

Development and calibration of an Air Quality Monitoring (AQM) appliance based on low-cost electrochemical and laser sensors

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(FORTH/ICE-HT)

Air Quality measurement devices

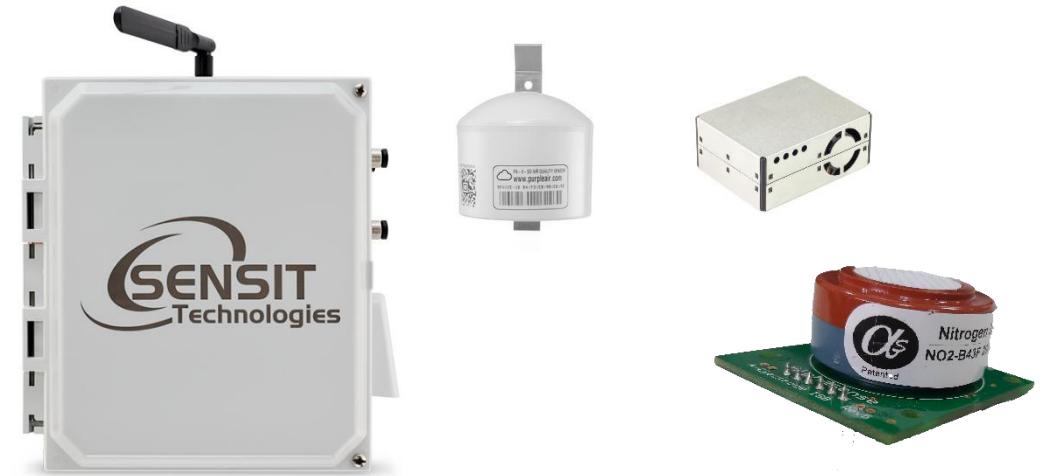
Regulatory Instrumentation

10k to 200k euros



Low-cost sensors

60 to 100 euros



Electrochemical sensors

CO, NO, NO₂, O₃

Laser sensors

PM_{2.5}

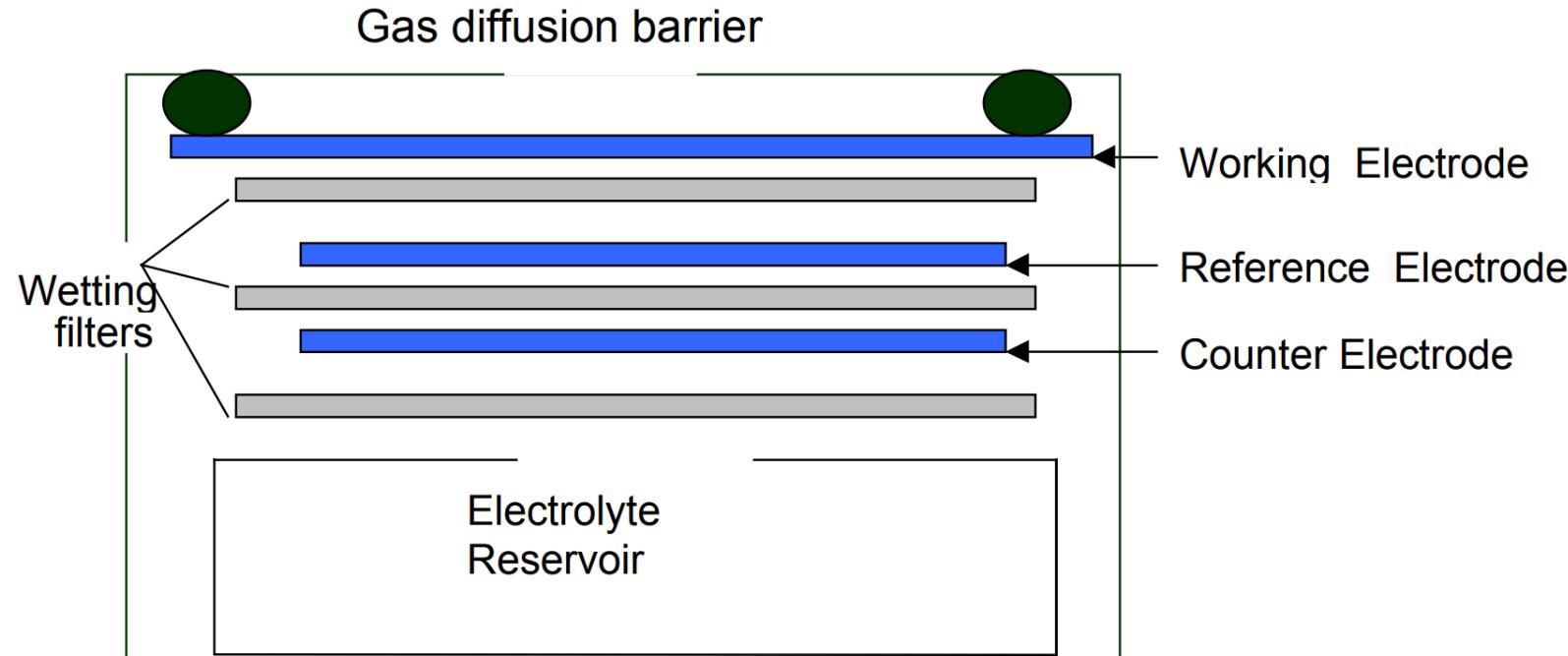
NDIR sensors

CO₂

MOx sensors

CO, Total VOC

Fundamental principles of electrochemical sensors



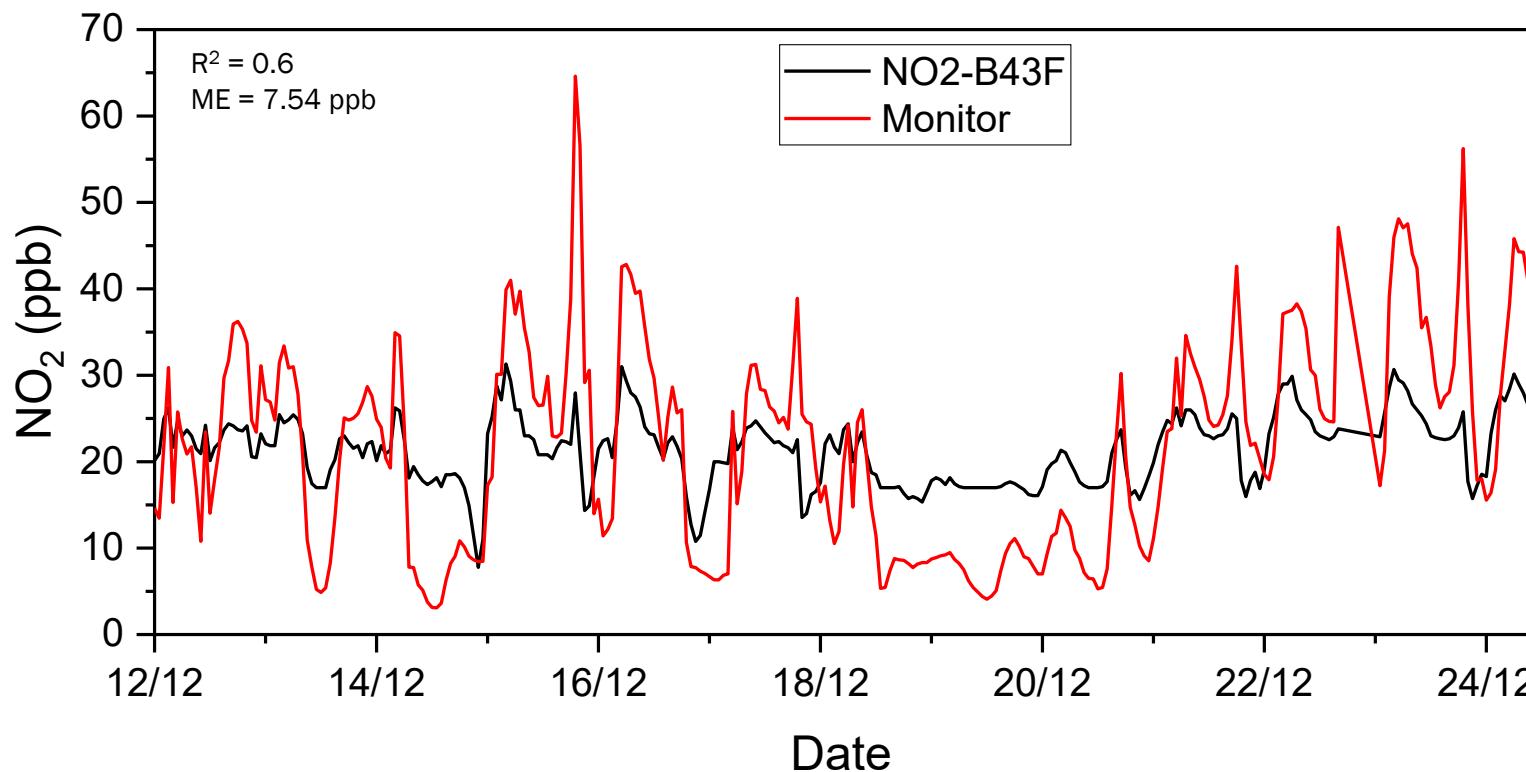
<https://docs.smartcitizen.me/Components/sensors/air/Electrochemical%20Sensors/>

- » Contamination
- » Temperature
- » Humidity
- » Sensor aging
- » Cross-sensitivity
- » Calibration

