Incorporation of timetable information and cheap off the shelf sensors to inform a classroom heating schedule

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Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Master of Science is entirely my own work, and that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Abbreviations

HVAC	Heating, Ventilation and Air-conditioning systems
SHGC	Solar Heat Gain Coefficient
VAV	Variable Air Volume
PMV	Predicted Mean Vote
ESO	Early Switch Off,
DR	Demand Reduction,
ASOO	Alternate Switch On/Off
CFD	Computational Fluid Dynamics
DCU	Dublin City University
BMS	Building Management Sensor
Bl	Back left
Br	Back right
Fl	Front left
Fr	Front right
M	Middlle

Abstract

Improving the energy performance of educational buildings is important for the promotion of an energy efficient culture among future generations. The examination of energy usage with maintained comfort levels is especially relevant for buildings like schools and colleges, where the occupancy has high variability within small time intervals and often periods of low to zero occupancy. This variation in occupancy is currently not taken into consideration on campus with the majority of classrooms run on a set heating schedule. With public sector bodies expected to reduce energy consumption by 33% by 2020 under Ireland's National Energy Efficiency Action Plan, there is an onus on universities in Ireland to reduce their energy consumption. This work aims to evaluate the benefit of incorporating timetable and occupancy information. The deployment of an adequate number of sensors and meters in retrofit applications can be cost prohibitive with installation costs alone accounting for 70% of the costs. Data gathered from the deployment of cheap off the shelf sensors in combination with occupancy information obtained from the schools timetable information resulted in a reduction in heating use of 25%. The incorporation of the j48 tree as a machine-learning technique helped create a decision network with 90% accuracy that could inform a new heating system that is responsive to current need.

Chapter 1

Introduction

Improving energy efficiency is an essential part of sustainable energy policy. Improving it will play a vital role in reducing our dependence on fossil fuels and will greatly contribute to mitigating climate change. The Intergovernmental Panel on Climate Change (IPCC) fifth assessment report on climate change details that the warming of the climate is unequivocal, with human activity clearly contributing to the rise. Figure 1 shows the catastrophic effects of climate change by the end of this century on surface temperature, precipitation, the melting of sea ice and change in our oceans pH levels leaving many parts of the world inhospitable. Even though policies and National plans have begun to be implemented throughout the world with Ireland introducing the National climate change plan in 2007, carbon dioxide and other greenhouse gases grew by 2.2% per year on average between 2000 and 2010, compared with 1.3% per year from 1970 to 2000[1]. With the IPPC warning that warming will continue to increase unless countries shift quickly to clean energy and cut emissions[1]. With buildings accounting for 40% of energy use, they represent a significant opportunity for reduction in energy. Reports have suggested that commercial buildings have the ability to reduce energy consumption by up to 30% through commissioning practices and energy efficiency strategies[2,3]. The cost of these savings is estimated to be around €60,000 - €70,000 per year. per building in large commercial buildings[2,3]. With people tending to spend 90% of their time indoors it is also important that comfort isn't sacrificed for energy reduction[4]. The examination of energy usage with maintained comfort levels is especially relevant for buildings like schools and colleges, where the occupancy has high variability within small time intervals and often periods of low but non-zero occupancy. This in itself presents a challenge while also presenting opportunities for significant energy saving. Besides the obvious benefits from a reduction in energy consumption (reduced fuel costs, reduction carbon foot print etc), it is important that educational institutions take a lead on energy efficiency, as this will help teach and embed an energy conservation culture in our future leaders, decision makers and citizens. This will be vital in steering clear of the worst case climate scenarios shown in figure 1.

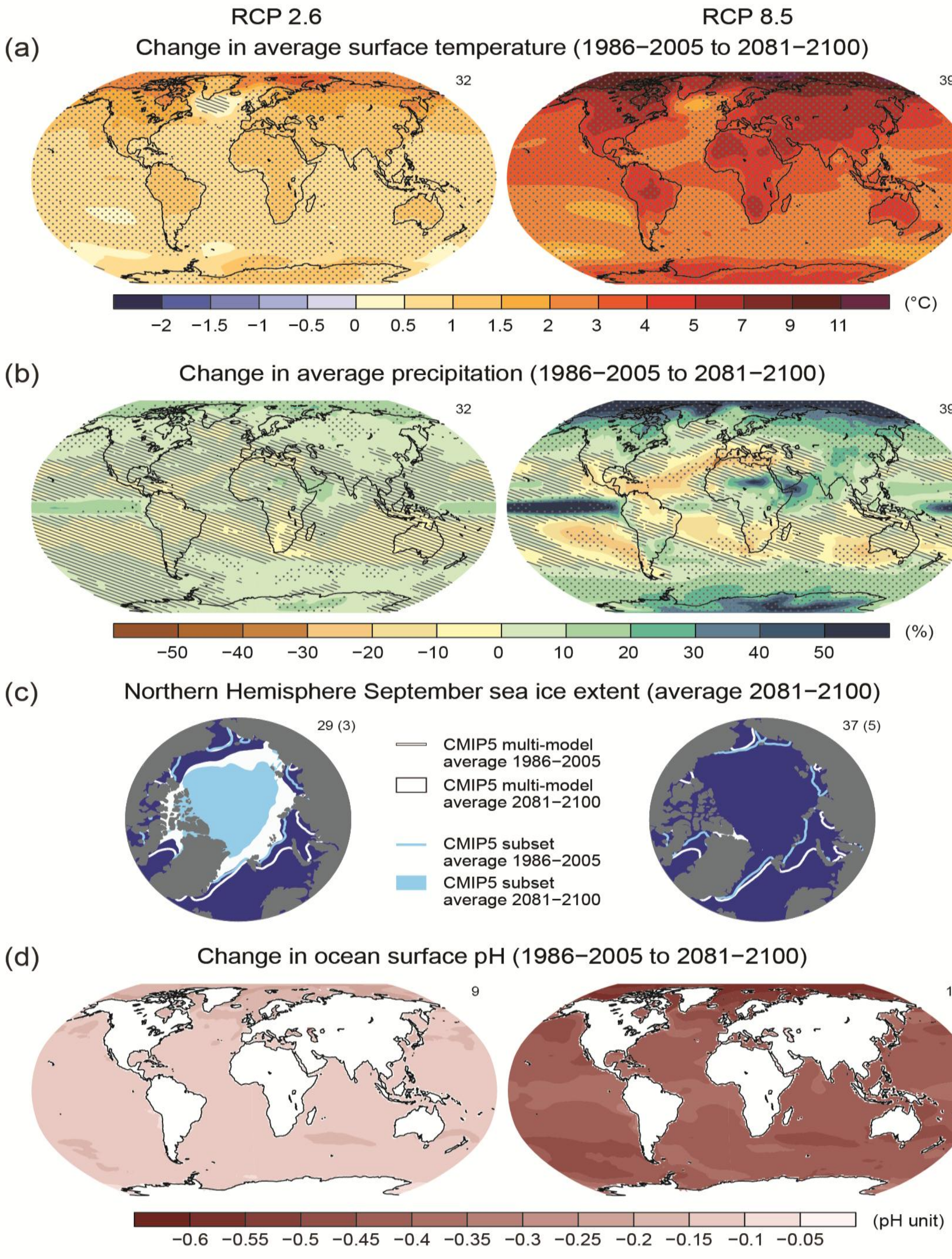


Figure 1: Changes in (a) surface temperature, (b)precipitation, (c) sea ice and (d)ocean surface pH from 1986-2005 and predicted changes from 2081-2100[1].

1.2 Motivation

With rising fuel prices and Ireland's reliance on importing 85% of its energy requirements, the need to monitor and reduce energy consumption is receiving greater attention than ever before in Irish commercial and public buildings[5]. Energy for thermal purposes accounted for 52% of final energy demand in Ireland in 2012, with a reduction in energy use of 4.4% in 2012 when adjusted for weather[5]. As discussed, improving the energy performance of public buildings is also important for the promotion of a culture of energy efficiency among the local population. Energy, CO^2 savings and targeted trajectory under the second national energy efficiency action plan is shown Figure 2[6].

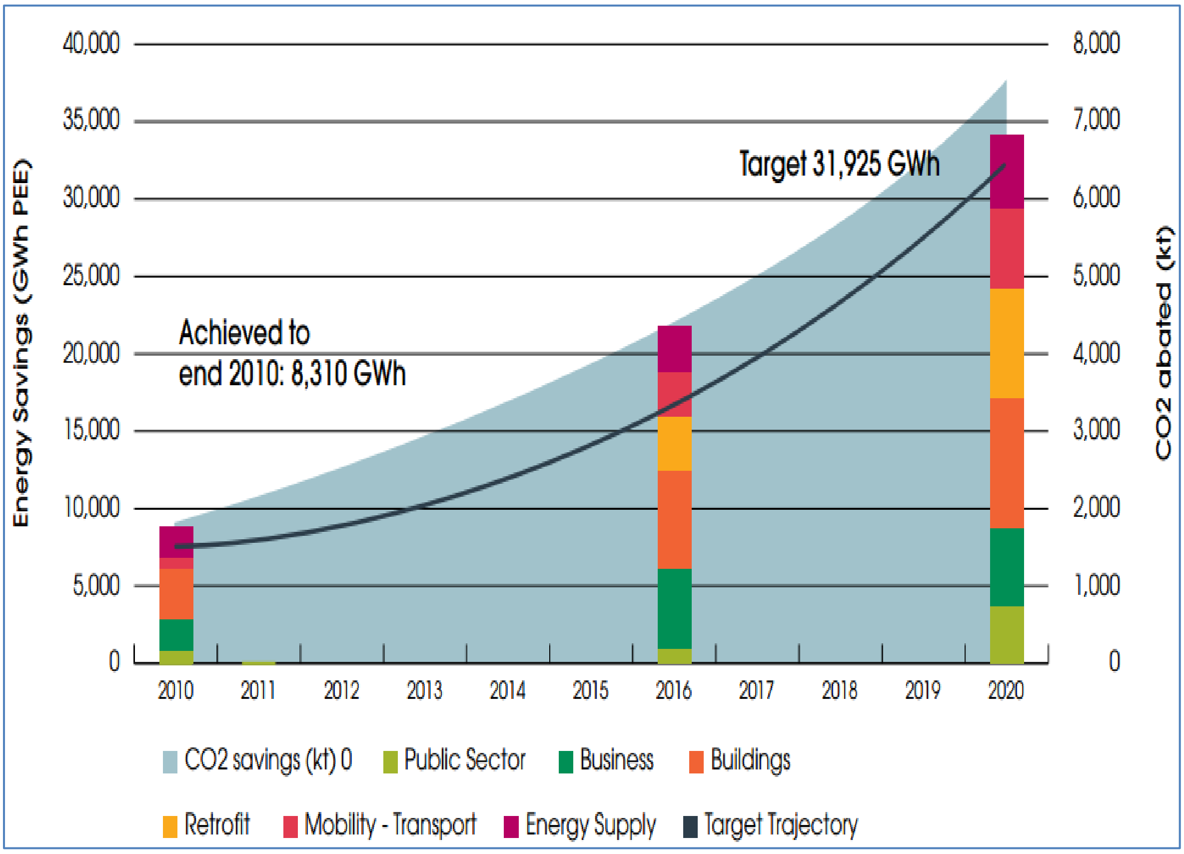


Figure 2: Energy and CO2 savings and targeted trajectory under the second national energy efficiency action plan[6].

Universities in Ireland have been set a target of reducing their energy consumption by 33% by 2020 under Ireland's second national energy efficiency action plan[6]. Studies have shown that efficient scheduling of a university heating system and its resources can lead to significant reductions in energy use on campus. Mata *et al.* developed an on/off protocol for the university heating system that incorporated occupancy schedule resulting in 40% reduction in gas consumption for space heating[7]. This was achieved through adaptation of the building's schedule of use, identifying times when it was minimally or completely unoccupied including shutdowns of the system programmed without interfering with the operation of the building[7]. Classroom temperatures were also evaluated and re-adjusted. The policy on allocating classrooms was also changed to prioritise filling all classrooms on the same heating circuit. An allocated out-of-hours area was also set up meaning a 70% reduction in night time heating as the whole building had previously been heated[7]. At the Polytechnic University of Valencia an energy management and control system was used to evaluate different control strategies for a Heating, Ventilation and Air-conditioning systems (HVAC) split system[8]. It was found that by pre-heating during off peak electricity prices, switching off at midday and switching off in advance of the evening to be the most efficient strategies. Simple energy saving techniques were also found to provide reductions up to 40% through reduction of temperature set-point by one degree thus highlighting the importance of closing windows or adjusting the set point temperature of a HVAC device on energy consumption[8]. Myo Sun Kim *et al.* also used on/off control in an intermittently occupied university building, this resulted in a 25% reduction in consumption during semester while maintaining thermal comfort and reducing energy consumption[9]. This was achieved using a dynamic simulation programme TRNSY after finding good agreement with experimental and simulated data[9]. In the current economic climate and reductions in public sector budgets, upgrade to modern sophisticated energy management systems is generally not a realistic option for existing university buildings as the installation costs account for 70% of the total cost of deploying an adequate number of sensors and meters in retrofit applications[10].

Thus, an optimisation and review of current energy practices should be the first port of call for any institution. Though aspects of a university can be very energy intensive with large scientific and computer laboratories, the intermittent occupancy of university classrooms and lecture rooms should present an opportunity for significant energy reductions. It has been said that even more awareness regarding energy saving among students and staff, can contribute to significant energy saving[11]. A survey conducted on Higher Education Institutions in the United Kingdom showed that non-technical strategies such as student and staff awareness campaigns can result in a combined saving of 25%**.** With 60% of the strategies costing less than £1000, behaviour modification schemes based on awareness programmes and several 'carrot and stick' schemes are generally used.

1.3 Legislative Drivers

The public sector will be seen to lead the way on energy efficiency in Ireland, as laid out in the National Energy Efficiency Action Plan 2. Public service buildings such as offices, hospitals, clinics, nursing homes, schools, prisons, barracks and Garda stations will be expected to reduce energy consumption by 33% by 2020[6].

The main legislative driver behind this is the Energy Performance of Buildings, which contains a range of measures to improve energy performance in new and existing buildings. This requires buildings >1000m^2 to display energy certificates[12]. As Certification is a one-off assessment, subsequent evaluation of building performance is not continuously monitored, making it difficult to maintain optimum operation[13].

The main driver for promoting energy efficiency in the EU is through The Energy End-Use Efficiency and Energy Services Directive[14]. This Directive sets out a 9% target for member states to achieve by 2016[14]. The purpose of the Directive is to improve energy end-use efficiency in a cost effective manner for the member states by:

- Providing the necessary indicative targets, mechanisms, incentives and institutional, financial and legal frameworks to remove existing market barriers and address imperfections that impede the efficient end-use of energy;
- Creating the conditions for the development and promotion of a market for energy services and for the delivery of other energy efficiency improvement measures to final consumers;

- Placing an emphasis on measurement and verification of energy savings;
- Stipulating the public sector must play an exemplary role.

The energy efficient public procurement legislation commits public bodies to only purchasing equipment and vehicles from the triple E register, while the green procurement outlines best practice in green procurement for public bodies in areas such as energy supplies, energy efficiency and renewable energy services[15].

1.4 Aims and objectives

The aim of this research is to explore the ability of cheap off the shelf sensors to evaluate the thermal climate of university classrooms and how they can help inform and improve the heating system within the university. The incorporation of occupancy information in determining heating schedules for classrooms will also be explored. Readily available occupancy data sources such as timetable will be used. The scanning of smart devices will be explored as to whether they can supply greater detail on the number of occupants within university classrooms. The data gathered will be used to inform a new, adaptable heating system that can react to current conditions. The benefit of proposed energy reduction schemes will be analysed and compared with the current flat heating system.

The objectives of this research are:

A. Investigate the benefit of using off-the shelf sensors in enhancing knowledge of thermal climate in classrooms
B. Explore the benefits of incorporating occupancy information for classrooms on heating schedules
C. Create a decision network that can inform when to turn on/off a heating system with regards to current conditions

Chapter 2

Energy consumption in buildings

The primary purpose of buildings is to provide shelter for its occupants; a building should also provide security, privacy and protection from the elements while also providing comfortable living conditions for its occupants. Modern buildings have to meet occupants demand for air quality, thermal and optical comfort as shown in figure 3. The consumption of the sources related to these demands such as space heating and cooling, ventilation, lighting and appliances, will determine the energy consumption of a public building. Energy consumption of buildings in developed countries comprises 20–40% of total energy use and is above industry and transport figures in both the EU and US[16].

There are four main factors playing a vital part in the energy consumption of a building:

- Physical properties including location, orientation, type;
- The equipment installed to maintain the desired internal environment such as heating ventilation, air-conditioning system, electricity or hot water;
- Outdoor environment and the meteorological factors such as temperature, solar radiation etc.
- Behaviour of occupants and associated heat gains

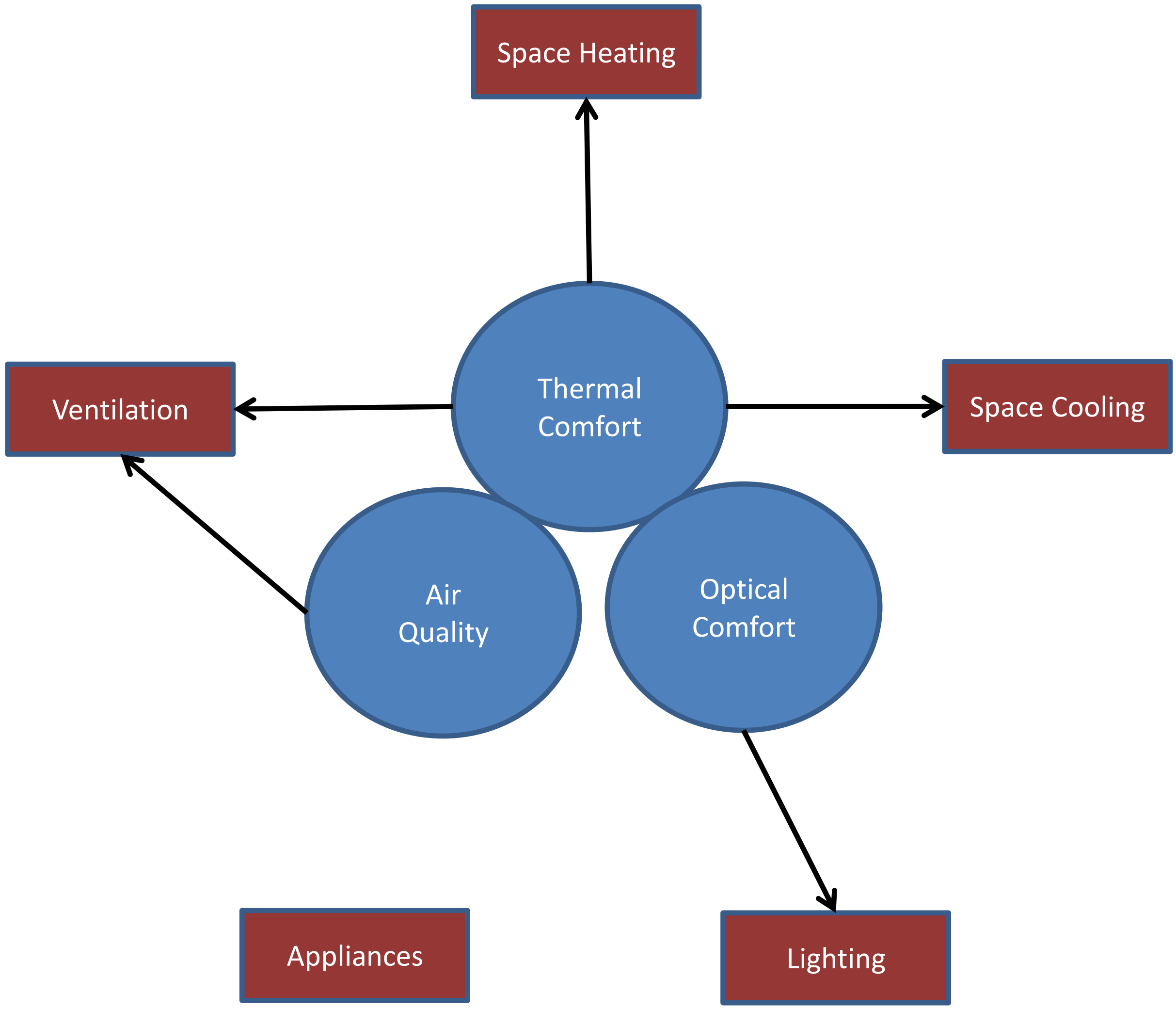
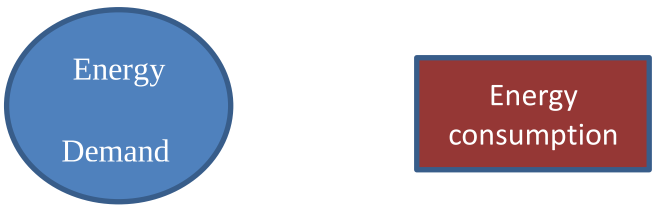


Figure 3: Sources of a buildings energy demand and consumption.



2.1 Heat Transfer in buildings

A building's energy balance is determined by the heat fluxes via the building fabric and the heat production and absorbance in it. Heat is lost and gained through conduction, convection and radiation[17]. The thermal performance of a building depends on a large number of factors which include

- Design variables (geometrical dimensions of building elements such as walls, roof and windows, orientation, shading devices etc);
- Material properties (density, specific heat, thermal conductivity, transmissivity, etc.);
- Weather data (solar radiation, ambient temperature, wind speed, humidity, etc.);
- Building's usage data (internal gains due to occupants, lighting and equipment, air
  exchanges, etc.)

Conduction: Heat transferred through a solid material e.g. Heat is transferred from warmer section of walls to cooler. Heat transfer though walls and roofs is dependent on the inside temperature T_i, the outside temperature T_o, the heat transfer area, the U - factor (the heat transfer coefficient) and thermal resistance R value (1/U)[18].

$$Qcond = UA(T_i - T_o) \qquad \text{Equation 1}$$

Qconduction = quantity of heat flow (W)

U = heat transfer coefficient of the material (W/m^2/K)

A = area (m^2)

$\mathbf{T_i}$ = inside temperature (K)

$\mathbf{T_c}$ = outside temperature (K)

The U –value or thermal transmittance is the measure of conductivity of a building material. The smaller the U rating of the material the lower the amount of heat loss from the building. Typical U values for common building material are shown in table 1[18]. To calculate the U value of a wall or roof with different materials the following equation can be used[18].

$$U_{Series\ combination} = \frac{1}{\frac{1}{U_1}+\frac{1}{U_2}} \quad \text{Equation 2}$$

Table 1:U-values for wall, floor, roof, and window materials[18].

	U- Values (W/m^2/K)		
	Old buildings	**Modern standards**	**Best methods**
Walls		**0.45-0.6**	**0.45-0.6**
Solid masonry wall	2.4		
Outer wall: 9 inch solid brick	2.2		
11 inch brick-block cavity wall, unfilled	1.0		
11 inch brick-block cavity wall, insulated	0.6		
Floors		**0.45**	**0.14**
Suspended Timber	0.7		
Solid concrete	0.8		
Roofs		**0.25**	**0.12**
Flat roof with 25 mm insulation	0.9	0.25	0.12
Pitched roof with 100 mm insulation	0.3		
Windows			**1.5**
Single-glazed	5.9		
Double-glazed	2.9		
Triple-glazed	0.7 – 0.9		

Convection: Is the transfer of heat by moving air e.g. warm air rises and transfers heat to the ceiling[17].

$$Q = hA(T_s - T_f) \qquad \text{Equation 3}$$

h = film (convection) coefficient not a property of the fluid

T_s= surface temperature

T_f = fluid temperature

A = surface area

R = 1/h (film resistance):

The higher the air speed, the larger the convective heat transfer coefficient (or the smaller the film resistance).

Radiation: The transfer of heat by electromagnetic waves. E.g. roof radiates heat to ceiling. Heat transfer by radiation can be calculated using the following,

$$Q = e\sigma T^4 A \qquad \text{Equation 4}$$

Q = heat transfer per unit time (W)

e = emissivity

σ = 5.6703 10^{-8} (W/m^2K^4) - *The Stefan-Boltzmann Constant*

T = absolute temperature Kelvin (K)

A = area of the emitting body (m^2)

Ventilation: The energy needed to heat incoming cold air in a room due to ventilation can be calculated using the number of air exchanges N, the volume of the space V and the temperature difference ΔT between the inside temperature[18].

$$P = CNV(T_i - T_o) \qquad \text{Equation 5}$$

P = Power (watts)

C = specific heat capacity of air (1.2 kJ/kg.K)

N = number of air exchanges per hour – one air exchange per hour is typical for a lecture room

V= volume of the room in (m^3)

$\mathbf{T_i}$ = inside temperature (K)

$\mathbf{T_c}$ = outside temperature (K)

The total heat flow within a building is equal to the sum of sensible heat and latent heat. Sensible heat is added directly to the conditioned space by conduction, convection, and/or radiation. Latent heat when moisture is added to the space (e.g., from vapour emitted by occupants and equipment). Figure 4 summarises the modes and sources for heat gains and losses within a building. Kulkarni *et al.* demonstrated how retrofitting a university building with more efficient materials can impact on energy usage. A lecture theatre was retrofitted with a false ceiling, wall insulation, different glazing types and lighting systems. They found the retrofits to be cost effective with annual saving ranging from 17% to 19.8%, with payback period generally in the order of 8 years[19].

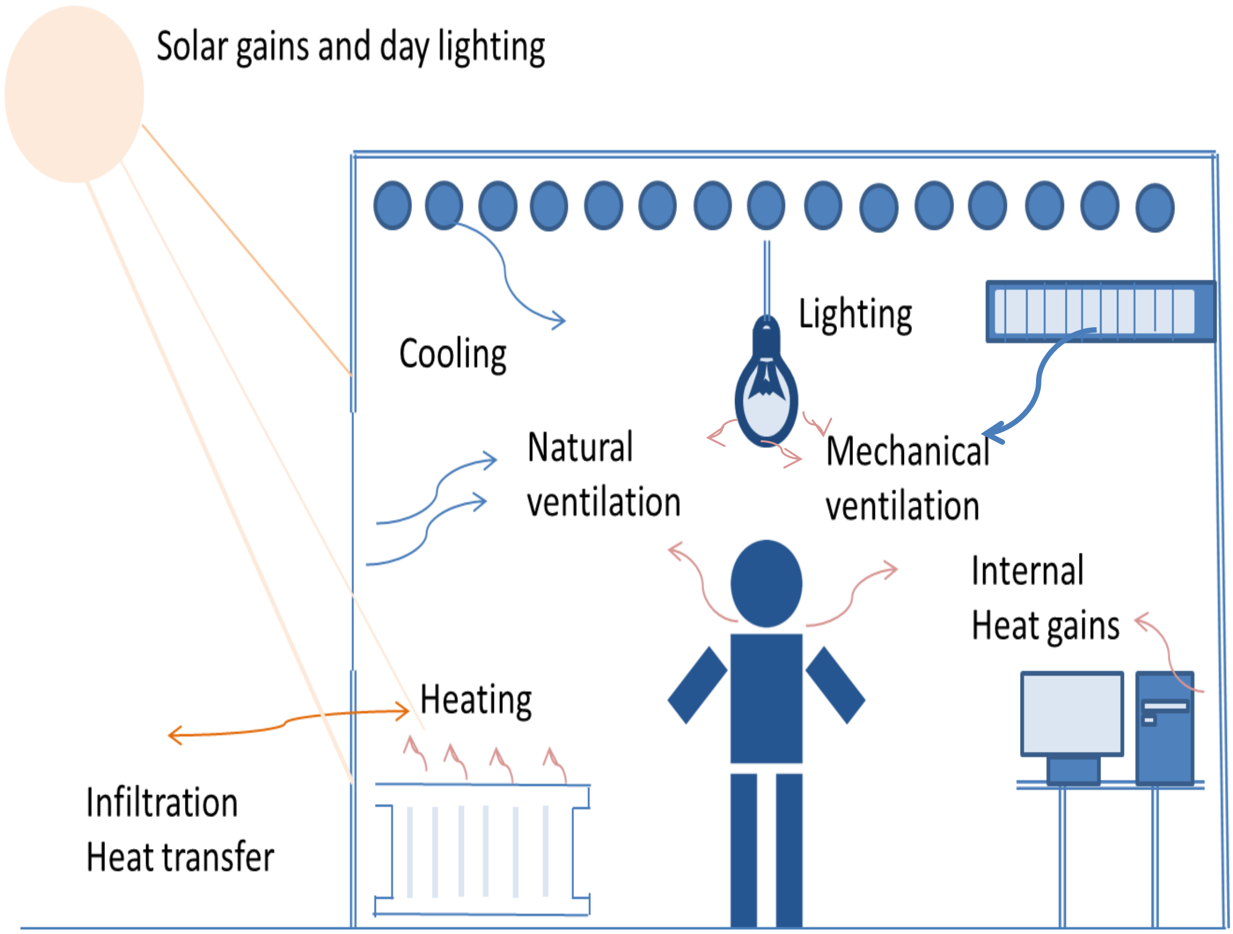


Figure 4: Sources and modes of heat gain and cooling within a building.

2.2 Internal Heat gains

Internal heat gain is the conversion of chemical or electrical energy to thermal energy in a building. People, lights and equipment represent the internal heat gains of a building. These sources of internal heat gain add to the cooling load off the building[20]. Internal heat gains are generally only considered in design cooling calculations[20]. They are generally ignored in design heating calculations to ensure the systems operate in the worst case scenarios without heat gains[20].

2.3 People

The metabolic heat generated in the body is dissipated to the environment through the skin and the lungs by convection (27%) and radiation (40%) as sensible heat and by evaporation as latent heat[17]. The modes of heat transfer generated by the human body are shown in figure 5[17].

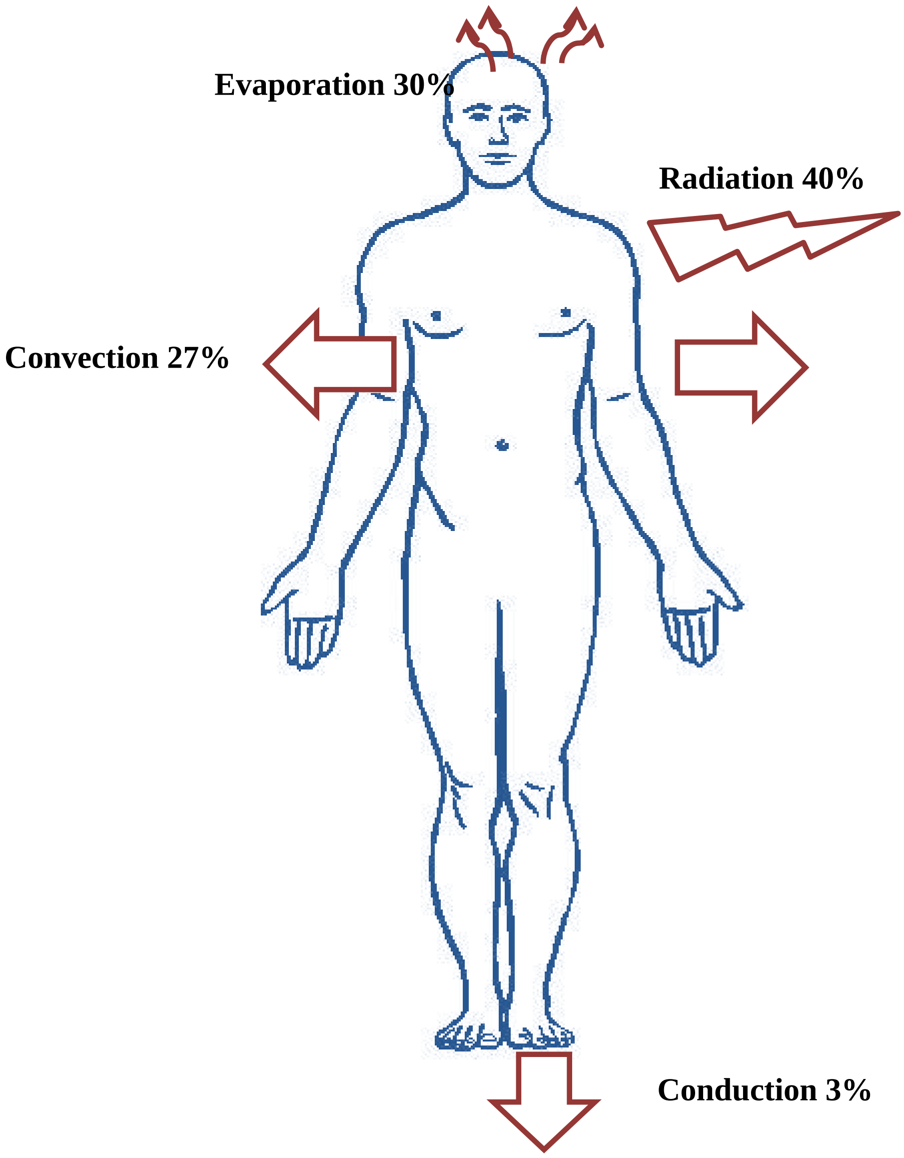


Figure 5: Modes of heat transfer through the human body[17].

The internal heat gain from people within a building is dependent on the number of people and the type of activity of the occupant[20]. This can range from 115 Watts seated in a theatre to over 500 watts during physical exercise[20]. Table 2 shows the heat gain from people during different activities[20].

Table 2: Sensible and latent heat gain given off by people during different activities[20].

Degree of activity	Application	Adult male (W)	Adjusted M/F/C (W)	Sensible (W)	Latent heat (W)
Seated at theatre	Theatre matinee	115	95	65	30
Seated at theatre	Theatre evening	115	105	70	35
Seated very light work	Offices, Hotels	130	115	70	45
Moderate active office work	Offices, hotels	140	130	75	55
Light work, walking	Retail Store	160	130	75	55
Walking standing	Drug store, bank	160	145	75	70
Sedentary Work	Restaurant[2]	145	160	80	80
Light bench work	Factory	235	220	80	80
Moderate dancing	Dance hall	265	250	90	90
Heavy Work	Factory	440	425	170	255
Heavy machine work	Factory	470	470	185	285
Athletics	Gymnasium	585	525	210	315

Heat emitted by people usually constitutes a significant fraction of the sensible and latent heat gain of a building, and may dominate the cooling load in high occupancy buildings such as theatres and concert halls. The difficulty in predicting the number of occupants in a building at any given time makes it difficult to quantify the effect of heat gain from people; the cooling load of a building is usually determined using full occupancy unless exact occupancy data is available. The following figures are used in estimating occupancy on the basis of one occupant per 1 m^2 in auditoriums, 2.5 m^2 in schools, 3–5 m^2 in retail stores, and 10–15 m2 in offices. Table 1.3 shows typical average and maximum sensible and latent heat gains in different types of buildings

Table 3: Typical average and maximum sensible and latent heat gains in different types of buildings.

