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 50% of the buildings, yet regulation of the energy centre production is presently sub-optimal.

Figure 1. Visualisation of Lancaster University Campus showing high energy use buildings

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 effected 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.

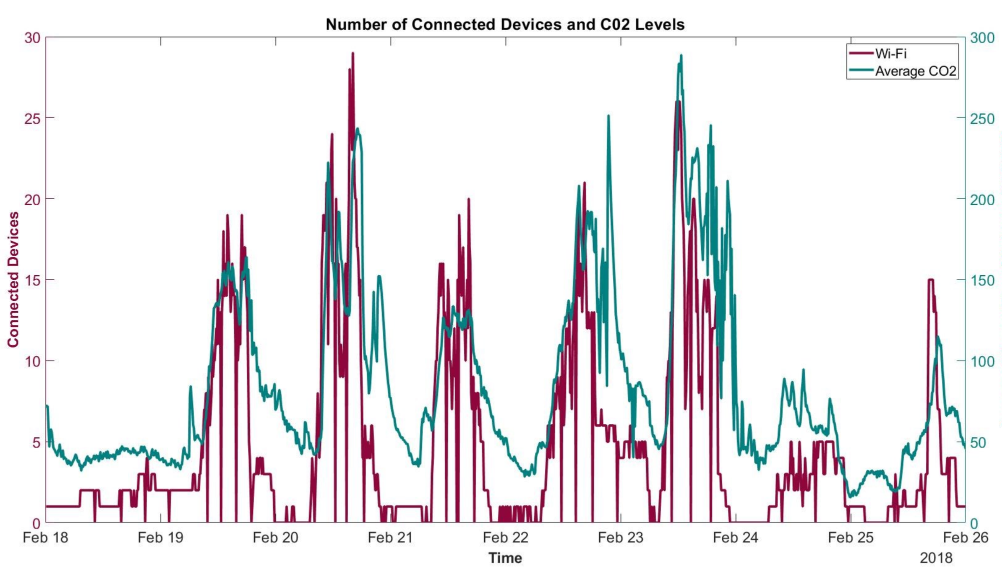

Figure 2. Comparison between the number of devices connected to the Wi-Fi hub and the average change from the minimum CO_2 levels measured at each AHU