Low-cost sensor estimation errors

Estimation errors

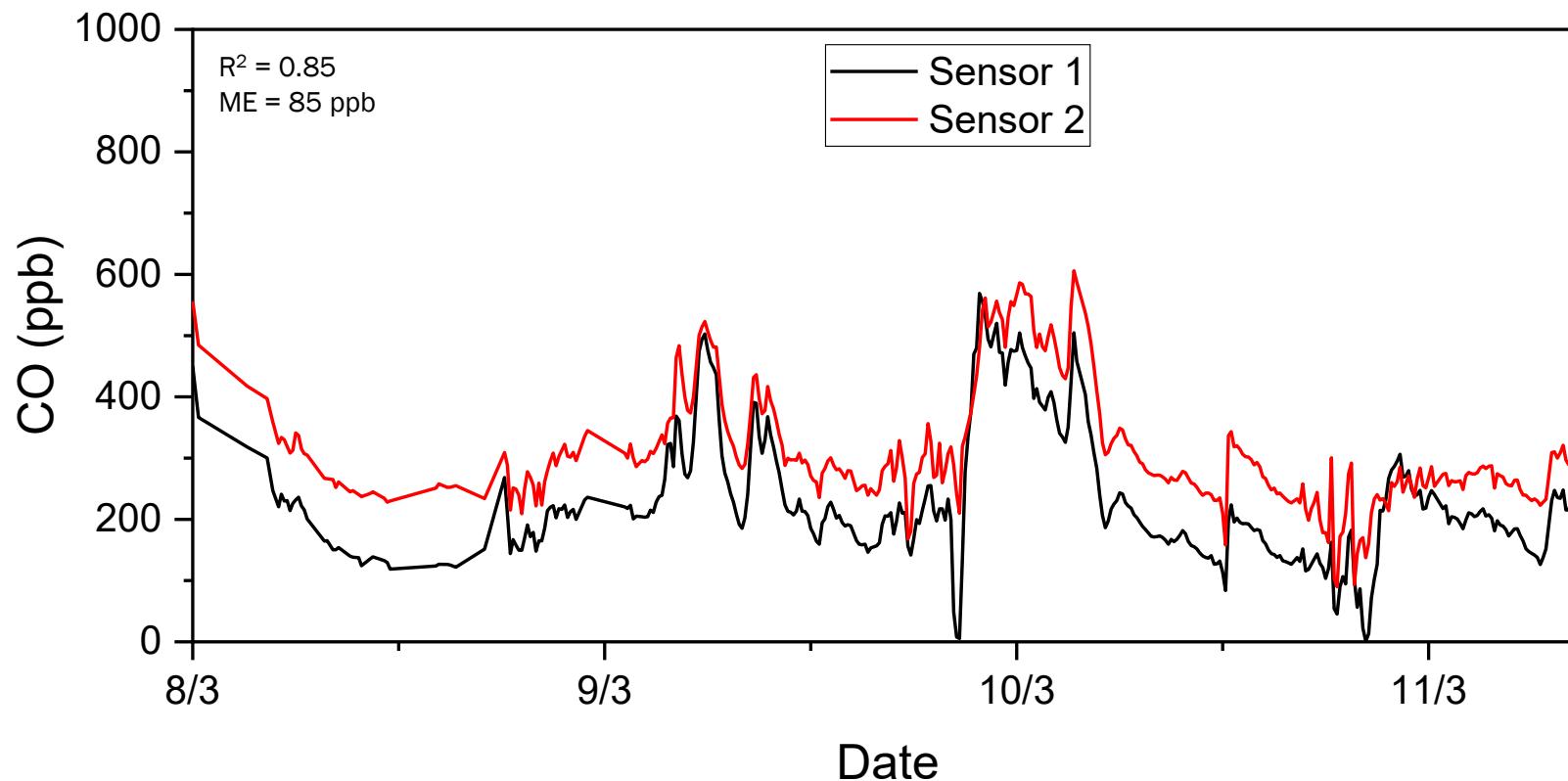
National Observatory of Athens (Ambient)
2022-12-13 to 2022-12-26
Low-cost sensor: NO2-B43F



Low-cost sensor inter-unit consistency

Discrepancy between the same sensors

Kastritsi (Ambient)
2023-03-08 to 2023-03-12
Low-cost sensors: CO-B4



Why low-cost sensors?

- Low-cost
- Multi-sensor networks (e.g. school classes)
- Though not ideal for accurate measurements, they can give us an estimation of the general conditions
- Are easily adjusted and calibrated to provide better estimations

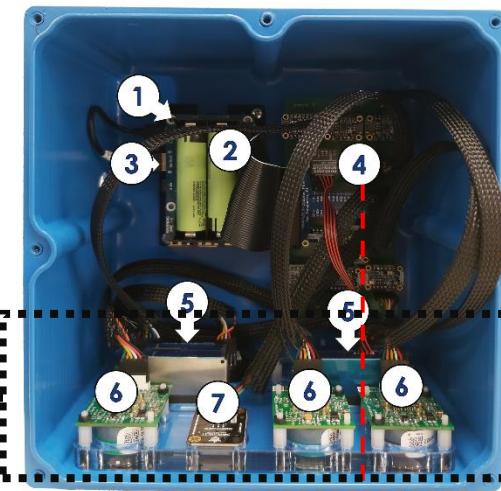
ENSENSIA sensors



EC sensors
NO2-B43F
NO-B4
CO-B4
OX-B431
SO2-B4
VOC-B4

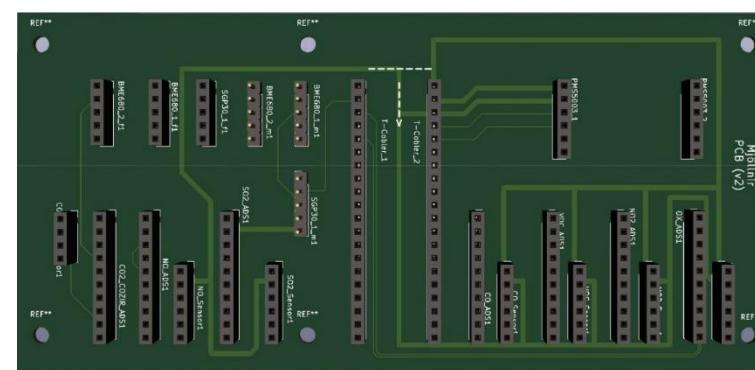


Laser sensor PMS5003

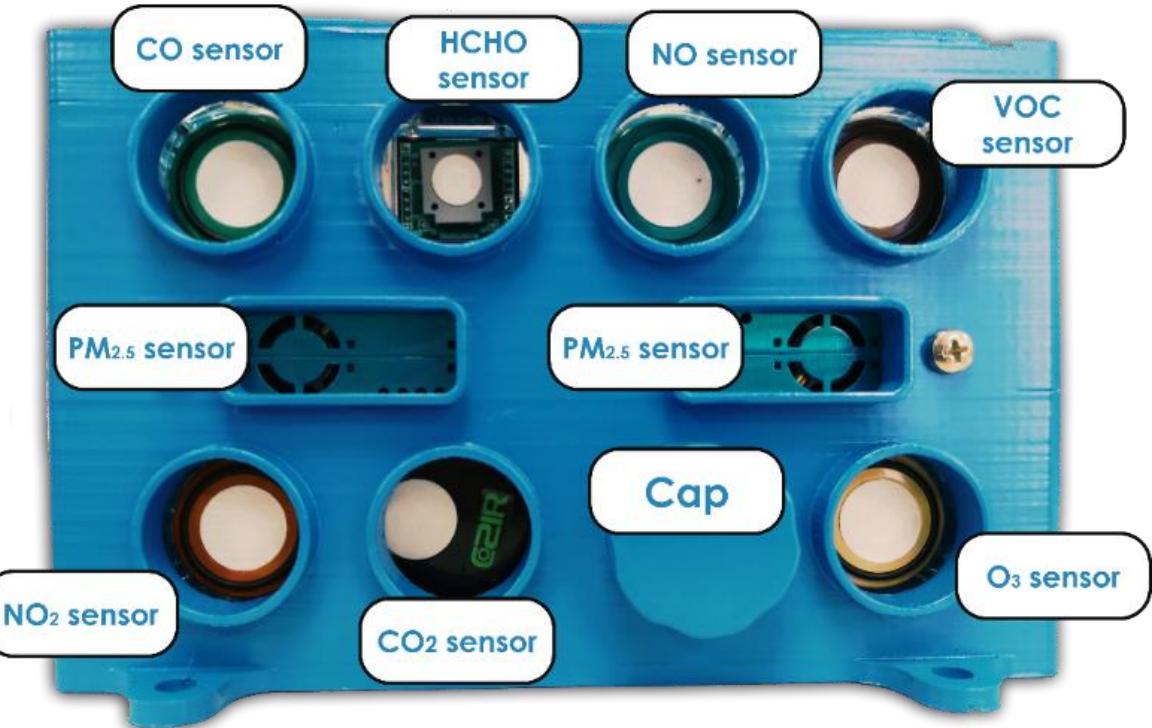
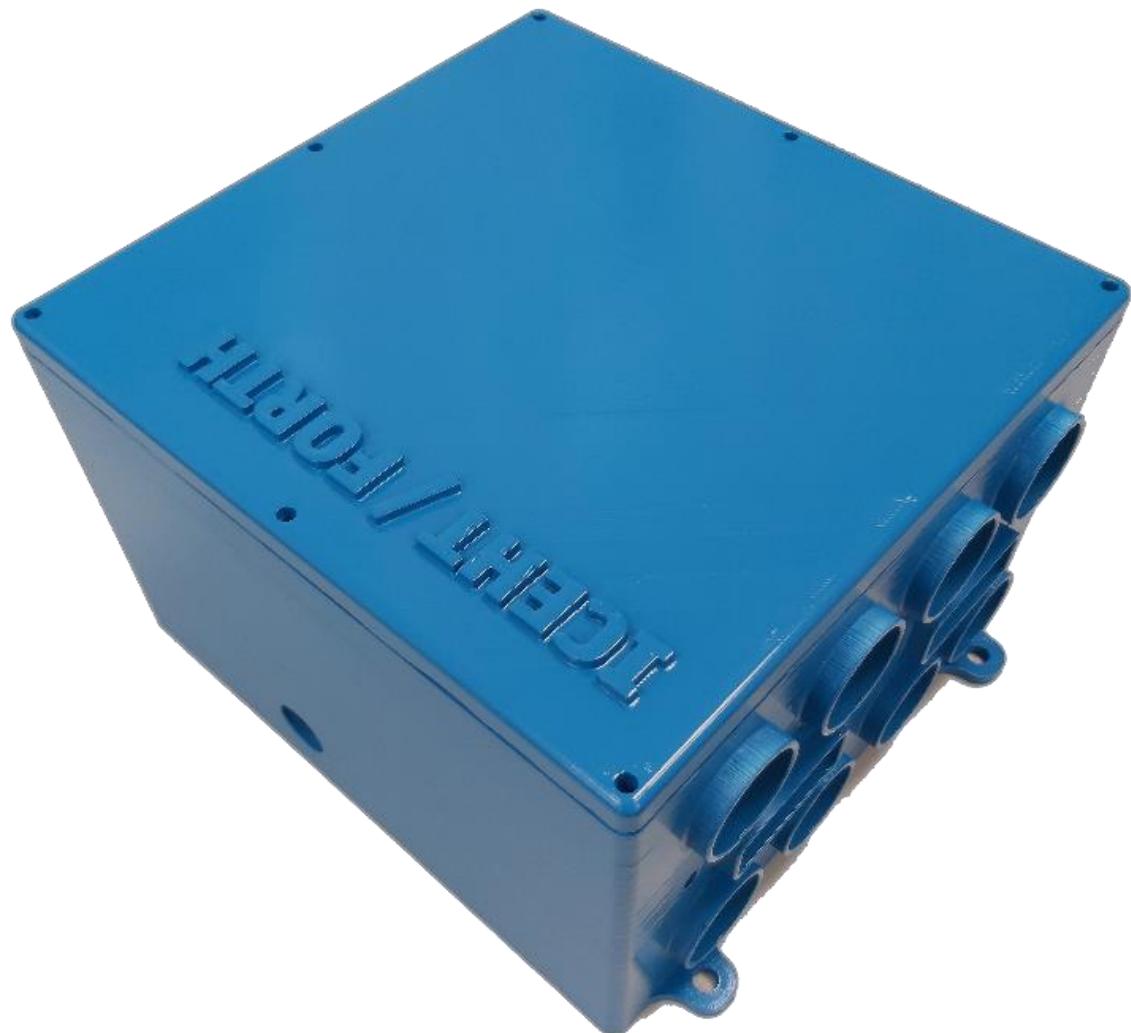


