Dynamic CO_2 and Occupancy Modelling for Predictive Control

Authors: A. Pantazaras, M. Santamouris, S.E. Lee

WORLD Sustainable Built Environment Conference HONG KONG 2017
Organisers: CONSTRUCTION INDUSTRY COUNCIL 建造業議會 HKGBC
International Co-owners: SBE SERIES CIB iiSBE UNEP Sustainable Buildings and Climate Initiative FIDIC Global Alliance for Buildings and Construction

Presentation Outline

1. Introduction
2. Model Development
3. Experimental Setup
4. Results
5. Conclusions

Introduction

Demand Controlled Ventilation

- HVAC systems are a significant contributor in the energy demand of a building and as such are one of the more popular targets for technological and operational optimisation.
- Demand Controlled Ventilation (DCV) is one such strategy.
- Best potential applications can be found in spaces with highly variable occupancy, like restaurants or auditoria.
- In DCV systems CO_2 is typically used as an indicator of human occupancy.
- The energy saving potential of CO_2 based ventilation control has been intensively investigated.

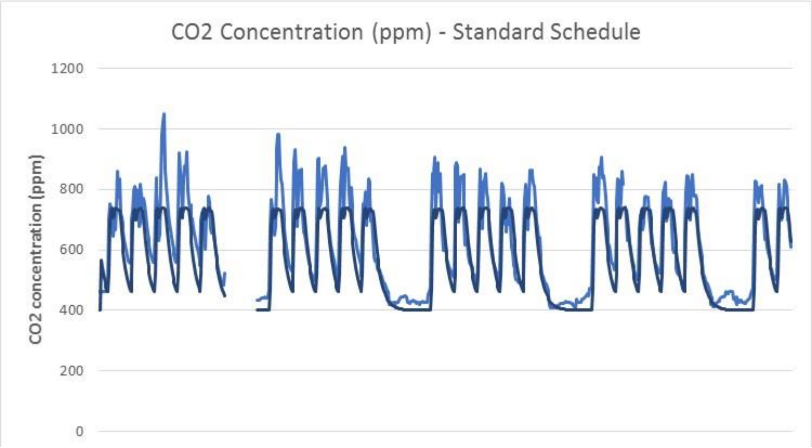
Reactive vs Predictive

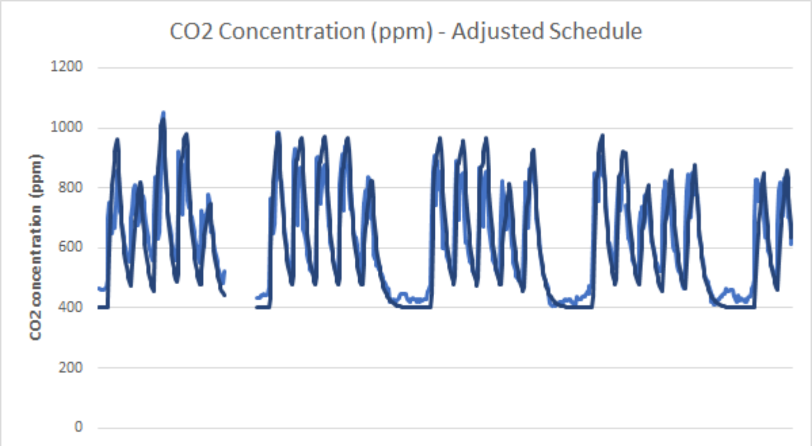
- Most BEMS equipped with automated control systems are reactive to changing climatic conditions and operational parameters.
- There has been extensive research in the field of building modelling for adaptive and, increasingly, for predictive control.
- Most predictive modelling methods are so far almost exclusive to the thermal dynamics of their modelled systems or sub-systems.
- The inclusion of predicted CO_2 levels as a factor in deciding optimum control strategies is limited.

Model Development

Occupancy Patterns

- Occupancy is the main driver in indoor CO_2 generation.
- Important to know how the occupancy varies on a daily basis with high granularity.
- Standardised occupancy schedules are not able to provide this level of information.
- If detailed occupancy data is difficult to acquire, data of indoor CO_2 concentration can help.





Selection of Variables

- A general model for depicting the change in CO_2 concentration, *C*, in a room or zone with volume V, under a ventilation rate of Q_{ven} and a CO_2 generation rate of G_{CO_2} is the following:

- $V\frac{dC}{dt} = Q_{ven}(C - C_{out}) + G_{CO_2}$

- Assuming a discrete time step and a stable level of activity, the discretised form of this relationship can be expressed as:

- $C_{t+1} = f(C_t, N_t, Q_{ven,t}, C_{out,t})$

State Space Representation

- The discrete-time state space model innovation form is given by:

- $x(t+1) = Ax(t) + Bu(t) + Ke(t)$
- $y(t) = Cx(t) + Du(t) + e(t)$

- ***x**:* state vector, ***u**:* input vector, ***y***: output vector, ***e**:* generalised disturbance
- ***A***, ***B***, ***C***, ***D*** and ***K**:* matrices with estimable parameters, the dimension of which corresponds to the model order, *n*.

Predicting CO_2 and Estimating Occupancy

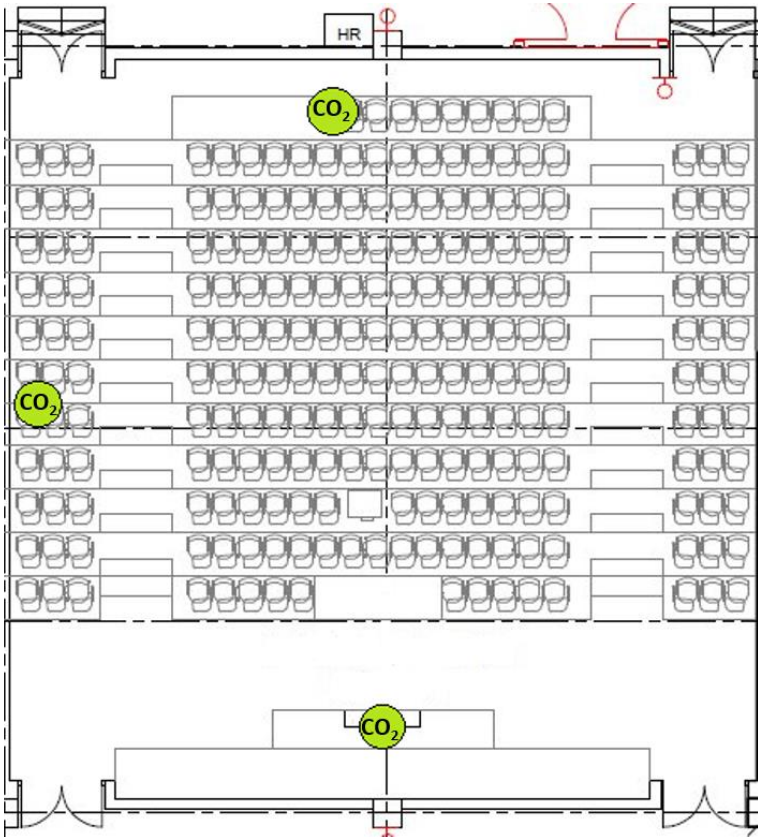
	Past	Present	Future
Prediction	Known Inputs and Outputs		Outputs estimated based on assumed Inputs
Simulation	Initial Conditions + Inputs at each step → Outputs		

	Past	Present	Future
Predicting CO_2	Known Occupancy, Ventilation and CO_2		Assuming Occupancy and Ventilation, future CO_2 is predicted
Estimating Occupancy	Initial Conditions + Ventilation and CO_2 at each step gives Occupancy		N/A

