# Inferring Knowledge From Building Monitoring Systems: The Case For Wireless Sensing In Residential Buildings

Elena I. Gaura*, James Brusey*, Ross Wilkins*, John Barnham**

* Cogent Computing Applied Research Centre, Faculty of Engineering and Computing, Coventry University, Coventry, CV1 5FB
{e.gaura.j.brusey,wilkin24}@coventry.ac.uk
** Orbit Heart Of England, 10 Greenhill Street, Stratford-upon-Avon, Warwickshire, CV37 6LG
john.barnham@orbit.org.uk

**Abstract**

The built environment offers the Wireless Sensor Networks (WSNs) research and commercial communities, potentially, the best set of applications yet, in terms of market size, revenue and strength of the business cases. The merits of using WSNs, however, to routinely perform empirical evaluations of old and new building stock have not been, as yet, fully appreciated by the domain's specialists (developers, construction contractors, surveyors, stock owners/users and regulatory bodies). It is hypothesised here that, in spite of their technological suitability, evident ability to generate vast amounts of data and commercial readiness, WSNs success (and thus their adoption) as tools for the built environment relies on negotiating the *data* to *knowledge* gap. The paper proposes a number of empirical metrics for holistic assessment of stock performance in terms of its heating and cooling systems, fabric and estimated occupant comfort. The metrics were developed iteratively in consultation with built environment practitioners.

***Keywords***: WSN, Built Environment, Energy Performance, Occupant Comfort, Metrics

## 1 Introduction and Problem Statement

Following more than a decade of intensive research work, Wireless Sensor Networks (WSNs) are commonly acknowledged today as proven research instruments for several application domains. In particular, they have made notable contributions to the understanding of our natural environment and wild life habitats[26], [15], [13], [9]. WSNs strengths are derived from their ability to unveil spatio-temporal patterns and thus enable both global and detailed interpretation of complex phenomena. The built environment has been, until recently, one of the least explored application domains for WSNs, in spite of their obvious suitability: i) data rates are low, given the slow changing nature of most environmental parameters in focus (temperature, humidity, air quality, electricity / gas consumption, building occupancy); ii) communication ranges are short, as servers and router / gateways can be situated in close proximity of the deployed sensing nodes within buildings and networks tend to be dense; iii) protected, indoors deployment environment; iv) wide availability, at low cost, of appropriate micro sensors for physical measurands of interest; v) mains power proximity and energy harvesting opportunities (e.g., solar) to ensure long lived deployments.

The increasing commercial and political interests in conservation, green buildings, energy efficiency and smart metering, have motivated thought towards i) the use of WSNs for museum environments monitoring [19], ii) enhanced and personalised buildings controls and particularly fine tuning HVAC systems [14], [23], [25], iii) integrated lighting and electrical appliances remote control [17], [7], [22], [18] and iv) automatic meter reading (AMR) (see [4] where Coronis Systems report to have deployed a 25,000 node AMR network; AMR plays an important role commercially—it reduces operating costs, produces more accurate bills, and improves customer service). A variety of academic solutions on all above are available today, together with an ever increasing pool of commercial WSN systems for data gathering within the built environment. Such systems either serve specialist niches (e.g., data centre energy / environment monitoring and control [3], [12]) or are of a generic nature enabling simply robust gathering and storage of environmental data (e.g., temperature, humidity and light [20], [5], [21]).

The authors propose that in spite of their technological suitability, evident ability to generate vast amounts of data and commercial readiness, WSNs success (and thus their adoption) as tools for the built environment relies on negotiating the *data* to *knowledge* gap.

In-situ, post occupied commercial buildings monitoring has seen a number of pilots in recent times, mostly based on wired instrumentation. Driven by the need for evaluation following the emergence of new materials and application of novel construction techniques, these pilots have typically drawn considerable financial and human resource. This is mainly due to the necessary wired monitoring infrastructure, semi-automated, at best, data logging facilities and extensive efforts needed to carry out observational data analysis. Monitoring investments have been perceived as worthwhile when the subject of evaluation was either i) a high profile construction, exhibiting technological innovations[24], [11] or ii) common commercial archetypes such as educational facilities[10], [16].