Building Type	**Sensible Heat gains (W/m^2)**	**Latent heat gains (W/m^2)**		
	Average	Maximum	Average	Maximum
Office	3	6	2	5
Education	8	23	6	19
Retail	6	26	6	44
Restaurant	6		5	
Lodging	3	4	2	3
Residential	2		2	

Sensible heat is heat that causes a change in temperature in an object. Heat that causes a change of state with no change in temperature is called latent heat. Sensible capacity is the capacity required to lower the temperature and latent capacity is the capacity to remove the moisture from the air. The following equations are used to estimate the sensible and latent heat gain from people in buildings[20].

Sensible heat gain $Q_{ps} = Np.Fu.qs.CLFh$ Equation 6

Latent heat gain - $Q_{pl} = Np.Fu.ql$ Equation 7

Q_{ps} = Sensible Heat Gain (SHG) from people

Q_{pl} = Latent Heat Gain (LHG) from people

Np = Number of people (maximum or design from occupancy criteria for building)

Fu = Diversity factor or percentage of maximum design for each hour of the day

= 0 when there are no people in the room

= 1 when the maximum design number of people is in the room

qs = sensible heat gain (SHG) per person for the degree or type of activity in the space (W/m^2)

ql = latent heat gain (LHG) per person for the degree or type of activity in the space (W/m^2)

CLF-h = Cooling Load Factor (CLF) for given hour. This depends on zone type, hour entering space, and number of hours after entering into space (ASHRAE Table 8.19)[20].

2.4 Lighting

Energy consumption for lighting in buildings, in particular, is a major contributor to CO_2 emissions, and has been estimated to account for 20–40% of the total energy consumption in buildings[21] . Lighting is also a major contributor to the peak electrical demand which is often met by expensive generators[22].

The energy input for lighting is converted into into visible light, convective, and radiant heat. Only the convective heat is picked up instantaneously by the air-conditioning apparatus[20]. The remaining radiant heat only affects the conditioned space after being absorbed and released by the surroundings[20]. This creates a lag time with some energy still being radiated after lights have been switched off[20]. This is important to consider when calculating the cooling load. Table 4 shows the light forms emitted by incandescent, fluorescent and LED light bulbs[23].

Table 4: Percentage of visible light, radiant heat and convective heat from common light bulbs[23].

	Incandescent (%)	**Fluorescent (%)**	**LED (%)**
Visible light	8	21	15-25
Radiant heat	73	37	
Convective heat	19	42	75-85

The thermal properties of a light source depend on the method of installation of the light fixture as shown in Figure 6. Incandescent lights are generally suspended from the ceiling, whereas fluorescent lights and LED lights are mounted on the ceiling in a recess. For suspended installation increase indoor cooling load as light fixtures emit radiant heat into the room along with visible light. Fluorescent lighting emits less radiant heat when installed in a recessed type fitting with the heat reaming in the ceiling as convective heat, this is also true for LEDS though as no radiant heat is produced all heat is transferred to the ceiling as convective heat, increasing the indoor cooling load. A review of energy saving light sources recommended that government and commercial buildings consider hybrid thermal photovoltaic and solar fibre optic illumination systems[21].

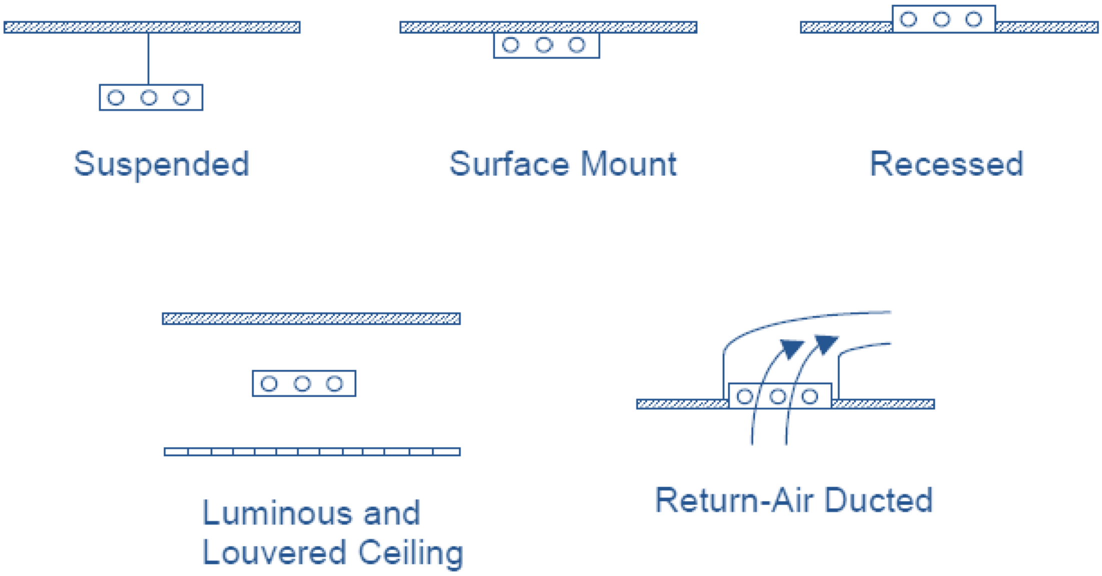


Figure 6: Common installation methods for light fixtures[24].

Ahn *et al.* were able to control the heat gain form LED lights due to the fact that the heat sink is divided across the LED chip and can be used to reduce the heating and cooling load of buildings[24]. They were able to use this to reduce heat gains during cooling periods and maximise during heating periods[24]. The relationship between lighting and heating and cooling load has been studied widely and contributes significantly to cooling loads[25-27] . Equation 8 can be used to calculate the sensible heat gain from lighting

$$Q_l = W.F_U.F_S.CLFh \qquad \text{Equation 8}$$

$\mathbf{Q_l}$ = Sensible Heat Gain (SHG) from lights

W = Lighting power output in Watts

$\mathbf{F_u}$ = Usage factor or percentage of maximum design for each hour of the day

= 0 when all lights are off

= 1 when the maximum design number lights are on

0 <= Fu <= 1 Example Fu = 0.5 when 50% of lights are on.

$\mathbf{F_s}$ = Service Allowance Factor or Multiplier (accounts for ballast losses in fluorescent lights

and heat returned to return air ceiling plenum in the case of air-light fixtures)

CLFh = Cooling Load Factor (CLF) for given hour. This depends on zone type, total hours that lights are on and number of hours after lights are turned on, The sensible heat has to be first absorbed by the surroundings and then released into the air. The cooling load factor accounts for this time delay.

2.5 Equipment

Heat gain from equipment is an important contributor to the overall heat gain of a space. When an electrical appliance consumes electrical power, the electrical energy of the appliance is converted into other forms of energy, such as heat, and mechanical work etc. Electrical appliances can be classified as heating systems or working systems[28]. Heating system appliances convert the total energy to heat[28]. A refrigerator, washing machine and electric fan would be examples of a Heating system that create mechanical equivalent heat as a result of the electric motor. Acoustic and electromagnetic waves produced are also eventually converted to heat[28]. For some appliances, the final form of work is not heat but crushing or grinding. These are known as Working Systems where the final energy is not only heat but also work[28].

Electrical appliances can also be characterised on their thermodynamic characteristics. Electrical appliances are broken up into closed system and open system and are displayed in Table 5[29]. Almost all electrical appliances only exchange their heat through their boundaries without any mass transfer this is known as a closed system[29].

Table 5:Thermodynamic classification of electrical appliances[29].

Classification	Examples	
Heating system	Closed system	Electric Kettle, PC, Monitor, Television,
	Open system	Clothes Dryer, Washing machine, Dish washer
Working system	Closed system	Electric Blender, Electric grinder
	Open system	

Very significant heat gains, sometimes greater than all other gains combined can be generated by computers, printers, copiers, etc. Nameplate data rarely reflect the actual power consumption of office equipment[30]. Actual power consumption of such equipment is assumed to equal total (radiant plus convective) heat gain, but its ratio to the nameplate value varies widely. For general office equipment with nameplate power consumption of less than 1000 W, the actual ratio of total heat gain to nameplate ranges from 25% to 50%[30]. Research conducted on heat gain measurements from office, laboratory and hospital equipment found that results for general office equipment could be generalized with results from laboratory and hospital equipment proving too diverse[30].

Heat gain values for computers and monitors are shown in Table 6 below. Engineers generally tend to be conservative when calculating cooling loads[20].

Table 6: Heat gains from computers and computer monitors in both continuous use and energy save mode[20].

	Continuous (W)	**Energy saver (W)**
Heat gain from computers		
Average Value	55	20
Conservative value	65	25

Highly conservative value	75	30
Heat gain form monitors		
Small (13 in. to 15 in.)	55	0
Medium (16 in . to 18in.)	70	0
Large (19 in. to 20) in.)	80	0

Equation 9 can be used to calculate sensible heat gain from electrical equipment.

$$q_s = q_{input} F_U F_R \qquad \text{Equation 9}$$

$$q_s = q_{input} F_L \qquad \text{Equation 10}$$

$\mathbf{q_s}$ = sensible heat gain

$\mathbf{q_{input}}$ = rated energy input

$\mathbf{F_U}$ = Usage Factor

$\mathbf{F_R}$ = Radiation factor

$\mathbf{F_L}$ = Load Factor

Table 7 shows typical usage and radiant factors for some kitchen appliances[20].

Table 7:Usage factor, radiation factor and load factor for common kitchen appliances[20].

Appliance	Usage Factor F_U	Radiation Factor F_R	Load Factor $F_L = F_U F_R$
Convection oven	0.16	0.45	0.07
Fryer	0.06	0.43	0.03
Steam cooker	0.13	0.30	0.04
Griddle	016	0.45	0.07

Though engineers are typically conservative in their calculations of cooling loads, overestimation of electrical equipment gains can result in increased capital and running costs of air conditioning plants. Dunn and Knight calculated the average gains from equipment to be 17.5 W/m^2 in over 30 offices across the UK, 158 w per person when normalised for occupancy levels[31]. The Building Services Research and Information Association (BSRIA) and the British Council for Offices (BCO) also reported the average equipment heat gains of 13 air conditioned offices to be 13.9 W/m^2 and 140 W per person[32]. Figure 7 shows the recommended heat gains from electrical equipment for different locations[33].

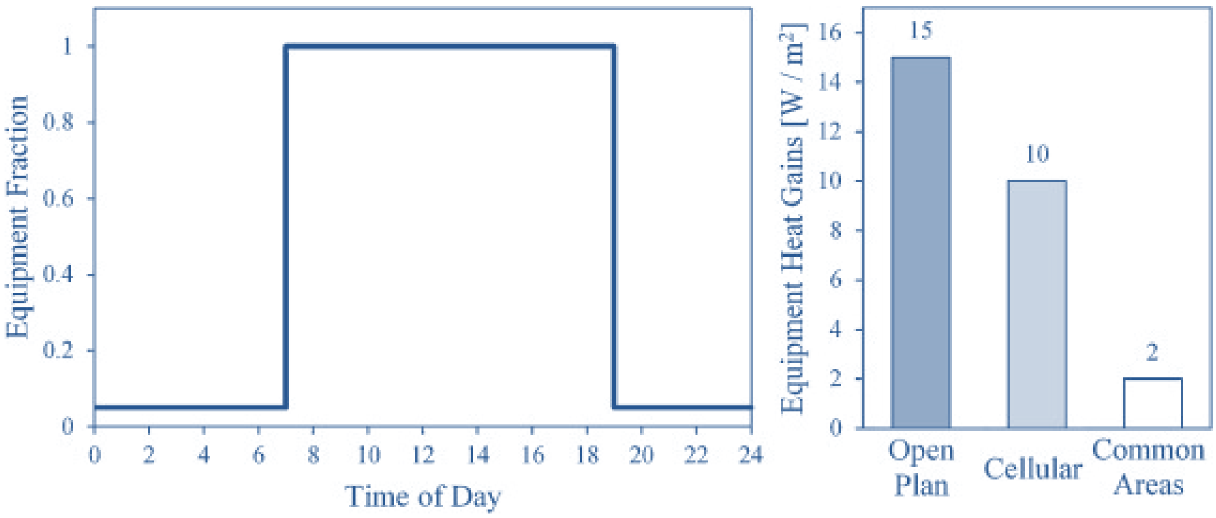


Figure 7: Recommended heat gains for different areas within an office building[33].

2.6. Solar Heat gains

Solar gain is the heat absorbed by a building from the sunshine which falls on it. About 8% of the sunshine that falls on uncoated clear glass is reflected back to outdoors, 5 to 50% depending on composition and thickness is absorbed within the glass, with the remainder transmitted indoors[17]. The amount of heat absorbed from the sun by a building will depend on a number of factors[34]

- The latitude of the site;
- The orientation of a building;
- Season of the year;
- Local weather;
- Angles between the rays of the sun and the building surfaces;
- Type of roof and walls.

During the heating season, while heat is gained from the sun it is simultaneously being lost through heat transfer from the interior, through the building fabric and through air infiltration. However, solar gain can be high for the spring and autumn months which fall within the heating season. When the sun is low in the sky, it penetrates further into the interior of the building through windows, raising internal temperatures and providing a sense of comfort through radiant heat[35].

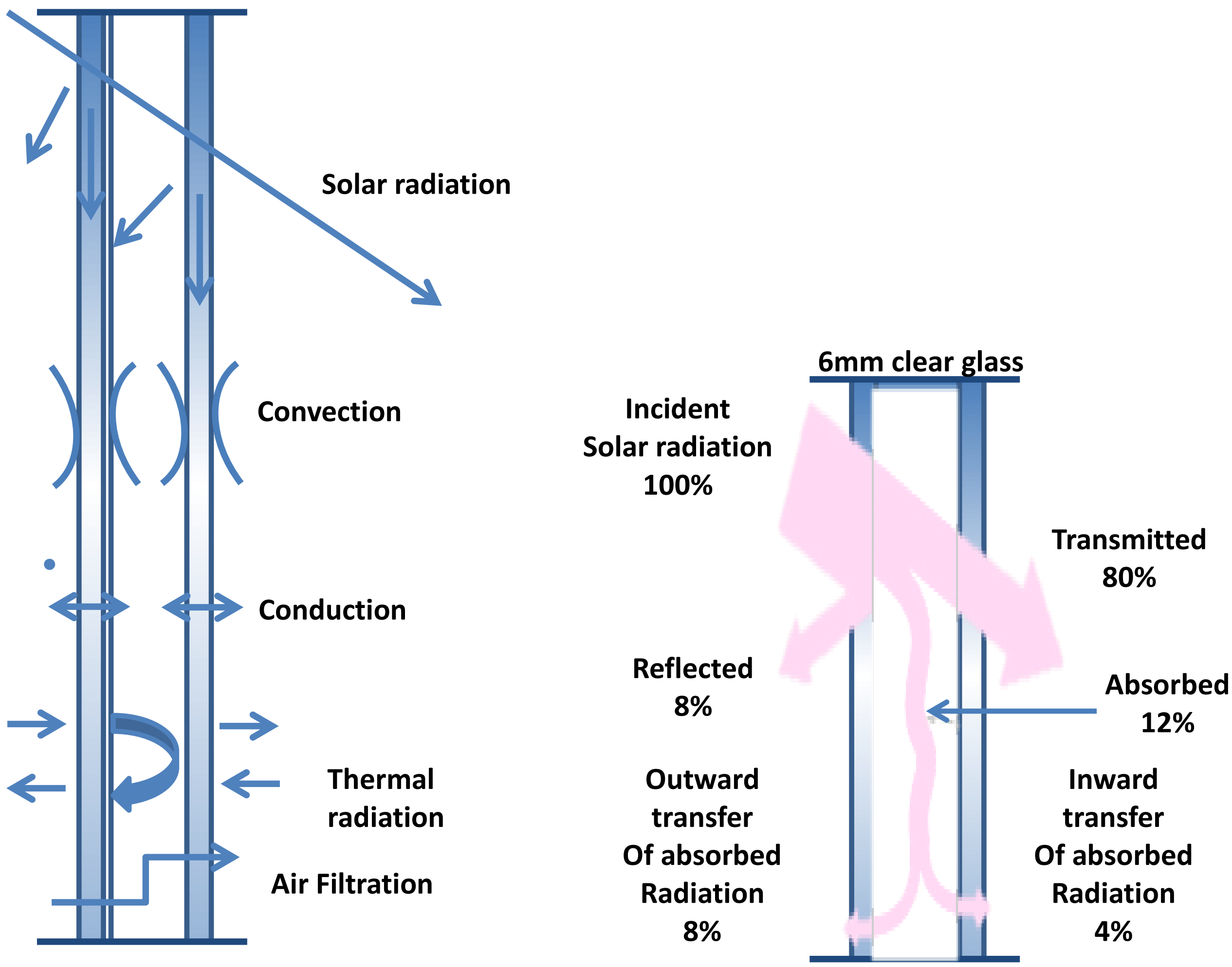


Figure 8: Modes of Heat transfer through a window and the percentages of transmitted absorbed and elected light.

The fraction of incident solar radiation that enters through the glazing is called the Solar Heat Gain Coefficient (SHGC) and is expressed as

$$\mathrm{SHGC} = \frac{\text{Solar heat gain through the window}}{\text{solar radiation incident on the window}} \qquad \text{Equation 11}$$

The solar heat gain through a glazed area can be calculated using the following[36]

QSolar = Area of window x solar intensity x Transmissivity Equation 12

2.7 Control of heating and cooling systems

As discussed throughout section 2.6, there are numerous parameters involved in maintaining a building's energy balance. Heating and cooling systems aim to maintain a balanced, thermally comfortable environment for their occupants.

Efficient control for heating, ventilation and air-conditioning systems (HVAC) is the most cost-effective way to minimize the use of energy in existing buildings. Heating and cooling systems account for approximately half of the total energy consumed in building[37]. With the upgrade of technologies often cost prohibitive in public buildings due to budget constraints, efficient use of the current heating and cooling systems is often the most cost effective solution. A review of HVAC control strategy technologies was carried out by Vakiloroaya *et al.*[38]

The efficient use of HVAC systems has been reviewed by a number of authors. The economic and energy savings of different scheduling strategies where reviewed by Fadzli Hannif *et al.*[39]. Table 8 shows the benefit of implementing a number of different scheduling patterns, with Early Switch Off (ESO) and Alternate switch on/off resulting in the biggest economic and energy savings.

Table 8:Comparison of different HVAC scheduling techniques and their economic and energy saving potential[40].

Technique	Description	Energy saving (%)	Economic saving (%)
Interruption	Switch-off period: 1200 - 1300 h	2.93	5.05
	Switch-off period: 1200- 1500 h	5.66	6.37
ESO	Switch-off time: 2000 h	4.48	5.45
	Switch-off time: 1900 h	11.19	8.78
DR	Pre-heating period: 0700 - 0800 h	-11.22	-13.91
	Switch-off period: 0800 - 0900 h		
	Pre-heating period: 0500 - 0800 h	-31.59	-1.18
	Switch-off period: 0800 - 0900 h		
DR	Pre-heating period: 0600 - 0700 h	2.74	8.36
Interruption	Switch-off period (1st): 0800 - 0900 h		
	Switch-off period (2nd): 1400 - 1500 h		
ASOO	On/Off (1 h): 0700 - 2100 h	20.31	19.4
ASOO	On/Off (1/2 h):1000 -2100 h	7.55	17.62
DR	Pre-heating period: 0600 - 0800 h		
	Switch-off period: 0800 - 0900 h		
DR	Pre-heating period: 0500 - 0800 h	7.48	21.11
Interruption	Switch-off period: 1200 - 1500 h		
ESO	Switch-off time: 1900 h		
	Pre-heating period: 0600 - 0800 h	18.82	19.25
	Switch-off period: 1300 - 1500 h		
	Switch-off time: 2000 h		
Linear-up		15.29	17.42
Step –up		21.49	24.35
5 period Division		25.31	28.52
ESO: **Early Switch Off, DR: Demand Reduction, ASOO: Alternate Switch On/Off**			

In most buildings the HVAC system is operated using primitive static control algorithms, based on fixed work schedules causing wasted energy during periods of low occupancy[40]. The Technical University of Catalonia adapted their heating system to the buildings schedule, shutting down the heating system during unoccupied hours. A management model for specific periods of non-classroom time in the heating season was also established along with specified heated zones during out of hours. The implementation of this management system resulted in a 40% reduction in gas consumption[7].

The alternate switch on/off method was employed by Guillermo Escrivá *et al.* at the Polytechnic University of Valencia[8]. They found that pre-heating during off-peak electricity prices, switching off at midday and switching off in advance of the evening to be the most efficient strategies[8]. Simple energy saving techniques were also found to provide reductions of up to 40% through reduction of temperature set-point by one degree, while savings could also be achieved by ensuring windows were closed[41].

Myo Sun Kim *et al.* also used on/off control in an intermittently occupied university building[9]. They found that heating consumption could be reduced by 25% during semester months while maintaining thermal comfort and reducing energy consumption[9]. Studies have found that the input of real-time occupancy information can reduce HVAC energy consumption by 10–20%[42,43]. Aggressive duty cycling is a HVAC scheduling strategy that is similar to the ASOO method, though on/off switching is done based to the current occupancy using the on-line sensor detection instead of pre-programmed on/off switching[40]. Besides the use of PIRs real - time occupancy detection has been used using Wi-Fi connection[44,45], wireless sensor networks[46,47], RFID and bluetooth[48,49].

Agarwal *et al.* used real-time occupancy information from occupancy nodes to inform energy management systems. This approach saved between 7.95 and 12.85% of thermal energy on one floor of a four floor building[40].

A multi-agent comfort and energy system was proposed by Klein et al. that coordinate both building system devices and building occupants through direct changes to occupant meeting schedules using multi-objective Markov Decision Problems[50]. A three-story university building including offices, classrooms, and conference rooms was used as a test bed[50]. The floor was divided into 33 rooms and 17 thermal zones based on the actual zoning of Variable Air Volume (VAV) boxes in the HVAC system. HVAC, lighting, and appliance agents along with VAV boxes, and temperature sensors that monitor and control the temperature and ventilation were selected as agents for energy optimisation in this study[50]. The data collected from these building agents were used to simulate three distinct control strategies, Baseline, Reactive and Proactive with Markov Decision Problem[50]. This approach resulted 12% reduction in energy consumption and a 5% improvement in occupant comfort[50].

Wi-Fi connections were used as a proxy for human activity on the Massachusetts Institute of Technology's campus to help inform energy management[51]. It was found that there is a poor correlation between temperature regulation and room usage[51]. The use of Wi-Fi activity could be used to create more accurate usage patterns. This approach could serve to help identify more energy efficient solutions for heating, cooling and lighting[51]. Corry et al have used semantic web technologies in a university setting as an indicator for a buildings use[52]. BMS information along with classroom scheduling where combined to help highlight time periods in which the HVAC system could be turned off. Social media was also used to gain knowledge on occupants comfort levels with students encouraged to tweet there comfort level[52]. It was found that students are only likely to tweet there comfort level in rooms where they feel too hot r too cold[52]. The combination of data sources such as room schedule, BMS schedule, Wi-Fi activity and social media can provide an extra layer of understanding of a buildings use and its occupants comfort.

2.8 Thermal Comfort

The overall aim of heating, cooling and air conditioning systems is to provide occupants with comfortable and healthy indoor living environments. Studies have shown that quality indoor environments significantly influence the occurrence of communicable respiratory illnesses, allergy and asthma symptoms, sick building symptoms, and worker performance[53].

Thermal comfort is about human satisfaction with their thermal environment. Theories of human body heat exchange with their thermal environment were developed by Fanger. Fanger stated that the human body strives towards thermal equilibrium[54]. He proposed the following formula:

$$S = M \pm W \pm R \pm C \pm K - E - RES \qquad \text{Equation 13}$$

Where;

S = Heat Storage

M = Metabolism

W = External work

R = Heat exchange by radiation

C = Heat exchange by convection

K = Heat exchange by conduction

E= Heat loss by evaporation

Res = Heat exchange by respiration (sensible and latent heat gain)

In order to predict appropriate thermal comfort conditions for this system, an index called a Predicted Mean Vote (PMV) is used. This indicates mean the thermal sensation vote on a standard scale for a large group of people, is used. Table 9 shows comfort vote units based on ASHRAE, Bedford, HSI (Heat Stress Index= the ratio of demand for sweat evaporation to capacity of evaporation (E_{req}/E_{max}), and zone of thermal comfort classification.

Table 9: Comfort vote units based on ASHRAE, Bedford, HSI (Heat Stress Index= the ratio of demand for sweat evaporation to capacity of evaporation (Ereq/Emax), and zone of thermal comfort classification.

Vote	ASHRAE	Bedford	HSI	Zone of thermal Zone
9				In compensable heat
8	Hot (+3)	Much too hot	40-60	

7	Warm (+2)	Too hot	20	Sweat evaporation
6	Slightly warm (+1)	Comfortably warm		Compensable
5	Neutral (0)	Comfortable	0	Vasometer compensable
4	Slightly cool (-1)	Comfortably cool		Shivering compensable
3	Cool (-2)	Too cool		
2	Cold (-3)	Much too cold		
1				In compensable cold

Fanger also introduced the importance of clothing resistance in predicting thermal comfort. This parameter is expressed as clo, and it ranges from 0 (for a nude body) to 3 or 4 (for a heavy clothing suitable for polar regions). 1 clo = 0.155 °C/W. He also stated that air temperature and radiant are two of the most important parameters when assessing thermal comfort[54]. Steady state climate chamber studies have resulted in standards such as ISO 7730- 1984 and AHRAE 55 being produced[55,56]. Table 10 below shows recommended temperatures and clo values for people at sedentary activity.

Table 10: Recommended temperatures and clo values for people at sedentary activity[54,55].

Standard	**Season**	**Clothing insulation (clo)**	**Activity level (met)**	**Optimum operative temp (°C)**	**Operative temp range (°C)**
ISO	Winter	1.0	1.2	22	20 – 24
	Summer	0.5	1.2	24.5	23 - 26
ASHRAE	Winter	0.9	1.2	22	2—23.5
	Summer	0.5	1.2	24.5	23-26

De Dear and Brager *et al.* conducted a filed study showing that the PMV prediction fitted closely with buildings that are centrally conditioned, though it is not applicable with naturally ventilated buildings[57]. This lead Ashrae to develop a separate standard for these conditions. Comprehensive reviews on thermal comfort are availble[54,58,59].

2.8 Estimating building energy requirements

2.8.1 Heating Degree Day

The degree-day method is the simplest method used in Heating, Ventilating and Air-Conditioning industries to estimate heating and cooling energy requirements[60]**.** Weather variations from year to year can have a significant effect on the energy demand of a country and in particular the energy demand associated with space heating. Although computers can simply calculate energy demand in finer detail, as will be discussed in section 1.7, heating degree days can provide a simple estimate of annual loads. This can be accurate if the indoor temperature and internal gains are relatively constant and if the heating or cooling systems operate for a complete season.

The number of heating degrees in a day is defined as the difference between a reference indoor value and the average outside temperature for that day. Due to obvious fluctuation in the outside temperature, the arithmetic mean of the high and low temperatures for the day is usually computed.

A degree-day is an expression of how cold or warm it is outside, relative to a day on which little or no heating would be required. A base indoor temperature is chosen with which heating degree days are calculated. For schools and classrooms 18.5˚C is generally used as the base temperature. This is due to the fact that classrooms operate at a temperature of around 22˚C. This value takes into account the internal heat gains from people, equipment and lighting etc. to achieve the desired temperature. If the air temperature outside is below 18.5˚C, then heating is required to maintain a temperature of about 22˚C.If the temperature was 10 degrees below 18.5 ˚C this would account for 10 degree days in the monthly/annual total. Heating degree days can be expressed using the following formula.

$$HDD = \sum_{t_{start}}^{t_{end}} \left(T_{HDD_{base}} - T_{out}\right) \qquad \text{Equation 14}$$

HDD = degree-days for heating

$T_{HDDbase}$ = the base indoor temperature for the considered heating period (°C)

T_{out} = mean daily ambient temperature (°C)

The heating season in Ireland generally runs from October to May. This can be seen on the degree days over the last three years in Dublin as shown in Figure 9. With heating degree days significantly reduced from June through to September. Figure 9 shows the significant variation in heating degree days from year to year and thus the variation in heating demand year on year.

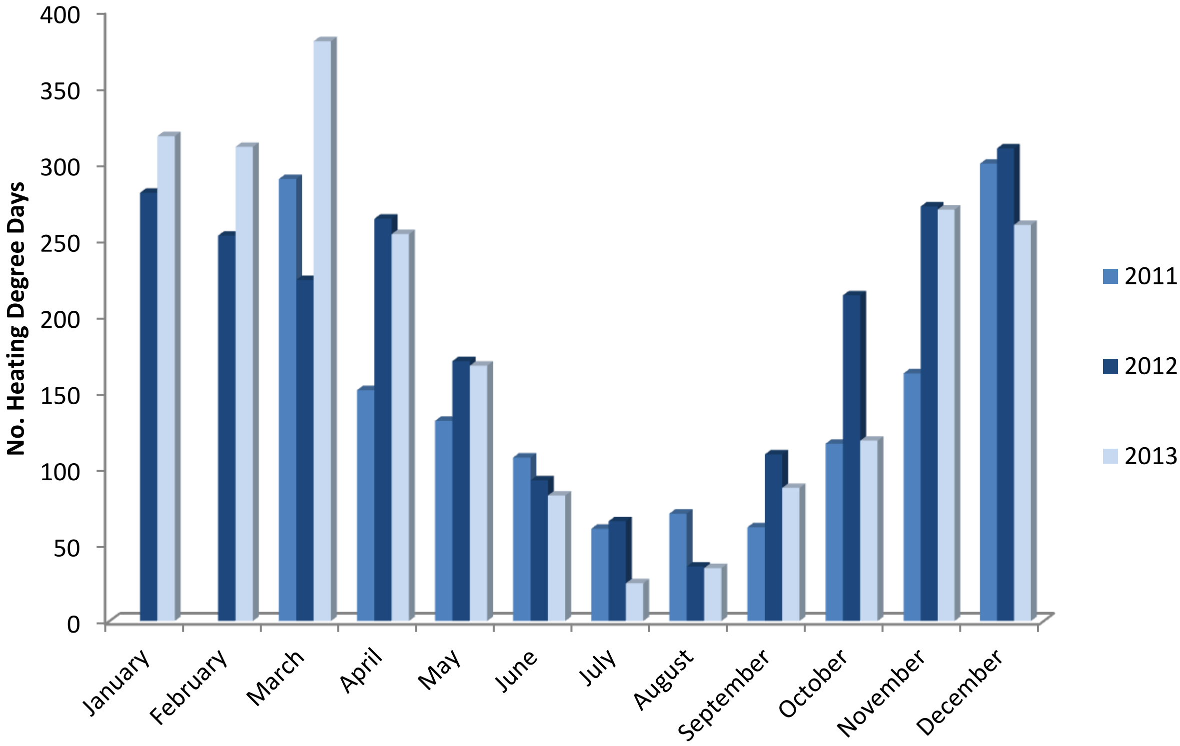


Figure 9: Number of heating degree days in Dublin over the past 3 years[60].

In most commercial buildings, energy consumption of different temperature intervals and time periods are evaluated separately using a bin method. This is due to the pronounced occupancy pattern in commercial buildings which affect heat gain, indoor temperature and ventilation rate. Occupancy has a pronounced pattern which affects heat gain, indoor temperature, and ventilation rate[20]. Consumption is calculated for several values of the outdoor temperature and multiplied by the number of hours *Nbin* in the temperature interval (bin) cantered around that temperature[20].

This can be calculated using the following

$$Q_{bin} = N_{bin} \frac{K_{tot}}{\eta_h} [t_{bal} - t_o]^{+} \qquad \text{Equation 15}$$

Q_{bin} = Heat loss

N_{bin} = number of hours

K_{tot} = Total heat loss coefficient

η_h = efficiency of HVAC system

t_{bal} = balance point temperature

t_o = outdoor temperature

The superscript plus sign indicates that only positive values are counted; no heating is needed when t_o is above t_{bal}. The Equation is evaluated for each bin, and the total consumption is the sum of the Q_{bin} over all bins.

When the indoor temperature is allowed to fluctuate, or when interior gains vary, simple steady-state models should not be used. Dynamic methods for energy estimation will be discussed in following sections.

The correlation between predicted and actual degree days for Ireland from 1961 – 1990 is shown in figure 10[61]. The winter month October shows the highest correlation. R values represent the correlation between observed station values and values predicted by the spatial models employed to predict monthly accumulated degree days[61]. Degree days were calculated on a daily basis for three selected threshold temperatures, 0°C, 5°C, 10°C, in order to provide a more accurate assessment of the accumulated monthly energy available at 50 stations[61].