Experimental Setup

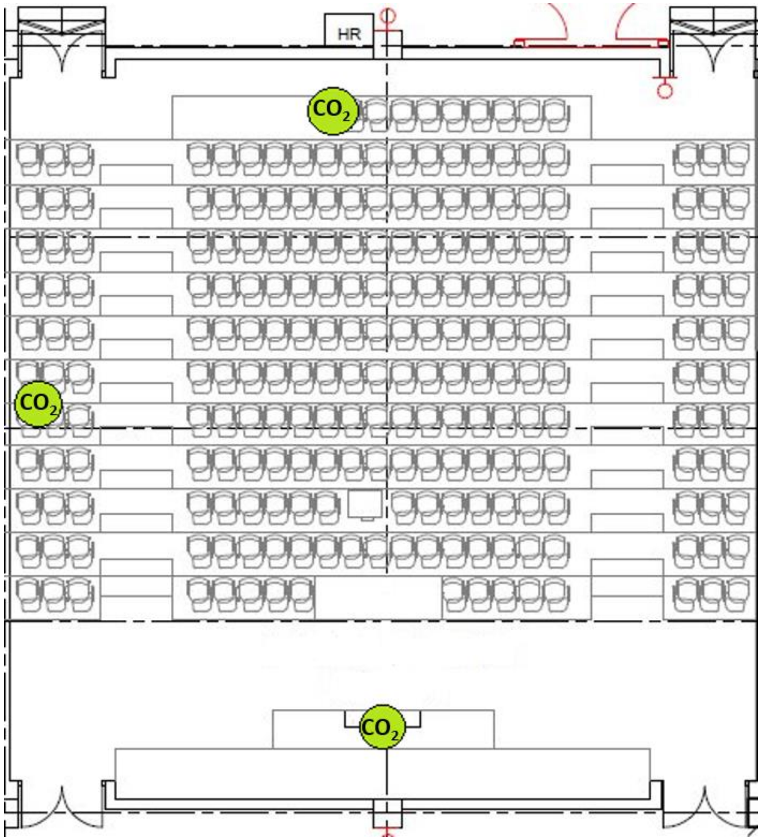
CO_2 Sensor Deployment

- 3 CO_2 sensors placed at different locations.
- Accuracy: 30ppm +/- 3% of reading.
- Sensors transmit data to server wirelessly at one minute intervals.
- Single minute data is grouped in 5 minute averages for each sensor.
- Average of 3 sensors used as the lecture theatre representative value.



Data Collection

- Data was collected for a period of five days.
- Lecture theatre was fully active and experienced great fluctuations in occupancy.
- 1440 data points collected.
- CO_2 data was used to calibrate EnergyPlus occupancy.
- EnergyPlus provided the occupancy and ventilation values.
- From the 1440 data points, 288 (20%) was used to train the CO_2 model and the rest was used to validate it.



Photographic Validation

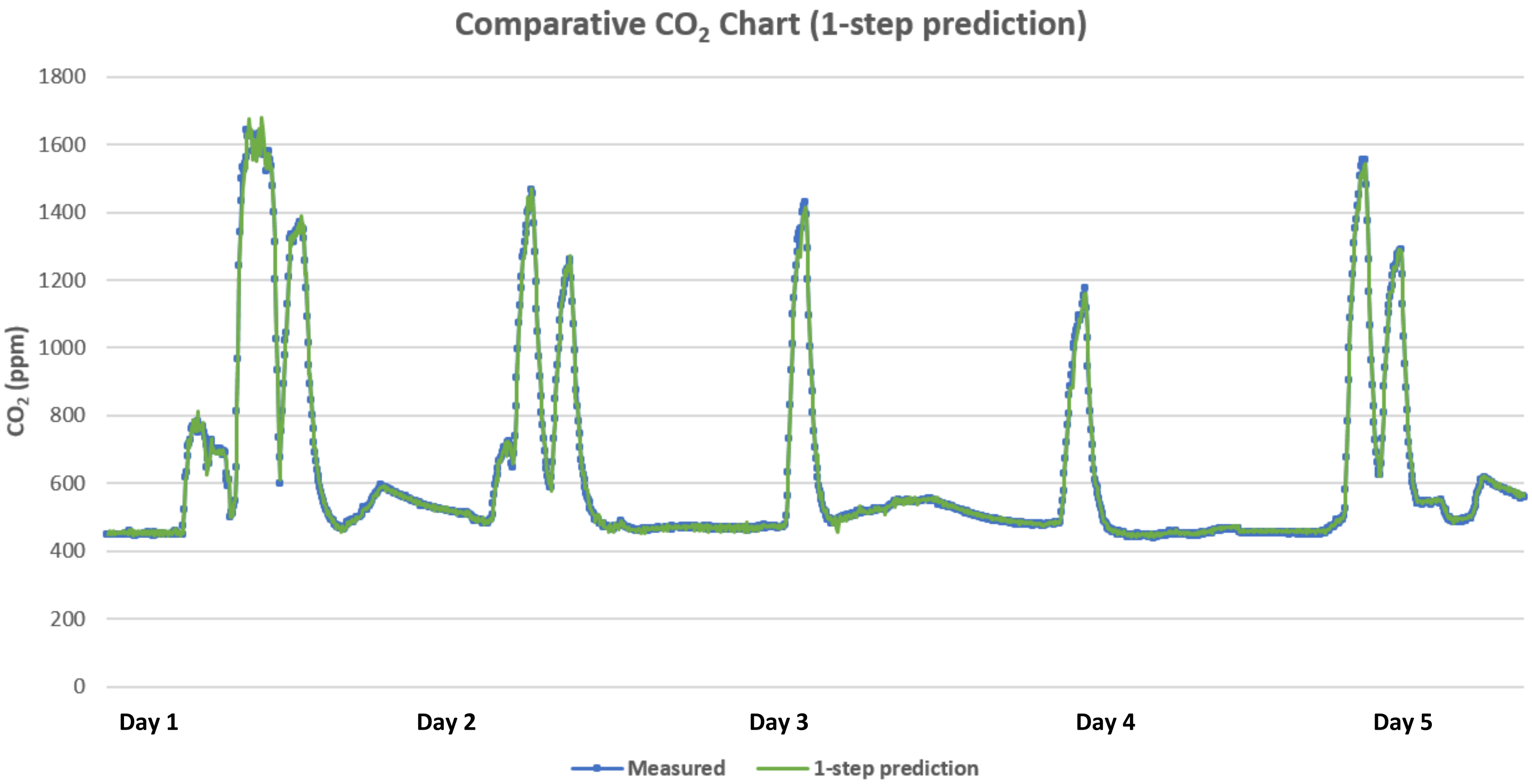
- Photographs from inside the lecture theatre were available at 5 minute intervals.
- These photographs were NOT used to provide the occupancy input for the CO_2 prediction model, since that was not the purpose of this study.
- These photographs were used as validation data for the occupancy model.

Results

Results

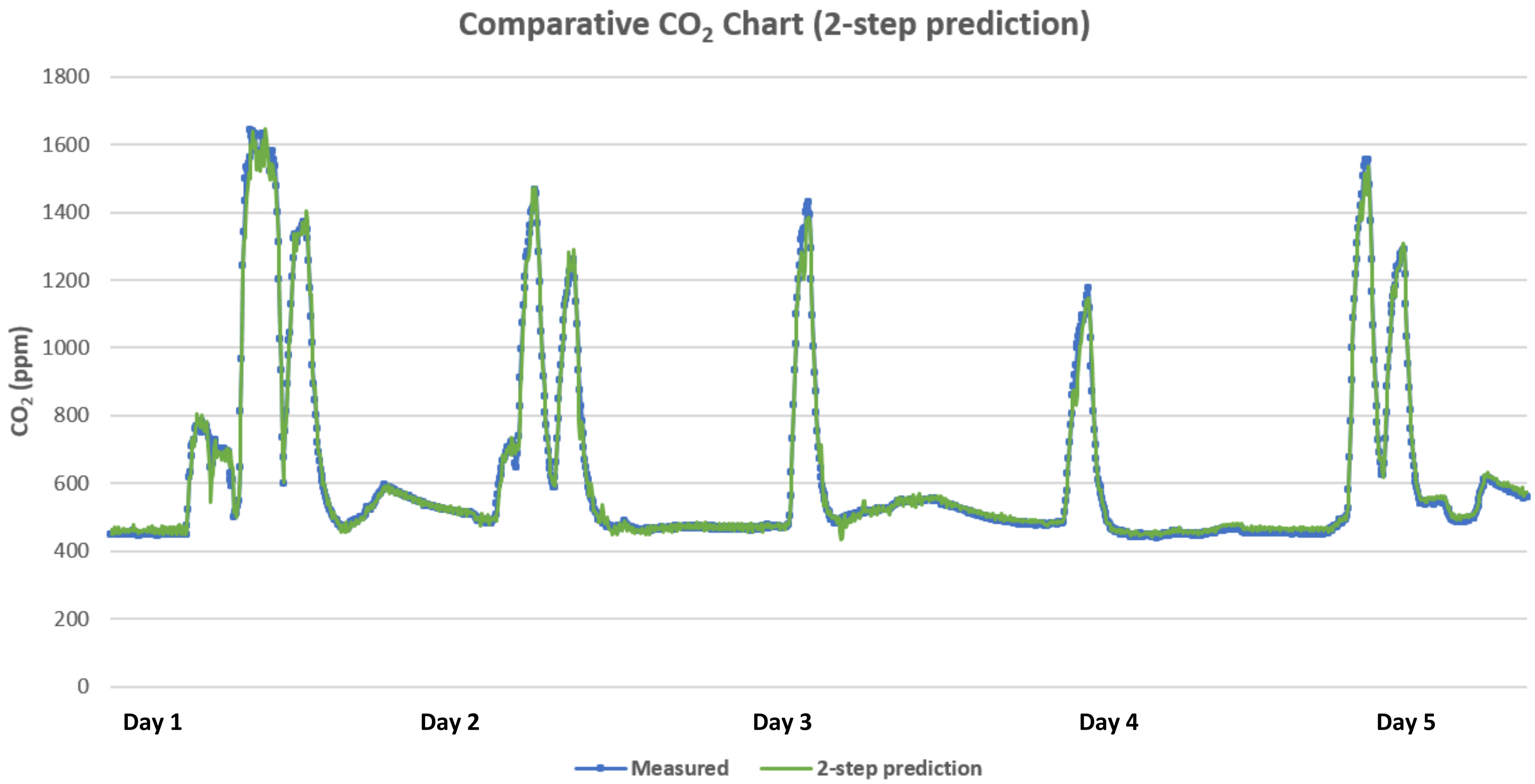
- Several models are considered prior to the selection of the best performing one.
- Different model properties are tested, such as the model order n (order of matrices) and the input delay (number of samples before an input affects the output).
- In this study the model is discrete and every “step” equals to 5 minutes.
- The prediction accuracy of the CO_2 models is evaluated at 1, 2, 3, 5, 10 and 20 steps into the future (i.e. 5 - 100 minutes).
- The Occupancy model is evaluated as a full simulation, as there is no prediction of occupancy into the future, only estimation at the current time.