Little effort has been directed to the residential sector, with less than a handful of pilots worldwide. The diverse ownership models for this stock type coupled with its overwhelming diversity (in terms of age, type, occupants, mechanical and electrical systems, etc.) made the business cases for pilot Empirical Performance Evaluations (EPE) less clear. EPE is not only more difficult for the residential sector than the commercial one (given the added complexity of building usage and extensive occupant control) but also of less value in the form of pilots. Large scale EPE roll-out, coupled with the establishment of empirical residential data banks will enable: i) archetype driven statistical inferences—by age, construction method, heating/cooling systems and occupant behaviour; ii) benchmarking and individual evaluation of fabric, systems and human-building interaction. The staggering multitude of building/occupants/systems cross-archetypes thus calls for: i) standardised methods of data collection, ii) standardised analysis and metrics to be applied to the data; iii) considerable financial investment and leadership from large stock owners and, most importantly, iv) their commitment to adopt WSNs as de-facto tools in post-construction, post occupancy assessment of environmental and energy performance of occupied homes.

In spite of the hardware availability, the issues above hinge on establishing empirical metrics which are easy to be understood and manipulated by construction specialists and stock owners. Such metrics needs to mitigate the *data* to *information* gap and enable straightforward generation of *knowledge* from the information, towards:

- Strategic reduction of stock carbon footprint, by identifying cost-effective, high impact refurbishments for poor performers,
- Assessing *as built* and *post-occupied* new built performance versus pre-built specifications,
- Diagnosing energy waste in homes and thus devising appropriate remedial actions (be them occupant education, fabric improvement or heating/cooling systems upgrade),
- Understanding occupant behaviour and consequmently devising effective behaviour change programs, and
- Assessing added value from novel building techniques and materials.

Recognising the presence of a complex and dynamic set of factors which impact the carbon footprint of an occupied property, the work here proposes, in the next section, two metrics for a home's holistic EPE: *time exposure* for a number of common environmental parameters and *comfort scoring* for global evaluations. Section 3 illustrates how these metrics are applied to residential data sets and how they can be effectively visualised and interpreted. Section 4 concludes the paper.

## 2 Empirical performance metrics for residential buildings

The development of measurement systems based on WSNs to cater for the accurate measurement of common parameters of interest in buildings such as temperature, humidity, air quality and water/gas/electricity/fuels consumption and is, in relative terms, technically unchallenging. However, extracting *knowledge* from monitoring *data* requires significant innovation. With WSN systems able to deliver, in an average sized home, several million data points per year, traditional approaches to "observation" based data interpretation and simple statistical analysis methods are no longer effective. A new metrics needs to be defined so that: i) they are commensurate with the *in-situ*, *continuous within a time frame* measurement methods used and ii) they account for the holistic, *integrative approach* taken when monitoring homes; the environment, as measured, is the combined result of the fabric, properties mechanical systems performance and the occupants lifestyles; iii) they enable fulfilment of the monitoring scope (be that generic evaluation or specific diagnosis). The metrics set will need to contain both *occupant-centric* and *holistic* measures. Occupant-centric metrics will establish the environmental impact of the home onto the occupant; holistic metrics will look at the fabric and systems delivery against an energy budget. (These are treated in [8])

Two occupant-centred metrics are presented below: time exposure (to various environmental parameters) and comfort scoring.

### 2.1 Time Exposure Metric—Temperature, Humidity, Air Quality and Comfort

The *time exposure metric* is space and parameter dependent. It simply considers, individually, each environmental parameter (i.e., temperature, humidity) and each well-defined space in the home (i.e., rooms, corridors, etc.) and quantifies its effect on the occupant (separating detrimental and beneficial effects). The metric delivers the percent time the occupant of the home would spend in various environmental conditions, should standard occupancy rules apply (i.e., the home is continuously occupied throughout).