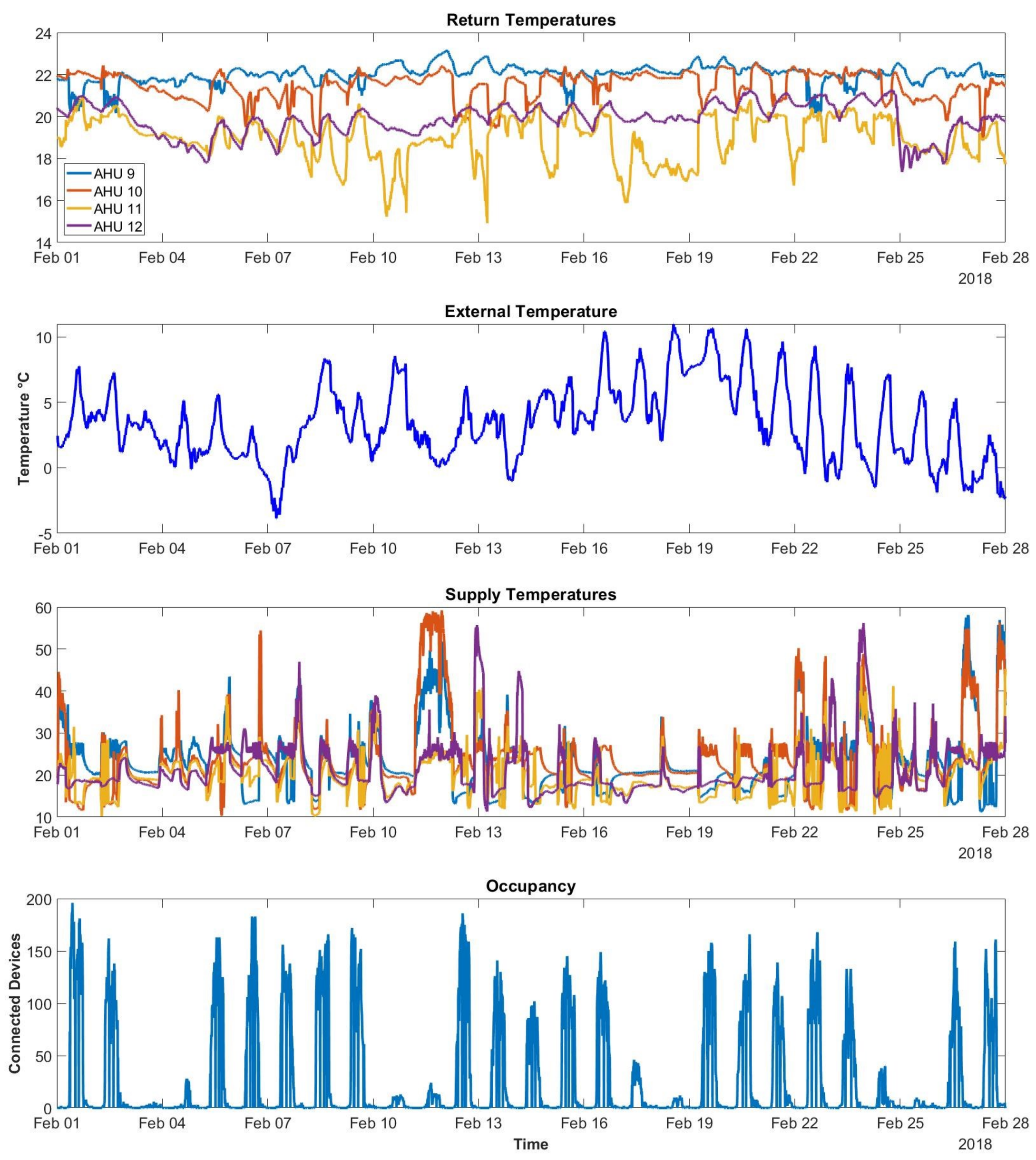

Figure 3. Subplots showing the historical data used for modelling

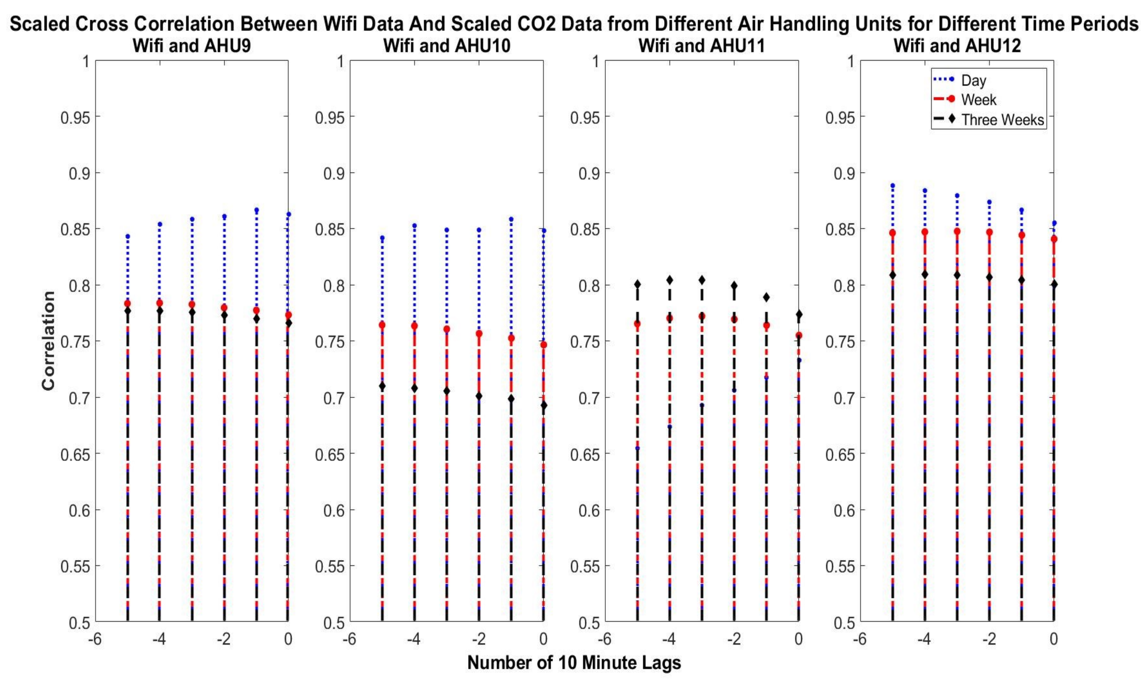

Figure 4. Scaled cross correlation between the Wi-Fi occupancy estimate and the change from the minimum CO_2 level as measured at each AHU. Data taken from the third floor during February 2018 and sampled every 10 minutes.