CO_2 Model



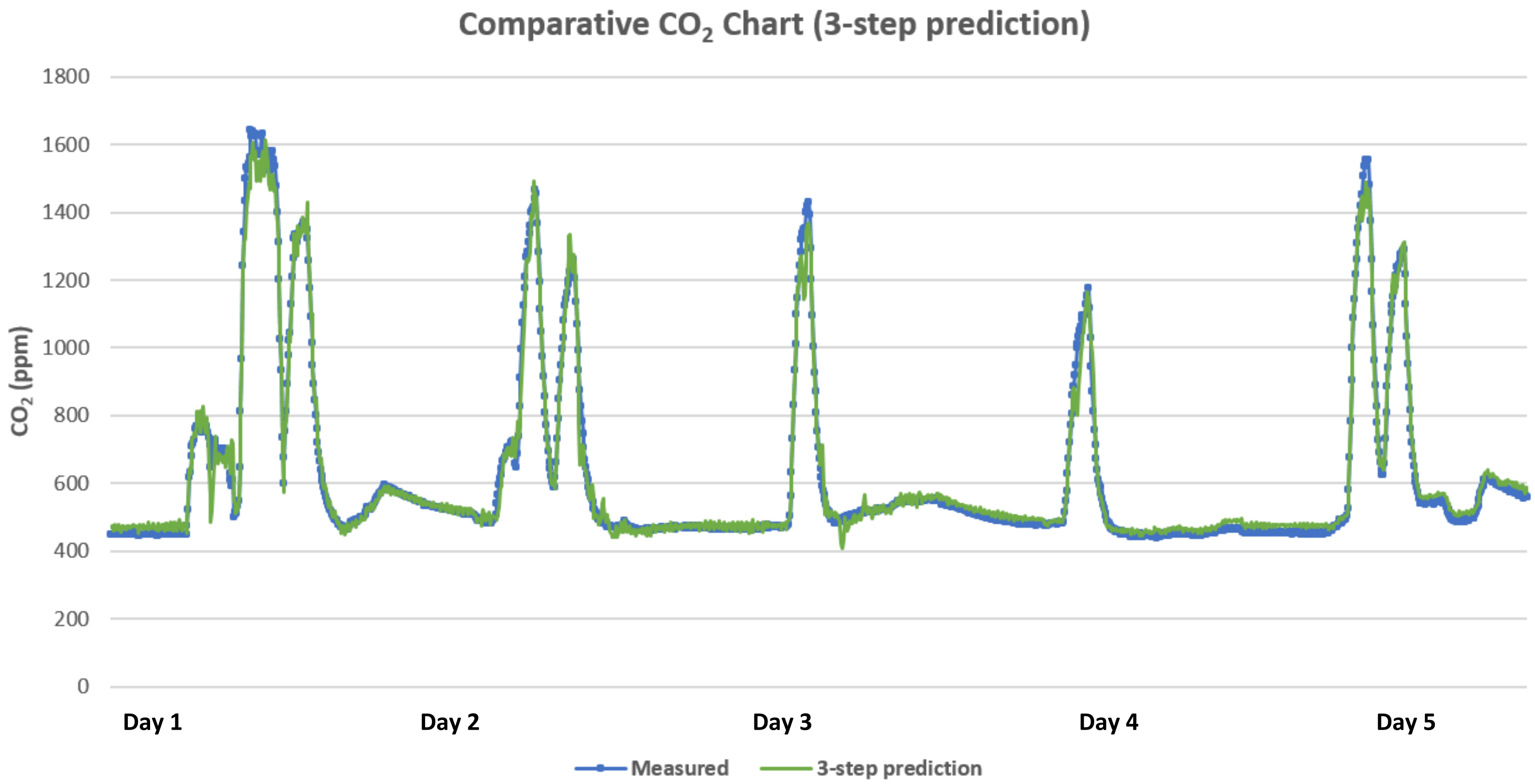
Comparative CO2 Chart (1-step prediction)
1800
1600
1400
1200
1000
800
600
400
200
0
CO2 (ppm)
Day 1
Day 2
Day 3
Day 4
Day 5
Measured
1-step prediction

CO_2 Model

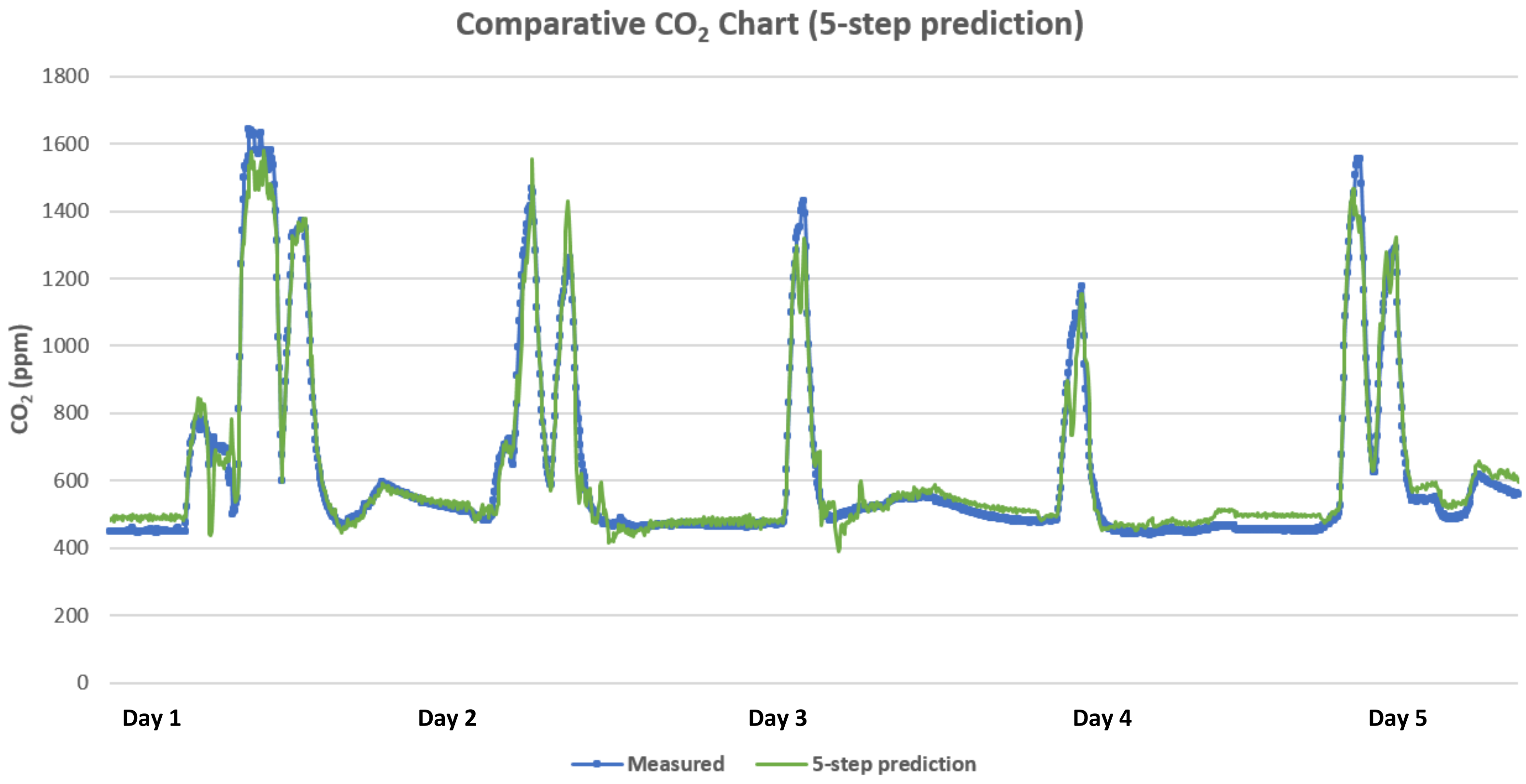


Comparative CO2 Chart (2-step prediction)
1800
1600
1400
1200
1000
800
600
400
200
0
CO2 (ppm)
Day 1
Day 2
Day 3
Day 4
Day 5
Measured
2-step prediction

