Occupancy Patterns Scoping Review Project

Final Report

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EXECUTIVE SUMMARY

This report provides findings from a scoping review on occupancy patterns carried out by the University of Southampton (UoS) on behalf of the Department of Energy and Climate Change (DECC).

DECC commissioned this scoping review with the aim to explore the evidence for occupancy-based smart heating controls to contribute to one of the Department's key policy priorities to decarbonise heat. The objectives were:

- To report on the current state of knowledge on domestic occupancy patterns;
- To review any evidence on the relationship between domestic occupancy patterns and heating patterns;
- To map out the key evidence gaps.

Scoping review method

The scoping review applied systematic literature review techniques following the guidance provided by DECC. First the boundaries of the scoping review were established. The search terms were defined as *'occupancy and/or heating patterns/profile/behaviour/schedule'* and included domestic and non-domestic, UK and non-UK studies. The second stage of the scoping review identified databases and search engines as well as journals, which addressed the relevant studies on occupancy and heating patterns. Initial searches lead to a total of 3,681 references on occupancy patterns and 2,818 references on heating patterns. A preliminary review of the papers' abstracts screened for the topic addressed, this brought total number down to 212 for occupancy patterns and 72 for heating patterns. The third stage of the scoping review applied a two tiers filtering process using inclusion and exclusion criteria and DECC's Quality Assessment Scale. This detailed screening resulted in 67 peer reviewed research papers, of which 41 specifically address domestic occupancy patterns in the UK.

Key Findings

- There is not enough evidence in the documents found to generalise categories of occupancy patterns in domestic buildings. Within UK studies, only 13 were found on the topic of domestic occupancy and within the 10 that passed the Quality Assessment, only 4 presented a set of pattern categories. Even though there are similarities in the categories presented by each study, the results cannot be generalised or considered representative of the UK's population;

- Occupancy studies are focused on developing profiles based on schedules but there is little focus on where occupants are within the household. Some studies differentiate whether a house is fully or partially occupied based on the type of residents but no one has developed a detailed analysis on occupancy profiles per zone of a house~~;~~

- To date Time Use Surveys are the main source used for inferring domestic occupancy patterns at a regional or national scale and the method most frequently employed to process this type of data and generate occupancy profiles are Markov Chain approaches. Markov models vary according to how many "presence" states are defined;

- Sensor networks are seen as the most efficient method for monitoring occupancy, provided appropriate algorithms are chosen to process the binary time series outputted by the sensors;

- All reviewed documents agree on the need to develop new categories of occupancy patterns. One schedule does not fit all and BREDEM proposed patterns need to be updated;

- Most documents focus on methodology for inferring patterns from data or generating models than can produce synthetic profiles, rather than analysing patterns at a regional or national scale;

- Heating patterns are considered highly dependent on occupancy patterns in most cases and based on the same characteristics as occupancy such as number of occupants, age, level of income, type of employment and the nature of domestic activities. However, further analysis is required to determine how each parameter affect heating and occupancy separately;

- Heating patterns depend on the type of control system installed and the possibilities for programming and heating zones independently. Additionally user engagement plays a key factor as 23% of household with central heating and programming controls reported not to use them;

- Occupancy based smart controls and HVAC management systems can offer savings of more than 10% in energy consumption in commercial buildings, provided the prediction of occupancy is accurate;

- There is not enough evidence to evaluate the efficiency of smart heating controls in domestic buildings and its impact in comfort and energy usage.

- Occupancy and heating patterns are analysed more extensively in commercial buildings;

- Domestic spaces present limitations for monitoring occupancy given the randomness of occupants movement's in the household;

- Inferring occupancy from metered electricity data is a promising methodology for both domestic and commercial buildings;

- Models for developing synthetic occupancy patterns have the limitation of having to be trained for each particular case, so far no global models have been developed;

- There is very little evidence on how to improve PIR and CO2 sensors in order to be able to determine number of occupants;

INTRODUCTION

Motivation for the Scoping review

In 2014 the domestic sector accounted for 27% of the UK's final energy consumption (DECC, 2015a). Heating energy demand has overall been declining due to milder winters, an uptake of energy efficiency improvements and higher energy costs (DECC, 2015b) (Summerfield et al., 2010). Yet, space heating remains the largest contributor to domestic energy use at 62%, which means that it is an important area for energy reduction in order to meet the 2050 carbon target (Palmer & Cooper, 2013). With the aim of reducing space heating energy demand, DECC is currently investigating the evidence base for standard and smart heating controls. However little is known about how these controls are used and their impact on energy saving and thermal comfort. One way to review how heating controls are used would be to ascertain current heating patterns and their relationship with occupancy patterns.

Objectives and Scope

This scoping review was commissioned by DECC with the aim of collecting, synthesising and assessing the quality of current knowledge on domestic occupancy patterns. Starting in February 2016, the review was completed in March 2016. Applying systematic literature review techniques, the report outlines evidence from academic and grey literature to inform a new policy setting mandatory level for heating system efficiency.

The objectives of the scoping review were:
- To report on the current state of knowledge on domestic occupancy patterns;
- To review any evidence on the relationship between domestic occupancy patterns and heating patterns;
- To map out the key evidence gaps.

The report is organised as follows; the applied scoping review methods are described in the Approach section, then the results are reviewed and discussed, and finally implications are reviewed and conclusions drawn.

APPROACH

Definitions: boundaries of the scoping review

In order to undertake a systematic review, replicable techniques were applied. First the boundaries of the review were established; in the context of this project these are described as follows:

- Unit of analysis: individuals in dwellings are primary the subject of the review, although non-domestic references were also included in the scoping review.

- Outcomes and/or actions that are being studied:

(1) Occupancy patterns - when and where are people indoors?
(2) Heating patterns - when and where are buildings being heated?

- Methods used to measure the outcomes and/or actions:

(1) Occupancy patterns may be reported actions from surveyed participants. The data collection methods include observations, interviews, focus groups, questionnaires and diaries. Occupancy patterns may also be recorded actions using monitoring methods such as geo-location and presence sensing. Presence sensing instruments may be categorised into (a) fixed sensors (e.g. video camera, optical or infrared tripwires on doorway, proximity sensors, light sensors, noise sensors and CO_2 sensors), (b) wearable sensors (e.g. RFID, Bluetooth tracking systems and inertial navigation system) (Spataru and Gauthier, 2014), and (c) a combination of fixed and wearable sensors.

(2) Similarly, heating patterns may also be reported and recorded actions. Monitoring methods include building thermal conditions and heating system surveys (Papafragkou, 2014).

Taking into account the boundaries of the research, the following search terms were employed in the investigation:

- *'Domestic'*
- *'Heating'*
- *'Occupancy'*
- *'Patterns or profiles or schedule or behaviour'*

These search terms were applied concurrently or as a combination (note: if '*domestic*' was not included in the search terms, then non-domestic documents were found). The search records in Appendix A list the search terms use for each databases and search engines.

Investigation

The second stage of the scoping review identified databases and search engines as well as journals, which addresses relevant studies on domestic occupancy and heating patterns. This scoping study used the Web of Sciences, Scopus, Google Scholar, OpenGrey, institutions databases (eScholarship from the University of California, ICE, IEEE, CIBSE and RIBA), industry groups (BRE and BSRIA) and governmental websites to identify academic and grey literature sources. These electronic search engines and databases were supplemented by manual searching in libraries and via personal contacts. Search queries were then undertaken within these databases. The query approaches include search for keywords. The citation of references was managed using bibliographic software (Mendeley).

Evaluation and synthesis

Having undertaken the first stage of the review, research summaries and abstracts were analysed using filters for inclusion and exclusion in the scoping review. As the project was limited in time, it was essential to establish a subset of sources of information, although this subset needs to be free of bias. The filters applied to the first stage of the scoping review were explicit, and formulated as follows:

Does the reference…

1. … focus on analysing patterns inferred from sample?
2. … focus on developing/analysing data mining techniques?
3. … focus on developing/analysing technology/methods for data collection?
4. … focus on developing/analysing models for inputting in building simulation?
5. … focus on developing/analysing models for BMS?
6. … focus on relationship between patterns and energy consumption/performance?
7. … focus on other topics but utilises detailed patterns data as an input for the analysis

Is the reference…

8. … based on the UK population
9. … based on the domestic UK population

These nine inclusion and exclusion filters were applied in parallel; if one document followed any of these statements it was included in the next stage of the scoping review (refer to Appendix B). The second stage of the scoping review applied DECC's '*Quality Assessment Scale'* (refer to Appendix B and C).

The resulting set of references was reviewed and the results summarised (refer to Appendix D). References were listed against the following categories:

- Methodology and approach to heating or occupancy patters
- Sample size and characteristics
- Location of the study
- Study design
- Key findings
- Strengths of the study
- Weaknesses of the study

Finally a thematic synthesis highlighted:

- The common methods used to determine domestic occupancy patterns;
- The categories of domestic occupancy patterns;
- The relationship between domestic occupancy and heating patterns.

As an application to domestic occupancy and heating patterns, occupancy-based smart heating controls were discussed, reviewing: heating system usability, indoor thermal comfort and potential energy saving. To conclude, gaps in current knowledge and associated recommendations were drawn.

RESULTS

As stated in the 'Approach' section, a systematic procedure was applied for the search. Different search methods were utilised, the number or results per each method can be seen in Figure 1. One criteria applied to all searches was to considers documents only from 1980 onwards. This was done due to the change in the heating systems in the UK and the introduction of central heating which started in the 1970's. Nevertheless, the oldest results found to be relevant to the focus of this review were from 2006.

After eliminating repeated results, all the documents were divided into three categories, regardless of the search method/s used. The categories are based on the type of patterns analysed: occupancy patterns, heating patterns or both. Additionally each category was classified according to whether the studies are from the UK or international and analyse domestic or non-domestic buildings as the main focus of the research. Finally DECC's Quality Assessment was applied leaving the total number of studies to analyse. Figure 2 to 4 show a summary of the classification of the results.

For each category, documents are classified according to the main focus of the study, which includes the following criteria:

C1. Analyses patterns inferred from sample
C2. Analyses mining techniques
C3. Analyses methods for monitoring
C4. Develops models for building simulation
C5. Develops models for BMS or system controls
C6. Analyses the relationship between patterns and energy consumption
C7. Other focus but utilises patterns as an input

As explained a Quality Assessment was performed focusing in the quality of the research and of the report. As a result of this evaluation, from the 81 documents selected for assessment of the whole text within all three categories a total of 14 (17%) were excluded because of not fulfilling quality requirements. The main reasons for exclusion include: lack of clarity and justification of the research purpose and methods and documents being preliminary studies not peer reviewed or from an author or organisation without track record. Almost half of the excluded documents showed a very small number of references and not enough or unclear justification of the purpose of the research as well as the methods selected. Additionally some did not validate the results or evaluated accuracy of the findings presented. Finally, most of the excluded papers belonged to conference proceedings that had not been peer reviewed or were from authors with no sustainable track record.

Furthermore, regarding the sources of the documents, Figure 5 shows the countries of origin of the 67 documents analysed. Given that the research was focused in the UK, it is reasonable that this country represents the second largest percentage (31%). The largest (34%) corresponds to the USA of which the majority are studies focused on commercial buildings, particularly offices. The remaining are in its majority from European countries.