..Front Side

1. Beneath the UPS HAT is the Raspberry PI Model 4B
2. UPS HAT
3. Power supply (8.4V 2A)
4. Printed Circuit Board
5. PMS sensor
6. Analog (Electrochemical) sensor
7. Digital (Electrochemical) sensor



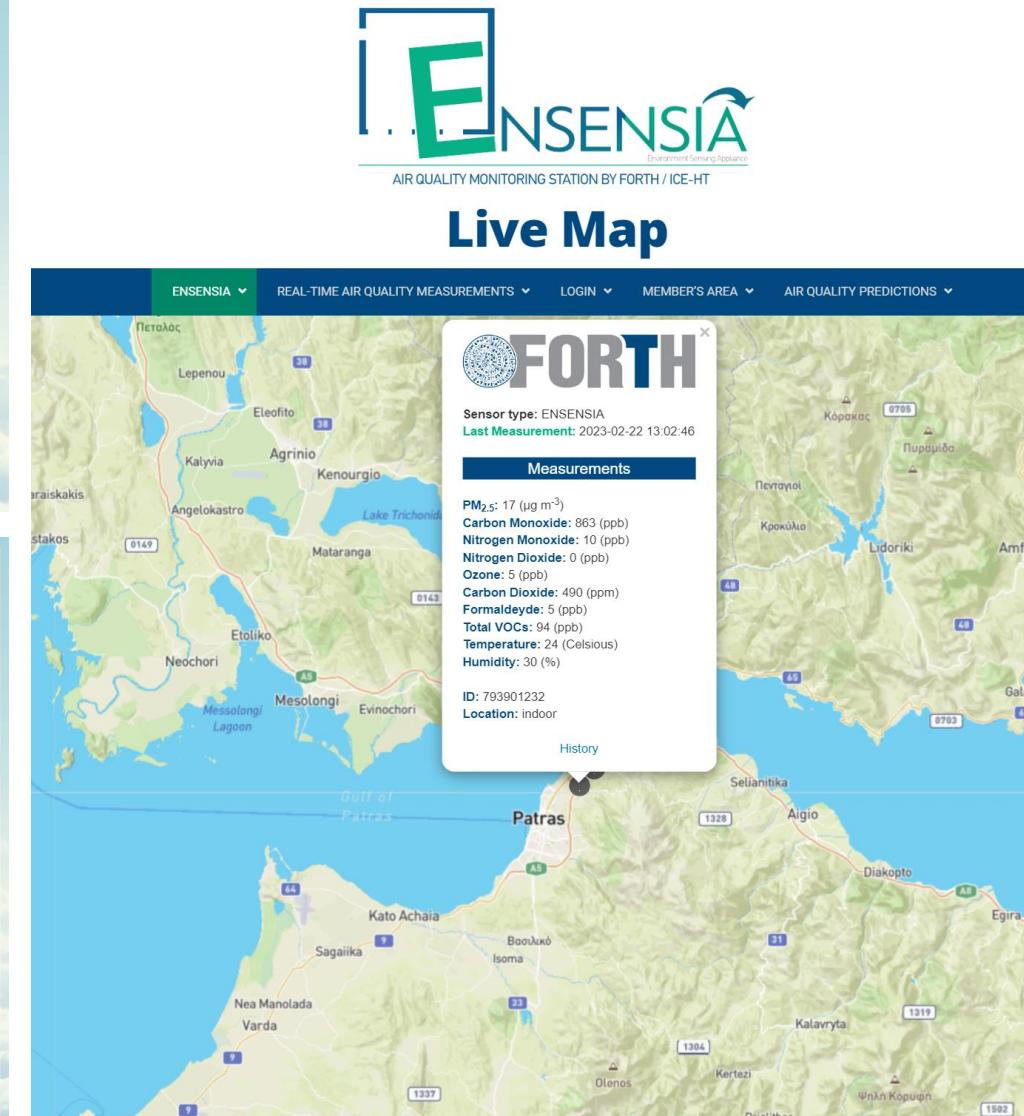
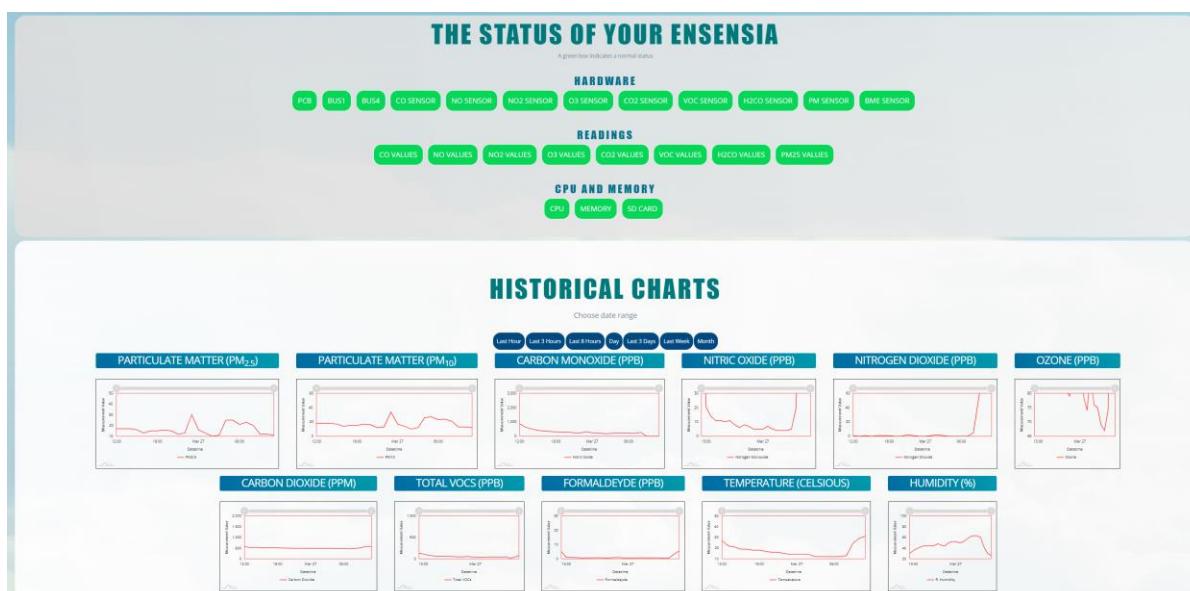
ENSENSIA packaging



