ENERNET: Studying the dynamic relationship between building occupancy and energy consumption

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ABSTRACT

With cities accounting for approximately two thirds of the global demand for energy, there is significant scope to optimize energy usage of cities, in particular by improving the use of the built form. Large non-domestic buildings are increasingly the focus of attention, due to their substantial demands and associated environmental impacts such as CO_2 emissions. Various approaches have been adopted to address building energy efficiency, with more recent studies relating consumption patterns to human occupancy. This paper proposes a new method to measure activity, using WiFi connections as a proxy for human occupancy. Data on the number of WiFi connections and energy consumption (electricity, steam and chilled water) were compared for two buildings within the Massachusetts Institute of Technology's campus. The results of the study demonstrate: the operation of the heating, ventilation and air conditioning (HVAC) systems adhered more closely to factors other than occupancy i.e. external temperature, whilst a small part of the electricity levels did correlate with the occupancy. In order to present possible solutions to address the disconnect between the HVAC system and occupancy levels, this paper identifies future steps that could begin to improve energy usage.

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1. Introduction

Optimizing the energy efficiency of large non domestic buildings is an increasing priority within the urban setting, given the high levels of energy consumed and associated CO_2 emissions. With increasing demands being placed upon heating, ventilation and air conditioning (HVAC) systems to provide thermal comfort all year round [1], there is clearly a need to address the underlying drivers of energy consumption. Commercial buildings account for nearly 20% of the US national energy consumption, or 12% of the national contribution to annual global greenhouse gas emissions [2]. Recent reports from TIAX [3] and ACEEE [4] conclude that commercial buildings may reduce their energy consumption by 20–30% through continuous commissioning practices and implementation of a small number of energy efficiency strategies. In large commercial buildings the total financial savings is estimated to be $80,000–100,000 per year per building [4].

In order to reduce the amount of energy consumed and to improve the efficiency of the supply systems one critical step is to understand how energy is currently utilized. The recent widespread deployment of pervasive Information and Communication Technology (ICT) infrastructures provides a new means of assessing energy consumption. With the capacity to sense the functioning of buildings as well as delivering historical analyses and real time notifications, such infrastructures could enable the continuous monitoring of energy usage patterns of different systems, such as chilled water provision, high temperature steam heating, and electricity supply amongst others under various different operating conditions. This network of devices could in turn support not only building operators but also policy makers in tackling the challenge of improving energy efficiency. Of course it is a combination of the infrastructure and the users' behaviour that provides the entire picture, and it is through the examination of both of these factors that it may be possible to ascertain what the underlying drivers of energy consumption are, within the context of commercial buildings.

The examination of energy usage is especially relevant for buildings like schools and colleges, where the occupancy profiles have some unique features (high variability within small time intervals and often periods of low but non-zero occupancy). The Massachusetts Institute of Technology (MIT) campus, in particular, provides a suitable setting to conduct a study of energy usage because of a unique network of more than 100,000 sensors that monitor the functioning of the building automation system and in turn reveal the consumption levels across campus. This line of inquiry is also enabled by the extensive WiFi network that exists across MIT. With almost one hotspot in each room and hallway across the campus that provide Internet access to the entire MIT community, it is possible to survey human occupancy at different levels of granularity: at the scale of the room, building or campus.

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2. Background

The analysis of the energy efficiency of the built environment has received considerable attention in the past, particularly over the last decade [5–7]. Various approaches have been taken to address system efficiency, from predictive modelling of energy consumption based on usage profiles, climate data and building characteristics [8], to the impact of public information displays and campaigns in serving to modify individual's behaviour [9,10]. Much of the literature considers electricity consumption, with more recent studies assessing the levels of use in relation to human occupancy. Within the context of improving energy efficiency in office spaces, timers and motion sensors provide a useful tool to detect and respond to the number of occupants and feedback information to encourage behavioural change.

Intelligent monitoring systems such as automated lighting systems do however, have limitations such as those identified by Garg and Bansal [11]. The time delay between the point when a room becomes unoccupied and the moment the automated lights switch off can make a significant contribution to the success and savings provided by a smart sensor system. A long time lag reduces savings, whilst too fast a response allows the lights to switch off when the room is still occupied. These monitoring systems albeit contributing towards energy efficiency, require significant investment into an intelligent infrastructure that combines sensors and actuators to control and modify the overall energy consumption. The cost and implementation of such networks often inhibits the uptake of such initiatives. Clearly an infrastructureless system that could employ existing technology may provide a cheaper alternative to building energy management.

With HVAC systems the wider literature indicates that reduced emphasis is currently placed upon the role of the individual occupants to regulate levels i.e. the cooling and heating of buildings is controlled at a higher level. Commercial and non-residential buildings (especially larger, older constructions) are often monitored and controlled through a facilities provider, which reduces the direct feedback of information to building occupants. With large-scale HVAC systems, the focus is often placed on maintenance rather than a rapidly responsive system that can adjust in real time to varying levels of occupancy. A noteworthy contribution to this field of research, has sought to identify the optimal internal building temperature [12] although similarly this approach is based on predicted occupancy rather than actual levels.

