TOWARDS SMART DESPATCH OF BUILDING HEATING AND COOLING USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Improving energy efficiency is one of the most cost-efficient approaches for decreasing the carbon footprint associated with the built environment as well as reducing the energy bills. This contribution advances the development of smart Building Management Systems able to dynamically respond to the ambient conditions and building usage patterns to minimise energy use for heating/cooling while ensuring the comfort and wellbeing of the users of indoor spaces. In comparison with traditional thermostats or responsive HVAC operation relying on occupancy detection in real time (e.g., using PIR motion sensors) our approach uses a look-ahead strategy employing a hybrid mechanistic-machine learning model. As it collects sensor data on the thermal performance and occupancy patterns of the various spaces within a building, the system improves its ability to predict energy flows between the indoor spaces as well as between the building and its external environment. In combination with short-term weather forecast, this enables our algorithm to minimise the amount of energy used for heating/cooling while ensuring that desired thermal comfort conditions are maintained whenever the space is occupied. The smart look-ahead model thus enables the space to be heated/cooled in anticipation of it being in use while also in many cases switching the heating off before the space is vacated which leads to a reduced overall energy consumption.

Keywords: Energy management, model predictive control, machine learning, artificial intelligence.

INTRODUCTION

Achieving Net Zero carbon emissions is an ambitious target necessary to reduce the rate of climate change. While the most effective way of reducing carbon emissions is the substitution of fossil fuel use by cleaner sources of energy, such as renewable energy resources, improvements in energy efficiency and reducing energy consumption play an important role in the UK's Net Zero strategy (BEIS, 2021).

In the UK, buildings are responsible for 17% of direct greenhouse gas (GHG) emissions primarily as the result of burning fossil fuels for heating (CCC, 2020). This fraction increases further when indirect emissions due to electricity use to power lighting and appliances (including air conditioning) are considered. Educational buildings and offices are examples of buildings with typically the highest energy use (Bourdeau et al., 2018; Gul & Patidar, 2015), where much of the energy is consumed through heating, ventilation, and air conditioning (HVAC) systems (Bourdeau et al., 2018; CCC, 2020). While switching to alternative fuels for heating such as hydrogen is being considered, their widespread adoption will require substantial financial investment and time to deploy (BEIS, 2021; CCC, 2020). Other solutions such as upgrading insulation can lead to saving energy, but can also be expensive, especially for existing buildings (CCC, 2020).

In contrast, building energy consumption and the associated GHG emissions can be reduced through smart energy control minimising unnecessary heating/cooling of indoor spaces when they are not in use while maintaining desired indoor air quality otherwise (Hidalgo-Leon et al., 2019; Nikdel et al., 2018; Wang & Ma, 2008). Current thermostats and HVAC systems have several limitations, the most important of which is their inability to anticipate events such as changes in occupancy or local weather conditions (Afram & Janabi-

Sharifi, 2014). The use of smart heating and cooling systems has been reported to offer energy savings in the range of ~18-24% compared with currently available systems (Bengea et al., 2014; Esrafilian-Najafabadi & Haghighat, 2022; Shi et al., 2017; Wang & Ma, 2008). Predictive control systems have been developed for both single zone and multi-zone (whole building) situations (Bengea et al., 2014; Esrafilian-Najafabadi & Haghighat, 2022; Png et al., 2019).