Visualization web-based platform

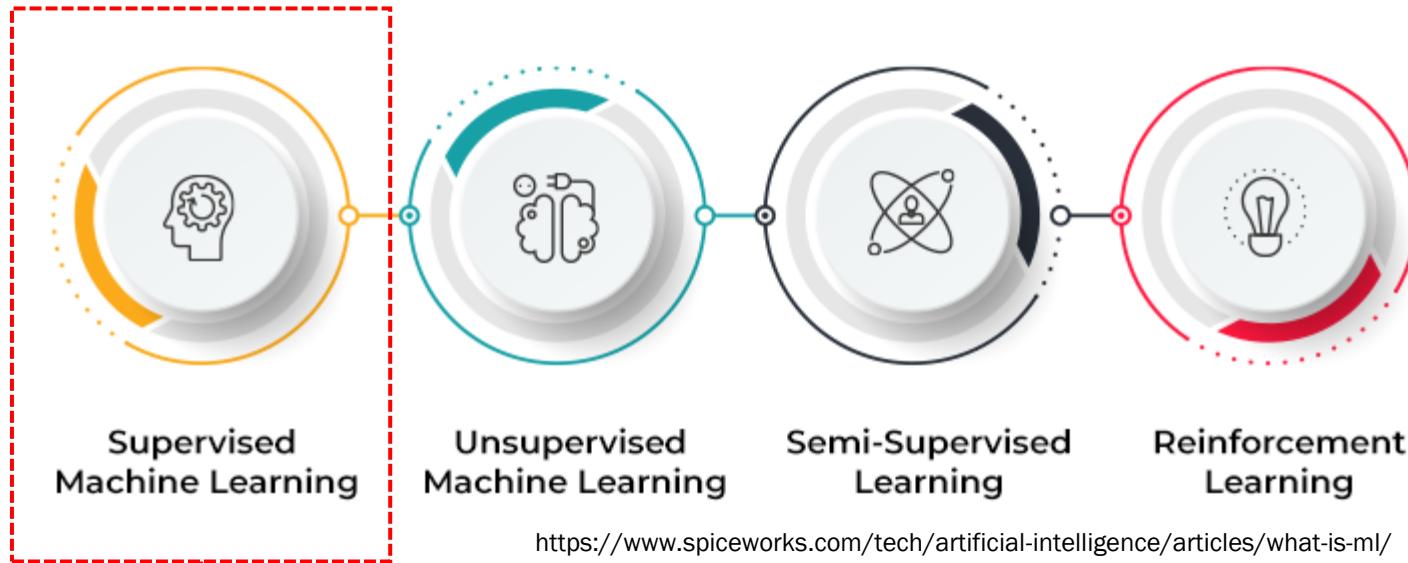
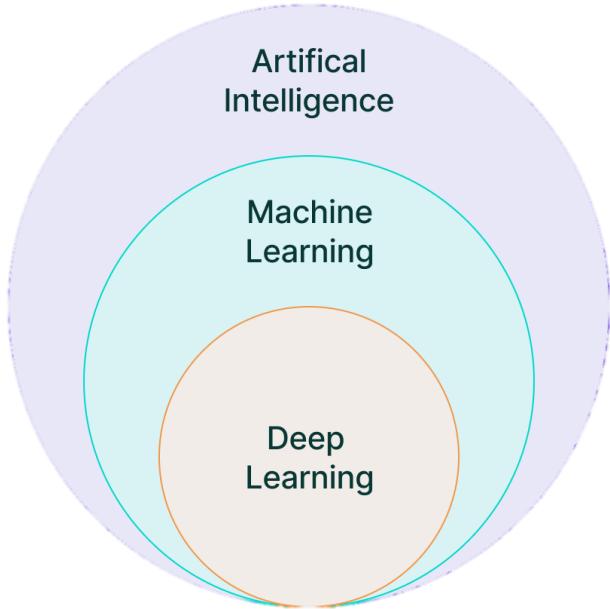


<http://aqmmon.iceht.forth.gr/>



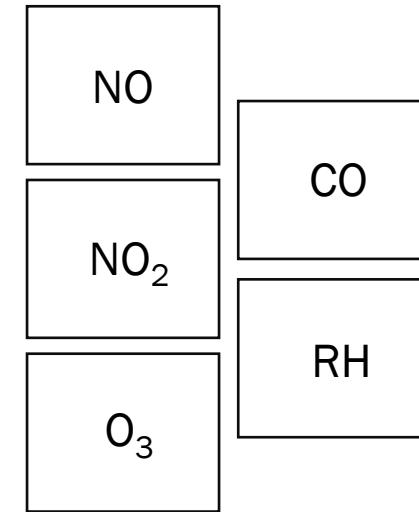
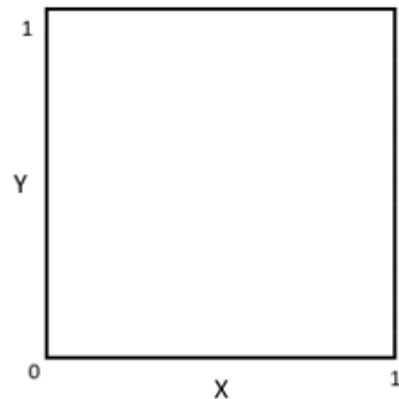
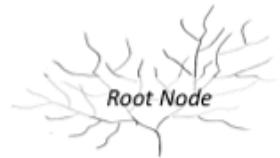
Machine Learning methodology for low-cost sensor calibration

Supervised Machine Learning



- Support Vector Machine
- Decision Trees
- Neural Networks
- Ensemble methods

The Decision Tree algorithm



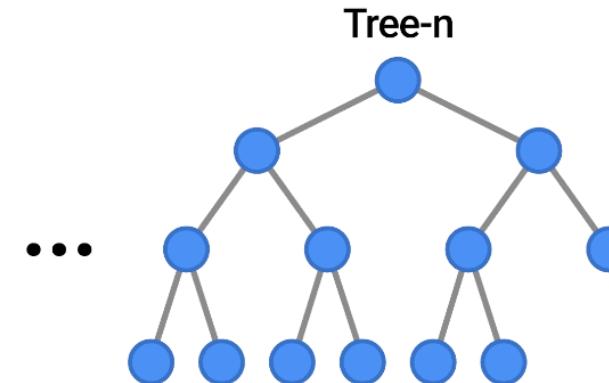
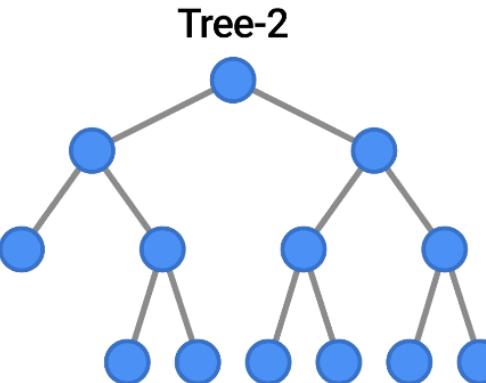
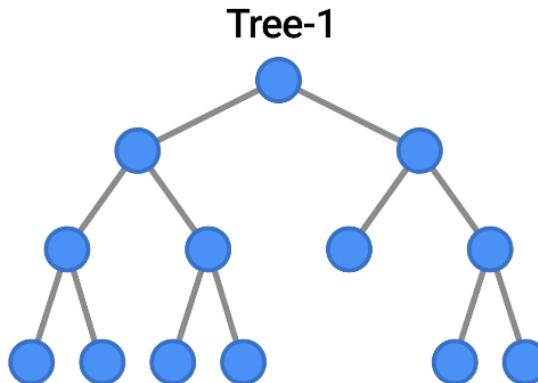
Features

NO_2

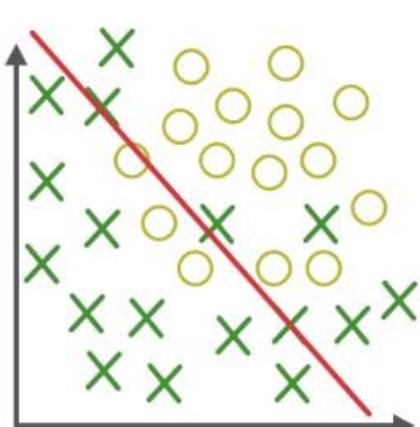
Ground Truth

The Random Forest algorithm

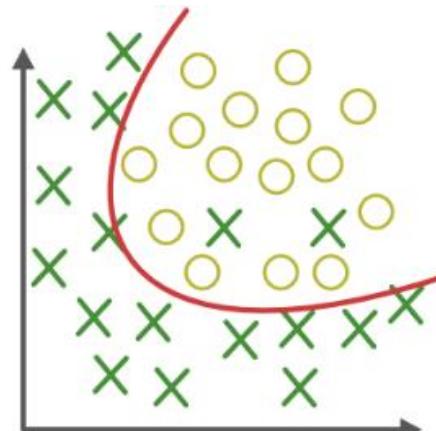
EXAMPLES



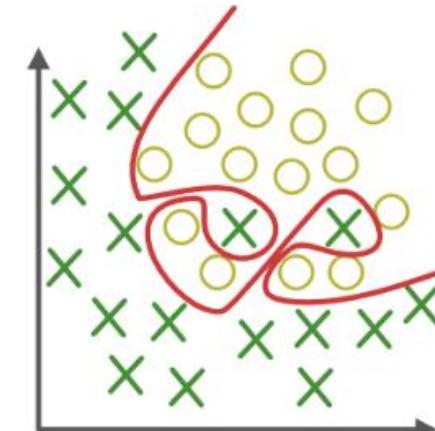
Random Forest weaknesses



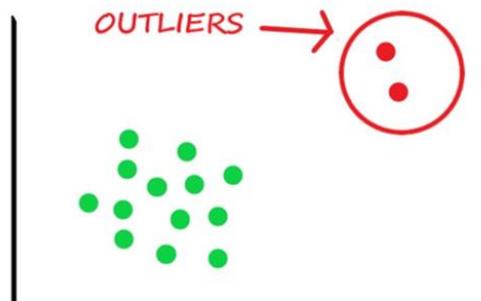
Under-fitting
(too simple to explain the variance)



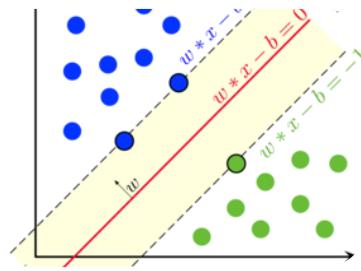
Appropriate-fitting



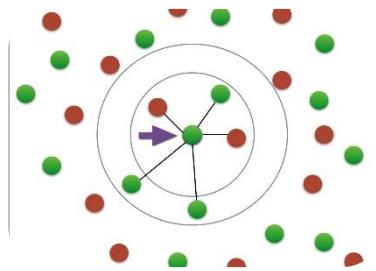
Over-fitting
(forcefitting--too good to be true)