The parameter ranges for temperature, humidity and air quality (in terms of $CO_2$ concentration) have been defined considering the ASHRAE Standard[1] and are detailed in Table 1.

Comfort relates to the interplay between temperature and humidity. These two variables can be fused

| Temperature | | Humidity | | CO2 | |
|---|---|---|---|---|---|
| Range (°C ) | Description | Range (%) | Description | Range (ppm) | Description |
| $T_r \leq 16$ | Room presents health risks to occupants | $H_r \leq= 45$ | Room is dry | $C_r <= 600$ | Acceptable |
| | | $45 < H_r \leq 65$ | Room is optimal | $600 < C_r \leq 1000$ | Minor Issues |
| $16 < T_r \leq 18$ | Room is cold and below ASHRAE comfort standards | $65 < H_r \leq 85$ | Room will feel damp - slight health risk | $1000 < C_r \leq 2500$ | Health Issues |
| $18 < T_r \leq 22$ | Optimal comfort levels | $H_r > 85$ | Room will have problems associated with damp such as mould, and presents a health risk to occupants | $C_r > 2500$ | Major Health Issues |
| $22 < T_r \leq 27$ | Room is too warm | | | | |
| $T_r > 27$ | Room is overheated | | | | |

Table 1: Time Exposure ranges

to produce a comfort index using a lookup table approach. The comfort lookup table has been adopted from [2] and rates comfort from 1 (least comfortable) to 10 (most comfortable).

## 2.2 Comfort Scoring

The Comfort Score is a holistic metric that is primarily based on measured room temperature and humidity but also accounts for typical room occupancy patterns. Rather than directly measure occupancy, the probability of occupancy is estimated based on whether it is day or night and the nominal use of the room (e.g. bedrooms are more likely to be used at night). Where there are several rooms of the same type, the probability of occupancy is shared evenly between those rooms. Comfort is calculated from the point of view of a single occupant (say occupant $X$). There may be a number of occupants in the house and in this case, it is assumed that they all have a similar experience of the house.

Given the comfort function $c(T, H) \rightarrow [1, 10]$ that maps air temperature $T$ and relative humidity $H$ to a scale from 1 (least comfortable) to 10 (most comfortable)[2], and an occupancy function $o_X(r, t)$ corresponding to the probability of $X$ being in room $r$ at time $t$, the probability of being "reasonably" comfortable (scoring over 5) is

$$P(c_X > 5) = \frac{1}{K} \sum_{0 \leq t < K} \sum_r [c(T_{r,t}, H_{r,t}) > 5] \, o_X(r, t)$$

where $T_{r,t}$ and $H_{r,t}$ are the temperature and humidity, respectively, for room $r$ at time $t$, and $K$ is the number of time periods. Note that Iverson brackets[1] are used in the above formulation. Similarly, the expected comfort for an occupant $X$ is,

$$E[c_X] = \frac{1}{K} \sum_{0 \leq t < K} \sum_r c(T_{r,t}, H_{r,t}) \, o_X(r, t)$$

[1]http://en.wikipedia.org/wiki/Iverson_bracket

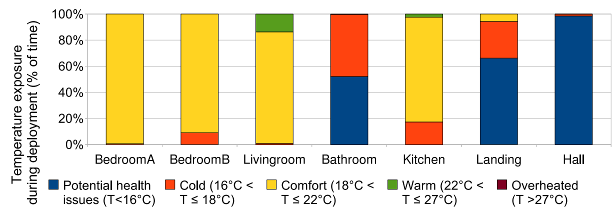


Figure 1: Temperature Exposure Graph

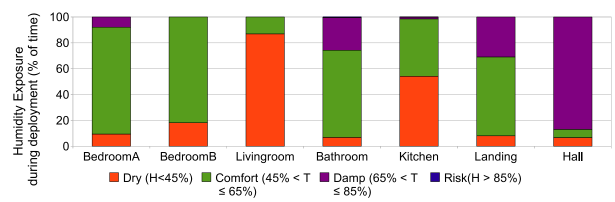


Figure 2: Humidity Exposure Graph

## 3 Occupant Centric Metrics In Use: Interpretation and Visualisation

This section presents some example applications for the metrics defined and discusses the knowledge inferred from their visual representation.

