Energy & Buildings 272 (2022) 112362

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Cost-effective occupation dependant infrared zonal heating system for operational university buildings

C. Scott [a,*], A.H. Ferdaus [a], T. Kenan [b], A. Albarbar [a]

[a] Smart Infrastructure and Industry Research Group, Department of Engineering, Manchester Met University, Manchester M1 5GD, United Kingdom
[b] Smart Infrastructure and Industry Research Group, Department of Computing and Mathematics, Manchester Met University, Manchester M1 5GD, United Kingdom

ARTICLE INFO

Article history:
Received 20 April 2022
Revised 25 July 2022
Accepted 4 August 2022
Available online 8 August 2022

Keywords:
Energy efficiency
Net zero buildings
Efficient heating
Non-domestic heating
Smart heating
Energy management systems and infrared heating

ABSTRACT

Recent legislations have necessitated policies for carbon print reduction. Buildings and in particular space heating are major energy consumers and responsible for over 34% of carbon print. This work presents a method of heating only certain parts of the building using far infrared (FIR) heating. This study gives an overview on the application of infrared radiation in heating by modern methods in tune and compatibility with climate developments for the public spaces in this decade. The case study is on a university lecture theatre and the space is split up into varyingly sized zones which enable different parts of the room to be heated depending on the time and occupation of the zone. The potential to heat each zone with FIR is implemented which runs according to the machine learning algorithm (MLA) through a practical study of real CO_2 data collection and validation. This allows heating to start running before the zone(s) is occupied to optimise thermal comfort. Results show that occupation zone FIR heating saves an average of 11.175kWh through various occupations compared to the currently equipped convection wall mounted radiators. Occupation forecasting of the room using random forest machine learning has an accuracy of 97.75% for 15-minutes intervals of a day. Cost analysis for the proposed occupation heating show savings of up to 76% and 14.6% compared to convection electric and gas heating respectively. FIR provides a more efficient method of heating with the capacity for zonal implementation. The results in this research demonstrate the feasibility of FIR zonal heating for non-domestic applications.

1. Introduction

Buildings in the UK use 34 % of the total energy consumption as heating and cooling loads with gas and electricity using 78 % and 12 % respectively [1]. The UK Government plans to eliminate greenhouse gas emissions from buildings by 2050 [2] stating that driving, manufacturing, heating, and electricity generation must emit as close to zero emissions as possible. The education sector is responsible for 13.74 % of total UK energy consumption [3]. Energy demand for heating is higher in colder climates such as the UK, making it a necessary focal point, but different climates will benefit from a heating and cooling system differently [4].

Smart heating practises have the potential to reduce heating demand but sometimes at the users' cost. Heating isn't always used because the user is cold. In [5] the heating is shown to be used for parental care, alleviating pain, fresh air, pets and animals, and social signalling etc. When at home, the user should have access to control over their heating to maintain comfort where there are different preferences. An investigation in [6] shows that larger buildings had worse return temperatures than smaller ones, meaning more heat is lost with larger areas. This is also shown in [7–9] where rooms have independent heating, allowing energy conservation when rooms aren't in use. Variable heating can be used to increase energy efficiency as a room that is heated to a lower temperature uses less energy, such as when unoccupied [10]. This can be controlled by a smart thermostat to optimise the temperature depending on occupancy to save energy [11,12], where 45 % and 43 % of occupancy based controls are commercial and domestic respectively [13]. Hot summers and cool winters also affect heating and cooling demand, where variable heating systems can be advantageous [14,15]. This also leads to longevity of the heating system as [16] estimates climate change will reduce heating demand between 2050 and 2080. Heating envelope contributes to the initial demand and how quickly the heat is lost [17]. Smart heating reduces heating demand, and involves automatic thermostats able to be set at a temperature by the user [18]. Heating demand can be predicted to allow the storage, selling, or purchasing of energy before the consumption has occurred. This is beneficial environmentally and economically as costs are reduced by 5 %

* Corresponding author.
E-mail address: connor.scott@stu.mmu.ac.uk (C. Scott).

https://doi.org/10.1016/j.enbuild.2022.112362
0378-7788/© 2022 The Author(s). Published by Elsevier B.V.

Nomenclature

Abbreviations

A	Area of receiving body
A_R	Area of irradiance
DI	Direct irradiance
IR	Infrared
FIR	Far infrared
K	Thermal conductivity
KNN	K-nearest neighbour
kWh	Kilowatt hour
MLA	Machine Learning Algorithm
mph	Miles per hour
NN	Neural network
PDT	Probability of occupation
P_{out}	Output power of the panel
PPM	Parts per million
Q	Rate of heat transfer
RF	Random forest
RP	Required power
Z	Occupation zone
ε	Emissivity of object
σ	Stefan Boltzmann's constant

to 12 % and comfort is increased by 15 % to 30 % using machine learning prediction [19]. There are various methods of machine learning (ML) for prediction that can predict air conditioning demand, or heat power demand for short-term forecasting [20,21]. Occupancy prediction has been researched within a residential building with 80 % accuracy [22] and up to 52 % energy savings [23]. Larger scale occupancy is predicted with an energy reduction of 8 % [24]. K-nearest neighbour (KNN) and neural networks have the highest accuracy when used for load forecasting and for improvement of energy performance for office buildings [25]. Random Forest (RF) and Neural Network (NN) MLA's have an error of 4.6 % and 4.09 % respectively for demand prediction [26] RF is also used for wind turbine wake forecasting [27].A NN is used for demand prediction with 4–6 % error [28]. A KNN is used in [29], and Gaussian regression is used for demand prediction in [30]. ML forecasting and categorisation is most used for heating and cooling, ventilation, lighting, demand response, and energy management [31]. No occupation heating system is combined with occupation forecasting through MLA's for optimisation of a heating system. Previous methods of heating use convection and variable air volume space heating. A more efficient way of heating is through far infrared (FIR) which can have an efficiency upwards of 92 % with an optimal response time of 1 s [32–34]. A zonal heating system is investigated by splitting a building up into respective rooms using a variable air volume heating system. This allows more control over the heating system and shows savings compared to conventional heating methods [35]. Natural gas will continue to produce carbon emissions whereas electricity can be generated through 100 % renewable sources [36].

Infrared heating (IR) is a method of heating an area through more efficient results than gas or electric convection heating. IR heats faster, more uniformly, and more efficiently when used to heat and dry food during food processing [37,38]. Applications of FIR consist of health care systems, beauty care, hair treatment, and food processing [37,39–42]. There is application of IR towards the deactivation of Covid-19 [43,44]. Variable heating is essential for FIR heating methods having high variability [45].FIR heating is applied to an 8 m^2 room with comparison against convection heating and an air source heat pump. The timing for each system to heat from the room surfaces 18.5 °C to 23.5 °C with an average of 0.4 °C/minute for the infrared system, taking 9.5 min to heat to 23.5 °C. This is faster than the convection heating which took 17 min to heat the room [46].

Infrared generators can come in many shapes and sizes, depending on output. They can be ceiling, wall, or floor mounted, with costs varying from £200 for a 5 m^2 room to £1,300 for a 29 m^2 room [47]. Four large brands of infrared panels cater to floor sizes from 2 m^2-24 m^2, depending on the panel [48–51]. They are all far infrared emitters where the smallest is 160 W, and the largest is 3 kW. The smallest floor size guideline is 2 m^2 and two separate suppliers have a panel size of 0.18 m^2 with 160 W and 180 W. Panels are most practical can be fixed to a wall or ceiling while maintaining appearance and taking less space. The inconvenience with some panels is that they have no insulation, so the surface can reach temperatures of 115 °C [52], whereas for ceramic FIR panel heaters, the surface temperature can remain cool to the touch while it's in operation [53]. This makes ceramic infrared heating suitable for more applications that involve more people. Spatial analysis is essential when deciding which heating method to use as convection heat is often lost through spaces with high ceilings [54]. Pipe placement within walls are assessed in [55] which states there must be more practical research, but FIR heating eliminates the need for heating pipes altogether.

Electric FIR panel heaters are shown to have up to 98.5 % efficiency from supply to production of heat with satisfactory thermal comfort, thermostatic control, and with low initial investment [56]. Convection heat with occupancy forecasting is previously most efficient with a 2.8 % reduction is heating demand [57] but can be inefficient as air rises to the top of a space and doesn't heat the occupants unless it passes through them. Air flow contributes to the temperature distribution in a room where a higher air flow moves the heat around the room and a lower air flow allows the heat to be controlled easier. Cost analysis provides incentives as initial investment is required and without profit, there is no incentive [58]. Lower air flow benefits heating control but there must be adequate air flow given by ASHRAE standards for health demands [59]. Higher thermal insulators are commonly used for the surrounding of the building to keep the heat in [60] whereas there's a variety of materials within the room that can be used to retain heat as well.