To provide energy-saving benefits compared with traditional thermostats, smart heating control strategies rely on the availability of occupancy information for the space/building of interest (Shen, Newsham, & Gunay, 2017). A number of different approaches to the formulation of the control problem are reported in the literature with some works employing purely data-based or rule-based approaches (Esrafilian-Najafabadi & Haghighat, 2022; Jain et al., 2020; Nacer et al., 2018; Png et al., 2019) while others employ energy balances with tuneable parameters (Bengea et al., 2014; Shi et al., 2017). Occupancy data can generally be of one of two types: pre-defined schedules of space usage or real-time sensor data indicating whether the space is in use at any particular time. While the utilisation of occupancy schedules in control is relatively straightforward, collecting and using real-time and historical occupancy data presents both technological and modelling challenges. There is a wide range of technologies used including motion, sound and CO_2 detectors, radio-frequency localisation devices (such as Wi-Fi, Bluetooth, RFID tags, etc.) and image processing techniques (Labeodan, Zeiler, Boxem, & Zhao, 2015; Shen et al., 2017; Zou, Jiang, Yang, Xie, & Spanos, 2017). While the above radio-frequency localisation technologies may provide accurate occupancy data and have found successful applications, their main drawbacks are (i) the requirement for the occupants to carry a special RF tag or a mobile device, and (ii) the associated privacy concerns (Zou et al., 2017). The latter also applies to image processing techniques. While motion, sound and CO_2 detectors are free from privacy concerns, the quality of the resulting occupancy data is generally lower resulting in higher uncertainty in machine learning (ML) models trained on such data (Shen et al., 2017).

Different types of occupancy prediction models have been considered in applications involving HVAC systems. Some predict occupancy states at different times while others predict occupants' arrival and departure times. Supervised learning, unsupervised learning, and reinforcement learning are the three most typical ML approaches used in occupancy prediction (Hastie, Tibshirani, & Friedman, 2009).

Supervised learning models include decision trees (Koklu & Tutuncu, 2019) such as the gradient boosting, classifiers such as the Bayes classifier, kNN, support vector machines, and neural network models (Kim, Kim, & Srebric, 2020). Unsupervised learning uses unlabelled training data (Hastie et al., 2009) and includes cluster analysis learning, principal component analysis (PCA), and various types of artificial neural networks (ANN) (Liang, Hong, & Shen, 2016; Nacer et al., 2018).

Building occupancy naturally depends on the time of day as well as on day of the week which are the main features used for training ML occupancy models (Afram & Janabi-Sharifi, 2014; Nikdel et al., 2018; Shi et al., 2017). Seasonal variations in occupancy as well as holidays can also affect the predictive performance of such models. It is, however, still subject to debate (and, arguably, subject to the nature of training data) as to which ML technique provides the most reliable occupancy predictions.

Physics-based models of heat transfer are typically formulated as lumped-parameter (ODE) models (i.e., assuming a uniform temperature distribution within the enclosed space of interest) or compartmental models (i.e., lumped-parameter models for each zone in a building). While heat transfer properties of the building envelope and any internal walls can often be found in building documentation, these parameters are usually estimated from experimental temperature measurements (Shi et al., 2017). This is due to inherent uncertainties in the overall values of these parameters (e.g., because of the composite nature of walls and non-uniformity of temperature driving forces) as well as other potential contributions such as leaks that are not generally included in the model.

The contribution of direct solar irradiation to the energy balance of the space has been recognised by many authors (e.g., in (Esrafilian-Najafabadi & Haghighat, 2022)) although models for this contribution are typically omitted a due to potential uncertainties in it.

In this work, we develop a smart heating and cooling control system for a simple indoor space to ensure thermal comfort of its occupants while minimising the overall energy usage. This approach relies on the availability of both historical and real-time occupancy measurements for training of a predictive occupancy model which plays a central role in the proposed Rolling Horizon Model Predictive Control (RH-MPC) algorithm. Different ML approaches to the construction of the occupancy model will be explored.

METHODOLOGY

This section describes the heat transfer model of an indoor space, data-driven modelling of occupancy and introduces model-predictive control of indoor heating or cooling while minimising the associated energy usage.

Energy balance model for an indoor space

A general lumped heat balance describing the time evolution of the enthalpy Q of air in a room can be written as:

$$\frac{dQ}{dt} = \dot{Q}_{heat}(t) + \dot{Q}_{solar}(t) - \dot{Q}_{diff}(t, T, T_{ext}) - \dot{Q}_{occ}(t) + \dot{Q}_{eq}(t) \quad (1)$$

where

$$Q = c_p^{air} \rho_{air} V_{room} T \quad (2)$$

with $c_p^{air} = 1{,}006\ J/kg\ K$ being the specific heat capacity of air, $\rho_{air} = 1.225\ kg/m^3$ the density of air under standard conditions, V_{room} the room volume and T the air temperature in the room at time t.

