Demonstration of Networked Gas Sensor Data-driven Calibration

EQ2443/EQ2444/EQ2445

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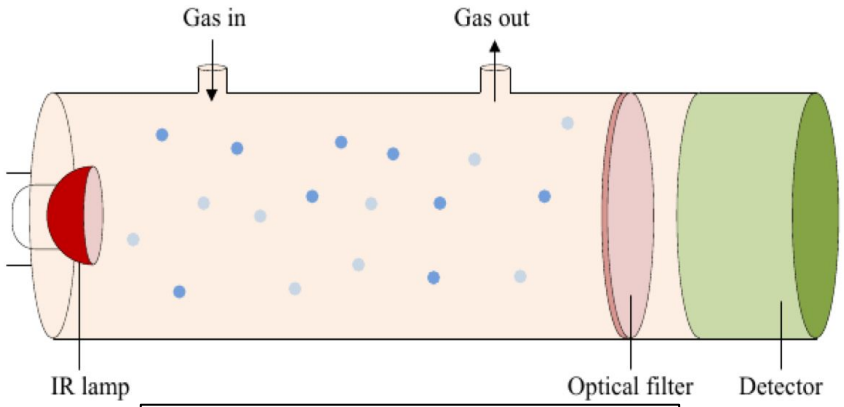
Contents

Background

Low-cost CO_2 sensors have insufficient accuracy

- Sensitive to aging
- Sensitive to environmental factors (e.g. temperature and pressure)



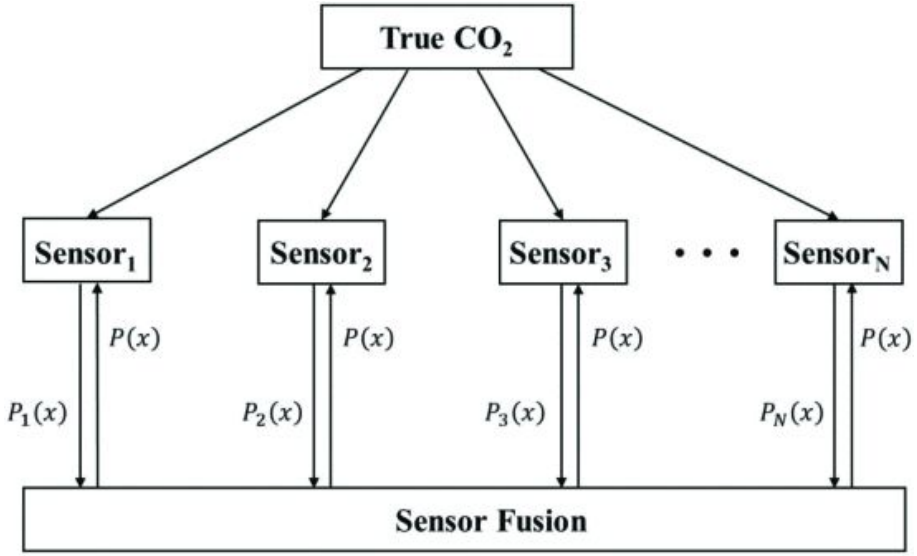
NDIR CO_2 sensor [1]

Previous work

- HMM for sensor calibration [1]
- Investigation of sensor fusion algorithms [2]

This project

- Combine both methods
- Analyse performance and different spatial setups



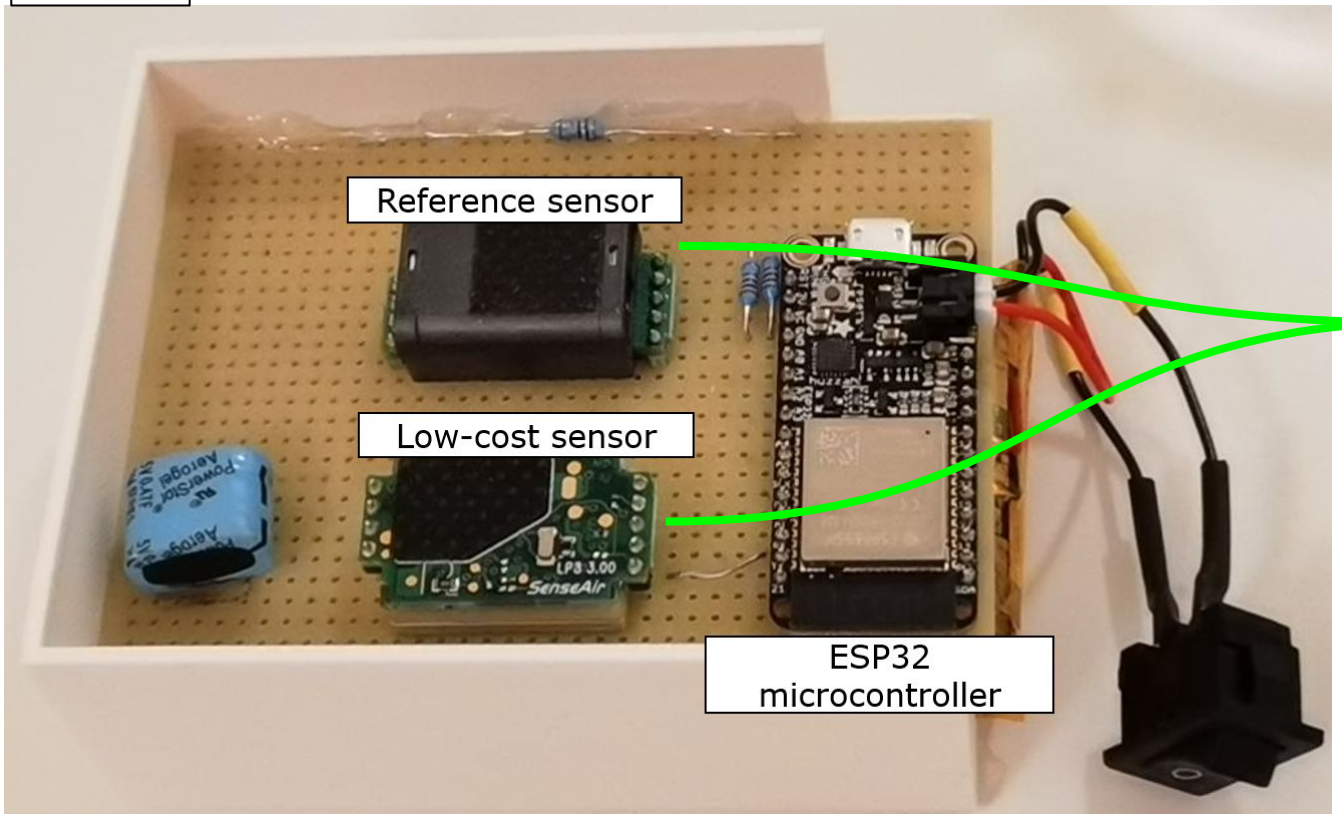
Sensor fusion [2]

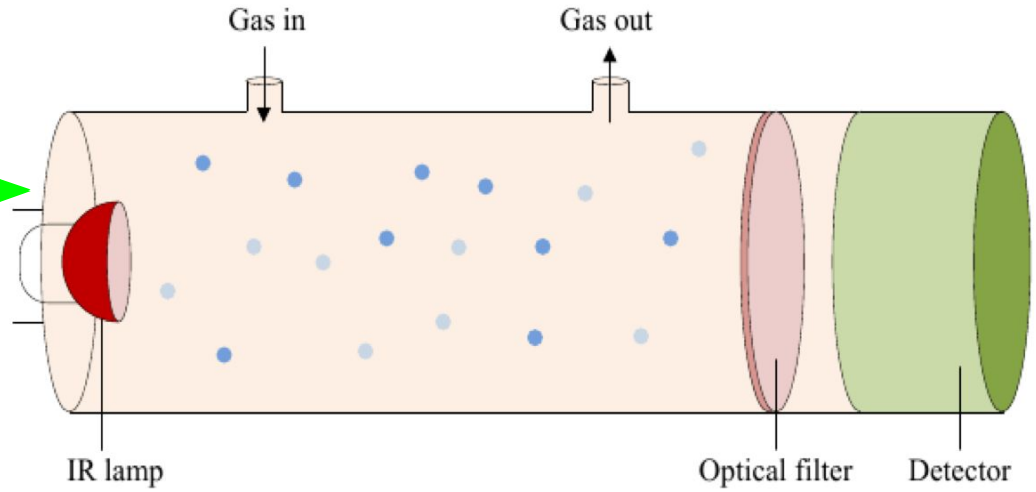
Project goals

- Collect data with NDIR CO_2 sensors
- Implement automatic calibration with supervised and unsupervised algorithms on each sensor
- Implement fusion algorithms at different spatial setting of sensors