Heating demand prediction heavily relies on occupancy as when a room isn't occupied, it doesn't need to be heated. Previously, when a room is occupied, the heating is on, whereas in this research, a more refined occupational analysis heating method allows variable heating to be applied to different zones within the room when they are occupied. The use of zonal FIR panel heaters are validated against the currently equipped convection wall mounted radiator heating system.

Energy consumption through heat demand is high in the UK in comparison with other countries, and with a target for carbon reduction and eventually elimination, heating efficiency must be improved. Machine learning can be used for accurate heating demand prediction, and materials within the room are analysed to show the benefit of various thermal conductivities when heated through FIR.

There is lack of research with applications and results of an installed FIR heating system for a public building. IR panels are shown to improve heating efficiency between 62 % and 88 % in residential homes [61] but nothing is previously applied to public buildings. Further to this, previous research splits a building up into rooms [35] whereas this research splits a room up into zones to analyse heating efficiency. Space heating only works if it is implemented per room, but FIR heating can be implemented into a room that has various heating zones as it doesn't heat space, and instead the materials within the room. Smaller heating zones are easier to control and can require less energy to heat. If rooms can be split into small sections to heat people individually, using efficient heating methods, the efficiency of heating improves, and the heating demand decreases. Occupation prediction is applied to optimise comfort and efficiency, using machine learning techniques and cost analysis is researched to show applicability and practicality of the proposed method. The occupation prediction of ML are combined with the high efficiency of infrared heating to show a novel method of heating a university lecture theatre. This has applications for both non-domestic and domestic buildings. Cost and applicability is analysed through a case study and simulation on an operational university campus. The novelty of this research is the simulated application of far-infrared heating to an operational university building through zonal heating and occupation forecasting to reduce energy costs and consumption.

2. Occupation prediction and application methodology

The methodology to retrofit the lecture theatre with infrared heating through machine learning occupation forecasting and heating of the room is demonstrated in Fig. 1 below.

A case study of a lecture theatre measuring 11 m × 10.25 m × 8.6 m with maximum capacity of 118 people, in a UK University, is investigated to have an occupation dependant FIR heating strategy. Wall mounted radiators are simulated with a comparison of ceiling mounted zonal FIR heating. Panels are taken from a retailer which is designed to replicate a ceiling tile with the dimensions 60 cm × 60 cm with a maximum rating of 350 W. They can be installed with wireless communication to a smart thermostat such as in [11]. In the simulations, they are used as ceiling tiles, but they can be fitted to a wall or any other flat surface. The wall-mounted convection radiators are 1 m × 2 m with a maximum rating of 2 kW. There are 118 zones within the room able to be independently heated through heat sensors and a smart thermostat such as in [11], but this would require that each infrared heating zone has a separate thermostat. These zones include the student seating area in the middle of the room, the balcony at the back, and the professor area at the front. Machine learning is used for occupation prediction for pre-heating to maintain comfort. The heating simulations are designed through SOLIDWORKS 2022.

As each room has unique characteristics and requirements, the retrofitting method is generalised for replicating. Characteristic data includes the size, shape, and occupation zones, whereas heating requirements depend on where the occupation zones are and how much of the room is occupied. This data is used to split the room into parts, depending on whether the user is sitting or standing, and the panel requirements are decided. Binary decision making is used for if the zone is occupied, the zone is heated and for no occupation, reduced or no heating may be in use. The results are simulated for both convection and FIR heating methods to analyse efficiency and comfort improvements. If these improvements are not satisfactory, the panels can be altered such as with variable heat, or larger panels for a less controlled, more easily heated area. Material characteristics of the room can be added into the simulation to show how long they take to heat, and how well they retain heat to determine how the panels work. The aim of this is to produce a more comfortable and more efficient heating method through zoned heating of any room.

The average required power to heat an occupant is 712 W whereas to heat the epidermis it requires 0.0005 W/m^2.K [62]. The average surface area of an adult is 2.74 m^2 [63] so to heat the epidermis of an occupant from 0 °C to 21 °C the required direct energy output from the FIR panels is 0.02877 W. It is assumed that each occupant is of the same dimensions and thermal conductivity, with nothing between them and the FIR panel to impede conductance, and direct FIR from the panel to the occupant. Tables and seats are made from wood with a thermal conductivity of 0.1664 (W/m.K) [64]. Infrared panels don't only provide direct heat, and instead evenly distribute the heat over 45° angles throughout the spectrum. Direct irradiance from the face of the panel and required power is explained below in Eqs. (1) and (2).

$$DI = \frac{P_{out}}{A_R} \tag{1}$$

$$RP = K * T \tag{2}$$

where '*DI*' is radiation direct from the face of the panel measured in Watts per meter squared, 'A_R' is area of radiance, 'P_{out}' is output power of the panel, '*RP*' is required power to heat the occupant in Watts per meter, and '*K*' is thermal conductivity of the occupant. Direct FIR isn't impeded by air and will travel until the occupant is reached.

The rate of heat transfer over time can be explained through Stefan Boltzmann's constant in Equation (3).

$$Q = \varepsilon\sigma A(T_1^4 - T_2^4) \tag{3}$$

where '*Q*' is rate of heat transfer over time, 'ε' is emissivity of the receiving body, 'σ' is Stefan Boltzmann's constant, '*A*' is surface area of receiving body (m^2), and '*T*' is the emitting and receiving temperature respectively.

2.1. Occupation probability and prediction

Rolling data of occupation is used to develop occupation prediction used for pre-heating. Previous data of occupation is analysed and added into the prediction to evaluate whether the heater will activate for pre-heating. Each zone has its own occupation prediction which is calculated using Eq. (4) below.

$$PDT = \frac{\sum_{Zx1}^{Zxn} PDT}{PDTZxn} \tag{4}$$

where 'PDT' is probability of occupation on a certain day at a certain time such as Monday at 9am. 'Z' is the unique occupation zone which is shown as '*x*', '*x*1′ and '*xn*' that show all of the collected data between the first and the last record. The Equation develops as more data is added where there are more points between 'x1′ and 'xn'. For the case study, each room has a timetable when it will be occupied as lectures are held there. This method is useful only for when only occupation data is accessible (Table 1).

A RF or a NN MLA can be equipped but only if more data is accessible surrounding the weather and building characteristics. This allows a more accurate prediction, for if there are more occupation zones, occupation prediction becomes more difficult. The RF and NN are shown to predict occupation density of the room. Actual collected data included in the two occupation prediction simulations are rain (mm), wind (mph), temperature (°C)(K), time of day (15-minutes), cloud coverage (%), and indoor CO_2 density (PPM).

The developed NN algorithm is made from an input layer, two hidden layers, and an output layer, with a sigmoid symmetric