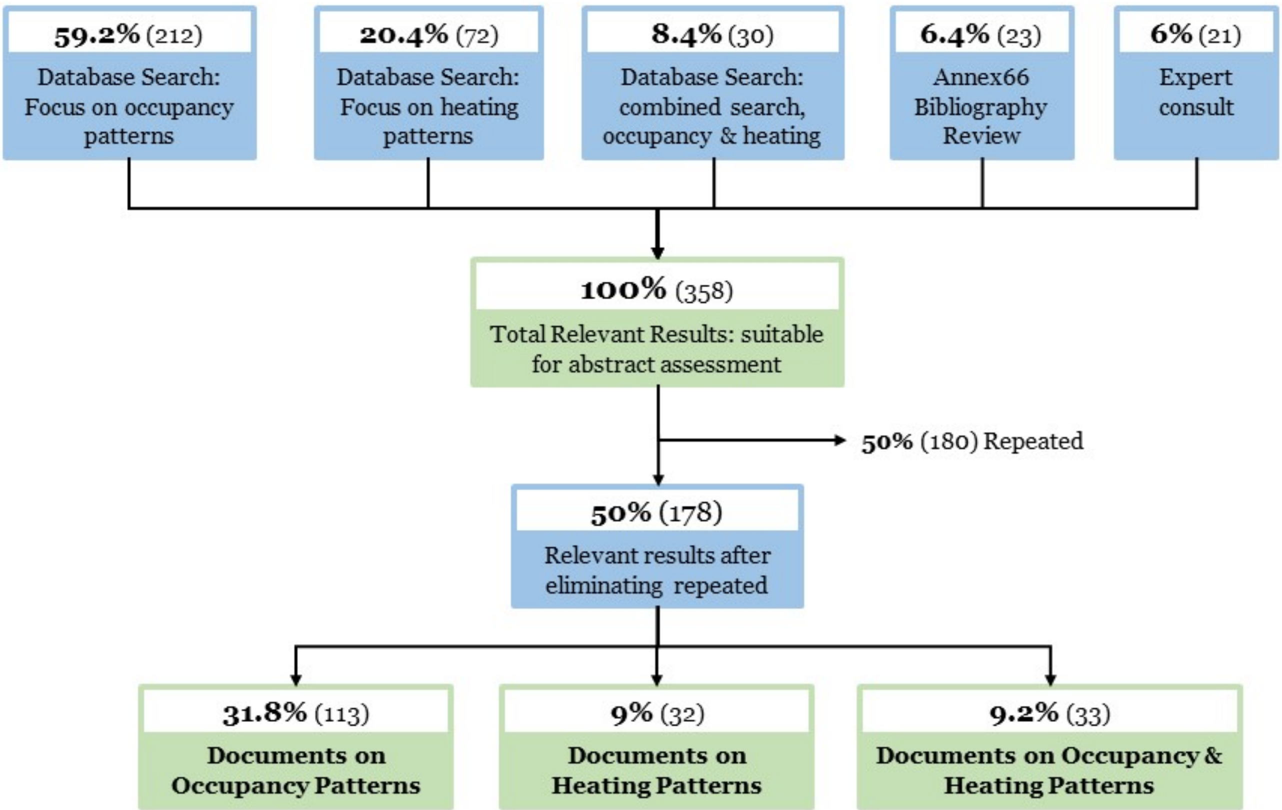


Figure 1 – Results by search method and category

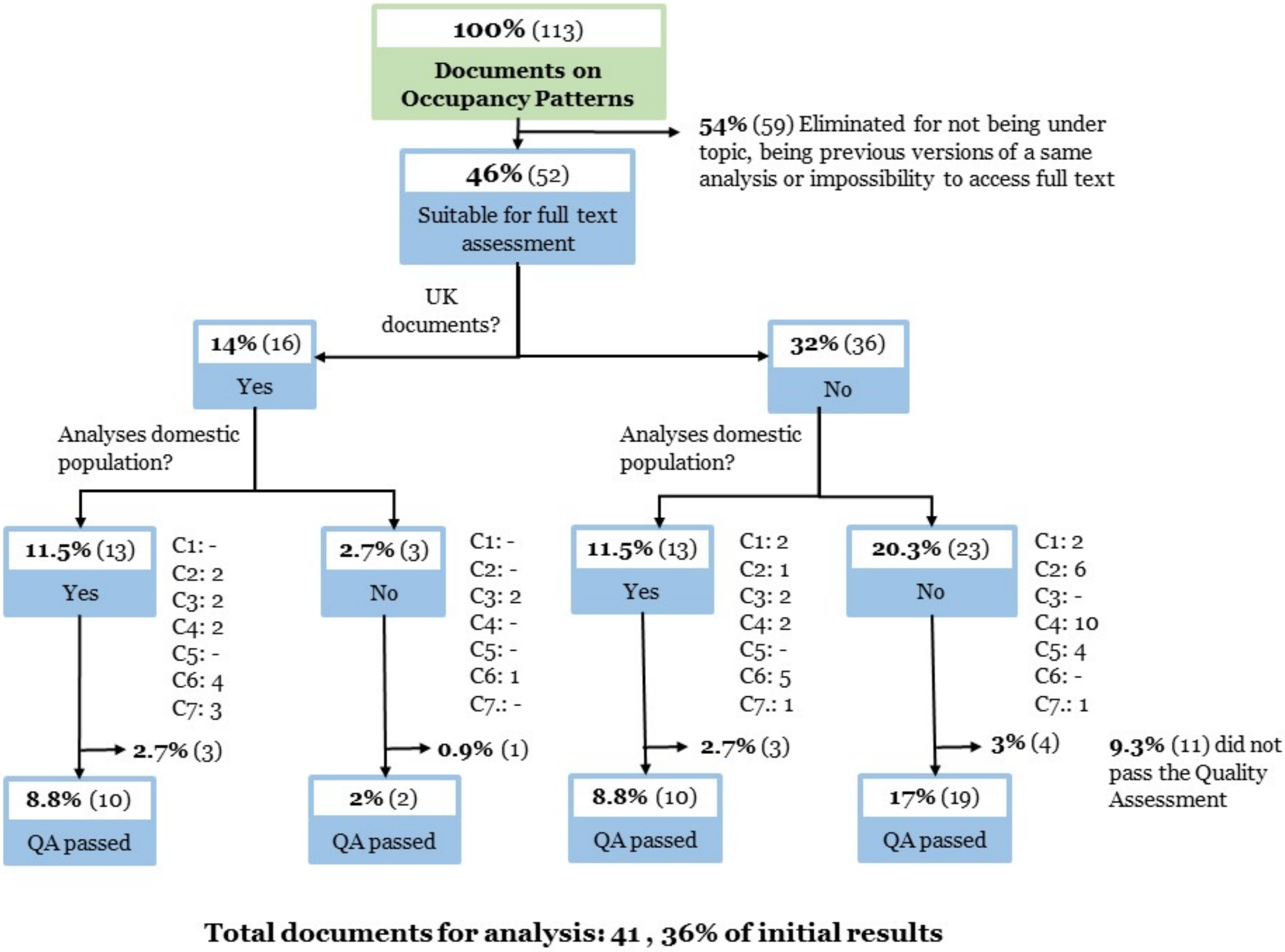


Figure 2 – Classification of documents on occupancy patterns

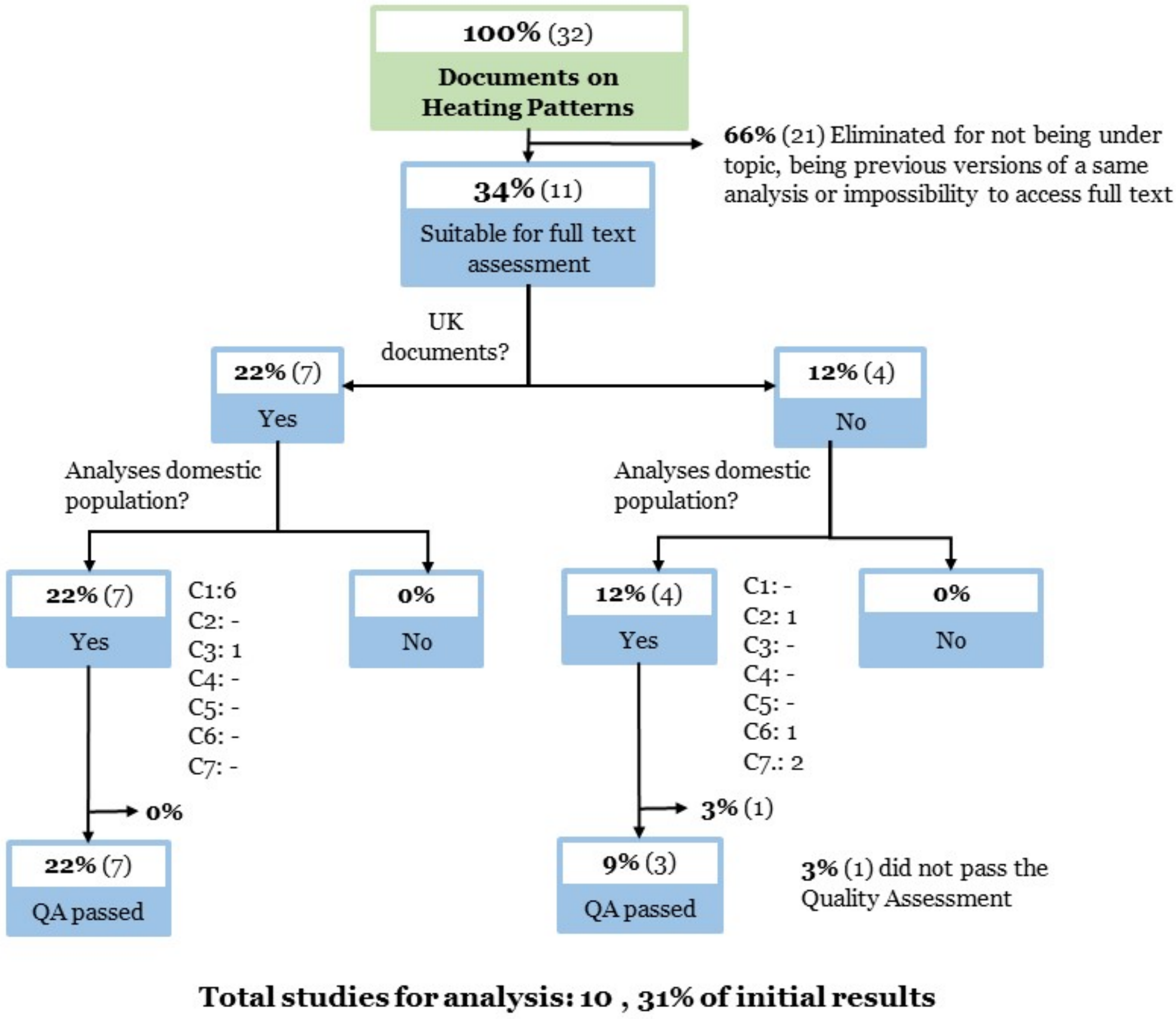
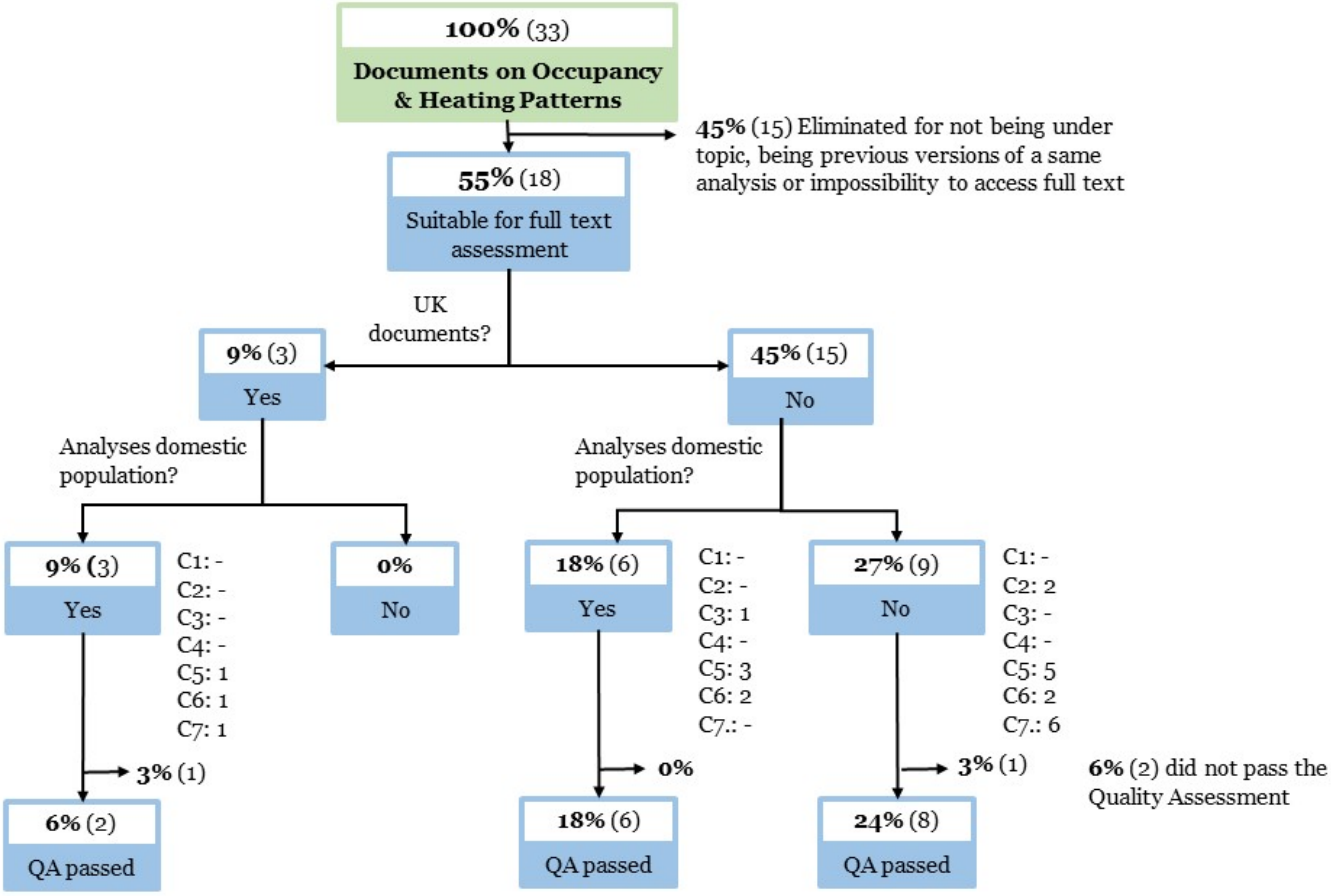


Figure 3 – Classification of documents on heating patterns



Total studies for analysis: 16 , 48% of initial results

Figure 4 – Classification of documents on occupancy & heating patterns

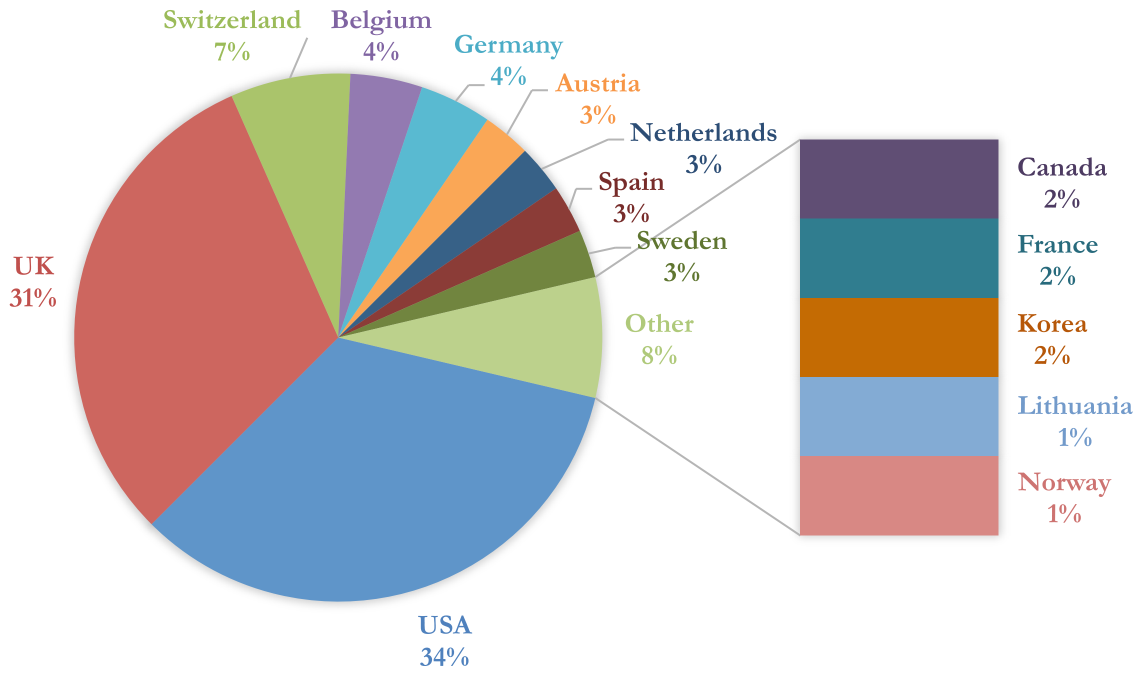


Figure 5 – Countries of origin of analysed documents (Total of 67 documents)

Analysis of the final sub-set of documents

Based on the findings the analysis is divided by country of the publication and whether it analysed domestic or non-domestic buildings. The following charts can be found in Appendix D:

A. DOMESTIC OCCUPANCY PATTERNS – UK DOCUMENTS

B. DOMESTIC OCCUPANCY PATTERNS – INTERNATIONAL DOCUMENTS

C. OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS – UK R DOCUMENTS

D. OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS – INTERNATIONAL REFERENCES

E. HEATING PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

F. HEATING PATTERNS IN DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

G. HEATING & OCCUPANCY PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

H. HEATING & OCCUPANCY PATTERNS IN DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

I. HEATING & OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

The characteristics summarised for the analysed documents are: Methodology of study and approach to patterns, sample type, location, study design, key findings, strengths and weaknesses.

References are organised by date of publication in descending order and alphabetically.

MAIN FINDINGS

This section presents the analysis of the documents on occupancy and heating patterns found through the scoping review, highlighting the most relevant findings and gaps in current knowledge.

Methods for determining domestic occupancy patterns

In this section two aspects are analysed: (1) methods of occupancy data collection such as sensors and surveys (2) strategies for modelling patterns inferring or defining categories from already existing data through statistical methods and data mining techniques. Additionally, both UK and international references are summarised together as the methods analysed are not specific to a type of population or geographical area.

Data collection methods

The documents analysed showed the use of diverse methodology for collecting data on occupancy based on the objective of the study and/or the availability of technology and information. Figure 6 shows the methods identified and what percentage they represent within all the documents analysed. The method most applied is monitoring, including techniques such as sensors and the use of mobile phones for tracking users. The second methodology consists of performing questionnaires to occupants, particularly the Time Use Survey. Finally some studies utilize metered electricity data to infer occupancy from electricity usage profiles. Each method is described in more detail in this section.

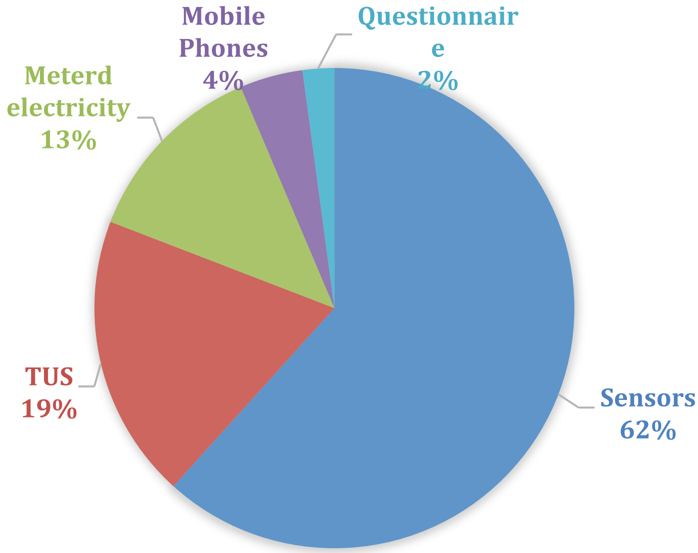


Figure 6 – Data collection methods identified in analysed documents

Monitoring

Several types of sensors are under analysis as well as the combinations between them, the most common being PIR (Passive Infra-Red) and CO_2 sensors as seen in Figure 7. PIR and CO_2 are mostly used due to being largely available, low cost and unobtrusive, but they present several limitations (Richardson et al. 2008; Yohanis et al. 2008)(Naghiyev et al. 2014; Calì et al. 2015; Spataru & Gauthier 2014):

- PIR: detect motion and because of this they can give out false negative occupancy registers if the person in the room is not moving or is moving very slowly. Also, they do not provide a register of the number of people in a space, just whether there are people or not. More accurate results were found in offices when combining PIR sensors and magnetic door switches which register when a door is open or closed. However this method requires a clear definition on what an open door represents, and whether a space is occupied or unoccupied; hence it may be less appropriate for domestic properties but more so for offices.

- CO2 sensors: measure the concentration of CO2 in the air which may be misleading as it depends on the activity that people are performing, their metabolic rate and the ventilation levels in a space. This makes these sensors unsuitable for evaluating the number of people in a space. Also, the leakiness of a building and windows or doors opening behaviours affect the mix of air in a space and can result in inaccurate occupancy measurements. Some methods develop algorithms incorporating air circulation and opening behaviours leading to higher efficiency but these methods rely on having these types of data available.

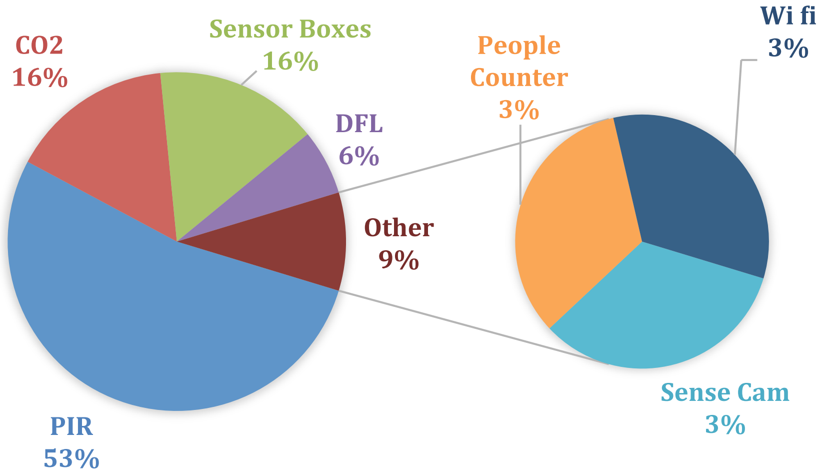


Figure 7 – Type of sensors evaluated and /or utilised in analysed documents

Other technology used repeatedly (Yang & Becerik-Gerber 2014; Yang et al. 2014; Dong & Andrews 2009; Gomez Ortega et al. 2015; Han et al. 2012) is sensor boxes, which consist of a box that holds a combination of different types of sensor such as sound, temperature, humidity, CO2 and PIR amongst others and the data from can be analysed together to evaluate occupancy and comfort. Moreover, People Counters are also utilised to monitor the number of people entering a building (Page et al. 2007) and another methods consists in measuring the number of Wi fi connections as an indicator of occupancy (Martani et al. 2012).

Furthermore, additional methods include wearable sensors, but given that people need to wear tags, these do not seem suitable for evaluating occupancy in domestic spaces at a large scale. For research purpose, wearable sensors such as SenseCam may be used in dwellings, enabling occupancy patterns to be monitored accurately (Gauthier & Shipworth, 2015). The main advantage this tool is to collect pictures and a sensors' log enabling researchers to determine when and where occupants maybe in their home. However this advantage lead to privacy concerns, which should be addressed by current development of this technology incorporating 'on-board' processing of the pictures. Additionally an emerging promising technology seems to be Device-free location sensors (Dfl), which is an unobtrusive method based on detecting changes in the strength of a Wi Fi signal caused by the presence of a person or persons. However, it is still under development with focus on achieving the detection of the number of occupants and improving the output data processing. One other technology under analysis, particularly for using in combination with smart heating controls are mobile phones. They can be used for tracking occupants and predict the expected arrival in order to activate the heating system (Lee et al. 2013) or also as a possibility for users to manage their heating system remotely and give notice of long absences or changes in their schedule (Bomhard et al. 2014)

Finally, research suggests that it is more efficient to deploy sensor networks composed of simple low cost sensors than utilising highly specific but costly methods such as wearable sensors. The key within sensor networks relies in developing algorithms that can analyse the data output correctly and how decision rules are defined (Dodier et al., 2006; Howard & Hoff, 2013).

Surveys & Questionnaires

The resource most used for inferring occupancy patterns in households in both UK and international references is Time Use Surveys (TUS). These studies, which can support analysis of changes over the last 20-30 years are generally performed in domestic households and consist of diaries where people record their activities throughout one or more days. The diary's entries are completed every 5 to 10 minutes, therefore participants may interrupt their task to complete the diary or report on memorised estimation of the activity type and duration. This data collection method relies on self-reported information and bear great uncertainties. TUS are carried out regularly in most European countries using a Eurostat-governed harmonised approach and they can provide information on the amount of time people spend in an activity, the time of day they do it and in some cases, the location within the dwelling can also be inferred. Moreover, some of the advantages of this data are that it is easily available and that the sample is intended to be representative of the population in the area analysed (usually a country).

In the UK the most recent TUS that is currently available for analysis was performed in 2005. However a more recent survey carried out in 2014/15 should be available for analysis within the next few months and will provide updated data on the use of appliances as well as more recent energy demanding habits. Additionally, one of the potential uses of this information is demand side response, as it provides detailed information of energy end-uses and occupancy in households (Widén et al. 2012).

Analysis of electricity consumption

One of the methodologies applied in several studies consists of inferring occupancy states from metered electricity usage (Akbar et al., 2015; Kim & Srebric, 2015; Albert & Rajagopal, 2013). It presents the advantages of relying on already existing technology such as smart meters and smart plugs, but it depends on the household or building using that system. This methodology has been more developed in the case of commercial buildings but it can also be applied to domestic residences as demonstrated by recent attempts to develop methods to identify times of high and low occupancy for survey research operational purposes.(Beckel et al. 2014; Newing et al. 2015; Anderson & Newing 2015)

Data analysis methods and occupancy modelling

The strategy used for developing occupancy models depends on the type of data analysed, and whether the purpose of the analysis is to generate patterns, clusters or categories or to develop a model that can predict and generate synthetic occupancy patterns for use in building simulation or building management systems. Figure 8 shows a summary of the models and algorithms used though the documents to analyse data from monitoring systems and TUS and predict occupancy.

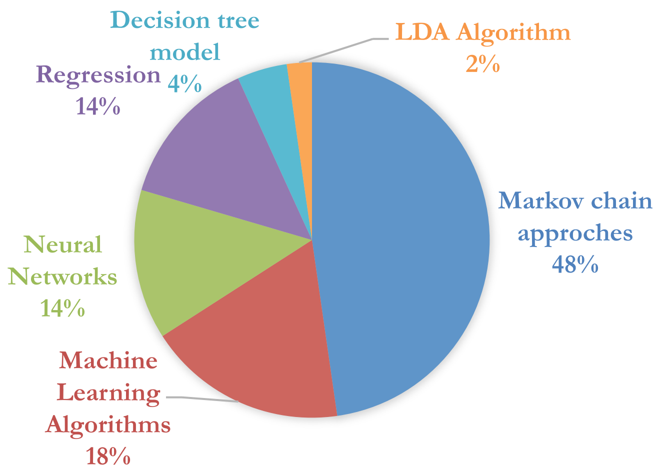


Figure 7 – Data analysis and processing methods used in analysed documents

The main classification of methods presented here relies on the source of data, whether it is information from TUS or outputs from individual sensors or sensor networks.

Analysis of TUS data

Whilst some analysis focuses on analysing patterns of occupancy and of the activities that generate peak electricity demand, in most cases approach most used for generating a predictive occupancy model from TUS data are Markov chains (Richardson et al., 2008; Widén & Wäckelgård, 2010; McKenna et al. 2015; Page et al., 2008, Torriti, 2014; Torriti et al., 2015). The differences within the selected documents depend on which and how many states of occupancy are defined in the chain. For example, some models use only two states, active and inactive, while others differentiate inactivity between being asleep or away from home. Additionally, given the information in the original data, activity states can also be created in order to evaluate the use of appliances for example. In all cases, a Markov chain approach has proven accurate in predicting realistic activity patterns both in terms of state probabilities and durations.