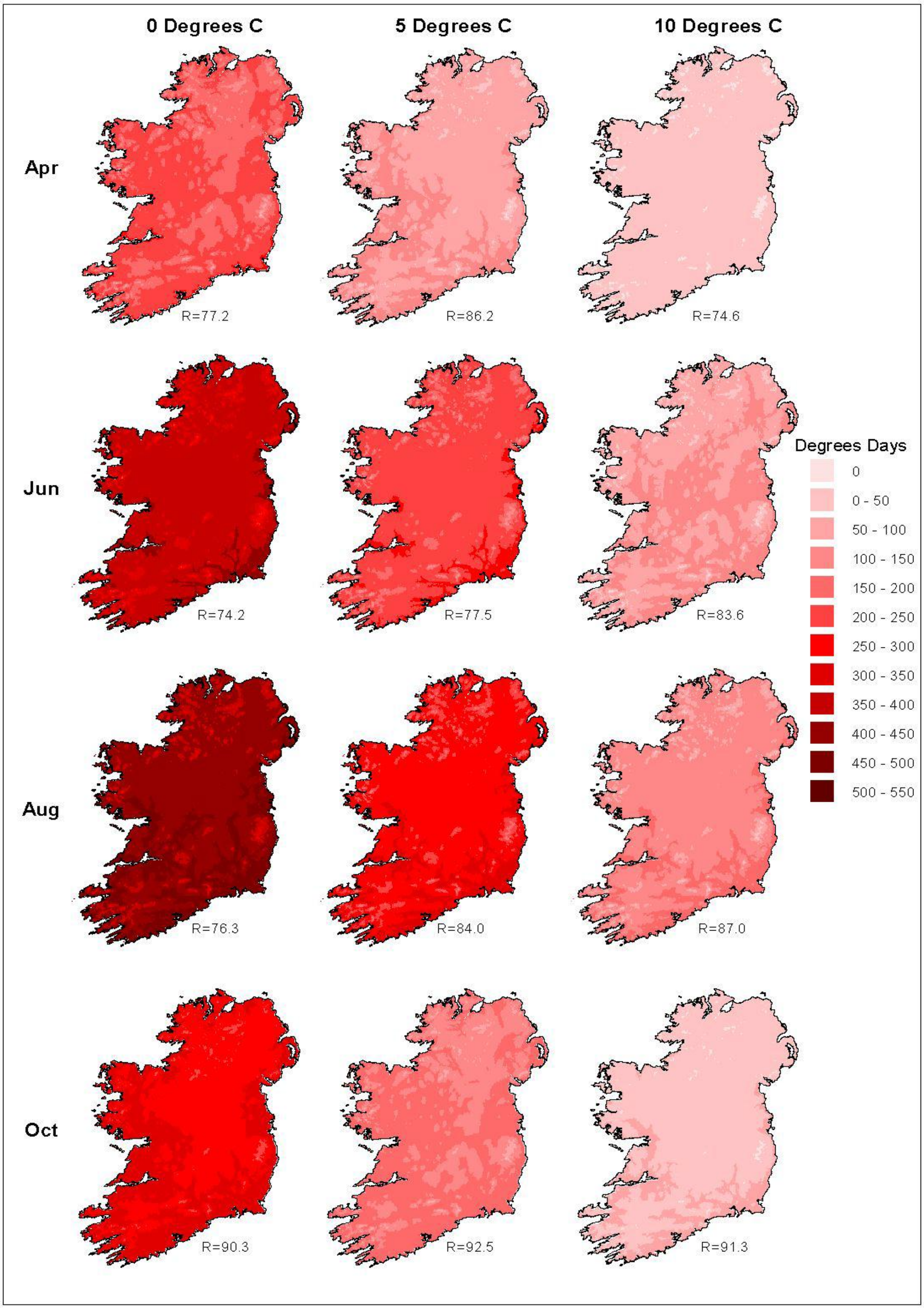


Figure 10: The spatial variation in degree days derived from locational attributes from 1961 to 1990[61].

2.8.2 Energy auditing

Energy audits of buildings are the most effective tool to promote energy retrofitting measures for existing buildings[62]. Energy audits have multiple goals, including reducing energy consumption, managing costs, and environmental impact[63]. Figure 11 shows the general process of a best practice energy audit.

Figure 11: Energy auditing process.

1) First or foremost is ensuring that there is buy in and commitment from senior management, this is vital in ensuring that there is an enthusiasm to reduce cost within the organisation along with the backing of resources to implement the energy management plan[63]. 2) The second step is to identify potential areas where energy usage may be reduced within the organisation. This is achieved through developing an overview of total energy usage within the building. Identifying the key energy users within the building as well as analysing the key factors that influence energy usage within the building[63]. The culmination of this information will allow for the identification of areas in which energy may be saved. 3) Once energy saving measures

have been identified it is then important to set objectives and targets for each measure identified. It is important to establish a formal programme plan with allocation of human, financial and system resources[63]. 4) Step 4 in implementing a best practice energy management plan is to take action and implement your programme plan. This includes the promotion of energy efficiency awareness and practices amongst employees, the training of key personnel in energy efficiency practices and the efficient operation, maintained and purchasing of significant energy users. 5) Continuously measure and monitor energy performance against targets, review energy plan against targets and identify and implement and corrective actions. A management review of the whole process is important for commitment to implement further energy saving measures in the future[63].

2.8.3 Building modelling

Thermal models of buildings are often used to identify energy savings within a building. Given that a significant proportion of that energy is typically used to maintain building temperature, establishing optimal control of the buildings thermal system is important. This requires an understanding of the thermal dynamics and heat flows of the building as discussed in previous sections. Physical thermal models are often used to understand the thermal dynamics of the building, though these models require detailed building parameters to be specified, which are often difficult to determine

One of the main challenges for intelligent buildings is to give comfort to its occupants and to increase the user's performance at a low cost. The excessive demand of electric energy due to HVAC systems require temperature forecast and control to make maximum reduction of the electrical energy.

Energy use in buildings is influenced by a wide number of variables and data sources, making prediction of energy consumption in buildings a difficult task. Table 11 shows the parameters that effect buildings energy consumption.

Table 11: Influential factors in determining buildings energy consumption

Influencing Factor	Example
Climate	Outdoor air temp, solar radiation, wind velocity/direction
User related characteristics	User presence
Building related characteristics	Area, orientation, type
Building operation	Space cooling/heating
Occupant behaviour and activities	Turn on/off lights
Social and economic factors	Cost of energy, awareness of occupants to energy saving
Indoor environment	Thermal comfort, air quality, lighting

Due to the range of parameters involved in forecasting a buildings energy performance, modelling of these attributes has proved useful in predicting energy use.

The 2005 ASHRAE 2005 defines two approaches for energy modelling.

Forward (classical) approach: This approach is ideal during preliminary design and analysis. In this approach the equations describing the physical behaviour of systems and their inputs are known and the objective is to predict the output. Accuracy increases as models become more complex and as detailed information on the building is known. The main advantage of this approach is that the system need not be physically built to predict its behaviour. Major government-developed simulation codes, such as BLAST, DOE-2, and Energy Plus, are based on forward simulation models[20].

Data-driven approach: Using this approach input and output variables governing the performance of the systems have been measured. The known data is used to define a mathematical description of the system. The data can be non-intrusive or intrusive. The intrusive data refers to data gathered under controlled experiments. When operation of the building limits the implementation of controlled experiments, non-intrusive data is gathered from normal operation. In contrast to the forward approach, the data-driven approach is relevant when the system has already been built and actual performance data are available for model development and/or identification[20]. Disadvantages of dynamic data-driven models include their complexity and the need for more detailed measurements to tune the model[20].

Both the Forward and Data driven approaches can either be steady state or data driven. Steady-state models do not consider the transient effect of variables that are used for analysis in time steps equal or greater than 1 day[20]. Dynamic models are able to track peak loads and are useful to capture thermal effects such as those obtained from setback thermostat strategies[20].

The data driven approach can be broken up into three categories:

Black Box: The black box approach uses simple or multivariate regression to find relationships between different building outputs and inputs[64].

Calibrated Simulation: This approach uses an existing building simulation computer program and calibrates the various physical inputs to the program so that observed energy use matches closely with that predicted by the simulation program[64]. The main challenges of calibrated simulation are that it is labour intensive, requires a high level of user skill and knowledge in both simulation and practical building operation, is time-consuming and often depends on the person doing the calibration[20].

Grey Box: This approach first formulates a physical model to represent the structure or physical configuration of the building or HVAC&R equipment or system. It then identifies important parameters representative of certain key and aggregated physical parameters and characteristics by statistical analysis[20]. This requires a high level of user expertise both in setting up the appropriate modelling equations and in estimating these parameters[20]. Often an intrusive experimental protocol is necessary for proper parameter estimation, which also requires skill[20]. This approach has great potential, especially for fault detection and diagnosis, but its applicability to whole-building energy use is limited[20].

2.8.3 Physical Models

Physical models use mathematical formulas that are based on the physical behaviour of heat transfer. These models tend to be more robust leading to greater model predictions. Physical models require elaborate experiment, thus it is not suited to large buildings in obtaining representative values of indoor fluctuations. Physical models contain three main approaches; Computational Fluid Dynamics, Zonal approach and the Multi-zonal approach

Computational Fluid Dynamics (CFD)

CFD is widely used due to its ability to produce detailed descriptions of the different flows inside a building. CFD models are predominantly based on Naiver-Stokes equations which are used to describe the motion of fluid.

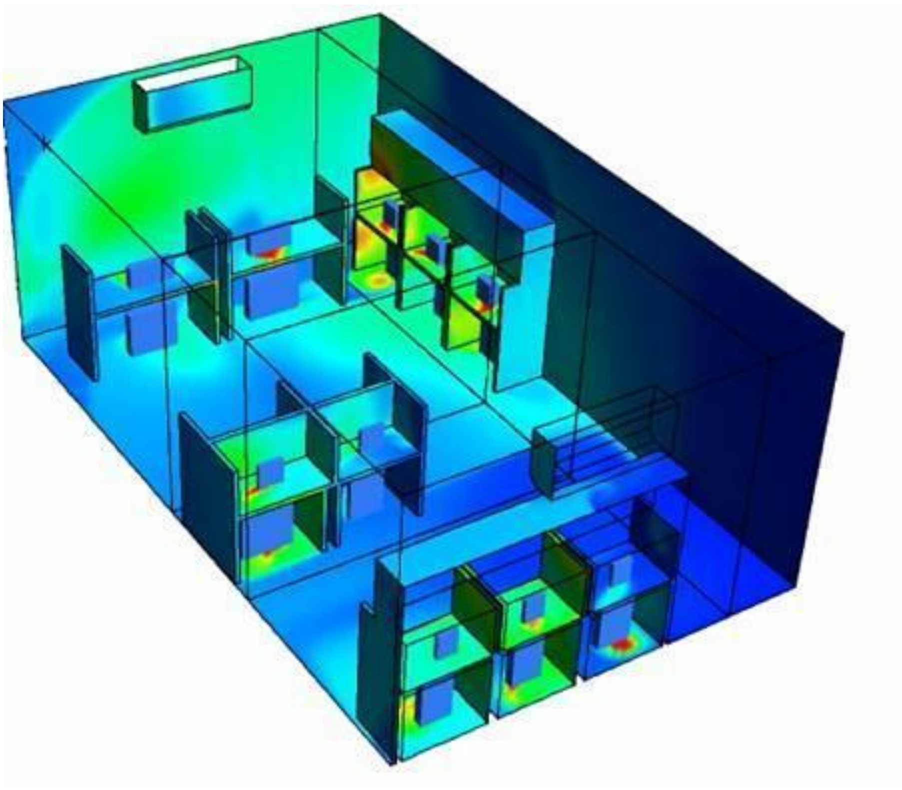


Figure 12: CFD predicts and graphically illustrates the complete 3D airflow patterns as well as

temperature and pressure distributions within a building[65.]

Stamou *et al.* successfully used CFD to assess the thermal comfort of spectators in the Gelatsi indoor arena[66]. CFD was used in a lecture hall to simulate the indoor comfort parameters such as temperature, airflow rate and relative humidity to assess the thermal comfort[66].

Due to the huge computational time involved with CFD, the technique has begun to be coupled with energy simulation software. Tan and Glicksman showed that CFD simulation on its own would take over 10 hours longer when predicting natural ventilation[67]. Zhai *et al.* also used CFD with energy simulation to calculate the cooling load of a large-scale indoor auto-racing complex[68].

CFD has the ability to predict the dynamic indoor environment conditions. When incorporated with energy simulation it can provide more accurate estimation of building energy consumption and dynamic thermal behaviours of building envelopes. Figure 11 shows the airflow, temperature and pressure patterns within a building[65]

Zonal approach

The Zonal approach is a simplification of the CFD approach. This method involves dividing a building into cells, with each cell representing a small part of a room. This approach is used to detail the indoor environment and estimate a zones thermal comfort[69].

Musy *et al.* created a zonal model of convective air flow to agree within 1°C of measurements using SPARK object-oriented simulation environment of a room with a radiative heater[70]. SPARK is widely used in zonal analysis and solves the set of equations resulting from a constructed model to obtain the air flow and temperature distribution in the building[71]. Inard *et al.* predicted the distribution of air temperature inside a room with the zonal approach, and were able to further predict the energy heat losses and energy consumption[72]. As with the CFD approach, this approach requires previous knowledge of the flow profiles, while it is limited on the study of pollutant transport[73].

Table 12: Comparison of physical modelling techniques.

Physical technique	Application field	Advantages	Drawbacks
CFD method	Contaminant distribution; Indoor air quality; HVAC systems	Detailed description of the fluid flows occurring inside the building; Large volume zones	Huge computation time; Complexity of the model implementation
Zonal method	Indoor thermal comfort; Artificial and natural ventilation	Spatial and time distribution of local state variables (temperature, concentration, pressure, airflow) in a large volume	Large computation time Requirement of a detailed description of the flow field and flow profiles
Nodal method	Determination of the total energy consumption/the average of the indoor temperature/the cooling or heating load; Time evolution of the global energy consumption/the space-averaged indoor temperature	Multiple zone buildings; Reasonable computation time; Easier implementation	Difficulty to study large volume systems Unable to study local effects as heat or pollutant source

2.8.8 Building performance simulation programs

Building performance simulation programs use detailed building characteristics along with weather data to simulate building energy performance. The Building Energy tools Directory gives a comprehensive list of whole building energy programs and their applications[74]. Nguyen *et al.* carried out a study on the utilisation of 20 of the major simulation programmes used in optimisation studies during the period of 2000 -2013[75]. Energy Plus and TRNSY were both found to be the dominant programs used, as seen in figure 12. This is believed to be due to their text-based format of inputs and outputs, which facilitates the coupling with optimization algorithms and of course, their strong capabilities. While GenOpt and MatLab environment optimization were found to be the mostly-used tools in building optimization

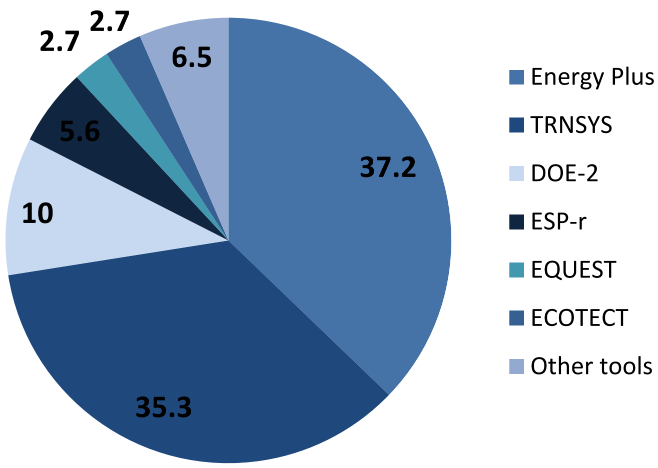


Figure 13: Popular energy simulation software[72].

2.8.9 Statistical

Statistical methods do not require physical information about the building or system as with the physical methods such as CFD and Zonal as described above. They also do not require heat transfer equations. They generally use large amounts of metered data to generate a statistically significant model. The main statistical methods for modelling building energy consumption will be discussed.

Regression

Regression equations can be used for predicting indoor air temperature, relative humidity and energy consumption in an easier and more rapid way than building energy simulation tools.

The principle of the linear multivariate regression is to predict Y as a linear combination of the input variables(X_1,X_2,…,Xp) plus an error term ϵi. equation

$$y_i = \alpha_0 + \alpha_1 . x_{i1} + \alpha_2 . x_{i2} + \cdots + \alpha_p . x_{ip} + \epsilon_i \quad i\epsilon[1, n] \qquad Equaiton\ 16$$

n is the number of sample data, p the number of variables and α_0 a bias. For example, if the predicted output is the internal temperature, inputs such as the external temperature, the humidity, the solar radiation and the lighting equipment can be used.

Multiple linear regression or conditional demand analysis is a simple technique ideal for beginners, as specific expertise is not required. This method does require a large amount of data for sufficient predictions. The major limitation of multiple linear regressions though, is its inability to deal with non-linear problems.

Linear regression has been used in prediction and forecasting of energy consumption, indoor air conditions and system management[76-79]. Regression analysis has been primarily used to predict building energy consumption from environmental data or building physical data[79]

Regression analysis has also been shown to be useful in the prediction of heating demand. Catalania et el found the building global heat loss coefficient, the south equivalent surface and the difference between the indoor set point temperature and the sol-air temperature to be the most influential factors determining heat consumption in buildings[80]. Givoni *et al.* have showed that it is possible to predict indoor air temperature using only outdoor average, minimal and maximal temperatures in residential buildings in Brazil[81,82].

Regression has been shown to be extremely useful tool in building energy prediction and forecasting, though its non-flexibility does make it unsuitable for some building applications. This is illustrated by Aydinalp-Koksal *et al.*, whereby the CDA method was shown to predict energy consumption in the residential sector as well as engineered and neural network methods. Though the introduction of socio-economic factors highlighted these method limitations due to the number of variables that can be accommodated[83].

Artificial Neural networks

Artificial neural networks are one solution to dealing with non-linear problems. Once trained, they can perform predictions and generalisations at high speed. Artificial neural networks have been developed as generalizations of mathematical models of biological nervous systems.

The neural network technique utilizes a simplified mathematical model based on the densely interconnected parallel structure of biological neural networks. The technique allows all end-uses to affect one another through a series of parallel “neurons”[84]. Each neuron has a bias term and array of coefficients that are multiplied by the value of the preceding layer's neurons. Similar to regression models, it seeks to minimize error and may apply scaling and activation functions to account for non-linearity[84]. As it is a parallel model, the coefficients have no physical significance[84].

Artificial neural networks have been shown to successfully predict the energy consumption of both residential and commercial buildings[85]. Artificial neural networks have been used to predict hourly building consumption using inputs such as temperature, the current load and the hour and the day as inputs[86-90]. They have also proven to be useful in the optimisation and control of HVAC systems[91,92].

Ruano *et al.* used climate and environmental data from a secondary school located in the south of Portugal to generate long-range predictive models for air-conditioning systems resulting in energy savings[93].

Neural networks have also been employed in assessing thermal comfort. Liu *et al.* used air temperature, air velocity, humidity and mean radiation temperature to create a neural network that can adapt air conditioning to individual thermal comfort[94]. The time of day was shown to affect the indoor temperature in a non-linear manner by Soleimani-Mohseni *et al.*[95]. A comprehensive review of the use of artificial neural networks in building modelling and prediction was carried out by Kumar *et al.*[84].

Figure 13 shows the flows of a neural network

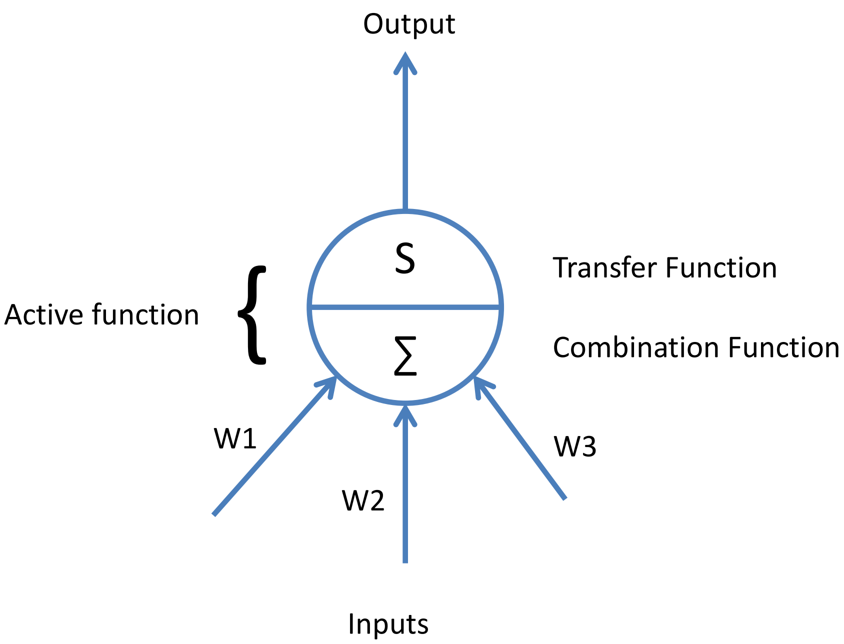


Figure 14: Typical flow of a neural network.

Support Vector Machine (SVM)

SVM is a novel type of machine learning, gaining popularity due to its many attractive features and promising empirical performance. The main advantage of SVM is that it adopts the structure risk minimization principle, which has been shown to be superior to the traditional empirical risk minimization principle employed by conventional neural networks[96]. Structure risk minimization seeks to minimize an upper bound of the generalization error consisting of the sum of the training error and a confidence level, which is different from commonly used empirical risk minimization principles that only minimize the training error[97]. This method has been proven to be very effective for addressing general purpose classification and regression problems. The basic idea of SVM for regression is to introduce a kernel function, map the input space into a high-dimensional feature space via a nonlinear mapping and to perform a linear regression in this feature space[73]. SVM has been successfully employed to predict building cooling loads and energy use[96-98].

Decision tree

Decision tress competitive advantage over other widely used modelling techniques, such as regression method and the ANN method, lies in the ability to generate accurate predictive models with interpretable flowchart-like tree structures that enable users to quickly extract useful information.

Another advantage of this methodology is that it can be utilized by users without requiring much computation knowledge. Geoffrey *et al.* found decision tree model, with its simpler structure, more accurate than artificial neural networks and stepwise regression. They found that flat size, number of members in the household, and ownership of air-conditioning to be significant factors in all three models[99].

Yang Gao *et al.* used the decision tree to predict comfort levels in a university based on the HVAC system performance and external environmental conditions. They found that external heat gains from sunlight, wind impacts and external temperatures strongly influence internal comfort conditions[100]. Figure 14 shows a decision tree based on whether residents turn on/off room air conditioners (RAC) during cooling season. They demonstrated that the use of decision tree method can classify and predict building energy demand levels accurately reporting 92% accuracy for test data[101]. Decision tree analysis and a balanced three-phase system where also used to schedule events in classrooms with minimum energy consumption[102].

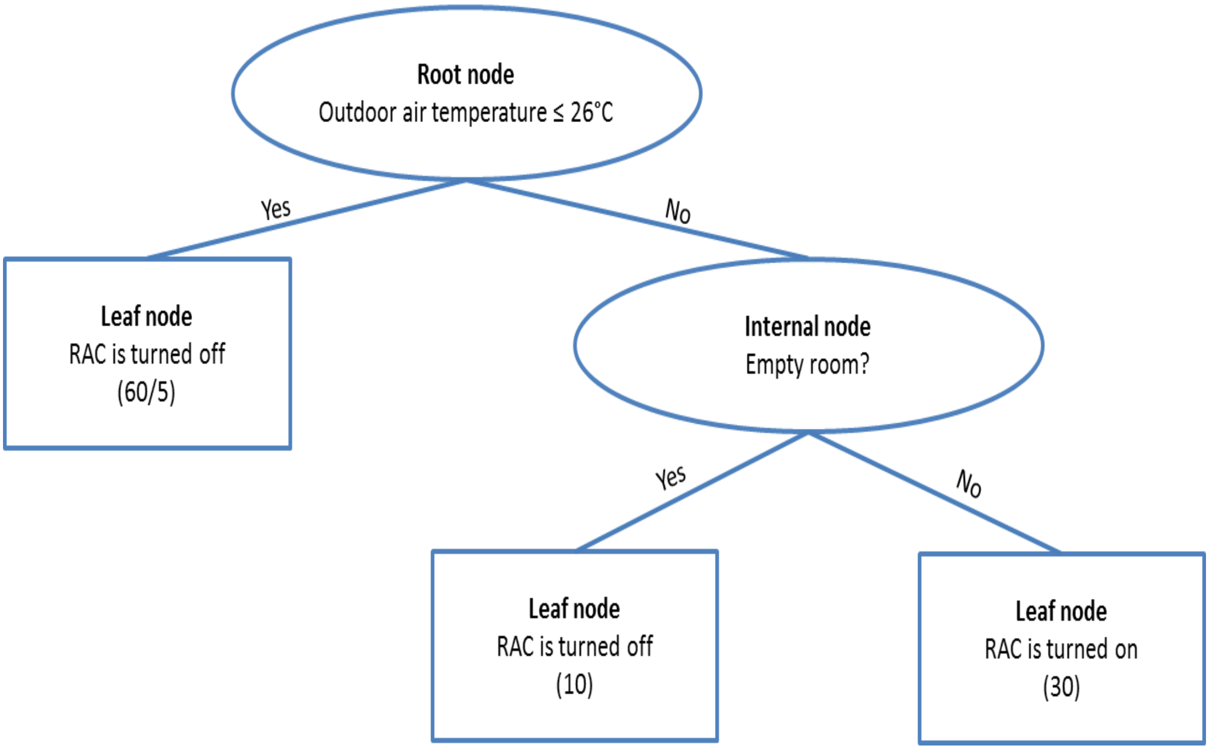


Figure 15: Schematic of a decision tree model.

Cluster analysis

Clustering analysis is conducted in such a manner that objects with similar characteristics are grouped within the same cluster[103]. The similarities between any pairs of observations are normally evaluated using distance-based metrics, such as the Manhattan and Euclidean metrics[104]. Clustering analysis aims to maximize observation similarities within the same cluster and minimize similarities between different clusters. Cluster analysis has long played an important role in a wide variety of fields including biology, statistics, pattern recognition, information retrieval, machine learning and data mining[104]. In the field of energy, cluster analysis has been applied to classify energy performance of buildings instead of equal frequency rating methods[105] [106] . Figure 15 shows an example of a bivariate example of cluster analysis.

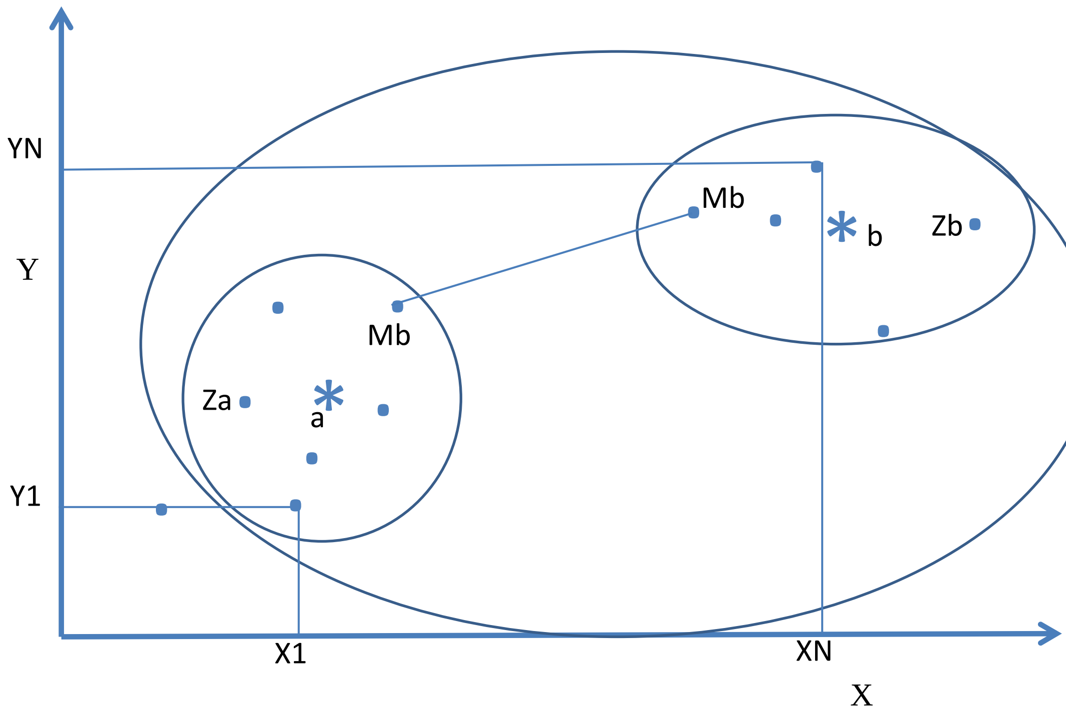


Figure 16: Graphical presentation of cluster analysis for a bivariate example

Cluster analysis was used to create a classification tool to evaluate the heating in 1100 school buildings in Greece[105]. Using the following variables; heated surface (m^2), age of the building, insulation of the building, number of classrooms, number of students, school's operating hours per day, age of the heating system[105]. They were able to define 5 energy classes based on oil consumption to help inform decision makers using k-means clustering[105]. Results have also shown the efficiency of clustering technology in the analysis of time series data such as load curves. Using historical data, the total accumulated energy at the end of the day, as well as the maximum peak demand of the day may be predicted[107]. The applications of fuzzy clustering techniques were applied to 10 schools in Athens. This resulted in energy saving for the heating load of between 36 and 72%, while the energy saving for the cooling load varied between 60 and 78% [108].

Chapter 3

Study sites and methods

3.1 Description of University

Dublin City University (DCU) was established in 1980 and currently caters for over 10,000 students across a 72 acre campus on the north side of Dublin (53.3850° N, 6.2565° W). The University comprises of four faculties

- Science and Health,
- Computing and Engineering,
- Social Sciences and Humanities
- Business School.

The university year is run over two semesters each comprising of twelve weeks each, the details of which are shown in table 13.

Table 13: Details of DCU location, structure and operating hours

Established	**1980**
Location	Glasnevin, Dulbin 9, Ireland
Co-ordinates	53.3850° N, 6.2565° W
Number of students	11,762
Size of campus	72 acres
Faculties	4
Semester 1	12 weeks - 30/09/13 – 21/12/13
Reading week	4/11/13 -8/11/13*
Lecture hours	9.00 – 18.00 Mon-Fri
***reading week is applicable to Social Sciences and Business**	

3.2 Description of Study sites

The science building situated to the east of the campus was chosen as the test bed for this study. It is currently the biggest energy user on the university campus, due mainly to the energy intensive laboratory equipment in use in the building. The building is comprised of teaching and research laboratories, academic offices and classrooms and has been given a D building energy rating or 635 kWh/m^2/year

Two classrooms with differing characteristics where chosen for this study, illustrated in figures 16 and 17. Classroom A and B were chosen as two typical types of lecture room throughout the campus. Both rooms have an occupancy capacity of 40 students and cater for 38 and 33 hours of lectures respectively during a typical week. As can been seen in figure 16 classroom A has large south facing windows which dominate the rear of the classroom, whereas classroom B has no source of natural lighting. Solar heat gains can be a significant contributor to a buildings heat gains, especially during autumn and winter months when the sun lies lower in the sky meaning heat can permeate further into a room. The heating of both classrooms is supplied through radiators which are part of a hydronic heating system which is fed by a gas fired boiler. There is an Air Handling Unit (AHU) in both classrooms which provide fresh air. This can air can also be heated through a battery reheat system. This system is also fed through the boiler. The characteristics of the two rooms are displayed in table 14.

Table 14: Comparison of characteristics of classroom A and B

Classroom A		**Classroom B**
Science Building DCU	**Location**	Science Building DCU
53.3850° N, 6.2565° W	**Orientation**	53.3850° N, 6.2565° W
88.4	**Floor area (m^2)**	64.75
262.98	**Volume**	259
40	**Occupancy Capacity**	40
38	**Timetable hours**	33

Figure 17: Classroom A used in study with a diameter of 5.6m and floor area of 88.4m^2

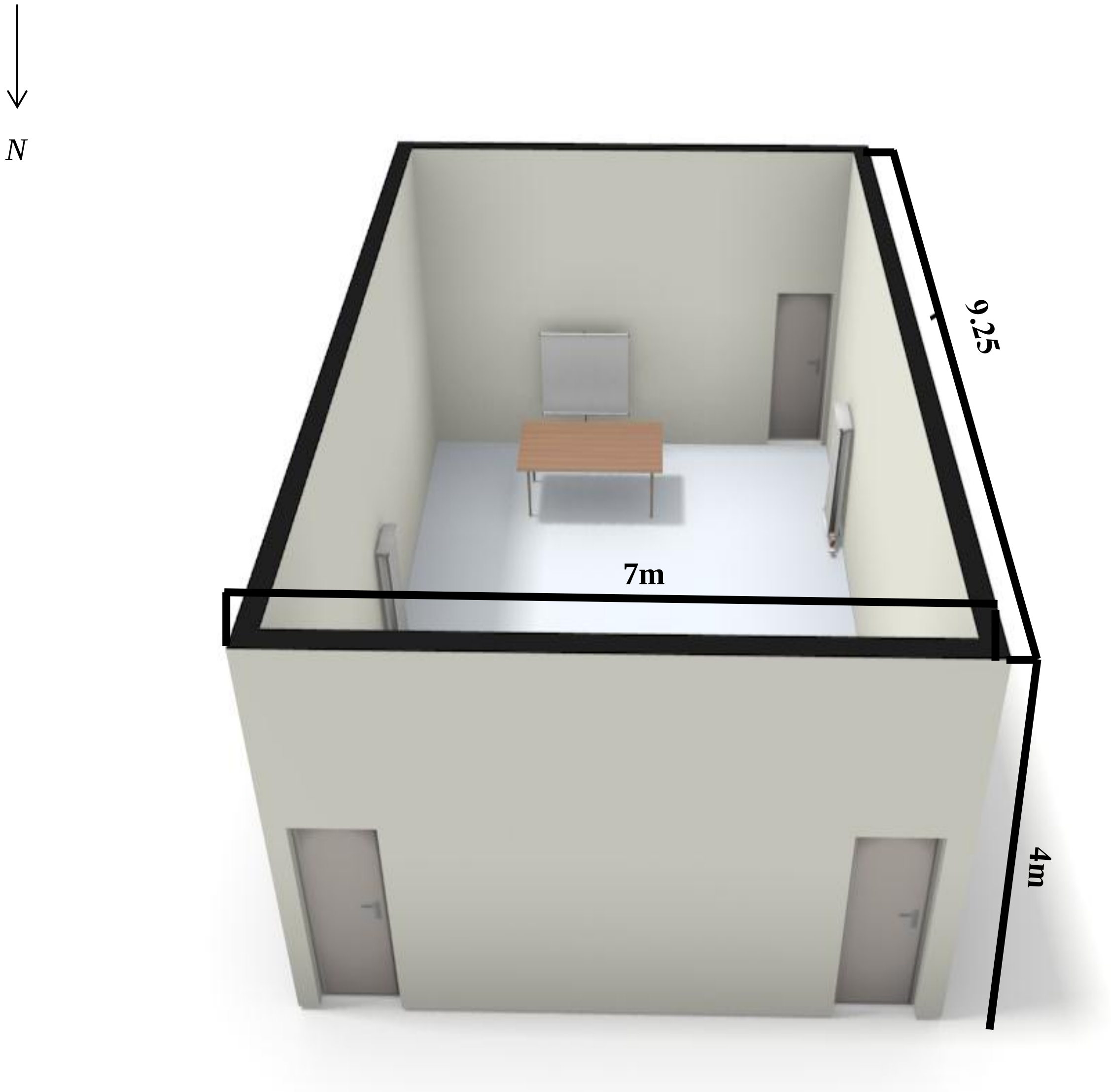


Figure 18: Classroom B with a height of 4m, width of 7m and a length of 8m with a floor area of 64.75m^2.