The terms on the right-hand side of Eq (1) describe the following heat transfer rates:

- $\dot{Q}_{heat}(t)$ is the heating input through HVAC, central heating (radiators) or local electrical heaters. This term is either pre-defined (for direct simulations) or is to be controlled (see below);
- $\dot{Q}_{solar}(t)$ is the rate of direct solar radiative heating through windows;
- $\dot{Q}_{diff}(t, T, T_{ext})$ is the rate of heat diffusion through walls, windows and doors of the room;
- $\dot{Q}_{vent}(t)$ is the convective heat transfer rate arising due to natural ventilation;
- $\dot{Q}_{occ}(t) = N_{occ}(t) \times \dot{Q}_{person}$ is heat generated by individuals present in the setting. A fixed thermal output, $\dot{Q}_{person} = 80\ W$, is assumed for an average human at rest. $N_{occ}(t)$ is time-dependent occupancy;
- $\dot{Q}_{eq}(t)$ represents any other heat sources in the room (electrical appliances, lights, etc.). In the case study below we assume that this term is zero.

Heat diffusion model

The energy balance in (1) assumes that the air in the room is well mixed so that the temperature distribution is homogeneous throughout. Hence, the rate of heat transfer through internal walls, external wall, windows, floor and ceiling of a room is proportional to the temperature driving forces across these boundaries:

$$\dot{Q}_{diff}(t, T, T_{ext}) = \sum_{i \in I} U_i A_i \left(T - T_{ext,i}\right) \quad (3)$$

where U_i is the heat transfer coefficient (in $\frac{W}{m^2 K}$) of the bounding surface i, A_i is its surface area (in m^2), T is the room temperature and $T_{ext,i}$ is the temperature value on the other side of the respective boundary.

Convective heat transfer

The term $\dot{Q}_{vent}(t)$ depends on the flow rate and temperature of incoming air. Airflows result from either natural convection through open windows and doors, mechanical ventilation or both. Mechanical ventilation allows for reliable measurement of airflow and temperature using standard sensors. However, natural convection and the associated heat flux are difficult to monitor due to the large open window/door areas, making airflow measurements inaccurate. This would render the above model unreliable, hence natural ventilation is not considered in the following.

Solar heat model

The direct solar heating term $\dot{Q}_{solar}(t)$ is computed based on window orientation, position of the sun and the attenuating effect of the atmosphere and clouds which is obtained from the current weather conditions

(in the following we ignore diffuse radiative heating due to its lower magnitude):

$$\dot{Q}_s(t) = (1 - cc) \times \tau_b T_s G(n) A_{window} \cos\theta \quad (4)$$

where cc is the average fraction of the sky covered by clouds, τ_b the average atmospheric transmittance under clear-sky conditions, T_s the solar heat gain coefficient of the window, $\cos\theta$ the cosine of the angle of incidence θ of solar radiation on the window surface at time t, and $G(n)$ the extra-terrestrial solar irradiance on day n of the year (Beckman, Blair, & Duffie, 2021):

$$G(n) = G_{SC}\left(1 + 0.034\cos\left(\frac{2\pi n}{365.25}\right)\right) \quad (5)$$

where $G_{SC} = 1.362\,\frac{kW}{m^2}$ is the solar constant (mean total extra-terrestrial solar irradiance per unit area).

The cosine of θ depends on the orientation and slope of the window and the solar zenith angle (see Fig. *1*):

$$\cos\theta = \cos\theta_z \cos\beta + \sin\theta_z \sin\beta \cos(\gamma_s - \gamma) \quad (6)$$

where θ_z is the solar zenith angle, β the slope of the window (typically 90°), γ the window azimuth angle, and γ_s the solar azimuth angle (Beckman et al., 2021).

The calculation of θ_z is not elaborated here (see Beckman, Blair, & Duffie, 2021) but involves such parameters as the latitude and longitude of the location of the building, the day of the year and the time zone as well as the current time.