Analysis of data from monitoring

There are many different data analysis methods varying according to the type and number of sensors and each requires different algorithms that can process data from these sensors. One of the most used methods is Auto Regression (Ai et al., 2014; Yang & Becerik-Gerber, 2014; Han et al., 2012) particularly the Auto Regressive Hidden Markov Model (ARHMM). This method has proved accurate even for situations when occupancy has a high variability, outperforming non-regressive models and can be applied in smart building systems and HVAC controls. Other approaches developed include machine-learning techniques such as Neural Networks (Yang & Becerik-Gerber, 2014).

In all cases, the models face limitations. One of the most significant is the need of training, meaning that the model needs to receive occupancy records of a certain duration in order to be able to generate predictions. So far, no global models have been developed but this is a focus of on-going research. Finally another limitation is not being able to predict long absences such as holidays, which becomes more relevant in the case of commercial buildings where total occupancy varies seasonally

Categories of domestic occupancy patterns

The general insight identified from this review in the UK domestic sector is the recognition that the standard BREDEM occupancy patterns need to be replaced by categories that are more appropriate for each type of resident. Not only should the application of the same patterns to all types of households be questioned, but also the adequacy of the schedules proposed. Unfortunately, as seen from the number of studies corresponding to the UK's domestic sector (13), there is currently insufficient evidence to generalise a set of categories or groups that are representative of the entire population. However, some common results can be identified within the research and are presented in this section. A simple initial classification can be done according to the days of the week differentiating occupancy patterns from weekdays and weekends. A second can be based on the profile of the residents, meaning household composition, age, main activity. The following section summarises an analysis of each approach.

Classification by day of the week

Studies identify a difference within the occupancy hours in weekdays and weekends but not a major one. The schedules utilised for the Standard Assessment Procedure (SAP) specify that during weekends occupancy is much larger than during weekdays. However recent studies showed that the only difference is that there is some late awakening on weekends the total hours of occupancy being very similar (Richardson et al. 2008; Yohanis et al. 2008). Tables 1 and 2 summarize the differences between SAP assumptions and evidences from the references. For the inferred categories, weekend profiles are very similar to weekdays. What is more, for SAP calculations, the two categories of occupancy schedules are not defined based on the composition of the household but on the type of heating system instead.

Classification by household composition

The analysis of data from the UK's 2005 Time Use Survey reveal that there are different patterns based on the number of people that live in a house, their age and relationship between each other (if occupants are a family, a couple, unrelated individuals, etc.). Table 2 shows a summary of the results from combining the main groups identified in the selected references and stating their corresponding characteristics (Marshall et al., 2015; BRE, 2012, Zhang, Siebers & Aickelin, 2012; Richardson et al., 2008; Yohanis et al., 2008).

Of the categories introduced in Table 2, only Short Occupancy A and B match the schedules used for SAP calculations. If these two categories represent the majority of the situations in UK households then it would seem reasonable to assume BREDEM standards for most calculations and building simulation scenarios. However, for those categories not represented by BREDEM, there is a significant difference in the schedules and distribution of occupancy. This may be due to result in completely different values of energy consumption and temperature profiles. Some scenarios are currently not represented in the BREDEM model.

Table 1. Occupancy and heating schedules for SAP calculations (Table 9, SAP 2012)

Category	Type of heating control	Occupancy & Heating Schedule	Occupancy distribution
1	Houses with programmers, thermostats or TRVs, or combination of those	Weekdays: All absent from 09:00 to 16:00. Heating on 07:00-0900 and 16:00-23:00 Weekends: Full occupancy all day. Heating on 07:00-23:00	Same schedule in living area and other spaces
2	A control system that allows the heating times of at least two zones to be programmed independently, as well as having independent temperatures	Weekdays: All absent from 09:00 to 16:00. Heating on 07:00-0900 and 16:00-23:00 Weekends: Full occupancy all day. Heating on 07:00-23:00	Living area
		All days: heating 07:00-09:00 and 1800-2300.	Other spaces

Table 2. Domestic occupancy categories identified in UK reviewed documents

Category	Type of residents	Occupancy Schedule	Occupancy distribution
Short Occupancy A	Working family of four 2 adults working externally and 2 children	Weekday: All absent from 08:30 to 16:00 Weekend: All absent from 10:30 to 16:00	All areas of the house occupied when at home
Short Occupancy B	2 adults working externally / all occupants with full time job / mostly under 40	All absent from 08:30 to 18:00 (4 days a week) or 08:30 to 21 (3 days a week)	House partially occupied when at home
Partial occupancy	One or more residents with part time jobs	House unoccupied from 09:00 to 13:00; or House unoccupied from 13:00 to 18:00	House partially occupied when at home
Home stay A	Retired couple or single (over 65) / Family with small children	House occupied all day	All areas of the house occupied when at home
Home stay B	2 adults one stays at home during the day	House occupied all day	House partially occupied all day

Furthermore it is not known what percentage of the population falls within each category. Table 3 shows the types of households based on family composition; based on this the largest household group corresponds to couple families with or without children, which coincides with categories of short occupancy A and B presented. However, further research is needed to confirm the distribution of these occupancy categories across the UK's population.

Table 3 – Household types in the UK in Millions (Office for National Statistics 2015)

Year	One person households	One family household: couple	One family household: lone parent	Two or more unrelated adults	Multi-family households	All households
2015	7.7	15.3	2.8	0.9	0.3	27.0

Additionally, it is important to comment on the weekend patterns presented in Table 2, which show almost the same schedule as weekdays. One assumption is that this could be attributed to the data utilised in the documents. Both Zhang et al. (2012) and (Yohanis et al. 2008) defined occupancy profiles based on annual electricity consumption data, which means that the patterns are not specific of the heating season but are an average of an entire year instead. Longer occupancies could be expected for the winter months in the UK. Another possibility is that the similarity between weekday and weekend patterns is due to people working on Saturdays and Sundays. Since 1961 the number of people working in services in England and Wales increased from almost 50% to more than 80% (Office on National Statistics n.d.) meaning that there is an elevated number of people who works during the weekends and might show a standard weekend profile during the week instead.

Moreover, regarding the distribution of occupants within the house, only the level is defined for the categories presented, whether all spaces are occupied or just a part of the house. There is very little analysis of profiles for each space of the household; however this type of information can be inferred from TUS leading to more detailed profiles.

Analysis of domestic occupancy profiles in international reviewed documents

Domestic activities are highly influenced by cultural and social aspects as well as climate, which leads to different countries showing contrasting occupancy profiles. Hence it is not recommended to use patterns from other countries. However, it might be worth analysing literature from those countries, which are comparable to the UK in terms of climate, working hours, schedule and composition of the population. As an example, when analysing TUS from Spain with the same methods used for analysing UK data, particular patterns deeply related to cultural aspects were found, which do not match the UK's profiles (López-Rodríguez et al. 2013). However, a study of Lithuanian population showed categories that match those described previously for the UK: Short occupancies with absences from 08:00/10:00 to 16:00 for families with actively working adults; and full day occupancies for retired individuals (Martinaitis et al. 2015).

Additionally, international research also agrees that one standard does not fit all cases and that the best predictors of occupancy characteristics are age, type of employment, main activity and income level. Aerts et al. (2014) analysed Belgian TUS data and defined categories based on short, medium and long occupancy and absences during daytime, afternoon or evening. (Dar et al. 2015) also based occupancy categories in the number of occupants and the employment type. With this in mind, the categories of schedules differences between each other in the length of the total hours of occupancy and its distribution during the day reinforce the need of having varied occupancy for building simulations.

Analysis of domestic occupancy profiles in commercial buildings

Regarding commercial properties, the focus of the reviewed research tends to be on evaluating actual occupancy against the standards used for calculations and building simulations. Most studies compare the occupancy diversity factors, which define the total level of occupancy of a building, obtained from measured data against ASHRAE defined profiles. The results show that ASHRAE highly overestimates diversity factors, in some cases leading to differences of more than 40% (Bouffaron 2014).

In contrast with domestic patterns, different patterns can be found within each day of the week. Research found divergent schedules for each weekday (D'Oca & Hong 2015), (Duarte et al. 2014) and (Duarte et al. 2013). In general Mondays have the highest occupancy levels and Fridays the lowest, Tuesday, Wednesday and Thursday showing similar patterns. In relation to the schedule and the distributions of occupants in space, the categories found in the analyses vary according to the use of the building and the type of activities performed, whether it is a school, an office, etc.

Furthermore, as the documents on commercial buildings are focused in two types of buildings: academic (Gul & Patidar 2015; Martani et al. 2012; Paudel et al. 2014; Agarwal et al. 2010) and offices (Akbar et al. 2015; D'Oca & Hong 2015; Kim & Srebric 2015; Tahmasebi & Mahdavi 2015a; Tahmasebi & Mahdavi 2015b; Andersen et al. 2014; Yang & Becerik-Gerber 2014; Zhao et al. 2014; Duarte et al. 2013; Castanedo et al. 2011; Alrazgan et al. 2011; Dodier et al. 2006; Page et al. 2008; Page et al. 2007), both for UK and international, weekend patterns are not much analysed as the levels of occupancy are very low on Saturdays and Sundays. The occupancy diversity factors defined by ASHRAE differentiate between weekday, Saturday and Sunday, however within the documents that analyse diversity factors, only one evaluated weekends (Duarte et al. 2013) finding small peaks but never reaching a diversity factor over 0.1, which attributes to maintenance and cleaning personnel. A difference scenario could be expected for retail properties, however the sample of documents analysed do not present any case of analysis

Relationship between domestic occupancy and heating patterns

Within the domestic sector in the UK, as with occupancy patterns the focus of past and current research has been on generating more representative profiles and analysing the difference between BREDEM schedules and assumptions and actual measured data. Table 4 presents a summary of the results of the Energy Follow up Survey, showing that the majority of the households in the UK present two or one heating period.

Table 4 – Number of heating periods by type of heating system and regularity of heating (REF EFUS)

Type of main heating system		Regularity of heating		Number of heating periods	
Centrally Heated	90%	Regular heating	75%	0	1%
				1	21%
				2	69%
				3+	8%
		Non-regular heating	25%	N/A	
Non- centrally heated	10%	Regular heating	60%	0	8%
				1	81%
				2	9%
				3+	1%
		Non-regular heating	40%	N/A	

Within houses non-centrally heated, 2/3 correspond to electric storage heaters and 1/3 to room heaters (Department for Communities and local government 2015). It is interesting to highlight that for these systems, the most common heating patterns is of only one period, in contrast of what happens with central heating systems. This could be related to lack of engagement with controls or be related to occupancy schedules, further research is required to identify the reason

Considering the results presented in Table 3 and the reviewed documents, the following can be said regarding the relationship between heating and occupancy patterns:

- Heating, as well as occupancy, does not vary randomly but depends on characteristics of residents such as number of occupants, age, employment situation, level of income and their heating-dependent habits. Consequently people heat their houses in different ways and at different times. Yohanis et al. (2008) Showed different heating profiles depending on number of occupants in the household, type of household and level of income. Additionally Kane et al. (2015) analysed the heating patterns of UK households discovering statistically significant relationships between number of occupants, age and employment and heating patterns. Finally Huebner et al. (2015) also analysed the statistical relationship of heating patterns with income and age finding that household with two heating peaks have the highest level of income.

It is important to highlight that even though occupancy and heating patterns are both influenced by socio economic factors they are so in a different way. For example, studies indicate that a large proportion of people with long daytime occupancy correspond to low income or unemployed individuals (Yohanis et al. 2008; Zhang et al. 2012). However, a person with limited economical resources might decide to heat their house in a limited way as shown by Dimitriou et al. (2014) where indoor temperatures were analysed in social housing buildings where occupants are responsible for their heating bills showing that residents under heated their houses. According to UK National Statics (DECC 2015) in 2013 10.4% of all household were in fuel poverty situation, so a considerable percentage of the population could be heating intermittently or not heating their homes due to financial impediments, even when they are at home.

- At the coarsest granularity however two main profiles can be found: a double schedule for heating (temperature peaks in the morning and again in the afternoon until night) or a simple schedule (constant temperature all day). These profiles seem to be based on active occupancy schedules and correspond to some of the occupancy categories listed in Table 2 and described as follows: 'Short Occupancy A and B' which are people with full time jobs leaving early in the morning and arriving in the afternoon or in the evening, and 'Long Occupancy A and B' which include people who stay at home during the day (Kane et al., 2015; Huebner et al., 2015; Hulme et al., 2013; Huebner et al., 2013). However, as analysed previously, heating schedules do not necessarily reflect occupancy. For example, the lack of use of heating controls or programmable schedules might result in patterns that resemble full daytime occupancy when it not. According to the Energy Follow up Survey (Hulme et al. 2013), of houses with central heating, 10% do not have a timer and 23% have but occupants do not know how to use them.

- In building simulation, heating patterns are directly dependent on occupancy and the type of data used (standard schedules or actual data). This has a large impact on the energy consumption of a building (Audenaert & Briffaerts, 2011).

- The difference in heating hours between weekdays and weekends seems not to be as large as suggested by BREDEM. (in Bredem, heating and occupancy schedules coincide) (Huebner et al. 2015) (Hulme et al. 2013) (Huebner et al. 2013)

- Heating patterns are mostly regular during the days of the week, as are occupancy patterns (Hulme et al. 2013)

- Unlike domestic occupancy patterns, space heating is strongly seasonal through the year (Zimmermann et al., 2012)

- The space that is heated depends largely on the type of heating system and controls installed, whether it is a central system or individual, gas or electric, and if there are thermostats, TRVs, programmable control or not (Hulme et al., 2013; Zimmermann et al., 2012)

- The space that is most heated in a household is the living rooms, which coincides with the space with highest duration of occupancy periods (Kane et al., 2015; Hulme et al., 2013)

Potential role of occupancy-based smart heating controls

The following analysis is based in both UK and international documents, given the small number of results originated in the UK on the topic of smart heating controls. Additionally, the majority of the documents that evaluate occupancy based controls are focused in managing HVAC systems in office buildings.

Most reviewed documents , UK and international, acknowledge the relationship between occupancy and heating patterns and focuses on developing occupancy predictive models to be incorporated in the management of HVAC systems in commercial buildings, or smart thermostats in houses. The objective of this approach is to generate energy savings by specifying setback periods that are related to the occupancy patterns and avoiding heating unoccupied areas of a building.

The use of smart thermostats is still in its infancy but studies show evidence to support the idea that they can result in energy savings without compromising comfort. The key to success relies on being able to accurately identify and predict occupancy patterns and so the occupancy detection system and the algorithms used for prediction must be designed accordingly. One focus is often on utilising mobile devices for tracking individuals and also for being able to control the heating system remotely (Gao & Whitehouse 2009) (Lee et al. 2013).

Moreover, the options allowed by the heating controls will ultimately define the possibilities that users have to adapt their heating to their demands and behaviour. The only UK document that evaluated occupancy based heating in the domestic sector from Beizaee et al. (2015) presents a comparison of comfort and energy consumption levels in two identical test houses with the same occupancy patterns but with different control strategies. One has a programmable room thermostat and the other has a zonal control system based on actual occupancy. The results showed that the same level of comfort could be achieved by both scenarios and that using a smart controls enabled a reduction in gas consumption although the overall efficiency of the boiler was also reduced. However, the sample of the analysis is too small to generalise the results

Regarding HVAC systems in commercial buildings, most analysis found that by using fixed schedules, high levels of comfort are achieved but at the expense of high energy usage (Dobbs & Hencey, 2014; Martani et al., 2012; Oldewurtel et al., 2013; Howard & Hoff, 2013). Additionally, the schedules of the HVAC systems are not based on occupancy patterns, as for example they do not take account reductions in occupancy at midday during lunch time, or variations within days of the week (Martani et al. 2012), which previous reviewed documents suggests was a patterns observed in many commercial buildings.

The use of occupancy based controls in commercial buildings has suggested savings between 10% to 15% through simulations in the energy consumption of the HVAC system (Agarwal et al. 2010) (Oldewurtel et al. 2013) (Dobbs & Hencey 2014). These are the results from simulations, and not the results from empirical evidences.

As with smart thermostats, analysis tends to be focused on which type of monitoring system and prediction algorithm is most accurate and can be deployed at the scale of commercial buildings (Dong & Andrews 2009)

As a whole for the domestic sector it can be said that there is not enough evidence to suggest that smart heating controls can reduce energy usage while maintaining comfort. Additionally, in order to investigate this issue it is important to analyse the types of smart controls available and how they are perceived by users in. The documents analysed (Lee et al. 2013; Gao & Whitehouse 2009; Beizaee et al. 2015; Bomhard et al. 2014) present the following categories for smart heating controls: room by room zonal control, geo-location, and smart learning. Table 5 shows example of smart systems of each category that are available in the UK market.

Table 5- Types of smart controls available in the UK market

Category	System in the market
Room by room zonal control	HeatGenius: Room heating schedules and temperatures programmable with a phone app Honeywell, Danfoss, e-Q3, Nest: Programmable TRVs available from different brands
Geo-location	Tado, heatmiser and Hive: utilise phone location to estimate arrival time and activate the heating system
Smart learning	Nest: A motion sensor is used to detect occupancy and the system learns and produces heating schedules based on occupancy Netatmo: generates schedule based on a questionnaire

One important aspect to consider when analysing heating controls and its possible impact on energy consumption is user engagement get involved with the system and its smart features and for how long. Already, the Energy Follow up Survey showed that most people do not even engage with common basic controls because of lack of understanding or interest, so what will be the case for smart controls? A study by Burchell et al. (2016) for example analysed user engagement with energy consumption feedback from in-home display systems showing that interest and engagement with this type of technology is often short term.

The lack of user engagement could lead to a performance gap of the system, or even worse, a rebound effect, consuming more energy than without smart controls (Sorrell & Dimitropoulos, 2008). Other possible cause of rebound effects could come from houses being pre heated before users arrive by using geo-location based controls, leading to more hours of heating use. Also, in the case of smart controls that learn and predict occupancy, on days where users have an unusual or unexpected schedule, heating could be activated when there is no occupancy unless the system counts with an occupancy detection sensor to turn off in these type of situations.

Gaps in current knowledge

The main gaps identified through the research are:

- The number of studies on UK's domestic occupancy patterns is not enough to generalise a set of categories that can be applied to building simulation or building management systems. Although there is strong evidence to suggest that BREDEM categories are too simplistic, there is currently insufficient evidence to derive in a new set of categories

- There is a strong focus on building performance and thermal characteristics but very little on user behaviour and its large but mostly under-researched role in energy consumption

- Most of the research is focused on modelling techniques, algorithms and data mining but not on analysing patterns inferred from a representative sample of real homes

- Within the reviewed documents that do analyse categories of patterns, not all relate them to socio economic attributes of the dwelling occupants but only define schedules and time of activity peaks

- Besides TUS data there is no other sample that is representative of the UK's households that contains data on daily activities and can be used for developing patterns

- There are no occupancy models that can be applied at a global scale

- There is very little evidence on how to improve PIR and CO2 sensors in order to be able to determine the number of occupants

- There is insufficient evidence to evaluate the effect of smart heating on comfort, especially on whether different setbacks periods or zonal heating can diminish the level of comfort in a house

- The analysis of costs vs benefits of installing smart thermostats is not advanced largely due to a lack of data

- There is no evidence on why non-centrally heated homes show a higher percentage households with one heating period

- The weekly occupancy diversity factors are not known for the case of retail buildings

- Occupancy profiles are not differentiated within days of the weekend, only between weekday and weekend

- Seasonality of occupancy profiles is not evaluated

- Occupancy prediction algorithms for domestic buildings are less developed than for commercial buildings

CONCLUSIONS

This scoping review sets out to collect, synthesise and assess the quality of current knowledge on domestic occupancy patterns. Its purpose was to support a new policy, setting mandatory level for heating system efficiency. Finally it addressed five objectives set out by DECC, described as follows:

- To review the common methods for determining domestic occupancy patterns
- To categories of domestic occupancy patterns;
- The relationship between domestic occupancy and heating patterns.
- Potential role of occupancy-based smart heating controls
- Gaps in current knowledge

The scoping review has shown that there is currently very little amount of evidences addressing UK domestic occupancy and heating patterns, as only 19 documents were selected through the systematic literature review process. However the scoping review included non-UK and non-domestic documents, this brought the final number to 67 documents.