Hardware

5x

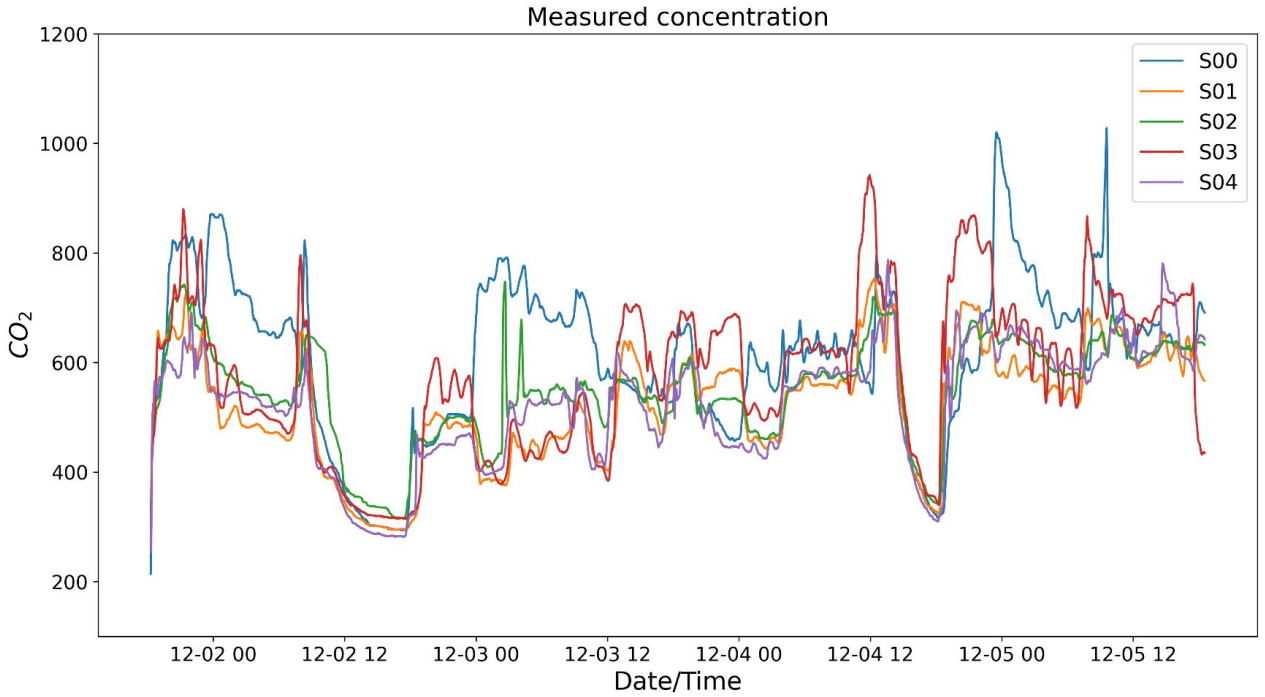




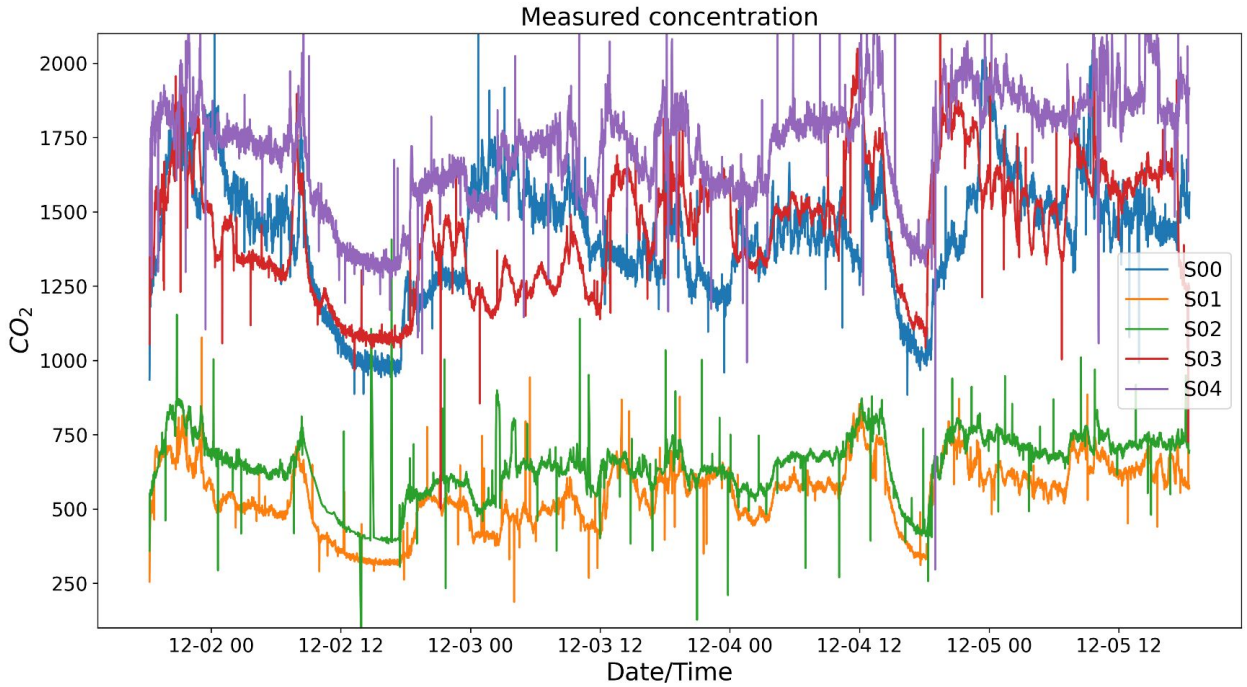
NDIR CO_2 sensor

Measurements

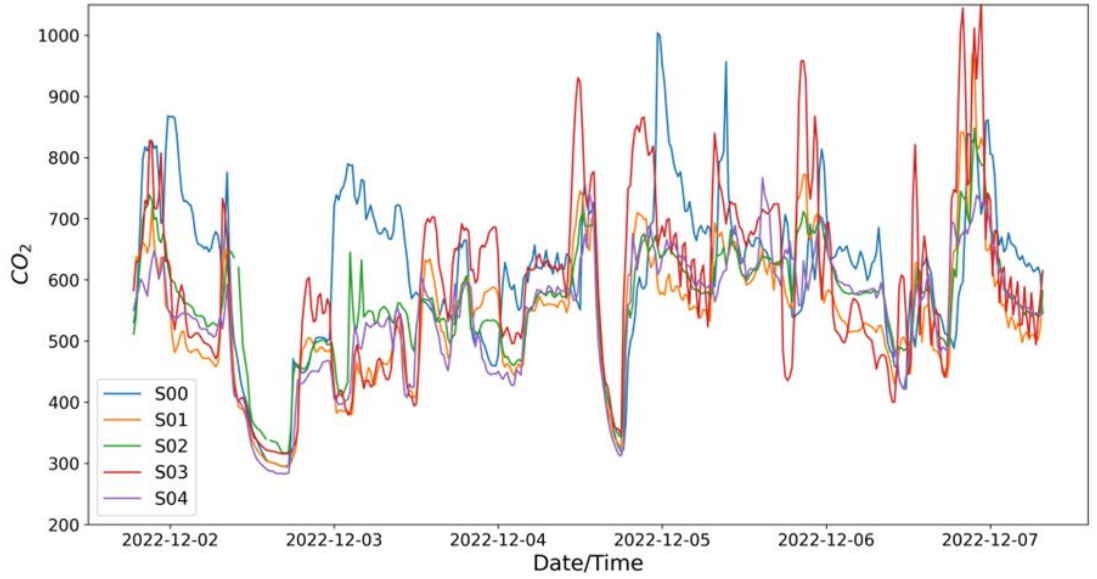
Reference sensors

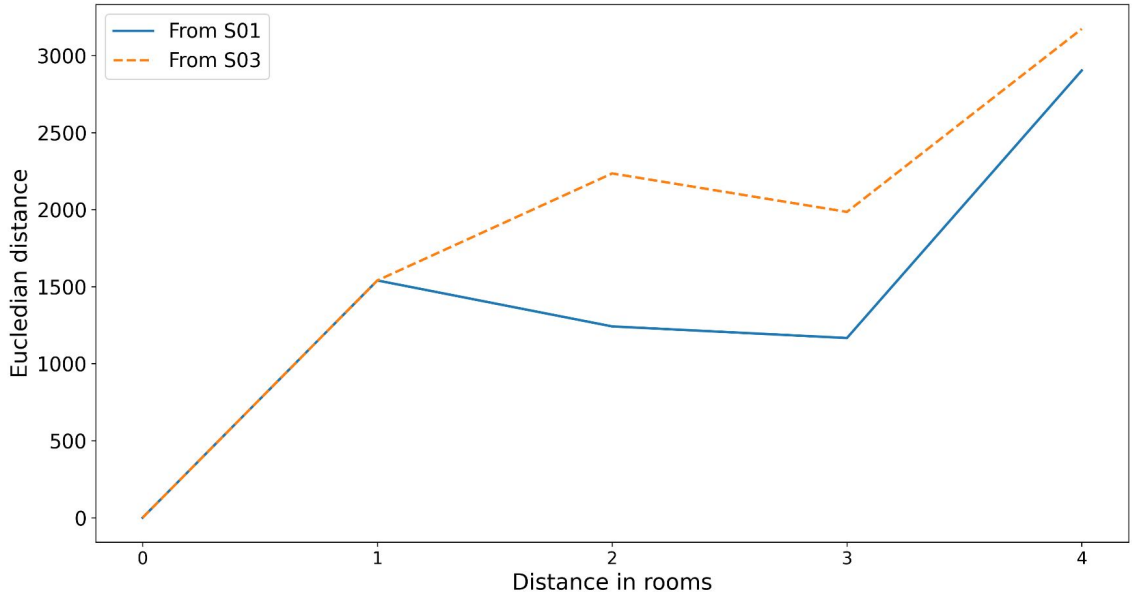


Low-cost sensors



Measurements

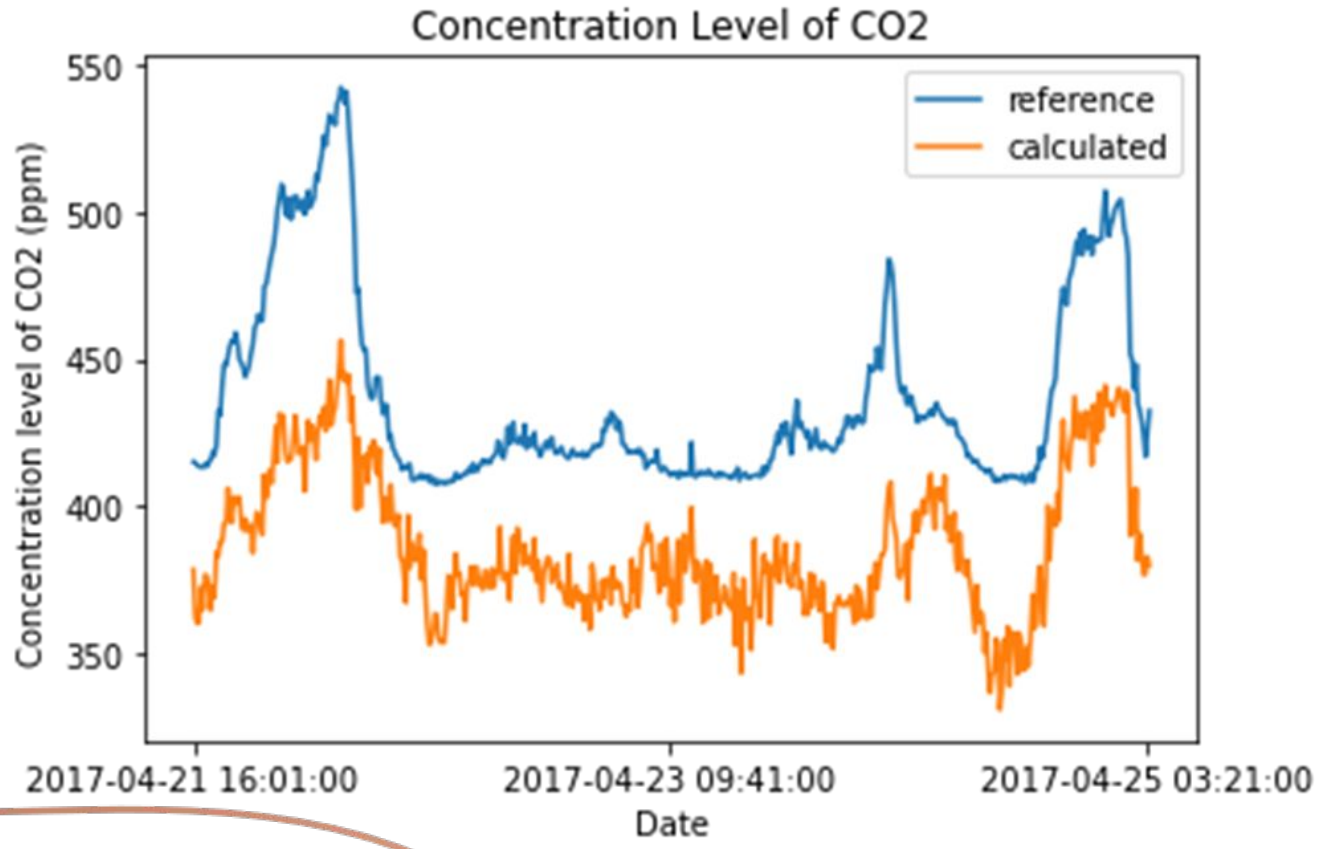




- Many factors that affect the CO_2 value
  - People
  - Distance
  - Airflow

Implementation of HMMs for auto-calibration

$$zero \xleftrightarrow{T, IR, etc.} transmittance \xleftrightarrow{Mapping} CO2$$



$zero$: zero coefficient