In the presence of architectural features designed to partially block sunlight (e.g., overhangs or solar screens) the effective window area is reduced depending on the size of the screen and the solar zenith angle. This more general situation is illustrated in Fig. 2 showing the street view of the meeting room at the University of Surrey used as a case study below. The window faces westward and has a solar screen above it and a protruding wall provides shielding from the south (see Fig. 3).

Considering the shading from these two features, the dimensions of the directly illuminated part of the window are:

$$h' = \max\left[0, h - h_s - \frac{d_s}{\cos(\gamma_s - \gamma)\tan\theta_z}\right] \quad (7)$$

$$w' = \max[0, w - d_s \tan(\gamma_s - \gamma)] \quad (8)$$

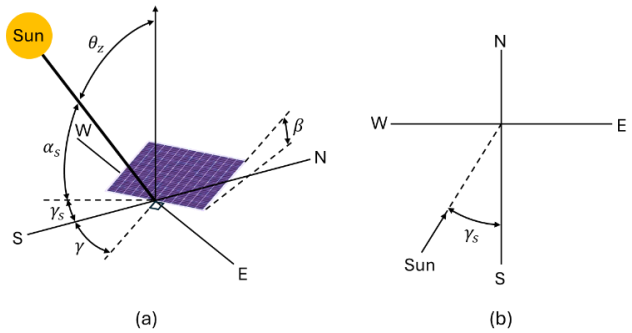

Figure 1: (a) Zenith angle θ_z, surface azimuth γ, surface slope β and solar azimuth angle γ_s for a tilted surface; (b) Plan view showing the solar azimuth angle γ_s.

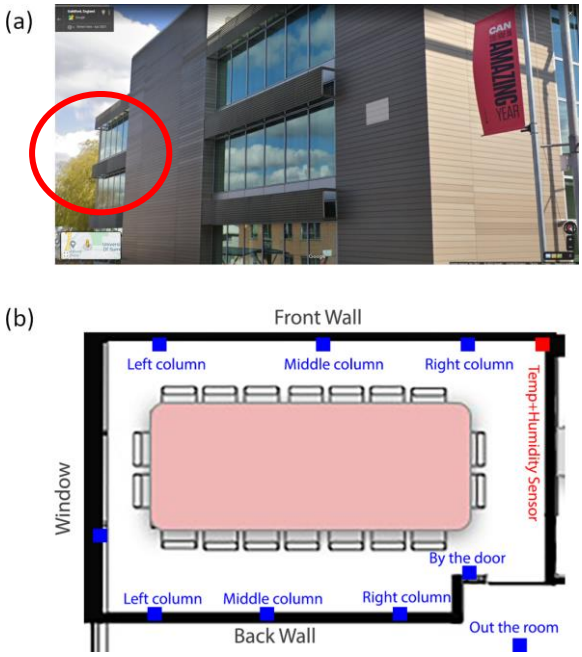

Figure 2: (a) Outside view of the meeting room (circled) on the University of Surrey campus (Google Maps); (b) Layout of the meeting room and locations of occupancy and temperature sensors.

Note that both the effective window height and width can become zero if the shadow of either the solar screen or the wall covers the respective dimension completely.

Finally, the value of $\dot{Q}_{solar}(t)$ should be zero when the sun is below the horizon or when the sun is behind the plane of the window (no direct sunlight through the window), which yields:

$$\dot{Q}_{solar}(t) = \begin{cases} 0, & \text{if } \theta_z > 90° \text{ or } \cos\theta < 0 \\ \dot{Q}_s(t), & \text{otherwise} \end{cases} \quad (9)$$

with $\dot{Q}_s(t)$ given by Eq (4) and the effective window area equal $A_{window} = h'w'$.

Occupancy modelling

Several ML approaches were used to train occupancy prediction models and to compare their predictive power for subsequent inclusion into the MPC framework (see below). The models included k-nearest neighbours (KNN), decision tree (DT), Random Forest (RF), and Multi-layer perceptron (MLP) (Hastie et al., 2009).