This paper proposes a new method to measure occupancy, using the number of WiFi connections as an indicator to gauge levels of activity within different spaces. Here we use the MIT campus to evaluate not only the energy consumption of the buildings but also to assess the suitability of this method for other large-scale studies. This work is in line with MIT's recently introduced energy initiative (MITEI) that demonstrates a strong commitment to reduce energy consumption and improve efficiency campus wide [13]. This includes but is not limited to the construction of new high-performance buildings [14], alongside other interventions that seek to improve the performance of existing buildings. This work also leverages previous studies into WiFi usage patterns across MIT's campus [15] and seeks to further investigate whether the MIT campus could act as a platform to identify, assess, and effectively communicate building energy efficiency opportunities based on the study of energy consumption and human occupancy.

3. Methodology

With the overall target of using the MIT campus as a test bed to examine energy efficiency of the built environment, this paper presents an initial study of the energy usage patterns of two

buildings contained within the campus (identified in Fig. 1). These buildings were chosen from a database containing a year worth of records for nine buildings. As a result of data availability, this pilot study utilized aggregated data on energy consumption at the building level. The two buildings used for this analysis were the McNair Building (M37), and the Sloan School of Management (E52), which were selected for a variety of reasons, primarily the buildings provide different functions and consequently were more likely to demonstrate distinguished energy usage profiles. M37 is predominantly composed of laboratories, whilst E52 is more an archetypal working space with classrooms, offices and open reception. They were constructed at different periods, E52 was built in 1983 and M37 was constructed 13 years earlier, potentially adding to differences in their energy profiles. As M37 and E52 have differing characteristics, they could possibly serve as indicators of the range of buildings contained within the campus. A final consideration in selecting the buildings was the availability of data, with both of these buildings presenting the most complete data records.

In order to compare this against energy consumption, data was collected on electricity supply, the heating system (steam in "kilopounds h^{-1}") and cooling system (chilled water in "tons of cooling"). Prior to analysis data on energy consumption was converted into a standardized unit, kilowatt (kW) in order to draw comparisons between the datasets. To allow an intercomparison of the energy consumption for the two buildings, data were normalized on a per unit area basis, resulting in $W\,m^{-2}$. Furthermore, in order to provide additional context, external air temperature (°C) was gathered from sensors located at Logan Airport's meteorological station in Boston [16].

The timeframe of this study initially covered a period of two weeks during the winter of 2006: 21st January–3rd February. This scale provided sufficient time for temporal trends (daily and weekly) to be observed, whilst this time frame also permitted the patterns of the HVAC system to be viewed most clearly as both heating and cooling were employed in tandem. Following this initial exploration, three further periods where examined in order to deduce seasonal variations in the energy usage.

4. Results

An initial comparison of the energy consumption of the two buildings revealed significant differences in their profiles. As shown in Fig. 2 the electricity consumption demonstrates pronounced diurnal trends for E52 during the week, and although this cycle is present in M37 electricity usage, the trend is far less prominent (Fig. 3). This may reflect the function of the facilities contained in M37, in that the laboratories may contain equipment that is continuously operative and requires constant electricity supply to maintain their operations. Chilled water shows far less distinctive patterns, with only a slight diurnal cycle emerging during the first week in M37. The range of the consumption data (expressed in $W\,m^{-2}$) was compared with other previous studies and the results were of the same order of magnitude.

In M37 the chilled water and steam consumption appear to follow the variation of the external temperature. Chilled water usage shows peaks and troughs with maximum and minimum temperatures respectively, whilst steam consumption appears inversely proportional to variations in the temperature i.e. as the external temperature decrease the amount of steam used increases. Notably E52 demonstrates considerably more variance in steam consumption with more frequent rises and falls, however overall approximately 80% of the data fell within the range of 20–50 $W\,m^{-2}$. In contrast M37 demonstrates more pronounced increases and decreases in levels of steam, with data encompassing a larger range of values. It is not clear why this is so, though it may be no more
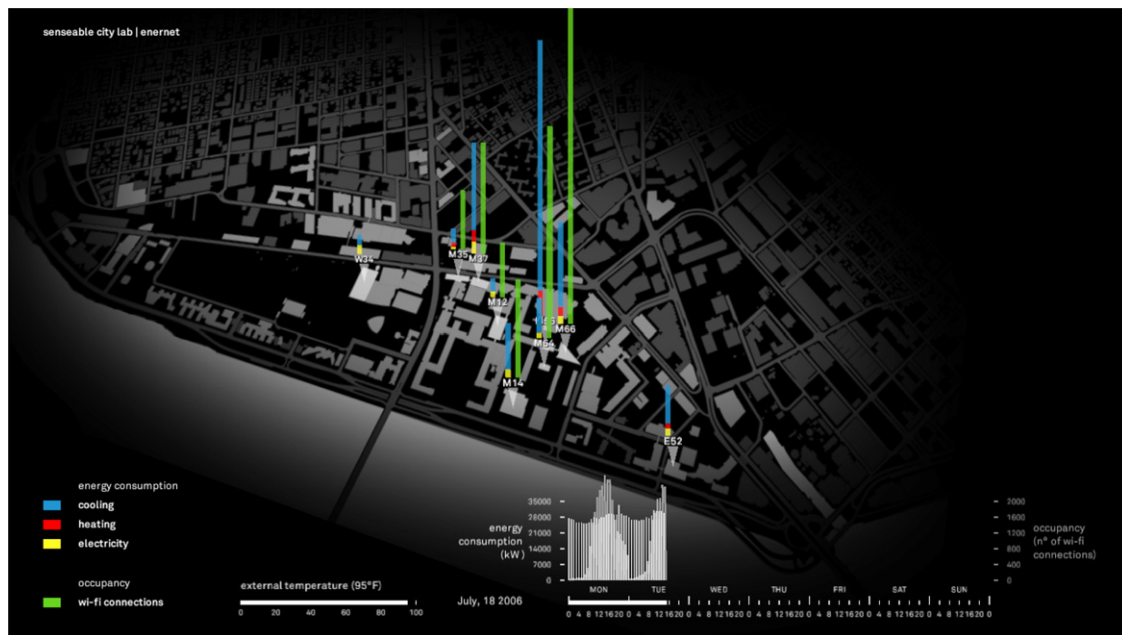
Fig. 1. The energy profiles and WiFi activity of 9 buildings within the MIT campus on 18th July 2006. The two buildings assessed in this study are E52 and M37 (image courtesy of Paolo Patelli).