The main conclusions are as follows:

- No common occupancy and heating patterns in domestic buildings. Although, the small number of studies are not representative of the UK's population.
- One schedule does not fit all. BREDEM patterns need to be updated.
- Heating patterns are highly dependent on occupancy patterns and relate to the same characteristics, including: number of occupants, age, level of income and type of employment.
- Heating patterns depend on the type of control system installed and the possibilities for programming and heating zones independently.

  With regard to data collection methods, TUS are so far the main method for inferring domestic occupancy patterns at a regional or national scale; although TUS have validity issues. Sensor networks are the best methods for monitoring occupancy, providing appropriate algorithms are chosen to process the binary time series output. Occupancy may also be inferred from metered electricity data, providing that the sampling rate is short enough. This is a promising method for both domestic and commercial buildings. Finally, occupancy based smart controls in dwelling and HVAC management systems in non-domestic may offer savings between 10 and 15% in energy consumption, providing the prediction of occupancy is accurate as these controls may lead to rebound effect. Also it is important to highlight that this estimated energy saving is based on a small number of studies, as this scoping review has underline the current lack of evidences on the occupancy and heating patterns.

To conclude, there is a need for future studies to investigate occupancy and heating patterns from representative sample of the UK's population. This will enable categories of patterns to be defined and variability in time, from socio-economic and physical factors to be estimated. Finally, there is a need for future studies to evaluate the effect of smart heating control on occupants' comfort, as different setbacks periods or zonal heating strategies may reduce the level of comfort in a home. Furthermore studies should investigate the uncertainty of the application of smart controls, and quantify their impact on energy demand for various occupancy patterns.

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APPENDIX A: SEARCH TABLES

(1) Occupancy patterns

					TOTAL	**3681**	**212**	**126**	**106**
Search Code	**Date**	**Database searched**	**Search Terms & limit applied**	**Search Field**	**Comments**	**Total Results**	**Appropiate for full abstract assessment**	**Appropiate for review of whole text**	**QA passed**
W1	18-Feb	Web of Science	*domestic AND occupancy AND (pattern* OR Profile* OR*	Title	Search not continued, included in W2	4	-	-	-
W2	18-Feb	Web of Science	*domestic AND occupan* AND (pattern* OR Profile* OR behavior)*	Title	None addresses occupancy directly, they develop the topic of occupancy patterns as an input for their analysis	5	2	**1**	1
W3	19-Feb	Web of Science	*domestic AND occupancy AND (pattern* OR Profile* OR behavior)*	Topic OR Title. Research Areas: Eng / Environmental Sciences Ecology / Behavioral Sciences /Physics / Physical Science other/ Sience Technology other/ Automation Control Systems)	Even with the filters, some are still related to Biology or Medicine.	111	25	**18**	15
W4	19-Feb	Web of Science	*domestic AND occupan* AND (pattern* OR Profile* OR behavior)*	Topic OR Title. Research Areas: Eng / Environmental Sciences Ecology / Behavioral Sciences /Physics / Physical Science other/ Sience Technology other/ Automation Control Systems)	This search includes all the results of the previous one.	219	46	**21**	17
W5	22-Feb	Web of Science	*occupancy AND pattern**	Title. Refined by: RESEARCH DOMAINS: (SCIENCE TECHNOLOGY) AND TOPIC: (building)	Results are much more specific than when including "domestic". Most results on methods for monitoring occupancy	25	9	**7**	6
W6	22-Feb	Web of Science	*occupancy AND profile**	Title. Refined by: RESEARCH DOMAINS: (SCIENCE TECHNOLOGY) AND TOPIC: (building)		6	3	**1**	1
W7	29-Feb	Web of Science	*occupan* AND schedule**	Title.	Most results are patents	41	0	**0**	0
W8	29-Feb	Web of Science	*occupan* AND schedule**	Title. Only Articles		15	3	**2**	2
W9	29-Feb	Web of Science	*occupan* AND schedule**	Topic OR Title. Research Areas: Eng / Environmental Sciences Ecology / Behavioral Sciences /Physics / Physical Science other/ Sience Technology other/ Automation Control Systems)		325	13	**10**	9
W10	29-Feb	Web of Science	*domestic AND occupancy*	Title	All results prebiously recorded	18	8	**6**	5
S1	18-Feb	Scopus	*domestic AND occupancy AND (pattern* OR Profile* OR behavior)*	Title OR Keywords. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	No new results form Web of Science search	11	4	**2**	1
S2	18-Feb	Scopus	*domestic AND occupan* AND (pattern* OR Profile* OR behavior)*	Title OR Keywords. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Mostly all focused on occupant behavior regarding window opening and/or electricity consumption	40	11	**3**	2

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed
S3	18-Feb	Scopus	*domestic AND occupan* AND (pattern* OR Profile* OR behavior)*	Title OR Abstract OR Keywords. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Includes previous, so the others do not include the words in either title or keywords	184	0	**0**	0
S4	22-Feb	Scopus	*ocuupancy AND (pattern* OR profile)*	Title. Source Title : "Building" All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	2 new results	13	6	**4**	3
S5	29-Feb	Scopus	*occupan* AND schedule**	Title. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	New results	18	8	**5**	4
S6	29-Feb	Scopus	*domestic AND occupancy*	Title. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Only 1 new result	22	11	**7**	6
G1	18-Feb	Google Scholar	*domestic AND occupancy AND (pattern OR patterns OR profile OR profiles OR behavior)*	With all words. Only title. Exclude patents and citations	Search filtering is limited in Google; does not allow truncation. AND automatically between words Only one related to the topic, other in biology / medicine	6	1	**1**	0
G2	18-Feb	Google Scholar	*domestic AND occupancy AND (pattern OR patterns OR profile OR profiles OR behavior)*	With all words. Anywhere in the article. Exclude patents and citations	Search narrowed to subject area	30400	-	**-**	-
G3	18-Feb	Google Scholar	*domestic AND occupancy AND (pattern OR patterns OR profile OR profiles OR behavior)*	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations	Search provides other results: Books, Protocols,	78	**4**	**0**	0
G4	18-Feb	Google Scholar	*domestic AND occupancy OR Occupant AND (pattern OR patterns OR profile OR profiles OR behavior)*	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations	As Keywords are mostly not in the title, the results are not related to the research. Using "occupant" did not add results	101	5	**0**	0
G5	22-Feb	Google Scholar	*occupancy AND patterns OR profiles*	With all words. Title. Exclude patents and citations	A lot of results on Biology	14	3	**2**	2
G6	22-Feb	Google Scholar	*occupancy AND patterns OR profiles*	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations		2	1	**1**	2
G7	29-Feb	Google Scholar	*occupan* AND schedule**	With all words in Title. Exclude patents and citations		2	0	**0**	0
G8	29-Feb	Google Scholar	*occupan* AND schedule**	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations		56	1	**1**	1

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed
G9	29-Feb	Google Scholar	*domestic AND occupancy*	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations		0	0	**0**	0
G10	29-Feb	Google Scholar	*domestic AND occupancy*	With all words in Title. Exclude patents and citations	All results included in previous searches	30	0	**0**	0
U1	12-Feb	UK GOV	*domestic occupancy patterns*	DECC; DEFRA; EA; Ofgem; Office of National Statistics	No advanced search option. It does not allow to use AND/OR. Most results on ECO and Green Deal	73	3	**2**	2
U2	18-Feb	UK GOV	*domestic occupancy profiles*	DECC; DEFRA; EA; Ofgem; Office of National Statistics		54	2	**1**	1
U3	18-Feb	UK GOV	*domestic occupancy behaviour*	DECC; DEFRA; EA; Ofgem; Office of National Statistics		40	2	**1**	1
ICE1 to ICE3	16-Feb	ICE virtual library	*domestic AND occupancy AND patterns*	All in Title | All in Keywords | All in Abstract		0	0	**0**	0
ICE4	16-Feb	ICE virtual library	*domestic AND occupancy AND patterns*	Anywhere	Search narrowed to subject area (too many results and of varied topics)	376	-	**-**	-
ICE5	16-Feb	ICE virtual library	*domestic AND occupancy AND patterns*	Anywhere. Subject: Sustainability		18	1	**0**	0
ICE6	16-Feb	ICE virtual library	*domestic AND occupancy AND patterns*	Anywhere. Subject: Energy		14	0	**0**	0
ICE7	16-Feb	ICE virtual library	*domestic AND occupancy AND patterns*	Anywhere. Subject: Buildings, Structure & Design		6	1	**0**	0
ICE8 to ICE9	16-Feb	ICE virtual library	*domestic AND occupancy AND profiles*	All in Title | All in Keywords		0	0	**0**	0
ICE10	16-Feb	ICE virtual library	*domestic AND occupancy AND profiles*	Abstract		1	0	**0**	0
ICE11	16-Feb	ICE virtual library	*domestic AND occupancy AND profiles*	Anywhere	Search narrowed to subject area (too many results and of varied topics)	230	-	**-**	-
ICE12	16-Feb	ICE virtual library	*domestic AND occupancy AND profiles*	Anywhere. Subject: Energy		12	1	**0**	0
ICE13	16-Feb	ICE virtual library	*domestic AND occupancy AND profiles*	Anywhere. Subject: Science		9	1	**0**	0
ICE14	22-Feb	ICE virtual library	*occupancy AND patterns OR profiles*	Title | Keywords		0	0	**0**	0
IE1; IE2	17-Feb	IEEE	*domestic AND occupancy AND pattern**	Document Title | Author Keywords		0	0	**0**	0
IE3	17-Feb	IEEE	*domestic AND occupancy AND pattern**	Metadata Only		7	3	**2**	1

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed
IE4	17-Feb	IEEE	*domestic AND occupancy AND pattern**	All Text & Metadata	Search narrowed to subject area (too many results and of varied topics)	456	-	-	-
IE5	21-Feb	IEEE	*domestic AND occupancy AND pattern**	All Text & Metadata. Refine by: Energy Consumption	A lot of Results on Smart Controls , AI and automation	255	5	**3**	2
IE6	21-Feb	IEEE	*domestic AND occupancy AND pattern**	All Text & Metadata. Refine by: Buildings	Same results as in the previous search	293	0	**0**	0
IE7; IE8	17-Feb	IEEE	*domestic AND occupancy AND profile**	Document Title | Author Keywords		0	0	**0**	0
IE9	17-Feb	IEEE	*domestic AND occupancy AND profile**	Metadata Only		4	1	**1**	1
IE10	17-Feb	IEEE	*domestic AND occupancy AND profile**	All Text & Metadata	Same results as in the previous search	268	0	**0**	0
IE12	17-Feb	IEEE	*domestic AND occupancy AND behavior*	Document Title | Author Keywords		0	0	**0**	0
IE13	17-Feb	IEEE	*domestic AND occupancy AND behavior*	Metadata Only		1	0	**0**	0
IE14	17-Feb	IEEE	*domestic AND occupancy AND behavior*	All Text & Metadata	Search narrowed to subject area (too many results and of varied topics)	627	-	-	-
IE15	22-Feb	IEEE	*occupancy patterns*	Metadata Only	Search narrowed to subject area (too many results and of varied topics)	301	-	-	-
IE16	22-Feb	IEEE	*occupancy patterns*	Metadata Only. RefRefine by: Buildings		56	8	**8**	7
B1	16-Feb	BSRIA	*domestic AND occupancy AND pattern**	Library. All Publications . Full Text	No new results from previous searches.	22	6	**5**	5
B2	16-Feb	BSRIA	*domestic AND occupancy AND pattern**	Library. All Publications. All words in Title		1	0		
B3	16-Feb	BSRIA	*domestic AND occupancy AND pattern**	Library. All Publications. All words in Keywords		0	0	**0**	0
B4	16-Feb	BSRIA	*domestic AND occupancy AND profile**	Library. All Publications . Full Text		9	4	**3**	2
B5	16-Feb	BSRIA	*domestic AND occupancy AND profile**	Library. All Publications. All words in Title		0	0	**0**	0
B6	16-Feb	BSRIA	*domestic AND occupancy AND profile**	Library. All Publications. All words in Keywords		0	0	**0**	0
B7	16-Feb	BSRIA	*domestic AND occupancy AND behaviour*	Library. All Publications . Full Text		3	0		
B8	16-Feb	BSRIA	*domestic AND occupancy AND behaviour*	Library. All Publications. All words in Title		0	0	**0**	0
B9	16-Feb	BSRIA	*domestic AND occupancy AND behaviour*	Library. All Publications. All words in Keywords		0	0	**0**	0

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed
O1	16-Feb	OPENGREY	*domestic AND occupancy AND pattern* OR profile**		Search narrowed to subject area	9020	-	-	-
O2	16-Feb	OPENGREY	*domestic occupancy patterns*			2	0	**0**	0
O3	16-Feb	OPENGREY	*domestic occupancy profiles*			0	0	**0**	0
C1	12-Feb	CIBSE	*domestic occupancy patterns*	CIBSE Knowledge; Membership; CIBSE News	Portal performs search with OR within all terms. Year, topic, etc Evaluated individually	328	0	**0**	0
C2	12-Feb	CIBSE	*domestic occupancy profiles*	CIBSE Knowledge; Membership; CIBSE News	Portal performs search with OR within all terms. Year, topic, etc Evaluated individually	328	0	**0**	0
C3	12-Feb	CIBSE	*domestic occupancy behaviour*	CIBSE Knowledge; Membership; CIBSE News	Portal performs search with OR within all terms. Year, topic, etc Evaluated individually	329	0	**0**	0
UC1	29-Feb	UC Digital Library	*occupancy pattern**	Title		1	0	**0**	0
UC2	29-Feb	UC Digital Library	*occupancy pattern**	Keywords. Discipline: Architecture, Engineering, Physical Sciences and Mathematics, Social & Behavioral Sciences		65	2	**2**	1
UC3	29-Feb	UC Digital Library	occupan* schedule	Keywords. Discipline: Architecture, Engineering, Physical Sciences and Mathematics, Social & Behavioral Sciences		107	3	**2**	2
R1	29-Feb	RIBA Library Catalogue	occupancy patterns	Title	No new results from previous searches.	2	1	**1**	1
R2	29-Feb	RIBA Library Catalogue	occupancy patterns	Title OR Keywords OR Subject	No new results from previous searches.	6	2	**2**	2
R3	29-Feb	RIBA Library Catalogue	occupancy profiles	Title OR Keywords OR Subject	No new results from previous searches.	1	1	**1**	1
R4	29-Feb	RIBA Library Catalogue	occupancy schedule	Title OR Keywords OR Subject		0	0	**0**	0
BRE1	29-Feb	BRE	occupancy	BRE Publications		24	1	**0**	0

(2) Heating patterns

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed?
					TOTAL	**2818**	**72**	**24**	**19**
W1	22-Feb	Web of Science	*domestic AND heat* AND (pattern* OR Profile* OR behavior)*	Title	Only one addresses heating patterns directly, but its based on Chines population. Mostly all on DHW,solar heaters, mechanics, chemistry, etc.	29	4	**1**	1
W2	22-Feb	Web of Science	*domestic AND heat* AND (pattern* OR Profile*)*	Title	All very technical, on solar heaters, mechanics, chemistry, etc. Same 2 specific papers as previous search	20	2	**0**	0
W3	22-Feb	Web of Science	*domestic AND heat* AND (pattern* OR Profile* OR behavior)*	Topic	Search narrowed to subject area	2319	-	-	-
W4	22-Feb	Web of Science	*domestic AND heat* AND (pattern* OR Profile* OR behavior)*	Topic. Research Areas: Eng / Environmental Sciences Ecology / Behavioral Sciences /Physics / Physical Science other/ Sience Technology other/ Automation Control Systems)	Search narrowed to subject area	1612	-	-	-
W5	22-Feb	Web of Science	*heating AND pattern**	Title. All document types. Refined by: RESEARCH DOMAINS: (SCIENCE TECHNOLOGY) AND TOPIC: (building)	Different results from W1 and W2, much more specific	25	6	**1**	1
W6	22-Feb	Web of Science	*heating AND profiles*	Title. All document types. Refined by: RESEARCH DOMAINS: (SCIENCE TECHNOLOGY) AND TOPIC: (building)		14	2	**1**	1
W7	29-Feb	Web of Science	*heating AND schedule**	Title. All document types. Refined by: RESEARCH AREAS: (SOCIAL SCIENCES OTHER TOPICS OR ENGINEERING OR PHYSICS OR AUTOMATION CONTROL SYSTEMS)	None related	20	0	**0**	0
W8	29-Feb	Web of Science	*domestic AND heating*	Title. Refined by: RESEARCH DOMAINS: (SCIENCE TECHNOLOGY) AND RESEARCH AREAS: (ENGINEERING OR AUTOMATION CONTROL SYSTEMS OR PHYSICS OR PHYSICAL SCIENCES OTHER TOPICS OR SCIENCE TECHNOLOGY OTHER TOPICS)	Most not related. Those related already showed in previous searches	322	0	**0**	0
S1	22-Feb	Scopus	*domestic AND heat* AND (pattern* OR Profile* OR behavior)*	Title, Abstract, Keywords. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Search narrowed to subject area	1152	-	-	-

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed?
S2	22-Feb	Scopus	*domestic AND heat* AND patterns*	Title, Abstract, Keywords. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Most results on hotwater, solar thermal, mechanics, etc	340	0	**0**	0
S3	22-Feb	Scopus	*domestic AND heat* AND (pattern* OR Profile* OR behavior)*	Title. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Same results as in Web of Science Search	11	4	**1**	1
S4	22-Feb	Scopus	*domestic AND heat* AND (pattern* OR Profile*)*	Title, Abstract, Keywords. Source Title : "Energy **OR** Building" All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Most results on hotwater, solar thermal, mechanics, etc	213	0	**0**	0
S5	22-Feb	Scopus	*domestic AND heat* AND (pattern* OR Profile*)*	Title, Abstract, Keywords. Source Title : "Energy **AND** Building" All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Only 3 are new results compared to previous search	30	10	**1**	1
S6	22-Feb	Scopus	*heating AND pattern**	Title. Source Title : "Energy **AND** Building" All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	All results in other searches too. No new results	9	6	**0**	0
S7	29-Feb	Scopus	*heating AND schedule**	Subject Areas: Physical Sciences and Social Sciences and Humanities	Results not related to domestic pace heating	31	0	**0**	0
G1	20-Feb	Google Scholar	*domestic AND heating AND patterns*	With all words. All in Title. Exclude patents and citations		0	0	**0**	0
G2	20-Feb	Google Scholar	*domestic AND heating AND (pattern OR patterns OR profile OR profiles OR behavior)*	With all words. All in Title. Exclude patents and citations		1	1	**0**	0
G3	20-Feb	Google Scholar	*domestic AND heating AND (pattern OR patterns OR profile OR profiles OR behavior)*	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations	Search narrowed to subject area	146	-	-	-
G4	22-Feb	Google Scholar	*heating AND patterns OR profiles*	With all words. Title. Exclude patents and citations		15	3	**1**	1
G5	22-Feb	Google Scholar	*heating AND patterns OR profiles*	With all words. Anywhere in the article. Articles published in: Energy and Building . Exclude patents and citations		1	0	**0**	0
U1	17-Feb	UK GOV	*domestic heating patterns*	DECC; DEFRA; EA; Ofgem; Office of National Statistics	No advanced search option. It does not allow to use AND/OR.Triple results than for occupancy search	313	2	**2**	2
U2	17-Feb	UK GOV	*domestic heating profiles*	DECC; DEFRA; EA; Ofgem; Office of National Statistics		305	2	**2**	2
U3	17-Feb	UK GOV	*heating patterns*	DECC; DEFRA; EA; Ofgem; Office of National Statistics		25	0	**0**	0

