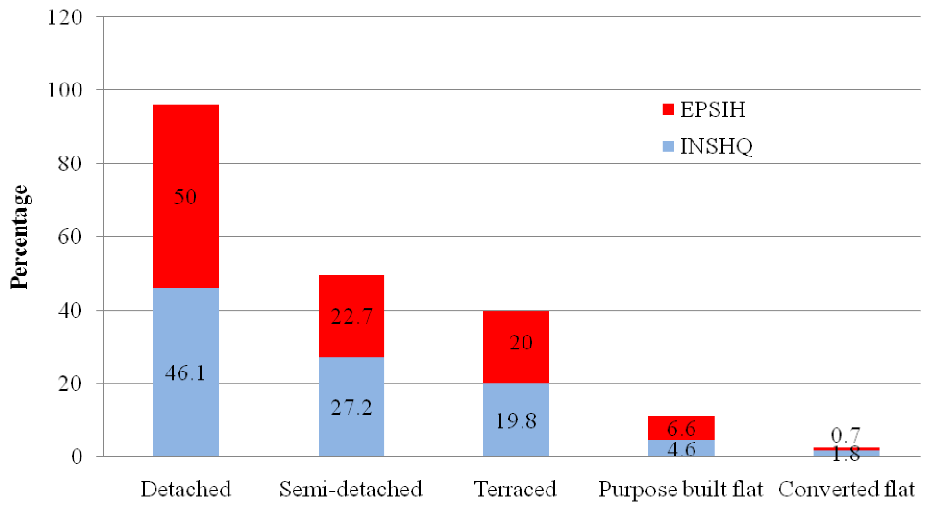

Figure 1: Comparison of dwelling types for both the EPSIH and INSHQ

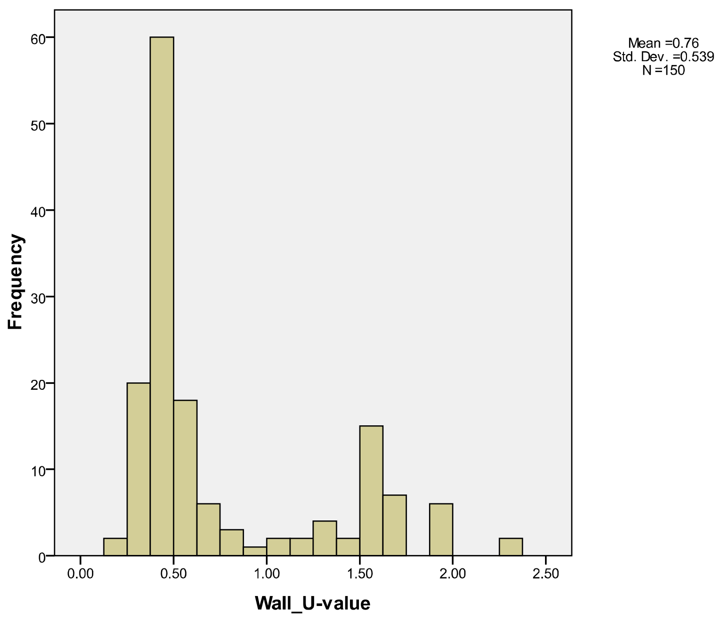

Figure 2- Frequency histogram of wall construction type

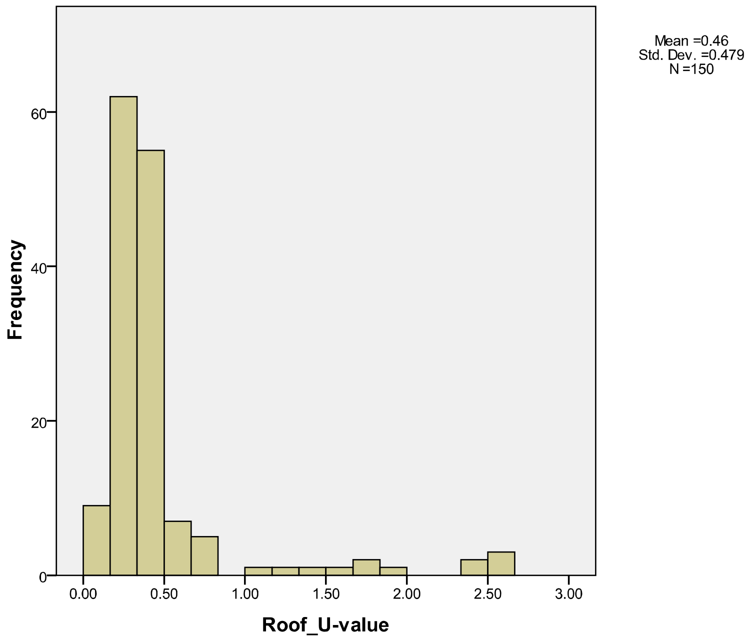

Figure 3 - Frequency histogram of roof construction type

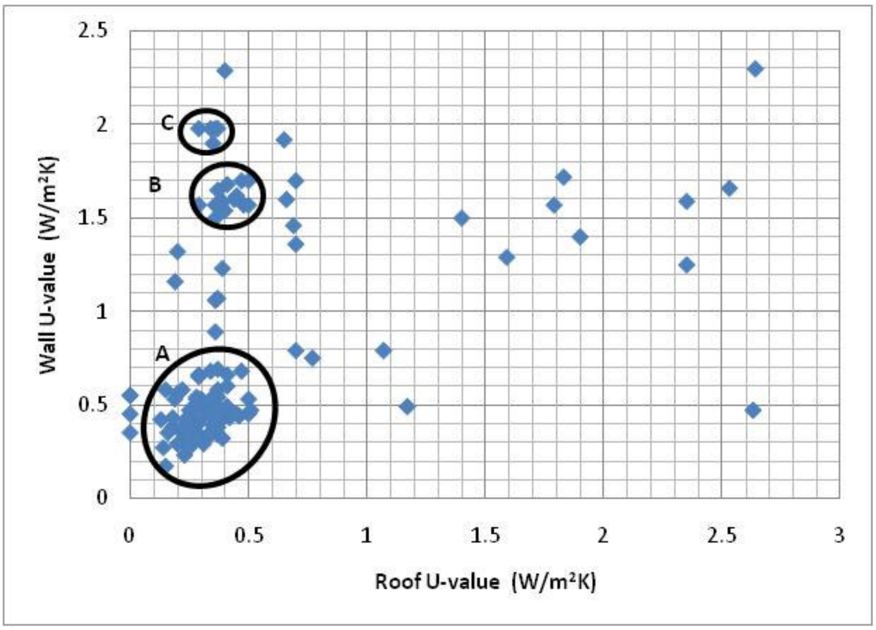

Figure 4 - Scatter plot: Roof vs. Wall construction types

Table 1: Ranking of determinants of household use as observed in literature

Reference	Study	Region/country code	Wall (U-value)	Roof (U-value)	Ground f floor U-value)	High performance window	Air change rate (ac/h)	Internal temperature (°C)	Window size (m^2)	Wall to floor area ratio	Heating system efficiency	Primary fuel type	Heat source	Floor area (m^2)	Number of occupants	DHW cylinder insulation	DHW cylinder size (litre)	Pipe-work insulation (mm)	Dwelling type