Rolling Horizon Model Predictive Control (RH-MPC)

The main purpose of a temperature controller is to maintain pre-defined thermal comfort conditions during the day and a set-back temperature overnight in an enclosed setting. Additionally, we would also like to minimise the overall energy consumption for space heating/cooling by switching it off when the occupancy is predicted to be negligible (less than 0.5 indicating that the probability of a single person to be in the space is less than 0.5). This bi-objective MPC problem can be scalarized in the following way:

$$\int_{t_0}^{t_0+PH} \left[\alpha \frac{\dot{Q}_{heat}(t)}{Q_{heat}^{max}} + (1-\alpha) H(N_{occ}(t) - 0.5) \frac{\left(T(t) - T_{setpoit}\right)^2}{\Delta T^2} \right] dt \rightarrow \min_{\dot{Q}_{heat}(t)} \quad (10)$$

$$s.t. \quad T(t) \geq T_{setback}(t), \ \forall t$$

$$\frac{dQ}{dt} = \dot{Q}_{heat}(t) + \dot{Q}_{solar}(t) - \dot{Q}_{diff}(t, T, T_{ext}) - \dot{Q}_{vent}(t) + \dot{Q}_{occ}(t) + \dot{Q}_{eq}(t)$$

$$0 \leq \dot{Q}_{heat}(t) \leq \dot{Q}_{heat}^{max}$$

$$0 \leq \dot{Q}_{vent}(t) \leq \dot{Q}_{vent}^{max}$$

$$T(t_0) = T_{measured}(t_0)$$

where $H(\cdot)$ is the Heaviside step function, $\alpha \in [0,1]$ is an adjustable parameter defining the preference between purely thermal comfort-based control ($\alpha = 0$) and pure energy minimisation ($\alpha = 1$). Note that, during cold seasons (i.e., when $T_{ext} \leq T_{setback}(t)$), the latter would result in simply maintaining $T_{setback}(t)$. Q_{heat}^{max} is the maximum power output of the heater and ΔT is the tolerance of following the setpoint temperature. Cooling (omitted here for brevity) can also be easily incorporated into the objective function.

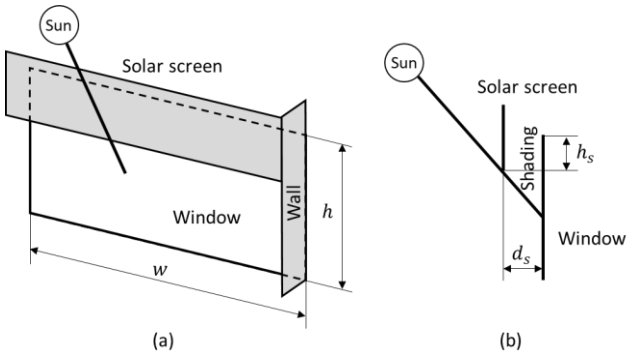

Figure 3: (a) Geometry of solar screen and wall shading of the window of width w and height h. (b) Side view showing the vertical overlap with the window h_s and window-screen distance d_s.

The RH-MPC problem (10) is solved over the "prediction horizon" of PH hours to obtain the optimum time sequence of heating inputs $\dot{Q}_{heat}(t)$. The latter is then implemented over the "control horizon" of $CH < PH$ hours. Then, at time $t = t_0 + CH$ new measurements of indoor temperature and occupancy and updated weather forecast are obtained, and problem (10) is solved again. This procedure is repeated in a loop. Because the prediction horizon is considerably longer than the control horizon at each iteration of RH-MPC, the algorithm is generating short-term control decisions while being "aware" of longer-term future (i.e., weather and occupancy forecasts). This look-ahead nature of the RH-MPC model (10) allows the control system to react to future events (significant changes in external conditions and/or occupancy) in advance by exploiting the thermal inertia of buildings. The weather forecast (including solar irradiation, cloud cover and outside temperature) is obtained by accessing external weather API while occupancy predictions are obtained using a machine learning occupancy model (see below).

Implementation

Both the ML models and the RH-MPC algorithm were implemented in Python using libraries such as Sklearn and Tensorflow for ML and Pyomo for optimisation (including the solvers Mindtpy, Ipopt and CBC).