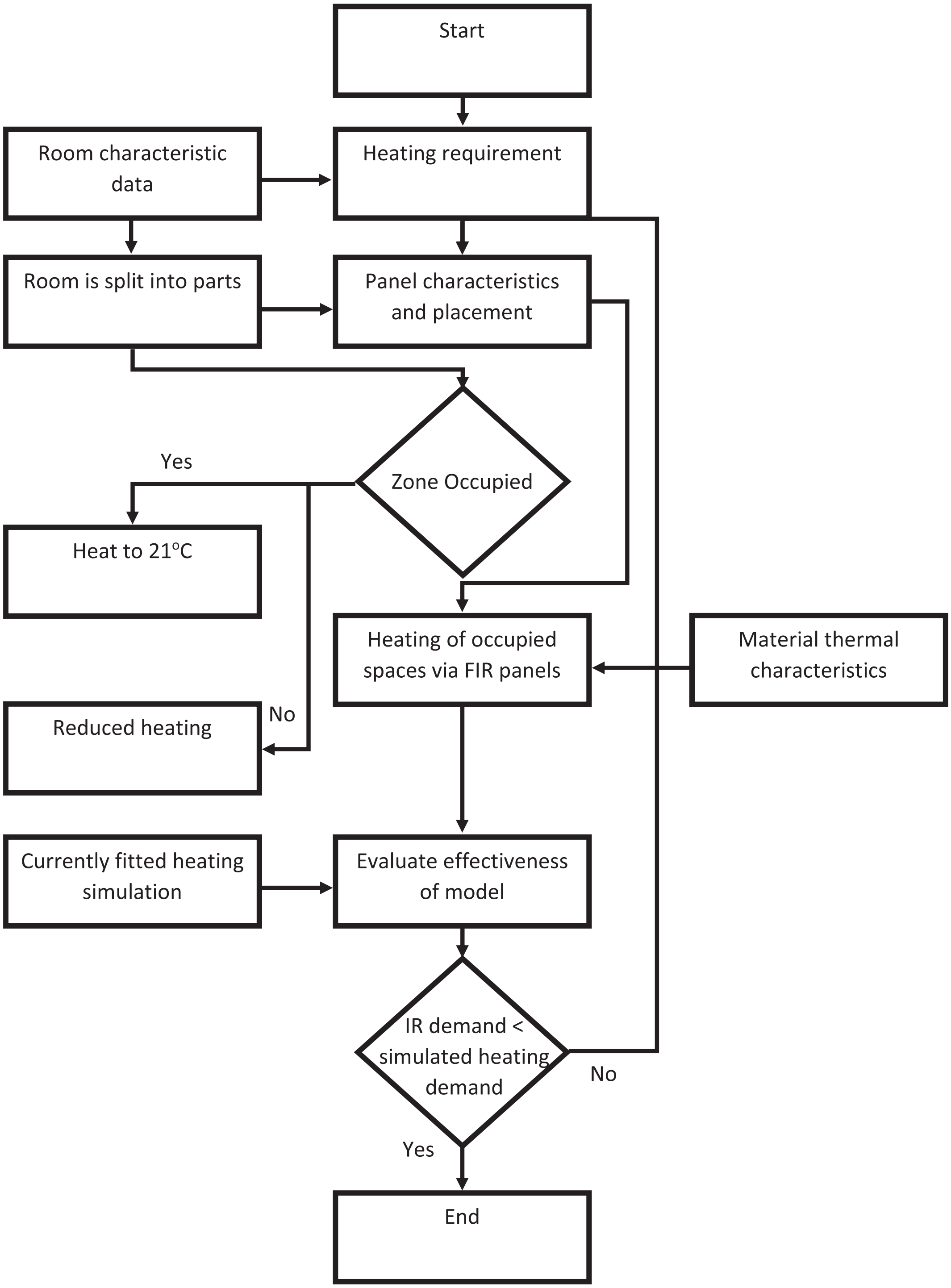

Fig. 1. Showing the process of retrofitting a generic room with FAR infrared heating.

transfer function. Inputs for training the algorithm are outdoor temperature, rain, cloud coverage, air pressure, time of the day and day of the week, with CO_2 data used for targeting using only 10 days of data for training. The RF algorithm contains the same data set as the NN with 50 decision trees for feature selection and regression.

New input data can be fed into the NN while it retains the same weights, bias, and functions, which allows it to make a prediction for the target. For the RF, when new data is added, the importance of each feature is saved from the training stage which allows an accurate output. Classification of input variables is part of pre-processing where each variable is replaced with random selections and the output error is measured. This eliminates correlation results and produces causation results instead, allowing any unwanted data to be removed from the training set. This is done through 50 decision trees too.

Table 1
Energy consumption and material temperature variance for FIR and convection methods.

Occupation and method	Energy demand (kWh)	Material temperature variance (K)	Air temperature variance (K)
Maximum FIR	4.04	11.08	12.37
Minimum FIR	2.41	10.39	10.64
Maximum Convection	14.4	52.89	39.85
Minimum Convection	14.4	52.89	25.22

2.2. Heating of the room

To determine how to heat the room, it is split into occupation zones. In the case study lecture hall, the zoned areas are the student seating area which is in the middle of the room separated by the steps, the professor area which is the grid at the front, and the balcony area at the back of the hall which in this case acts as an overflow if there aren't enough seats. This is shown below in Fig. 2.

Each zone is a different size and so are the panels for them can be too. Each heated zone for the 96 seat student area is 0.75 m wide by 0.4 m high, for the standing balcony area it is 0.75 m by 0.75 m, containing 13 zones, and for the professor zone they are 0.55 m by 0.55 m for 9 zones. The professor area could have one large panel but for a seating professor, smaller zones give more control. This allows for independent zones to be heated depending on occupancy.

Each FIR heater is equipped with a smart thermostat allowing it to control the temperature depending on the occupancy or expected occupancy for pre-heating of the zones. The zones are independent from each other as they are occupied but to maximise energy efficiency in convection heating when there are multiple occupied zones that are connected, the zones have various energy requirements to maintain the same heat. This is determined by heating of the first zone to be occupied, and then the surrounding zones will be heated using less energy as they are occupied.

To simulate the occupiers of the room, two variations are implemented: standing and sitting. Both occupier types are cylinders with an emissivity of 0.98. The standing occupier has a height of 1.75 m and the sitting occupier has a height of 1.55 m.

The results from six convection heating simulations are shown in the results section. Occupation density is varied from minimum, medium, and maximum. This is tested with both the convection system and FIR heating. Minimum occupation is assumed to have 10 occupants, medium has 27, and maximum has 98 occupants.

3. Results

The results section is split into energy use, time taken to heat, air flow, and efficiency for specified occupation densities of minimum, medium, and maximum.

The current radiator system is shown below in Fig. 3.

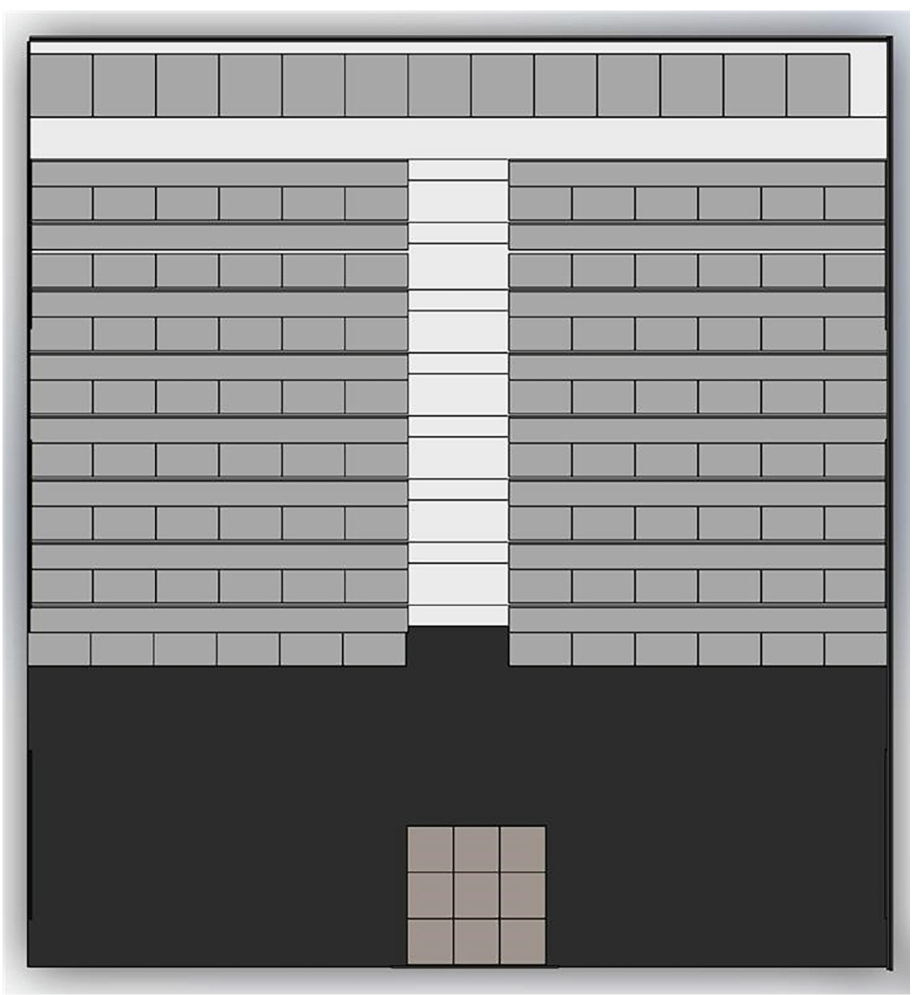

Fig. 2. Division of the lecture hall into occupation zones.

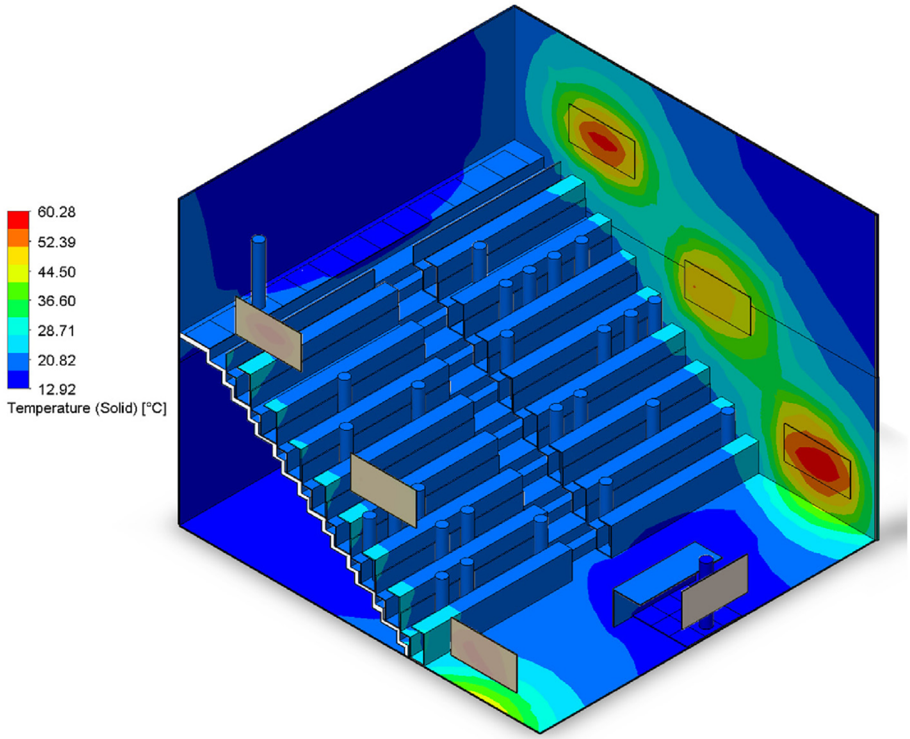

Fig. 3. The current fitted radiator system.