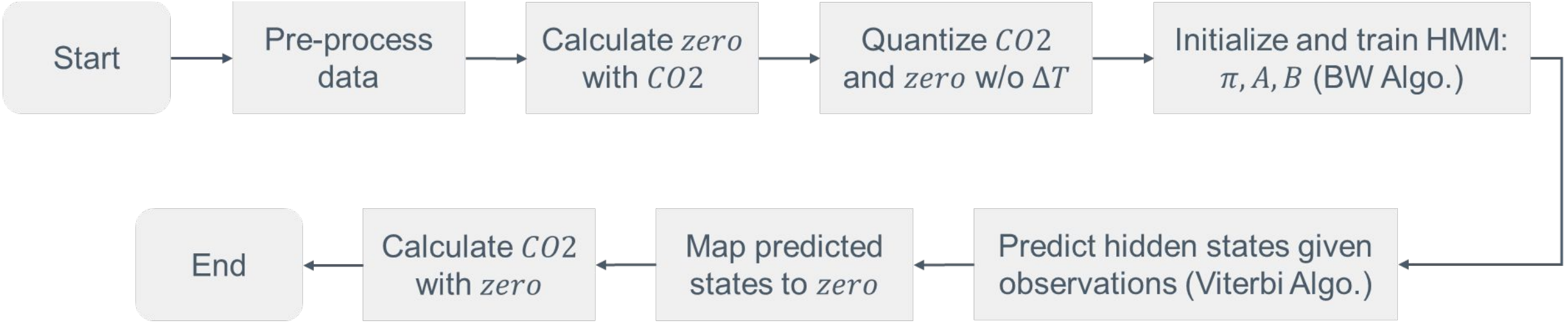
- calibration parameter compensating for drift

T: environmental temperature

IR: amount of IR light received by detector

$CO2$: $CO2$ concentration level

Process



Data:

- CO2 concentration level $CO2$, temperature T, time, etc.
- collected by 5 LP8 sensors and corresponding reference sensors in different setups

$zero$:

- reference $zero$

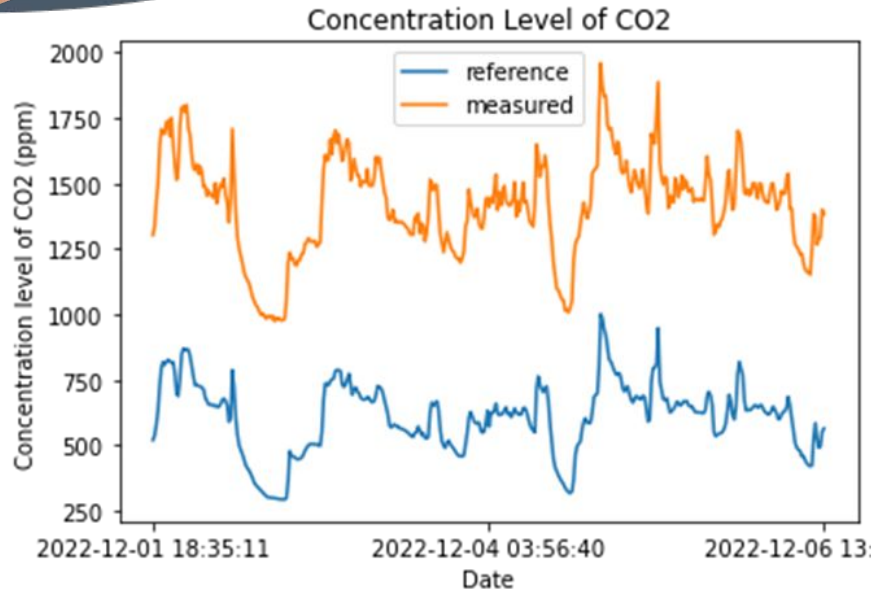
⇒ baseline $zero$

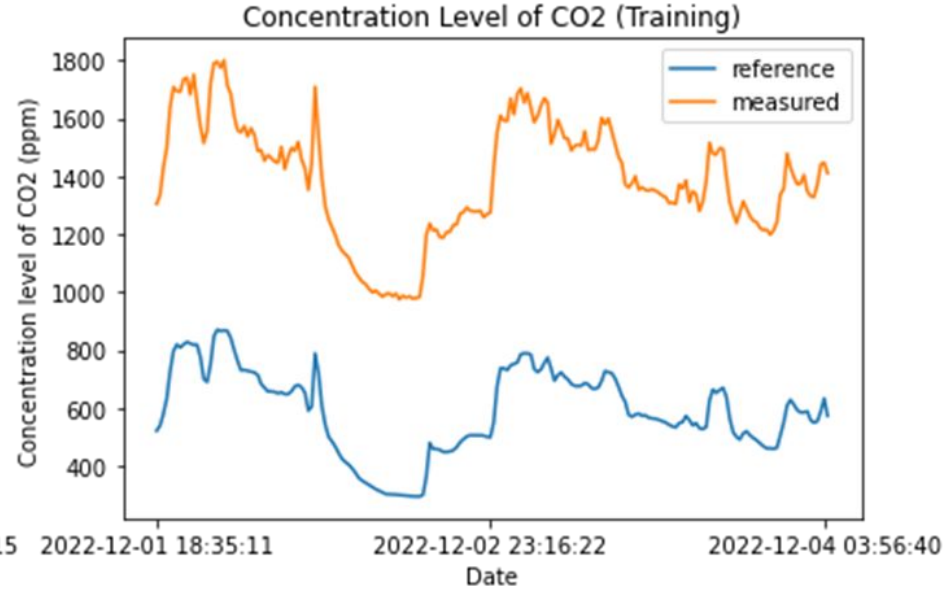
- measured $zero$

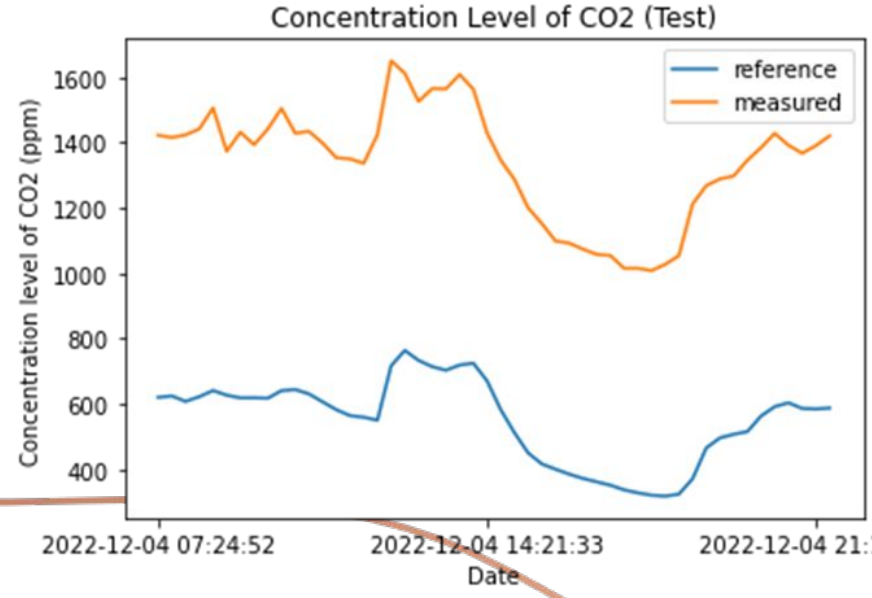
HMM:

