MODELS FOR HEATING SYSTEM OPTIMISATION
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Lancaster University Main Campus, for which a central energy centre supplies the hot water used to heat around 90% of the buildings, yet regulation of the energy centre production is presently sub-optimal.

Figure 1. Visualisation of Lancaster University Campus

Introduction
Due to the large quantity of energy used by Heating, Ventilation and Air Conditioning (HVAC) systems, the wider scope of this project is to improve the control of HVAC systems on Lancaster University’s campus. To achieve this a model that represents the behaviour of a building on the campus needs to be developed, that represents the significant temperature responses while retaining sufficient simplicity to allow for simulation without requiring cluster computing. Furthermore the model must be identified from what can be physically derived, or is already measured by the Building Management System (BMS). This constraint poses challenges such as determining where occupants are within the building, given that no existing single data set provides this information, therefore novel solutions are required.

Model Development

Physical Derivation
A heat balance is constructed, assuming that the zone is well mixed, thus the return temperatures measured by the Air Handling Units (AHU) are considered to be the temperature in the zone, e.g. the area covered by AHU09 in Figure 7. The thermal-electrical analogy is employed, in which walls are treated as resistors, and thermal mass as a capacitor. Supply air and occupancy are used as model inputs causing internal heat gains, see figure 3. The external temperature is also included but the effect is regulated by the large resistance of the outer offices and external walls. Solving in this form produces a set of differential equations describing the temperatures in the zones.

Figure 2. Comparison between the number of devices connected to the Wi-Fi hub and the average change from the minimum CO2 levels measured at each AHU

Results
Figure 6 shows the historical data and the model output based on the historical inputs for one zone on C Floor. The model clearly captures some of the real behaviour of the building, particularly the clear temperature changes such as on the 20th, and is consistently within a few degrees of the true value. Conversely the model appears to overestimate temperatures, and on occasion deviates from the historical data such as the night between the 23rd and 24th. This may be due to poorly estimated parameters, or a separate input that has not been included in the model, therefore this issue is currently under investigation.

Figure 3. Subplots showing the historical data used for modeling

Figure 4. Scaled cross correlation between the Wi-Fi occupancy estimate and the change from the minimum CO2 level as measured at each AHU. Data taken from the third floor during February and sampled every 30 minutes.

Occupancy
The number of occupants has a large effect on the indoor environment. At rest a human produces roughly 100w, meaning the difference in temperature response between a 20 person office occupied during the day and empty over night is significant. Two sets of data are available for estimating occupancy, the number of connections to the Wi-Fi hubs on a floor, and the CO2 return levels measured at each AHU. Figure 2 indicates that the CO2 levels are a useful indicator of occupancy. The Wi-Fi data gives an estimate of the total number of people, and the logged change in CO2 in the different areas is used to distribute the occupants into the different areas. Figure 5 indicates that the CO2 return levels probably lag the Wi-Fi data by 30 minutes.

Further Work
There are many options for developing the model further. Currently using the CO2 levels and Wi-Fi data gives an estimate of the total internal heat gains in the building, given that no existing single data set provides this information, therefore novel solutions are required.

References