The convection method heats the room from the radiators installed at the sides under medium occupation.

The FIR heating system is shown below in Fig. 4.

The FIR heating method is done through zones that are activated when under occupation, enabling concentrated heated parts of the room.

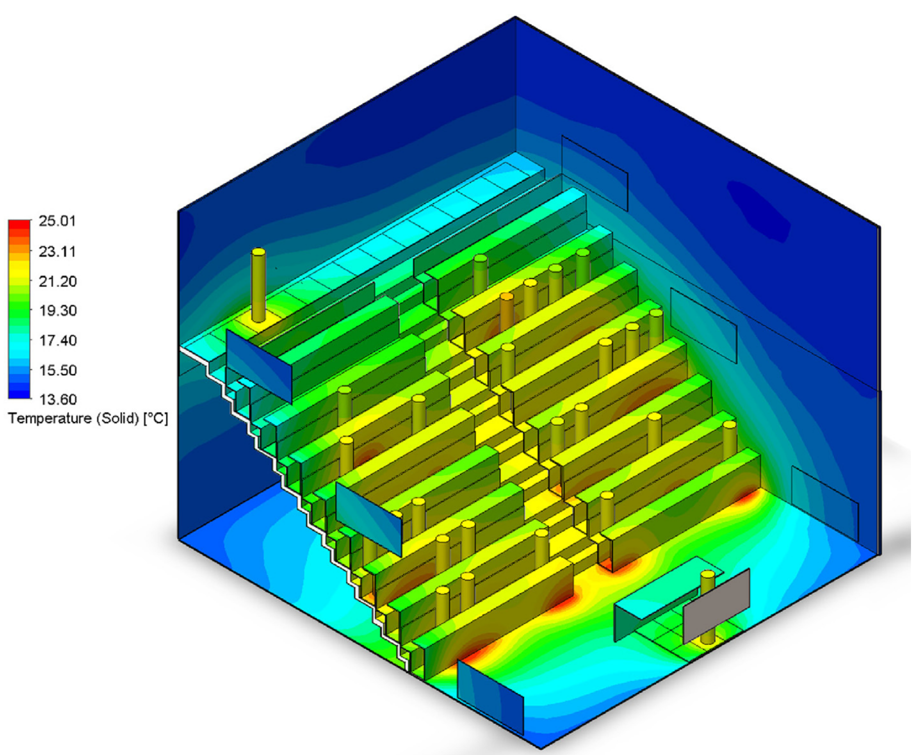

Fig. 4. The FIR zonal heating system for medium occupation.

The FIR panels can be placed at any point in the room so long as they provide heat to the required zone. In this case, the occupant is heated from above, so it is important that they are heated evenly from top to bottom. Each occupant and zone has a corresponding ceiling fitted FIR panel. The temperature of the bottom and the top of the professor is 21.19 °C (294.34 K) and 20.6 °C (293.75 K) respectively, giving a difference of 0.59 K. The seating area heating varies between 0 W and 320 W to heat the occupiers with a variance of 0.05 K from the top to the bottom of the occupier in the best case. The highest variance results are 2.17 K between the bottom and the top of the occupier.

3.1. Energy use

The FIR heaters vary in power, depending on the time of occupation for each zone. When all heaters are activated in the seating area, the heat is too high, so some of the heaters operate at a lower wattage or in the case of medium occupation, they don't operate at all.

To heat the room using occupation dependant heating with medium occupation, the FIR heating uses 3.46 kW. For the same occupation, the wall mounted radiators used 14.4 kW to heat the occupiers to the same temperature as the occupation dependant method. The energy needed to heat the professor per zone is 130 W. There are 9 panels/zones in the area allowing room for movement.

When in medium occupation, the energy requirements for each panel are shown below in Fig. 5.

The highest energy demand is 320 W and the lowest is 0 W. To heat just one occupied space it requires 320 W and when all spaces around an occupied space is heated, that space doesn't require any, or as much heat. This method maintains the required heat for each zone while saving 5.2 kW compared to heating all the zones with 320 W.

Minimum and maximum occupations for both FIR and convection heating are simulated to show how the effectiveness of the method vary depending on occupation.

The energy demand, material, and air temperature variance simulation results for minimum and maximum occupations using FIR and convection methods show that FIR has a much lower demand for both minimum and maximum occupations. FIR also has lower material and air temperature variance.

The energy demand for the methods are shown below in Fig. 6.

The FIR occupation dependant heating system used 75.9 % less energy than the convection wall mounted radiators. These results occur when all methods are in medium occupation with 25 seated and 2 standing occupiers out of the possible 118 zones.

3.2. Air flow

Air quality and flow provide important information on how the health of occupants is affected. The air flow for medium occupation for the occupation dependant system is shown below in Fig. 7.

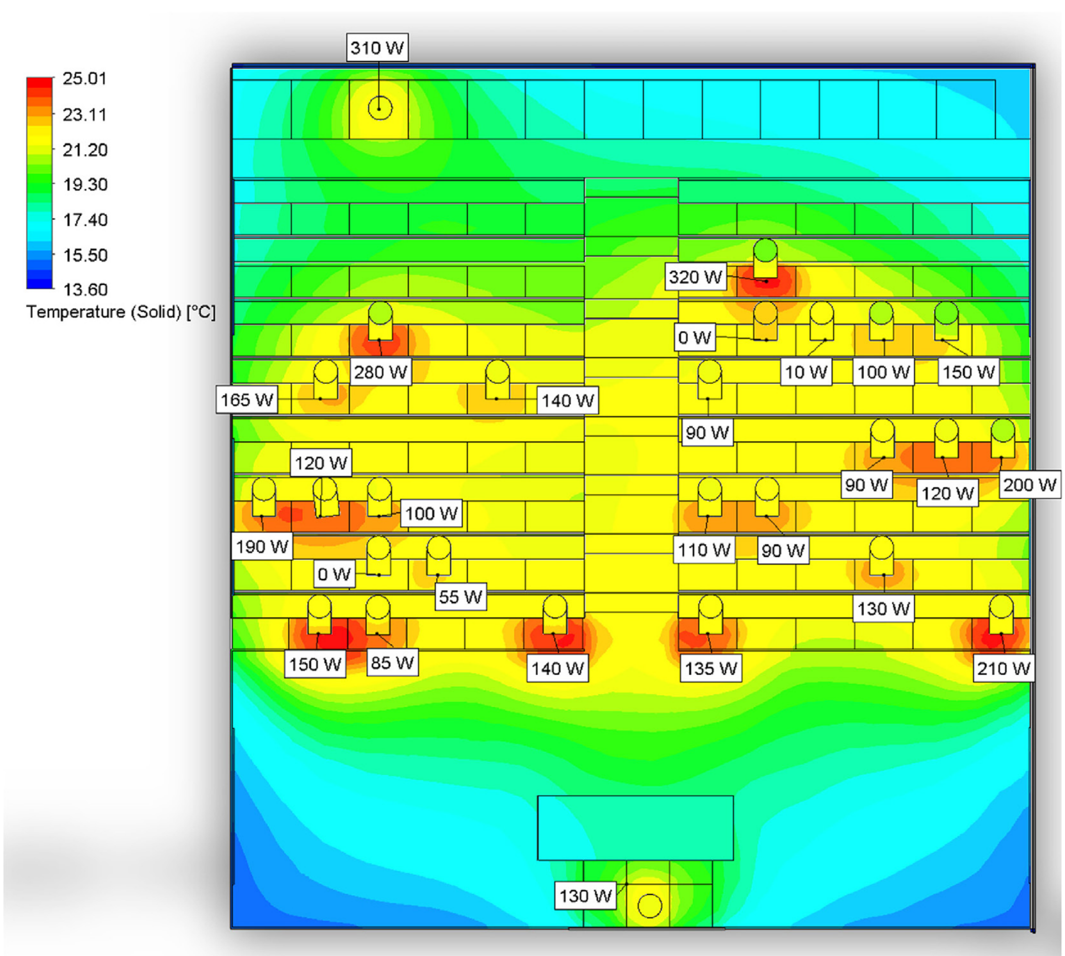

Fig. 5. The varied energy requirements of the FIR heating zones to maintain the same heat.