than a reflection of the different building construction and building use. Further inquiry would likely show all the buildings have their own particular "signature". Knowledge of these different signatures across the campus and the seasons may be enlightening in determining appropriate operating strategies.

4.1. Seasonal variations in energy profile

In order to determine seasonal trends in the energy usage profiles of the two buildings, additional data for the spring, summer and autumn months were extracted and examined. Overall electricity consumption within both buildings is dominated by the base line consumption across all seasons. Furthermore it also demonstrates pronounced diurnal trends across all seasons: peaking in the daytime and reaching baseline levels during the night and at weekends. The HVAC systems of both buildings display far more variance in levels of consumption compared with electricity, with seasonal trends less apparent in the datasets.

In E52 chilled water shows two different usage signatures across the four seasons: one apparent in the winter and spring, where values vary only moderately from baseline levels of consumption (approximately $7\,W\,m^{-2}$), and the other for the summer and autumn, where values demonstrate significant variance over short intervals although they are largely consistent with the trends of the external temperature (Figs. 4 and 5). The steam shows the inverse usage signatures, although the diurnal cycle underlies all the seasons consumption patterns to varying degrees (most pronounced in the summer and autumn).

In contrast to E52, M37 does not demonstrate seasonal signatures in the levels of chilled water consumption, with the only trend apparent being an overall reduction in the amount of chilled water in the winter and to a lesser degree autumn. Similarly to E52 the steam used in building M37 shows two pronounced signatures, one for the summer and autumn with values remaining stable near baseline consumption (approximately $25\,W\,m^{-2}$) and the other that is applicable to the spring and winter
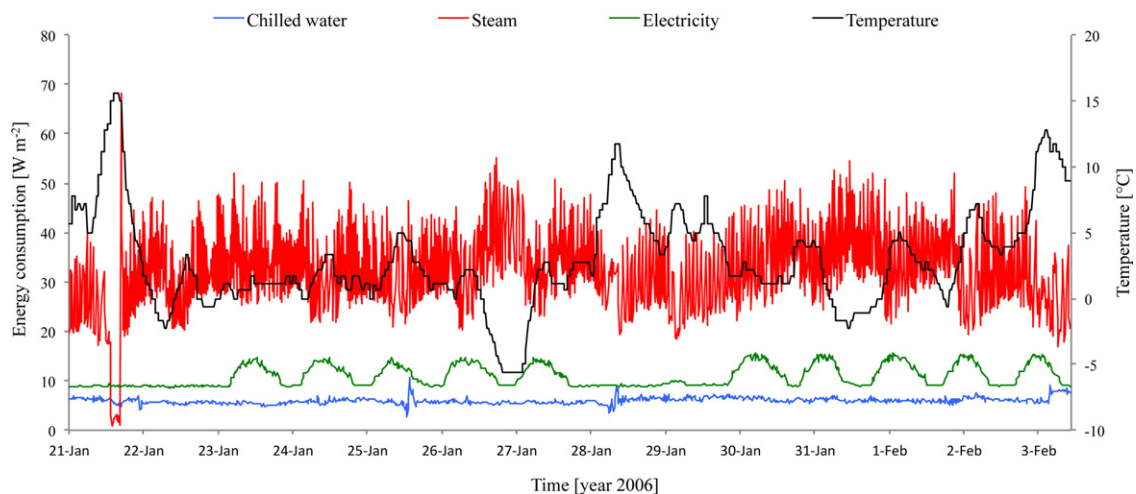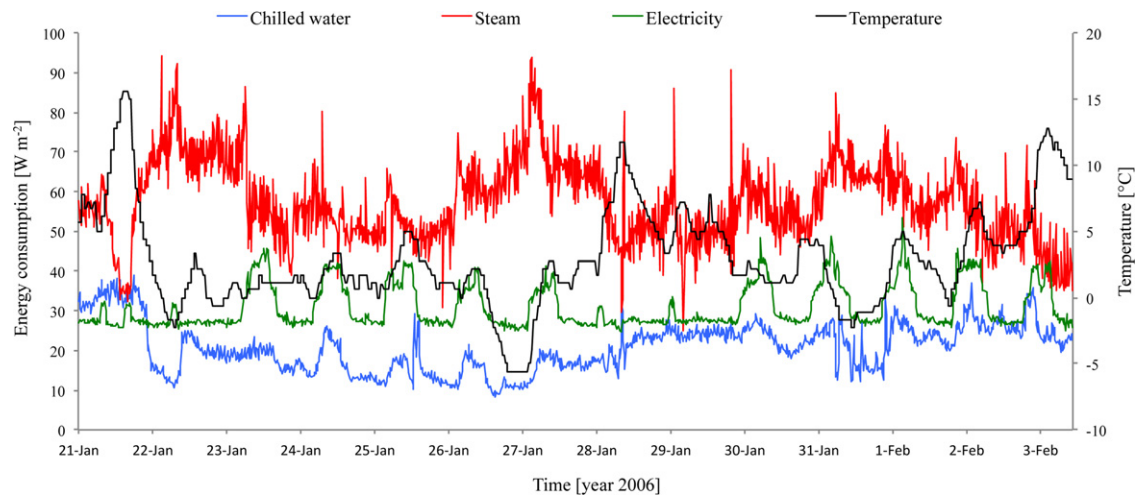