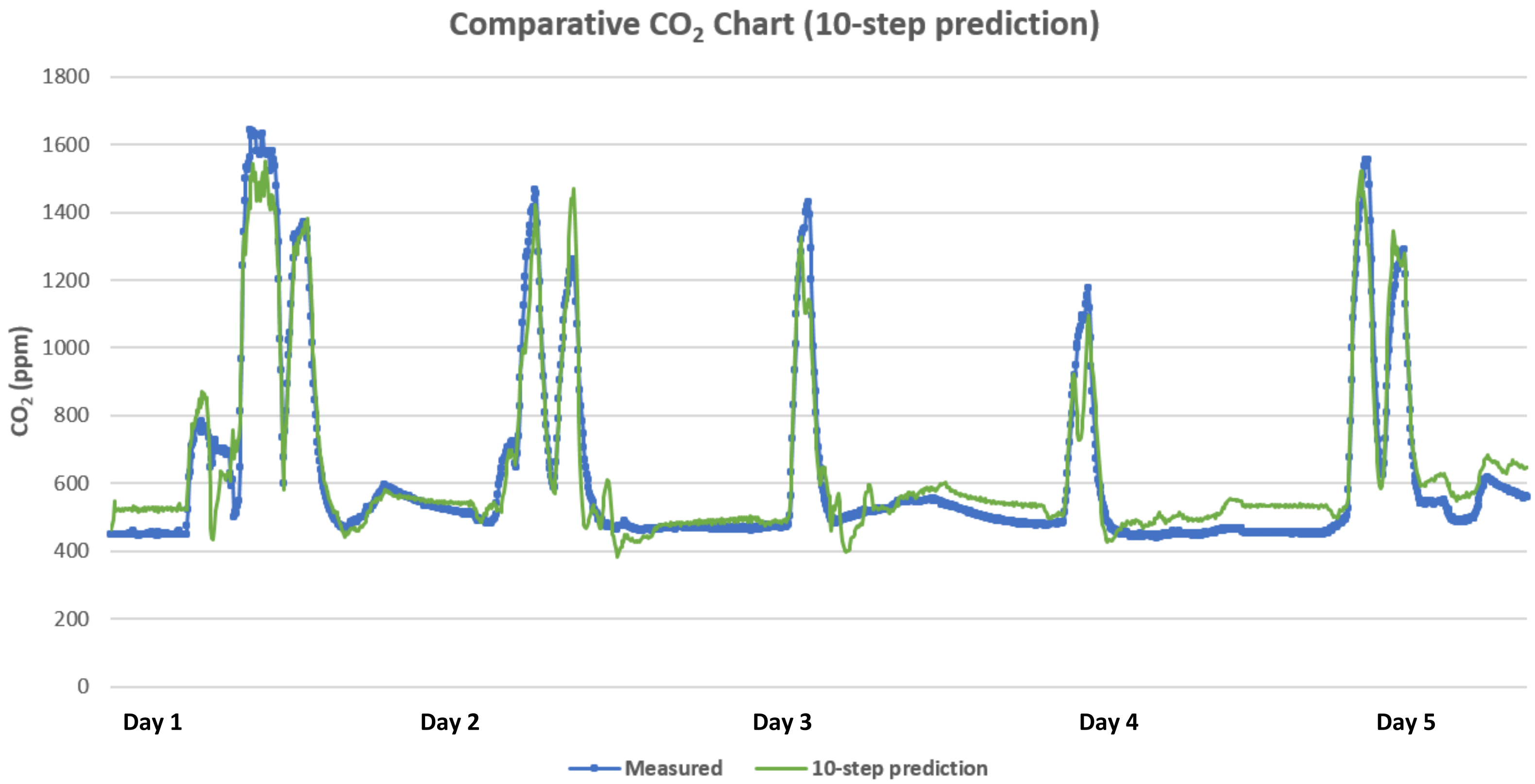
CO_2 Model


Comparative CO2 Chart (3-step prediction)
CO2 (ppm)
0
200
400
600
800
1000
1200
1400
1600
1800
Day 1
Day 2
Day 3
Day 4
Day 5
Measured
3-step prediction

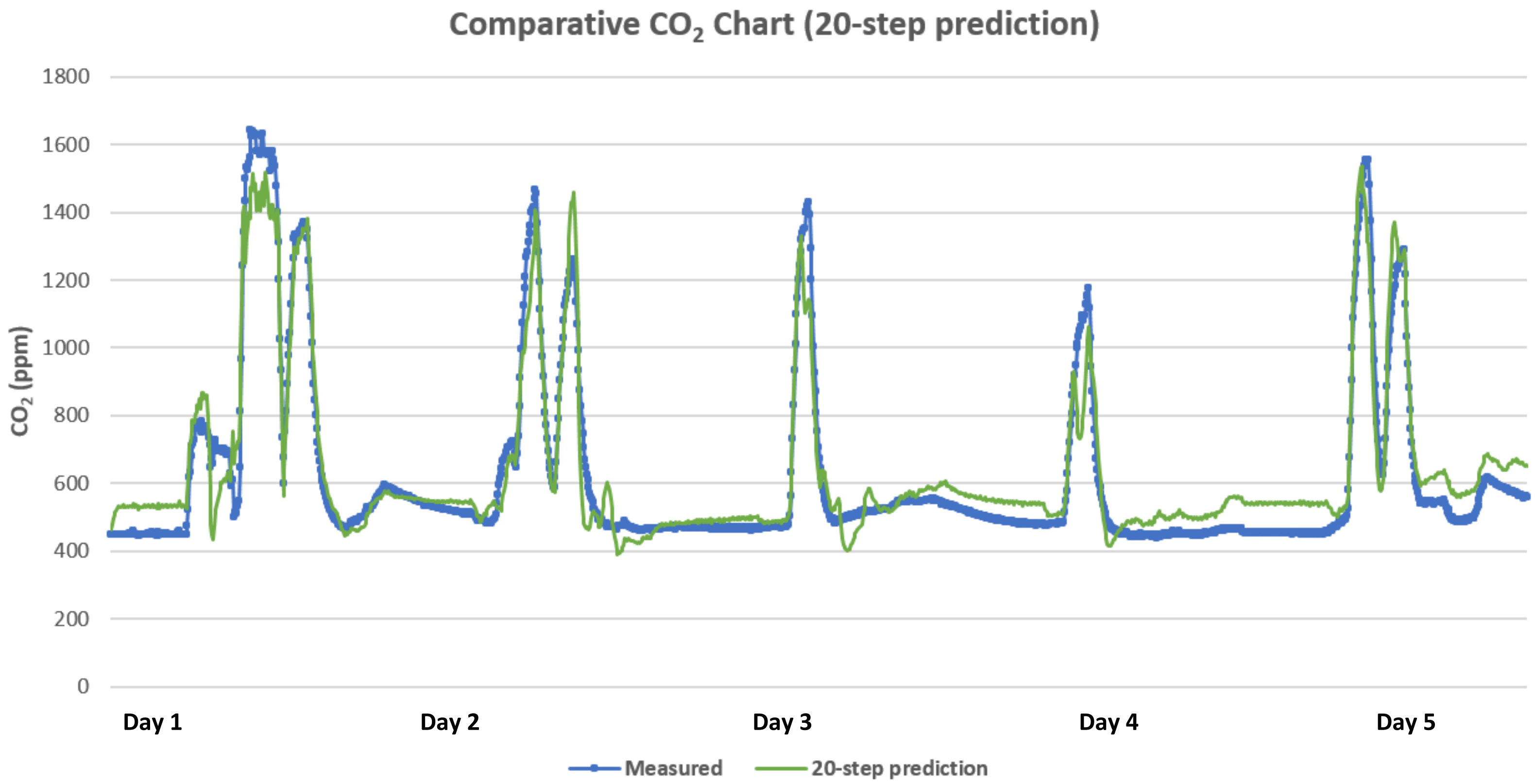
CO_2 Model


Comparative CO2 Chart (5-step prediction)
CO2 (ppm)
1800
1600
1400
1200
1000
800
600
400
200
0
Day 1
Day 2
Day 3
Day 4
Day 5
Measured
5-step prediction