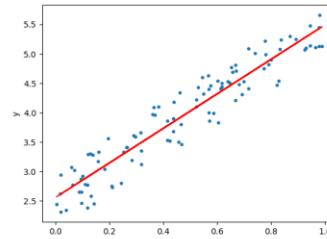
Why we chose Random Forest



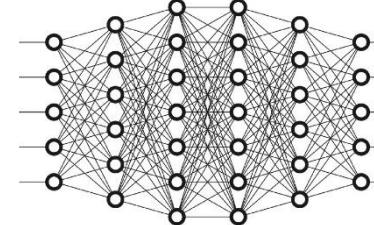
Support Vector
Machines



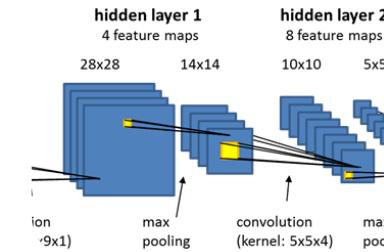
K-nearest
Neighbors



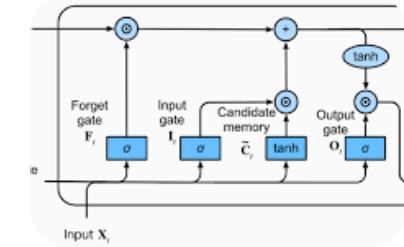
Linear Models



Neural Network



2D Convolutional
Neural Networks



Long-Short Term
Memory Networks

Better results with RF

LSTM performed similarly, but is a black-box and requires many resources to operate in real time. RF provides more explainable decisions and is lightweight

Field calibration experiment and results

Field calibration experiment

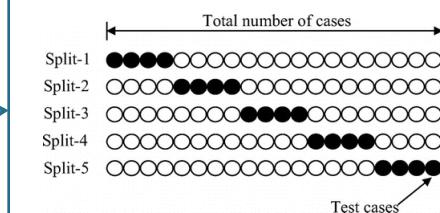


Data Clean

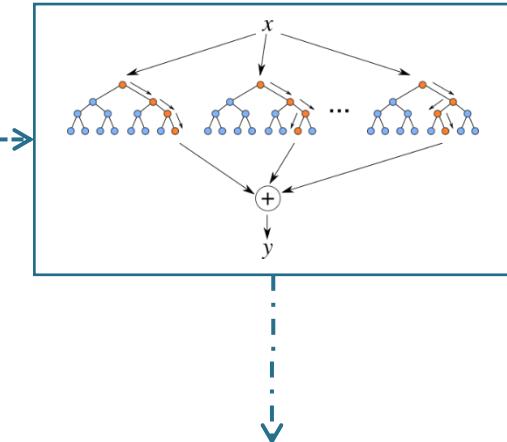
- Remove Zeros
- Remove Negatives
- Average (1H)

Training Data
2021
Drosopoulou Sq.

Training - Validation



Trained Model



Test Data
2022
Drosopoulou Sq.

- Location: Patra (center)
- Period: 2021-2022
- Time resolution: hourly average values
- Training Set: 2021
- Gas sensors for calibration: NO_2 , O_3
- Test Set: 2022 (same location)

Features

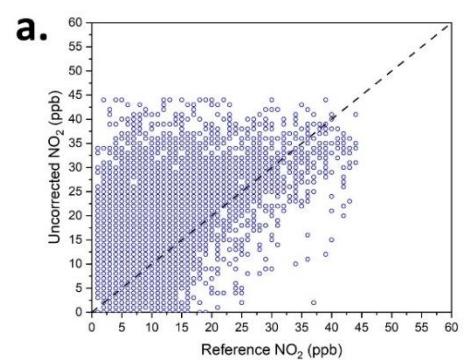
NO , CO , O_3 ,
 NO_2 , $\text{PM}_{2.5}$, T