Fig. 2. Time series of energy consumption (steam, chilled water and electricity in $W\,m^{-2}$) for E52 over 21st January–3rd February 2006 [17], alongside external air temperature (°C) [16].

Fig. 3. Time series of energy consumption (steam, chilled water and electricity in W m^{-2}) for M37 over 21st January–3rd February 2006 [17], alongside external air temperature (°C) [16].
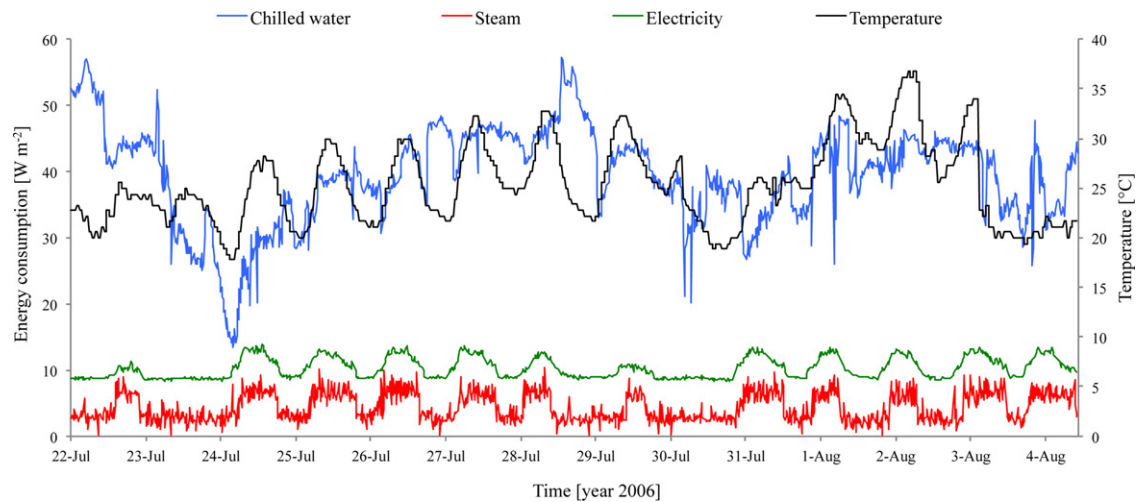

Fig. 4. Time series of energy consumption (steam, chilled water and electricity in W m^{-2}) for E52 over the summer 22nd July–4th August 2006 [17], alongside external air temperature (°C) [16].
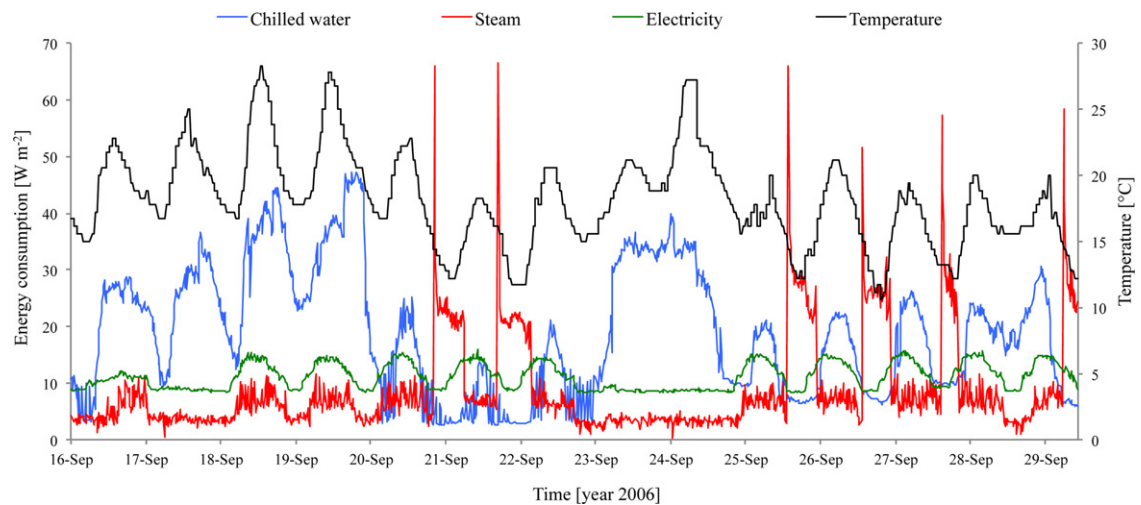