Over the course of 2 years, the authors performed 15 WSN deployments in residential homes, using a bespoke monitoring system developed around commercially available ArchRock nodes and servers[20]. The deployments

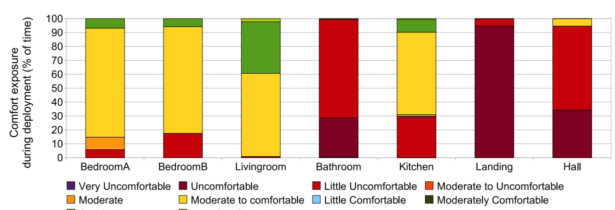


Figure 3: Comfort Exposure Graph

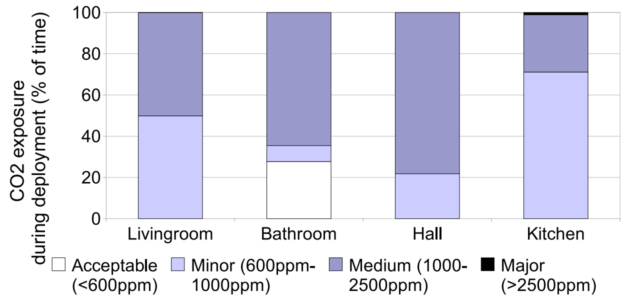


Figure 4: CO2 Exposure Graph

duration varied between 2 weeks (mostly within the heating season) and 2 years; nodes were placed in every room/defined space, and sensed temperature, humidity and CO2; on average, 12 nodes were deployed in each home, including an outdoor node; the energy consumption (gas and electricity) was audited periodically for some deployments and continuously recorded for others. The homes exhibited large variations in their energy and environmental performance, were heated by a variety of mechanical systems and occupied by several family archetypes. The WSN systems deployed had an average yield of 95% and generated in excess of 10 million data points.

## 3.1 Metrics development methodology

The development of good metrics requires a robust methodology that supports objective evaluation. The methodology used here was based on the use of real data for real properties and evaluation based on feedback from end-users.

The metrics were developed iteratively. At each iteration, built environment practitioners gave feedback on the metric and associated visualisation, in the context of data gathered from recent deployments. The feedback was given in terms of how readily the metric and visualisation were understood and their usefulness in making decisions. For example, a number of iterations were used simply to find a colour scheme that was intuitive and avoided misunderstanding. This iterative approach successfully produces strong metrics as it focuses on both what the practitioner *can* understand and what they *need* to *know*. Nevertheless, it is not possible to determine from this process whether the derived metrics are optimal and further optimisation might be possible.

On the other hand, it is also clear that in their final version, the metrics lend insight and enable decisions in a way that was simply not possible with their initial versions. The metrics and their representations presented here were deemed by the domain specialists as easy to understand, concise, representative of the home's performance and, most importantly, delivering added value compared to common surveying procedures.

When coupled with occupant questionnaires, sufficient insight was gained from the application of the metrics to allow judgements regarding: i) necessary refurbishment actions—addressing for example damp and mould, ii) performance of the heating systems against specification and expectation, and iii) suitability of the living conditions in the home—such as comfort level affordability and air quality.