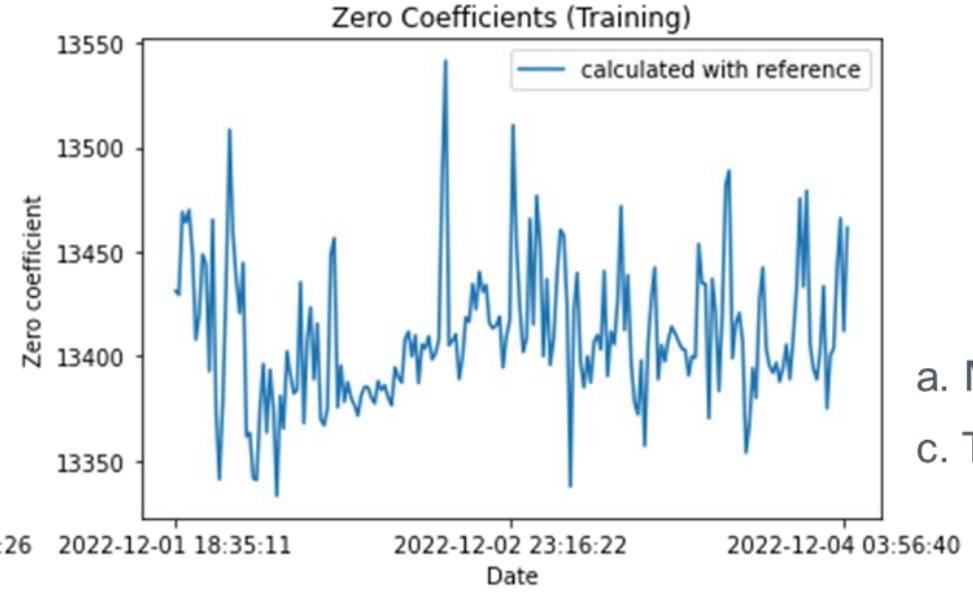
- Hidden states: quantized reference $zero$ or $(zero, \Delta T)$
- Observations: quantized measured $CO2$

Example









a. Measured $CO2$

b. Training $CO2$

c. Test $CO2$

d. Training $zeros$

Example: $(zero, \Delta T)$, supervised HMM

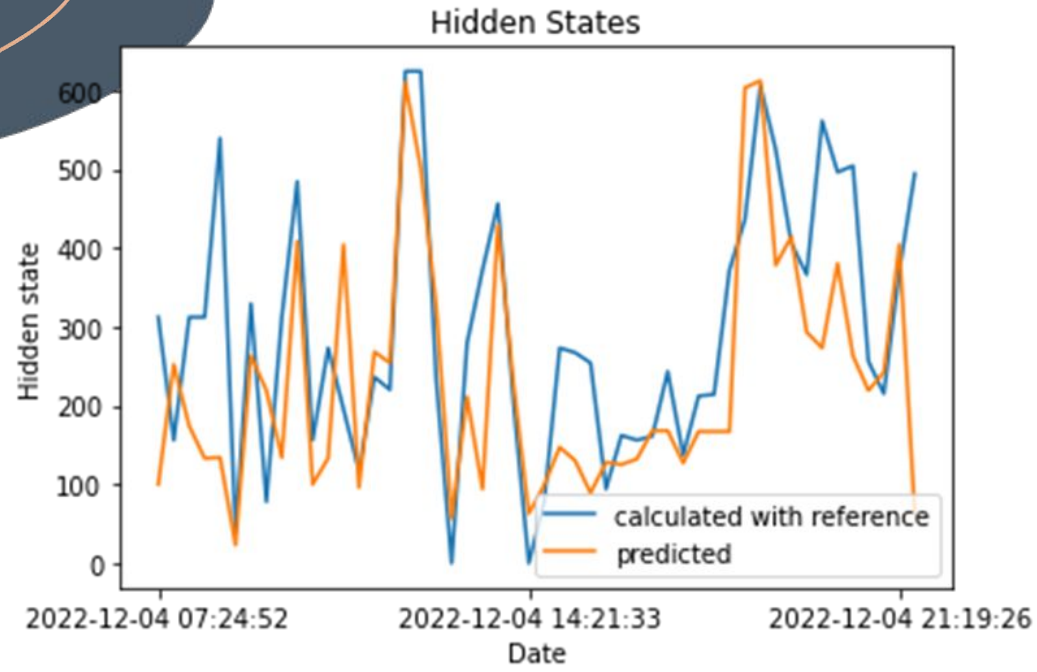
- Data pre-processing:

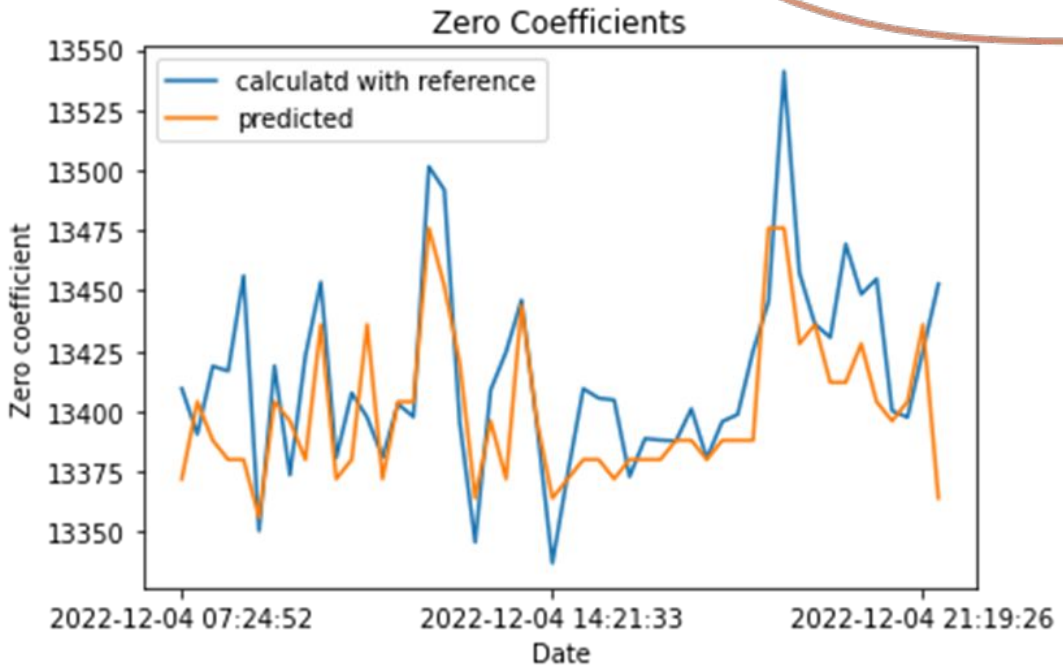
  Down sample and take average every 16 minutes

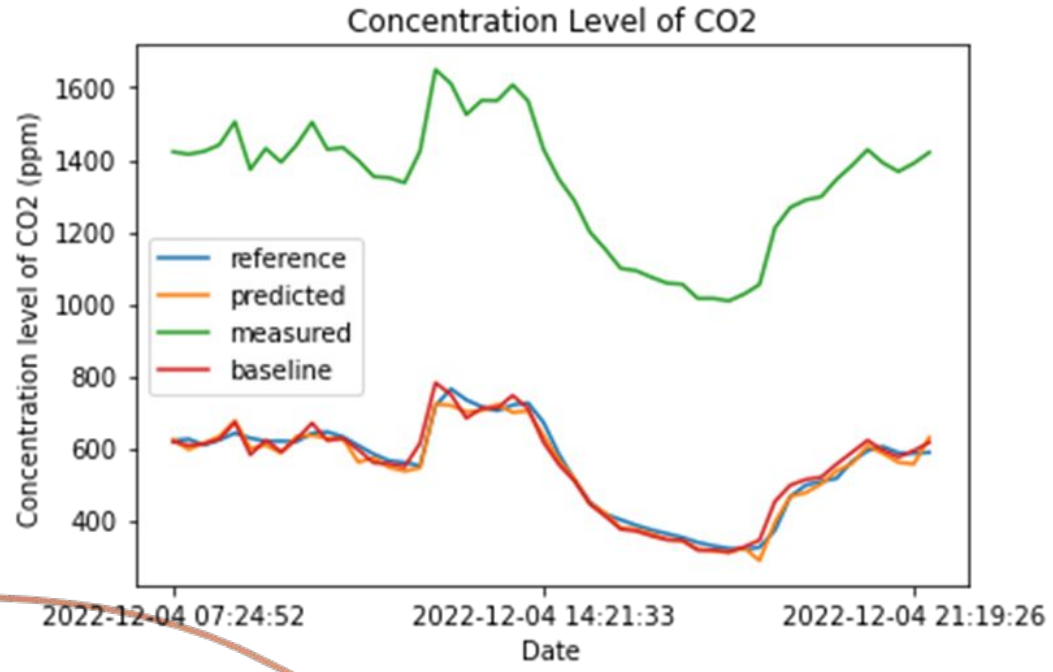
  Remove irrational data based on 3σ rule

- High-resolution quantization

	min	max	q_min	q_max	$stepsize$
$zero$	13333	13541	13360	13480	8
ΔT	-0.126	0.920	-0.0672	0.068	0.0035
$CO2$	975	1800	992	1770	22