Fig. 5. Time series of energy consumption (steam, chilled water and electricity in W m^{-2}) for E52 over the autumn 16th September–29th September 2006 [17], alongside external air temperature (°C) [16].

periods, which shows far more rapid fluctuation in the steam supply.

In order to determine the potential influence of external temperature on energy consumption the correlation between these two variables was examined in closer detail, although data availability only permitted an examination of E52. As can be seen in Table 1, the chilled water levels supplied to building E52 are closely correlated with the external temperature. Similarly there is a statistically significant inverse correlation between steam and temperature. As might be expected electricity demonstrates no significant correlation with the outside temperature. Clearly the HVAC system is informed by the conditions of the external environment. But the question arises as to the relationship between the energy consumption and human occupancy. Do levels of WiFi connections serve as an indicator not only for human occupancy but as a means of estimating energy consumption?

4.2. Inter comparison between energy consumption and occupancy

In order to determine if human occupancy could be used as an indicator of energy consumption, WiFi connections were compared to HVAC levels and electricity supply. As depicted in Fig. 6, WiFi usage (number of connections) shows a distinctive diurnal trend during the week, with values leveling off at the weekend when they reach their minimum level.

The number of WiFi connections clearly reflects human occupancy, with the weekends witnessing a reduction in persons based on campus. Over the period examined E52 has a larger number of users occupying the building both during the week and weekend, although the difference between the occupancy levels are less pronounced at the weekend. With increased occupancy of E52, there may be an assumption that this is inherently reflected in the levels of energy consumption. In order to examine the relationship between human occupancy and energy consumption the linear correlation was assessed. Steam and chilled water demonstrate a weak relationship with human occupancy, with WiFi connections accounting for only a small amount of variation in the overall HVAC levels. Despite the variation resulting from human occupancy and temperature fluctuation, a high level of baseline energy drawn tends to dominate the time series (Table 1). Finally, the electricity consumption demonstrates a significant positive correlation with the occupancy rate, even with a large proportion remaining constant over time (Figs. 2 and 3). As depicted in Fig. 7a and b, over 21st January–3rd February 2006, WiFi connections were able to account for 69% of variation shown in electricity levels in building E52, and for 63% in building M37.

5. Discussion

Extensive research has focused on the relationship between room occupancy and energy usage patterns, with the introduction of more automated, intelligent energy systems to monitor and respond to human occupancy providing one interesting line of inquiry. Prior research on HVAC control systems shows that occupancy information can be used to drive a more optimized HVAC [7,19,20] system. This could lead to significant savings in the campus' overall energy expenditure. By reducing the degree of control that an individual occupant has over the energy used within a room or space and by regulating supply more objectively may provide a solution for other systems, such as HVAC. The question then arises, that within a large scale built environment, such as the MIT campus where occupancy patterns are often very changeable, could the HVAC system not only be informed by user profiles of the rooms but also by a more holistic view, assessing the occupancy of rooms

in relation to one another, as well as in relation to the building in its entirety. For example, the 'waste' of energy and increase in entropy resulting from two rooms adjacent to one another with different levels of heating, could be minimized if the spatial configuration of rooms, was such that rooms that typically require a similar temperature were grouped together. In many ways, a campus setting is an ideal test bed for this kind of experiment, as although room occupancy can vary significantly, to a degree it is underlined by classing schedules, providing scope to predetermine demands placed on buildings and rooms and appropriately regulate.

As an example, Fig. 8 clearly illustrates that the first floor has the highest levels of WiFi connections over 23rd January 2006. Furthermore when the fine-grained data is examined in closer detail, it is possible to detect where the highest number of users are at a given time on a room by room basis (Fig. 9). In the case of E52's first floor, three different usage patterns emerge from the data: high occupancy (e.g. E52–101), medium occupancy (e.g. E52–100, 126 and 143) and very low occupancy (e.g. E52–171 and 175). These different usage profiles are also temporally constrained, in that the most significant usage of these rooms occurs between 08:00 and 19:30. Using this information as an example, with extensive analysis of room usage patterns this approach could serve to help identify more energy efficient solutions for heating, cooling, lighting etc.

WiFi connections may be a useful proxy for human occupancy within a campus context. The pervasive nature of WiFi networks not only ensures widespread spatial coverage but also provides a cheap solution to monitoring occupancy levels, removing the necessity for additional smart sensors to be installed. Furthermore their sampling frequency, in this study every 15 min, provides a temporal resolution that is capable of depicting incremental increases or decreases in the number of occupants. The reliance on existing infrastructure to garner new insights into energy consumption, specifically electricity usage provides unprecedented scope for the wider community. At a campus wide scale WiFi connections could be used to assess electricity demands being placed on buildings in real time. Furthermore, if the HVAC system were to be synched more closely to patterns of human occupancy, it could also be informed by WiFi connections across campus. However, it must be noted that this method of using WiFi activity as a proxy for human occupancy has limitation as identified in Sevtsuk et al. [15] such as measurement inaccuracies arising from inactive devices that are left connected to wireless Internet whilst the occupant has left the space.