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed?
U4	17-Feb	UK GOV	*heating profiles*	DECC; DEFRA; EA; Ofgem; Office of National Statistics		12	0	**0**	0
ICE1 to ICE3	20-Feb	ICE virtual library	*domestic AND heating AND patterns*	All in Title | All in Keywords | All in Abstract		0	0	**0**	0
ICE4	20-Feb	ICE virtual library	*domestic AND heating AND patterns*	Anywhere	Search narrowed to subject area (too many results and of varied topics)	398	-	-	-
ICE5	20-Feb	ICE virtual library	*domestic AND heating AND patterns*	Anywhere. Subject: Science		25	1	**0**	0
ICE6	20-Feb	ICE virtual library	*domestic AND heating AND patterns*	Anywhere. Subject: Energy		16	0	**0**	0
ICE7	20-Feb	ICE virtual library	*domestic AND heating AND patterns*	Anywhere. Subject: Buildings, Structure & Design	Same as ICE5	24	1	**0**	0
ICE8	20-Feb	ICE virtual library	*domestic AND heating AND profiles*	All in Title | All in Keywords		0	0	**0**	0
ICE9	20-Feb	ICE virtual library	*domestic AND heating AND profiles*	Abstract		2	0	**0**	0
ICE10	20-Feb	ICE virtual library	*domestic AND heating AND profiles*	Anywhere	Search narrowed to subject area (too many results and of varied topics)	276	-	-	-
ICE11	20-Feb	ICE virtual library	*domestic AND heating AND profiles*	Anywhere. Subject: Buildings, Structure & Design	Same as ICE5	34	1	**0**	0
ICE12	20-Feb	ICE virtual library	*domestic AND heating AND profiles*	Anywhere. Subject: Science	Same as ICE5	25	1	**0**	0
ICE13	20-Feb	ICE virtual library	*domestic AND heating AND profiles*	Anywhere. Subject: Energy	Same as ICE5	24	1	**0**	0
ICE14	22-Feb	ICE virtual library	*heating AND patterns OR profiles*	Title | Keywords		0	0	**0**	0
ICE15	22-Feb	ICE virtual library	*heating AND patterns OR profiles*	Title | Keywords	Review search methods in ICE	21	0	**0**	0
IEEE1	17-Feb	IEEE	*domestic AND heating AND patterns*	Document Title	Result already recorded	1	1	**1**	0
IEEE2	17-Feb	IEEE	*domestic AND heating AND patterns*	Metadata Only	Result already recorded	46	2	**2**	0
IEEE3	17-Feb	IEEE	*domestic AND heating AND patterns*	Author Keywords	Result already recorded	1	1	**1**	0
IEEE4	17-Feb	IEEE	*domestic AND heating AND patterns*	All Text & Metadata	Search narrowed to subject area (too many results and of varied topics)	3708	-	-	-
IEEE5	21-Feb	IEEE	*domestic AND heating AND patterns*	All Text & Metadata. Refine by: Buildings	Search narrowed to subject area (too many results and of varied topics)	2666	-	-	-
IEEE6	17-Feb	IEEE	*domestic AND heating AND profiles*	Document Title | Author Keywords		1	0	**0**	0
IEEE7	17-Feb	IEEE	*domestic AND heating AND profiles*	Metadata Only		71	0	**0**	0

Search Code	Date	Database searched	Search Terms & limit applied	Search Field	Comments	Total Results	Appropiate for full abstract assessment	Appropiate for review of whole text	QA passed?
IEEE8	17-Feb	IEEE	*domestic AND heating AND profiles*	Metadata Only. RefRefine by: Buildings		23	0	**0**	0
IEEE9	17-Feb	IEEE	*domestic AND heating AND profiles*	All Text & Metadata	Search narrowed to subject area (too many results and of varied topics)	2567	-	-	-
IEEE10	22-Feb	IEEE	*heating AND patterns OR profiles*	Metadata Only	Search narrowed to subject area (too many results and of varied topics)	69456	-	-	-
IEEE11	22-Feb	IEEE	*heating AND patterns OR profiles*	Metadata Only. RefRefine by: Buildings	Search narrowed to subject area (too many results and of varied topics)	4086	-	-	-
B1	22-Feb	BSRIA	*domestic AND heating AND pattern**	Library. All Publications . Full Text	Four new results	70	8	**6**	5
B2	22-Feb	BSRIA	*domestic AND heating AND profile**	Library. All Publications . Full Text	1 new result	46	5	**3**	3
O1	17-Feb	Opengrey	*domestic occupancy patterns'*			2	0	**0**	0
O2	17-Feb	Opengrey	*domestic heating patterns'*			4	0	**0**	0
C1	17-Feb	*CIBSE*	*domestic heating patterns'*	CIBSE Knowledge; Membership; CIBSE News		395	0	**0**	0
UC1	23-Feb	UC Digital Library	*heating pattern**	Title		1	0	**0**	0
UC2	29-Feb	UC Digital Library	*heating pattern**	Keywords. Discipline: Architecture, Engineering, Physical Sciences and Mathematics, Social & Behavioral Sciences		45	2	**0**	0
UC3	29-Feb	UC Digital Library	*heating schedule**	Keywords. Discipline: Architecture, Engineering, Physical Sciences and Mathematics, Social & Behavioral Sciences		24	1	**0**	0
R1	29-Feb	RIBA Library Catalogue	*heating pattern**	Title OR Keywords OR Subject		5	1	**1**	1
R2	29-Feb	RIBA Library Catalogue	*heating profile**	Title OR Keywords OR Subject		5	0	**0**	0
	29-Feb	RIBA Library Catalogue	*heating schedule**	Title OR Keywords OR Subject		6	0	**0**	0
BRE1	29-Feb	BRE	heating	BRE Publications		164	4	**0**	0
BRE2	29-Feb	BRE	heating patterns	BRE Publications		1	0	**0**	0

(3) Occupancy and heating pattern & (4) Expert review

					TOTAL	733	74	44	38
Search Code	**Date**	**Database searched**	**Search Terms & limit applied**	**Search Field**	**Comments**	**Total Results**	**Appropiate for full abstract**	**Appropiate for review of whole text**	**QA passed?**
Combined search: Occupancy and Heat									
CS1	#####	Scopus	occupancy AND heating AND (pattern* OR profile * OR schedule*)	Title. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities	Results already recorded from previous search	1	0	0	0
CS2	#####	Scopus	occupancy AND heating AND (pattern* OR profile * OR schedule*)	TITLE-ABS-KEY. All document types. Subject Areas: Physical Sciences and Social Sciences and Humanities		214	30	22	18
Expert Review: Ben Anderson									
BA							21	6	5
Annex 66 Bibliography Review									
A66						518	23	16	15

APPENDIX B: INCLUSION AND EXCLUSION CRITERIA

RESULTS POTENTIALLY RELEVANT : Appropiate for full abstract assessment		RESULTS APPROPIATE FOR REVIEW: Assessment of full text									Quality Assessment									
Ref	Topic	**C1.**	**C2.**	**C3**	**C4**	**C5.**	**C6.**	**C7.**	**C8.**	**C9.**	(2)Rationale & questions clear and justified	(2)Acknowledge resource contributions and conflicts of interest	(1)Methods suitable for aim	(2)Peer Reviewed or Verified	(1) Conclusions match data	(1) Org/Auth or Record	**TOT Reporting Quality**	**TOT Research Quality**	**Total Points**	**Threshold passed? (Y/N)**
(Dar et al. 2015)	Occ							X	No	Yes	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Dong et al. 2015)	Occ						X		No	Yes	1	1	0	1	1	1	**2**	**3**	**5**	NO
(Tahmasebi & Mahdavi 2015)	Occ					X			No	No	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Akbar et al. 2015)	Occ			X					Yes	No	2	2	1	1	1	1	**5**	**3**	**8**	Yes
(Beizaee et al. 2015)	Occ&Heat						X		Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Burak Gunay et al. 2015)	Occ&Heat					X			No	No	2	1	1	2	1	1	**4**	**4**	**8**	Yes
(Cali et al. 2015)	Occ			X					No	Yes	1	2	0	2	1	1	**3**	**4**	**7**	Yes
(D'Oca & Hong 2015)	Occ		X						No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Feng et al. 2015)	Occ				X				No	No	1	1	1	2	1	1	**3**	**4**	**7**	Yes
(Gomez Ortega et al. 2015)	Occ		X						No	Yes	1	2	1	1	1	1	**4**	**3**	**7**	Yes
(Gul & Patidar 2015)	Occ						X		Yes	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Huebner et al. 2015)	Heat	X							Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Kane et al. 2015)	Heat	X							Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Kim & Srebric 2015)	Occ				X				No	No	1	1	1	1	1	1	**3**	**3**	**6**	Yes
(Marshall et al. 2015)	Occ							X	Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Martinaitis et al. 2015)	Occ						X		No	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(McKenna et al. 2015)	Occ				X				Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Ren et al. 2015)	Heat		X						No	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Tahmasebi & Mahdavi 2015a)	Occ				X				No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Taylor 2015)	Occ&Heat						X		No	No	1	1	0	2	1	0	**2**	**3**	**5**	NO
(Aerts et al. 2014)	Occ				X				No	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Andersen et al. 2014)	Occ				X				No	No	1	1	1	2	1	1	**3**	**4**	**7**	Yes
(Bomhard et al. 2014)	Occ&Heat			X					No	Yes	2	1	1	2	1	1	**4**	**4**	**8**	Yes
(Duarte et al. 2014)	Occ				X				No	No	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Naghiyev et al. 2014)	Occ			X					Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Paudel et al. 2014)	Occ&Heat		X						No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Spataru & Gauthier 2014)	Occ			X					Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Ai et al. 2014)	Occ					X			No	No	1	1	1	1	1	1	**3**	**3**	**6**	Yes
(Bouffaron 2014)	Occ				X				No	No	1	2	1	1	1	1	**4**	**3**	**7**	Yes

RESULTS POTENTIALLY RELEVANT : Appropiate for full abstract assessment		**RESULTS APPROPIATE FOR REVIEW: Assessment of full text**									**Quality Assessment**									
Ref	Topic	**C1.**	**C2.**	**C3**	**C4**	**C5.**	**C6.**	**C7.**	**C8.**	**C9.**	(2)Rationale & questions clear and justified	(2)Acknowledge resource contributions and conflicts of interest	(1)Methods suitable for aim	(2)Peer Reviewed or Verified	(1) Conclusions match data	(1) Org/Auth or Record	**TOT Reporting Quality**	**TOT Research Quality**	**Total Points**	**Threshold passed? (Y/N)**
(Dobbs & Hencey 2014)	Occ&Heat					X			No	No	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Kleiminger et al. 2014)	Occ&Heat						X		No	Yes	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Munton et al. 2014)	Heat	X							Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Papafragkou et al. 2014)	Heat			X					Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Yang & Becerik-Gerber 2014)	Occ				X				No	No	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Yang et al. 2014)	Occ&Heat					X			No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Zhao et al. 2014)	Occ		X						No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Hulme et al. 2013)	Heat	X							Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Kleiminger et al. 2013)	Occ			X					No	Yes	1	2	1	1	1	1	**4**	**3**	**7**	Yes
(Albert & Rajagopal 2013)	Occ	X							No	Yes	2	1	1	1	1	1	**4**	**3**	**7**	Yes
(Blight & Coley 2013)	Occ						X		Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Chang & Hong 2013)	Occ	X							No	No	1	1	0	2	1	0	**2**	**3**	**5**	NO
(Duarte et al. 2013)	Occ	X							No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Howard & Hoff 2013)	Occ&Heat					X			No	Yes	2	2	1	1	1	0	**5**	**2**	**7**	Yes
(Huebner et al. 2013)	Heat	X							Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Lee et al. 2013)	Occ&Heat					X			No	Yes	1	2	1	1	1	1	**4**	**3**	**7**	Yes
(López-Rodríguez et al. 2013)	Occ						X		No	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Oldewurtel et al. 2013)	Occ&Heat					X			No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Han et al. 2012)	Occ&Heat		X						No	No	1	2	0	1	1	1	**3**	**3**	**6**	Yes
(Zimmermann et al. 2012)	Heat	X							Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(BRE 2012)	Occ&Heat							X	Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Ekwevugbe et al. 2012)	Occ			X					Yes	No	1	2	1	0	0	1	**4**	**1**	**5**	NO
(Martani et al. 2012)	Occ&Heat						X		No	No	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Widén et al. 2012)	Occ				X				No	Yes	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Zhang et al. 2012)	Occ							X	Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Alrazgan et al. 2011)	Occ		X						No	No	1	2	1	1	1	0	**4**	**2**	**6**	Yes

RESULTS POTENTIALLY RELEVANT : Appropiate for full abstract assessment		**RESULTS APPROPIATE FOR REVIEW: Assessment of full text**									**Quality Assessment**									
Ref	Topic	**C1.**	**C2.**	**C3**	**C4**	**C5.**	**C6.**	**C7.**	**C8.**	**C9.**	(2)Rationale & questions clear and justified	(2)Acknowledge resource contributions and conflicts of interest	(1)Methods suitable for aim	(2)Peer Reviewed or Verified	(1) Conclusions match data	(1) Org/Auth or Record	**TOT Reporting Quality**	**TOT Research Quality**	**Total Points**	**Threshold passed? (Y/N)**
(Scott et al. 2011)	Occ&Heat					X			Yes	Yes	1	1	0	1	1	1	**2**	**3**	**5**	NO
(Audenaert & Briffaerts 2011)	Heat							X	No	Yes	1	1	0	2	1	1	**2**	**4**	**6**	Yes
(Blight & Coley 2011)	Occ							X	Yes	Yes	1	1	0	1	1	1	**2**	**3**	**5**	NO
(Castanedo et al. 2011)	Occ		X						No	No	1	1	1	1	1	1	**3**	**3**	**6**	Yes
(Cui et al. 2011)	Occ						X		Yes	Yes	1	1	1	0	1	1	**3**	**2**	**5**	NO
(Guerra Santin 2011)	Heat						X		No	Yes	1	2	1	2	1	1	**4**	**4**	**8**	Yes
(Vázquez & Kastner 2011)	Occ		X						No	No	1	1	1	1	1	1	**3**	**3**	**6**	Yes
(Agarwal et al. 2010)	Occ					X			No	No	1	2	1	1	1	1	**4**	**3**	**7**	Yes
(Lu et al. 2010)	Occ&Heat						X		No	Yes	2	2	1	1	1	1	**5**	**3**	**8**	Yes
(Goldstein et al. 2010)	Occ							X	No	No	1	1	0	1	1	1	**2**	**3**	**5**	NO
(Mahmoud et al. 2010)	Occ		X						Yes	Yes	2	1	1	1	1	1	**4**	**3**	**7**	Yes
(Spataru et al. 2010)	Occ						X		Yes	Yes	1	1	0	1	1	1	**2**	**3**	**5**	NO
(Widén & Wäckelgård 2010)	Occ						X		No	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Gao & Whitehouse 2009)	Occ&Heat					X			No	Yes	1	2	1	1	1	1	**4**	**3**	**7**	Yes
(Dong & Andrews 2009)	Occ&Heat					X			No	No	1	2	1	2	0	1	**4**	**3**	**7**	Yes
(Mahmoud et al. 2009)	Occ		X						Yes	Yes	2	1	1	0	1	1	**4**	**2**	**6**	Yes
(Page et al. 2008)	Occ				X				No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Richardson et al. 2008)	Occ				X				Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Yohanis et al. 2008)	Occ						X		Yes	Yes	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Page 2007)	Occ				X				No	No	1	2	1	0	1	0	**4**	**1**	**5**	NO
(Page et al. 2007)	Occ				X				No	No	1	2	0	1	1	1	**3**	**3**	**6**	Yes
(Dodier et al. 2006)	Occ		X						No	No	2	2	1	2	1	1	**5**	**4**	**9**	Yes
(Al-Mumin et al. 2003)	Occ						X		No	Yes	1	1	0	2	1	0	**2**	**3**	**5**	NO
(Papakostas & Sotiropoulos 1997)	Occ	X							No	Yes	0	1	1	2	1	0	**2**	**3**	**5**	NO
(Becker & Paciuk 1993)	Heat							X	No	Yes	1	1	0	2	0	1	**2**	**3**	**5**	NO
(Tarr 2012)	Occ					X			No	No	1	2	1	0	1	0	**4**	**1**	**5**	NO

C1. Analyses patterns inferred from sample
C2. Analyses mining techniques
C3. Analyses methods for monitoring
C4. Develops models for building simulation
C5. Develops models for BMS or system controls
C6. Analyses the relationship between patterns and energy consumption
C7. Other focus but utilises patterns as an input
C8. Analyses UK population
C9. Analyses domestic population

APPENDIX C: DECC QUALITY ASSESSMENT SCALE

Quality Assessment Scale for Occupancy Patterns Scoping Review Project

Reporting Quality:

- 2 points: Are the rationale and research questions clear and justified?
- 2 points: Does the document acknowledge resource contributions and possible conflicts of interest?
- 1 point: Are the methods used suitable for the aims of the study?

Research Quality:

- 2 points: Has the document been peer reviewed or independently verified by one or more reputable experts?
- 1 point: Do the conclusions match the data presented?
- 1 point: Does the author / publishing organisation have a track record in the area?