## 3.2 Metrics in practice

Figures 1 to 4 present example applications for the time exposure metrics for one data set, and knowledge inferred by domain specialists from their visual representation. The home is a two story (72 m$^2$ living footprint) , two bedroomed, detached house in Warwickshire, England. The home has 24/7 occupancy (3 occupants— 2 elderly, 1 young adult). The gas central heating system is based on wet radiators, 1 in each room) and is set "on" continuously. For the 2 weeks monitoring period, the average temperature indoors was 17.6 ℃ ± 2.7 ℃, whilst the outdoor was 3.4 ℃ ± 2.3 ℃.

Figure 1 shows that the main living areas (living room, bedrooms and kitchen) are mostly in thermally acceptable conditions. The two transition rooms (hall, landing) are in the region of potential health risks; the bathroom is another area for concern as 99.71% of the time it is cold or in a state where potential health risks can occur. With regard to humidity (Figure 2), the main problem areas are the landings which show long exposure to dampness; the living areas are generally within acceptable bounds, although the living room, where occupants spend most of their time, experiences prolonged dry conditions. Figure 3 shows that home offers a wide mix of comfort levels. The hall, bathroom and landing are poor performers. Figure 4 shows that maintaining suitable levels of air quality is not a priority for the occupants, against the main concern of retaining the heat within the home.

The Comfort Scoring metric revealed a score of 5.15, against an energy consumption of 0.11 kWh/m$^2$/Degree Day. When presented with the assessment, it was clear to the surveyors team that: i) the existing fabric and heating systems performance is poor (in terms of damp and zonal comfort/thermal variations), ii) given that this home is using approximately 15% less energy than the UK's average home (0.13 kWh/m$^2$/Degree Day (assumed house size of 76 m$^2$, Yearly degree days from 2008 and average home consumption of 22 MWh[6]), the occupants choice of set temperature may not be optimal for the property, ii) remedial measures to the fabric are needed to resolve the damp problems; iv) occupants need to be made aware of the potential health consequences of poor air quality and large variations of thermal comfort within the home.


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## 4 Conclusions

It is concluded here that the value of WSN based monitoring goes beyond a summary evaluation of energy consumption and: i) provides, when applying innovative metrics, a wealth of information about the health of the indoor environment (comfort and air quality); ii) allows for problem diagnosis if sufficiently detailed data is obtained- separating the effects of fabric, mechanical systems and the occupier on the building performance; iii) provides quantitative evidence to accompany subjective evaluations and allows research into relationships between perception of buildings quality by occupiers and actual performance.

## REFERENCES


[1] ASHRAE. Ashrae standard 55-2004 – thermal environmental conditions for human occupancy. Technical report, ASHRAE, 2004.

[2] AutomatedBuildings.com. Are your customers comfortable? how do you know? avaliable from `http://www.automatedbuildings.com/news/jul06/articles/indatsys/060628112808indatsys.htm`, n.d.

[3] SynapSense Corporation. Synapsense wireless environmental monitoring and energy management. avaliable from `http://www.synapsense.com/go/index.cfm`, 2011.

[4] Christophe Dugas. Configuring and managing a large-scale monitoring network: solving real world challenges for ultra-low-powered and long-range wireless mesh networks. *International Journal of Network Management*, 15:269–282, 2005.

[5] EnOcean. Energy harvesting wireless sensor solutions and networks from enocean. Online at: http://www.enocean.com/en/, 2011.

[6] Joseph Rowntree Foundation. Housing & neighbourhoods monitor. avaliable from `http://www.streetlinenetworks.com/`, 2011.

[7] Matthias Gauger, Daniel Minder, Pedro Jose Marron, Arno Wacker, and Andreas Lachenmann. Prototyping sensor-actuator networks for home automation. In *Proceedings of the workshop on Real-world wireless sensor networks*, 2008.

[8] Elena I. Gaura, James Brusey, Ross Wilkins, and John Barnham. Wireless sensing for the built environment: Enabling innovation towards greener, healthier homes. In *Proceedings of Clean Technology 2011*, 2011.

[9] Mark Holler. High density, multiple depth wireless soil moisture tension measurements for irrigation management. Technical report, Camalie Vineyards, 2008.