CO_2 Model

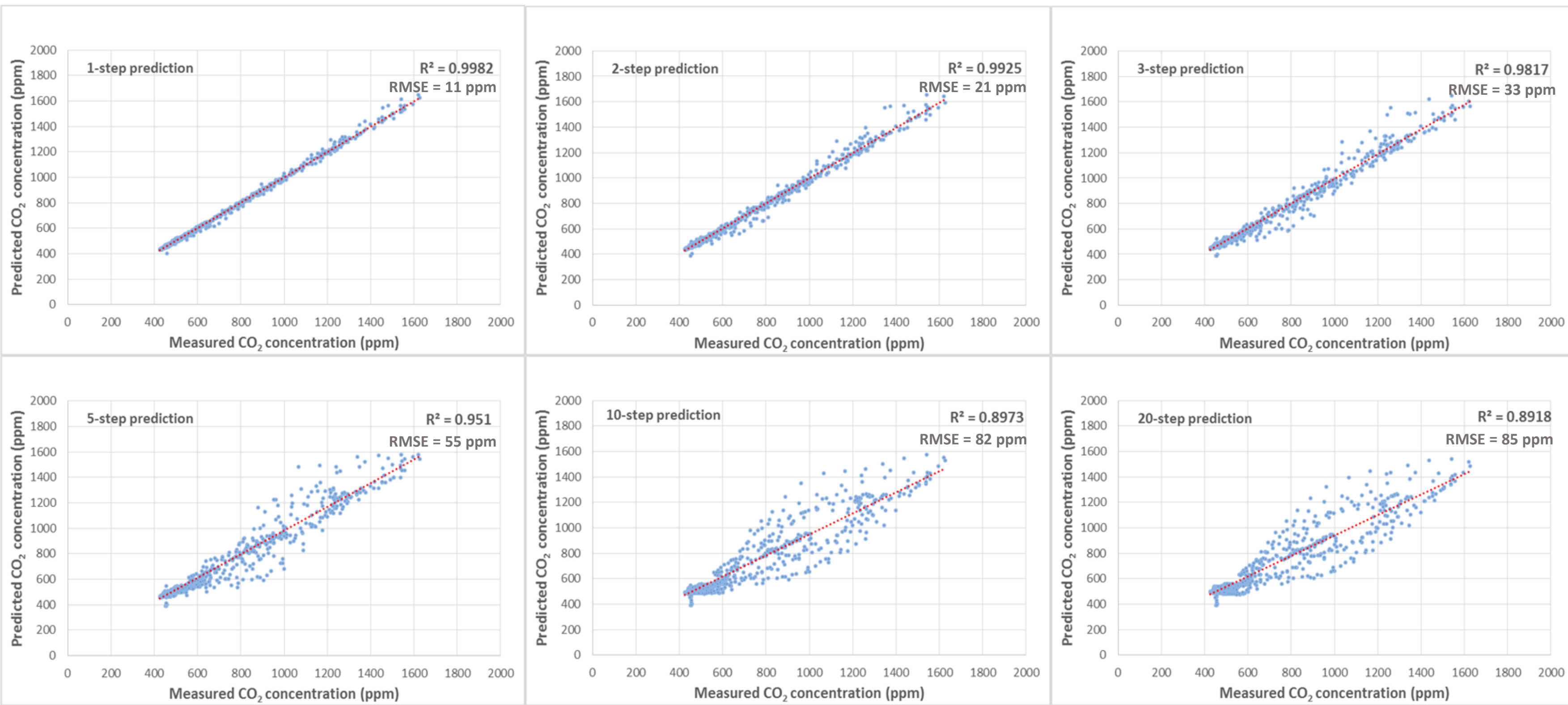

Comparative CO2 Chart (10-step prediction)
CO2 (ppm)
1800
1600
1400
1200
1000
800
600
400
200
0
Day 1
Day 2
Day 3
Day 4
Day 5
Measured
10-step prediction

CO_2 Model



Comparative CO2 Chart (20-step prediction)
1800
1600
1400
1200
1000
800
600
400
200
0
CO2 (ppm)
Day 1
Day 2
Day 3
Day 4
Day 5
Measured
20-step prediction

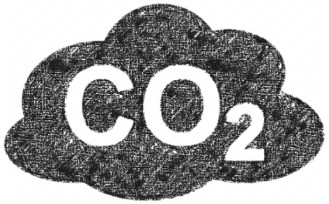
CO_2 Model



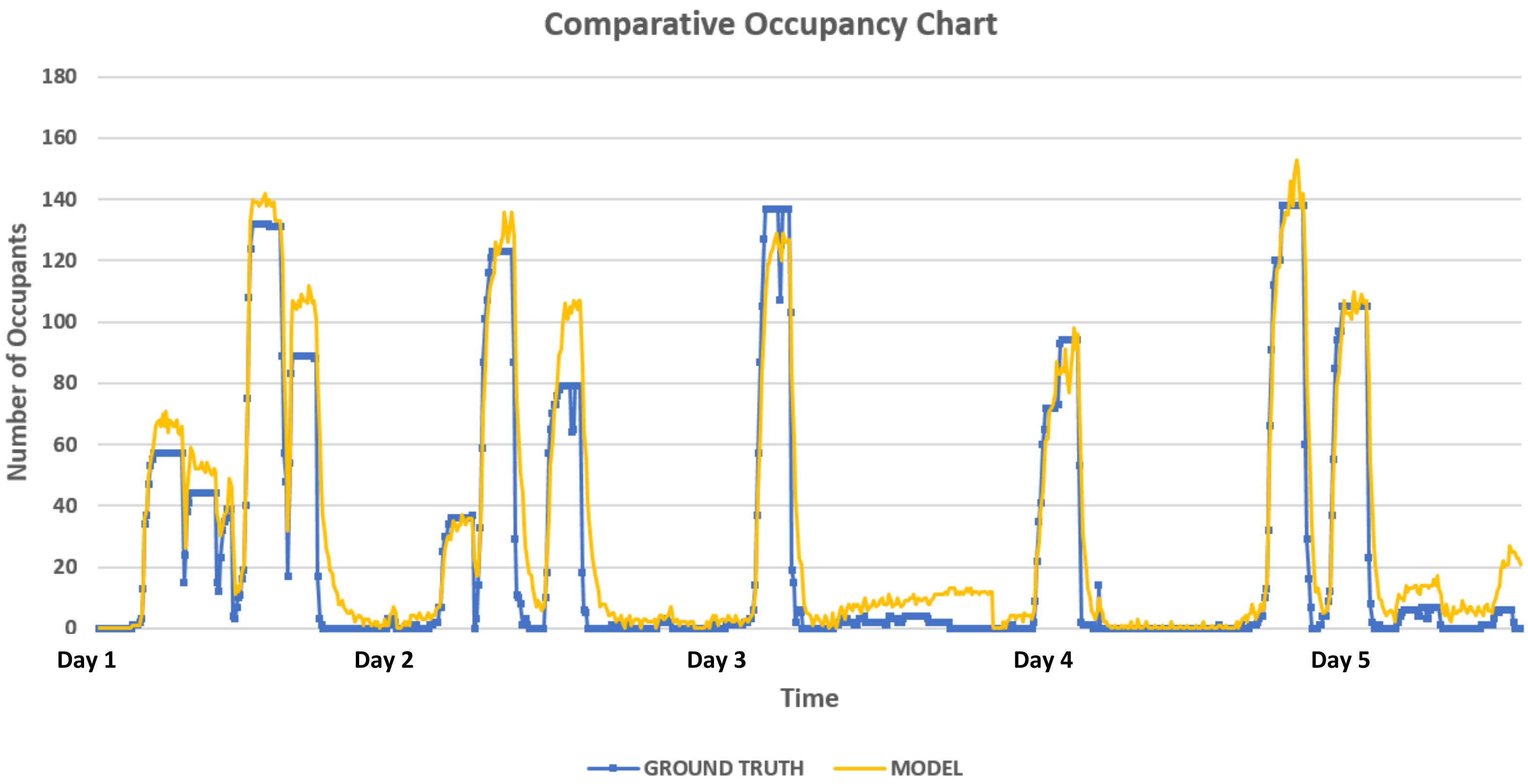
1-step prediction
R² = 0.9982
RMSE = 11 ppm
2-step prediction
R² = 0.9925
RMSE = 21 ppm
3-step prediction
R² = 0.9817
RMSE = 33 ppm
5-step prediction
R² = 0.951
RMSE = 55 ppm
10-step prediction
R² = 0.8973
RMSE = 82 ppm
20-step prediction
R² = 0.8918
RMSE = 85 ppm
Predicted CO2 concentration (ppm)
Measured CO2 concentration (ppm)