1	[11]	**EU****	1*	1*	1*	1*													
2	[12]	**UK**	2*	2*	2*	2*	2*				1*	1*	1*	2*		1*			2*
3	[23]	**IE**	4	2				3	5		1					6			
4	[25]	**SE**	2*	2*	2*	2*	2*				1*	1*	1*						
5	[27]	**EU-27**	2*	1*		2*	3												1*
6	[28]	**UK**	1*	1*	1*	1*					2								
7	[29]	**BE**		1	2	3					4								
8	[30]	**EL**	1			3	2												
9	[31]	**DK**	1*	1*	1*	1*	2				4							3	1*
10	[32]	**UK**	1																
11	[33]	**SE**				3	1	5			2				4	7	6		
12	[34]	**UK**	9	3	2	5	1												
13	[35]	**EU-15**	1*	1*	1*														
14	[36]	**SE**										2	1						
15	[37]	**UK**	1*	1*	1*	1*	2		3	5									4
16	[38]	**SE**	1*	1*	1*	1*	2												
17	[39]	**PT**						1							2				

*Equal rankings for determinants, **Housing stock of the EU-27, Norway, Iceland, Croatia, and Leichtenstein.

Table 2: Multiple linear regression results for Total Energy Use (kWh/m^2.yr) as the dependent variable