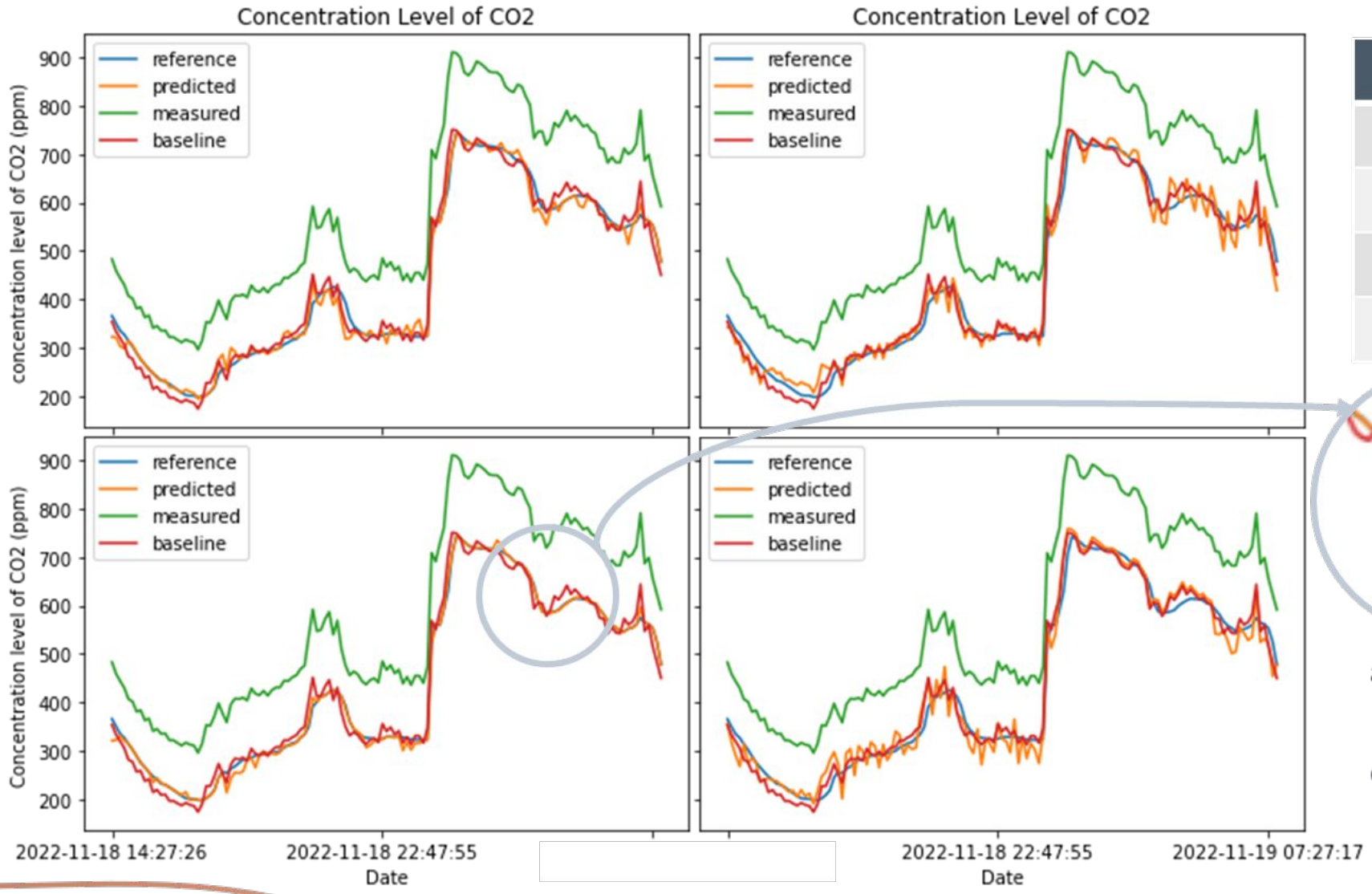




(ppm)

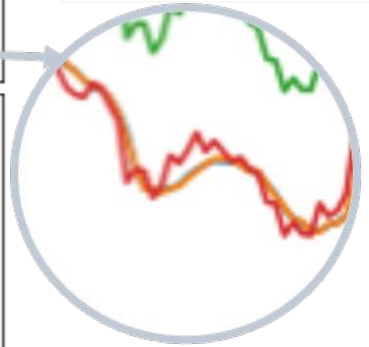
$RMSE(reference, \_)$	
Measured	789.620
Baseline	27.136
Predicted	21.211

HMMs



(ppm)

$RMSE(reference, \_)$	
17.574	26.974
9.238	27.093
Baseline: 21.556	
Measured: 137.818	