Of course university campuses have a variety of functions to perform. The morphology of the built environment of campuses reflects these functions, with different buildings having unique energy requirements and consequently consumption profiles. With over 100 buildings, containing laboratories, offices, residences, conference spaces, auditoriums amongst others, the way these spaces are utilized is often very different. For example, laboratory spaces may require 24 h electricity and HVAC supply with equipment and services that require constant electricity, heating or cooling. In contrast large venues such as lecture halls/auditoriums may only be occupied for a small portion of the day, and require minimal energy supply. Albeit that a large proportion of class-based activity is scheduled and associated energy demands may be predetermined (at least during term time), there is also a significant amount of sporadic use of rooms across campus. Occupancy is not limited to daytime use, and there are no constraints as to an individual's use of space. Large common areas, such as studios, may be used by one person or a large number of people often with no alteration in the amount of energy supplied to the space. Rather than seeking to place constraints on this 'spatial freedom', we propose a new approach that could serve to maximize the utility of the energy supplied and in turn improve the efficiency of the campus overall.
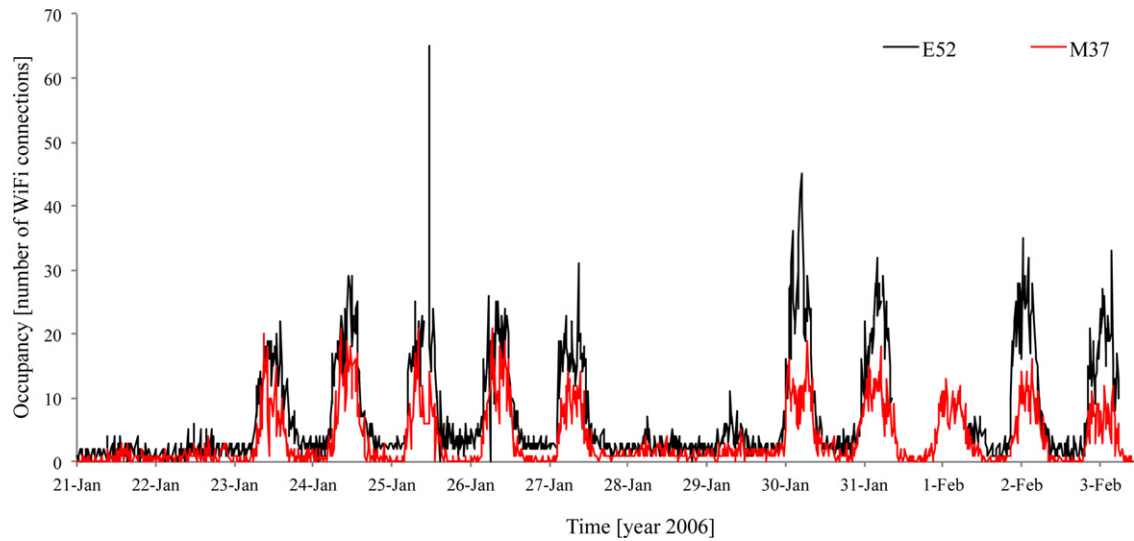
Fig. 6. Time series of human occupancy (number of WiFi connections) for E52 and M37 over 21st January–3rd February 2006 [18].
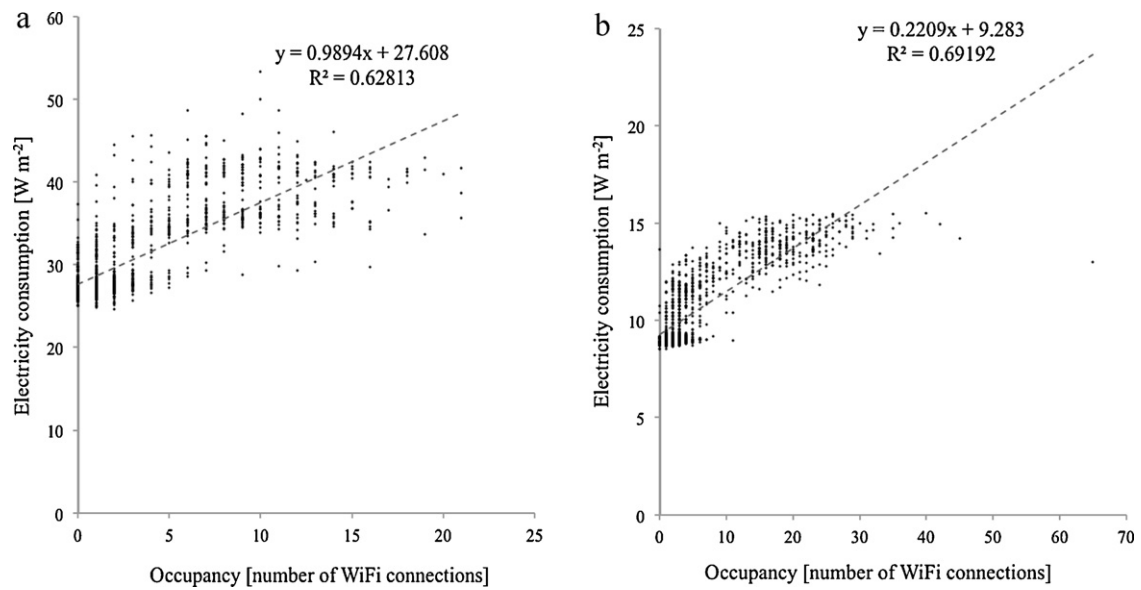