[10] Maria Kolokotroni, Yunting Ge, and D. Katsoulas. Monitoring and modelling indoor air quality and ventilation in classrooms within a purpose-designed naturally ventilated school. *Indoor and Built Environment*, 11:316–316, 2005.

[11] Eduardo Krügera and Baruch Givonib. Thermal monitoring and indoor temperature predictions in a passive solar building in an arid environment. *Building and Environment*, 43:1792–1804, 2008.

[12] Jie Liu, Feng Zhao, Jeff O'Reilly, Amaya Souarez, Michael Manos, Chieh-Jan Mike Liang, and Andreas Terzis. Project genome: Wireless sensor network for data center cooling. avaliable from `http://msdn.microsoft.com/en-us/library/dd393313.aspx`, n.d.

[13] Ting Liu, Christopher M. Sadler, Pei Zhang, and Margaret Martonosi. Implementing software on resource-constrained mobile sensors: Experiences with impala and zebranet. In *In MobiSYS 04: Proceedings of the 2nd international conference on Mobile systems, applications, and services*, pages 256–269. ACM Press, 2004.

[14] Jiakang Lu, Tamim Sookoor, Vijay Srinivasan, Ge Gao, Brian Holben, John Stankovic, Eric Field, and Kamin Whitehouse. The smart thermostat: Using occupancy sensors to save energy in homes. In *SenSys '10 Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*, 2010.

[15] Kirk Martinez, Royan Ong, and Jane Hart. Glacsweb: a sensor network for hostile environments. In *The First IEEE Communications Society Conference on Sensor and Ad Hoc Communications and Networks*, 2004.

[16] D Mumovic, J Palmer, M Davies, M Orme, I Ridley, T Oreszczyn, C Judd, R Critchlow, H A Medina, and G Pilmoor. Winter indoor air quality, thermal comfort and acoustic performance of newly built secondary schools in england. *Building and Environment*, 44(7):1466–1477, 2009.

[17] Georgia Institute of Technology. Aware home research initiative at georgia tech. available from `http://awarehome.imtc.gatech.edu/`.

[18] Massachusetts Institute of Technology. House_n: the home of the future. avaliable from `http://architecture.mit.edu/house\_n`.

[19] L. M. Rodríguez Peralta, L. M. Pestana Leão de Brito, B. A. Teixeira Gouveia, D. J. Gomes de Sousa, and C. Da Silva Alves. Automatic monitoring and control of museums environment based on wireless sensor networks. In *Electronic Journal of Structural Engineering*, 2010.

[20] Arch Rock. Arch rock official site. Online at: http://www.archrock.com/, 2009.

[21] Wireless Sensors. Sensinet. Online at: http://www.wirelesssensors.com/, 2011.

[22] Vipul Singhvi, Andreas Krause, Carlos Guestrin,

James H. Garrett Jr., and H. Scott Matthews. Intelligent light control using sensor networks. In *Proceedings of the 3rd international conference on Embedded networked sensor systems*, 2005.

[23] Sana Sultan, Tehmina Khan, and Sairah Khatoon. Implementation of hvac system through wireless sensor network. In *Second International Conference on Communication Software and Networks ICCSN '10.*, 2010.

[24] Paul Torcellini, Shanti Pless, Michael Deru, Brent Griffith, Nick Long, and Ron Judkoff. Lessons learned from case studies of six high-performance buildings. Technical report, National Renewable Energy Laboratory, 2006.

[25] Joshua Wall, Glenn Platt, Geoff James, and Philip Valencia. Wireless sensor networks as agents for intelligent control of distributed energy resources. In *2nd International Symposium on Wireless Pervasive Computing*, 2007.

[26] Geoff Werner-Allen, Jeffrey B. Johnson, Mario Ruiz, Jonathan Lees, and Matt Welsh. Monitoring volcanic eruptions with a wireless sensor network. In *Second European Workshop on Wireless Sensor Networks*, 2005.