3.3 Heat loss potential

The heat loss coefficient from both classrooms was evaluated, using U-value for materials within the classrooms, along with heat loss through ventilation. Data for Outdoor temperature (T_o) was obtained from the iButton placed outside the science building. This was calculated using equation 1 and 5. This information is displayed in table 15. Classroom A and B have heat loss coefficients of 9.96 and 13.78 W/°C/m^2 respectively.

Table 15: Heat loss through Floors, walls, windows, doors ceilings and ventilation in both test classrooms.

Classroom A				Classroom B		
Area (m^2)	***U value***	***W/°C***		***W/°C***	***Area (m^2)***	***U value***
88.24	*0.9*	*79.4*	***Floor***	58.27	64.75	0.9
68.18	*1.6*	*109.1*	***Walls***	198.4	124	1.6
19.4	*2.9*	*56.26*	***Windows***	0	0	2.9
11.66	*1.6*	*18.65*	***Doors***	9.6	6	1.6
88.24	*3*	*264.72*	***Ceiling***	194.25	64.75	3
		350.64	***Ventilation***	345.33		
		879.11	***Total(W/°C)***	892.28		
		9.96	***Heat loss W/°C/m^2***	**13.78**		

3.4 Description of heating Schedules

Classrooms within the science building and throughout the campus in general are thermally controlled on a set schedule. Classrooms within the school of sciences are run on a heating schedule of 08.00 – 22.00 and an air handling unit (AHU) schedule of 08.00 – 17.00 Monday – Friday.

3.5 Occupancy of classrooms

A semester week has 45 available lecture hours. Due to the variability in occupancy in university classrooms, maximum capacity is generally rarely achieved during a typical day in a university setting. Figure 18 shows the percentage of occupancy hours allocated during a semester for classroom A. On average, classroom A is scheduled for lectures for 70% of the available time. Taken that there is a total of 45 available lecture hours during the week, this equates to 31.5 hours being allocated during a typical week, with 13.5 unoccupied or 162 hours over the course of a twelve week semester. This equates to 3.6 lecture weeks, nearly a third of semester heating costs. Though the incorporation of heating and cooling rates would have to be considered, there is considerable scope to tailor the heating schedule to incorporate timetable information which could result in significant financial savings for the university. Some faculties within the university incorporate a reading week into their semester. This sees a reduction in occupancy to 55%, weeks such as these could represent a significant opportunity for energy saving.

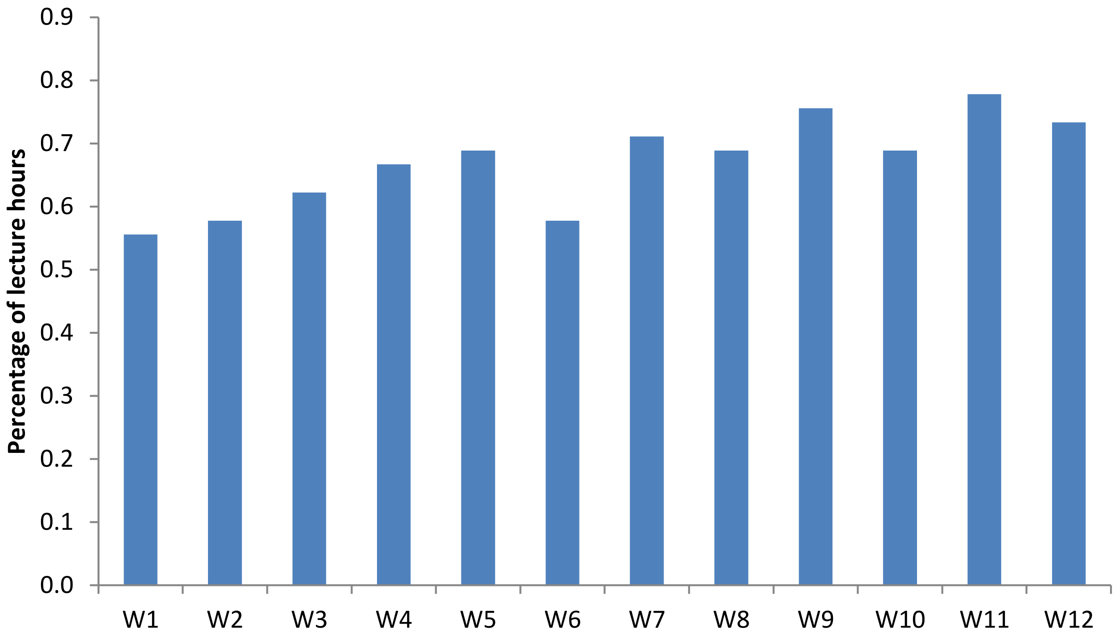


Figure 19: Percentage of available lecture hours allocated to the timetable in classroom A.

Figure 19 breaks down the 12 semester weeks shown in figure 2.3 into percentage of total occupancy per day. Thursdays operate at 90% – 100% capacity during the semester, meaning that there is 1 available hour to switch heating system off during the respective days.. In classroom A Mondays, Wednesdays and Fridays operate at only approximately 50% throughout the semester. When the timetable schedule is analysed, classroom A is only scheduled until lunch time for lectures on Wednesdays and Fridays. With the heating schedule turned off at 17.00 on a Friday for the weekend this could represent an opportunity to reduce heating dependency for the room by 4 hours per week or 36 hours per semester. Wednesday afternoons also provide an opportunity for similar energy reduction with lectures ending at 13.00 meaning that with the AHU is kept on for 4 unnecessary hour along with 8 additional hours of space heating. Wednesdays and Fridays immediately provide incentive to incorporate timetable information into a universities energy policy. With the other two days in the week requiring further investigation into the viability of intermittently heating the classroom during the 30% of time it is unoccupied.

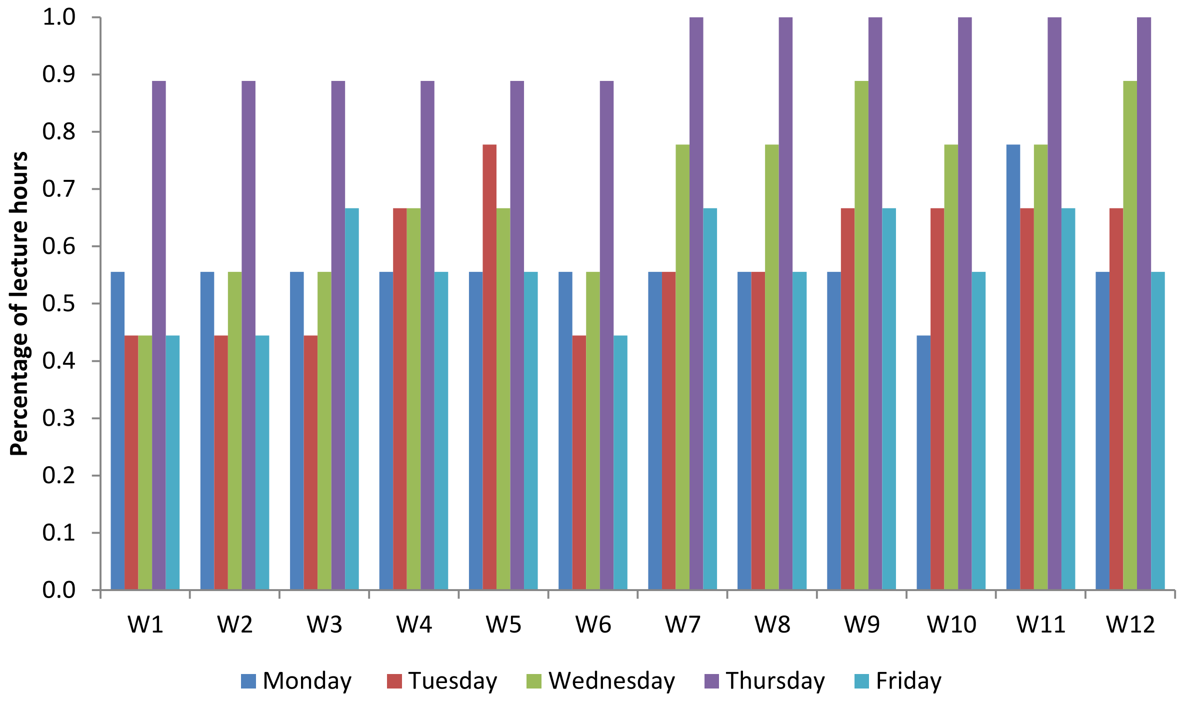


Figure 20: Weekly breakdown of occupancy percentages per week in a semester for classroom A.

Figures 20 and 21 profile the occupancy patterns for classroom B. As with classroom A the average occupancy throughout the semester is 70% with again a big drop off in timetabled lectures during reading week, week 6. This once again illustrates the opportunity to save over 3 weeks in heating energy.

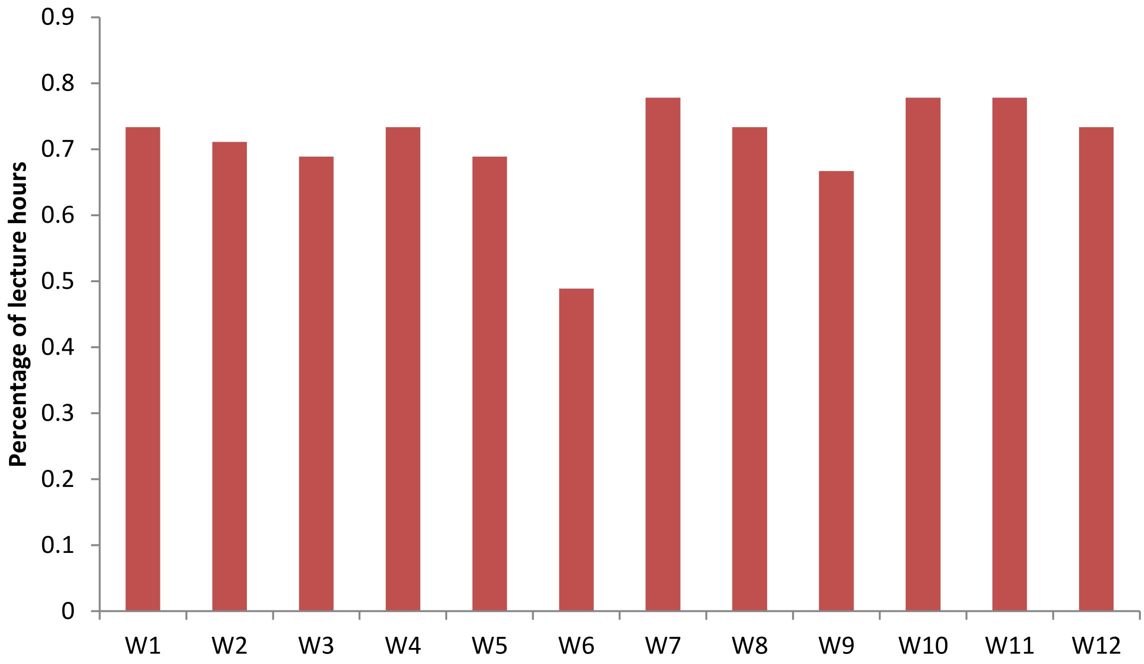


Figure 21: Percentage of available lectures hours that are timetabled for in classroom B

As with classroom A, Wednesdays and Fridays are generally operating at 50% of their total lecture hours, again providing an opportunity for early shut down of the heating system. Wednesday afternoons in the university are generally allocated for extra-curricular and society time. The increase in occupancy on a Wednesday in the last few weeks of society is due to use by the games society which, in itself brings extra internal heat through large flat screens and game consoles. These in themselves will generate extra heat within the room with each flat screen and console contributing a conservative 145 W[20].

The two classrooms both display areas in which incorporation of timetabled information could reduce energy usage within the university. An energy saving reduction strategy that could be applicable campus wide is the lunchtime finish of lectures on a Wednesday and Friday. This could be investigated and incorporated into current heating schedules across the campus.

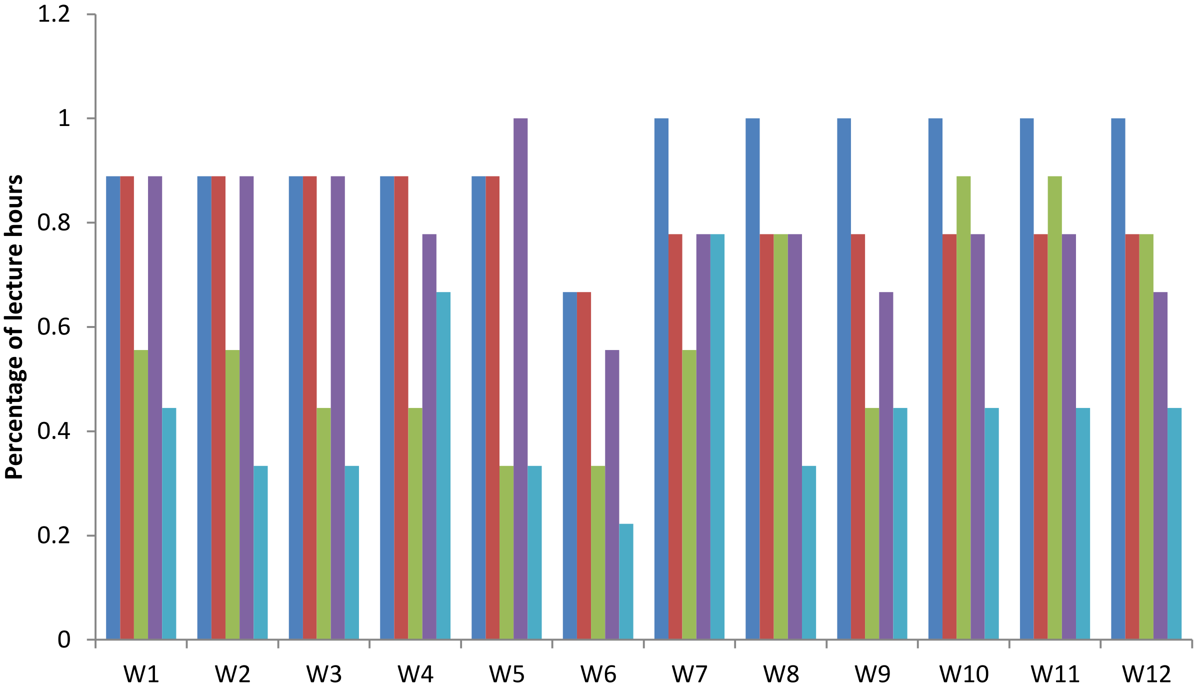


Figure 22: Weekly breakdown of occupancy percentages per week in a semester for classroom B

3.6 Description of sensor

The Thermochron iButton from radionics was used as the temperature sensor for the study. It is a small, low cost standalone data logger that has entered the market over the last ten years. Initially developed in the cargo industry for monitoring temperature sensitive shipments, its use has become widespread in ecological, physiological and environmental studies.

The iButton is 17.35 mm in diameter, 3.3g in weight with a temperature range of -40^{0}C - +140^{0}C. It has an accuracy of ±1^{0}C and a resolution of 0.5^{0}C [109]. The Thermochron is powered by a non-replaceable lithium battery that will last for up to 10 years or 1 million readings. The small size of the logger can be seen in figure 1(a) along with the disassembled logger in figure 1(b).

(a) (b)

Figure 23: iButton parts, from left to right, top to bottom: DS1923 can (bottom), DS1922L can (bottom), DS1923 board+battery (top view), DS1922L board+battery (bottom view).

The Thermochron iButton is based on two technologies, a computer chip enclosed in a stainless-steel can (called an iButton) and a communications protocol (called 1-Wire). The iButton is a standalone instrument with a battery and protective housing. Each can has a data contact, called the 'lid' and a ground contact called the 'base'. Each of these contacts is connected to the silicon chip inside. It is composed of a temperature sensor, a clock and a memory [110]. The Thermochron uses a DS18S20 temperature sensing integrated circuit to measure temperature. This sensing element is a band gap circuit, which outputs a differential voltage proportional to temperature; this employs two diodes operating at different currents to derive temperature. Differential voltage is less prone to process variations compared to single diode [111].

The internal clock measures seconds to years accurately to within ± 1 min per month.The 1-Wire protocol is used to command the iButton and to retrieve data that is stored on the computer chip inside. The 1-Wire interface has two communication speeds: standard mode at 16kbps, and overdrive mode at 142kbps.

The Thermochron can be programmed to record temperature readings at a desired interval from 1 min to 255 min and can record between 2048 and 8192 data points depending on the model [110]. It can also be programmed to activate at a specified time to begin recording. The temperatures can later be retrieved along with the time of each reading.. Every iButton is unique in that it has an address stamped on the face of the can. Once it is programmed it will run for 10 years or 1 million readings and without any external connections.

3.7 iButton Calibration

iButtons were calibrated at a room temperature of 21°C using a water bath and NIST certified thermometer from a pH meter. Though water resistant, iButtons were sealed with Vaseline and placed in the water bath for 20 minutes at 21°C. iButtons have a stated accuracy of ±1°C. All 24 iButtons fell within this stated accuracy. 70% of the iButtons on average fell within 0.1° C. With all iButtons falling within a range of ±0.5°C. This is also in agreement with literature Hubbart et al showed that all 61 iButtons fell within the stated manufacturer accuracy. Figure 23 shows the temperature distribution of the 24 calibrated iButtons.

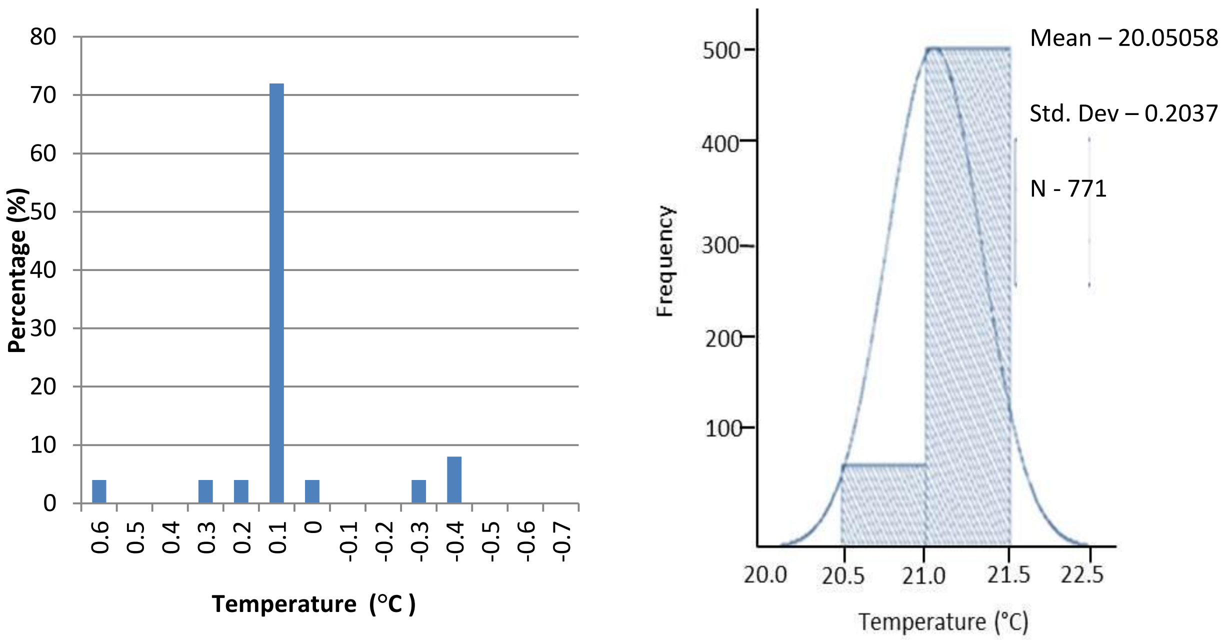


Figure 24: Temperature frequencies as recorded by 24 iButtons at 21°C.

3.8 Deployment

The iButtons were deployed as depicted in figure 4.3 and 4.4. The sensors were deployed at a height of 1, 2 and 3 metre at locations; Front Right (FR), Front Left (FL), Back Right (BR) Back Left (BL) and Building Management Sensor (BMS). A sensor was also deployed at 3 metres in the centre of the room, with another placed beside the existing estate temperature sensor. iButtons were deployed using a string, strung from the ceiling to the floor and placed at the desired height. A number of deployments were made during the year under varying conditions as previously mentioned to gain a good understanding of the thermal characteristics of the room.

The experiments were carried out as follows

1. Period of no heating and no lectures scheduled; ;
2. Period with heating and no lectures scheduled;
3. Period with heating and lectures scheduled.

iButtons were set to record at 10 minute intervals during all of the above deployments

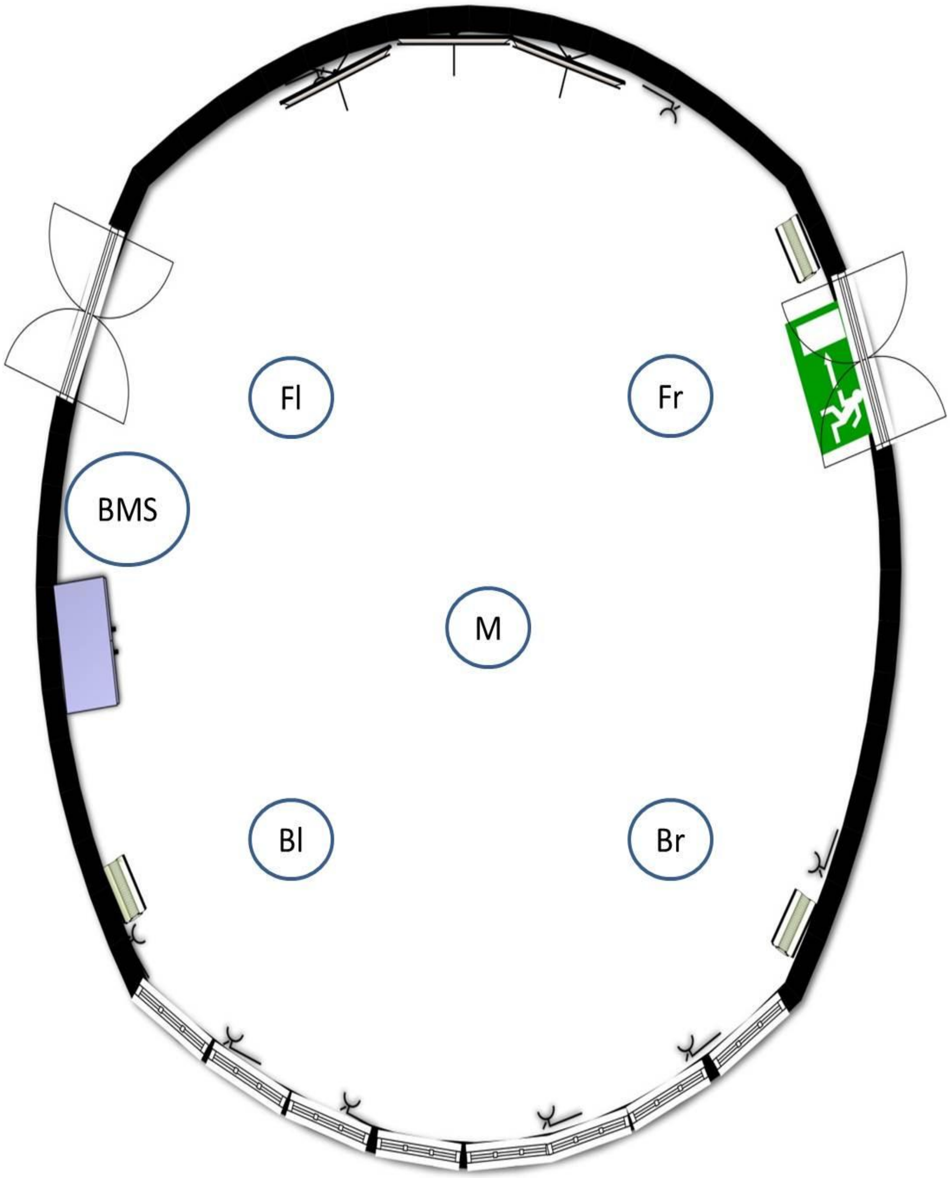


Figure 25: Floor plan of classroom A along with deployment locations of iButtons, Front left (Fl) Front Right (Fr), Middle (M), Black Left (Bl). Back Right (Br) and existing BMS location.

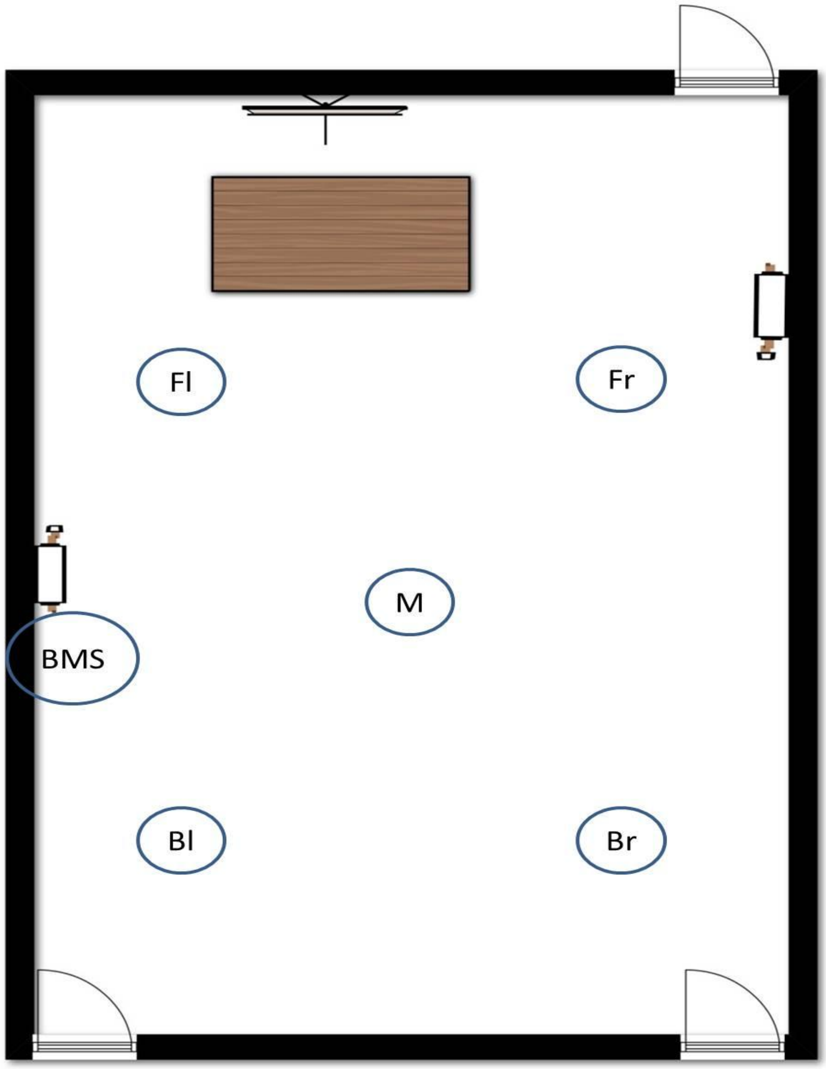


Figure 26: Floor plan of classroom B along with deployment locations of iButtons, Front left (Fl) Front Right (Fr), Middle (M), Black Left (Bl). Back Right (Br) and existing BMS location.

3.9 Occupancy Detection

In order to obtain real time of occupancy within the classrooms and the effect of class size on the thermal environment the scanning of Bluetooth as a proxy for human activity was investigated. Studies have found that the input of real-time occupancy information can reduce HVAC energy consumption by 10–20%[42,43]. Aggressive duty cycling is a HVAC scheduling strategy whereby the on/off switching is done based on the current occupancy using the on-line sensor detection instead of pre-programmed on/off switching[40]. Besides PIR's real - time occupancy detection, information has been derived using the following technologies Wi-Fi connection[44,45], wireless sensor networks[46,47], RFID and Bluetooth[48,49].This work aimed to evaluate the use of Bluetooth to determine occupancy levels within a lecture hall to help inform and create a smarter heating system for the university. Bluetooth has been used to date for crowd mapping at large events and for the tracking of traffic, though it is believed that it has not been employed in the estimation of small static crowds such as in a classroom setting at the time of writing[49].

A mobile computer was used (Dreamplug) with a Bluetooth antenna (SENA Parani UD-100) attached. A Bluetooth scanning program Gyrid was run from 08.00 – 18.00 to capture lecture occupancy levels. Figure 27 shows the mobile computer with antenna and its deployment location with classroom A.

Bluetooth detection was tested using a Sony Xperia P along with a Dell HHP-L-674 laptop to ensure the range of the Bluetooth detection was sufficient. Figure 27 shows the range of the Bluetooth scanning device. The scanner picks up devices that pass by the outside of the classroom, it is thought that that these devices could be easily filtered out as there should be little or no change in occupancy after the commencement of the lecture.

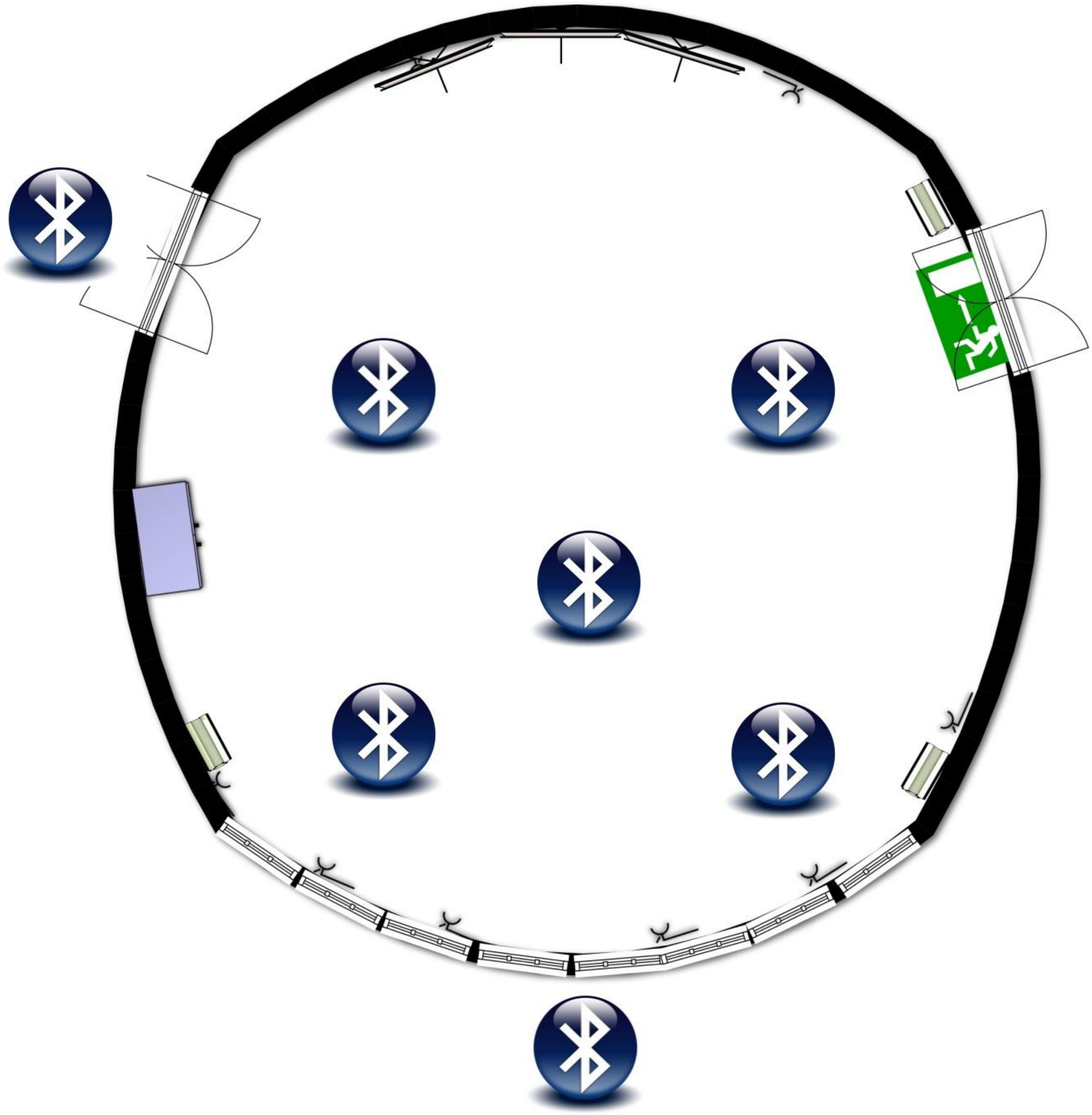


Figure 27: Bluetooth signal test locations in classroom A during semester 1.

Chapter 4

Heating and cooling characteristics of test classrooms

The use of small, cheap off the shelf sensors have been shown to enhance the knowledge of a building in terms of energy management. Painter *et al.* used off the shelf sensors to highlight the importance of calibrating previously installed BMS systems[112]. Scott *et al.*l used iButtons to create a more efficient way to heat homes[113]. The iButtons were used in conjunction with a model to help inform smarter heating systems for homes, with an 11%-21% saving reported across 27 houses[113].

The use of off the shelf sensors such as iButtons allow for a specific room model to be built. An initial temperature study of classroom A was undertaken to evaluate the temperature distribution within the classroom and to evaluate the use of the iButton suitably for use in this study. The study was conducted under different heating periods, the room was analysed during holiday periods when the heating was turned off. The room was analysed for periods during the typical heating schedule where there was no timetabled classes for that week and finally, during a typical timetabled week during semester with the typical heating schedule.