a) $zero$ supervised

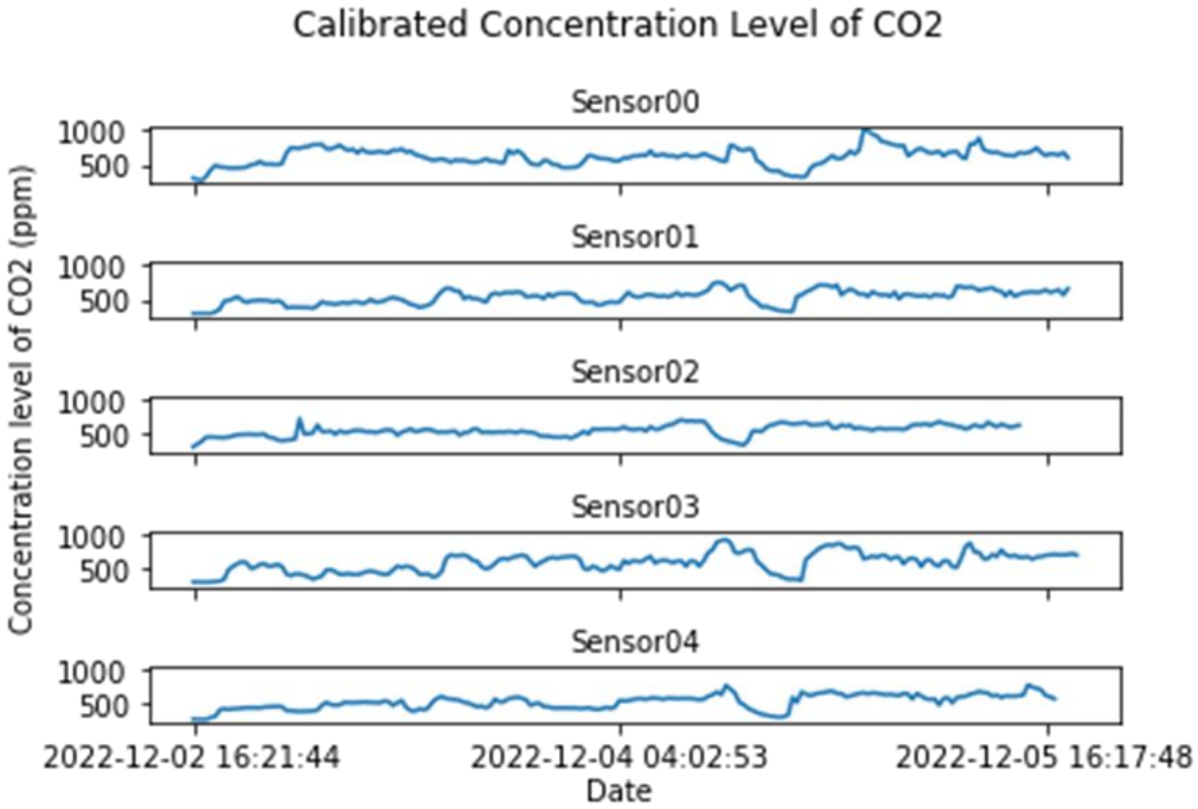
b) $zero$ unsupervised

c) $(zero, \Delta T)$ supervised

d) $(zero, \Delta T)$ unsupervised

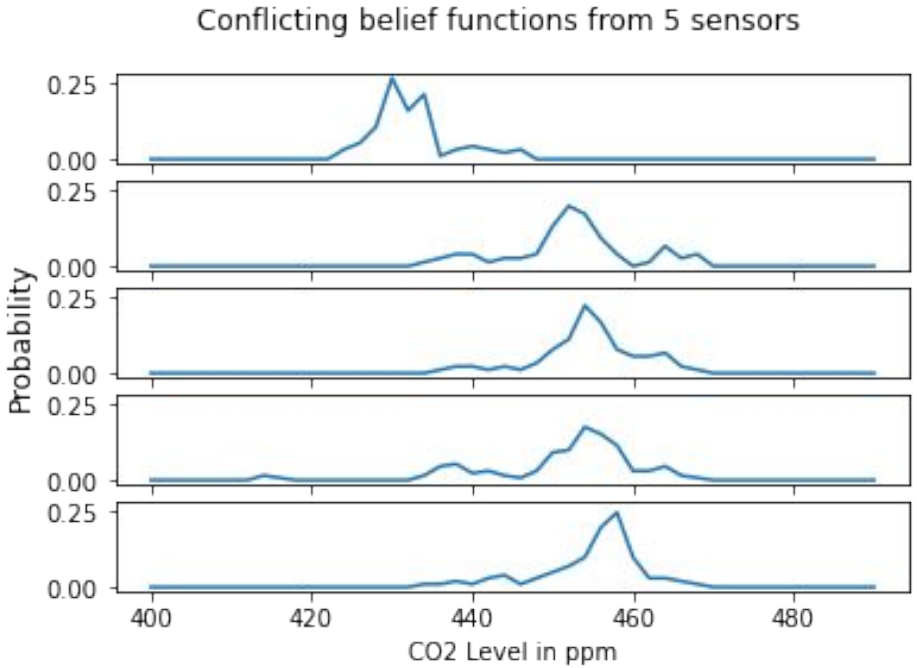
Sensor Fusion

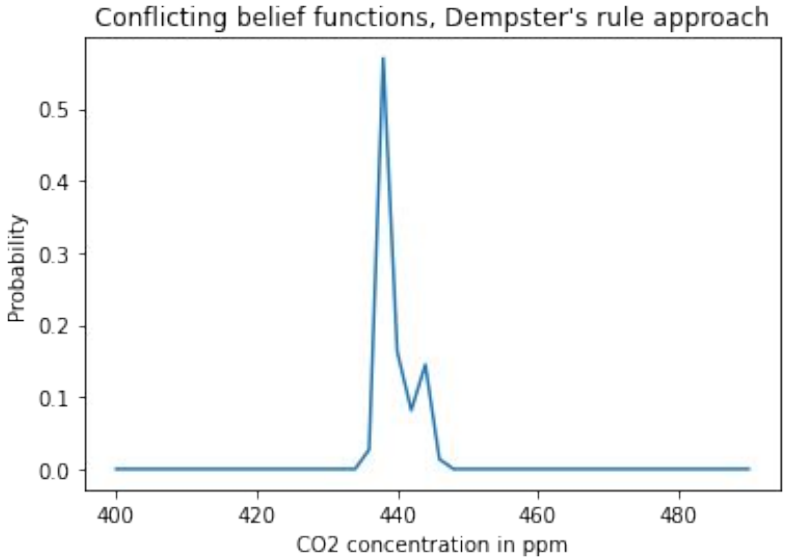
Setup: Place sensors in different rooms.

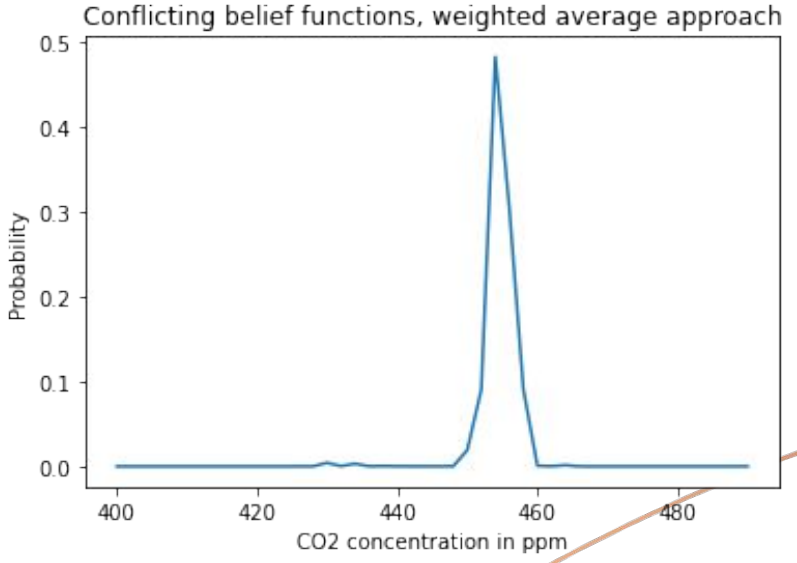


Calibrated concentration levels of $CO2$

Sensor Fusion





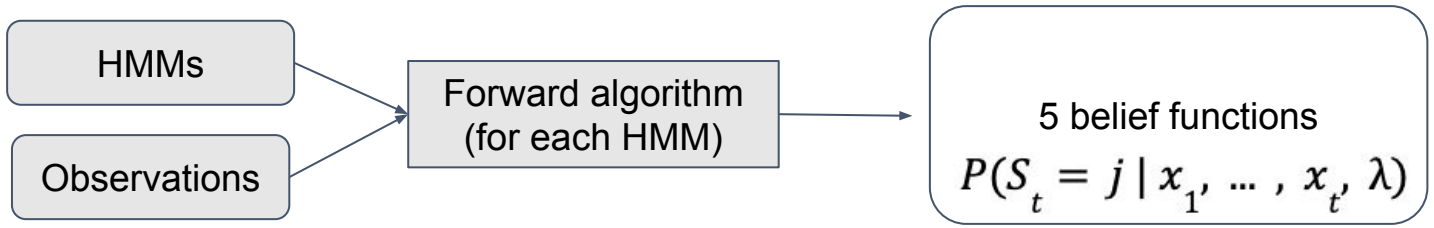


- Verified the Belief Function Fusion methods in [2] with constructed belief functions.
- Weighted average approach
  - More appropriate when we have conflicting belief functions.

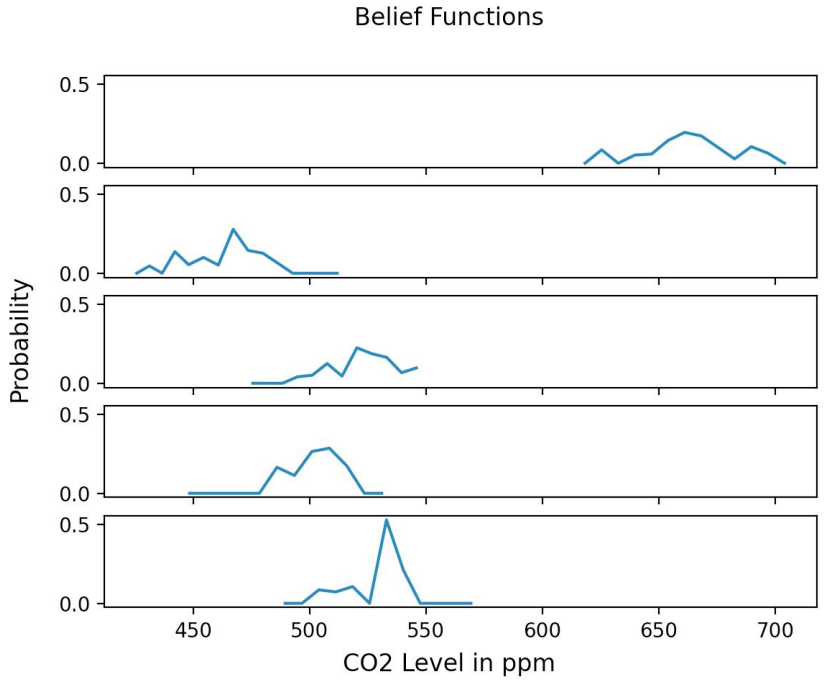
Sensor Fusion

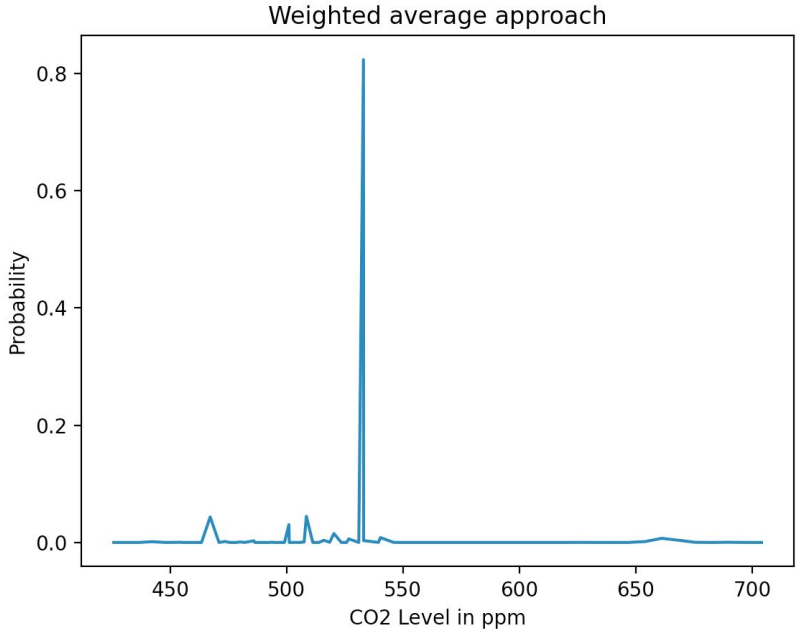
- Example belief functions from our collected data and models.
  - Conflicting

- Belief functions determined through the forward algorithm.



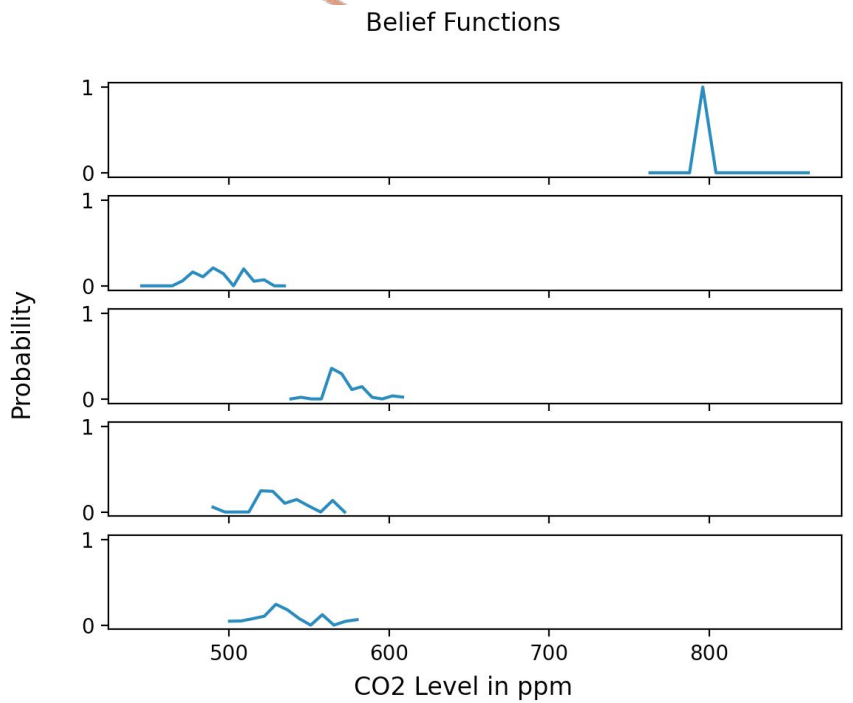
- Example: Conflicting belief is attenuated.
  - Fusion results: 533.00
  - mean of references: 533.84 ppm