Total number of points: 9
Threshold: 6/9

APPENDIX D: SUMMARY OF THE REVIEWED DOCUMENTS

A. DOMESTIC OCCUPANCY PATTERNS – UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Marshall et al. 2015)	Utilises occupancy patterns as an input for modelling the effect of energy efficiency interventions in households. Reviews previous literature to summarize patterns categories	N/A. Patterns are derived from literature review from UK	1. Review of literature on occupancy patterns and energy saving retrofits. 2. Identification of common household scenarios and occupancy profiles. 3. Selection of energy efficiency retrofits. 4. Modelling of a 3 bedroom house with TRNSYS under 15 retrofit scenarios for each occupancy profile. 5. Comparison of resulting energy savings per scenario and type of household and against expected values.	• Three categories of occupancy are defined: Working family (2 adults working externally and 2 children, all absent from 08:30 to 16:00, all areas of the house used when at home). Working couple (2 adults working externally, all absent from 08:30 to 18:00 4 days a week and 08:30 to 21:00 three days a week, House partially occupied when at home) Daytime-present couple (2 adults one that generally stays at home during the day, Partial occupation all day) • Insulation measures provide the highest energy savings for all household types. • Installing TRVs resulted in higher savings in households with high levels of occupancy. • Zonal controls had the best results for a household with a working couple where the house is generally never fully occupied.	• Analyses energy measures both individually and in combinations. • Contrasts results against previous studies	• The simulation model does not include occupant behaviour and activities, only presence of occupants. •The model used is limited in the internal gains it considers • Occupancy based on literature.
(McKenna et al. 2015)	Generate a representative Occupancy model from Time Use Data that can be used in energy simulations using a first order Markov chain technique	1,702 entries from the UK Time Use Survey Data UK	1. The study reviews literature on modelling 2. After working through the data in order to identify states of activity and location, the transition probability matrices are developed generating the model 3. The data from the TUS is then compared to the synthetic patterns generated from the model evaluating probability and duration of states. 4. The model is evaluated for representation of specific cases: 24 hour occupied or unoccupied dwellings and multiple occupied dwelling with independent occupants	• The first-order Markov chain technique produces representative results in terms of state probabilities and state durations. • The technique under-represents dwellings with 24 h occupancy and dwellings that are frequently left unoccupied • Models than assume occupant independency show more discrepancies when compared with real data	• Develops analysis of available data like TUS • Analysis single and multiple occupancy	• Evaluates the model only for one person dwellings

DOMESTIC OCCUPANCY PATTERNS – UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Naghiyev et al. 2014)	Evaluates three unobtrusive monitoring technology for domestic spaces, CO_2 , PIR and Dfl by measuring occupancy through several time periods	One three bedroom house with three occupants UK	1. Review of each technology principles and limitations. 2. Presentation of study methodology, house monitored, location of sensors, equipment, etc. 3. Evaluation of results for each type of technology	• PIR sensors give out false negative occupancy registers. Increasing density of sensors or incorporating prediction algorithms could be evaluated to solve the issue. • CO_2 highly depend of air circulation and. circulation patterns and predictive algorithms could incorporate circulation patterns and information on opening on windows and doors • Neither PIR or CO_2 are adequate for measuring number of occupants • Dfl successfully measures occupancy but needs further research for processing its output data	• Analysis different methods under the same scenario therefore results are comparable	• The house analysed counts with MHRV which could affect the CO_2 levels and result in inaccurate measurements
(Spataru & Gauthier 2014)	Presents occupancy monitoring technologies and evaluates their performance based on their outputs for measuring a known occupancy. Also, it analyses how they can contribute to identifying potential energy savings	Slots of two weeks in different seasons in 1 flat with two occupants London, UK	1. Review of technologies for monitoring occupancy, type and characteristics of devices. 2. Practical assessment of methods, analysis of limitations and results obtained by each. 3. Review of methods for data analysis	• PIR sensors do not register reduced movement resulting in false negative occupancy • CO_2 sensors results depend on people's activity and air flow in the space • Wearable sensors like RFID and Sense Cam would be better if they used bracelets instead of necklace tags • The combination of UWB and RFID systems proved accurate	• Analysis different methods on same scenario therefore results are comparable • Deep analysis of sensors' technology, strengths and limitations	• Comparison is based in only one day of measurements

DOMESTIC OCCUPANCY PATTERNS – UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Blight & Coley 2013)	Utilises occupancy schedules as an input for modelling heating consumption in Passivhaus buildings.	Utilises model from (Richardson et al. 2008) derived from UK TUS data of 21,000 weekly household journals. UK	1. Discussion of energy modelling techniques. 2. Occupancy and behaviour profiles are generated from TUS data through a Markov-Chain approach. 3. Thermal modelling of Passivhaus units (three storey family house). 4 Validation of results comparing against measured data from Passivhauses in Central Europe. 5. Examination of sensitivity of heating demand to occupant behaviour.	• Inactive occupancy (sleeping or absent) is defined from 22:00 to 07:00 • Occupancy patterns are shown to be less significant factors to total heating energy than others like set point temperature and appliance use	• Relates occupant behaviour to heating demand.	•Limited to Passivhaus only and to the case analysed
(BRE 2012)	Defines standard household occupancy patterns for SAP calculations based on BREDEM methodology	N/A UK	Statement of methodology for calculating the heat output of the main heating system defining heating periods and temperatures according to the type of controls of the heating system	• Weekday active occupancy: 07:00 to 09:00 and 16:00 to 23:00 for all areas • Weekend active occupancy: 07:00 to 23:00	• Standardised patterns mean that performance evaluation and SAP ratings can be comparable for different types of households	• Same beginning and end hours for weekends and weekdays • Does not differentiate by type of household or number of occupants •No data that backs the choice of patterns
(Zhang, Siebers, & Aickelin, 2012)	Analyses residential occupancy as a factor that affects energy consumption in order to define "consumer types". Infers patterns from review of literature.	N/A Review of previous literature UK	1. Review of studies on residential energy consumption, categories, factors that affect it, consumer behaviour and profiles. 2. Propose consumer archetypes based on review. 3. Analysis of implications of archetypes for policy making and suggest types of policies accurate for each archetype.	• The main factors affecting energy consumption are: property efficiency, occupant attitude towards energy saving and length of occupancy period. • Occupancy divided in long and short based on 5 scenarios: (1) House unoccupied from 09:00 to 13:00; (2) House unoccupied from 13:00 to 18:00,; (3) House unoccupied from 09:00 to 16:00; (4) House unoccupied from 09:00 to 18:00 and (5) House occupied all day. (1) and (2) correspond to one of the occupants having a part time job; (3) to a family with a child, (4) to all occupants with a full time job and (5) a family with small children or a stay home person.	•Summarizes key findings from other studies	• Archetypes based on UK analysis, not applicable to other countries • Based only in Literature Review, no actual data analysis performed to identify consumer categories

DOMESTIC OCCUPANCY PATTERNS – UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Mahmoud et al. 2010)	Presents an approach for managing binary data from sensors. A space with elderly independent occupants is monitored through sensors and a model is developed for predicting occupancy through data mining with the non-linear auto regressive exogenous model - NARX	1 household monitored for more than a year and UK	1. Review of sensor data and NARX networks. 2. Experimental evaluation of model with real and simulated data. 3. Evaluation of NARX networks against a simple recurrent network	• NARX networks can predict the next movement of the occupant, and also whether the occupant stays in a specific area in the environment.	•Presents a data mining process for a type of data largely available (binary sensor data)	• Analysis data for only one type of occupant
(Mahmoud et al. 2009)	Investigates data mining methods for sensor networks in intelligent environments in order to obtain and predict occupancy patterns. A particular case of neural network, the ENS - Echo State Network is used to solve the problem of temporal relationships between values of a binary time series	1 flat occupied by an elderly person monitored over 10 days UK	1.Introduction to sensor networks and neural networks. 2.Presentation of ESN principles. 3.Experimentation: data collection and comparison of performance against two other neural network methods: BPTT (Back Propagation Trough Time) and RTRL (Real Time Recurrent Learning) 4.Analysis of results comparing RMSE (Root Mean Square Error) of predictions and time used by each method	• ESN shows promising results when utilising a large number of hidden neurons •Compared to the other methods, ESN predictions were more accurate and the data processing was faster	• Performs a direct comparison with largely used methods	• The size of the sample analysed is small • Small number of references are used in the paper

DOMESTIC OCCUPANCY PATTERNS – UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Richardson et al. 2008)	Analyse TUS data and develops a model to be used in energy demand simulations through Markov-Chain techniques	2,000 households from UK TUS 2000 UK	1. Analysis of TUS data characteristics categorizing by number of occupants and day of the week (weekday or weekend). 2. Generation of transition probability matrices. 3. Verification of synthetic results against TUS data	• Individual occupancy profiles show minimal activity from 00:00 to 07:00 and maximum at evenings • Delayed awakening at weekends in comparison with weekdays • The model produces data with statistical characteristics similar to the original TUS data	• Develops analysis of available data like TUS	• The model does not consider patterns of consistency from day to day because TUS data is not continuous.
(Yohanis et al. 2008)	Analyses the correlation between occupancy and electricity consumption in households through evaluation of load profiles	27 dwellings representative of Northern Ireland households, measured over a 20-month period Northern Ireland, UK	1. Description of study: household sample including property type, location, occupant's demographics, heating systems, lighting systems; electricity measurement methods. 2. Description of results of measured energy consumption by household characteristics and analysis of type of loads.	• Active occupancy peaks are between 06:00 and 9:00 and 17:00 to 22:00 • Houses with 4 or more occupants have electricity consumption peaks that range from 15:00 to midnight. • Energy consumption per person decreases with the number of occupants. • Houses with no daytime occupancy have higher average electricity consumption than those occupied all day. •Large income houses show lower daytime occupancy •Age of occupants influences patterns: over 65 generally show daytime occupancy, under 40 very low daytime occupancy and 50 to 65 show the largest energy consumption and have low daytime occupancy. •Very low active occupancy from 23:00 to 06:00 in all cases	• Analyses houses composition thoroughly including income, age, number of occupants	•Sample size is not big enough to generalise results

B. DOMESTIC OCCUPANCY PATTERNS – INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Calì et al. 2015)	Presents and evaluates an algorithm for detection of occupants based on CO_2 concentration in the air. Validation is done in both residential and non-residential buildings	5 different rooms: 3 offices, one kitchen and a living room monitored from 6 to 8 days Aachen Germany	1. Introduction to indoor environment in buildings and CO_2 based algorithms. 2. Analysis of algorithm for detecting occupant presence and its limitations 3. Presentation of test rooms and its characteristics. 4. Evaluation of detection algorithm comparing real and simulated CO_2 concentrations. 5. Evaluation of occupant detection for 3 scenarios based on availability of window and door data for the 5 rooms. Comparison based on two indexes: PM (presence matching) and OM (occupants matching) 6. Sensitivity analysis of algorithm's parameters	• The best results on presence matching were obtained when window and doors information was an input. •All scenarios resulted in imprecise prediction of the number of occupants. • Both openings information and the level of air changes per hour have a large influence on the results of the algorithm	• A deep analysis of the algorithm, its limitations and the influence of its parameters is performed	• CO_2 measurements results depend highly on where the sensors are places and the type of activity of occupants. • By analysing 5 different rooms there are too many variables that could affect the measurements
(Dar et al. 2015)	Investigates the effect of occupant behaviour and family size on the energy demand of a building and the performance of the heating systems. Patterns are inferred from TUS data based on (Richardson et al.,2010) methodology using a first order Markov chain approach	8,000 people surveyed over a 2 day period for the Norwegian TUS survey in 2010. Norway	1. Background to performance gap and effect of occupants interaction with building in energy demand. 2. Definition of simulation parameters, household properties and parameters. 3. Derivation of occupancy profiles from TUS data. 4. Analysis of effects of occupancy aspects in the performance of heating systems and overall energy demand	• Nine occupancy categories are defined based on number of occupants and working hours combining: single occupancy, double occupancy, family with up to 3 children and regular working hours, irregular working hours and staying home	• It utilises TUS data which is easily available and representative of the analysed population. • 3,000 large number of simulations are run with different occupant behaviour, heating system and envelope thermal properties in order to give statistically significant results for the analysis	• Houses simulated are only energy efficient houses, either a Low Energy House or Passivhaus, it does not include poor thermal performing houses. • The paper does not specify the daily occupancy profile, only categories

DOMESTIC OCCUPANCY PATTERNS – INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Gomez Ortega et al. 2015)	Develops and evaluates a pattern-recognition model using Machine Learning approaches for identifying occupancy and activities patterns. Compares utilising SVM (Support Vector Machines) against HMM (Hidden Markov Model) and KNN (k-Nearest Neighbour) methodologies	3 houses monitored 25, 14 and 19 days each Amsterdam, Netherlands	1. Review of types of sensors and previous models for sensor networks. 2. Discretisation of sensor data. 3. Evaluation of approached through Matlab analysis	• SVM outperformed the other models in accuracy and consistency of results • All methods show difficulties with differentiating between an inactive occupancy state and an "away from home" state • Data from sensor networks needs deep and complex and specific processing	• Thorough analysis of the methodology implemented by each model. • Comparison of performance of different models under the same scenarios	• Little specification on the characteristics of the scenarios analysed.
(Martinaitis et al. 2015)	Continuation of (Motuziene & Vilutiene 2013) study. Analyses, in building simulation, the effect of occupancy profiles on the energy performance of an energy efficient house.	Occupancy patterns defined according to literature research. For simulation: 4 different occupancy scenarios and 4 heating strategies making a total of 16 combinations. Climate data from Kaunas, Lithuania. Profiles based on European and Lithuanian literature	1. Review of previous studies on integrated building design, rebound effect, performance gap, and energy consumption patterns. 2. Presentation case study, building properties, simulation software, heating strategies and occupancy profiles. 3 Results showing influence of occupancy and heating strategies on the total energy demand.	• Defines four categories of building occupancy: (1) family of 4 leaving the house between 08:00 and 10:00 and returning at 16:00; (2) family of 4 leaving at 8:00 and returning at 16:00; (3) 2 people actively working leaving at 08:00 or 09:00 and returning at 16:00; (4) retired couple with full day stay • Different occupancy results in very varied values of energy demand, therefore one standard does not fit all cases	• Presents occupancy patterns by space in the house, including kitchen and bathroom • Utilises known and available software for simulation (Energy Plus), the study can be repeated and extended	• Simulation of an energy efficient house, patterns and behaviour might change based on the type of household and its thermal performance • Very little justification on selection of patterns, the literature used should be reviewed to understand the choice

DOMESTIC OCCUPANCY PATTERNS – INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Aerts et al. 2014)	Presents a three state (home & awake, sleeping, absent) probabilistic model that generates realistic occupancy sequences . Also, it identifies 7 typical occupancy categories from applying hierarchical agglomerative clustering algorithms to TUS data	3,455 households with 6,400 people interviewed for one weekday and one weekend day. 2005 combined Belgian Time-Use Survey (TUS) and Household Budget Survey (HBS) Belgium	1. Introduction to user behaviour modelling approaches. 2. Analysis of sample data characteristics, principles of model and its development and methodology for clustering. 3. Analysis of results: occupancy categories, model calibration and verification and generation of yearly sequences for building simulation	• Defines 7 categories based on the amount of time spent at home, sleeping or absent, the times at which users change between states and the amount of transitions in a day. • The categories are: (1) mostly absent, age 25-64, full time employed, middle income; (2) Mostly at home, age 40-75, retired, low to middle income; (3) Very short daytime absence, age 25-64, varied employment status and low to middle income; (4) Night time absence, age18-39, at school or full time employed and low to middle income; (5) Daytime absence, age 25-64, full time employed and middle income; (6) Afternoon absence, age 25-64, full time employed and low to middle income); (7) Short daytime absence age 25-64 or under 18, full time employed, retired or at school and low to middle income	• The model defines probabilities of changing from one state to another based on analysis of real data (TUS) • Analyses a large number of cases and data representative of Belgian population •Combines occupancy with socioeconomic aspects of population	• The model cannot accurately define activities after 4 am. However this is affect the representatively of the overall model
(Albert & Rajagopal 2013)	Analyses electricity time series data in order to infer occupancy states. The method used to analyse the probability of occupancy states is a hidden Markov model characterising duration, magnitude and variability of each state	952 households monitored for 8 months USA	1 Review of methodology for interpreting metered data and evaluating the connection between occupancy and electricity consumption. 2.Presentation of algorithms of the hidden Markov model 3. Definition of experiment parameters, description of the data and its processing. 4 Analysis of occupancy states.	• Given the dynamics of electricity time series, it is possible to utilize hidden Markov models to infer consumption and occupancy patterns	• Thorough analysis of model's performance	• The sample analysed is not representative of the population; the model might be good for detecting certain type of patterns and not others

DOMESTIC OCCUPANCY PATTERNS – INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Kleiminger et al. 2013)	Evaluates the possibility of detecting occupancy from electricity metered data	5 houses, monitored during 8 months Switzerland	1. Review of occupancy monitoring through sensors and analysis of metered data. 2. Data collection, selection of households and monitoring instrumental. 3 Data pre-processing. 4. Occupancy classification defining features used for classifying and algorithms. 5. Analysis of accuracy of results	• The methodology achieves more than 80% accuracy in most scenarios	• Long term monitoring including winter and summer seasons • Utilises two complementing methods for monitoring occupancy: PIR and a digital tablet for users to indicate their presence. • The methodology is based on existing technology	• Only two occupancy states are evaluated: present and absent • Requires installation of meters and smart plugs
(López-Rodríguez et al. 2013)	Utilises TUS data to generate synthetic occupancy profiles through a stochastic model based on Markov chain Monte Carlo techniques. Occupancy patterns are then used to identify electricity demand patterns and be TUS data to identify use of appliances, all in order to evaluate possible Demand Side Management solutions.	9,541 houses from the Spanish TUS data Spain	1. Review of methods for measuring electricity demand and occupancy patterns. 2. Presentation of methodology, development of Markov Chain and determination of occupancy states to model. 3. Results for 10,000 profiles modelled, only those corresponding to 2 and 3 people households shown 4. Extraction of appliances usage data from TUS and day profiles from the model, analysis peaks of active occupancy. 5. Evaluation of opportunities for DSM based on the variation of the occupancy states	• Daily occupancy profiles show 3 peaks of active occupancy: one between 09:00 to 10:00, a second one from 14:10 to 15:10 and the third and highest one from 21:30 to 22:30. On the weekend the only change is on the first peak which shows from 10:00 to 11:00. • Evening peaks show lower variation therefore might be more adequate for applying DSM strategies • Occupancy profiles are significantly different than those from the UK or other countries, which needs to be considered when analysing Super grids	• This methodology for inferring electricity demand profiles can be applied to countries where, like Spain, there are almost no smart meters installed • The model showed to accurately predict daily profiles for different households	• Only two occupancy states used, therefore no differentiation between absence and inactive presence at home • The analysis does not include socioeconomic factors • Results partially presented (only for households with 2 or 3 occupants)

DOMESTIC OCCUPANCY PATTERNS – INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Widén et al. 2012)	Analyses the implementation of improvements to stochastic occupancy models derived from TUD (Time Use Data) in order to provide more detailed end-use data and be applied to DSR (Demand Side Response)	179 households Sweden	1. Introduction to user behaviour applications and models from TUD (time use data) 2. Background of study: time use measurement, stochastic models and relationship between occupancy and energy use. 3. Methodology used for collecting TUD and for converting the models into more detailed ones 4. Analysis of application examples such as building simulations and DSR	The models generated from TUD data can generate both varied and detailed patterns of occupancy, activities and end-uses.	• Detailed analysis of TUS data and separate analysis of different areas of energy consumption	• Analysed based on 1996 TUS on a small number of people
(Widén & Wäckelgård 2010)	Presents a modelling framework for stochastic generation of high-resolution series of realistic occupant behaviour, presence and energy use data. The model is based on non-homogeneous Markov chains.	431 people in 191 households from TUS data Sweden	1. Review of occupant behaviour influence on energy demand and modelling of power demand. 2. Introduction of model framework: synthetic activity patterns are generated through the Markov Chain model and then these activities are converted into power demand. 3 Analysis of data used for each step and for validation of results. 4. Validation of methodology and results 5. Analysis of model's applicability	• The Markov Chain model can accurately produce realistic activity patterns that reproduce a spread of different end-use loads over time	• Combination of different TU data for validation the steps of the process • The model can be applied to other areas such as DSR and building simulation • The model included several states, differentiating activities when at home	• The study does not present patterns or analyse characteristics of a sample, only the methodology to generate them

C. OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Akbar et al. 2015)	Proposes an approach to detect occupancy from electricity consumption data to be used in BMS (Building Management Systems).	4 employees workspaces at an office UK	1. Introduction to motivation behind the study and previous works on the subject of occupancy detection. 2. Review of system approach and particularities as well as data source, processing and analysis methods. 3 Analysis of results from the model, training and performance	• Occupancy can be accurately detected from electricity consumption data	•The method proposed is based on an existing infrastructure as it is based on data from smart meters • Introduces the "stand by" state to reflect short absences from the workspace which is different from total absence	• Applicable to offices that have smart meters installed
(Gul & Patidar 2015)	Evaluates the sensitivity of energy consumption to occupancy patterns in order to identify opportunities for energy saving	Electricity, gas and water consumption from June 2012 to 2013 in 2,000 m2 university building. Post graduate centre of Heriot Watt University, Edinburgh, Scotland	1. Review of previous analysis on factors that affect energy consumption in commercial buildings. 2. Presentation of study methodology, study case, data collection methods and participants. 3. Analysis of Electricity consumption patterns. 4. Results from questionnaires, monitoring and analysis of its relationship with the Electricity consumption	• The building's BMS was not programmed to follow occupancy patterns • Electricity peaks from 08:00 to 18:00	• Use of questionnaires to complete occupancy patterns within the building combined with one sensor in the entrance	• Occupancy of rooms is based on their capacity and not measured

D. OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(D'Oca & Hong 2015)	Presents a three step data mining methodology for discovering occupancy patterns in offices, First monitored data is mined through a decision three classification model, then an algorithm is applied to induce decision rules and finally a clustering analysis obtains consistent patterns	16 offices monitored for 2 years Frankfurt am Main, Germany	1. Introduction to ASHRAE standards, occupancy models and data mining methodology. 2. Presentation of mythology of analysis, selection of processing software and data sets as well as each of the three steps. 3 Analysis of results through each step to finally obtain clusters. 4. Transformation of data into user profiles	• The process identifies for clusters: (A) with highest occupancy rates, (B) medium rates, (C) variable rates and (D) lowest rates. • All clusters show variations for each day of the week • The profiles generated show the distribution of activities for each cluster	• The method is clearly described as well as the selection of each step. • The technique shows accuracy for processing large data streams	• The results are circumstantial to the data set and cannot be generalised
(Feng et al. 2015)	Performs a literature review of occupancy models categorised according to the problem they address. A selection of models is implemented in the development of a software tool for predicting occupancy that will represent spatial and temporal diversity	N/A	1. Review of occupancy models per category. 2. Selection of best performing models 3. Creation of software tool combining the selected models 4. Application of tool to a model of an office building	• Four levels of occupancy were identified: number of total occupants in a buildings, number of occupants in a space, occupancy state of a space and space location of individuals	• The software tool created can be used alone for generating occupancy patterns or in simulation software	• The tool generated needs validation against real data
(Kim & Srebric 2015)	Analyses the relationship between occupancy rates and electricity consumption through linear regression.	6,140 m2 office building (40% open offices and 60% common areas) monitored over two weeks Philadelphia, USA	1. Introduction to building performance and simulation and occupancy monitoring methods. 2. Evaluation of methodology: sample data and statistical method 3. Evaluation of linear regression results	• Occupancy is highly correlated to plug loads, not to total electricity consumption as this includes all uses in the buildings some which do not depend on user activity	• The method for evaluating occupancy relies on existing infrastructure (electricity metering)	• Short monitoring period

OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Tahmasebi & Mahdavi 2015b)	Evaluates a probabilistic occupancy models that use past monitored data in order to predict future presence of occupants. Examines monitoring and training methods for the model and statistical evaluations to compare the performance in each case.	8 workspaces monitored during 90 days University campus, TU Wien, Vienna, Austria	1. Review of methods for quantifying occupancy and probabilistic models that can capture the randomness of occupancy patterns. 2. Data collection in workspaces with sensors (wireless, ceiling mounted, motion sensors) and selection of data for training the model (varying type and number of days). 3. Stochastic modelling for predicting occupancy and training under each selected scenario. 4 Evaluation of results observing errors (duration, error of first arrival and last departure and number of transitions error). 100 Monte Carlo simulations are run and the distribution of errors is analysed for each scenario	• All the scenarios showed a low prediction accuracy (the prediction with less error was the first arrival time). More research is needed to evaluate whether the error comes from the model	• Evaluates different training possibilities for the model • Clearly defined statistics for evaluating predictive performance	• The sample is very small
(Tahmasebi & Mahdavi 2015a)	Continuation of (**Tahmasebi & Mahdavi 2015)** . Evaluates occupancy models to explore the potential of monitored past occupancy data towards predicting future presence of occupants. The models evaluates are two existing probabilistic occupancy models and an original non-probabilistic occupancy model to. The predictions were evaluated via comparison with monitored daily occupancy profiles	8 workspaces monitored during 9 months University campus, TU Wien Vienna, Austria	1. Review of occupancy modelling. 2. Data collection in workspaces with sensors (wireless, ceiling mounted, motion sensors) and selection of models: two probabilistic and one non-probabilistic. 3 Training of models and predictions 4 Evaluation of results observing errors (duration, error of first arrival and last departure, error of number of transitions and occupancy state matching error). 100 Monte Carlo simulations are run and the distribution of errors is analysed for each scenario	•The predictive accuracy is low for all cases in general • The non-probabilistic model outperforms the others •The two probabilistic models perform similarly	• Clearly defined statistics for evaluating predictive performance	• The sample is very small, not enough data to infer conclusions

OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Ai et al. 2014)	Analysis of an ARHMM (Auto Regressive Hidden Markov Model) for estimating the occupancy in a laboratory using a wireless sensor network. Continuation of (Han et al. 2012) adding the presentation of methods for determining the coefficients for the Auto Regression of the model	1 research laboratory Connecticut, USA	1. Review of occupancy states algorithms. 2. Presentation of sensor network and algorithms for it. 3. Experimentation in two occupancy states (with 6 and 10 occupants). 4 Evaluation of accuracy of prediction against ground truth and RMSE for each scenario	• by taking correlation of observation data into consideration using the ARHMM method, the estimation results are consistently better than using the conventional HMM method • When occupancy varies more the ARHMM model performs better yet similar to the HMM, but when variation is higher it shows an improvement of almost 70%	• Combines different types of sensors in the network	• The methods are only analysed for one laboratory
(Andersen et al. 2014)	Presents a framework for modelling "typical" occupancy in office environment. The method is based on inhomogeneous Markov chains where the transition probabilities are estimated using generalized linear models with polynomials, B-splines, and a filter of passed observations as inputs.	52 office workspaces monitored during 16 days San Francisco, California, USA	1. Introduction to occupancy modelling. 2. Methodology for data collection (sample and sensors) and description of all models used (Markov chain, two-state Markov chain, natural splines and exponential smoothing. 3. Analysis of results: overview of measured data and simulations	• Simulated patterns showed similar mean occupancy over the day to the measured data, and the distribution of the occupancy per day had the same two-peak property as the data.	• The method can be used for generating reliable occupant presence sequences in building simulation tools.	• The data used (from infrared sensors that activate lights) does not reflect only one occupant, but the Markov process is based on occupant behaviour
(Bouffaron 2014)	Analyses sensor data to evaluate the variation of occupancy diversity factors daily, weekly and monthly. The sensors used are all PIR	67 private offices and conference rooms monitored for 18 months UC Berkeley, California, USA	1. Background analysis on energy consumption, HVAC and occupancy patterns. 2. Data collection, calculation of diversity factors and clustering of months. 3.Results evaluating daily, weekly and monthly profiles	• Mondays have the highest occupancy levels and Fridays the lowest; the other days show similar levels. • The diversity factors obtained show a difference of 40% compared to a daily profile based on ASHRAE	• Provides direct comparison to ASHRAE standards • Analyses daily, weekly and monthly trends	• Utilises only PIR sensors which do not measure number of people, yet the diversity factor is calculated based on the PIR data

OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Duarte et al. 2014)	Evaluates the impact of using different occupancy diversity factors in the energy consumption of a building. Through different building simulation models, compares the results for using ASHRAE diversity factors and other obtained from sensor data in previous literature (Duarte et al. 2013)	2 diversity factors evaluated in 8 building models Data used for patterns and reference buildings from Idaho, USA	1. Introduction to building diversity factors, building simulation, model calibration and occupancy simulation. 2. Description of building models used: 4 existing and three reference ones. Analysis of schedules obtained from previous literature. 3. Analysis of results through NMBE (Normal Mean Bias Error) and CV(RMSE) coefficient of variation of the root mean square error.	• Occupancy schedules show a significant impact on the resulting energy consumption with differences of up until 40% •In general, electricity demand was lower for the sensor schedule than for ASHRAE and the opposite case for gas consumption for heating • It is not occupancy alone what affects the energy consumption, but its link to lighting and use of equipment	• Evaluates a variety of models and clearly described the statistical variables for comparing results	• Relies on data from previous studies for the measured schedules (depends on its accuracy)
(Yang & Becerik-Gerber 2014)	This paper proposes a framework to model personalized occupancy profiles that represent occupant's long-term occupancy patterns. Occupancy is presented as a time series for each user instead of a fixed design based on statistical methods. Through simulation personalized profiles are compared against actual occupancy data monitored for an office building	Office building with up to 50 occupants. For each stage of the process different numbers of rooms were used: 3 for occupancy detection and profiling and 7 for collecting data for simulation based evaluation University of Southern California campus, California, USA	1. Review of previous research on prediction methods and monitoring technology. 2. Data collection for creating model from 3 offices with sensor boxes that include multiple sensors (CO_2, PIR, temperature, motion, humidity) 3. Analysis of algorithms for detecting occupancy and for profile modelling (ARMA, Markov Chain, Neural Network, Logit Regression). 4. Evaluation of personalised profiles against fixed profiles and actual occupancy data through simulation.	• ARMA and Neural Networks approximate better to actual day occupancy. • Using a combination of sensors allows for more accurate detection and differentiation of situations. • Personalized profiles showed more accuracy than fixed schedules through simulation	• Evaluates different techniques for modelling profiles. • The technology utilised is unobtrusive	• The model does not model long absences like holidays. • So far the model was only evaluated for single occupancy, it is known how it performs in spaces of multiple occupancy. • More research is needed to evaluate the performance of the method in other buildings

OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Zhao et al. 2014)	Develops data mining techniques on office appliance power consumption data to learn occupant behaviour. Compares different algorithms for identifying individual and group behaviour it compares	10 office workers monitored during 49 working days Pittsburgh, Pennsylvania, USA	1. Introduction to impact of occupant behaviour in energy consumption. 2. Methodology for data collection and calculation algorithms. 3. Results of monitored data, data validation, and use of appliances. 4. Results of algorithms performance	• The C4.5 algorithm was the best performing for identifying individual occupant behaviour and Linear Regression for group behaviour.	• Presents a non-intrusive method for monitoring occupancy and behaviour patterns	• The size of the sample is very low, it is still a preliminary analysis
(Duarte et al. 2013)	Analysis of occupancy sensor data for a large commercial, multi-tenant office building. It details occupancy diversity factors for private offices and summarizes the same for open offices, hallways, conference rooms, break rooms, and restrooms in order to better inform energy simulation parameters. This paper introduces new deterministic occupancy diversity factors for common commercial office building space types	1 office building with 629 infrared occupancy sensors distributed throughout the building. Monitored during two years Boise, Idaho, USA	1. Review of background, studies of occupant behaviour, ASHRAE standards, occupancy diversity factors, occupancy sensor and data mining. 2. Presentation of building characteristic and data collection method, distribution of sensors and data processing. 3. Results of monitoring comparing occupancy levels (diversity factors) against ASHRAE standards	• Monitored data differs from ASHRAE assumptions, not in the occupancy schedule but in the level of occupancy, particular for private offices. • Seasonality does not seem to affect the schedule but yes the level of occupancy due to holidays. • A variation in the schedule was observed for different days of the week as well as level of occupancy	• Evaluates both monthly and weekly seasonality and different areas of the building	• The type of sensors used, infrared, cannot measure number of people, only level of activity. • More research need to be done to evaluate different buildings
(Castaneda o et al. 2011)	Analyses building an occupancy model using data only from binary sensors (PIR for lighting) by utilizing an LDA (Latent Dietrich Approach) model to discover patterns in the data	1 building monitored during three months. Approximately 50 rooms in the building and half were monitored Innotek office building, Belgium	1. Review of previous LDA applications and data mining algorithms. 2. Building of the LDA model specifying number of routines. 3. Experimentation with data set	• The LDA model seems to be a good choice for building a long-term occupancy model of sensor's data but further research is required	• The model analyses patterns of rooms and also between them	• The outputs of the model highly depend on the number of routines defined

OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Alrazgan et al. 2011)	Proposition of a model for predicting occupancy that can maximise energy savings and limit discomfort, built using Decision Guidance Query Language (DGQL)	4 offices of university faculty members USA	1. Review of previous work on occupancy prediction models, prototypes and limitations. 2. Presentation of model principles and application to case study. 3. Review of predicting processes and data processing techniques. 4. Analysis of results in case study scenario	• There are very few prediction methods that are optimized by concrete occupancy data. • Using Decision Guidance Query Language (DGQL) provides an adequate platform for a prediction system • the model could potentially be extended for larger domains	• Provides a detailed explanation of Decision Guidance Query Language and its application to occupancy prediction models	• The DOPM model has a limited prediction, given that it relies on the rules inputted by the energy manager. • Model evaluated in a small number and simple scenarios
(Vázquez & Kastner 2011)	Evaluates clustering methods for identifying occupancy patterns. Compares the representatively of the clusters and also, through simulation, their performance when used for a heating system temperature control. The clustering methods analysed are: SOM (Self organizing Maps), XSOM (Exclusive Self Organising Maps), Fuzzy C-means clustering, K-means, K-means with Repeated Bisection, Graph clustering, SVC (Support Vector Clustering)	3 rooms monitored for five years Basque Country, Spain	1. Analysis of study scenario: setback temperature control systems based on predicted schedules, simulation model (HAMBase) and scenario (120m2 office separated into 4 zones). 2. Review of clustering methods compared. 3. Definition of comparison indexes for evaluating of clusters represent the original data and the building performance results from simulating with each cluster data. 4. Simulation with each cluster data in 3 occupancy scenarios (low, medium and high)	• Fuzzy C- means had the best results; it produces more global clusters and ignores subgroups which can be favourable for control purposes • The following best performing where SOM and XSOM which give out more refined clusters	• Clear definition of evaluation indexes, separating cluster representation and its impact on the heating control system	• Clusters need to be evaluated with different types of data to prove their efficiency on producing representative clusters

OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Page et al. 2008)	Proposes an algorithm for the simulation of occupant presence, to be used as an input for building simulation tools. The model uses an inhomogeneous Markov chain which considers occasional periods of long absence and generates a time series of the occupancy of each person in a zone	20 zones of an office building monitored two years Switzerland	1. Introduction to building modelling and occupant interaction with buildings. 2. Overview of Markov chain model used and how long absences are incorporated. 3. Data collection and training of the model. 4. Discussion of results based on: Times of arrivals and departures and presence periods	• The model is capable of producing time series for building simulation • Arrival and departure times vary according to the day of the week	• Compares the proposed model against other from different authors • The model includes occasional long absences	• Zones are regarded as completely independent from each other, it does not analyse a building as a whole, but separated zones.
(Page et al. 2007)	Analyses stochastic models for predating occupants' presence and behaviour as a way of being able to statistically represent aspect that affect the energy consumption of a building. Uses separate models for occupant presence (Markov chain), use of appliances, opening of windows, and lighting.	5 singly occupied offices. Switzerland	1. Review of problems and limitations of determination of occupancy patterns. 2. Introduction to models used for occupant presence, window opening and use of appliances. 3. Analysis of results for each model in predicting occupant behaviour	• The Markov chain approach proved accurate for predicting occupant presence.	• The model is appropriate for different types of buildings and user as it is based in analysis of zones. • The model includes simulation of no occupancy like holidays or illness	• The comfort standard used for opening windows is based on Fanger's predicted mean vote theory. • The study is preliminary and all models were analysed separately, it cannot be generalised
(Dodier et al. 2006)	This paper describes a pilot study describing new sensing and data analysis techniques, applied to the determination of space occupancy. The sensor proposed consists of a combination of simple sensors that function as a system and data is processed using Bayesian probability theory.	2 offices monitored during two days University of Nebraska, Omaha, Nebraska; USA	1. Introduction to monitoring, occupancy modelling. 2. Principles of belief networks and sensor networks. 3. Data collection. 4. Analysis of the performance of the combination of sensors and the generation of typical occupancy patterns	• the system performs accurately for individual offices • Using a sensor network allows improving the assumptions made for state transitions in the Markov chain	• Shows that belief networks can be applied for processing data from sensor networks. • Proposing utilising already existing and low costs sensors.	• Only testes in individual offices • Sample is very small

E. HEATING PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Kane et al. 2015)	Heating patterns are inferred from temperature data monitored with Hobo sensors in residences and related to household characteristics obtained from surveys and questionnaires.	249 houses monitored from July 2009 to February 2010 Leicester, in the UK Midlands	1. Evaluation of Data: collection methods, selection of households. 2 Validation of sample representability by comparison against English Housing Survey. 3. Determination of pattern categories. 4 Evaluation of results for each property analysed	• Heating does not vary randomly but it is related to characteristics of the household, age of occupants and employment situation. • More than 50% of households show a double heating pattern (06:00 to 09:00 and 15:00 to 22:00), around 30% show a single pattern (07:00 to 23:00) and the remaining multiple patterns. • The average duration of heating hours is of 12.6 (standard deviation of 3.5). • People aged 60-69 or unemployed show longer heating periods and single patterns. • In more than 60% of cases living rooms are more heated than bedrooms. • Heating temperatures are lower than those stated BREDEM (21 and 18) • The duration of heating is similar in weekdays and weekends	• Direct comparison with BREDEM assumptions • Uses monitoring data and questionnaires to asses social and household aspects • Good definition of metrics to evaluate patterns	• The sensors used, although inexpensive, not very accurate. • Temperature only measured in 2 rooms (living rooms and bedrooms) • Interviews performed by people with no experience in the subject • Almost 100% of the sample corresponds to houses with central heating, therefore the results cannot be extended to other types of systems
(Huebner et al. 2015)	Continuation of (Huebner et al. 2013). A Cluster analysis of measured indoor temperatures is performed to identify temperature profiles analysing minimums and maximum temperatures as well as variability. The results are compared to BREDEM Standard assumptions	275 dwellings chosen from the Carbon Reduction in Buildings Home Energy Survey UK	1. Statement of methodology for data collection: surveys, temperature loggers and energy consumption. 2. Findings of surveys. 3. Findings of temperature loggers. 4. Findings of metered consumption	• The majority of households heat their homes on a regular manner, with some variations on different days. • Of those houses with central heating, the majority heats their homes in two periods. • Of houses with central heating, the average number of hours heating is on is 7.5hours, 14.5 for houses with only one heating period and 2 and 5 hours for those with two heating periods. •Non centrally heated houses show an average heating duration of 13 hs for both weekdays and weekends • Weekends show the same amount of heating hours as weekdays • More than 60% of households have one room that is not heated. • Main heating systems are mostly installed in living rooms, dining rooms, studies and bathrooms • The average thermostat temperature is of 20C •The average temperature for living rooms is of 20.2C	• The sample is very large and representative of English homes • Both temperature data and survey data are analysed • Analyses different types of heating systems, central and non-central	•Further analysis on variations by type of households is needed

HEATING PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Munton et al. 2014)	The report presents on the use of controls for heating systems within the UK's households. Regarding patterns, it analysed main results from the Energy Follow up Survey (Hulme et al. 2013) and the main findings from related literature on heating patterns and controls	N/A UK	1. Introduction to heating systems characteristics and smart heating controls. 2. Development of methodology for study. 3. Findings related to heating controls and heating use. 4.Analysis of lessons learnt in relation to energy demand and heating controls 5. Analysis of evidence gaps found in the review	• 74% of households with central heating use a timer to switch their heating system on and off •Of those with central heating reporting timed heating, 77% used two heated periods per day, and about 14% used one with only about 9% using more on an average weekday. Weekend periods were reportedly very similar • In households with more than two heating periods the average duration of heating was 10 hours 24 minutes on a weekday, and 10 hours 51 minutes on a weekend day. In homes with two heating periods the average weekday on time was 6 hours 45 minutes, compared with 7 hours 14 minutes on a weekend day. •for single periods most heating is on from around 7.00am to 10.00pm, while for two periods there were fairly distinct peaks around 6am to 9am and 4.00pm to 10.00pm. Weekend periods were found to be very similar though it was found that heating comes on slightly later on weekend mornings.	• Clear, transparent and reproducible methodology for the literature review	
(Papafragkou et al. 2014)	Proposes a methodology for diagnosing heating in a property detecting issues related to thermal performance or occupant behaviour regarding heating and ventilation, by measuring indoor temperatures for a week. Additionally, based on monitored data it proposes clustering categories for buildings based on their thermal performance and source of their heat losses	25 houses, monitored for a week at 2 minutes intervals. All houses with programmable central heating systems North of Southampton, Hampshire, UK	1. Review of literature on improving the efficiency of the built environment in the UK and its challenges. 2. Explanation of methodology used for measuring temperature and collecting data on the houses. 3 Presentation of algorithm for thermal diagnosis and for clustering. 4. Experimental evaluation of algorithms with monitored data 5. Deployment of prototype system for evaluating building thermal performance	• Thermal performance of a building can be evaluated by analysing the temperature decay rate when the heating system is off • Four clusters of households identified based on high or low leakiness and high or low variability rate of temperature • Analysing daily profiles and temperatures allows for detecting opportunities for energy savings • The method proposed is reliable for houses with programmable central heating systems	• Methodology validated against known data of household temperatures and thermal properties • The methodology proposed is simple, unobtrusive and low cost with potential for identifying target areas for efficiency improvement	• The sample is not big or varied enough to generalise clusters