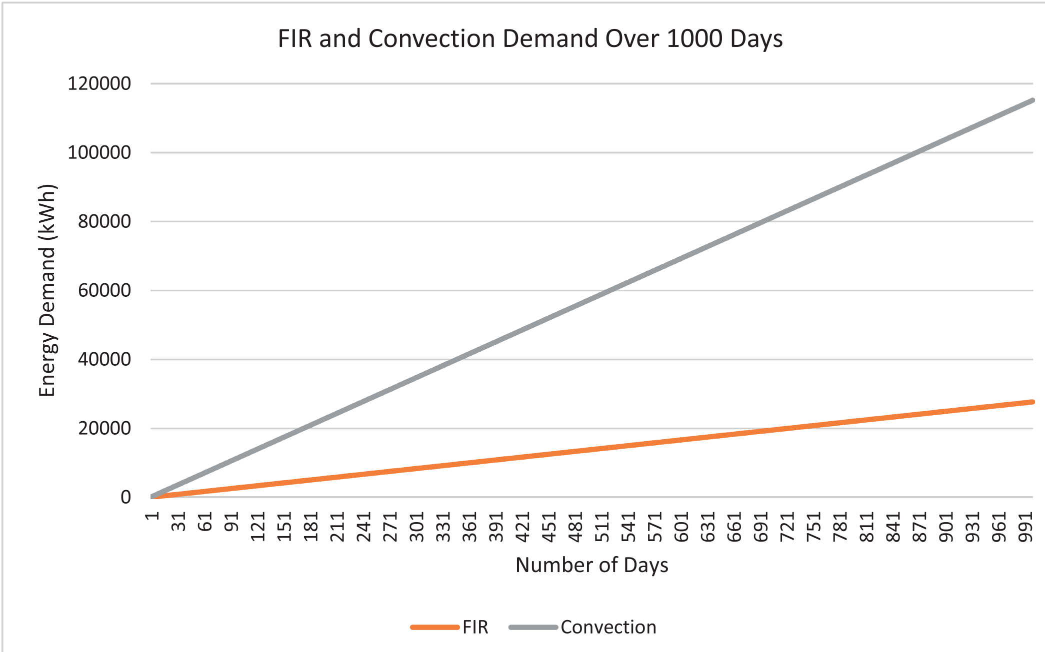

Fig. 6. FIR and convection demand over 1000 days. The energy demand (kWh) for the convection wall mounted radiators and the FIR heating system's energy demands over 1000 days under medium occupation.

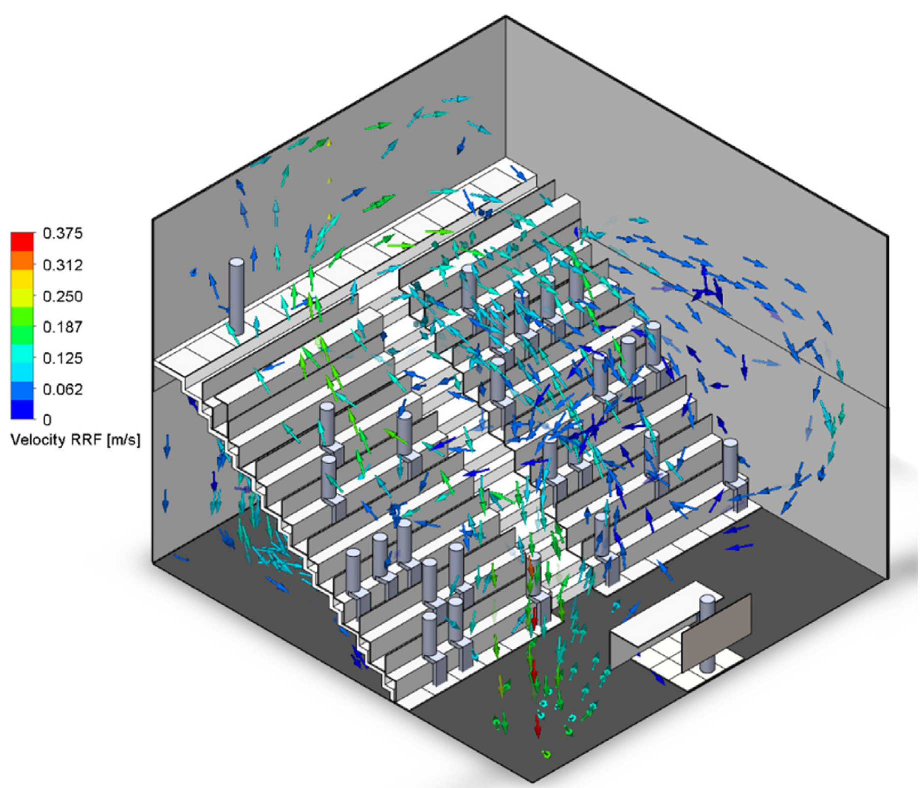

Fig. 7. The FIR occupation dependant air flow and speed when heated to 21 °C (294.15 K) in medium occupation.

The air flow has a range of 0.375 m/s all through the room, as heated air moves up the steps to the back of the room, then cools as it falls and moves towards the front of the room to be recycled. The temperature of the air has a range of 13.39 K.

The air flow for medium occupation for the currently installed radiator system is shown below in Fig. 8.

The air flow has a speed range of 0.263 m/s through the room but has most of the movement at the front of the room where

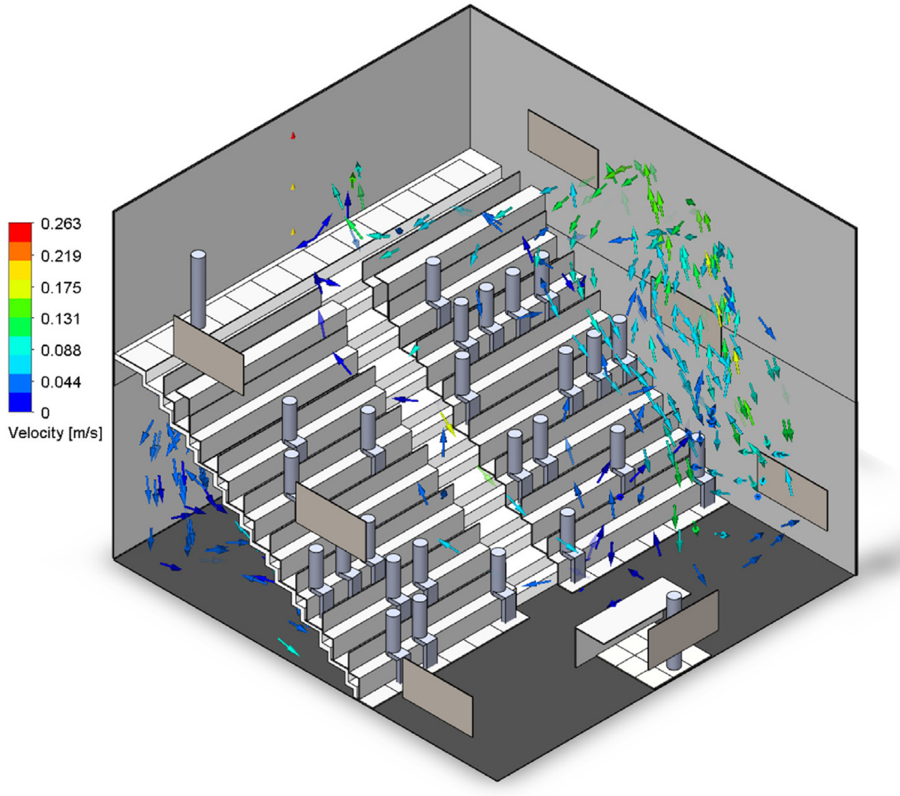

Fig. 8. The air flow for the convection system when occupants are heated to 21 °C (294.15 K).

Table 2
Showing air speed and air temperature variance for FIR and convection heating for varied capacities.

	Minimum FIR	Maximum FIR	Minimum convection	Maximum convection
Maximum Air Speed (m/s)	0.322	0.278	0.350	0.856
Air Temperature Variance (K)	10.64	12.37	25.22	39.85

the air is cooling while also being heated by the radiators as a whole room. The SOLIDWORKS simulation is used to compare air temperatures of the hottest and coldest air temperature between FIR and convection heating methods.

For the medium FIR heating, the air flow has a maximum speed of 0.375 m/s whereas the convection heating has a maximum air flow of 0.263 m/s. Minimum and maximum occupation air flow speed and temperature for occupational and convection heating are shown below in Table 2.

Air Temperature variance is the difference between maximum and minimum temperatures throughout the air in the room at the same time. This is simulated through SOLIDWORKS. Convection heating has a higher temperature variance from materials in the room to the occupant compared to FIR, showing lower efficiency.

3.3. Cost analysis

The retrofitting space for the heating is 28.8 m^2 for the student area, 7.3 m^2 for the balcony area and 2.75 m^2 for the professor area equalling 38.85 m^2 of heating overall. A quotation for wall mounted radiators and installation from a supplier costs £4,613, whereas the ceiling mounted FIR panels and installation costs £6,138. For medium occupation, the simulated methods are shown below in Fig. 9.