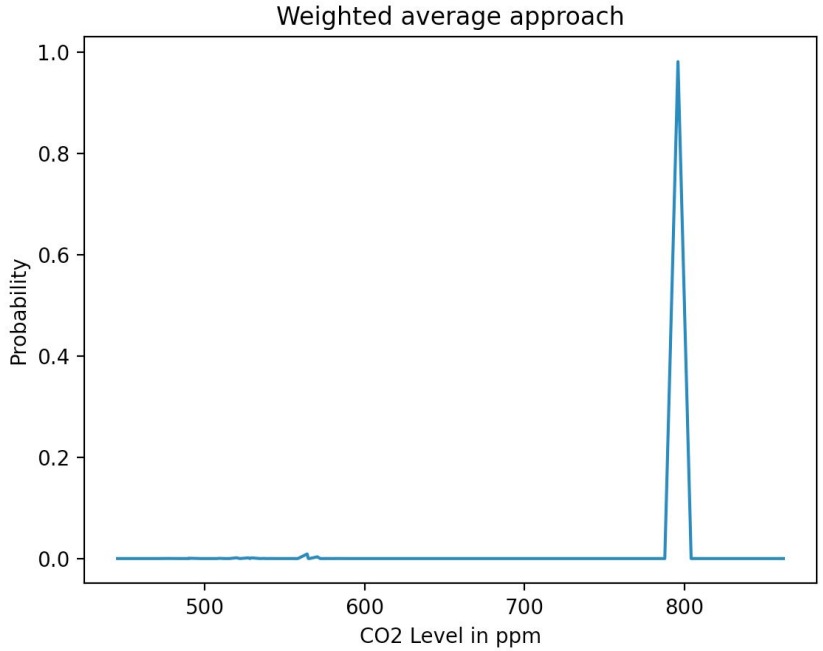




Sensor Fusion

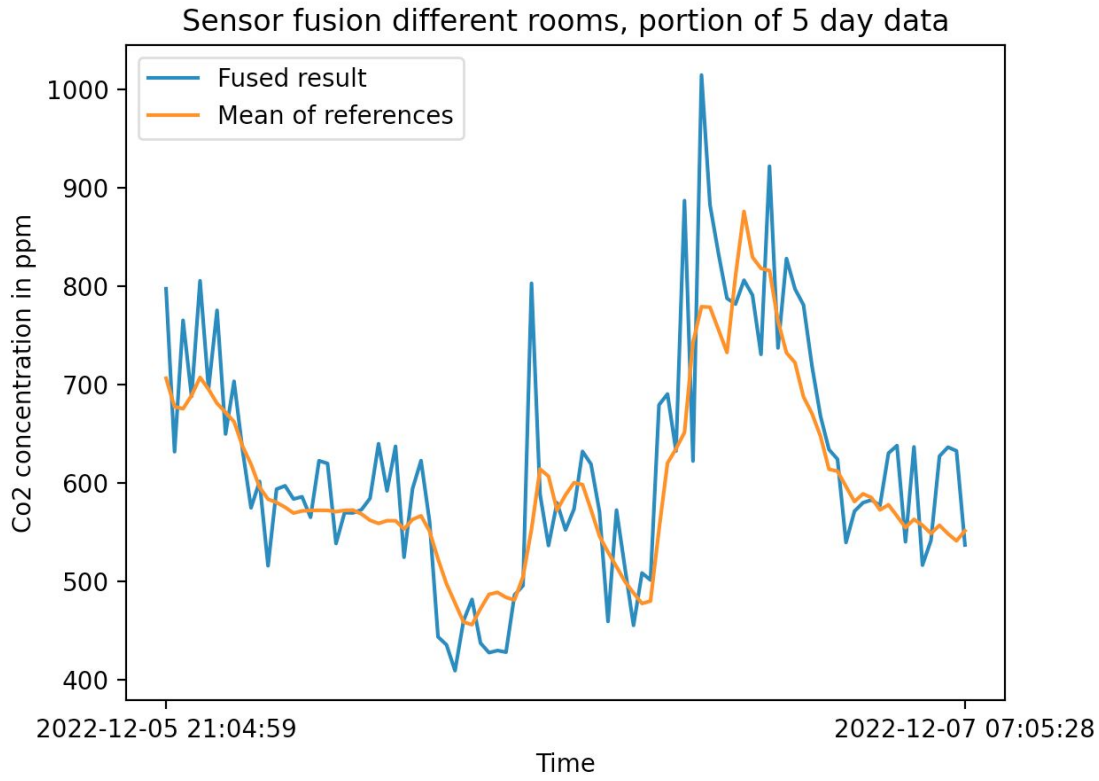
- Example of when the conflicting belief is chosen.
  - Higher probability seem to outweigh the large distance.
- Fusion results: 795.92ppm.
- Mean of references: 597.25ppm.