4.1. Heating Degree Day

The degree-day method is the simplest method used in Heating, Ventilating and Air-Conditioning industries to estimate heating and cooling energy requirements[60]**.** Weather variations from year to year can have a significant effect on the energy demand of a country and in particular the energy demand associated with space heating. Heating degree days can provide a simple estimate of annual loads, which can be accurate if the indoor temperature and internal gains are relatively constant and if the heating or cooling systems operate for a complete season.

Figure 28 shows the number of degree days for selected weeks (Mon-Fri) during semester 1 2014. Degree days were calculated using equation 14 with a base temperature of 15.5°C which is used as the base temperature in the university heating system. Temperature data was gathered from an iButton placed outside of the science building. There were a total of 302 heating degree days during the semester with an evident increase toward the end of the semester and the colder winter months.

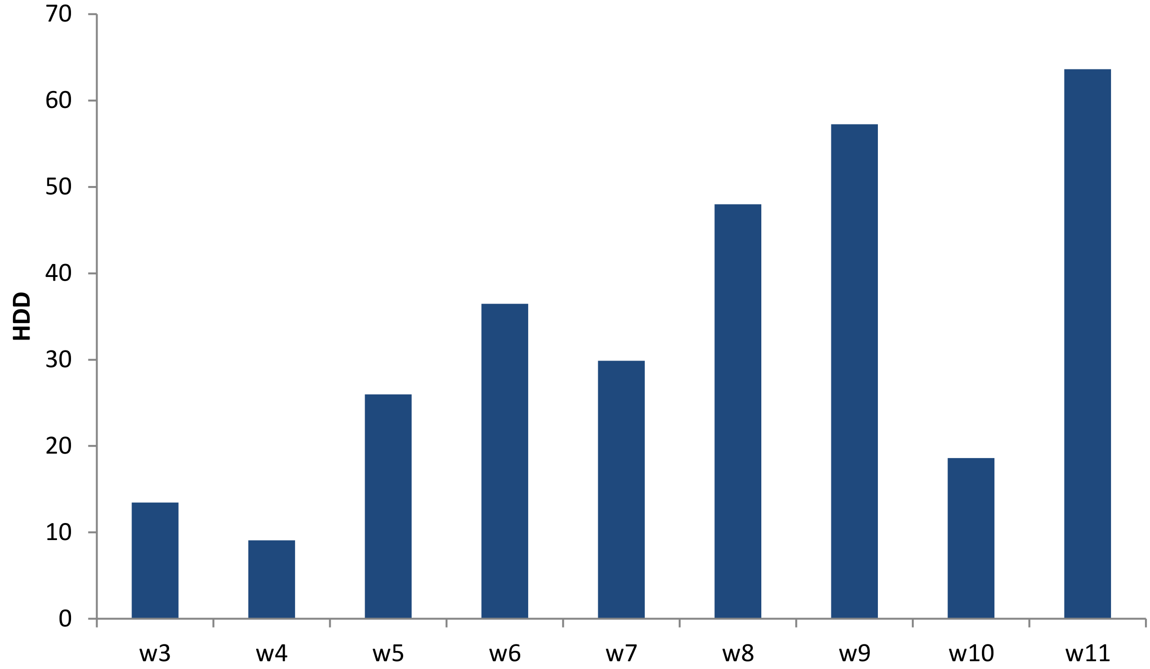


Figure 28: Heating degree days during semester 1.

The projected energy loss of the two studied classrooms over the semester is shown in figure 25. The energy loss for each classroom was calculated for a typical 14 hour day heating period (08.00 -22.00) Monday to Friday. The energy loss in kWh per day was calculated using the heat loss values (W/°C) obtained from table 15 and the calculated heating degree days in figure 28.

$$Energy\ loss = \frac{W/°C \times 14}{1000} \times HDD \div 5 \qquad Equation\ 17$$

Using equation 17 above, the energy demand for each room is displayed in figure 25. As heating demand is closely related to the outdoor temperature, figure 26 follows the same pattern as figure 25. The energy use for both classrooms was calculated to range from 22 kWh/d to 158 kWh/d. The cost of a unit of gas for the university is €0.06. The cost of heating a classroom for the nine weeks shown using the information in figure 26 is €405.

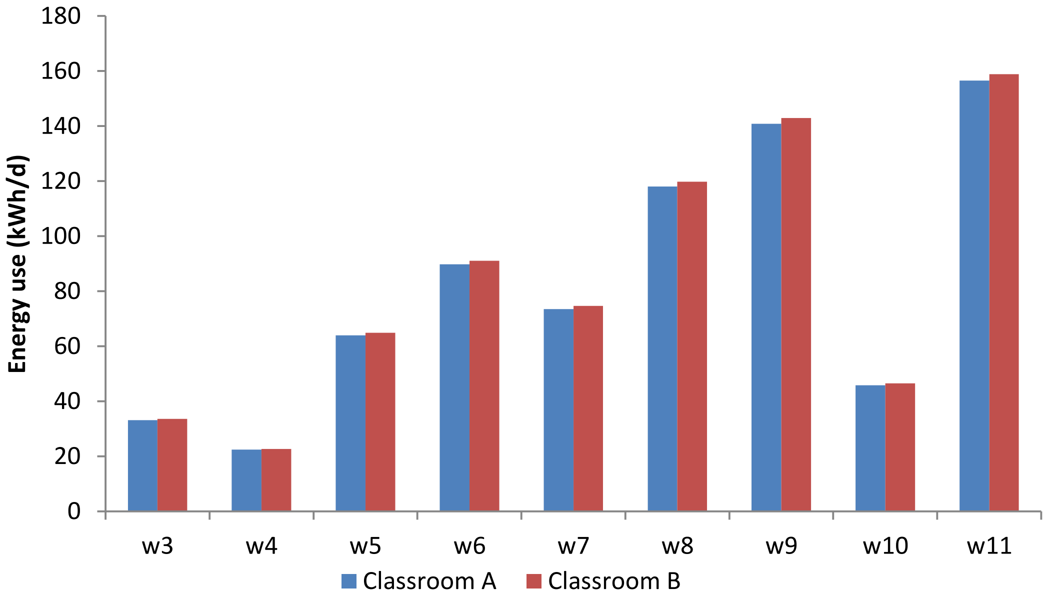


Figure 29: Energy demand of the two studied classroom.

The reduction in set point temperature for a room is one of the easiest and simplest ways to save energy, though in an educational building it is also important to ensure that a comfortable thermal environment is maintained.

Figure 26 shows the prospective energy and financial savings of dropping the set point temperature, above which the room does not require heating to 20°C. The results show that by reducing the temperature by 1 degree, a 11% reduction in energy costs can be achieved this equates to a €92 saving per classroom during the studied semester.

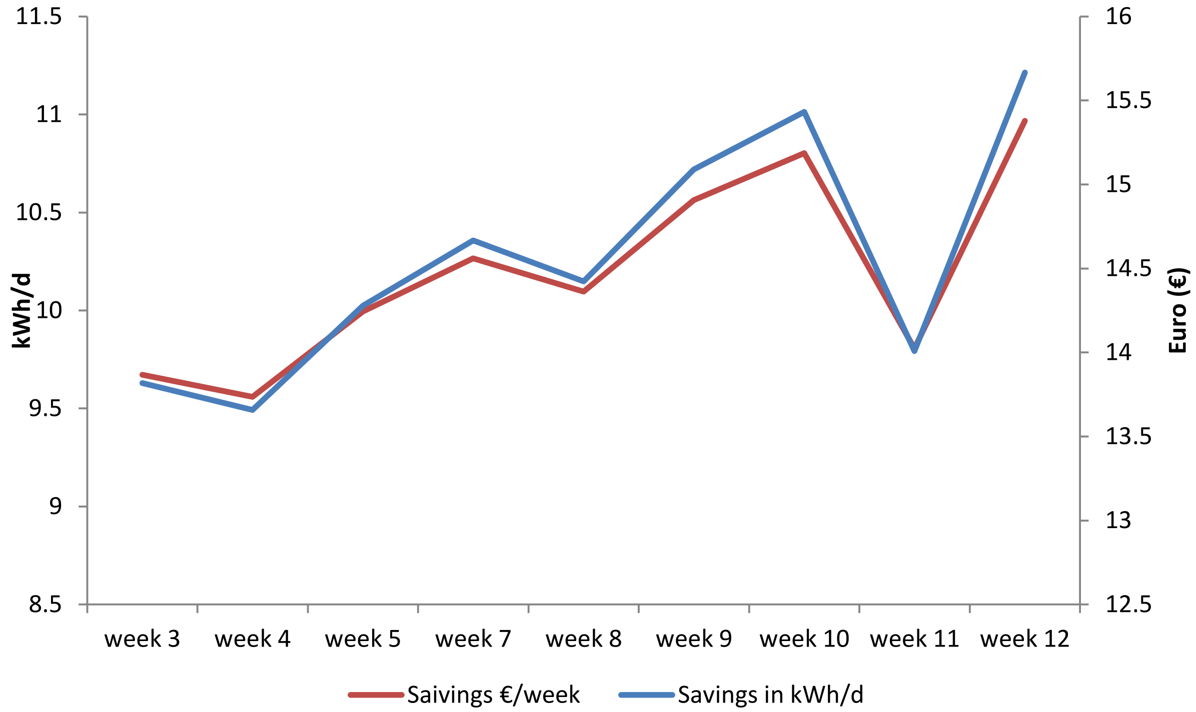


Figure 30: Energy and financial savings by reducing the set point by 1 degree.

4.2 Classroom A

The average temperatures for each location in classroom during each of the 3 conditions in which the iButtons were deployed is shown in figure 29.

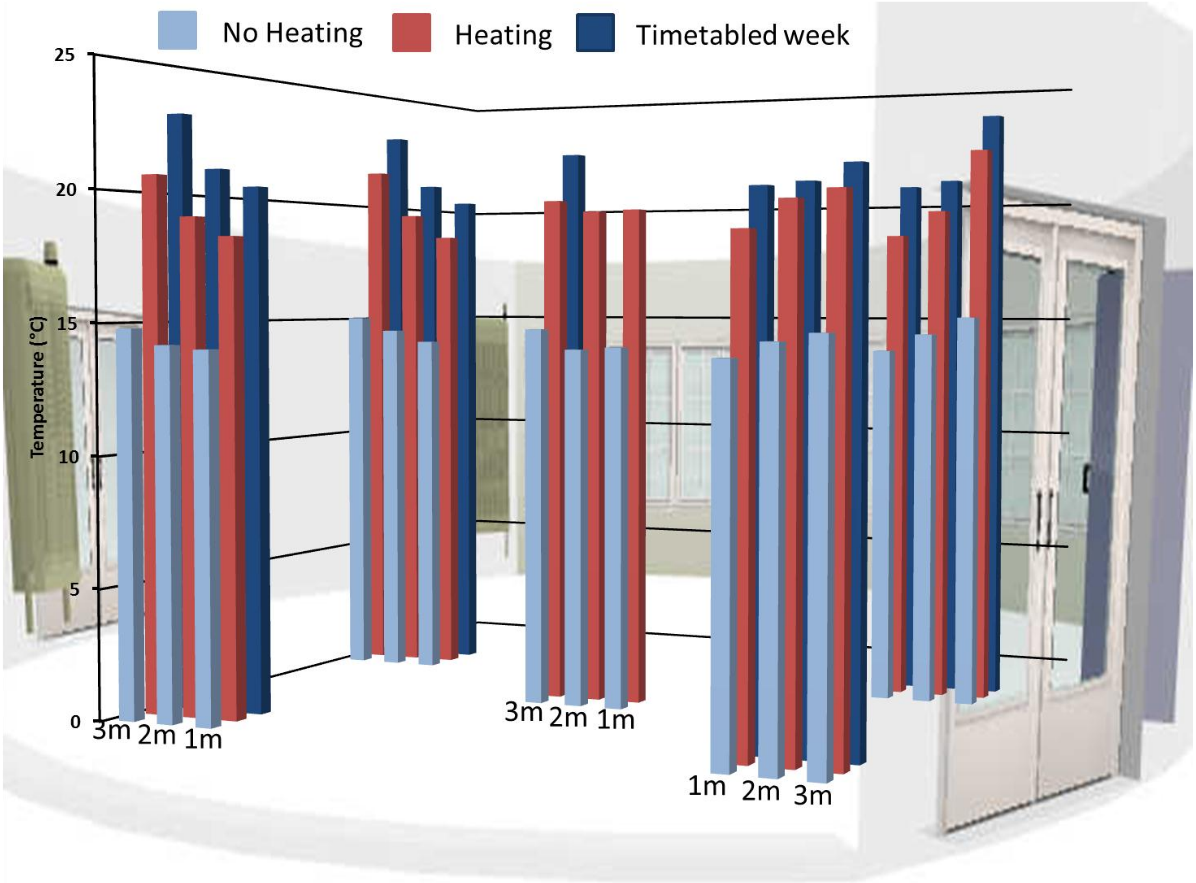


Figure 31: Average weekly temperatures for iButtons at varying heights and conditions.

4.3.1 No Heating

It was found when the heating schedule is off, the average temperature throughout the room is 14.4°C. As heat rises, it was found that there is a small increase in temperature with each height increment. This is seen as a 0.4°C increase on average from 1 metre to 2 metres and 0.5 and a 0.6°C rise from 2 metres to 3 metres.

A significant spike in temperature was found during the middle of day from 12 -2pm approximately. From the deployment it was found that the iButtons placed at the back of the room at a height of 3 metres showed the largest increase in temperature, with temperatures reaching up to 23°C and the middle of the room reaching temperatures up to 21°C. This demonstrates the heating effect of the solar radiation coming in through the large south facing window at the back of the classroom. Figure 32 illustrates the number of sunshine hours for each day along with the number of hours the lecture room spent above 20°C at 3 metres.

Figure 32 shows that sunshine hours influence the temperature in the room. 3 of the 5 days have less than 1 hour of sunshine which is illustrated in the fact that the temperature does not reach above 20° C for longer than an hour on those days. It appears that a duration of 2 or more hours is required to lift the room above 20°C for longer than an hour during the day. The influence of solar radiation is short lived within the room and its affect dissipated after 2 hours. It appears sunshine hours, and not outside temperature is responsible for the rise in indoor temperature. Friday is 3°C warmer than any of the previous 4, though without any sunshine hours, the room fails to rise above 20°C at any time during the day.

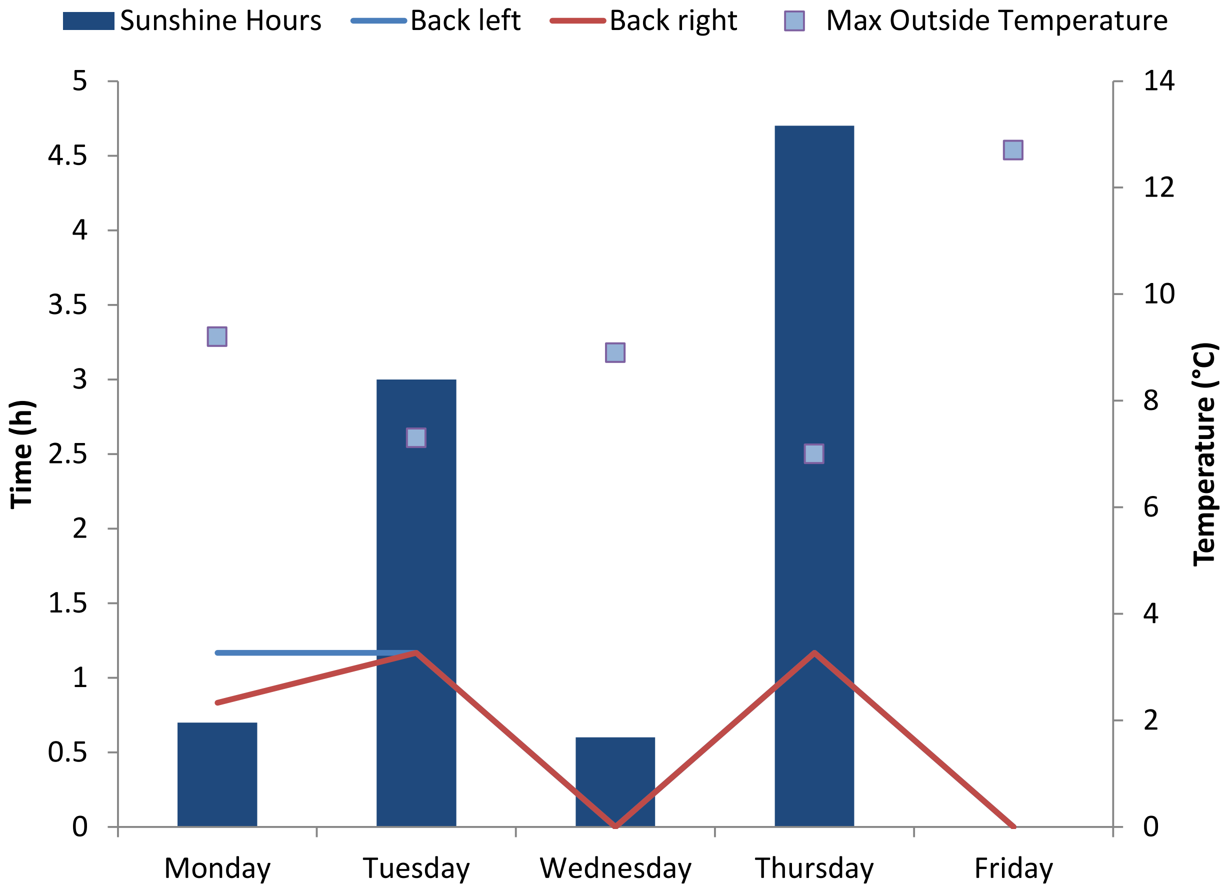


Figure 32: The number of hours the room at 3 metres spent above 20°C.

4.3.2 Period with heating with no lectures scheduled

A study was conducted to investigate the influence of heating within the classroom during a period when no lectures were scheduled. This was conducted during the holiday period at the end of semester 1. As can be seen in figure 31, there is a dramatic increase in temperature when the heating is on. There are four radiators within the room each emitting 52°C. These four point sources account for a 5°C rise in temperature throughout the room on average. The same pattern is observed with a clear step in temperature through each height. A 1°C step from 1metre to 2 metre is witnessed in all locations besides from the middle of the room. This is again evident from 2 to 3 metres with other locations in the room experiencing an increase > 1.5°C. The temperature column in the middle of the room appears to remain constant when compared to the other locations within the room. The front left of the room, which is located beside the entrance to the room, does not follow the trend in temperature rise. This could be due to the air mixing with draught air coming through the door.

The Chartered Institution of Building Services Engineers (CIBSE) environmental design guide recommends comfort temperature as 21°C - 23°C[114]. As with the period of no heating there is a strong heating effect at the back of the room at 3 metres. This is shown in figure 33 which shows the number of hours the room spends over 22°C the upper end of comfort requirements. It is significant in that at least 4 hours a day are spent above this upper requirement, illustrating the benefit of redistribution of this unused heat.

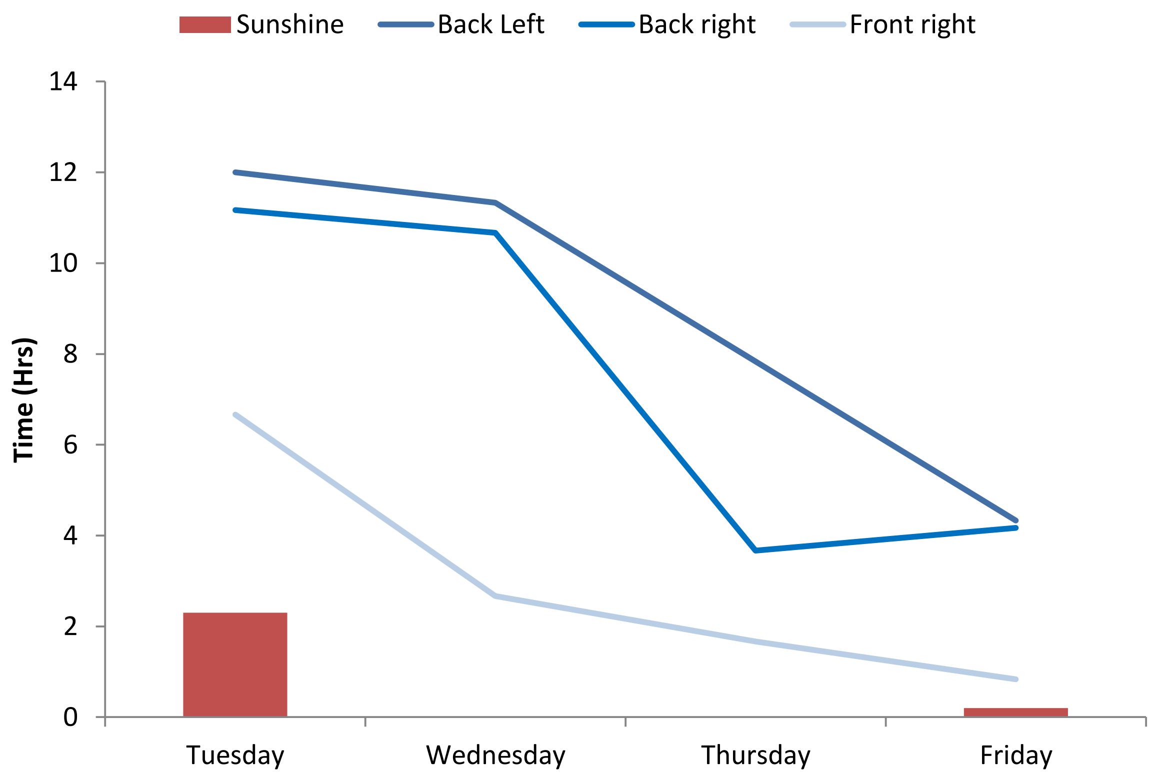


Figure 33: Time (Hrs) temperature > 22°C .

4.3.4 Period with heating and lectures scheduled

The addition of occupancy i.e. lectures being held in the classroom was also investigated. As can be seen in figure 32, the addition of lectures increases the temperature by 1.5°C on average throughout the room. This effect again has less of an effect on the front left of the room with only 0.5°C and 1°C felt between 1 and 2 metre and 2 and 3 metre. This again shows cooling effect of the large double door entrance. This is evident in figure 31 which show the percentage increase in temperature during lectures. The effect of internal heat gains within the classroom may be negated from the opening of windows within the classroom. Figure 32 illustrates that human presence in the lecture room has the greatest effect at 1 metre increasing temperatures by 1.5 -2% .

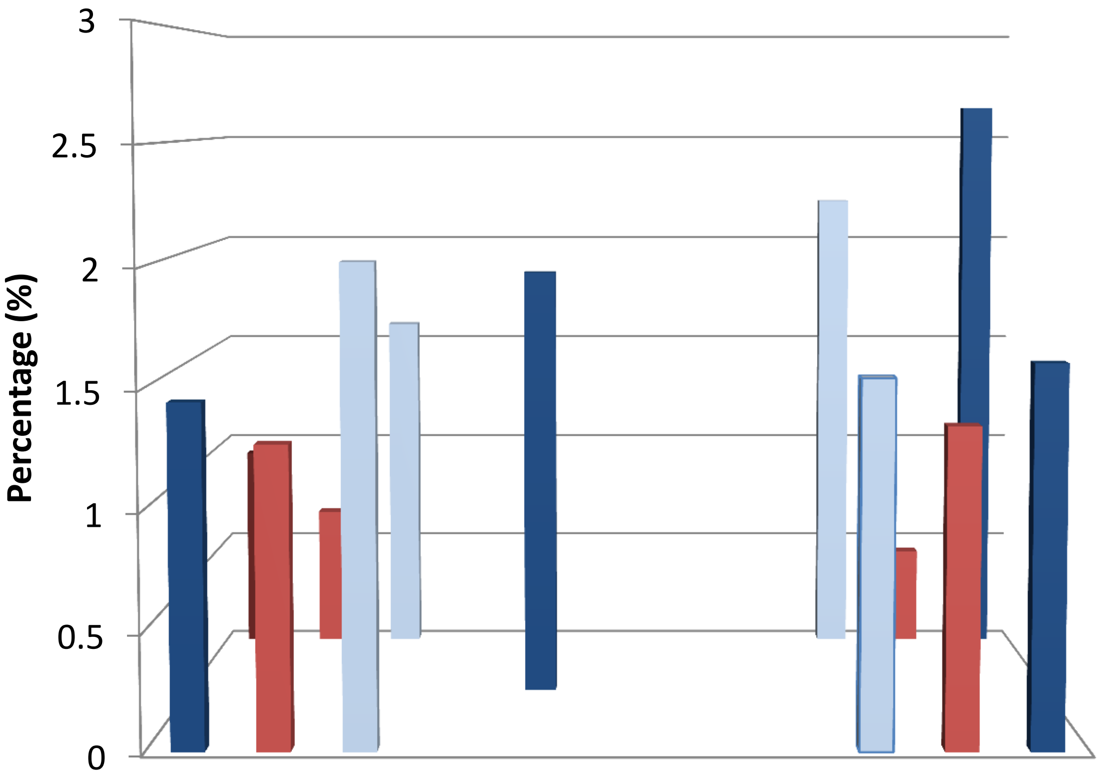


Figure 34: Percentage increase of temperature with the introduction of lectures.

4.4 Comparison with classroom B

Classroom A and B are similar in occupancy capacity and number of lectured hours per week. They differ characteristically in terms of shape and building materials. As can be seen when comparing figures 27 and 28, classroom A is a large circular room with southerly facing windows which dominate the rear of the room. Fifty per cent of classroom A's walls are exterior facing, whereas classroom B is sandwiched between two classrooms either side, with the room opening into a corridor at either end. Though Classrooms A and B differ structurally, they are both run on the same heating schedule, with heating turned on from 08.00 to 22.00 and the AHU is switched on from 08.00 to 17.00.

Figure 33 compares classroom A and B during the week of the 20th December 2013 when the heating schedule was switched off during the holiday period. Figure 33 indicates the base temperature of each room, the base temperature for classroom A is 15 – 15.5°C. This rises to between 15.5 and 16.5°C during the day. As can be seen in figure 33 the indoor temperature fluctuates with outdoor temperature. The room maintained a temperature difference of between 6 and 10°C during the week.

Classroom B maintains an indoor temperature between 18.0°C and 18.5°C, with outdoor temperature not having as pronounced an effect on indoor temperature as classroom A. This is due to classroom B having no external facing walls. This is also illustrated in the greater difference between internal and external temperatures ranging between 8 and 14°C. The 18°C base temperature would suggest that with the added internal heat gains of people and equipment generally accounting for 3.5°C[20], should suffice in maintaining a comfortable room temperature of 21 – 21.5°C without requirement of any extra heat source.

The difference of base temperatures of each room suggests that different heating schedules should be considered for these opposing types of classrooms.

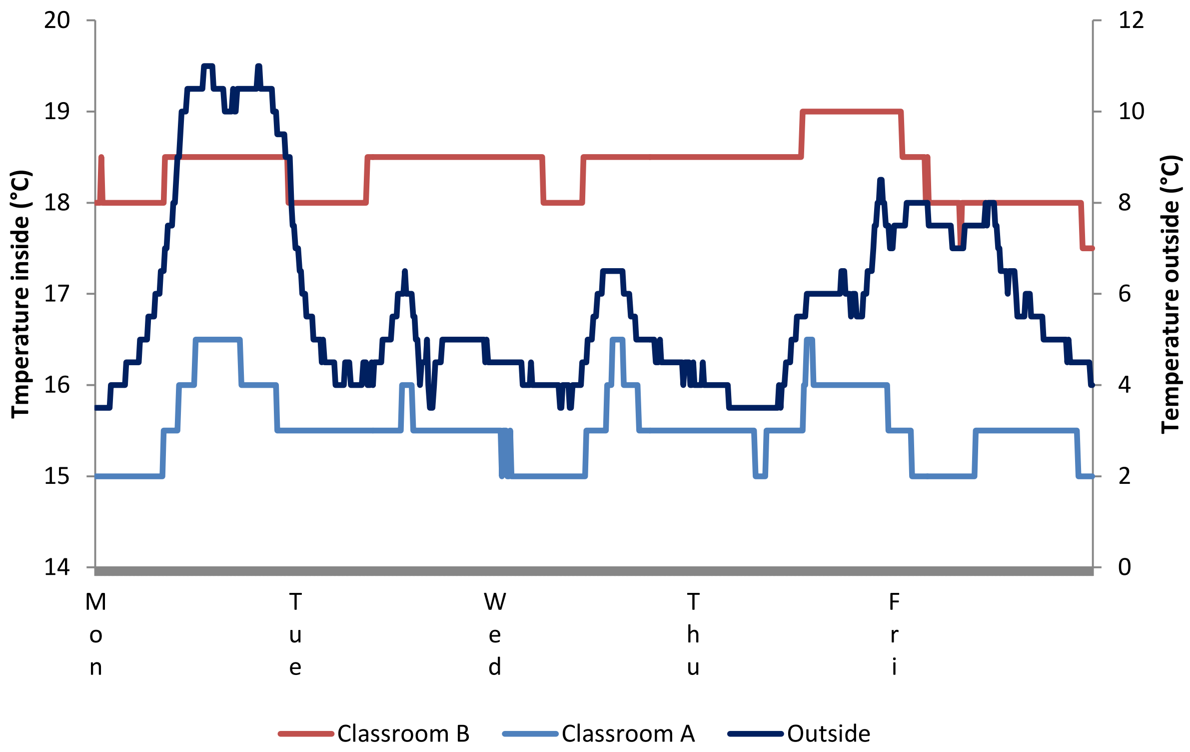


Figure 35: Comparison of classroom A and B and outdoor temperature during no heating schedule conditions

A comparison of classrooms A and B during a set heating schedule of 08.00 to 22.00 for heating and the AHU from 08.00 to 17.00 is shown in figure 34. The data displayed is from the week starting 14th January 2014 before the commencement of semester 2. The influence of outdoor temperature on classroom A appears to be lost under the heating schedule with both classroom A and B mirroring each other under the set heating schedule. Classroom A's set point rises to 16°C with a temperature of 17.5° - 18°C during the day. This would agree with internal heat gains adding 3- 3.5°C to bring the temperature within comfortable limits for an educational building according to CIBSE[114].

The temperature of classroom B rises a further 2°C under the heating schedule to give the room range between 20 - 22°C. This would again indicate that an alternative schedule should be considered for different room types throughout the university. The initial comparison between the two classrooms shows that the current schedule for heating in classroom B could be dramatically reduced. With similar classrooms across the campus, this could lead to significant financial savings and reduction in carbon foot print.

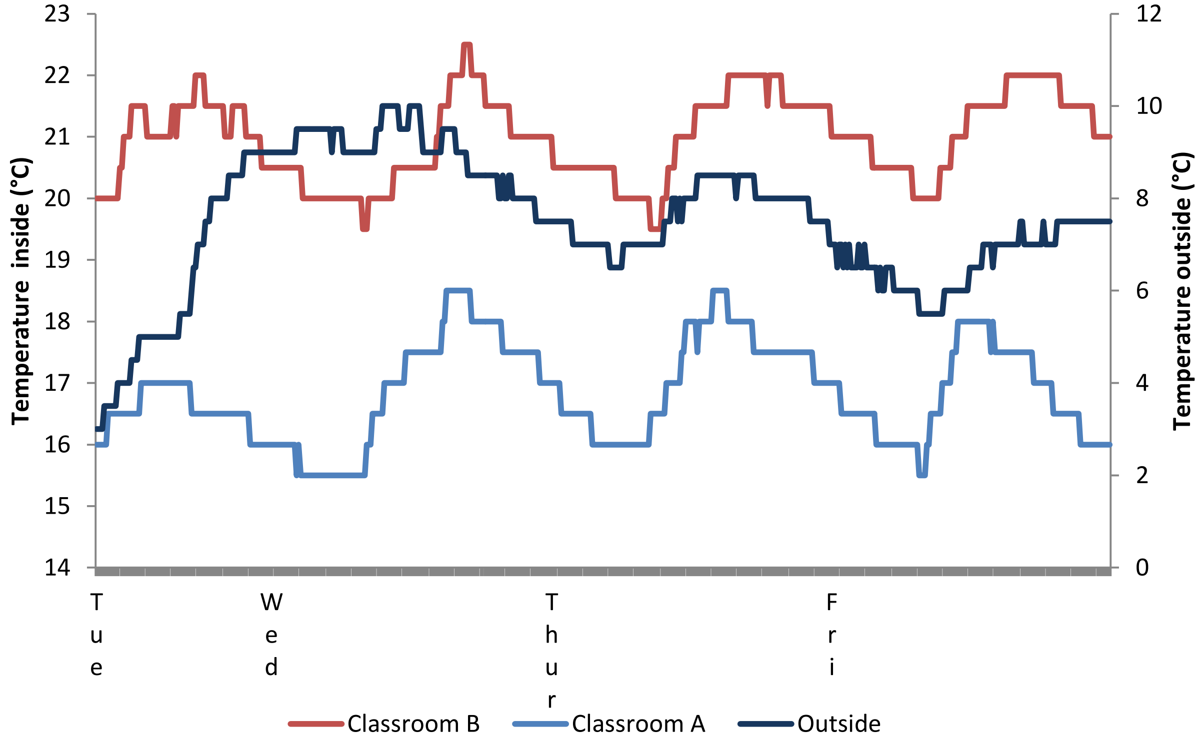


Figure 36: Comparison of classroom A and B and outdoor temperature under normal heating schedule conditions pre-semester.

Figures 37 – 41 show time series plots of both classrooms during week 7 of semester with shaded boxes overlaid to indicate when each classroom is occupied. The difference in temperature profiles of the two contrasting classrooms is again quite striking. Classroom A fails to achieve recommended indoor temperature during the week with temperature generally rising until mid-afternoon whereby it begins to fall again. This again is associated with classroom A's strong correlation with outside conditions compared to classroom B. On the other hand Monday mornings is the only in time in which classroom B fails to maintain recommended temperature. This is due to recommencement of the heating system on Monday morning. This is slow heat up pattern is evident in both classroom and should be investigated to ensure classrooms are at optimum temperature for classes at 9am on a Monday Morning. An earlier recommencement of the heating schedule may be required to ensure classrooms are at a comfortable room temperature first t thing on a Monday morning. Wednesday and Friday figures 39 and 41 highlight where the addition of occupancy information could result in significant energy savings. Temperature is maintained at 20-21°C for an entire afternoon while the room is unoccupied. This type of lecture schedule is typical throughout the college on Wednesdays and Fridays and poses a significant area of savings if implemented throughout the college.