Ground truth

Either O_3 or
 NO_2

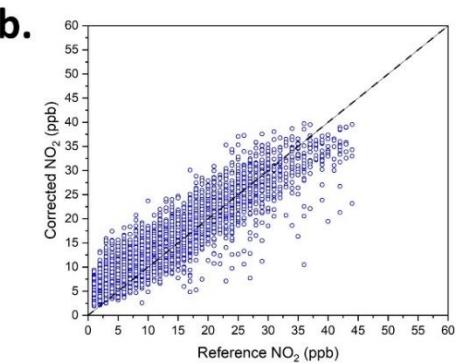
RF performance on the test data

Uncorrected

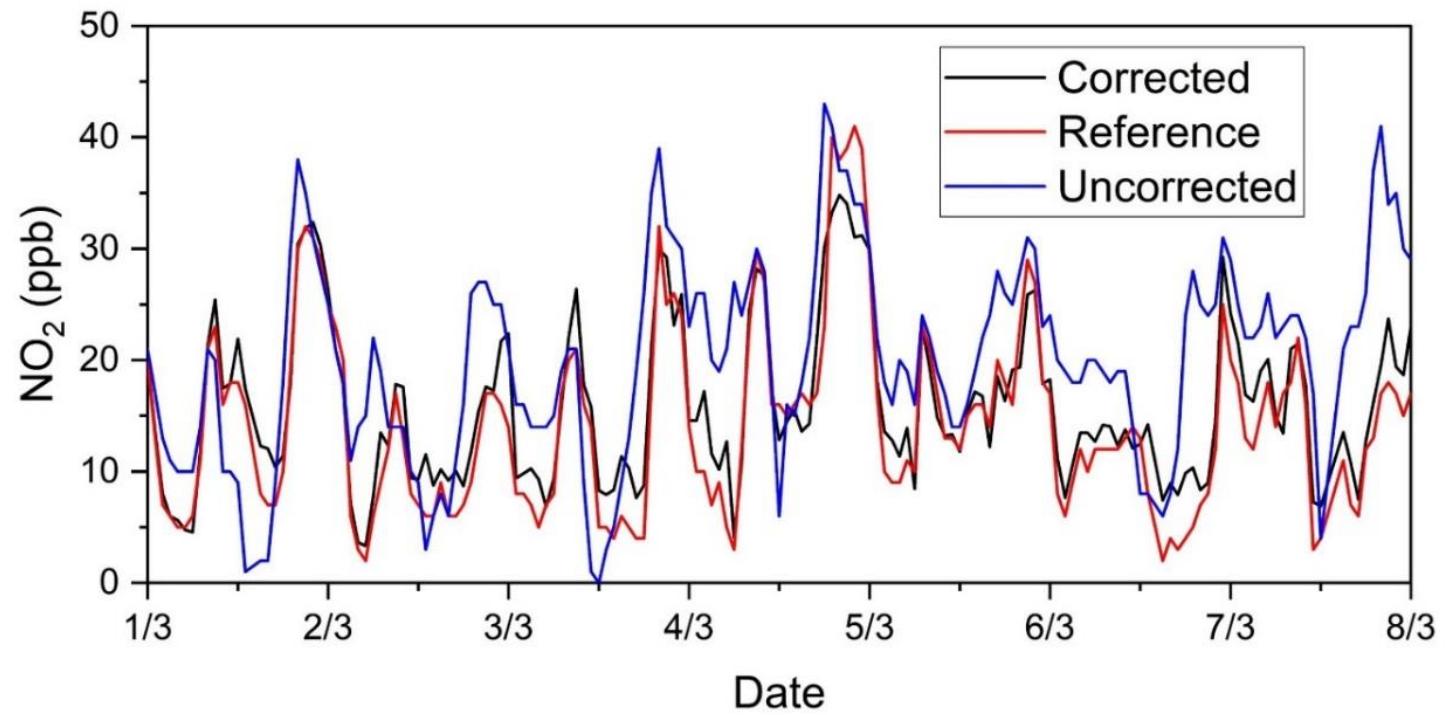


R^2 : 0.22
ME(ppb): 9.4
MB (ppb): 7.3
nME: 0.67

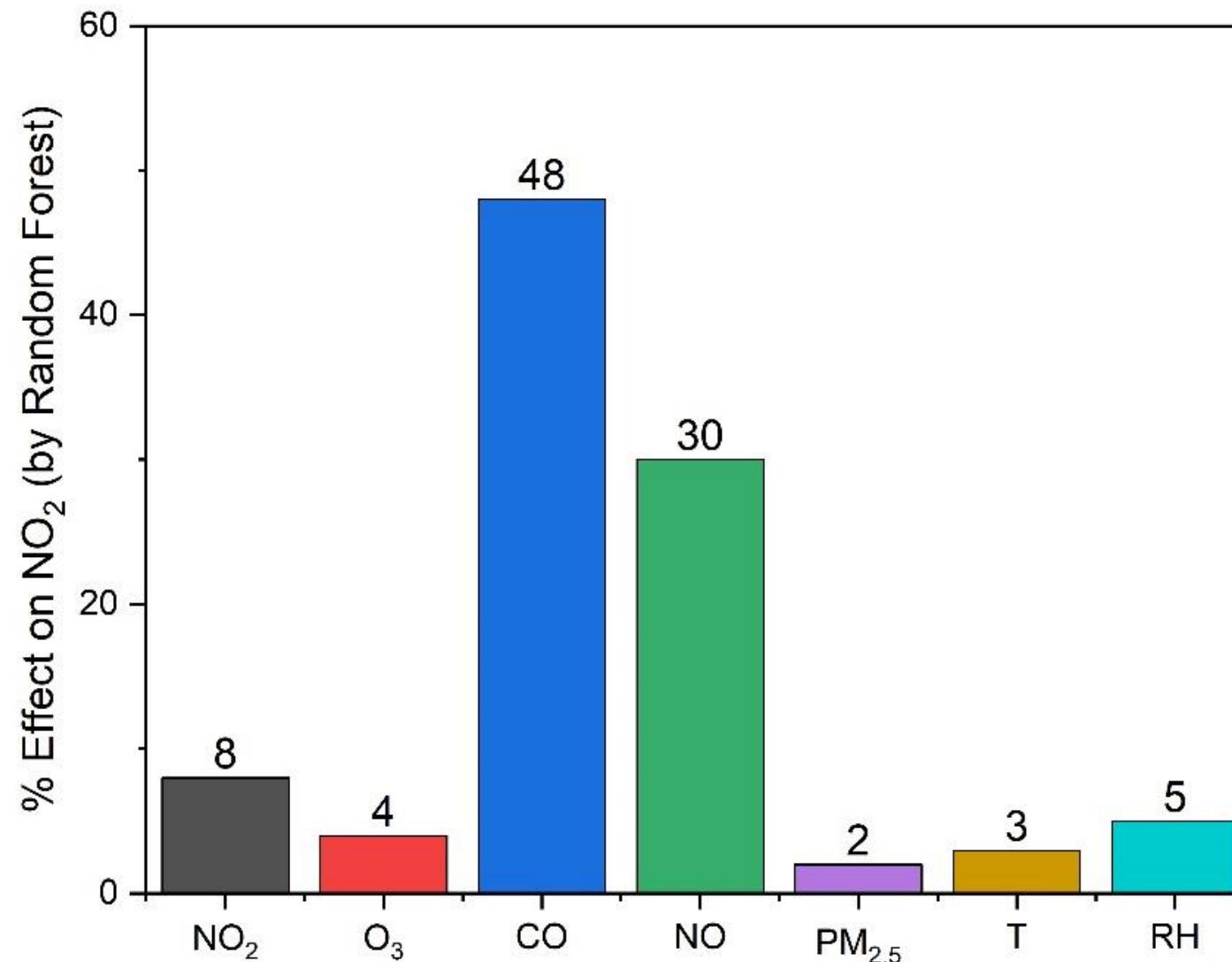
Random Forest



R^2 : 0.86
ME(ppb): 3
MB (ppb): 1.7
nME: 0.3

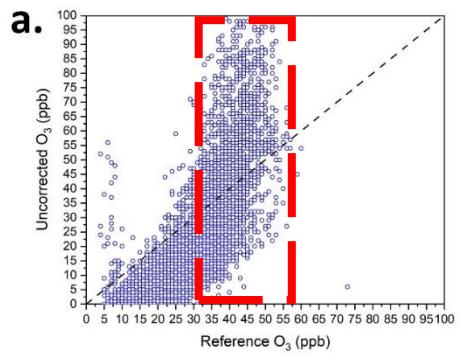


RF feature importance



RF performance on the test data

Uncorrected



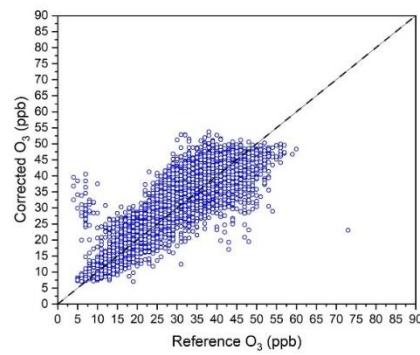
R^2 : 0.52

ME(ppb): 13

MB (ppb): -5.9

nME: 0.55

Random Forest

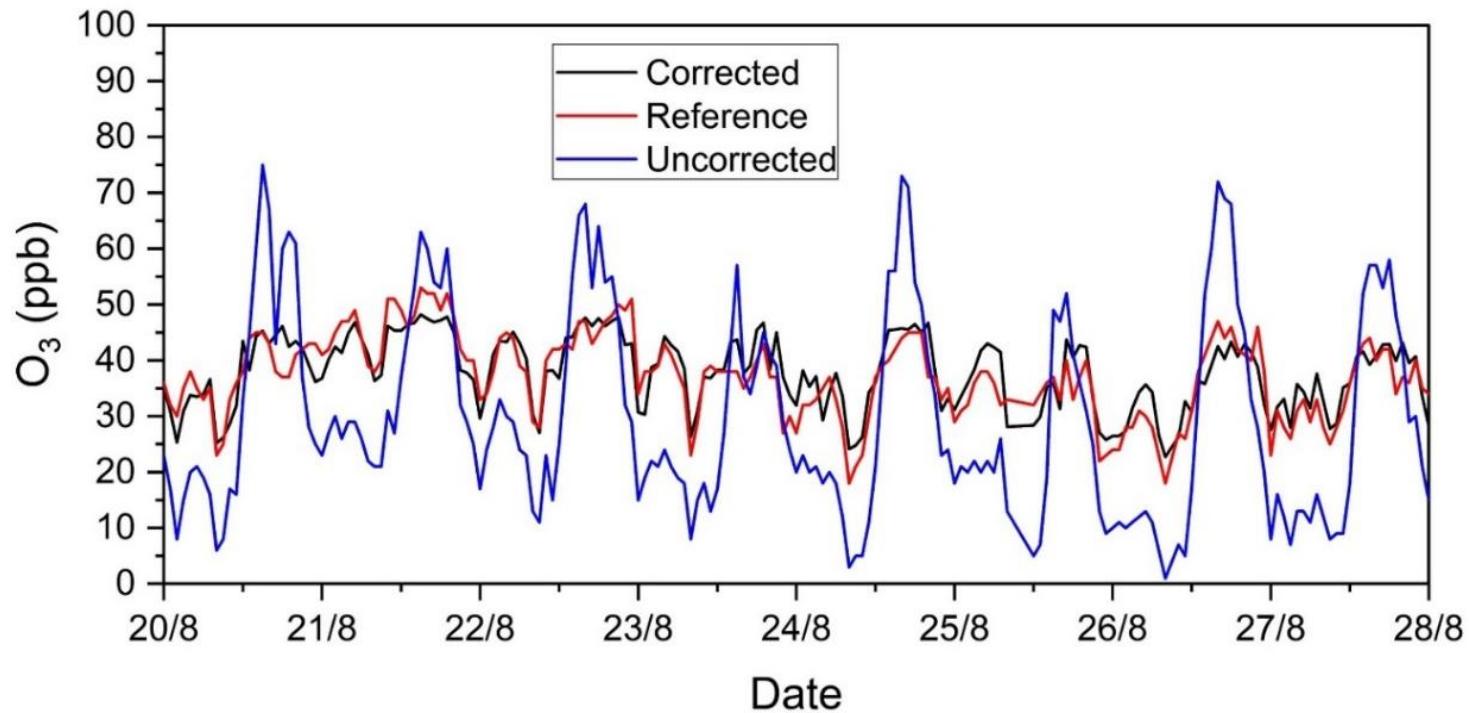


R^2 : 0.69

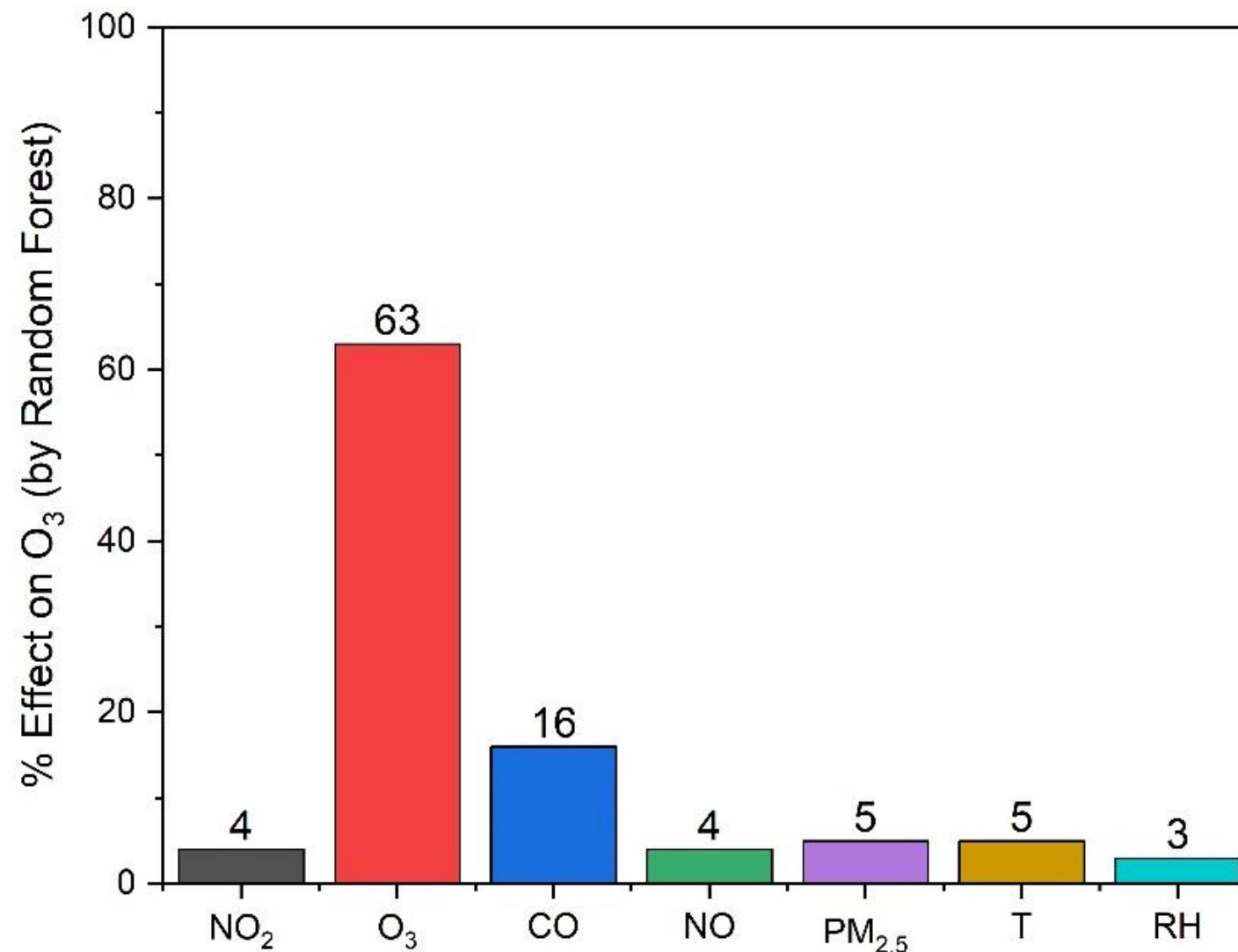
ME(ppb): 4.3

MB (ppb): 1.3

nME: 0.15



RF feature importance



Conclusions

- » Low-cost sensors exhibit errors and need calibration
- » Utilizing all sensor readings besides the gas under examination for building the algorithm shows promising results
- » Random Forest seems to perform well at least for NO_2 and O_3 sensors
- » One-year training data are adequate for at least one year correction (on the same site)
- » Machine Learning can help in field calibration of low-cost sensors