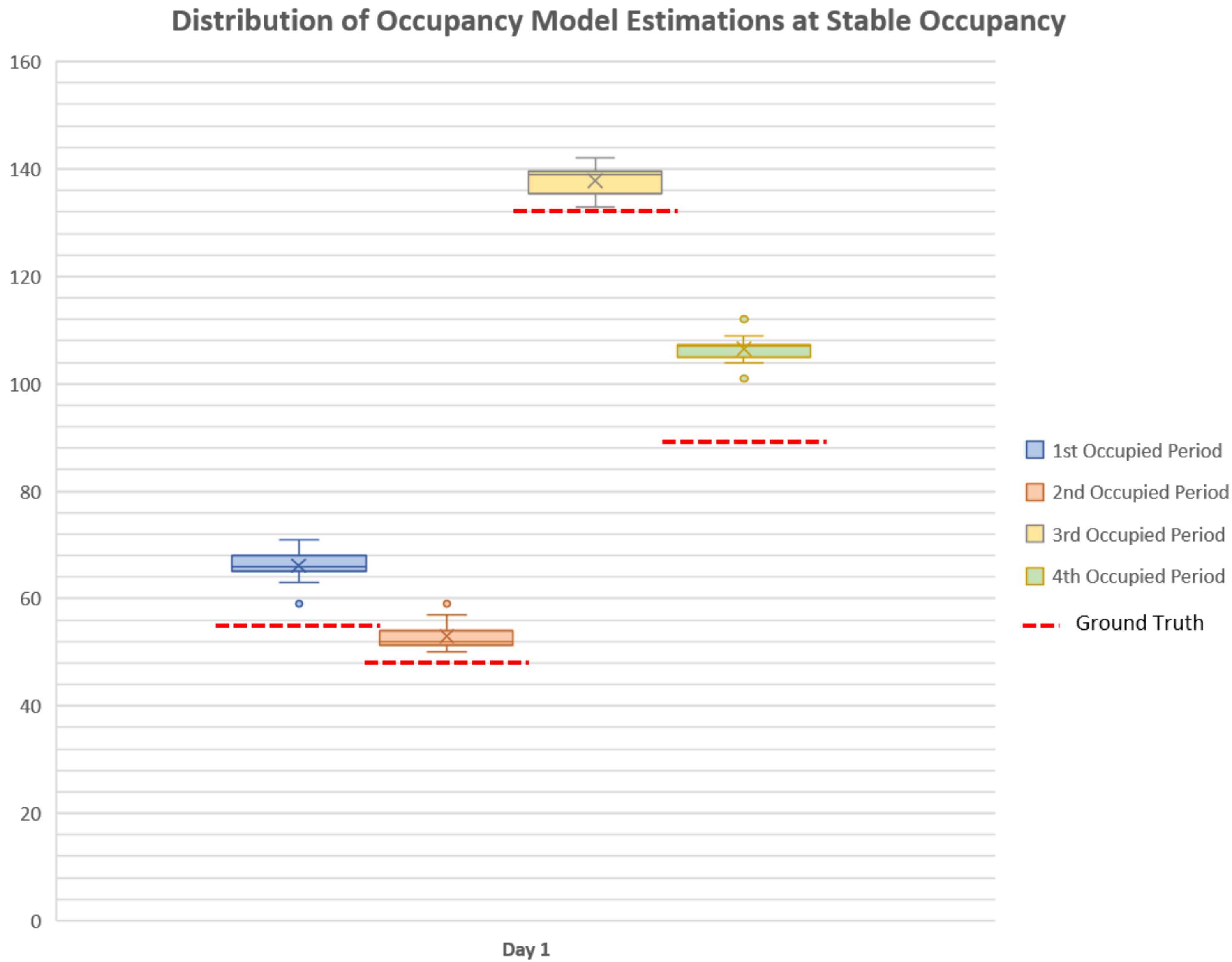
CO_2 Model

- On the whole, the model is able to accurately predict the CO_2 concentration even at the furthest prediction horizon that was tested.
- There is however a notable performance drop after the third and especially after the fifth step.
- Even so, the model is performing very well for predictions between 5 and 25 minutes, which are time periods that are highly relevant for HVAC control actions.