RESULTS AND DISCUSSION

The layout of the room used to test our approach is shown in Fig. 2b with the street view in Fig. 2a. The room dimensions are $4.53\ \mathrm{m} \times 3.6\ \mathrm{m} \times 3\ \mathrm{m}$ (L×W×H). Fig. 2b also shows the locations of the temperature/occupancy sensors in blue. Readings from individual sensors are averaged to reduce uncertainly.

Heat diffusion model training

U values in the heat diffusion term (3) can be estimated by fitting the model to measurements of indoor temperature when contributions of other terms in (1) are known. In the case under study, however, reliable estimation of U values was not feasible due to lack of measurements of the thermal output of central heating. Thus, typical U values for the external wall ("Front wall" in Fig. 2b) and the double-glazed window have been adopted for simulations: $U_{ext} = 0.18\,W/Km^2$ and $U_{window} = 1.8\,W/Km^2$. Heat transfer through internal walls was assumed to be negligible.

Occupancy model training

The meeting room occupancy was recorded at 30-second intervals using the Smart Indoor Management System (SIMS) by DIREK Ltd (https://www.direk.io), capable of detecting the number of occupants in an indoor space, over a period of 16 days including working days and weekends during the hours from 7:00 to 22:00.

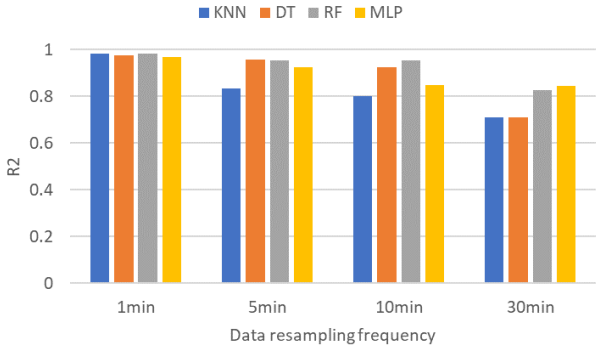

Figure 4: R^2 for the occupancy models with different sample frequency with T-1 time occupancy.

The ML models listed above were trained with resampled occupancy data to reduce training times and computational intensity. Fig. 4 shows that model accuracy decreases as the sampling interval increases, but frequencies between 1 and 10 minutes yield R^2 values over 0.9, indicating good predictions. Based on accuracy and training time, the Random Forest model with a 5-min sampling frequency was chosen for occupancy prediction for RH-MPC. Fig. 5 illustrates that RF consistently outperforms other models when trained on data sampled at 5-min intervals.

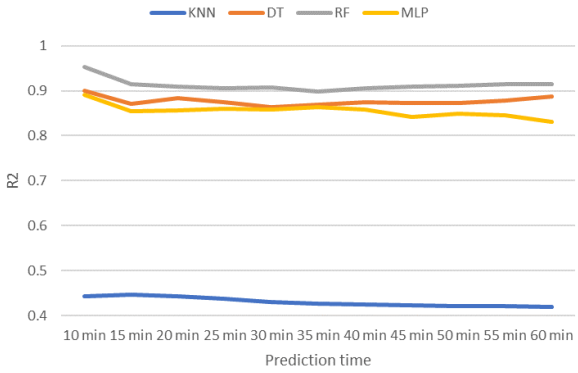

Figure 5: R2 for the occupancy prediction models trained on data with 5 min frequency.

Smart heating control

To illustrate the performance of the proposed smart heating control, we consider a three-hour period in late afternoon on a working day in April with weather conditions shown in Fig. 6a. During this time, outside temperature decreases from 12°C to 10°C while cloud cover increases from 70% to 90%. OpenWeather API ('Weather API - OpenWeatherMap') was used to obtain weather information. Since the room's window faces west, direct solar heating takes place with the effective power also shown in Fig. 6a. This alleviates some of the need in space heating. Thermal comfort conditions are set at the desired temperature $T_{setpoit} = 23$°C with the tolerance level of $\Delta T = 1$°C.