Work in progress

Work in progress

- EC Sensors Under Investigation:
 - » NO sensor
 - » CO sensor
 - » CO₂ sensor
 - » VOC sensor
- General Calibration model
- Indoor applications

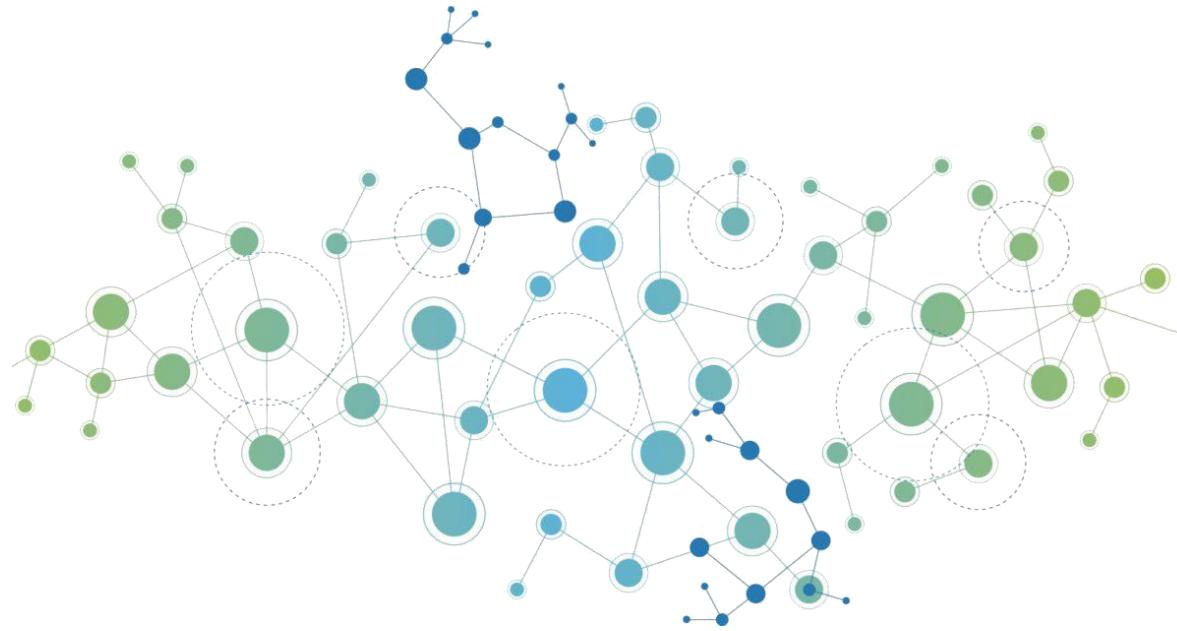


Acknowledgements

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Eleni Dovrou, and Silas Androulakis

Funding Projects





FORTH

INSTITUTE OF CHEMICAL ENGINEERING SCIENCES

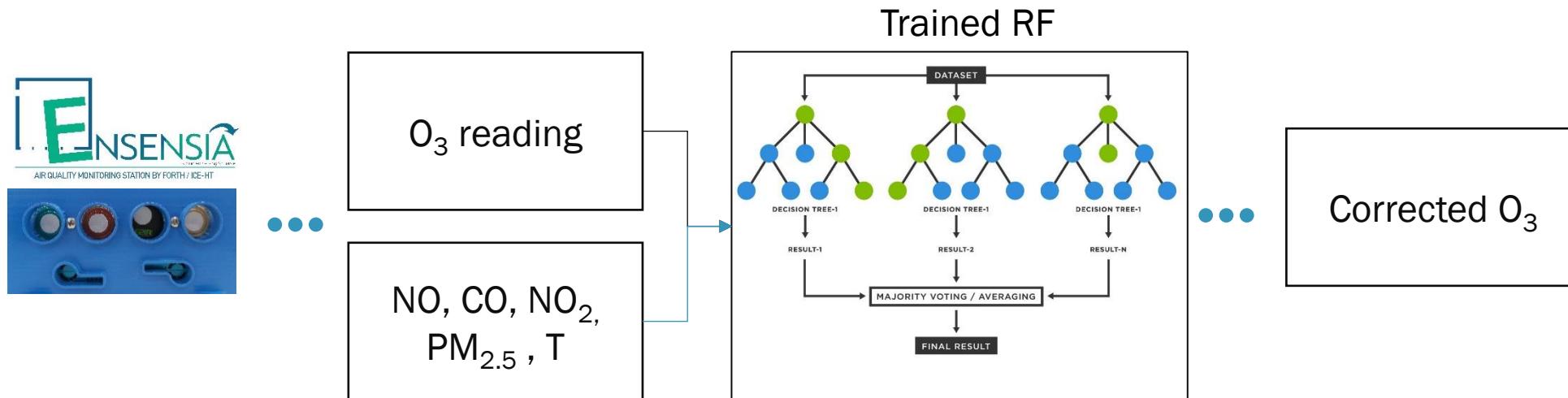


C-STACC
Center for the Study of Air Quality & Climate Change



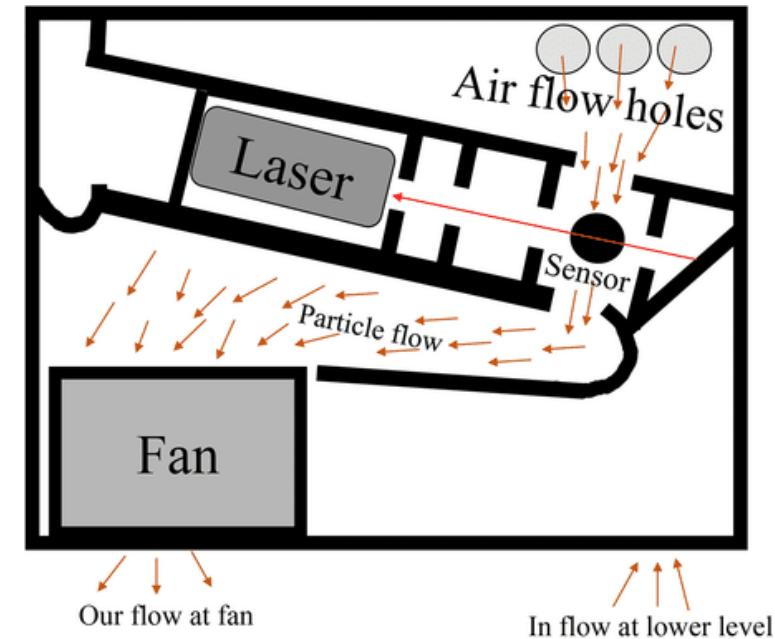
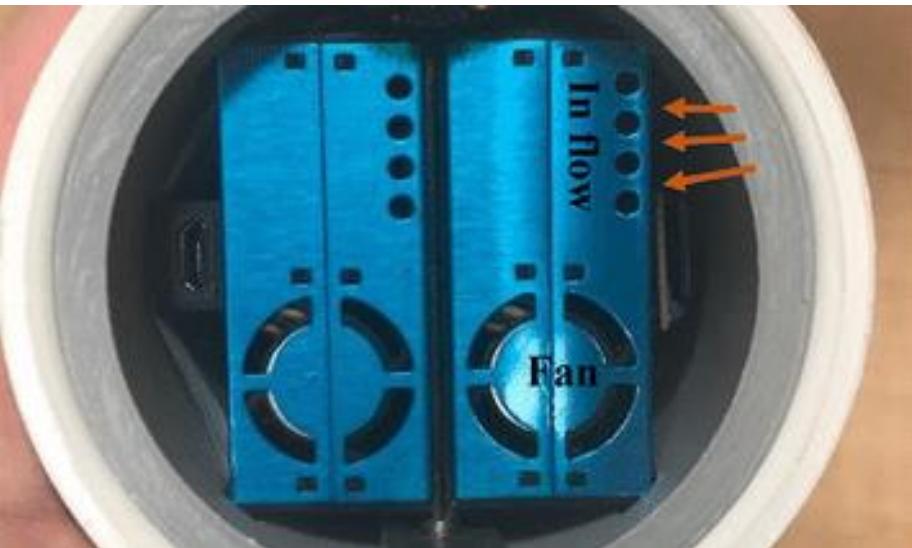
Thank You!