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 CO_2 return levels measured at each AHU. Figure 2 indicates that the CO_2 levels are a useful indicator of occupancy. The Wi-Fi data gives an estimate of the total number of people, and the lagged change in CO_2 in the different areas is used to distribute the occupants into the different areas. Figure 5 indicates that the CO_2 return levels probably lag the Wi-Fi Data by 30 minutes.

Model Identification

Method

Incorporating the physical derivations into the model adds robustness for extreme cases, e.g. sustained outdoor temperatures above 30°C, as statistical methods cannot incorporate cases for which there is no historical data. Therefore the derived equations are used to inform the structure, yet using the actual physical parameters would require complete knowledge of the building, which is infeasible. As heat transfer can be described by a first order differential equation. A state space model provides a concise method for representing the cross-dependant nature of the states, in this case the temperatures in each area.

To identify the model the known structure of the state space model is passed to Matlab, then Matlab ssest optimisation algorithm is used to identify the desired parameters using historical input data, this process is shown in Figure 5. To reduce the dependency of the parameters on any one set of input data, different lengths of data (days, weeks and month) are passed in for different times of the year.

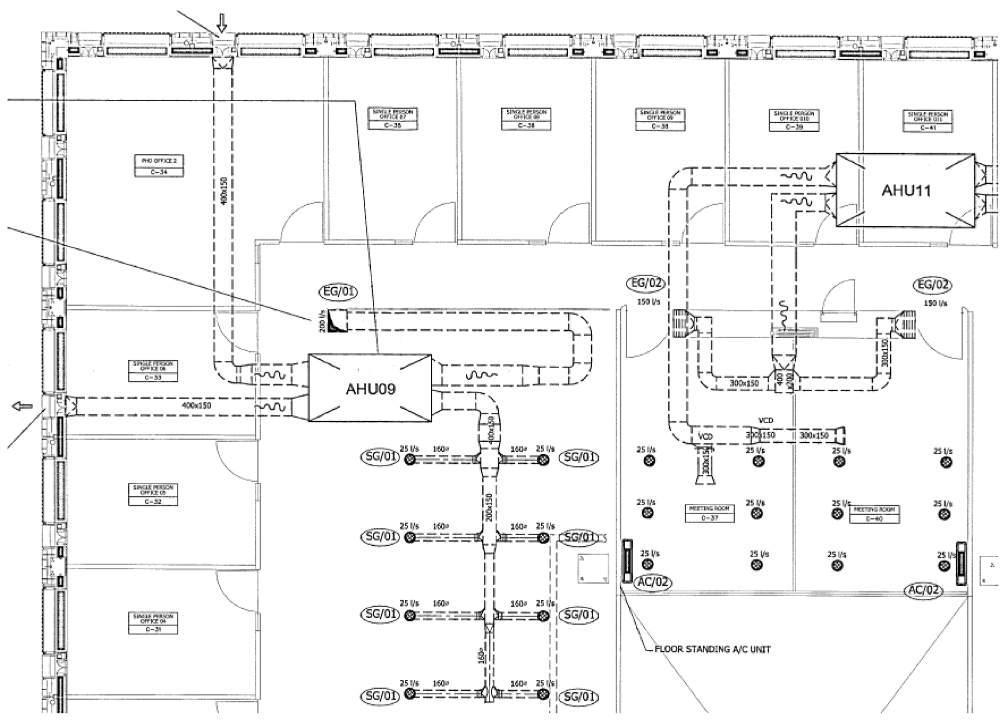

Figure 7. Section of the Ventilation Schematic for Charles Carter Building C Floor, Showing Air Handing Unit Placement