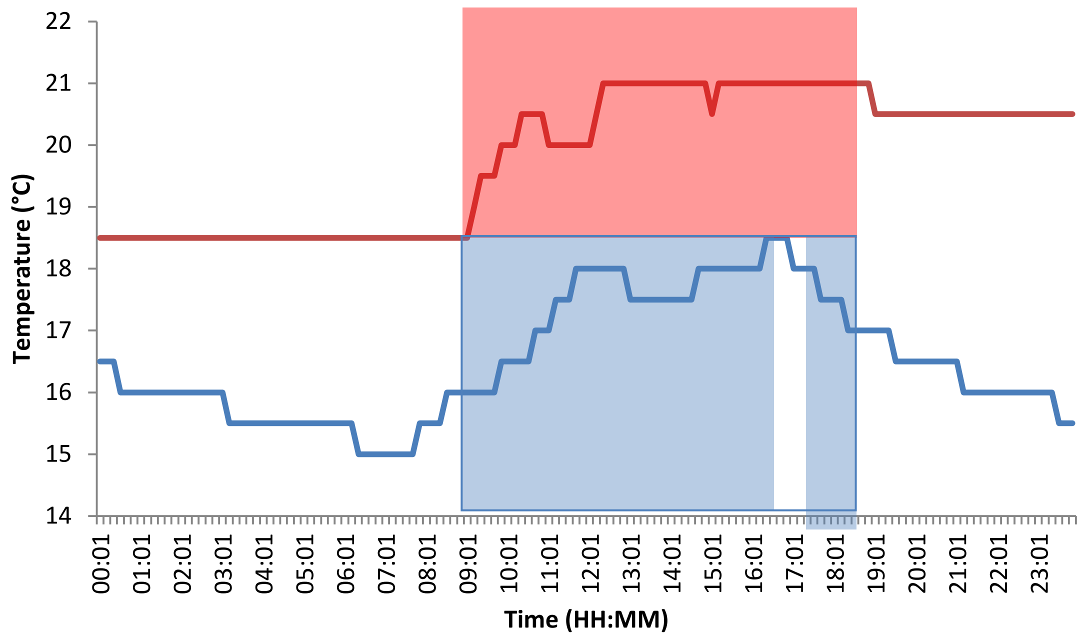


Figure 37:: Temperature profile of classroom A and B, Monday week 7 with occupancy

Classroom A
Classroom B

Lecture scheduled in Classroom A
Lecture scheduled in Classroom B

Free period

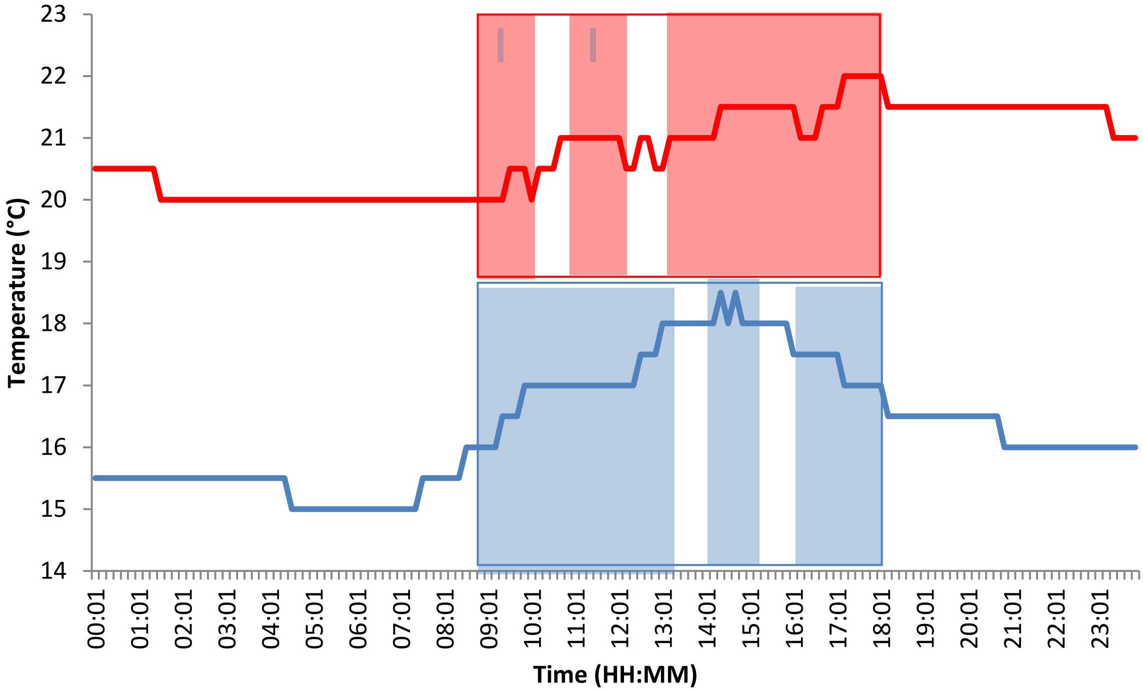


Figure 38:Temperature profile of classroom A and B, Tuesday week 7 with occupancy overlay

Classroom A Classroom B

Lecture scheduled in Classroom B Lecture scheduled in Classroom B

Free period

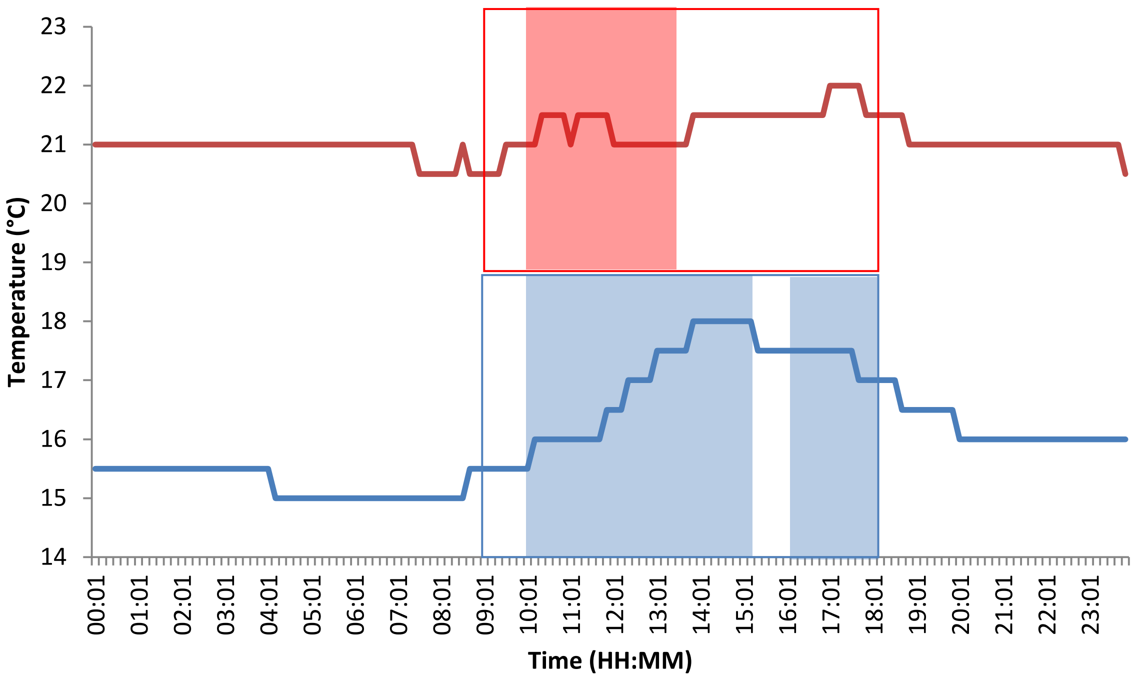


Figure 39:**Temperature profile of classroom A and B, Wednesday week 7 with occupancy overlays.**.

Classroom A Classroom B

Lecture scheduled in Classroom A Lecture scheduled in Classroom B

Free period

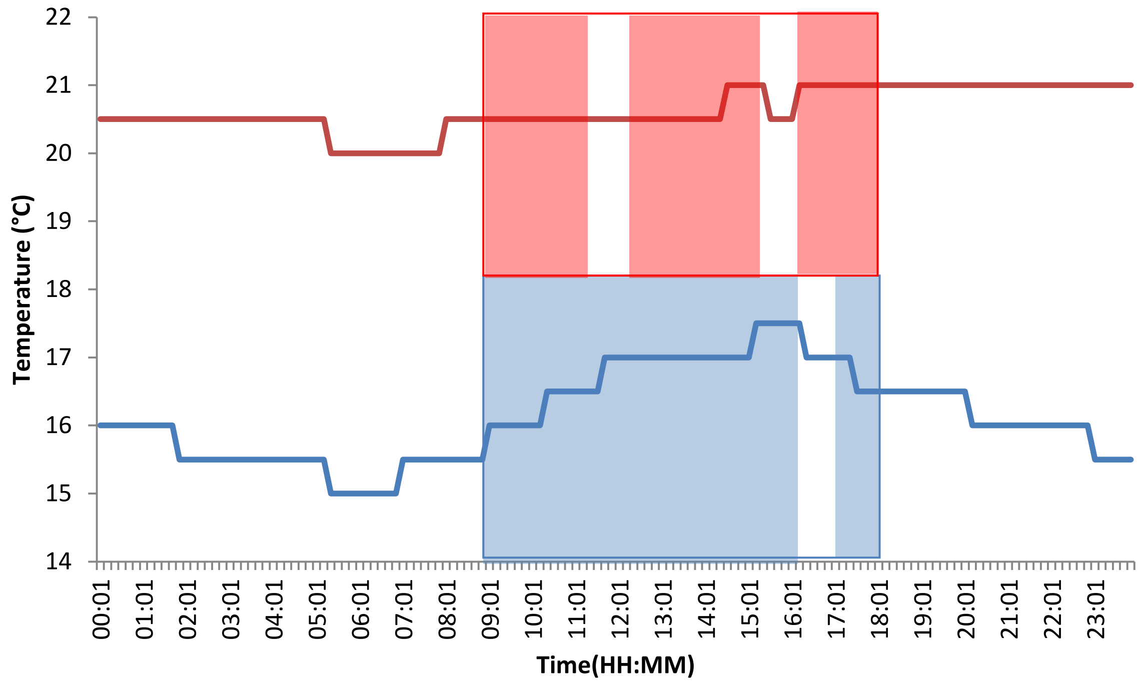


Figure 40:Temperature profile of classroom A and B, Thursday Week 7 with occupancy overlays

Classroom A Classroom B

Lecture scheduled in Classroom A Lecture scheduled in Classroom B

Free Period

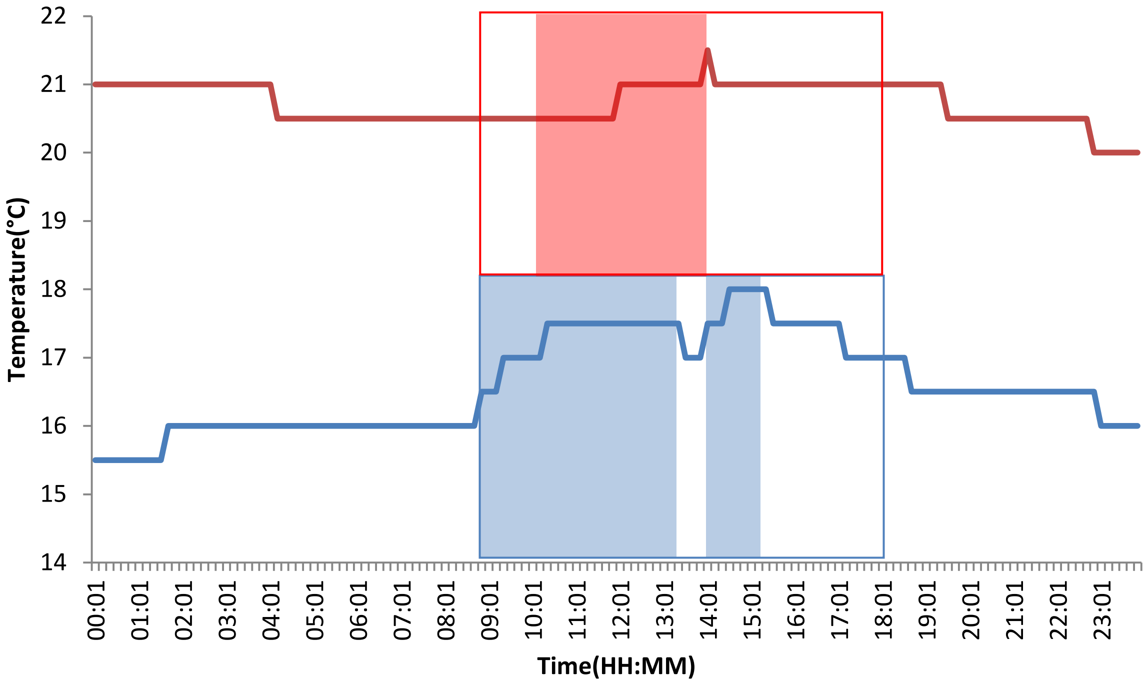


Figure 41: Temperature profile of classroom A and B, Friday Week 7 with occupancy overlays

Classroom A Classroom B

Lecture scheduled in Classroom A Lecture scheduled in Classroom B

Free period

4.6 Cooling Rate

In order to implement an intermittent heating system to compliment the variability in classroom occupancy, the rate at which each classroom cools when the heating system is turned off was studied. It is important to be able to inform the system as to how long the heating system can be turned off when high temperatures are experienced within both of the classrooms. The rooms were studied under three different conditions,

1) Heating and Air Handling Unit (AHU) switched off together, Friday evenings across the semester were studied across the semester as both heating and AHU are shutdown at 17.00.

2) AHU switched off, The AHU is switched off first during the week (Mon – Thu) at 17.00.

3) The heating system is then switched off at 22.00 during the week ((Mon – Thu).

4.6.1 Heating and AHU switched off simultaneously

The cooling rate of both classrooms was studied at the shutdown point for both space heating and AHU at 17.00 on a Friday evening. This point was chosen to study the effect of shutting down both systems simultaneously on room temperature. This was to help inform cooling strategies for excessive high temperatures in the test bed classrooms, while also informing the rate of cooling if the system was shut down completely during vacant periods of the day. The average change in temperature over time was taken for each of the Fridays in the semester. The rate of change in temperature for classroom A and B are show in figures 42 and 43 below.

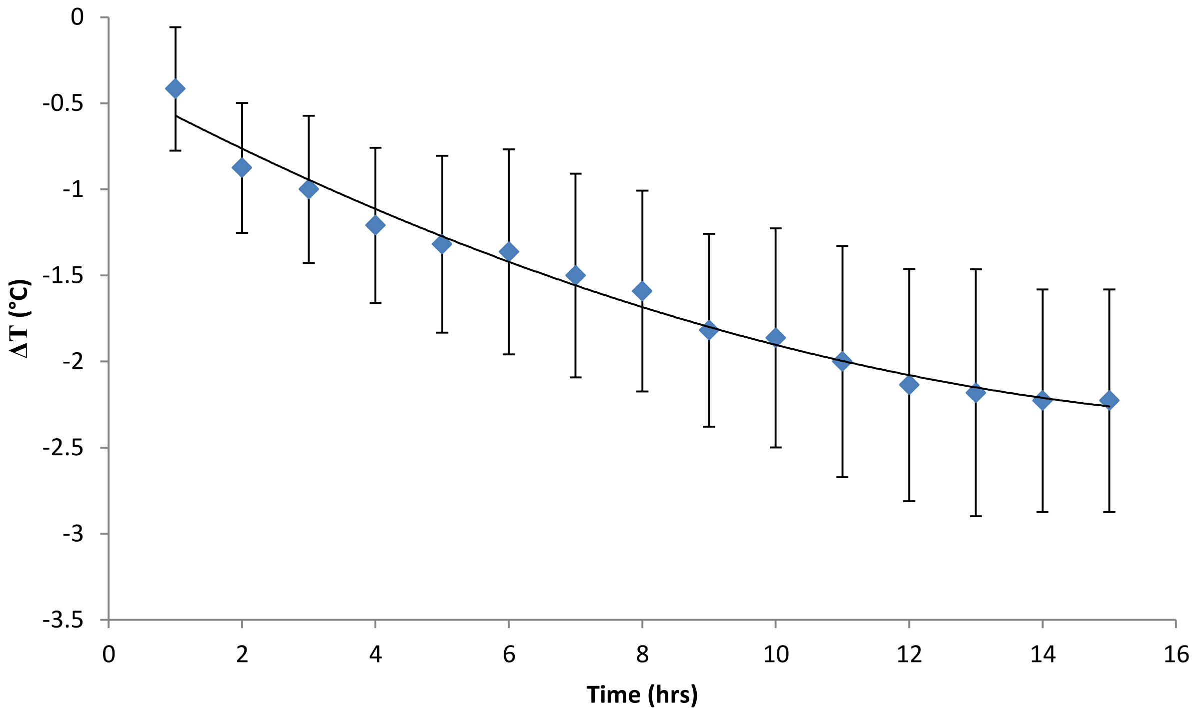


Figure 42: Cooling rate for classroom A when AHU and space heating turned off simultaneously.

$y = 0.0055x^2 - 0.208x - 0.3694$. $R^2 = 0.9828$

The cooling rate of room A can be modelled using the equation

$$T(t) = 0.0055t^2 - 0.208t - 0.3694 \qquad Equation\ 18$$

The average rate of change for classroom A where $0 \leq t \leq 15$

$$\frac{\Delta T}{\Delta t} = \frac{T(15) - T(0)}{15 - 0}$$

$$= \frac{[0.0055(15)^2 - 0.208(15) - 0.3694] - [0.0055(0)^2 - 0.208(0) - 0.3694]}{15 - 0}$$

$$= \frac{-2.2519 - (-0.3694)}{15}$$

$$= -0.1255\ °C/hr$$

Classroom A shows a good fit with temperature change over time with an R^2 value of 0.98 after the initial 15 hours after shutdown. Classroom A has an average rate of cooling over the 15 hour shutdown period 0.1255°C/hr. Classroom A has temperature change range of 0 – 2.23°C±0.5°C. Classroom A shows a greater rate off cooling during the first 2 hours with an average cooling rate 0.2025°C/hr. Rates of cooling for both classroom A and B under different cooling conditions are shown in table 16. Typical breaks in lecture schedule are usually between 1 and 3 hours and it is interesting to note that the room will lose a conservative estimate 0.5°C during the initial hour after the system is switched on/off. This estimate is conservative in the fact that the cooling rates are based on an empty lecture hall and does not take into account internal heat gains which can be up to 115 W per person in a classroom setting. This would allow for the system to be turned off for an hour for every half degree the temperature is above the comfort value of 21°C.

Similarly the rate of cooling for classroom B is shown in figure 43. Classroom B shows a strong correlation with temperature change over time when the heating system is shut down. Classroom B has temperature change range of 0 – 1.5°C±0.5°C. Classroom B does not lose heat at the same rate as Classroom A, with classroom B having a lower rate of cooling of -0.1011°C. This also appears to indicate that different heating schedules should be considered for both of these contrasting classrooms. These results would indicate that there is more scope to shut down the heating in classrooms for long periods during the day.

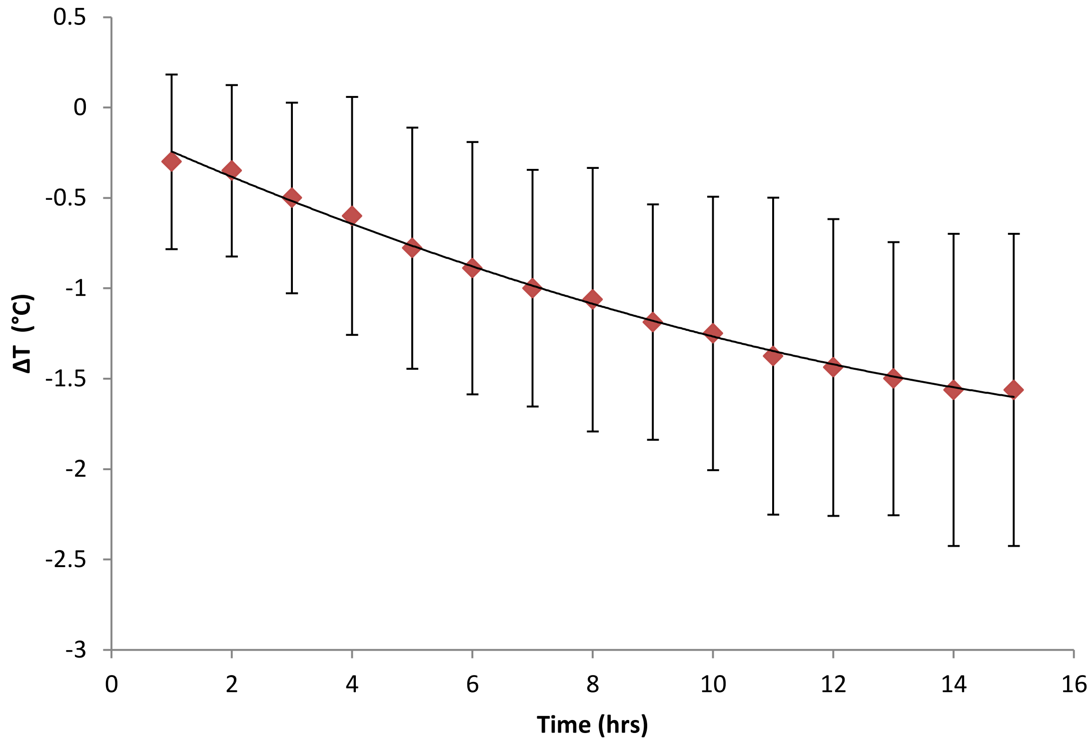


Figure 43: Cooling rate for classroom B when AHU and space heating turned off simultaneously.

$y = 0.0033x^2 - 0.1505x - 0.0961 \quad R^2 = 0.9959$

The cooling rate of room B can be modelled using the equation

$$T(t) = 0.0033t^2 - 0.1505t - 0.0961 \qquad \textit{Equation } 19$$

The average rate of change for classroom B where $0 \leq t \leq 15$

$$\frac{\Delta T}{\Delta t} = \frac{T(15) - T(0)}{15 - 0}$$

$$= \frac{[0.0033(15)^2 - 0.1505(15) - 0.0961] - [0.0033(15)^2 - 0.1505(15) - 0.0961]}{15 - 0}$$

$$= \frac{-1.6111 - (-0.0961)}{15}$$

$$= -0.1010\ °C/hr$$

4.6.2 AHU and Heating alternate switch off

During a typical semester week the AHU is switched off at 17.00 Monday to Thursday, followed by the heating being switched off at 22.00. Figure 44 shows the cooling rate of classroom A when the heating and AHU are turned off alternatively. From the data obtained the switching off of the AHU at 22.00 does not have a further effect on the cooling rate of the room. The average rate of cooling for the initial hour (0.1505°C/hr) is lower than when both systems were switched off together (0.2025°C/hr). The switching off of the two systems simultaneously has a greater initial cooling effect on the room. This information is useful when choosing a cooling method for the classroom. The alternative switch off has a slightly larger temperature range over the 15 hours then switching them off simultaneously off 0 – 2.5°C±0.7°C with change in temperature with an R^2 value of 0.99. The ability to accurately predict the effect of turning off the heating for short periods of time are important when looking to optimise a room with a high variability in occupancy.

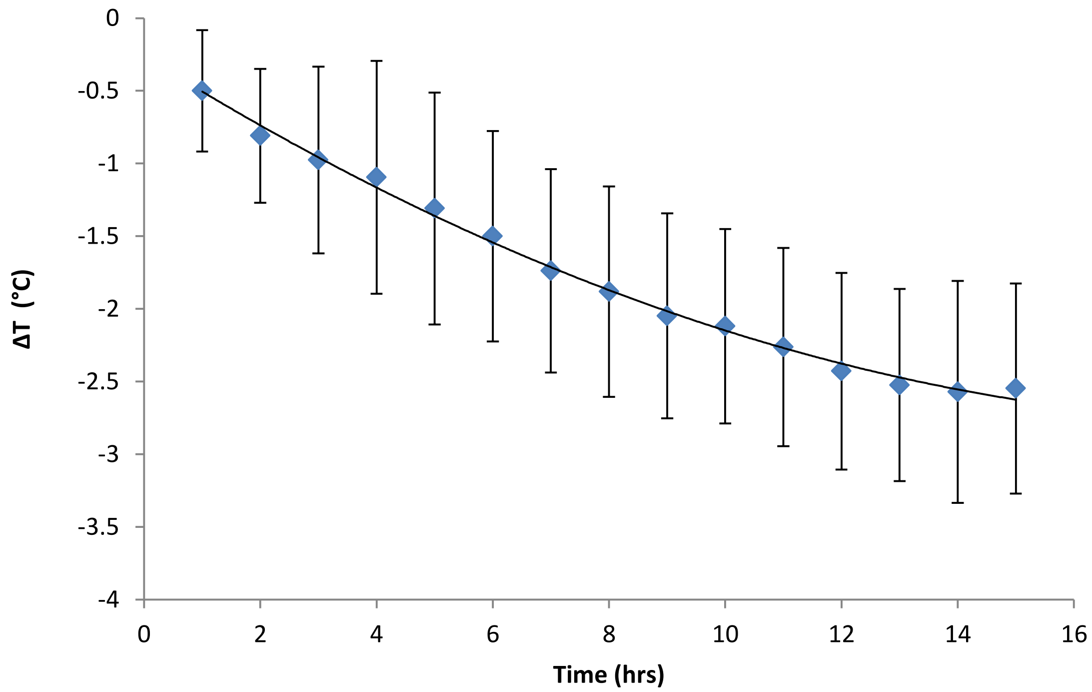


Figure 44: Cooling rate for classroom A from alternate AHU and heating switch off Mon-Thu.

$y = 0.0062x^2 - 0.2513x - 0.2598$ $R^2 = 0.9956$

It was found that the reduction is less pronounced after 22.00 when the heating schedule is turned off. The turn off of the space heating does not affect the average rate of cooling within the classroom with a cooling rate of 0.1142°C during the initial hour after the system was switched off. Over the 10 hours that both the heating and AHU are off there is a loss, on average of 1.25°C±0.8°C. Over the twelve hour period that the heating is ramped down there is on average a loss of 3.25°C or at a conservative estimate 5.5°C. This information along with outdoor air temperature, can help inform a more intuitive heating system to ensure that the classroom is at optimum temperature for the first lecture of the day.

Classroom B shows two distinct cooling rates compared with classroom A as shown in figure 45, with both the turn off of the AHU and the turn off of the heating system showing distinct cooling patterns. This indicates that both space heating and AHU have a greater initial impact on classroom B when switched off. This is shown in the average rates of cooling; Classroom B has a rate of cooling of 0.3046°C/hr though this reduces greatly to 0.9°C after 3 hours. The switch off of space heating within the room again increases the rate of cooling to 0.1303°C/hr. This shows that classroom B is more responsive to changes in heating conditions, though overall it cools at a lower rate with an overall heat loss of 1.5°C±1°C over the 15 hours shut down period compared to 2.25°C of classroom A.

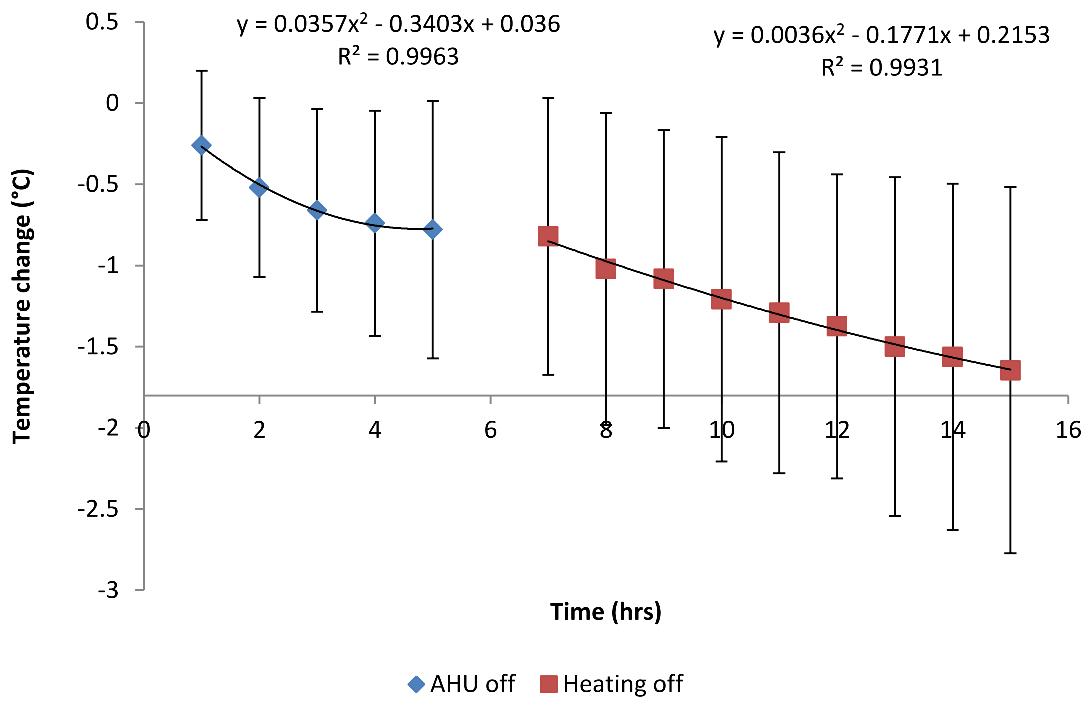


Figure 45: Cooling rate for classroom B from alternate AHU and heating switch off Mon-Thu.

Both figure 46 and 47 shows that there is no difference in the rate of heat loss by leaving the heating system on an extra five hours in the evening from Monday to Thursday. This shows that turning off both the AHU and heating systems at 17.00 does not result in a larger temperature difference to be made up when the heating schedule resumes at 08.00. Classroom A was found to lose an extra degree Celsius through the night on average. This would suggest that a review of the start time of the heating system should be taken into consideration, which may account for the lower temperatures in classroom A as seen in section 4.5.

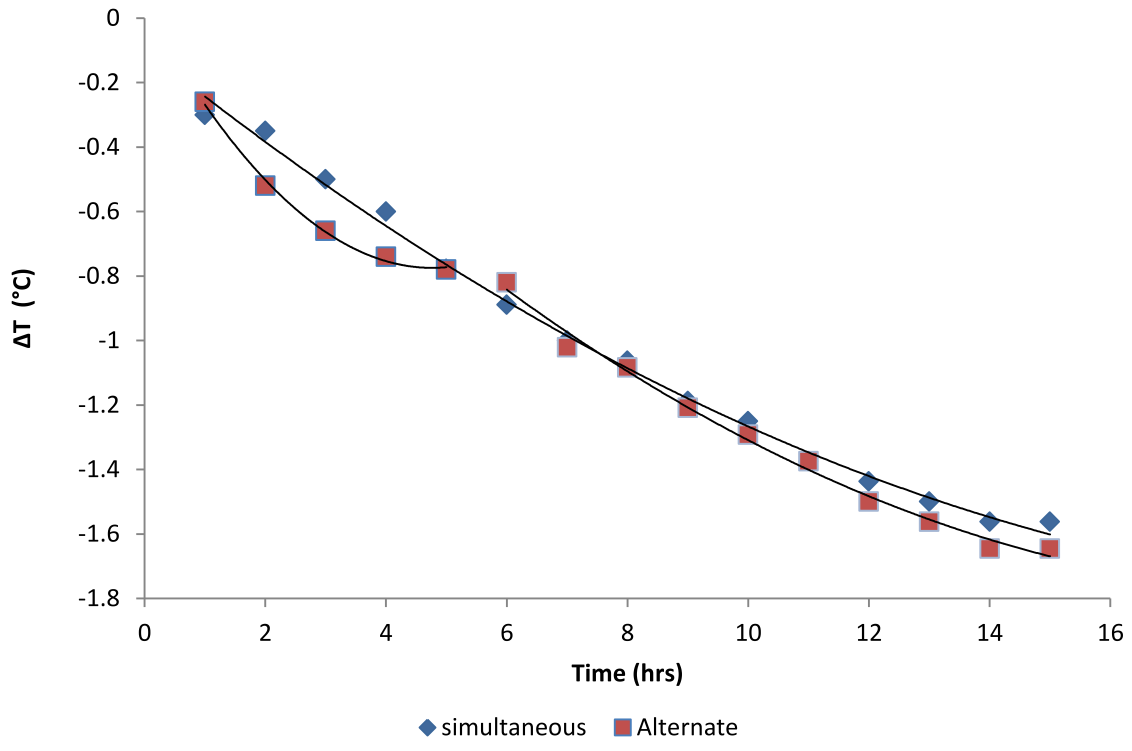


Figure 46; Comparison of simultaneous and alternate switch off of AHU and heating system from 17.00 – 08.00 in classroom B.