A meeting takes place in the room between 18:00-19:00 which is indicated with a shaded area in Figs. 6b and 6c which illustrate the solutions of the RH-MPC problem (10) in either the "smart" mode with $\alpha = 0.7$ (Fig. 6b) or in the "thermostat" mode ($\alpha = 0$ and $N_{occ} = 1$ at any time). The graphs show that in "smart" mode (providing a reasonable compromise between thermal comfort and energy saving), minimal heating is used before the meeting, which is sufficient to keep the room above the setback temperature. Thanks to the occupancy model's look-ahead capability, the room is pre-heated 20

minutes before the meeting to ensure thermal comfort, which is maintained throughout its duration by periodic heating bursts. The heater is turned off before the anticipated end of the meeting to save energy. In the "thermostat" mode, the room is immediately heated to the comfortable temperature, which is then maintained regardless of occupancy. The total amounts of heating performed in the two modes are E_{smart} = 0.833 kWh and E_{th_stat} = 1.25 kWh. Hence, a thermostat uses 50% more energy in this scenario than a smart control system.

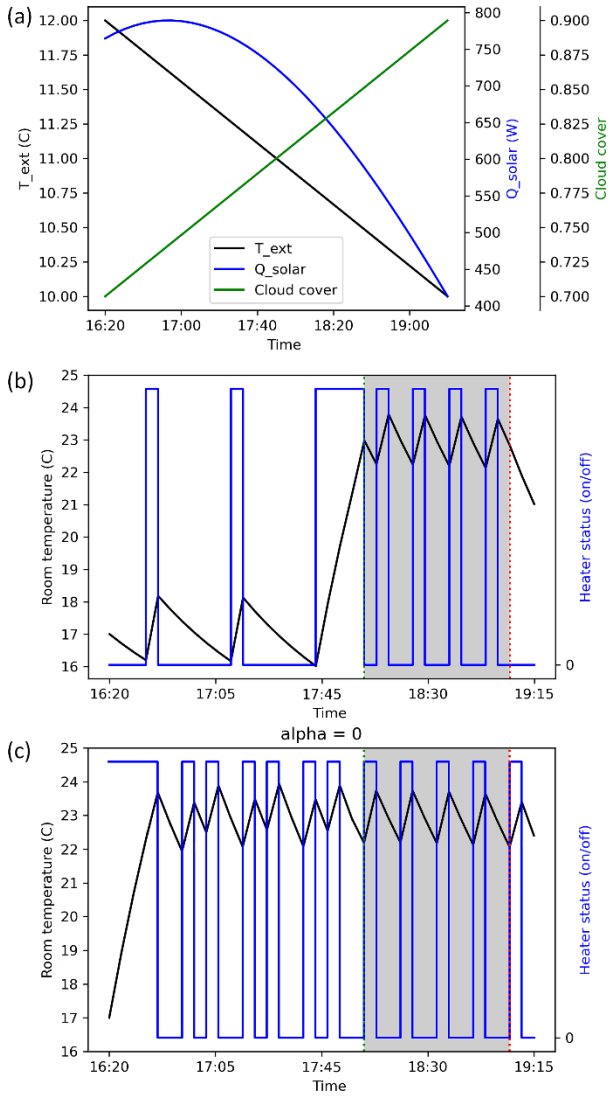

Figure 6: (a) weather conditions in the afternoon of a working day in April in Guildford, UK; (b) room temperature and heating schedule under smart control; (c) same under thermostat control.

CONCLUSIONS

Given the substantial carbon footprint of the built environment and the challenges of decarbonizing heating, smart despatch of HVAC systems can significantly reduce emissions and energy bills. Progress in this area is driven by the increasing availability and lower cost of sensors, along with advances in machine learning and model predictive control. Our approach demonstrates that substantial savings can be achieved by operating HVAC systems in a smart way by "learning" occupancy patterns for indoor spaces and making use of simple but sufficiently accurate predictive thermal models. It is important to note that the presented smart HVAC control system is at worst as efficient as a thermostat either in the absence of occupancy data or when the indoor space is used continuously. However, its efficiency would be gradually improving during online operation as it gathers data on the occupancy patterns and thus improves its predictive capability. Scaling this approach to entire buildings could provide a more holistic view of energy and people flows, leading to significant environmental and financial benefits.

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