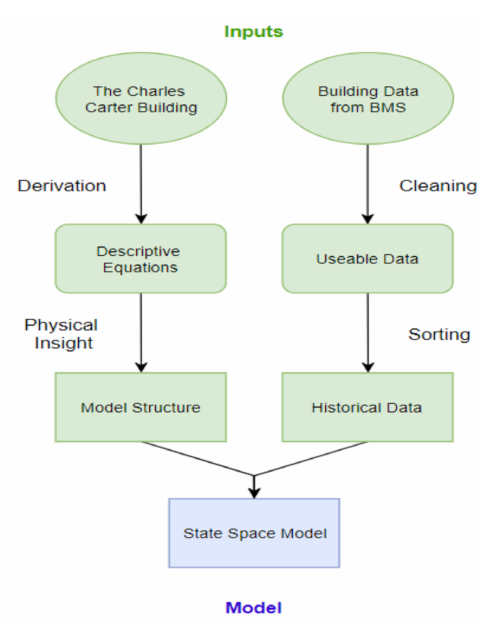

Figure 5. Flow diagram depicting how both physical insight and

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 often overestimate temperatures, and on occasion diverges 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.

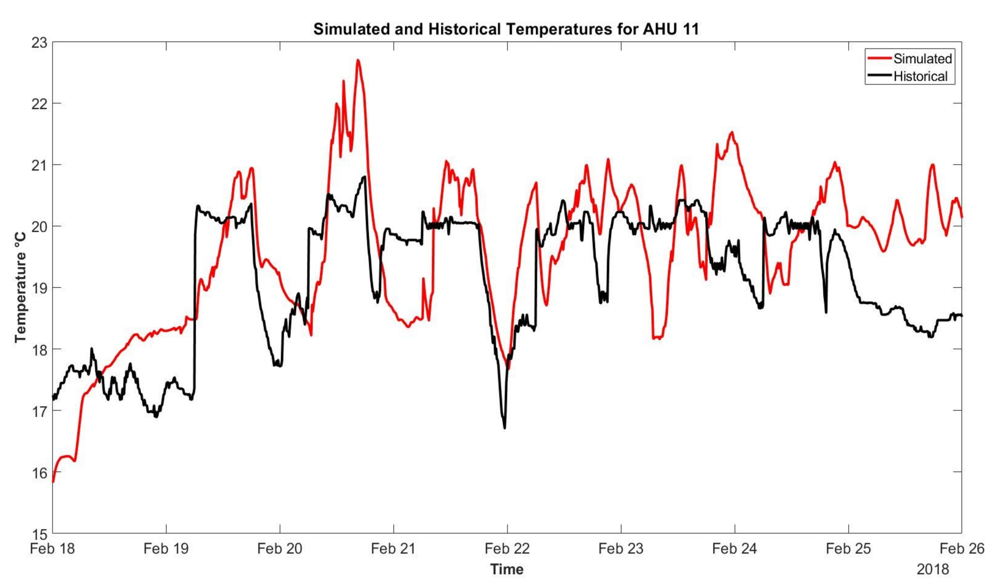

Figure 6. Real and Simulated Temperatures at AHU 11 for a Week in February

Model Use

This project concerns simple, flexible models suitable for improving control system robustness and overall system optimisation. Lancaster's energy centre provides multiple methods of heat production, such as gas boilers and a biomass generator. The models are being used to explore options for hierarchical control, with a particular focus on optimising the use of the boilers and generator. To achieve this, non-minimal state space model predictive control methods [1] are being adapted for this application. A novelty of the research is the incorporation of the existing BMS human occupancy data into the control calculations.

Further Work

There are many options for developing the model further. Currently using the CO_2 levels and Wi-Fi data is still an imprecise way of estimating the space occupancy, therefore inclusion of other estimating parameters such as humidity could be informative. In addition the lack of data of the temperatures in the perimeter offices means that the offices simply act as large resistances to the external temperature, ideally they would instead be used as model inputs.

References

[1] L. Wang, P. C. Young, P. J. Gawthrop, and C. J. Taylor, "NMSS model-based continuous-time model predictive control with constraints," Int. J. Control, vol. 82, pp. 1122–1137, 2009.

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