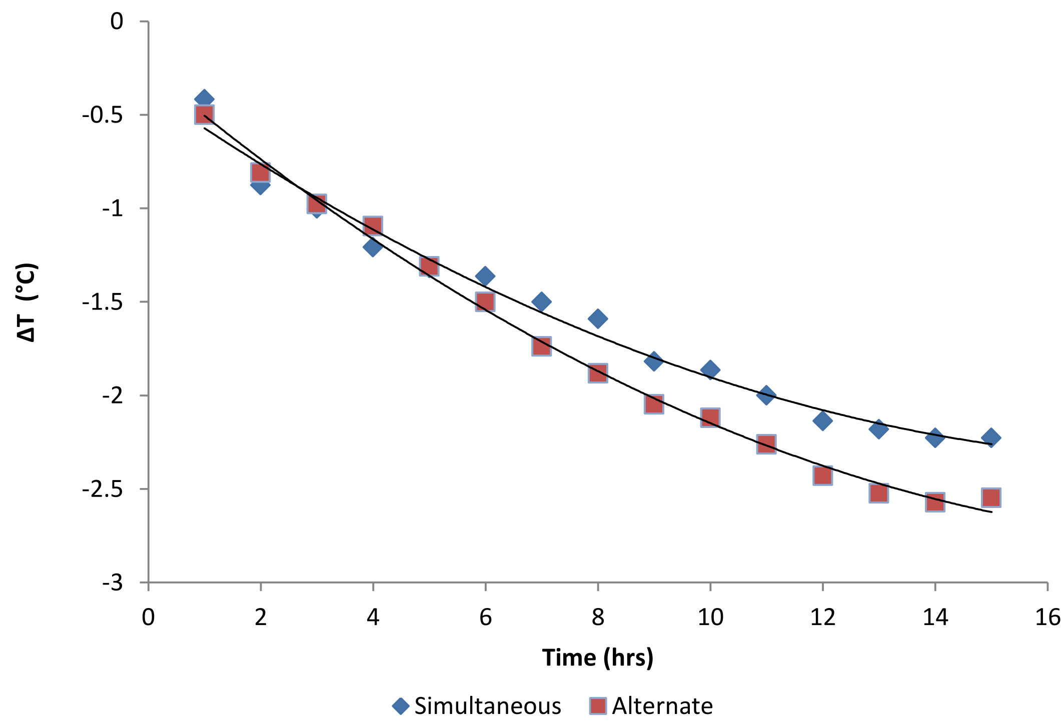


Figure 47: Comparison of simultaneous and alternate switch off of AHU and heating system classroom A.

Table 16: Average rate of cooling for classroom A and B over a 15 hour period under simultaneous and alternative switch off conditions.

Average rate of cooling				
	Simultaneous switch off ($°C/hr$)		Alternative switch off ($°C/hr$)	
Time(hr)	Classroom A	Classroom B	Classroom A	Classroom B
1	-0.2025	-0.1505	-0.1505	-0.3046
2	-0.1915	-0.1406	-0.1406	-0.2332
3	-0.1805	-0.134	-0.134	-0.1618
4	-0.1695	-0.1274	-0.1274	-0.0904
5	-0.1585	-0.1208	-0.1208	-0.019
6	-0.1475	-0.1142	-0.1142	
7	-0.1365	-0.1076	-0.1076	-0.1303
8	-0.1255	-0.101	-0.101	-0.1231
9	-0.1145	-0.0944	-0.0944	-0.1159
10	-0.1035	-0.0878	-0.0878	-0.1087
11	-0.0925	-0.0812	-0.0812	-0.1015
12	-0.0815	-0.0746	-0.0746	-0.0943
13	-0.0705	-0.068	-0.068	-0.0871
14	-0.0595	-0.0614	-0.0614	-0.0799
15	-0.0485	-0.0548	-0.0548	-0.6061
Overall 0-15(hrs)	-0.1255	-0.101	-0.1583	

The analysis of the cooling rates of both classrooms has shown that there is good relationship between changes of temperature over time. The analysis of the cooling rate of both classrooms has revealed that classroom A has a greater cooling rate over night compared to classroom B, which cools nearly 1°C over a 15 hour period or a cooling rate of 0.1255°C/hr compared to 0.101°C/hr for classroom A. This indicates that an earlier start point for the heating schedule in classroom A may be required in order to ensure the room is at a comfort level of 21°C or greater for a 9 o'clock lecture.

It has been shown that alternatively switching off the AHU unit has no effect in reducing the cooling of the room and switching both systems off simultaneously results in a similar cooling pattern. This result would indicate that the heating system could be switched off 5 hours earlier from Monday to Thursday; this would represent a reduction of 240 heating hours a semester. Currently the heating runs for 840 hours during a 12 week semester.

This would represent a significant reduction of 29% in the number of hours the heating is turned on during a semester.

4.7 Heating rate

The rate at which the indoor temperature changed over a period of the initial four hours after the heating system is switched on at 08.00 was studied during the semester. Classroom A shows a good fit with change in temperature over time as shown in figure 48, with an average rate of heating of 0.0097°C/min over the four hour period. The temperature of the classroom increases by 2.5°C over the studied four hour period. The average rates of heating for both classrooms is shown in table 17. The two classrooms contrast in the rate at which they are heated, with classroom A increasing by 0.5°C every 30 minutes over the first 90 and 0.5°C an hour over the final two hours (120 -240 min), though after 180 mins the error increases to ±1°C above the error of the sensor itself, although for the implementation of an intermittent heating system the recommencement of the heating system is unlikely to be at periods over 120 mins.

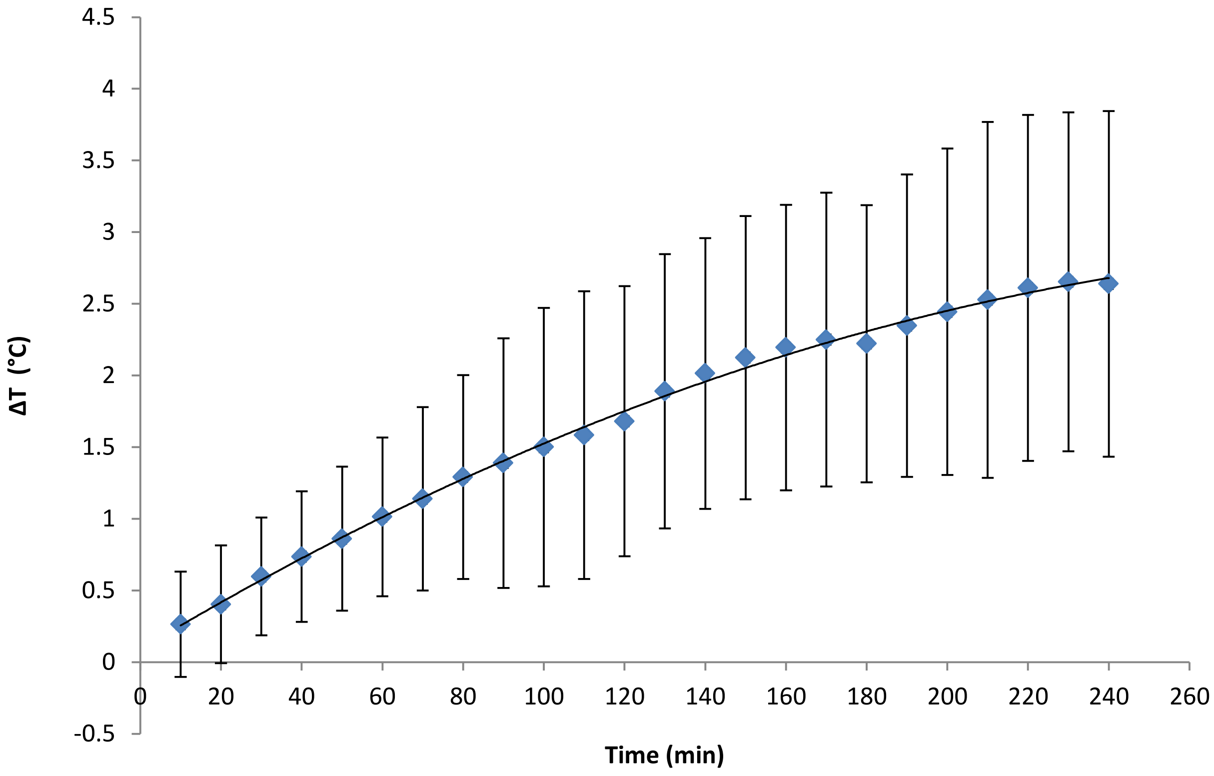


Figure 48: Heating rate for classroom A over the initial four hours after commencement of heating system. y = -0.00003x^2 + 0.0169x + 0.0887. R^2 = 0.9973

$$T(t) = -0.00003t^2 + 0.0169t - 0.0887 \qquad Equation\ 20$$

The average rate of change for classroom B where $0 \leq t \leq 240$

$$\frac{\Delta T}{\Delta t} = \frac{T(15) - T(0)}{15 - 0}$$

$$= \frac{[-0.00003(240)^2 - 0.0169(240) - 0.0887] - [0.00003(0)^2 - 0.0169(0) - 0.0887]}{240 - 0}$$

$$= \frac{2.4167 - (0.0887)}{240}$$

$$= \ 0.0097\ °C/min$$

In contrast to classroom A, the rate classroom B’s room temperature is increased with the introduction of space heating is considerably slower with an average rate of heating of 0.009°C/min compared to 0.0658°C/min for classroom A.

From the obtained data classroom B does not increase in temperature after the initial hour of heating. Each hour in classroom B under heating conditions has a distinct heating rate with four distinct segments A,B,C and D over the four hour period. Due to fact that Classroom B has 50% less (2) radiators than classroom A, the contrast in heating rates is no surprise, with Classroom B only increasing in temperature by 1°C on average over the four hour period studied compared with classroom A which sees an increase on average of 2.5°C. The difference of both rates of heating would indicate that classroom A would be suitable to increase the temperature of the room over a short period of time (20 minutes) this is useful in returning the room quickly to a required temperature after a shutdown period. Classroom B would appear not to be suitable at heating the room up to required temperature over a short period time after a system shutdown due to the heating requiring 60 minutes to take effect. The slow cooling rate of both classrooms 0.2025°C/hr and 0.1505°C/hr respectively, may present an opportunity to switch off the system for long periods (2-8 hours) when the temperature is 0.5 - 1°C above required temperature of 21°C.

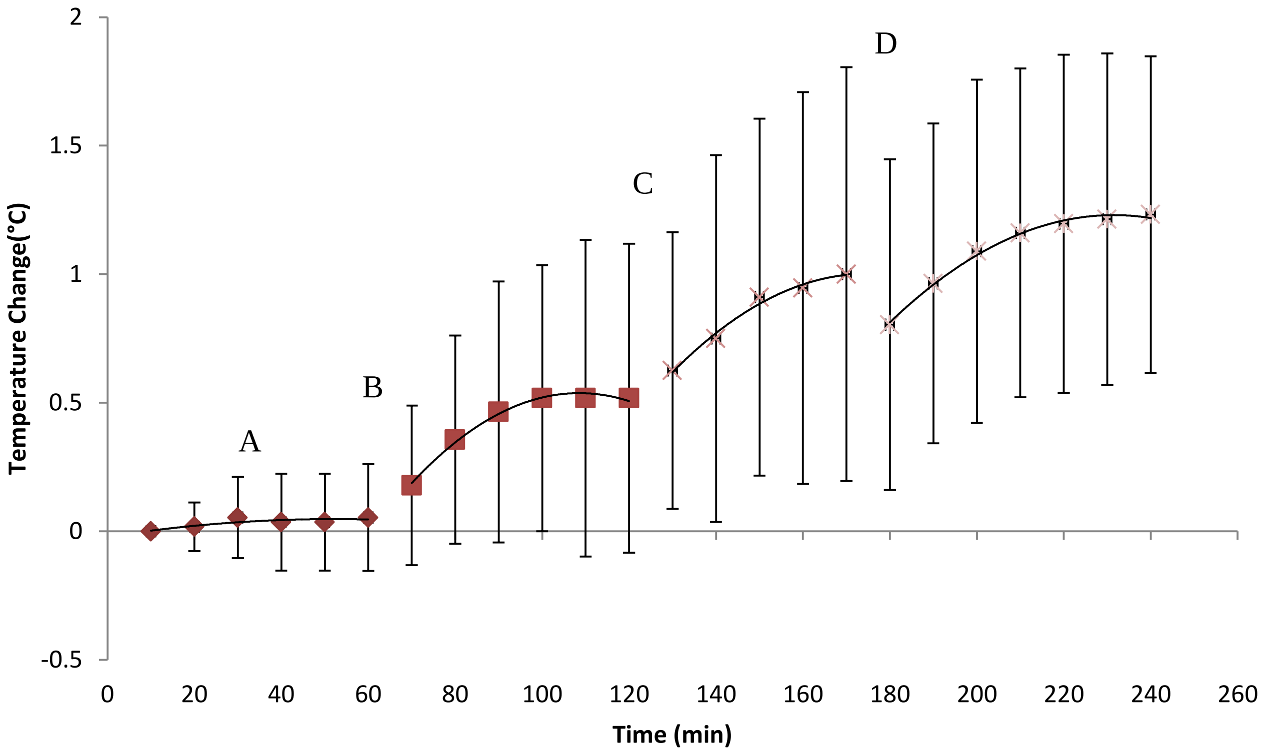


Figure 49: Heating rate for classroom B over the initial four hours after commencement of heating system.

A. $y = -3E\text{-}05x^2 + 0.0027x - 0.0214$ $R^2 = 0.7157$ Equation 21

B. $y = -0.0002x^2 + 0.0512x - 2.2411$ $R^2 = 0.9916$ Equation 22

C. $y = -0.0002x^2 + 0.0669x - 4.8398$ $R^2 = 0.986$ Equation 23

D. $y = -0.0002x^2 + 0.0728x - 7.1998$ $R^2 = 0.9937$ Equation 24

Table 17: Average rate of heating for Classroom A and B over intial four hours after heating system is turned on.

Average rate of heating (°C/min)		
	Classroom A	Classroom B
0	0.0658	0.0009
120	0.069	0.011
180	0.0474	-0.00587
240	0.0258	-0.0112

The study of the two classrooms over the semester would suggest that the introduction of a timetable adapted heating system may not be suitable in classroom A. This is due to the fact that it is currently failing to maintain an average temperature of 21°C, as seen in figure 35. It is believed that this is due to the opening of windows during the day because of uncomfortable thermal conditions. This would indicate that a more adaptive system would be suitable to improve temperature within in the classroom. An accelerometer could be placed on the windows to log when the room is opened and closed and track the effect on cooling within the room. Classroom B, on the other hand, lies above 21°C 25% of the time showing that there is scope to lower temperatures within the room. The slow cooling rate of the classroom 0.01505°C/hr would indicate that the heating could be shut down for a prolonged period during the day while maintaining recommended temperatures. The investigation of a timetable adaptive heating system for classroom B is discussed in section 5.2.

4.8 Comparison with building management sensor location

Figure 50 shows the temperature difference across the lecture room at a height of 1 metre between the estate sensor and the location of the estate sensor, which is located to the right of the door as you enter the room. Figure 50 shows that the estate sensor shows a good representation of the front left area of the room with +/- of 0.5^{o}C across the week.

As you move across to the right hand side of the room you can see this temperature difference begin to increase to +/- 1^{0}C. The discrepancy becomes greater between estate sensor locations when compared to the back of the lecture room. This shows the unrepresentative nature of having one temperature sensor in a lecture room. The building management underreports the temperature right across the room. This can be significant in both thermal comfort and energy saving. It is evident from figure 8 that the occupants at the back of the room have a totally different comfort experience from their classmates at the front of the room. The large south facing window causes a large increase in temperature to the rear of the room. This points to the benefit of having extra temperature sensors dispersed throughout the room.

The temperature disparity between the position of existing BMS sensor is also illustrated in classroom B in figure 51. In the case of classroom B, however, the difference in temperature is homogenous throughout the room indicating that the location of the current BMS sensor is inappropriate to get a representation of conditions within classroom B. This may be due to the placement of the sensor near the radiator on the right hand wall of the room. It would be predicted that the senor should over-predict the temperature whereas currently the readings throughout the room at 1 metre are higher than those of the BMS at 2 metre. This under-prediction of temperature could also give scope to reduce heating even further as temperature are 1-2°C higher than recorded by the temperature sensor in its current location.

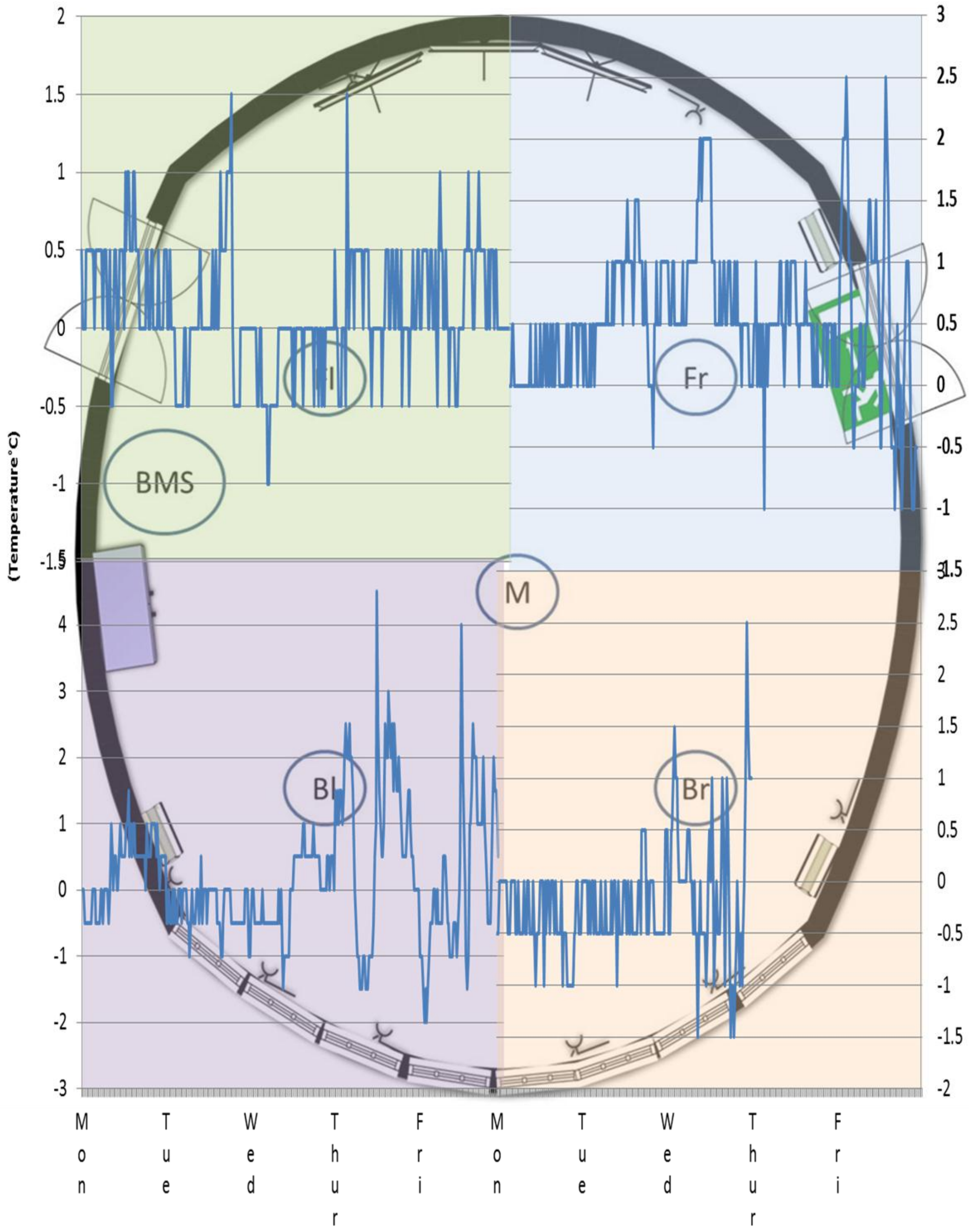


Figure 50: Comparison with BMS sensor with iButtons deployed at 1 metre in classroom A.

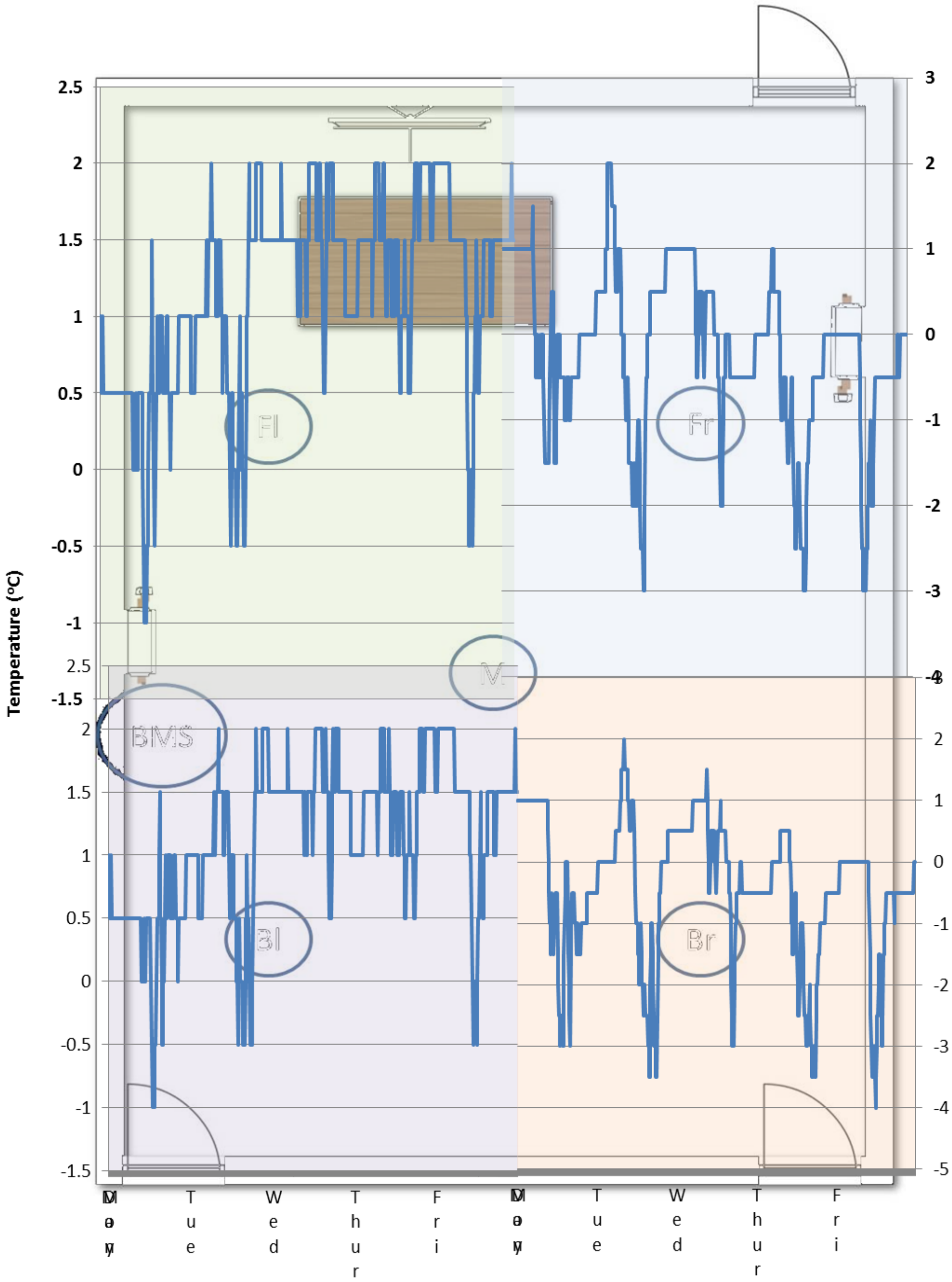


Figure 51: Comparison with BMS sensor with iButtons deployed at 1 metre in classroom B.

The use of a cheap off the shelf sensor such as the iButton for a temperature study of two contrasting classrooms has shown to be extremely useful. They have shown that they are a useful tool in carrying out short term audits and calibrations of existing sensors to ensure the current system is responding correctly. They have allowed for the monitoring of the temperature stratification in classroom A, which showed the high temperatures that are present at 3 meters to the rear of the room, showing that re-distribution of this heat may allow for a reduction in the need for continuous heating. The iButtons have shown to be useful in highlighting the temperature discrepancy throughout both rooms by comparison to current sensor locations. iButtons could be used to calibrate existing temperatures around campus to ensure they are representative of what is happening in the classrooms. The iButton is useful as a standalone logger to help identify problem areas. This is particularly important in situations as those highlighted above, whereby the existing sensor is underestimating temperature felt by occupants. This will mean that students will be learning within a thermally uncomfortable environment which is not conducive to a healthy environment[53]. This also represents an opportunity to reduce the dependency on space heating. The financial significance of reducing the set point by 1°C was highlighted in Section 3, reducing the heating costs by 11% per degree.

The use of the iButtons to monitor both classrooms over the one semester has enabled an assessment on whether the implementation of a timetable adapted heating schedule is possible in the two contrasting classrooms. At present, classroom A needs further investigation into the frequent use of the classroom windows to cool the room. Classroom B is a suitable candidate to implement a heating system based on occupancy patterns due to its slow cooling rate and its frequent time (>25%) spent above 21°C. Perhaps the most significant finding of the iButton deployment is the indifference between the simultaneous turn off AHU and heating system and the alternate switch off used Monday to Thursday. These findings would imply that a switch off of both systems at 17.00 is possible without any disturbance to the thermal conditions within the room. This would represent a reduction in 25 hours or 33% saving in the amount of heating required for each classroom.

Chapter 5

Modelling and temperature optimisation

One of the main challenges for intelligent buildings is to give comfort to its occupants and to increase the user's performance at a low cost. The excessive demand of electric energy due to heating, ventilating, and air-conditioning (HVAC) systems require temperature forecast and control to make maximum reduction of the electrical energy. In this section, the prediction of temperature at various locations within the room will be discussed along with the evaluation of the input of timetable information into the heating schedule. Data mining was carried out using Weka[115]. Weka is an open source collection of machine learning algorithms and data mining tasks.

5.1 Temperature prediction

The ability to predict future temperatures is important when informing a heating system when it is due to turn on/off. The use of a small, cheap standalone off the shelf temperature logger in Section 4 illustrated the temperature gradient throughout both classrooms. This could have a significant impact on the thermal comfort of students with the location of the current sensor giving lower values than those felt by occupants. The under representation of temperature within the room could also mean that there are significant savings that could be made in the two test classrooms as temperatures may already be at the required level. Due to the temperature gradient throughout the room, linear regression was used to predict the temperatures at each location using the iButton placed at 3 meter, in the centre of the room. Weka was used for classification and a 50/50 split of data was used for training and testing the model. The correlation between the actual and predicted temperature are shown in figure 52.

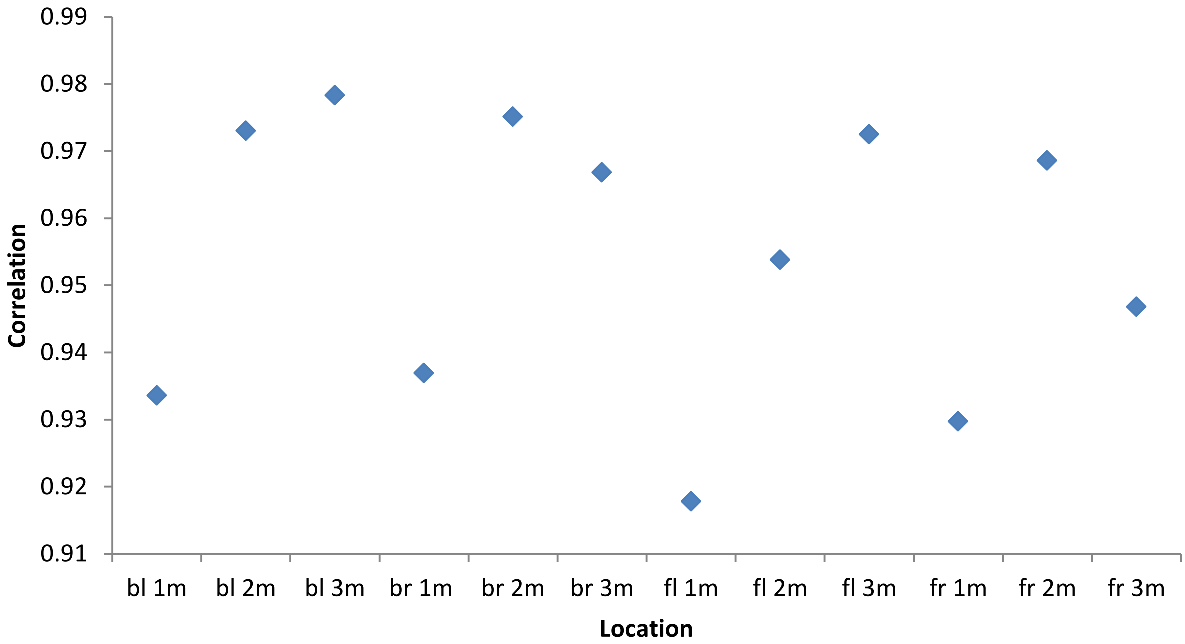


Figure 52: Correlation of predicted temperatures for 12 different locations as illustrated in figure 27.

All locations showed a strong correlation over 0.90. Sensors at 3 metre showed the best correlation > 0.97. The sensors at 1 meter to the front left of the room show the lowest correlation at 0.92. This is thought to be due to the sensor being located near to the large double door entrance with the draft created thought to affect the accuracy of predictions. These predictions show the ability to train one sensor to predict multiple temperature locations over a short term deployment. In a room where the temperature change can be 1oc across this can be highly beneficial information in upgrading a heating system and reducing energy costs. This could lead to informing the management system to turn off some of the four radiators that are present in this room.

The difference between predictions at 3 metre and 1 metre heights can be seen in Figures 52 and 53. It can be seen that at 3 metre the predicted values fit almost perfectly to the actual values, as would be expected with a correlation coefficient of 0.98.

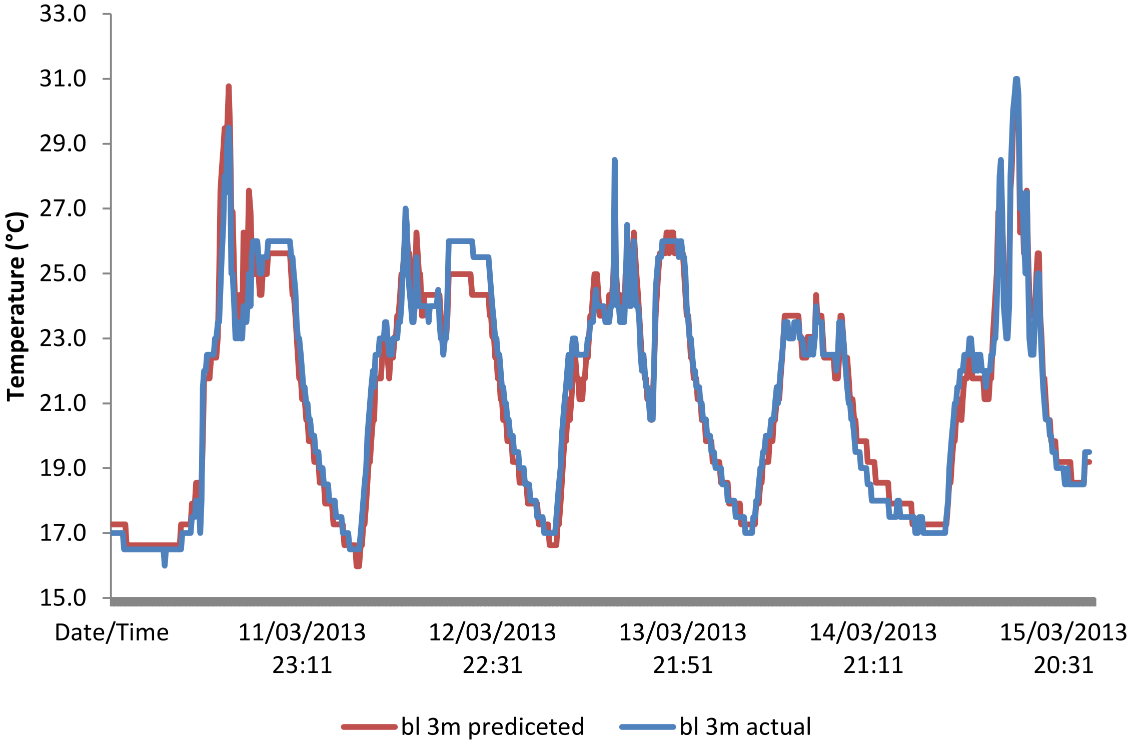


Figure 53: Predicted Values vs. Actual values for a sensor at 3 metres at back left of the room

On moving down to the 1 metre predictions you can see that it fails to predict the initial warm-up period on a Monday morning when the heating is turned back on. This appears to be the main deviation in predictions for sensors at 1 metre.

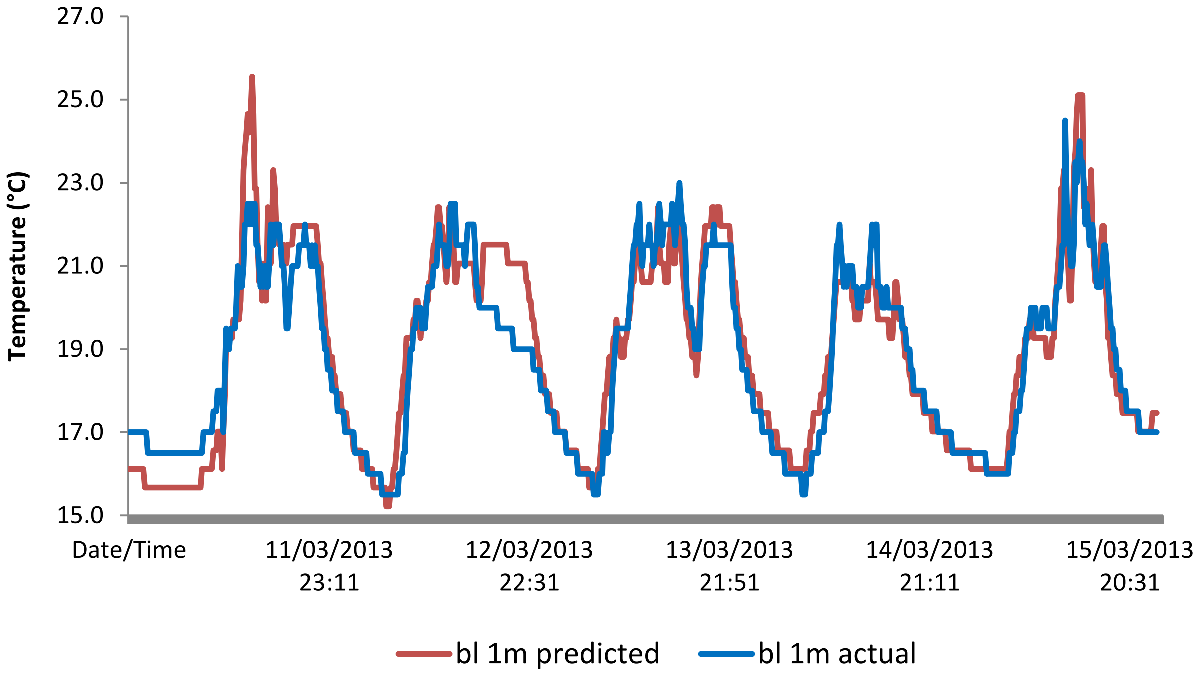


Figure 54: Predicted Values vs. Actual values for a sensor at 3 metres at back left of the room.