The FIR and convection heating systems installation costs £6,138.30 and £4,613 respectively. The average cost of energy is 13.5p/kW, meaning daily FIR and convection cost £3.73 and £15.52 respectively. The FIR operation costs 42 % less than convection heating, giving an ROI of 520 days and an annual saving of £4,312.

3.4. Occupation prediction

A random forest and feed forward neural network MLA are created with collected data surrounding the case study and added occupation data to show the results of the models. The CO_2 data is collected through 2 installed CO_2 sensors in the ceiling. Data points are predicted in 15-minute increments from midnight to 15:45 for both methods, with results shown below in Fig. 10.

The NN had an average error of 15 % with a high of 47.76 % and a low of 0.22 %. The RF method had an average error of 2.24 % with a high of 17.72 % and a low of 0.0187 %. There is a large peak between 12:00 and 13:00 which is followed by the RF but not the NN. This CO_2 peak produces the highest error for both algorithms. Average variance between data points is 6.8PPM which is 13.6 % of average PPM for the training set. The average PPM for the peak is 1026 which is 2051 % compared to the average of the rest of the data set. The RF produced results in 6.9 s whereas the NN took less than 1 s. Classification of input data shows time of

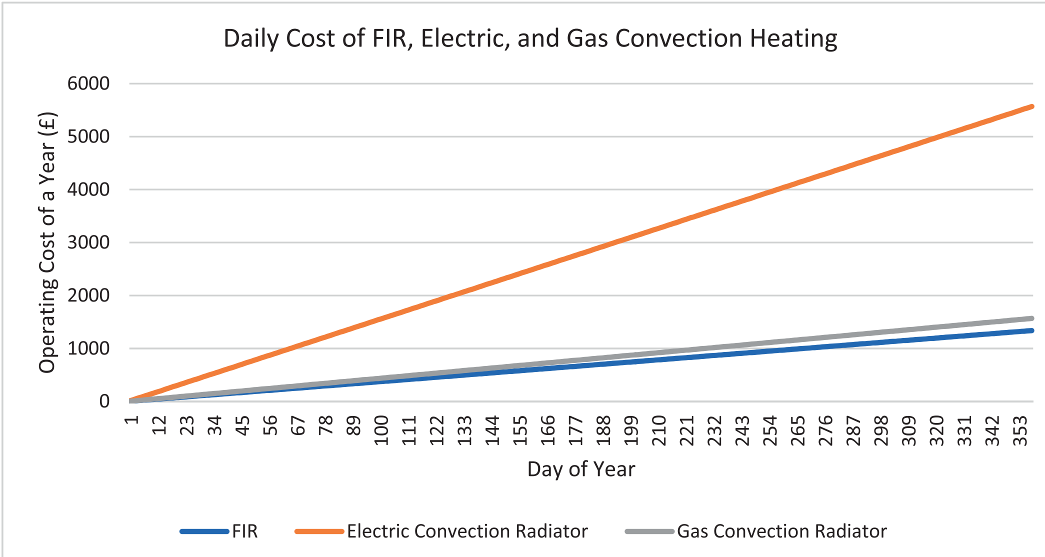

Fig. 9. The cost to run FIR, electric convection, and gas convection heating over 1 year.

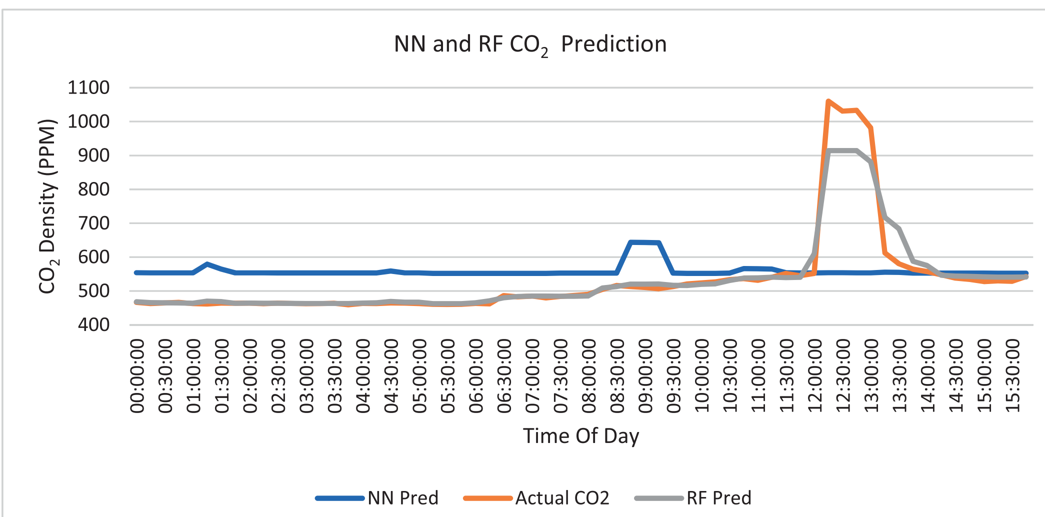

Fig. 10. Showing forecast results from NN and RF algorithms for CO_2 density.

day, outdoor air temperature and pressure are the most important variables. Rain, cloud coverage, and the day of week don't affect the levels of CO_2 as much, although they still aid the algorithm to an accurate prediction.

The occupation densities are split into minimum, medium, and maximum, with minimum CO_2 density from 490PPM to 550PPM, medium is from 550PPM to 580PPM, and maximum is from 580PPM to 1060PPM or higher. Any lower than 490PPM and the room is deemed to be out of use until sensors are activated or the room is heated manually.

4. Discussion

Six simulations are explored for FIR and convection heating for minimum, medium, and maximum occupation of the lecture theatre. The highest benefit of using the FIR system is when the room is under minimum occupation. Space heating must heat the room no matter how many people are in it, so minimum and maximum occupation require the same energy output from the convection radiators. This is improved with the FIR heating as the minimum occupation heating scenario saves 12kWh, but maximum occupation FIR saves less at 10.36 kW, compared to convection heating. This is due to the convection radiators heating the room regardless of the occupation, but FIR demand is linked to the occupation.

Occupation zones are split into seating and standing which is quantified through the fixed layout of the room. There is a seating area in the middle with a standing area at the back. This isn't always the case as a room can have any layout, so for this method to have the best performance, the room layout must be established and maintained. An independent zone for each seat is developed in this research, but more practicality may involve larger zones which could heat more than one person at a time. For an ideal shape for a room, less space above the occupants head is better as the heat is more easily controlled and less energy is required to heat the space. Higher insulation is better for heat control but another method which can be retrofitted is ceiling fans which is a good method for directing heated air back towards the occupants before it cools [65]. This is applicable to domestic buildings, which FIR heating is already commercially available for.

Efficiency of the models are distinguished through the distribution of heat throughout the room. The goal is to heat the occupants without heating the rest of the room to reduce energy waste. The variance of materials and air heat throughout the room for FIR is 10.753 K and 7.945 K respectively. This is much lower than that of the convection heating methods which are 52.89 K and 34.81 K respectively. The temperature variance is linked to the efficiency of the heating method, and the FIR system has a much lower temperature variance than convection heating. The convection radiators have to be hotter than the FIR panels and thus heats up the surrounding walls and floor before the occupants in the middle of the room.

Air flow and air quality play a major role in the performance of heating systems. Air flow and temperature are compared for both FIR and convection heating. FIR and convection have an average air flow and temperature of 0.325 m/s and 0.499 m/s, meaning there is less probability of infectious diseases and poor quality air such as dust travelling around the room. Variable FIR heating has the potential to kill Covid-19 and related pathogens too [43,44]. Lack of air flow from the FIR method makes it easier for artificial ventilation to maintain the required air movement rate at 15 L/second/person [66].

Initial investment for FIR and convection radiators are £6,138.30 and £4,613 respectively, making FIR 33 % more expensive to purchase and install. This can be a deciding factor for buildings that are reducing carbon emissions as the ROI is 520 days. Once the ROI is met though, in this research, the FIR heating saves £4,312 annually compared to convection heating. The IR panels from a selected supplier has a 5 year warranty, meaning the building would save at least £15,415.40 on the electricity bill before the warranty ended.

The occupation forecasting allows the method to be optimised. The heating can be activated in advance for larger rooms, and it gives greater insight into how the heating system works. Various MLA's can be used for occupation forecasting and will give different accuracies and training times for the number of features and samples that are being used to train the algorithm. For this method, RF performed better then NN as it was 12.76 % more accurate on average when predicting the CO_2 density of the air. This is due to there being limited training data at 10 days. The RF was able to build multiple regression trees with this data and aggregate the results whereas the NN could still only generate one algorithm.

Infrared heating is able to heat quicker than convection heating due to the infrared waves bypassing the air and being absorbed by solid mass instead. This is one of the main advantages of FIR as it doesn't need to be pre-heated much in advance. This doesn't dismiss the importance of pre-heating and occupation forecasting as the FIR heating doesn't heat the room immediately. Previous studies show that infrared heating is able to heat an 8 m^2 room 44.12 % quicker than convection heating, taking 10 min to heat.