Re		Explanatory variables	Un-standardized	Standardized	t-stat	p-value

		Coefficients		Coefficients		
		B	Standard error	Beta		
	Constant	520.13	2,895.23			.86
1	Wall overall U-value (W/m^2K)	16.01	23.68	.07	.68	.50
2	Roof overall U-value (W/m^2K)	-16.02	22.76	-.06	-.70	.483
3	Floor overall U-value (W/m^2K)	44.08	42.93	.11	1.07	.307
4	Window overall U-value (W/m^2K)	23.04	13.18	.14	1.75	.083
5	Air change rate (ac/h)	150.49	59.38	.21	2.53	.013*
6	Internal temperature (^oC)	71.04	24.60	.24	2.89	.005**
8	Heating system (%)	-.01	.21	-.01	-.06	.952
11	House volume (m^3)	-.05	.05	-.08	-.84	.405
12	Number of storeys	3.01	7.22	.03	.42	.677
13	Dwelling type	-16.63	8.99	-.17	-1.85	.067
14	Number of occupants	3.01	7.22	.03	.42	.677
15	Cylinder insulation thickness (mm)	-1.03	.71	-.13	-1.45	.149
16	DHW cylinder size (litre)	.30	.21	.14	1.47	.145
17	Pipe-work insulation (mm)	-20.72	20.84	-.08	-.99	.322
18	Typical weekly occupancy pattern (Heating Season)	40.28	13.33	.23	3.02	.003**
19	Immersion heater weekly frequency	1.30	.59	.17	2.19	.030*
20	Electricity tariffs	-26.14	24.91	-.08	-1.05	.296
21	Draughts	-18.56	15.25	-.09	-1.22	.226
22	Humidity	1.13	10.62	.01	.11	.915

23	Temperature controls	-10.02	18.43	-.05	-.54	.588
Note: $R^2 = .39$; **(p < .01); *(p < 0.5)						

Table 3: Formation of archetypes

	Building Element Variable												
Dwelling Type	**Archetype number**	**Wall U-value ($W/m^2.K$)**	**Roof U-value (W/m^2K)**	**Window U-value ($W/m^2.K$)**	**Floor U-value ($W/m^2.K$)**	**Window size (m^2)**	**Floor Area (m^2)**	**Heating Systems %**	**Air Change Rate (ac/h)**	**Primary Fuel Type**	**Primary Heat Source**	**DWH Cylinder Insulation (mm)**	**Sample Distribution**
Detached	1	Partial fill cavity wall, ceiling insulation, double-glazed UPVC window, insulated solid floor											
		0.5	0.33	3.0	0.5	23	133	80	0.87	Oil	Conv[a]	30[b]	23
	2	Partial fill cavity wall, ceiling insulation, double-glazed UPVC window, insulated solid floor											
		0.5	0.46	3.0	0.58	23	133	80	0.74	Oil	Conv[a]	30[b]	11
	3	Partial fill cavity wall, ceiling insulation, draught-proofed single-glazed wooden window, insulated solid floor											
		0.5	0.46	4.75	0.58	23	133	70	0.67	Oil	Conv[a]	30[b]	6
	4	Insulated single-leaf wall, rafter insulation, double glazed UPVC window, insulated solid floor											
		0.5	0.33	3	0.58	23	133	80	0.87	Oil	Conv[a]	37[c]	8
	5	Partial fill cavity wall, rafter insulation, double-glazed UPVC window, insulated solid floor											
		0.5	0.33	3.0	0.58	23	133	80	0.74	Oil	Conv[a]	35[c]	6
	6	Full fill cavity wall, ceiling insulation, low-e UPVC window, insulated solid concrete floor											
		0.375	0.33	2.25	0.5	23	133	80	0.67	Oil	Conv[a]	37[c]	4
Semi-Detached	7	Insulated single-leaf wall, ceiling insulation, double-glazed wooden window, insulated solid floor											
		0.5	0.33	3.25	0.5	20	100	80	0.94	Gas	Conv[a]	35[c]	6
	8	Partial fill cavity wall, ceiling insulation, double-glazed UPVC window, insulated solid floor											3

		0.5	0.33	3.0	0.5	20	100	80	0.94	Gas	Conv[a]	50[b]	
	9	Insulated single-leaf wall, rafter insulation, double-glazed UPVC window, insulated solid floor											
		0.5	0.33	3.0	0.5	20	100	80	0.87	Gas	Conv[a]	30[b]	3
	10	Partial fill cavity wall, ceiling insulation, double-glazed UPVC window, insulated solid floor											
		0.5	0.33	3.0	0.5	20	100	80	0.94	Gas	Conv[a]	35[c]	12
M-terrace /Apartment (i.e. ground – second floor)	**11**	Partial fill cavity wall, ceiling insulation, double-glazed wooden window, insulated solid floor											
		0.5	0.33	3.25	0.5	20	100	80	0.87	Gas	Conv[a]	30[b]	8
	12	Partial fill cavity wall, rafter insulation, double-glazed wooden window, insulated solid floor											
		0.5	0.33	3.25	0.5	20	100	80	0.87	Gas	Conv[a]	30[b]	5
	13	Un-insulated cavity wall, rafter insulation, draught-proofed single-glazed wooden window, un-insulated suspended timber ground floor											
		1.625	0.46	4.75	0.58	20	133	80	0.94	Gas	Conv[a]	35[c]	3
Total sample distribution											98		
Total sample houses											150		
Percentage covered											65		

[a]Conventional boiler; [b]DHW cylinder lagging jacket; [c]DHW cylinder factory applied foam