Random Forest application example (Ozone)



Fundamental principles of laser sensors

Particle Matter (PM_{2.5}) sensor



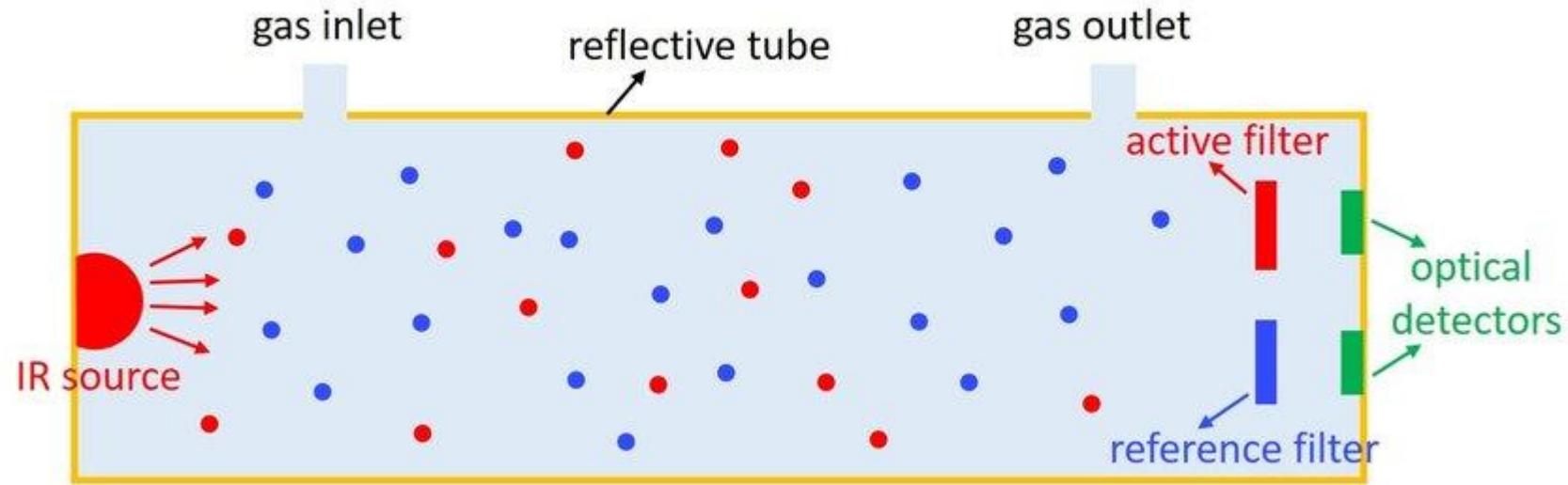
Ardon-Dryer, K., Dryer, Y., Williams, J. N., and Moghimi, N.: Measurements of PM2.5 with PurpleAir under atmospheric conditions, *Atmos. Meas. Tech.*, 13, 5441–5458, <https://doi.org/10.5194/amt-13-5441-2020>, 2020

ENSENSIA Properties

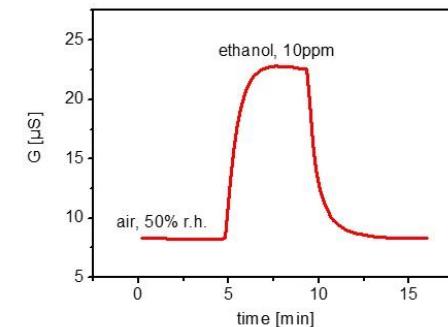
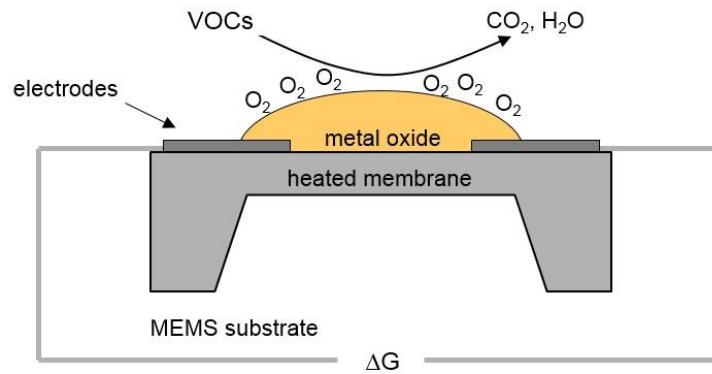
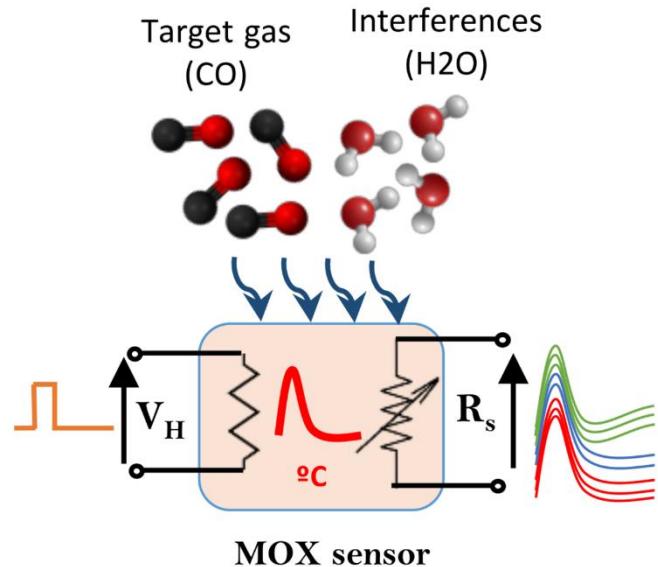


- Low-level info for each sensor estimate (electrodes voltage)
- Enough CPU power to process sophisticated dynamic calibration / correction algorithms (Edge computing)
- Fully remote managed appliance
- Improved precision of measurements based on Machine Learning
- Bundled with a friendly visualization web-based tool

Fundamental principles of NDIR sensors



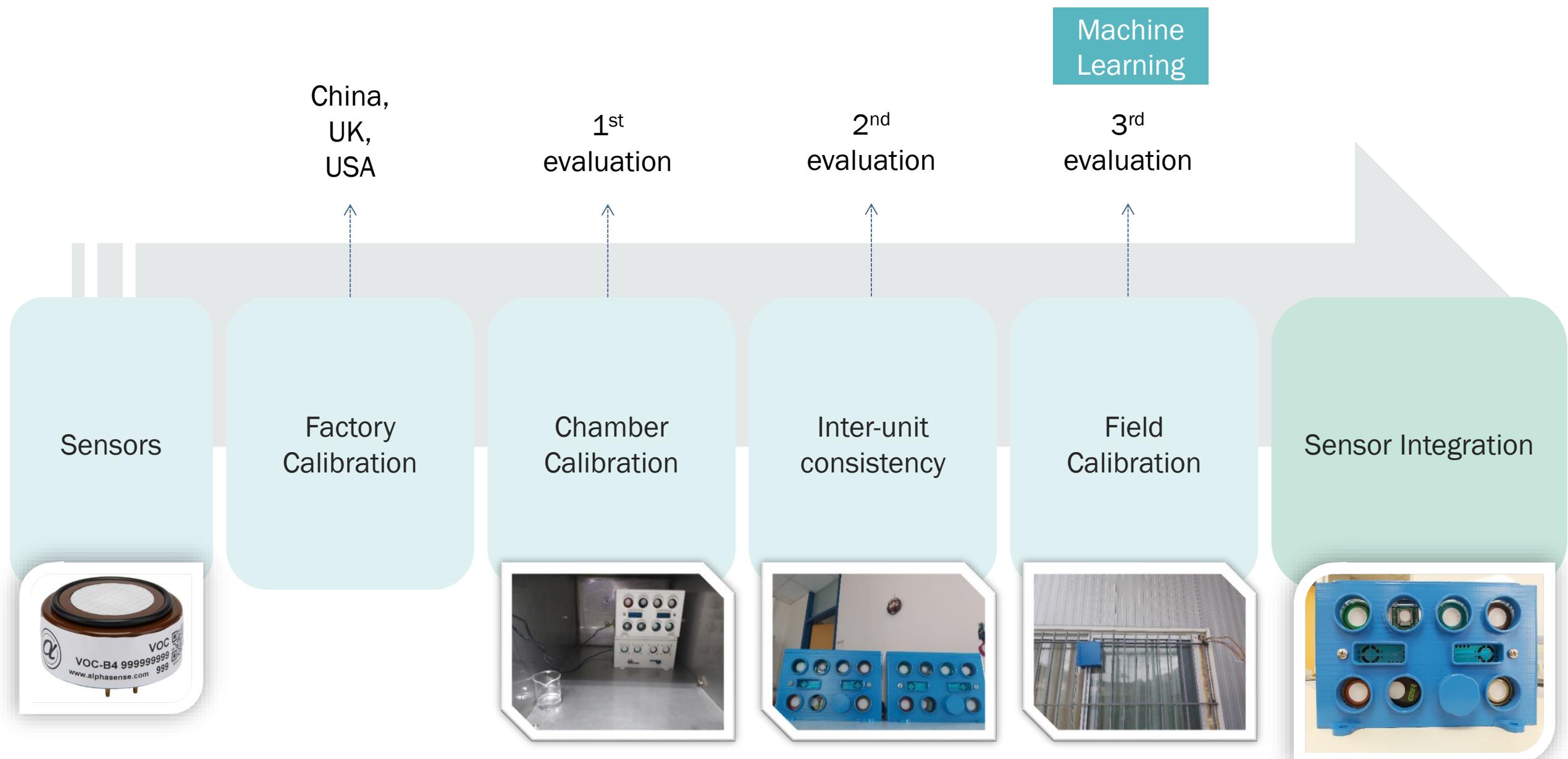
Fundamental principles of Mox sensors



VOC Sensor Operating Principle with Sensor Diagram and Example Response to VOC

- The gas-sensitive Metal Oxide Material [MOX] consists of a highly porous and granular semiconducting material.
- The grains form a resistor with distinct conductive paths between the electrodes
- Interaction of the VOC with the MOX (Combustion/chemical reaction driven by the heated membrane) results in predictable modulation of the measured electrical resistance

Sensor evaluation and calibration



General calibration model

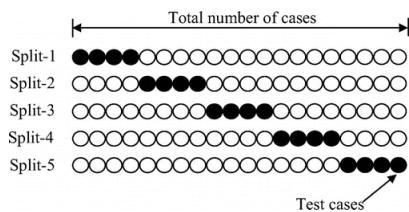


Data Clean

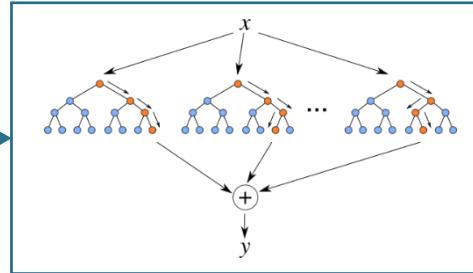
- Remove Zeros
- Remove Negatives
- Remove Outliers

Training Data
2021-2022
Drosopoulou Sq.

Training - Validation



Trained Model



Patra

2021 - 2022
Georgiou Sq.

1 month
Outside a school
in Kato Kastritsi

2023
Drosopoulou Sq.

Athens

10 months
In the National
Observatory