5. Conclusion

This paper focused on the retrofitting of a single non-domestic lecture theatre with a FIR occupation dependant heating system to improve energy efficiency, thermal comfort, and flow of air. This was done through occupation prediction for pre-heating of occupied spaces to improve thermal comfort. Machine learning forecasting is implemented for occupation prediction in 15-minute segments over a day with comparisons between convection and FIR heating methods. A UK university lecture theatre was used as a case study to base the simulations on, allowing an accurate representation on the heating requirements, behaviour of the room, and occupation analysis.

Results show the FIR occupation heating was more energy efficient by 10.36kWh in maximum occupation, 10.94kWh in medium, and FIR heating required 11.99kWh less than convection heating in minimum occupation. Air velocity is higher for convection heating at 0.633 m/s compared to FIR heating at 0.379 m/s. Financial benefits show a saving of 75.97 % or £11.79/day with a return on investment of 520 days, providing incentives. Occupation prediction from the RF MLA show an accuracy of 97.75 % for 15 min intervals which allows the preheating of rooms and zones for optimal comfort. Zonal FIR heating is more efficient than convection methods by 75.97 %.

Future work includes more research and application of FIR heating which will lead to more optimised heating systems in large and small-scale methods. Research on the timescales of heating and cooling of FIR heating systems will provide more information of the applications.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] "International Comparisons of Heating, Cooling and Heat Decarbonisation Policies " p. 61, 2017. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/699674/050218_International_Comparisons_Study_MainReport_CLEAN.pdf.

[2] C. o. C. Change, "Reducing UK emissions Progress Report to Parliament " p. 196, 2020. [Online]. Available: https://www.theccc.org.uk/publication/reducing-uk-emissions-2020-progress-report-to-parliament/.

[3] M. Fooks, "The Non-Domestic National Energy Efficiency Data-Framework 2020 (England and Wales)," p. 46, 2020. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/936797/ND-NEED.pdf.

[4] Y. Chen, J. Guo, S. Yuan, C. Hu, Effects of climate change on the heating indices in central heating zone of China, Build. Environ. 195 (2021), https://doi.org/10.1016/j.buildenv.2021.107743 107743.

[5] B.K. Sovacool, J. Osborn, M. Martiskainen, A. Anaam, M. Lipson, Humanizing heat as a service: Cost, creature comforts and the diversity of smart heating practices in the United Kingdom, Energy Clim. Change 1 (2020), https://doi.org/10.1016/j.egycc.2020.100012 100012.

[6] D.S. Østergaard, M. Tunzi, S. Svendsen, What does a well-functioning heating system look like? Investigation of ten Danish buildings that utilize district heating efficiently, Energy 227 (2021), https://doi.org/10.1016/j.energy.2021.120250 120250.

[7] B.K. Sovacool, J. Osborn, M. Martiskainen, M. Lipson, Testing smarter control and feedback with users: Time, temperature and space in household heating preferences and practices in a Living Laboratory, Global Environ. Change 65 (2020), https://doi.org/10.1016/j.gloenvcha.2020.102185 102185.

[8] J. Cockroft, A. Cowie, A. Samuel, P. Strachan, Potential energy savings achievable by zoned control of individual rooms in UK housing compared to standard central heating controls, Energy and Build. 136 (2017) 1–11, https://doi.org/10.1016/j.enbuild.2016.11.036.

[9] Y. De Bock, A. Auquilla, E. Bracquené, A. Nowé, J.R. Duflou, The energy saving potential of retrofitting a smart heating system: a residence hall pilot study, Sustain. Comput. Informat. Syst. 31 (2021), https://doi.org/10.1016/j.suscom.2021.100585 100585.

[10] K. Kołek, "Central Heating Energy Saving Strategies for a Public Building," in *Advanced, Contemporary Control*, Cham, A. Bartoszewicz, J. Kabziński, and J. Kacprzyk, Eds., 2020// 2020: Springer International Publishing, pp. 264-274.

[11] L. Özgür, V. K. Akram, M. Challenger, and O. Dağdeviren, "An IoT based smart thermostat," in *2018 5th International Conference on Electrical and Electronic Engineering (ICEEE)*, 3-5 May 2018 2018, pp. 252-256, doi: 10.1109/ICEEE2.2018.8391341.

[12] H. Stopps, M.F. Touchie, Residential smart thermostat use: an exploration of thermostat programming, environmental attitudes, and the influence of smart controls on energy savings, Energy Build. 238 (2021), https://doi.org/10.1016/j.enbuild.2021.110834 110834.

[13] M. Esrafilian-Najafabadi, F. Haghighat, Occupancy-based HVAC control systems in buildings: a state-of-the-art review, Build. Environ. 197 (2021), https://doi.org/10.1016/j.buildenv.2021.107810 107810.

[14] X. Li, R. Yao, W. Yu, X. Meng, M. Liu, A. Short, B. Li, Low carbon heating and cooling of residential buildings in cities in the hot summer and cold winter zone – A bottom-up engineering stock modeling approach, J. Clean. Product. 220 (2019) 271–288.