Fig. 7. The occupancy (as estimated by number of WiFi connections) plotted against electricity consumption (W m^{-2}), for M37 (left) and E52 (right), over 21st January–3rd February 2006. The best-fit line for electricity consumption against occupancy is shown, along with r^2 [18].
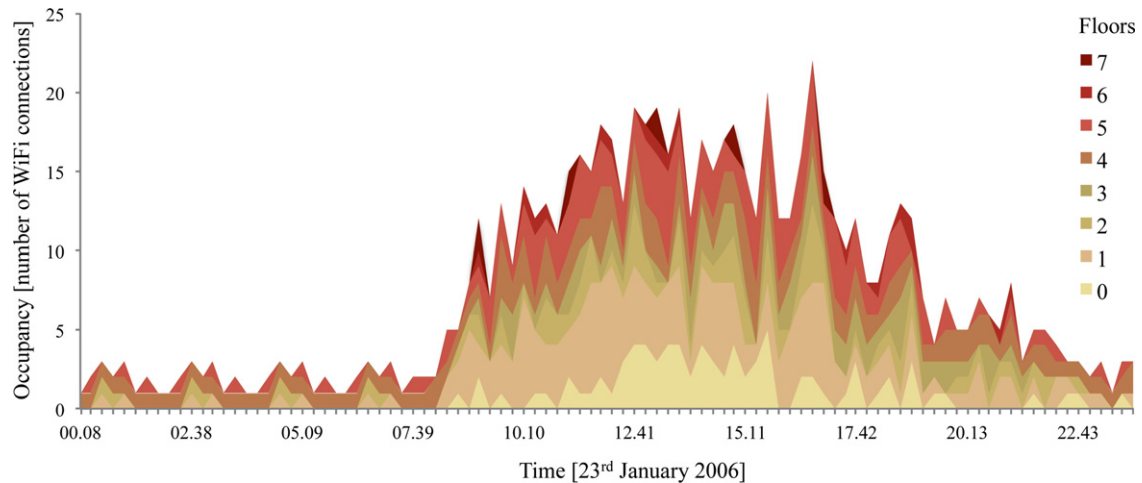

Fig. 8. The number of WiFi connections (as an estimate of human occupancy) stratified by floor for building E52 over 23rd January 2006 [13].

Table 1
Linear regressions between energy consumption (W m⁻²), temperature (°C) and occupancy (number of WiFi connections) for M37 [16,18], over 4 periods (21st January–3rd February; 22nd April–5th May; 22nd July–8th August; 16th September–29th). Italic values indicate statistical significance at the 99% level.

	Constant	WiFi users	Outdoor temperature (°C)	R^2	F	df
Chilled water (W m⁻²)	77.386 (109.04)**					5375
	78.177 (86.66)**	−0.201 (1.42)		0.00	2.01	5374
	25.577 (28.41)**		3.742 (70.03)**	0.48	4904.58**	5374
	26.955 (27.55)**	−0.367 (3.58)**	3.746 (70.17)**	0.48	2464.06**	5373
Steam (W m⁻²)	35.156 (170.41)**					5375
	34.956 (133.29)**	0.051 (1.23)		0.00	1.52	5374
	50.816 (201.77)**		−1.131 (75.68)**	0.52	5726.83**	5374
	50.437 (184.26)**	0.101 (3.51)**	−1.132 (75.82)**	0.52	2875.64**	5373
Electricity (W m⁻²)	30.714 (455.43)**					5375
	27.819 (487.29)**	0.738 (82.15)**		0.56	6748.61**	5374
	30.458 (257.57)**		0.019 (2.64)**	0.00	6.99**	5374
	27.686 (323.09)**	0.738 (82.11)**	0.010 (2.08)*	0.56	3378.56**	5373

Absolute value of *t* statistics in parentheses.

* Indicates statistical significance at 5%.
** Indicates statistical significance at 1%.

Currently the HVAC system is disconnected from human occupancy and appears to be more closely aligned with other factors such as external temperature. By using WiFi connections as a surrogate for usage patterns, we suggest two possible future steps over different scales that could serve to align the HVAC system with the number of users of the space. The first line of inquiry would be to investigate the heating and cooling fluxes at a building-wide scale. By identifying how heating and cooling is supplied on a room by room basis, and also examining floors in relation to one another this information may be used to determine the spatial configuration of energy supplies. Fundamentally this could inform a rethink about how heating and cooling is provided across campus using the underlying principles of how energy fluxes transfer and interact across space. One of the main objectives of the HVAC system could be to minimize entropy, and in turn maximize the utility of energy supplied. By reducing large variations in heating and cooling of adjacent rooms, and by using the thermal seepage through internal walls as another means of heat supply, energy may be utilized more effectively. This approach would require a broad overview of energy supply at the building scale taking into account the spatial configuration of rooms and how their individual profiles impact on one another, consequently removing control from room occupants to make thermal modifications. However, totally eliminating individual's freedom to alter and modify internal room temperatures is not an entirely ideal solution; this points to our second line of inquiry.