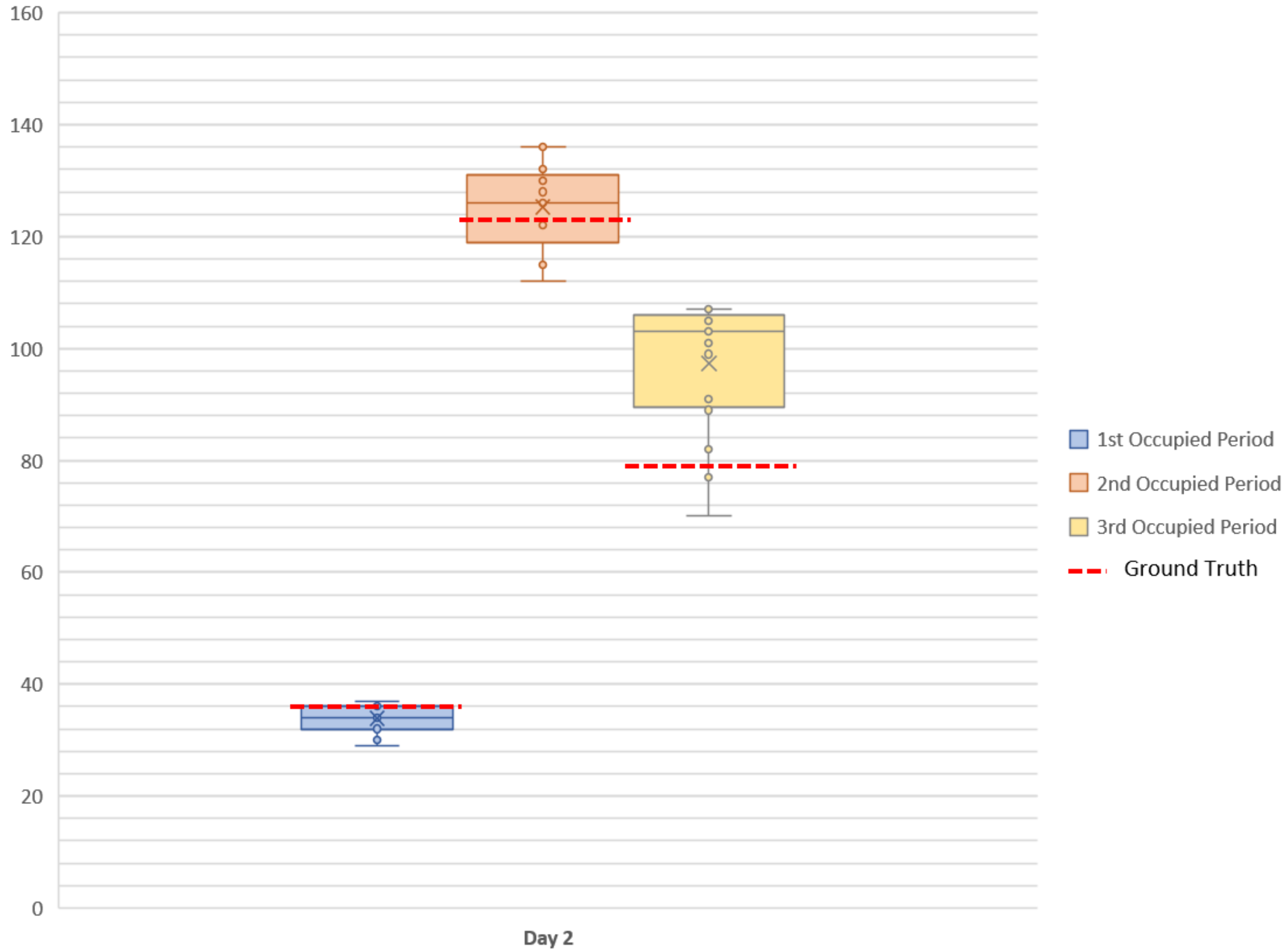
Occupancy Model

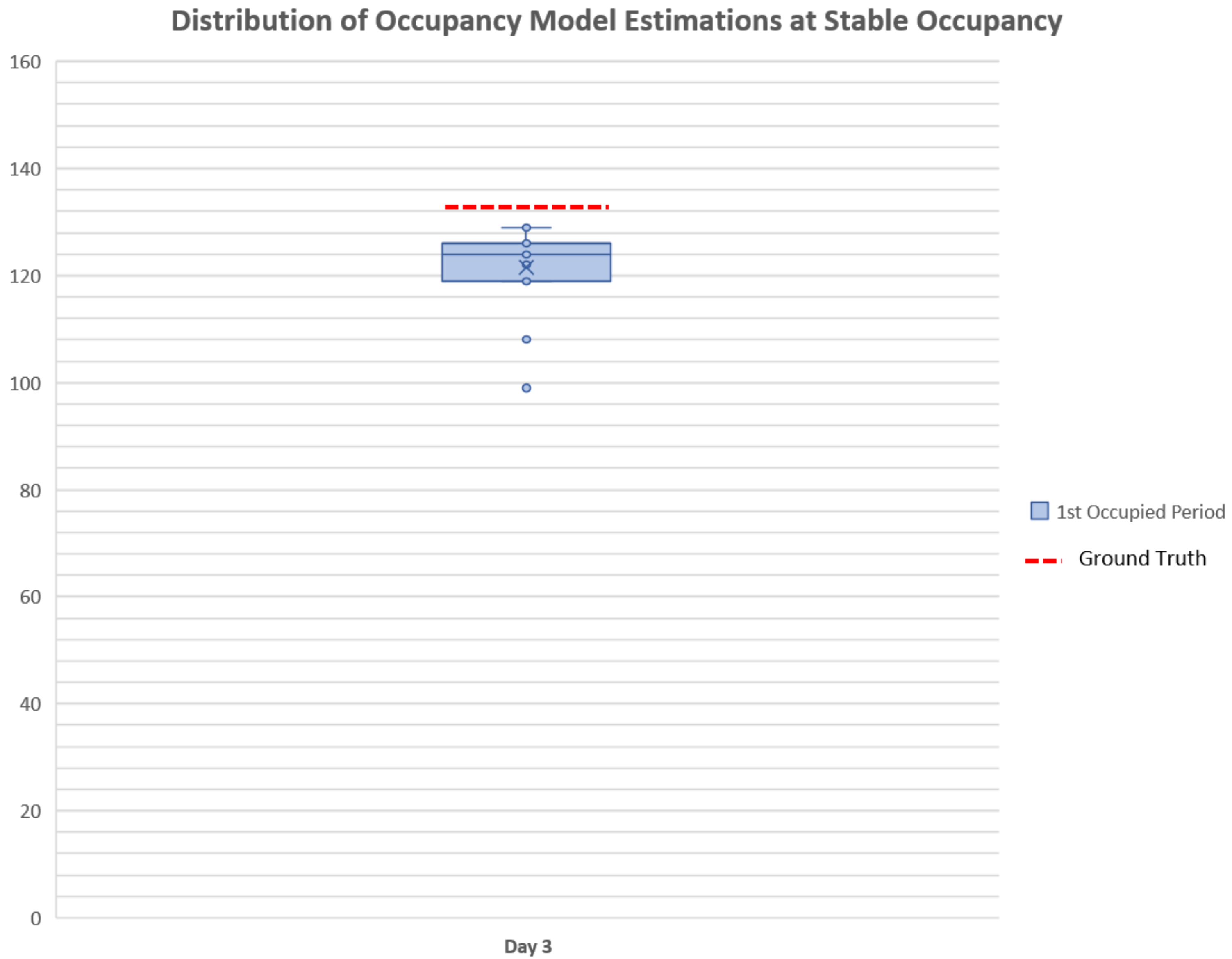


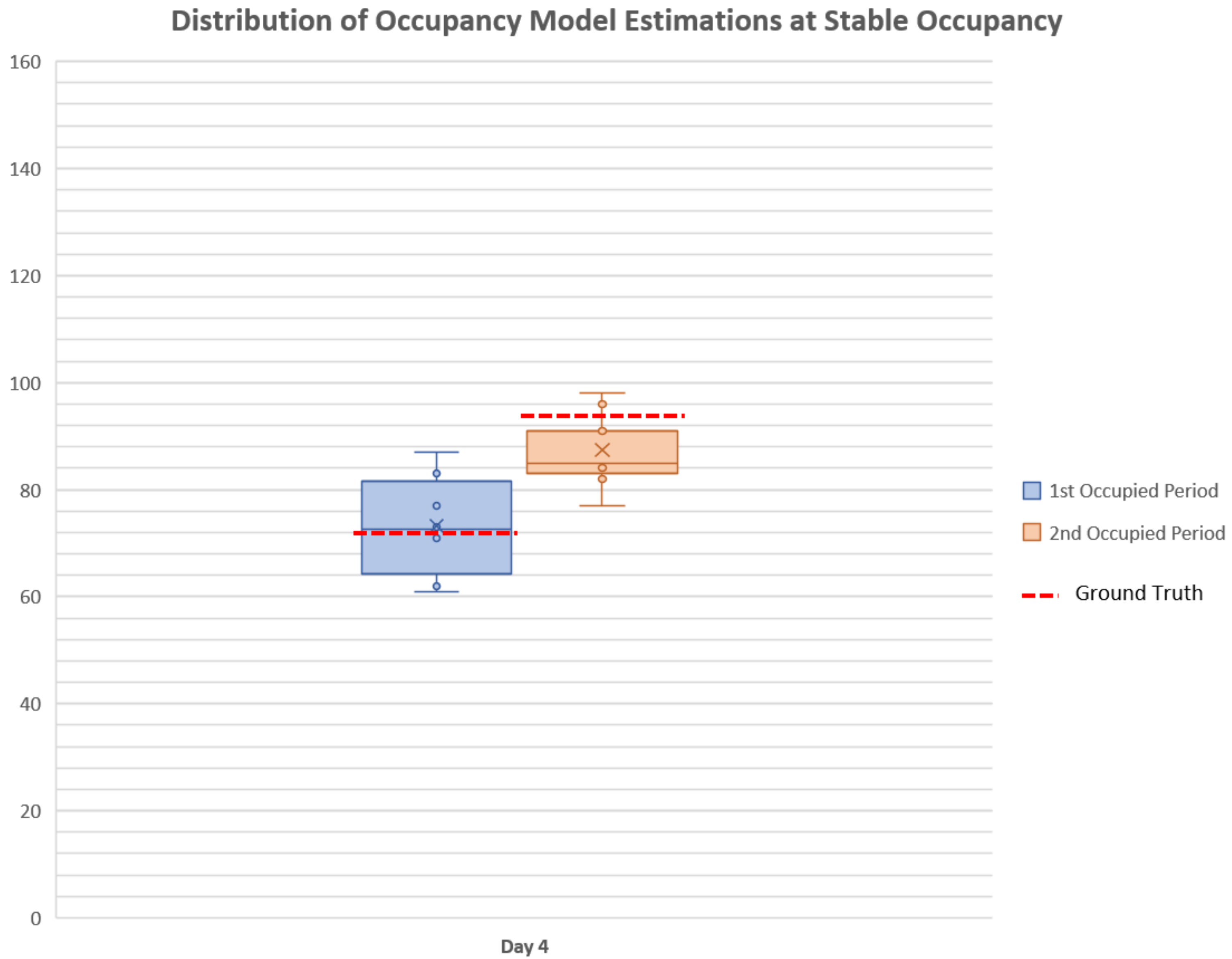


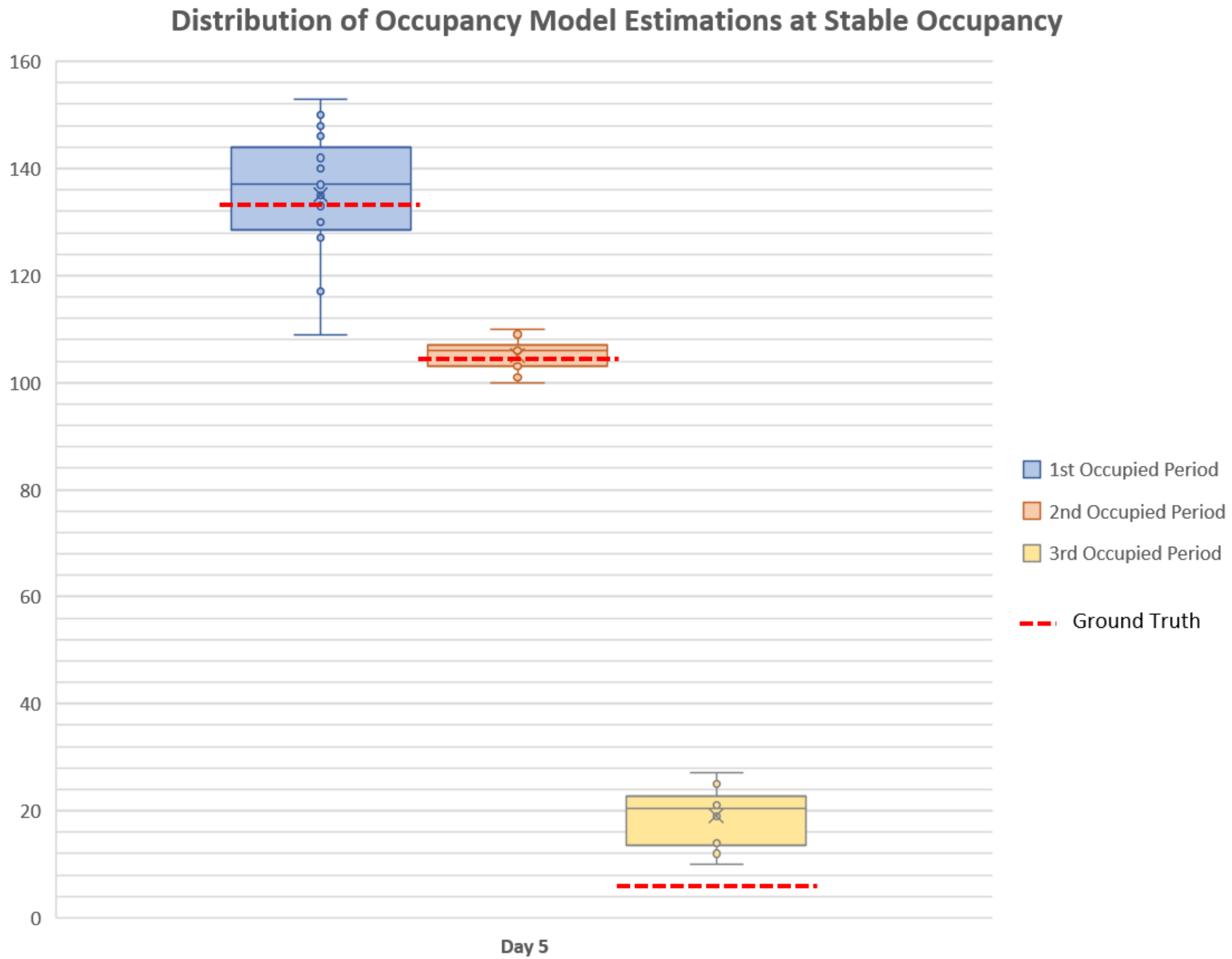
Distribution of Occupancy Model Estimations at Stable Occupancy
160
140
120
100
80
60
40
20
0
Day 1
1st Occupied Period
2nd Occupied Period
3rd Occupied Period
4th Occupied Period
Ground Truth

Distribution of Occupancy Model Estimations at Stable Occupancy



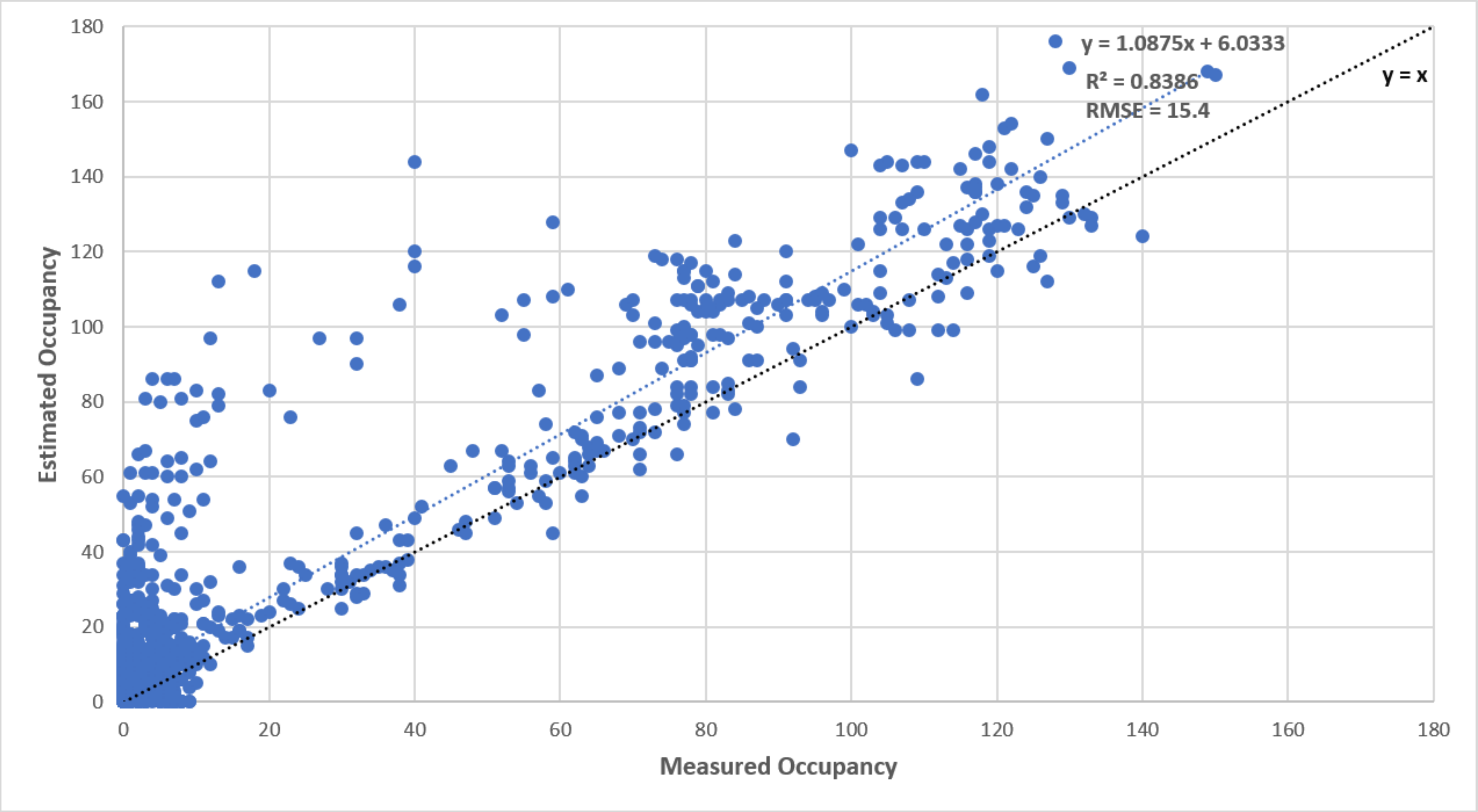

Distribution of Occupancy Model Estimations at Stable Occupancy
160
140
120
100
80
60
40
20
0
Day 3
1st Occupied Period
Ground Truth


Distribution of Occupancy Model Estimations at Stable Occupancy
160
140
120
100
80
60
40
20
0
Day 4
1st Occupied Period
2nd Occupied Period
Ground Truth



Distribution of Occupancy Model Estimations at Stable Occupancy
160
140
120
100
80
60
40
20
0
Day 5
1st Occupied Period
2nd Occupied Period
3rd Occupied Period
Ground Truth

Occupancy Model



Occupancy Model

- Although the model performs well on average, it generally overestimates the number of occupants, especially when the occupant number is low.
- Most of the larger differences between estimation and actual occupancy occur at transitional periods at the end of classes, which may explain the much bigger discrepancy at low occupancies.
- The opposite effect doesn't happen as often, since student arrival is much more gradual than their exit.

Conclusions

Conclusions

- This study has shown that it is possible to create an accurate predictive model of CO_2 for a selected space using only a few commercially available CO_2 sensors.
- If past data on CO_2 is available, a well defined and CO_2-calibrated deterministic model (like EnergyPlus) of the space/zone can provide the rest of the data required for the identification procedure.
- Using the same setup it is possible to create a reasonably accurate model that can estimate current levels of occupancy, however it has a tendency to overestimate numbers especially at low occupancy.

Thank you