[15] N.O. Bell, J.I. Bilbao, M. Kay, A.B. Sproul, Future climate scenarios and their impact on heating, ventilation and air-conditioning system design and performance for commercial buildings for 2050, Renew. Sustain. Energy Rev. 162 (2022), https://doi.org/10.1016/j.rser.2022.112363 112363.
[16] T. de Rubeis, S. Falasca, G. Curci, D. Paoletti, D. Ambrosini, Sensitivity of heating performance of an energy self-sufficient building to climate zone, climate change and HVAC system solutions, Sustain. Cit. Soc. 61 (2020), https://doi.org/10.1016/j.scs.2020.102300 102300.
[17] Z. Tian, X. Shi, S.-M. Hong, Exploring data-driven building energy-efficient design of envelopes based on their quantified impacts, J. Build. Eng. 42 (2021), https://doi.org/10.1016/j.jobe.2021.103018 103018.
[18] A. Nacer, B. Marhic, and L. Delahoche, "Smart Home, Smart HEMS, Smart heating: An overview of the latest products and trends," in *2017 6th International Conference on Systems and Control (ICSC)*, 7-9 May 2017 2017, pp. 90-95, doi: 10.1109/ICoSC.2017.7958713.
[19] A. Gupta, Y. Badr, A. Negahban, R.G. Qiu, Energy-efficient heating control for smart buildings with deep reinforcement learning, J. Build. Eng. 34 (2021), https://doi.org/10.1016/j.jobe.2020.101739 101739.
[20] T. Cholewa, A. Siuta-Olcha, A. Smolarz, P. Muryjas, P. Wolszczak, Ł. Guz, C.A. Balaras, On the short term forecasting of heat power for heating of building, J. Clean. Product. 307 (2021) 127232, https://doi.org/10.1016/j.jclepro.2021.127232.
[21] A. A. Connor Scott, "Machine Learning Forecasting for Optimisation of Green Energy Generation in Non-Domestic Buildings," presented at the International Virtual Conference on Cyber-physical systems 2022, 2022, 53.
[22] W. Kleiminger, F. Mattern, S. Santini, Predicting household occupancy for smart heating control: a comparative performance analysis of state-of-the-art approaches, Energy Build. 85 (2014) 493–505, https://doi.org/10.1016/j.enbuild.2014.09.046.
[23] Y. Peng, A. Rysanek, Z. Nagy, A. Schlüter, Using machine learning techniques for occupancy-prediction-based cooling control in office buildings, Appl. Energy 211 (2018) 1343–1358, https://doi.org/10.1016/j.apenergy.2017.12.002.
[24] J. Shi, N. Yu, W. Yao, Energy efficient building HVAC control algorithm with real-time occupancy prediction, Energy Procedia 111 (2017) 267–276, https://doi.org/10.1016/j.egypro.2017.03.028.
[25] D. Ramos, M. Khorram, P. Faria, Z. Vale, Load forecasting in an office building with different data structure and learning parameters, Forecasting 3 (1) (2021) 242–254.
[26] M.W. Ahmad, M. Mourshed, Y. Rezgui, Trees vs neurons: comparison between random forest and ANN for high-resolution prediction of building energy consumption, Energy Build. 147 (2017) 77–89, https://doi.org/10.1016/j.enbuild.2017.04.038.
[27] G. Nai-Zhi, Z. Ming-Ming, L. Bo, A data-driven analytical model for wind turbine wakes using machine learning method, Energy Convers. Manage. 252 (2022), https://doi.org/10.1016/j.enconman.2021.115130 115130.
[28] C. Scott, M. Ahsan, A. Albarbar, Machine learning based vehicle to grid strategy for improving the energy performance of public buildings, Sustainability 13 (7) (2021) 4003.
[29] M. Gómez-Omella, I. Esnaola-Gonzalez, S. Ferreiro, B. Sierra, k-Nearest patterns for electrical demand forecasting in residential and small commercial buildings, Energy Build. 253 (2021), https://doi.org/10.1016/j.enbuild.2021.111396 111396.
[30] Y. Zhou, Y. Liu, D. Wang, X. Liu, Comparison of machine-learning models for predicting short-term building heating load using operational parameters, Energy Build. 253 (2021), https://doi.org/10.1016/j.enbuild.2021.111505 111505.
[31] K. Alanne, S. Sierla, An overview of machine learning applications for smart buildings, Sustain. Cit. Soc. 76 (2022), https://doi.org/10.1016/j.scs.2021.103445 103445.
[32] Jigsaw, "Jigsaw Infrared Heating," *Infrared Heating Guide 2020,* p. 11, 2020 2020. [Online]. Available: https://www.jigsawinfrared.com/wp-content/uploads/2020/11/Free-Infrared-Heating-Guide-2020.pdf.
[33] K.J. Brown, R. Farrelly, S.M. O'Shaughnessy, A.J. Robinson, Energy efficiency of electrical infrared heating elements, Appl. Energy 162 (2016) 581–588, https://doi.org/10.1016/j.apenergy.2015.10.064.
[34] I. Das and S. Das, "Emitters and Infrared heating system design," *Infrared Heating for Food and Agricultural Processing, Z. Pan and GG Atungulu, Eds,* pp. 57-88, 2010.
[35] M. Khatibi, S. Rahnama, P. Vogler-Finck, J.D. Bendtsen, A. Afshari, Investigating the flexibility of a novel multi-zone air heating and ventilation system using model predictive control, J. Build. Eng. 49 (2022), https://doi.org/10.1016/j.jobe.2022.104100 104100.
[36] M. Hammerle, P.J. Burke, From natural gas to electric appliances: energy use and emissions implications in australian homes, Energy Econ. 110 (2022), https://doi.org/10.1016/j.eneco.2022.106050 106050.
[37] K. Krishnamurthy, H.K. Khurana, J. Soojin, J. Irudayaraj, A. Demirci, Infrared heating in food processing: an overview, Comp. Rev. Food Sci. Food Saf. 7 (1) (2008) 2–13.
[38] M.H. Riadh, S.A.B. Ahmad, M.H. Marhaban, A.C. Soh, Infrared heating in food drying: an overview, Dry. Technol. 33 (3) (2015) 322–335, https://doi.org/10.1080/07373937.2014.951124.
[39] X. Li, A. Zhang, G.G. Atungulu, M. Delwiche, R. Milczarek, D. Wood, T. Williams, T. McHugh, Z. Pan, Effects of infrared radiation heating on peeling performance and quality attributes of clingstone peaches, LWT – Food Sci. Technol. 55 (1) (2014) 34–42.
[40] Y. Liu, Y.a. Zeng, Q.i. Wang, C. Sun, H. Xi, Drying characteristics, microstructure, glass transition temperature, and quality of ultrasound-strengthened hot air drying on pear slices, J. Food Process. Preserv. 43 (3) (2019) e13899.
[41] H. Xi, Y. Liu, L. Guo, R. Hu, Effect of ultrasonic power on drying process and quality properties of far-infrared radiation drying on potato slices, Food Sci. Biotechnol. 29 (1) (2020) 93–101, https://doi.org/10.1007/s10068-019-00645-1.
[42] G.H. Lang, I.d.S. Lindemann, C.D. Ferreira, R.S. Pohndorf, N.L. Vanier, M. de Oliveira, Influence of drying temperature on the structural and cooking quality properties of black rice, Cereal Chem 95 (4) (2018) 564–574.
[43] S. Shahi, R. Khorvash, M. Goli, S.M. Ranjbaran, A. Najarian, A. Mohammadi Nafchi, Review of proposed different irradiation methods to inactivate food-processing viruses and microorganisms, Food Sci. Nutr. 9 (10) (2021) 5883–5896, https://doi.org/10.1002/fsn3.2539.
[44] S. Pawar, A. Stanam, M. Chaudhari, and D. Rayudu, "Effects of temperature on COVID-19 transmission," *medRxiv,* p. 2020.03.29.20044461, 2020, doi: 10.1101/2020.03.29.20044461.
[45] Z. V. Shepitchak V., Spodyniuk N., "The study of the intensity of infrared heating systems radiation," *Building Physics in Theory and Practice,* pp. 29-32, 2016 2016. [Online]. Available: https://yadda.icm.edu.pl/baztech/element/bwmeta1.element.baztech-8ce720a5-b742-4a2c-9fb7-f9b59236d646.
[46] A. University, "Enabling Technologies & Innovation Competences Challenge Project," 2021. Accessed: 31/05/2022. [Online]. Available: https://www.jigsawinfrared.com/wp-content/uploads/2021/12/Solutions-by-Jigsaw_Report-Aston.pdf.
[47] I. h. direct. "Infrared Panels." https://www.infraredheatersdirect.co.uk/view-all-infrared-panels/?filterbyprice=511&product_list_dir=desc (accessed 16/12, 2021).
[48] Warm4Less. "320 Watt Platinum Ceiling." https://www.warm4less.com/ (accessed 02/02, 2022).
[49] S. Heating. "Infrared Heating Specialists." https://www.suryaheating.co.uk/ (accessed 02/02, 2022).
[50] Herschel. "Infrared Heaters." https://www.herschel-infrared.co.uk/ (accessed 02/02, 2022).
[51] Tansun. "World Leaders In Radiant Heating." https://www.tansun.com/gb_en/ (accessed 02/02, 2022).
[52] Ener-j. "360W Infrared Heating Panel 595*595." https://cdn.manomano.com/files/pdf/11712683.pdf (accessed 02/02, 2022).
[53] F. Vatansever, M.R. Hamblin, Far infrared radiation (FIR): Its biological effects and medical applications: ferne Infrarotstrahlung: biologische Effekte und medizinische Anwendungen, Photon. Lasers Med. 1 (4) (2012) 255–266, https://doi.org/10.1515/plm-2012-0034.
[54] C. Su, H. Madani, B. Palm, Heating solutions for residential buildings in China: current status and future outlook, Energy Convers. Manage. 177 (2018) 493–510, https://doi.org/10.1016/j.enconman.2018.10.005.
[55] Y. Yang, S. Chen, T. Chang, J. Ma, Y. Sun, Uncertainty and global sensitivity analysis on thermal performances of pipe-embedded building envelope in the heating season, Energy Convers. Manage. 244 (2021), https://doi.org/10.1016/j.enconman.2021.114509 114509.
[56] G. Martinopoulos, K.T. Papakostas, A.M. Papadopoulos, A comparative review of heating systems in EU countries, based on efficiency and fuel cost, Renew. Sustain. Energy Rev. 90 (2018) 687–699, https://doi.org/10.1016/j.rser.2018.03.060.
[57] J. Hou, H. Li, N. Nord, Nonlinear model predictive control for the space heating system of a university building in Norway, Energy 253 (2022), https://doi.org/10.1016/j.energy.2022.124157 124157.
[58] S. H. Britt Aronsonn, "An International Comparison of District Heating Markets " *Economics and Business,* 2009 2009. [Online]. Available: https://energiforskmedia.blob.core.windows.net/media/1217/an-international-comparison-of-district-hetaing-markets-fjaerrsynsrapport-2009-27.pdf.
[59] *Ventilation for Acceptable Indoor Air Quality* R. a. A. C. E. American Society for Heating, 2015.
[60] T. Mohammed Salih, *Insulation Materials.* 2016.
[61] D. Anastaselos, I. Theodoridou, A.M. Papadopoulos, M. Hegger, Integrated evaluation of radiative heating systems for residential buildings, Energy 36 (7) (2011) 4207–4215, https://doi.org/10.1016/j.energy.2011.04.023.
[62] M.L. Cohen, Measurement of the thermal properties of human skin. a review, J. Investig. Dermatol. 69 (3) (1977) 333–338, https://doi.org/10.1111/1523-1747.ep12507965.
[63] M. Mance, M. Prutki, A. Dujmovic, M. Miloševic, V. Vrbanovic-Mijatovic, D. Mijatovic, Changes in total body surface area and the distribution of skin surfaces in relation to body mass index, Burns 46 (4) (2020) 868–875, https://doi.org/10.1016/j.burns.2019.10.015.
[64] N. Saeed, Experimental data for thermal conductivity and dielectric properties of wood and wood-based materials, Data in Brief 42 (2022), https://doi.org/10.1016/j.dib.2022.108027 108027.
[65] S. Omrani, S. Matour, K. Bamdad, N. Izadyar, Ceiling fans as ventilation assisting devices in buildings: a critical review, Build. Environ. 201 (2021), https://doi.org/10.1016/j.buildenv.2021.108010 108010.
[66] "Consulation on the Future Buildings Standard: Consultation on changes to Part L (conservation of fuel and power) and Part F (ventilation) of the Building Regulations for non-domestic buildings and dwellings; and overheating in new residential buildings. ," p. 61, 2021. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/901517/Manual_to_building_regs_-_July_2020.pdf.