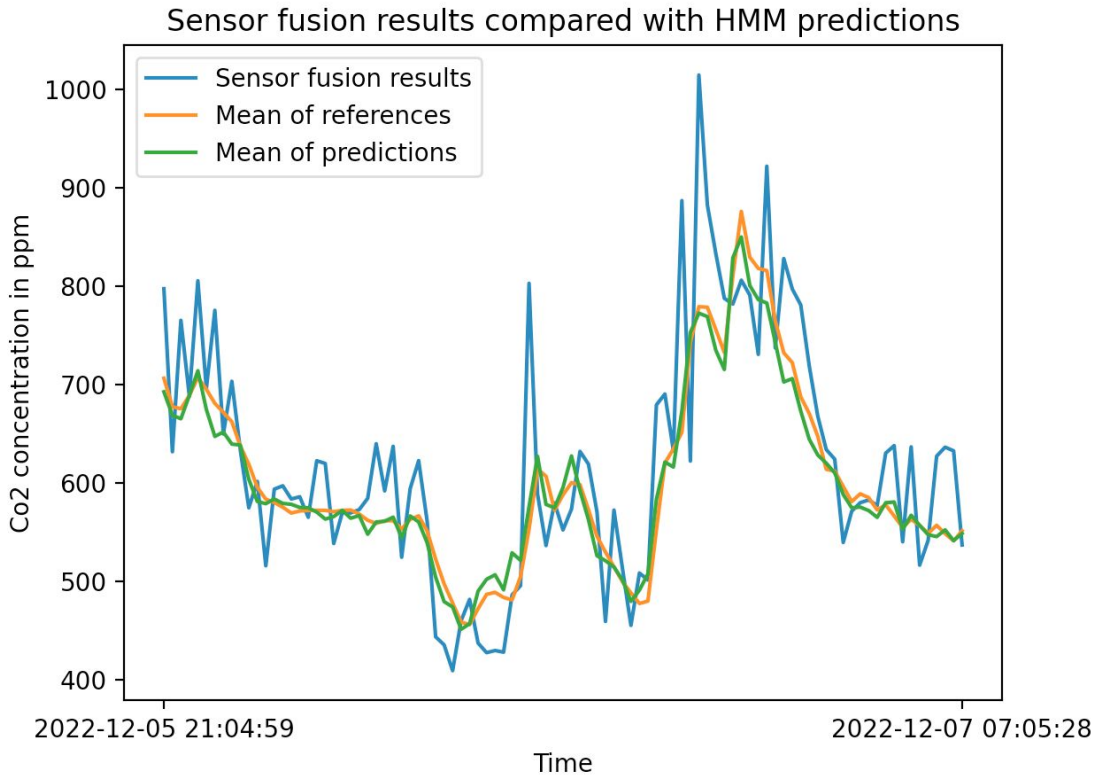


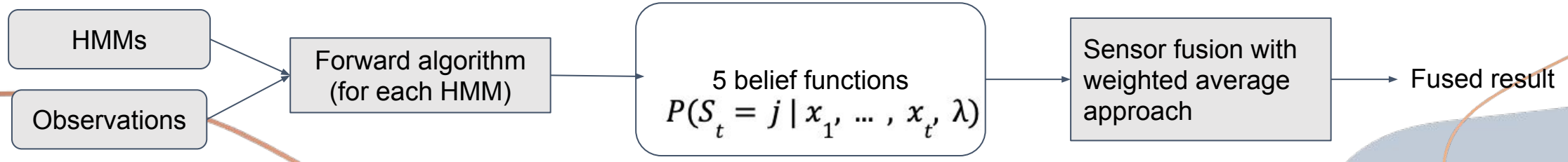


Sensor Fusion - Demonstration

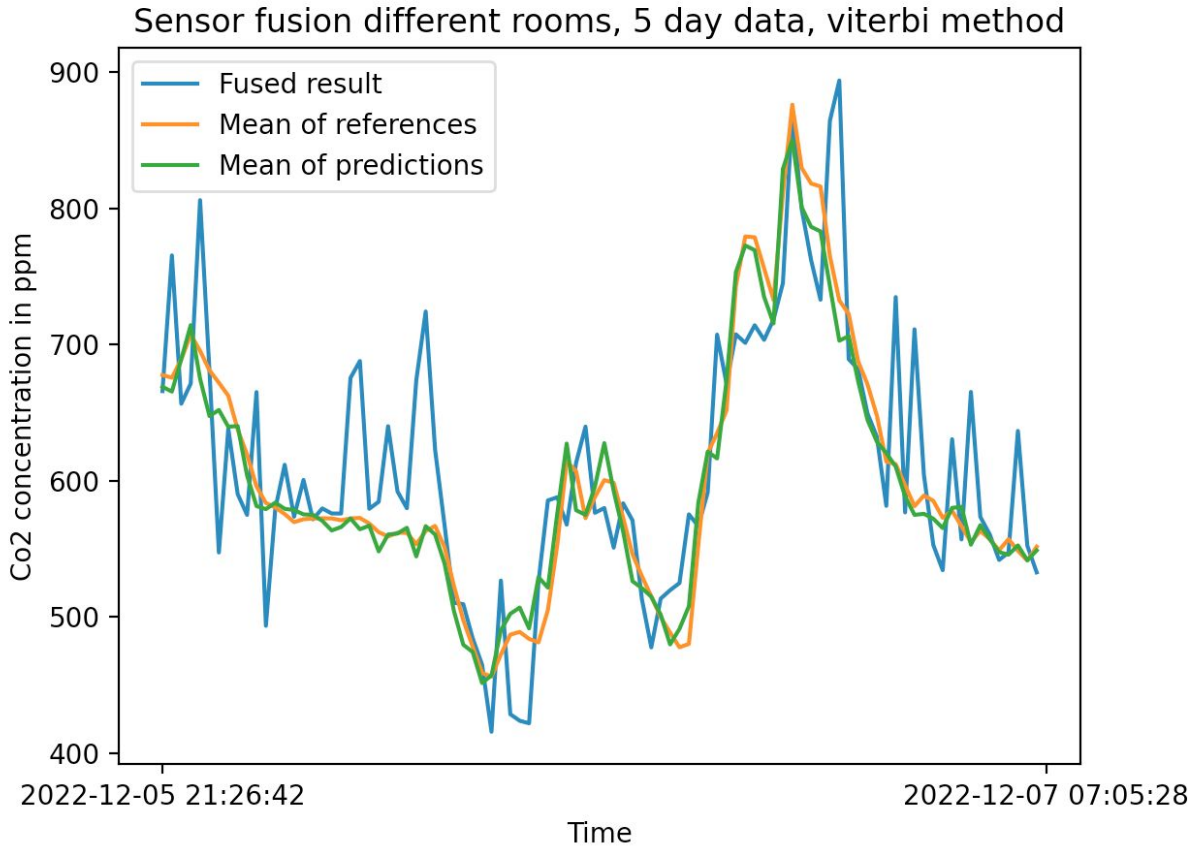
Results of sensor fusion every 20th minute given past observations







Sensor Fusion - Extra Demonstration



HMMs

Observations

Viterbi algorithm (for each HMM)

Most probable state sequence (for each HMM)

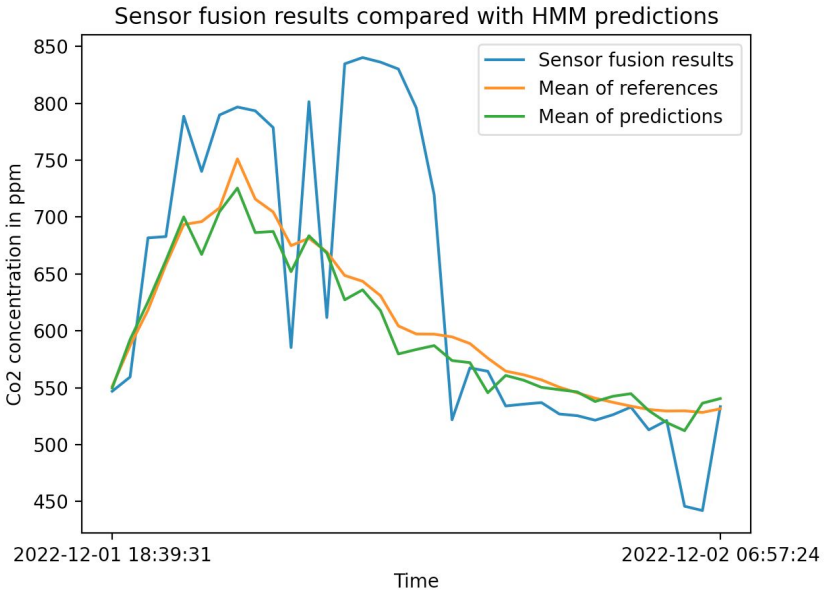
Belief functions based on state transition probability

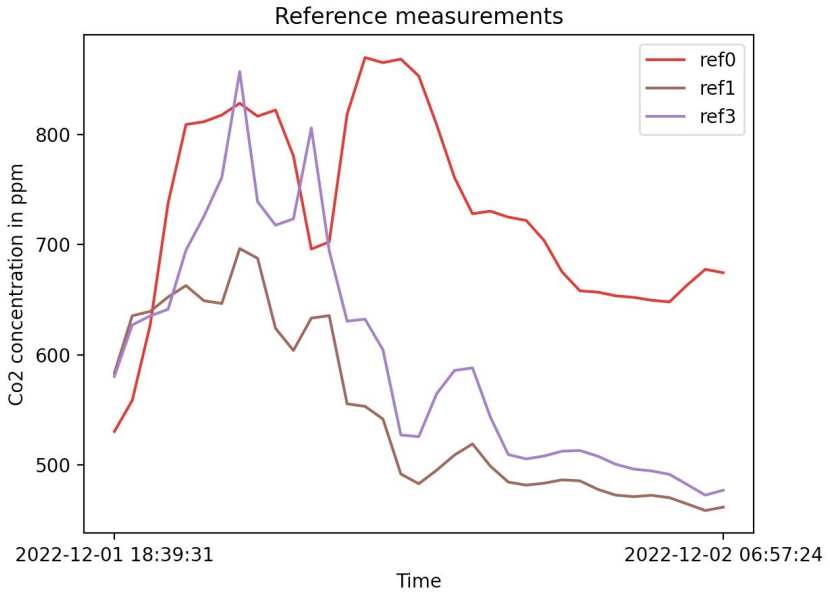
$$P(S_{t+1} = j \mid S_t = i)$$

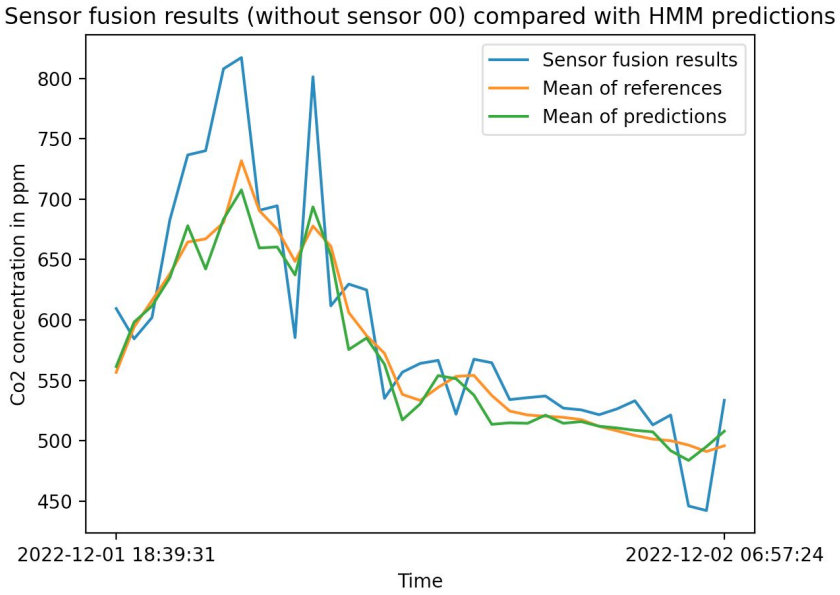
Sensor fusion with weighted average approach

Fused result

Sensor Fusion

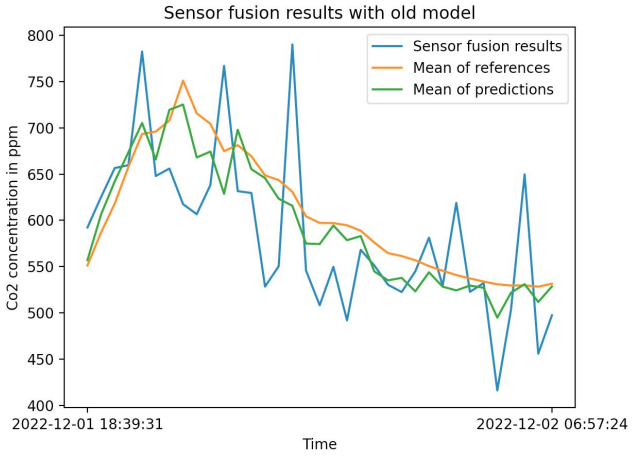






Discussion of results

- Very conflicting belief functions
  - The references
- Highly dependent on model



Conclusions

- Successfully demonstrate the networked gas sensor data-driven calibration methods proposed in [1] and [2] by Yang and Tobias.

- The success of the “Data collection-> HMM -> Sensor Fusion -> Calibrated Data” flow is sensitive to the non-fixed & human-involved aspects within the process.

Reflections

- The current assumption for the data, coming from the HMM, is too strict to use it in every situation.
- Outdoor data collection could have provided better training data due to regular temperature variations.
- The HMM needs a better initialization mechanism.（e.g. meta-learning）
- Processing the data is important and time consuming (synchronization)

Reflections

Lesson learned:

- Have consistent meetings (with and without project owner).
- Pay attention to the time plan throughout the entire project.
- Do a thorough risk analysis and plan for changes.
- Difference between theory and real-world application.

Merry Christmas ! @~@

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References

[1] You, Yang, and Tobias J. Oechtering. "Hidden markov model based data-driven calibration of non-dispersive infrared gas sensor." *2020 28th European Signal Processing Conference (EUSIPCO)*. IEEE, 2021.

[2] You, Yang, Anran Xu, and Tobias J. Oechtering. "Belief function fusion based self-calibration for non-dispersive infrared gas sensor." *2020 IEEE SENSORS*. IEEE, 2020.