The current system has rooms responding to the room-local thermostat setting. That is whether there is a single occupant or
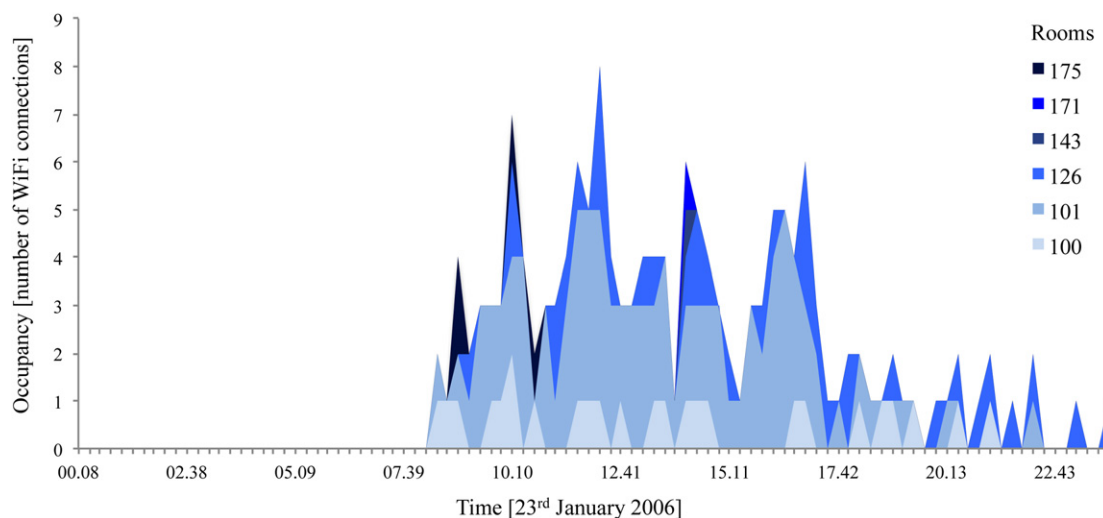

Fig. 9. The number of WiFi connections (as an estimate of human occupancy) stratified by room for the first floor of building E52 over 23rd January 2006 [13].

thirty people in a room, they all have equal weight in altering the room's temperature. It would be relatively simple to "weight the thermostat demand" by the current (or possibly predicted) occupancy. The number of occupants could be determined by WiFi connections, with a larger number of persons permitted a greater degree of control over the thermostat and resultant room temperature. The result would be that the room would heat up or cool down more quickly for the larger class whilst the one or two students in a room would be relying on thermal seepage through the internal walls. By pairing these two approaches, it may be possible to reduce energy 'wastage' whilst also allowing a degree of control by occupants to modify the internal room temperature. These future steps present just two options amongst a plethora of creative strategies that use existing infrastructures to improve energy usage on campuses.

6. Conclusion

The first step of this work that assessed the energy consumption on the MIT campus was to understand how closely the energy flows currently overlap with people flows. In other words, primary consideration was given to understanding the drivers of energy consumption i.e. if most of the energy was used to satisfy occupants of the space or if there were other factors at play that accounted for consumption levels. The results of the study demonstrate that overall the operation of the HVAC systems of the buildings, somewhat unsurprisingly, closely followed the external temperature, with M37 data showing a slightly stronger correlation with the outside temperature. However, and surprisingly, the data analysis revealed a distinct lack of correlation between the occupancy of the two buildings and the amount of energy supplied by the HVAC system. In contrast, the occupancy showed a significant correlation with the overall amount of electricity used; the occupancy accounted for 63% and 69% of variation in electricity consumption for buildings M37 and E52, respectively. The electricity consumption profiles of the two buildings differ: M37 varies little from baseline consumption levels (approximately 26 W m^{-2}), whilst E52 demonstrates greater variation. The marginal shift in electricity usage during the week in E52 correlates with an increase in occupancy i.e. WiFi connections. The fixed part of the consumption in the building M37 is around 80% of the total (Fig. 3) and in building E52 is about 70% of the total (Fig. 2).

Two possible future lines of questioning are identified to help target more efficient use of the HVAC system: using the spatial configuration of rooms to inform the heating/cooling supplied, alongside regulating the degree of control that individuals are able to exercise over the thermostat. These are just two examples from a suite of possible strategies that could be employed to not only improve the operation of the overall system, but also encourage behavioural change across campus. For example, if the range of a thermostat becomes increasingly limited with fewer occupants, individuals may be more inclined to share a space in order to achieve thermal comfort or they may compromise temporary discomfort in order to use the aforementioned space. In many ways providing this option to users brings to the fore the question of energy efficiency but also actively engages individuals by demonstrating practical solutions.

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