5.1. Investigation of sensor reading correlation

In order to improve predictions for the various locations, it was investigated as to whether temperature readings 10 and 20 minutes ahead of predicted location, (t+1, t+2) and after (t-1,t-2) showed a better correlation. The results shown in table 18 show that t is the most appropriate sensor reading to use in predicting future temperatures. This shows that all the locations have an immediate response to temperature change within the room, showing that there is no delay in temperature change from 3 metres down to 1 metre or vice versa.

Table 18: Correlation coefficients showing the relationship between sensor readings and sensor locations.

	Correlation				
Location	Current time (t)	t+1	t+2	t-1	t-2
bl 1m	0.9336	0.9372	0.9291	0.9373	0.9181
bl 2m	0.973	0.9652	0.9537	0.9682	0.959
bl 3m	0.9783	0.972	0.9609	0.9704	0.9568
br 1m	0.9369	0.9369	0.9121	0.9342	0.9279
br 2m	0.9751	0.9673	0.9545	0.9698	0.9612
br 3m	0.9668	0.9636	0.9549	0.9576	0.9436
fl 1m	0.9178	0.9109	0.91	0.914	0.9066
fl 2m	0.9538	0.9436	0.9542	0.9598	0.956
fl 3m	0.9725	0.97	0.95	0.9586	0.949
fr 1m	0.9297	0.9217	0.9201	0.9256	0.9187
fr 2m	0.9686	0.9671	0.9483	0.9606	0.9491
fr 3m	0.9468	0.9469	0.9361	0.9421	0.9349

5.2 Addition of occupancy information

To improve upon the accuracy of predictions, timetabled information was added to the temperature data. An occupied period was given a 1, with 0 representing an unoccupied period in the timetable. Again linear regression was used for predictions and a 50/50 split for training and testing was used on the weekly data. Figure 55 shows the improved correlation with sensors placed at 1 meter throughout the room. The correlation shows the significance of human traffic on temperature predictions at 1 meter level. The previous poor correlation with the front left has been increased when accounting for people coming into the room. All locations show improved prediction, with the addition of occupancy data apart from the Br of the room. It is not known the reason for this apart from the fact that students may tend not to fill this area of the room. These results also point to the significance of taking occupancy into account when planning a heating schedule.

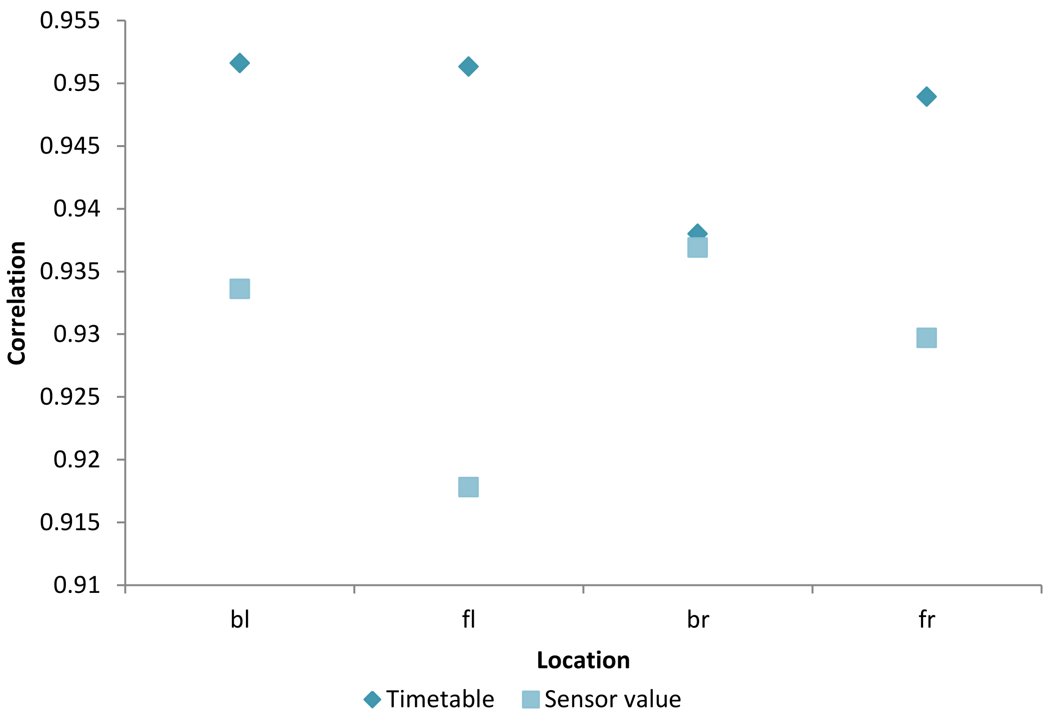


Figure 55: Correlation coefficients when occupancy is included in the model.

5.2 Heating optimisation

The use of timetable information during semester 1 2014 was used along with the linear equations created in section 4.6 and 4.7 for heating and cooling to optimise the use of heating within university classrooms. As previously stated, classroom A was not considered for optimisation due to the rooms inability to maintain recommended temperatures for prolonged periods of time. Figure 56 shows the new heating schedule for Monday to Friday for Classroom B. The introduction of timetable information reduces the heating by 11 hours a week. This combined with turning the heating system combined at 5 O'clock would save 30 hours a week which would represent a reduction in the use of heating by 49% during a semester week. This has the potential to bring significant savings to the university

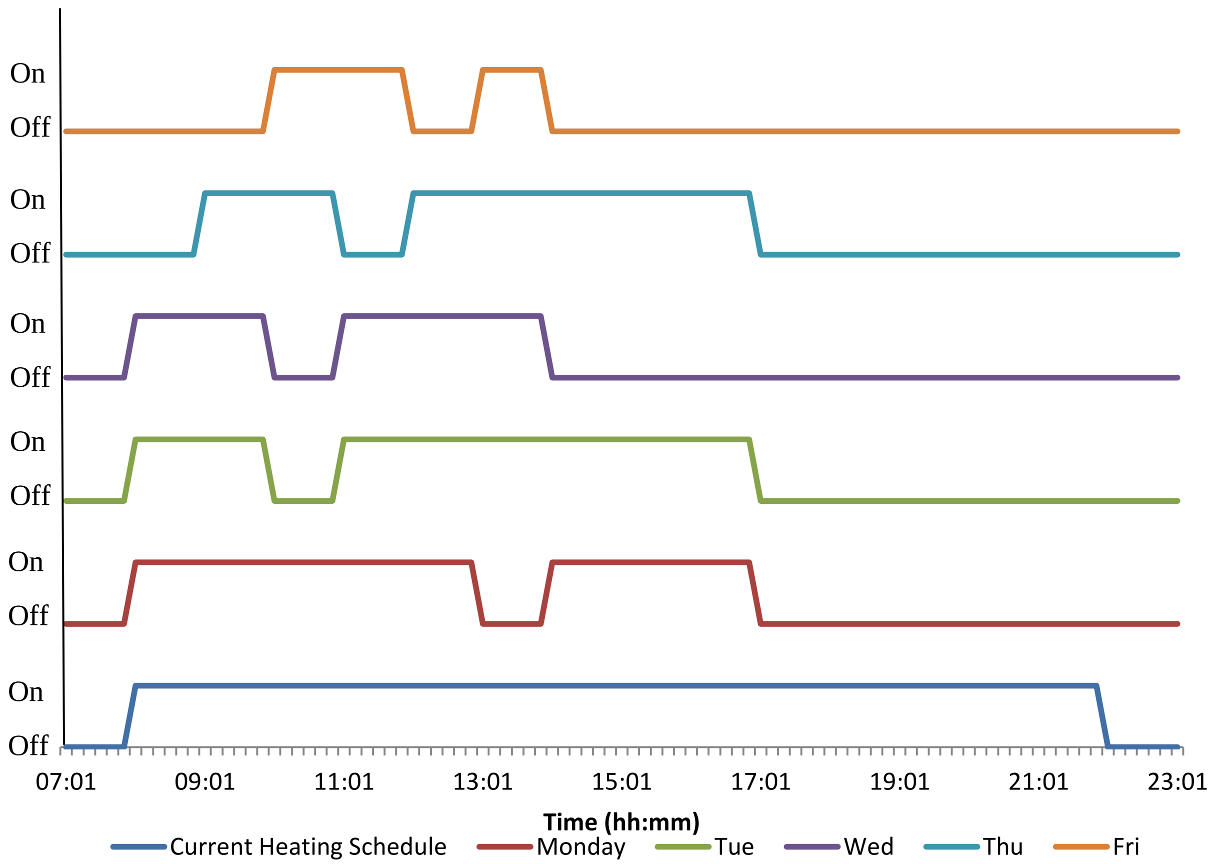


Figure 56: Comparison of current heating schedule with a heating system adapted to timetable information.

The equations generated in section 4.6 and 4.7 were used to calculate room temperatures from turning on and off the heating system. The use of these equations are likely to under-predict the temperature within the room as they are generated from a period when there are no internal heat gains. The temperatures generated are seen as a conservative estimate. Figure 57 shows how the timetable adapted heating system has little impact on room temperatures. Wednesday shows the only significant drop off due to the heating being shut off at 14.00.

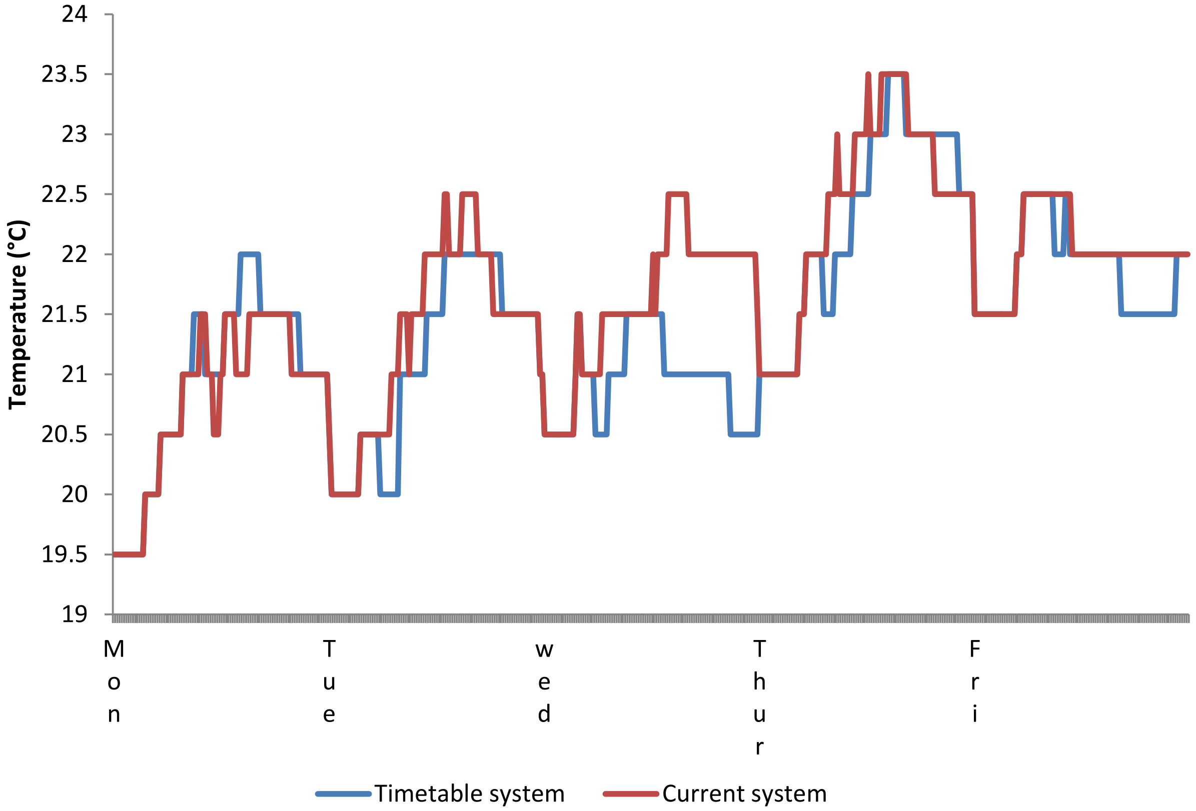


Figure 57: Comparison of room temperature of current and timetable system

The use of a timetabled heating system has great economic viability in reducing heating costs and it has been shown that room temperatures remain unaffected. This new system as discussed above, would see a reduction in the use of heating by 49%. This would equate to saving of €201 per classroom, per semester. This would represent significant savings across the campus. As temperatures remain unchanged there remains scope to reduce the heating further with a more intuitive system. The cooling rate of classroom B suggests that there will be little or no change after an hour of the system being turned off, thus in the cases of prolonged high temperatures (>21°C) there is room to switch off the system for a number of hours with the room remaining at recommended temperatures. This more intuitive system will also be more effective as classrooms within DCU work on a block with all rooms having to being turned on and off together, both classroom A and B are ran on different blocks. A system which runs on the turn off at a set temperature and which knows the cooling rate of the room and the future occupancy pattern may be more adaptable, appropriate and economically beneficent. The inputting of a timetable information into the building management is quite labour intensive in setting a schedule up for each individual classroom throughout the university and may not be flexible to change during the semester. The implementation of a more intuitive system is discussed below in section 5.3

5.3 Early Switch off

Due to the persistent high temperatures within classroom B after the implementation of a timetabled system, a more intuitive system could be used taking into account the room temperature, cooling rate of the classroom and the number of upcoming lectures decide upon the shut off point for the heating system within the room. Figure 58 displays the heating pattern for the same week shown under the timetable system discussed above in section 4.2. It can be seen that throughout the week heating can be switched off early between 12.00 – 14.00, reducing the duration of heating to 28 hours. This is a reduction of 54% from the current number of 61 hours that is currently used in a typical week.

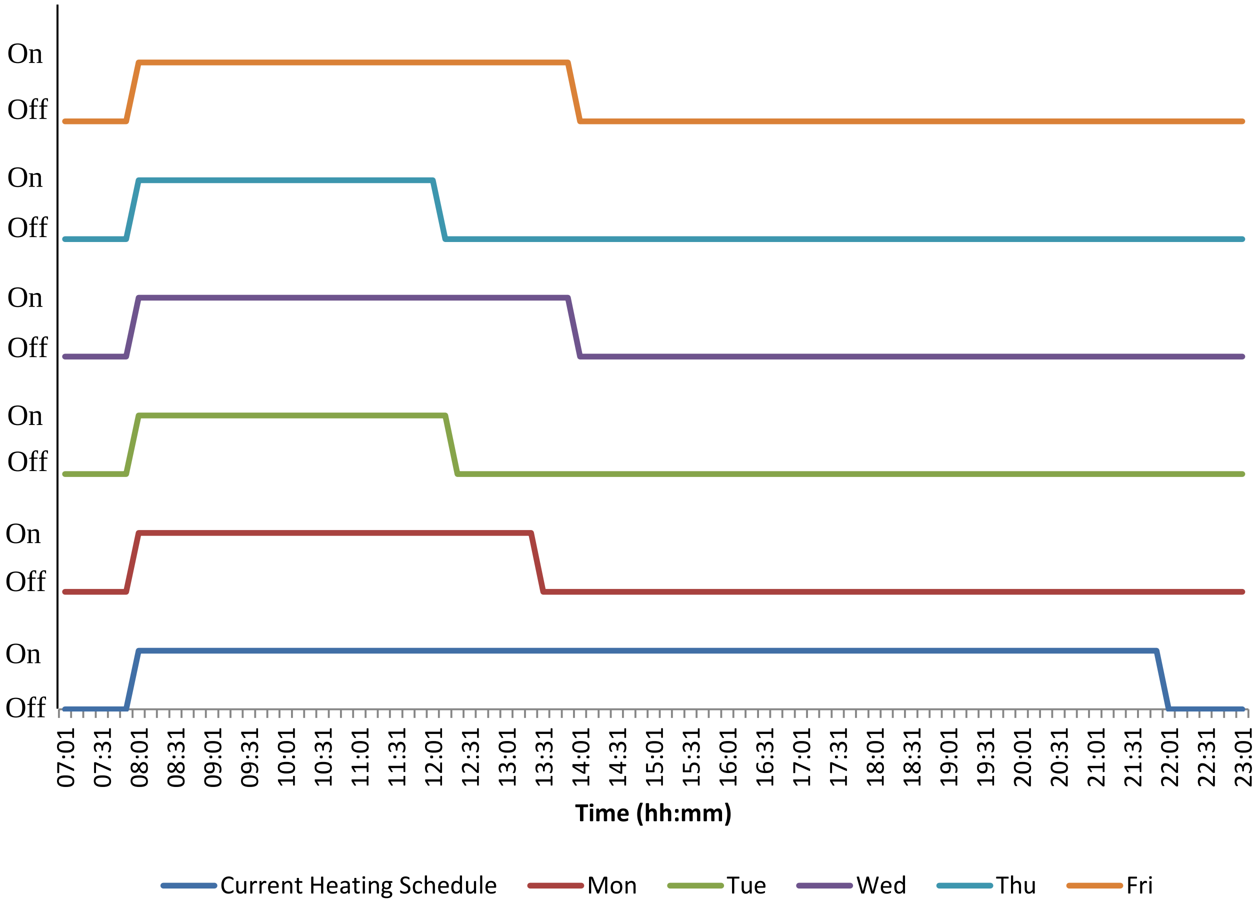


Figure 58: Comparison of current heating schedule with an early turn off heating system.

Figures 59 and 60 show the reduction in the peak temperatures above 22°C experienced by classroom B with the room temperature now ranging from 20 -21°C throughout the same week as shown in figure 58, with the classroom operating at 21 degrees during lecture hours. Figure 59 compares the temperatures of the current system and the new proposed system over a 6 week period. The temperatures were similar to that of the current system with the elimination of the high temperatures above 22°C and temperatures maintained between 20 -21°C, the minimum temperature of 16.5°C is due to the loss of heating the week previous.

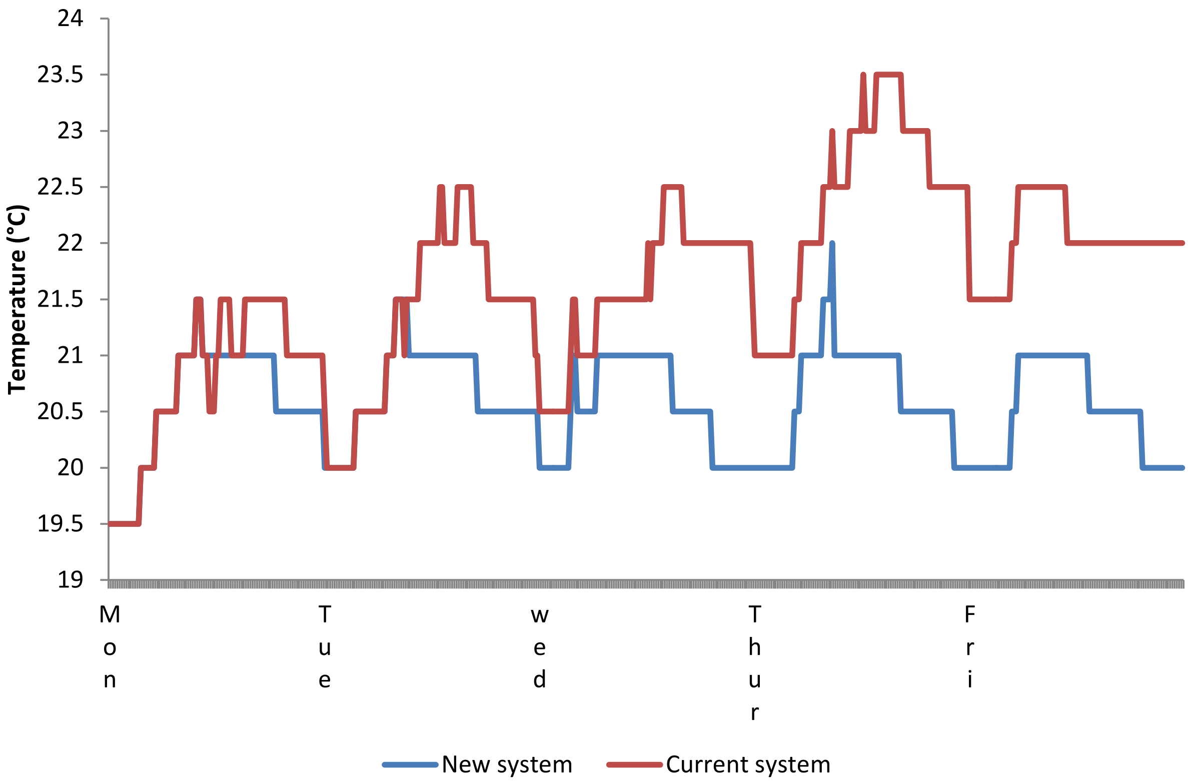


Figure 59: Comparison of temperature between current and early off system.

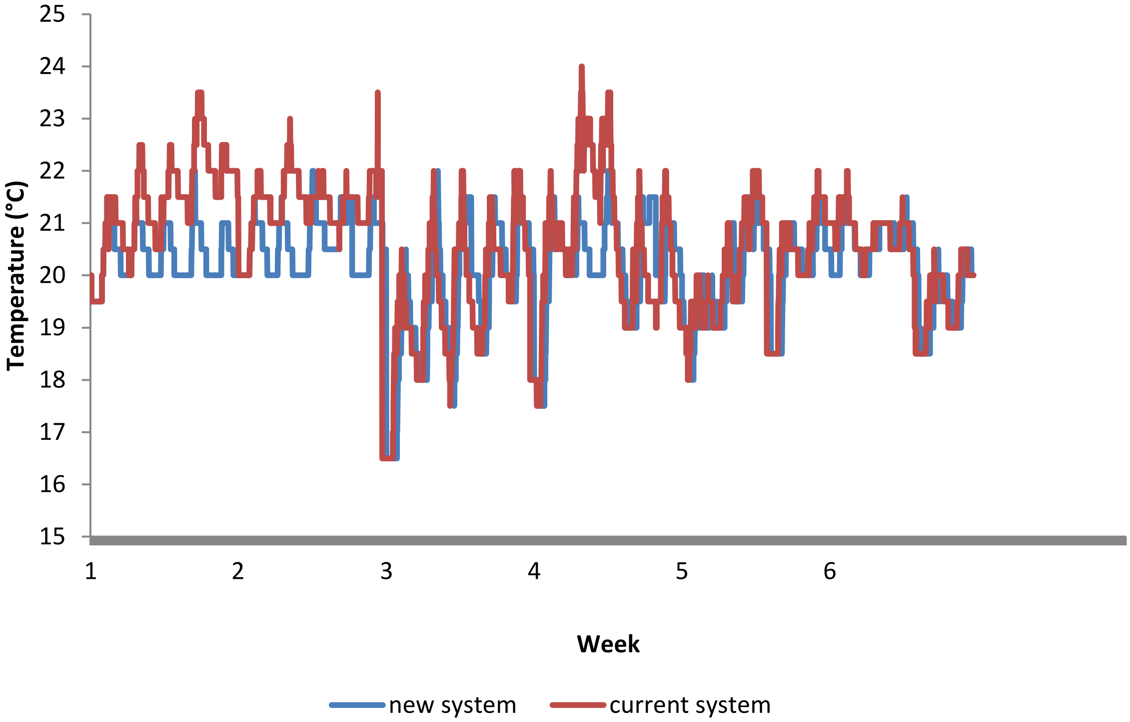
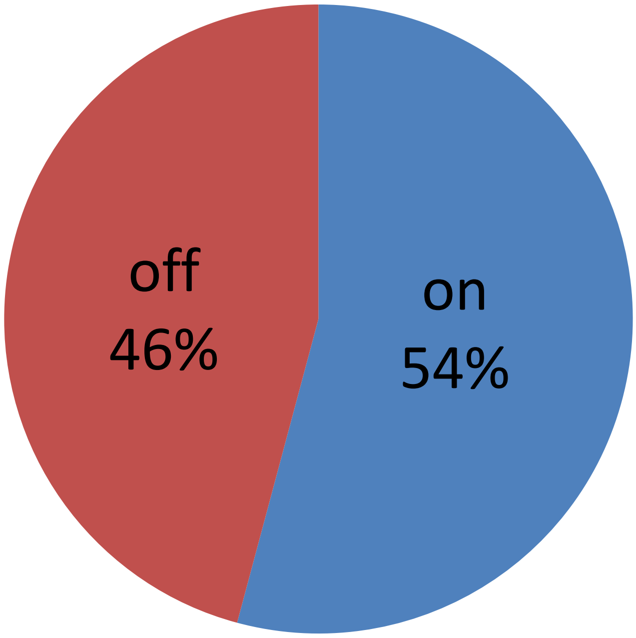
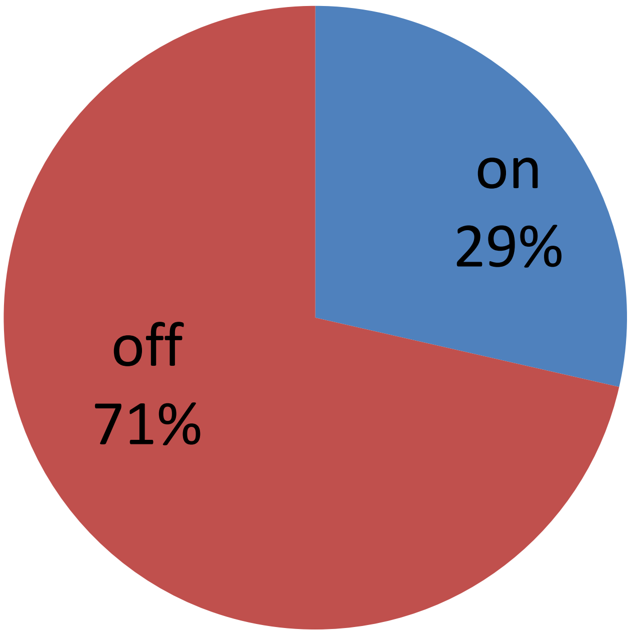


Figure 60: Comparison of current and new system over 6 weeks during semester 1.

The introduction of this new system would reduce the dependency on space heating by 25% over the six week period. A 25% reduction in use of heating would result in savings of €236 per classroom, per semester from the data obtained. This is less than the predicted 49% savings from the timetabled system or the 54% savings predicted by the early switch off system. The week used for comparison for the two weeks had particularly high temperatures which allowed for the system to be shut down for long periods. The week used was week 1 in figure 36. The 25% reduction takes into account room temperature during the 6 weeks. Due to the early turn off of the heating system in the afternoon it is often necessary to turn the system on an hour earlier than usual to ensure the room reaches the required temperature in time for the first lecture of the day. The reduction in heating time required is displayed in figure 62. The training of this system, to enable the forecasting of when the heating system can be turned on and off is discussed in section 5.4



(A)



(B)

Figure 61: Comparison of the time the heating system is turned on in the current system(A) and new system (B).

5.4 Decision Network

In order to be able to inform a system in real time as to when the heating should be turned on/off a decision tree was used. The decision tress competitive advantage over other widely used modelling techniques, such as regression method and ANN method, lies in the ability to generate accurate predictive models with interpretable flowchart-like tree structures that enable users to quickly extract useful information. Another advantage of this methodology is that it can be utilized by users without requiring much computation knowledge. The J48 tree was implemented to achieve an optimised pruned tree. The J48 tree has previously been used to inform the energy management system of a university of the thermal comfort of its occupants[116].

The decision-tree model was built by analysing training data created in section 4.4 and the model was then used to classify unseen data. Five features where chosen to create a decision for turning on and off the heating within classroom B. The nodes of the generated decision tree evaluate existence or significance of each of these individual features. The decision trees are constructed in a top-down fashion by choosing the most appropriate attribute each time. An information-theoretic measure is used to evaluate features and assigns a "classification power" to each feature. The training data are divided into subsets corresponding to different values of the selected feature and the process is repeated for each subset, until a large proportion of the instances in each subset belong to a single class[116]. Table 19 shows the selected attributes used to create a decision tree along with an explanation and sample of each.

Table 19: Attributes used to create decision tree with an explanation and sample of each.

Attribute	Explanation	Sample
Day	Day of the week	Mon
Time	Timestamp	08.01
Temp inside	Temperature in classroom	21
Temp outside	Outdoor temperature	11
Occupancy	Whether room was occupied	lecture
Heating	Whether heating was on/off	Off

The decision tree correctly classified 90% of instances correctly, as shown in table 20, along with the trees built using individual attributes. The use of the j48 tree has shown to be successful in pinpointing when the heating system should be turned off and the duration for which it can be turned off. The use of the j48 decision tree can help inform a heating system in real time of the shutdown and start-up of the heating system for classroom B when the supplied attributes are available. Interestingly, when outside temperature is removed a slightly higher classification percentage of 92% is achieved. The use of j48 algorithm has shown that the heating schedule can be accurately forecast, which is important for the implementation of such a system in a real time environment to ensure thermal comfort for students.

Table 20: Percentages of correctly and incorrectly classified instances along with confusion matrixes for each explored tree and attributes.

			Confusion Matrix		
Attributes	Correctly Classified (%)	Incorrectly Classified (%)	On	Off	
Inside Temp	75.5	24.5	1631 529	0 0	On Off
Inside Temp **Outside Temp**	58	42	1053 327	578 202	On Off
Inside Temp **Occupancy**	78	22	1367 377	88 328	On Off
Inside Temp **Outside Temp** **Occupancy**	75	25	1356 280	275 249	On Off
Inside Temp **Outside Temp** **Occupancy** **Day**	70	30	1224 233	407 296	On Off
Inside Temp **Outside Temp** **Occupancy** **Day** **Time**	90	10	1448 25	183 504	On Off
Inside Temp **Occupancy** **Day** **Time**	92	8	1497 30	134 499	Off On

5.5 Occupancy Detection

The Bluetooth scanner was placed in classroom A during the semester. The scanner failed to pick up significant amount of devices to be able to generate a prediction on the number of occupants within the room. The number of scanned devices ranged from 0-3 devices per class with occupancy of 25 plus within the classroom. Bluetooth scanning has been successfully employed to estimate large crowd with 16,000 devices picked up over 256 km cycling course, with a reported detection ratio of 13.0 ± 2.3%[49]. This detection ration would fit with the number of devices being picked up (0-3) for a crowd size of 25-40. The use of Bluetooth scanning may not be suitable for the prediction of small sized crowds. Laptops and Apple Macs were generally detected along with older phone models such as Nokia 6303 classic, Nokia 6303i classic. This research might indicate that the use of Bluetooth as a medium for sharing and transferring data is not popular among this demographic (18-24) with a wide amount of apps now available for sharing data. The power-hungry nature of modern smartphones also means that Bluetooth may be turned on sporadically when needed, while the widespread free Wi-Fi coverage across campus means that other transfer options are easily accessible. Wi-fi connections have been shown to be a useful proxy for occupancy in a campus setting, showing to correlate with 69% of the electricity use on campus. The widespread nature of WiFi networks ensures widespread spatial coverage as well as a cheap solution to monitoring occupancy levels, removing the necessity for additional smart sensors to be installed. This might be a valuable exercise to carry out around campus as a source of accurate occupancy information

5.6 Adaptation of system

The addition of timetable information with room temperature has shown that it can provide significant savings on energy. There are currently 56 similar sized classrooms in DCU this would equate to a saving of €6,384 for the university per semester. This type of saving would be worth investigation by the university. In order to adapt the system campus wide, a short term calibration study of the classroom stock would need to be undertaken to ensure reliability of sensor readings on installed BMS sensors. This information would also be required to gain knowledge on the specific heating and cooling rates of the building stock. Once temperature readings can be trusted and heating and cooling patterns have been confirmed middleware software would need to be introduced to integrate the timetabling and building management software to enable heating scheduling based on current and future occupancy. This has been successfully introduced in Leeds Metropolitan University using Niagra framework to integrate the two systems[117]. This work could be continued by a Msc or Phd student, the expected economic savings on implementation of the system be likely to almost cover the cost of hiring a new student (€16,000). This would mean nearly immediate pay back once the system was fully integrated throughout the campus.

6. Conclusion

There is an onus on public bodies in Ireland to reduce energy consumption by 33% by 2020. The improvement of energy performance in educational buildings is also important for the promotion of an energy efficient culture among future generations. Due to the cost-prohibitive nature of retrofitting existing buildings with additional sensors, one of the aims of this work was to look at the incorporation of cheap off the shelf sensors within an energy management system. The iButton was chosen as a cheap standalone logger in this study. The iButtons were deployed in two contrasting classroom types that are found on campus. The benefit of using a standalone sensor highlighted the need for frequent calibration of existing sensors. This was illustrated in section 4.8 where it was shown that the current BMS is not representative of either of the classrooms chosen as test sites. The deployment of cheap off the shelf sensors enhanced the understanding of the thermal climate within each of the two studied classrooms. This illustrated the contrasting thermal environments of the two classrooms, with median temperature values of 17.5°C and 20.5°C for classroom A and B respectively. This has shown that different heating schedules should be considered for different classroom types.

Exploring the benefits of incorporating occupancy information for classrooms on heating schedules was another aim of this study. The heating schedule at present does not take into account the variability found in occupancy in a timetabled room. The incorporation of timetable information combined with thermal cooling and heating obtained from the deployment of iButtons resulted in an optimised heating schedule for classroom B resulting in a 25% reduction in the use of heating throughout the semester. This resulted in a €114 saving in heating cost during the studied semester.

The construction of a decision network that could inform the heating system as to when to turn on and off was the final objective of this study. A j48 decision tree was used to classify whether the heating system should be turned on or off. This resulted in a 90% classification, showing that the system can be reliably informed as to when to turn on and off. The use of machine learning algorithm demonstrated how real time temperature and timetable data can be used to optimise and reduce energy costs, reducing the need for space heating by 25%.

The implementation of such a system campus wide could be expected to save the university somewhere in the region of €10,000 – €12,000 per academic year highlighting the value of combining timetable information with building management information. The use of cheap off the shelf sensors combined with machine learning algorithm have highlighted areas that can be explored to help reach the 33% energy target required.

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