HEATING PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Huebner et al. 2013)	Determines heating patterns by measuring indoor temperatures in houses and evaluating the probability of the heating being on or off. The results are compared to BREDEM Standard assumptions	275 dwellings chosen from the Carbon Reduction in Buildings Home Energy Survey. Monitoring lasted a period of 92 days	1. Introduction of assumptions for modelling and limitations of BREDEM. 2. Presentation of methodology for data collection, sample selection, evaluation of sample characteristics. 3. Data analysis for determination of probabilities, temperatures, duration of heating. 4. Results of state probabilities, and variability of temperatures	• The highest probabilities of heating being on are between 06:00 and 9:00 and from 16:00 to 22:30 for weekdays. • Homes are not heated every day • The mean demand temperature is of 20.58C •The estimated duration of heating is very similar for weekdays and weekends, around 10hs (1h longer than BREDEM for weekdays and 6hs shorter for weekends)	• Results directly comparable to BREDEM analysis. • Differentiation of characteristics such as duration, peak time, temperatures	• Only analyses living rooms to determine if heating is on or off but factors such as open windows could affect the reading indicating off when it is on. • It is more accurate to measure temperature of radiators than air temperature, sensors could be wrongly placed. • Sample is not completely representative on English Homes
(BRE 2012)	Defines standard household occupancy patterns for Assessment calculations	N/A	UK	• Weekday heating hours: 07:00 to 09:00 and 16:00 to 23:00 except when zonal controls or non-central systems are installed, then it only applies to living areas and 18:00 to 23:00 is the heating schedule for other areas • Weekend heating hours: 07:00 to 23:00 • Homes are heated every day	• Standardised patterns mean that performance evaluation and SAP ratings can be comparable for different types of households	• Same beginning and end hours for weekends and weekdays • Does not differentiate by type of household or number of occupants •No data that backs the choice of patterns

HEATING PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Zimmermann et al., 2012)	Analyses electricity consumption in houses from monitored data. As part of the study it evaluates the characteristics of households with electric heating systems	251 owner occupied households, 26 monitored one whole year and the rest at one month intervals during the year. Excludes houses where electricity is provided by renewables England, UK	1. Selection of sample 2. Methodology for monitoring electric power consumption and installation of monitoring devices. 3,Analysis of sample characteristics and surveys. 4. Processing of collected data. 5. Results presented by category of electrical consumption 6. Assessment of potential energy savings	• Space heating is strongly seasonal through the year. •Electric heating is not that common within households and for those which do have it its in the form of individual or portable heaters. • In houses where electric heating is the primary system, there are two power demand peaks in the average daily profile, the biggest one at 7:00 and a smaller one at 18:00 • Electric water heating peak is in the morning around 7:00	• Sample demographics are very similar with national data, the only difference is that the sample shows a higher percentage of retired individuals. • Differentiates within households where electric heating is the primary system and where its additional	• Only addresses electrical heating which is not the major system installed in houses

F. HEATING PATTERNS IN DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Ren, Yan, & Hong, 2015)	Identifies patterns in room temperatures and operation of space heating and evaluated comfort heat demand for a selected building. For identifying patterns it uses data mining techniques such as clustering and decision trees	62 units multifamily apartments in an affordable housing complex monitored over a year Revere, Massachusetts, USA	1. Introduction to data mining techniques and energy consumption in residential buildings. 2. Analysis if data set used and previous data mining studies. 3. Presentation of methodologies user for data mining: clustering and decision trees. 4 Results of approaches: temperature profiles and heating operation profiles	• Data mining techniques are effective for analysing large datasets and extract patterns • 6 clusters were identified for room temperature profiles based on temperature (low, middle, high) and whether it is stable or variable; most of the households fell within the categories Mid and stable or varied temperature and high and stable temperature. • Regarding operation, most houses kept their heating on 24hs	• Develops a descriptive approach (clustering) and predictive one (decision tree) that can provide data to be used in building simulation. • It targets a key area such as affordable housing	• The decision tree model was not validated because the sample was not big enough. • The analysis is only applicable to one type of housing, not representative
(Audenaert & Briffaerts, 2011)	Studies the influence of consumer behaviour and socioeconomic characteristics on the consumption of energy for space heating. Evaluates the different results from monitored consumption data and EAP software calculations (similar to SAP calculations)	5 households each with a family of 4 (two adults and two children). All gas heated Belgium	1. Introduction to energy performance calculation and influence of occupant behaviour. 2 Selection and analysis of sample houses; evaluation of EAP calculations and development of questionnaire of energy related habits. 3. Results of EAP simulation, questionnaire and monitored utilities data based analysing energy consumption for heating, temperature profiles and occupancy schedules	• A difference is observed in the consumption for heating between the results from the software and the actual consumption. This is attributed to the impact of user behaviour which is not as the software defines; indoor temperatures vary in each household as well as occupancy schedules	• Compares real data to results of a software used for categorising buildings, showing a gap in household classification	• The number of households analysed is too low to generate statistically significant results.

HEATING PATTERNS IN DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Guerra Santin, 2011)	Statistically determines Behavioural Patterns associated with the energy spent on heating and identify User Profiles that can be linked to the behavioural patterns.	313 households. Data obtained through questionnaire survey Netherlands	1. Introduction to studies on Behaviour patterns and user profiles for space heating. 2. Presentation of methodology used for each stage: data collection and a validation and statistical methods for inferring patterns and profiles. 3 Results for each analysis determining Behavioural Patterns, User Profiles, relationship with energy consumption and within each other	• 5 behavioural patterns were identified: spenders (more use of space and electronics), affluent cool (more use of space and ventilation), conscious warm (more use of space and heating), comfort (more use of electronics heating and ventilation) and convenience cool (more use of electronics and ventilation). •The user profiles identified were: family (more use of appliances and space), seniors (prolonged heating hours), high-income couples (energy intensive use), singles and low-income couples (low energy use)	• Behaviour patterns can be used for energy simulation • The sample of houses is representative of the Netherlands housing stock •Validates data resulting from questionnaire	• The sample used is very small and therefore groups resulting from it are quite similar • Only new houses (built after 1995) were included in the survey

G. HEATING & OCCUPANCY PATTERNS IN DOMESTIC BUILDINGS– UK DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Beizaee et al. 2015)	The study measures the impact on comfort and energy savings from using zonal space heating controls. Two 1930 replica test houses with synthetic occupancy profiles are evaluated comparing the zonal controls with conventional ones.	A pair of 1930 test houses evaluated for 2 weeks in winter Loughborough, East Midlands, UK	1. Introduction to heating systems and controls in the UK residential stock. 2. Experimental methodology: characteristics of test houses, thermal properties, heating systems, occupancy schedules and instrumentation for the experiment. 3 Analysis of control strategies: One conventional based on minimum requirements of Building Regulations Part L1B and the other a zonal control based on active occupancy. 4. Analysis of experimental results comparing indoor temperature profile and evaluating comfort, boiler heat output, gas usage and boiler efficiency .5. Evaluation of potential savings in other regions of the UK and NPV for different type of zonal heating control systems	• Occupancy schedule were obtained from previous literature based on TUS data and contain occupancy per zone of the house. • Utilizing zonal controls resulted in a reduction of the boiler heat output of 14.1% but a 2.4% reduction in the efficiency, meaning a reduction of 11.8% in the gas consumption. • The same level of comfort was achieved with the zonal controls but with less energy consumption	• Both systems were tested under the same conditions in identical houses •The type of house evaluated represents 26% of the UK's building stock	• The results obtained depend on the behaviour modelled (window and door opening, etc.) as well as the occupancy schedule; the schedule of a family with working parents differs from the one of a retired couple, as well as their energy related behaviour. • Only air temperature, instead of mean radiant temperature was used to evaluate comfort

H. HEATING & OCCUPANCY PATTERNS IN DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Bomhard et al. 2014)	Presents a prototype for an individual room heating system that automatically detects occupancy, predicts a schedule and controls the heating. The system is based in room climate sensors, radiator valves and a smartphone app	2 bedrooms and 1 bathroom of a house Germany	1. Introduction to energy usage in German houses and heating controls. 2. Overview of the system: climate sensors, app, server. 3. Analysis of occupancy detection system: data collection, data mining and results of experimental tests. 4. Review on occupancy prediction and heating controls	• Occupancy detection showed a good performance • Bathroom occupancy is too erratic to predict	• Involving a smart app allows for users to give direct input and for example adjust the system in cases where the schedule could not be predicted	• CO_2 sensors are utilised without considering the effect of opening windows and doors. • The study is preliminary, the prediction phase of the system has not been developed yet
(Gao & Whitehouse 2009)	Analyses a self-programming thermostat system that automatically creates an optimal setback schedule by sensing the occupancy patterns in a home. The system monitors occupancy statistics using a small number of simple sensors and based on the statistics of the data it defines a setback schedule.	2 individuals Virginia, USA	1. Study of background and related to work for programmable thermostats, their limitations and options. 2. Presentation of sample chosen and its characteristics. 3. Analysis if algorithms applied by the system. 4. Results of potential savings that the system could achieve for each case analysed	• Even though it is a preliminary analysis there is evidence to support the hypothesis that programmable thermostat can result in energy savings	• The profiles analysed differ greatly from one another. • The system uses simple and low cost sensors like motion sensors and magnetic reed switches in the doors. •The overall cost of the system is much less than the potential savings.	• The sample is too small, only two cases analysed. • The system can be improved to analyse in more detail, e.g. Specify day of the week.
(Kleiminger et al. 2014)	Evaluates occupancy prediction algorithms for smart heating control	45 houses with known schedules Switzerland	1. Review of smart heating controls characteristics. 2. Review of occupancy prediction methods, analysis of selected algorithms, their approaches and techniques. 3Presentation of methodology employed to build occupant schedules and the model to test the controller of the heating system. 4. Review of the performance of each algorithm	• The best performing algorithm is the Presence Probabilities approach (PP, PPS)	• Large data set of more than 18 months • Number of simulations sufficient for evaluating accuracy of models	• Schedules are built from data, there could be error in the calculation • The model for simulating the heating system is more suited for forced air systems and not for the case analysed

HEATING & OCCUPANCY PATTERNS IN DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Howard & Hoff 2013)	Presents a technology system to automatically the occupancy state and patterns of a house and implement them in the HVAC system in order to save energy by changing setback temperature, or turning the system off	8 houses monitored for 1 to 2 weeks USA	1. Introduction to occupancy monitoring and HVAC controls. 2. Analysis of related work on setback schedules and thermostats. 3. Presentation of system principles: occupancy sensors, reaction algorithms to predict current occupancy state, decision algorithms for running the system 4. Set up of the experiments: data collection and simulation framework. 5. Definition of evaluation metrics: energy savings and miss time. 6. Analysis of contribution of the system to energy savings	• The system can provide energy savings when compared to standard approaches like a fixed schedule. • Given the low cost of the system there is large potential for deployment • Further analysis and improvements are required	• Combines simple and low costs sensors • Differentiates sleeping state from away	• The ground truth data used to validate the model is based on a combination of surveys and monitoring results, it is not exact. • The system needs vast training
(Lee et al. 2013)	Presents an automatic thermostat control system based on the prediction of users mobility, using contextual information obtained by mobile phones	21 users monitored over a month Korea	1. Review of occupancy monitoring methods and limitations. 2. Analysis of automatic thermostatic controls, issues with utilizing mobile phones, principles of mobile detection and occupancy prediction methods. 3. Evaluation of system: implementation in 21 cases and evaluation of predictions accuracy against other methods	• The system managed to predict more than 70% case within 10 minutes of error. • The implementation of the system can reduce energy consumption in more than 25%	• The prediction method is compared against stochastic methods and proven better The study analyses possible problems and limitations of the technology	• The sample used is very small, the system needs stronger validation

I. HEATING & OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Burak Gunay et al. 2015)	Presents a self-adaptive control algorithm that learns occupancy schedules (arrival and departure times) recursively and based upon data from motion sensors, and adapts the temperature setback schedule of a a heating system accordingly	7 private offices in an academic building monitored for a year Canada	1. Introduction to BMS, setback periods and occupancy detection methods. 2. Analysis of data set from motion sensors. 3 Evaluation of learning algorithm. 4. Implementation of algorithm to monitored data. 5. Simulation in Energy Plus of default schedule and algorithm based schedules evaluating energy consumption and temperature setback period	• Heating systems need to know the likelihood of occupancy presence to program, not the actual state. • The occupancy algorithm maintained the temperature setback for over 70% of the year without affecting occupant comfort compared to 30% when using a default schedule. • Reductions of 15% in cooling loads ad 10% in heating loads were obtained with the occupancy algorithm in Energy plus	• Detailed analysis of occupancy monitored data • Evaluation specific to spaces where data was monitored	• Only private offices evaluated
(Dobbs & Hencey 2014)	Presents an occupancy-predicting control algorithm HVAC systems in buildings. It incorporates the building's thermal properties, local weather predictions, and a self-tuning stochastic occupancy model to reduce energy consumption while maintaining occupant comfort.	Conference room, monitored 3 months NY, USA	1. Introduction to HVAC controls and occupancy modelling. 2 Statement of the problem, objectives and limitations. 3. Development of a thermal model of the building. 4. Analysis of stochastic occupancy modelling process. 5 Formulation of model predictive control. 6 Comparison against different controls scenarios	• The use of predictive controls resulted in a decrease in the energy consumption • Scheduled controls yield high comfort but at the expense of high energy usage	• Vast analysis of prediction process and integration to the control system • Focuses on overcoming limitations from previous systems	• The system relies on developing a thermal model of the building • The analysis considers weather forecast to be completely accurate

HEATING & OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Paudel et al. 2014)	Analyses introducing occupancy prediction to heating plant systems. Introduces a novel pseudo dynamic model and a neural network is used for interconnecting inputs and predicting the heating demand.	1 academic building of 25,000 m2 with 600 students and 200 employees monitored for a month in Winter Ecole des Mines de Nantes, France	1. Introduction to building energy demand prediction, occupancy prediction and neural networks. 2. Definition of methodology: scope of the research, characteristics of the pseudo dynamic model and of the neural network model. 3. Data collection. 4. Analysis of results for each model based on accuracy of prediction compared against real data	• Occupancy profiles and operational data are not enough to determine and generalise the building's heating demand function. •The Pseudo dynamic models achieves the most accurate predictions of heating demand for a short term horizon	• Thorough analysis of model and prevention of development of errors through each step. • Collection of ground truth data for all variables that affect the heating demand	• The timespan chosen does not represent the entire winter period; some characteristics of the demand might have been included, particularly in the beginning and end pf heating season where the demand is not constant
(Yang et al. 2014)	First it evaluated the performance of different occupancy modelling algorithms and occupancy sensors. Then it examines the possibility of developing a global occupancy model that does not require training for each location. Finally, it examines the potential energy saving of using demand-response HVAC controls by using selected occupancy prediction models.	4 rooms (two with single occupancy and 2 with multiple) user for ground truth data and model training. 103 rooms monitored for evaluating sensor and models performance University of Southern California campus, California, USA	1. Introduction to occupancy monitoring and HVAC controls. 2. Analysis of related work on setback schedules and thermostats. 3. Presentation of system principles: occupancy sensors, reaction algorithms to predict current occupancy state, decision algorithms for running the system 4. Set up of the experiments: data collection and simulation framework. 5. Definition of evaluation metrics: energy savings and miss time. 6. Analysis of contribution of the system to energy savings	• The system can provide energy savings when compared to standard approaches like a fixed schedule. • Given the low cost of the system there is large potential for deployment • Further analysis and improvements are required	• Combines simple and low costs sensors • Differentiates sleeping state from away	• The ground truth data used to validate the model is based on a combination of surveys and monitoring results, it's not exact. • The system needs vast training

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Oldewurtel et al. 2013)	This paper investigates the potential of using occupancy information to realize a more energy efficient building climate control.	N/A occupancy states generated with a model Office building in Switzerland	1. Introduction to HVAC controls and occupancy models. 2. Presentation of MPC (Model Predictive Control), building characteristics, HVAC system characteristics and occupancy model. 3. Analysis of simulation results	• Taking into account occupancy information in building control has a significant energy savings potential.	• Because its simulated, each scenario is directly comparable to other, given that parameters that are not an input remain the same (building properties, weather, HVAC system properties)	• The analysis assumes that all occupancy measurements are correct, that weather is predicted perfectly and that building characteristics and HVAC system detail are completely known
(Han et al. 2012)	Presents a technique to determine the occupancy and indoor environment quality (IEQ) in buildings. It utilises a sensor network of PIR, CO2 concentration, air velocity, temperature and relative humidity sensors and an Autoregressive Hidden Markov Model (ARHMM) is developed to model the occupancy pattern.	1 research laboratory with 6 occupants monitored for three weeks Connecticut, USA	1. Introduction to HVAC energy consumption and occupancy monitoring. 2. Selection of sensor network, types of sensor and data obtained. 3. Review of models, ARHMM (Auto Regressive Hidden Markov Model), HMM (Hidden Markov Model) and SVM (Support Vector Machines). 4. Data collection and model training. 5 Analysis of performance comparing accuracy and RMSE (Root Mean Square Error)	• All models perform well and are suitable for incorporating into HVAC control systems • Of the three models, the ARHMM has the highest accuracy and the lowest RMSE • No models works well in detecting sudden changes in occupancy (could be attributed to sensors and not the models)	• Accurate methodology for processing sensor network data	• Preliminary study only, given the small data sample analysed and the type of space

HEATING & OCCUPANCY PATTERNS IN NON DOMESTIC BUILDINGS– INTERNATIONAL DOCUMENTS

Reference	Methodology & patterns' analysis	Sample Size & Location	Study Design	Key Findings	Strengths	Weaknesses
(Martani et al. 2012)	Analyses the relationship between the level of occupancy and the energy consumption of the building. Proposes a new method to measure activity, using the number of Wi-Fi connections as an indicator of levels of activity within different spaces.	2 university buildings MIT campus, Massachusets, USA	1. Background study of monitoring systems and HVAC relation to occupancy. 2. Methodology for data collection, selection of buildings and gathering of data for electricity consumption and heating and cooling demand. 3 Analysis of results: trends in energy consumption and correlation to occupancy measured through the Wi-Fi usage	• HVAC consumption does not follow occupancy patterns (important to address efficiency) • Highest occupancy between 08:30 and 19:30	• The method is efficient for university buildings where occupancy is highly variable and the number of hotspots is very large.	• The method depends on occupants connecting to Wi-Fi • The study does not validate the occupancy measurements against real data
(Agarwal et al. 2010)	Presents the design and implementation of a presence sensor platform that can be used for accurate occupancy detection at the level of individual offices.	10 rooms in a faculty building, monitored over 2 weeks USA	1. Background analysis on intelligent controls for HVAC systems and occupancy monitoring. 2. Construction of sensor systems (PIR and magnetic reed switch door sensors), analysis of algorithm, wireless network and server. 3. Deployment of system. 4. Evaluation of accuracy against a system with PIR sensors only. 5 Evaluation of the energy consumption of the network. 6. Simulation in Energy Plus and estimation of savings in HVAC energy consumption	• The sensor systems works accurately and performs better than an only PIR system. •Simulation shows 10% to 15% energy savings when using the occupancy system deployed	• Spaces with different uses and type of occupants analysed • The system proposes easily deployable and low cost sensors	•Data sample very small, only a preliminary study
(Dong & Andrews 2009) managemen t in intelligent buildings	Develops and studies algorithms for sensor-bases modelling and prediction of user behaviour in intelligent buildings. The occupancy model is constructed by mining sensor network data for significant patterns and then a semi Markov model is generated from the patterns which is then integrated into the BMS.	1 conference room monitored for 3 months with 6 different sensors Pittsburgh Pennsylvania, USA	1. Review of occupancy models and integration to BMS 2. Recognition of occupancy patters: analysis of sensor data (motion, CO2, sound, lighting), episode discovery and generation of semi Markov model. 3. Integration to BMS: overview of approaches for incorporating occupancy data and simulation of different scheduling scenarios in Energy Plus (fixed schedule, occupancy based schedule)	• Utilizing fixed schedules for the HVAC system maximizes comfort but result highly energy inefficient. • Largest energy savings are observed when using sensor based occupancy data	• The approach does not require extensive training of the model • A combination of sensors is used to measure occupancy more accurately	• Only one room (conference room) is evaluated