CurrentSense

A novel approach for fault and drift detection in environmental IoT sensors

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13 ZB

Produced by IoT Devices in 2019

https://www.statista.com/statistics/1017863/worldwide-iot-connected-devices-data-size/

Determining Sensor Data Quality is an Imperative

Determining Sensor Data Quality is an Imperative

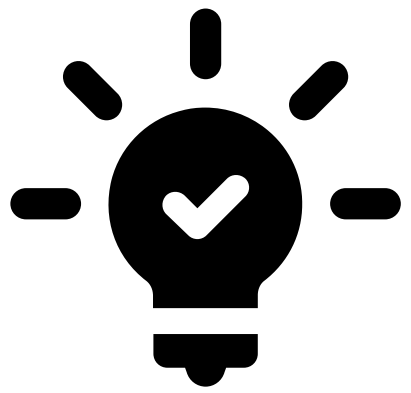
✓ Working

Faulty

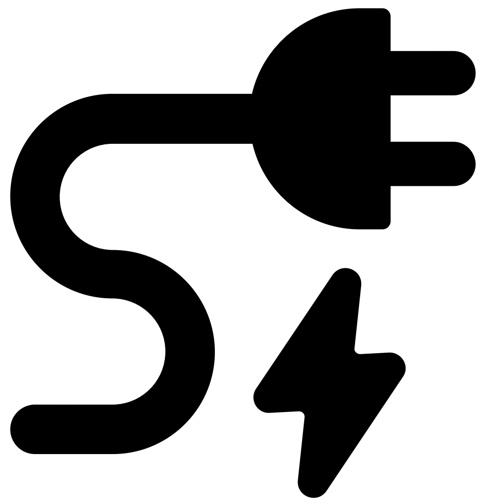
Drifted

The Challenge

Typically, A Sensor Keeps Sending Data After It Fails

The Solution 

Every electrical sensor draws current from the IoT device



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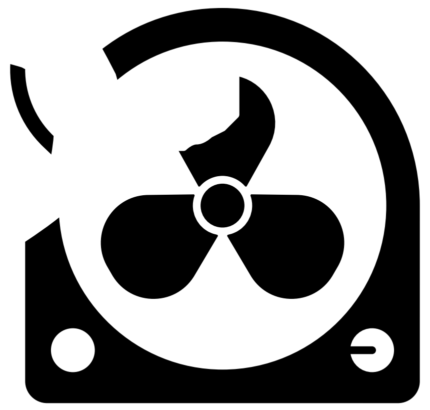
Damage to a sensor affects its current consumption.



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We can derive an electrical fingerprint that differs between **Working**, **Faulty** and **Drifted** sensors.

CurrentSense

1. Distinct for a **working**, **drifted**, and **faulty** sensor

2. Quantifies the amount of **drift**

3. Independent of the measured phenomena

4. Non-intrusive with no or minimal hardware modification

Agenda

2. Background and $PM_{2.5}$ Sensor Faults
3. CurrentSense and its Working
4. Experimental Setup
5. Fault Detection and Isolation
6. Detecting and Measuring Drift
7. Applicability of CurrentSense to other Sensor Types

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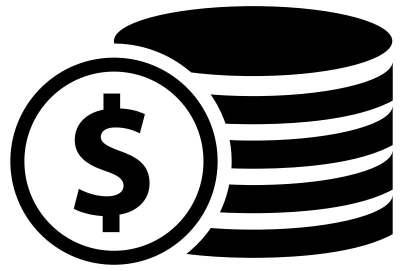
What is $PM_{2.5}$?

$PM_{2.5}$

Particulate Matter two and one half microns or less in width

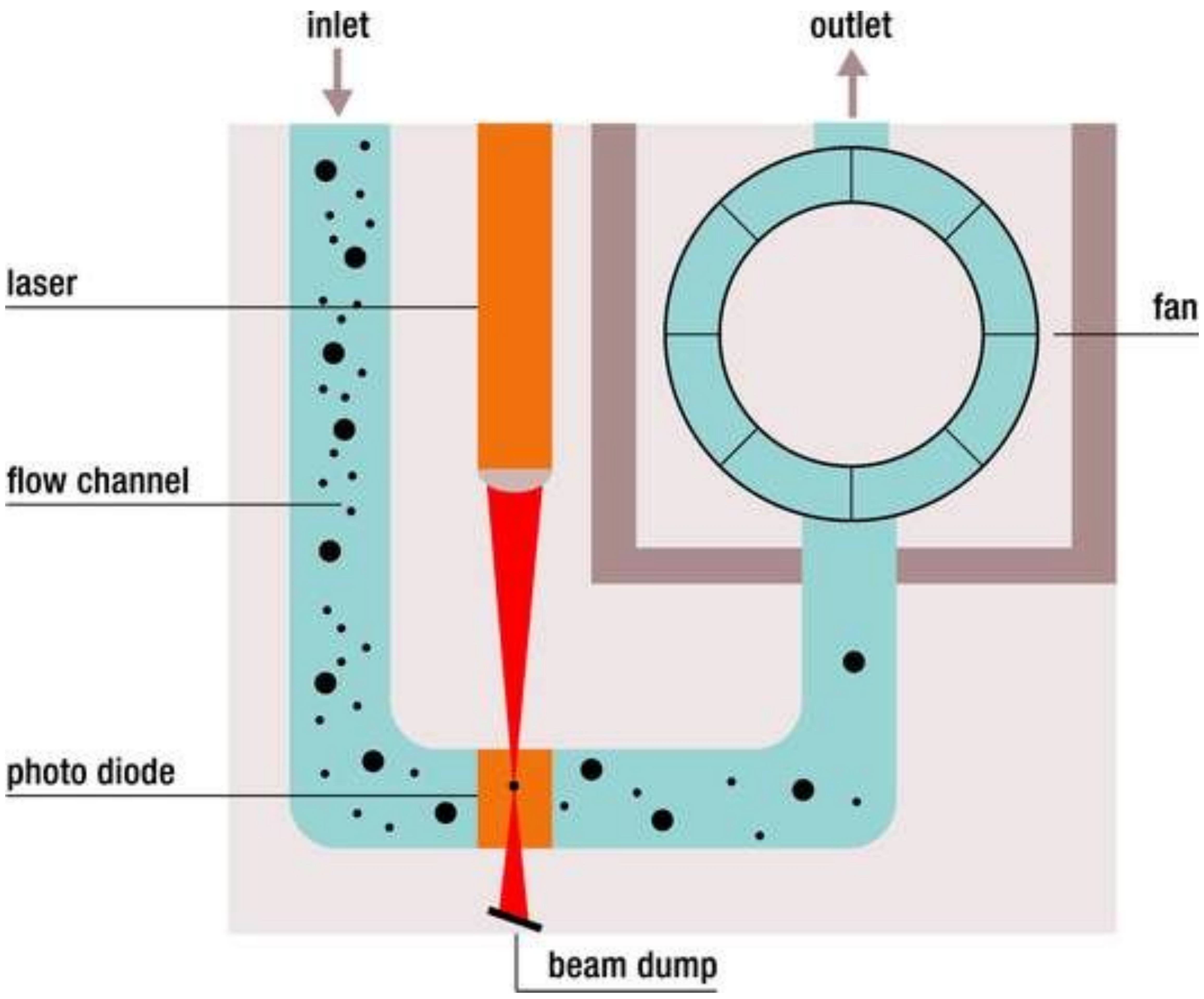
$30 - $100



Frequent Data Faults

Low-cost $PM_{2.5}$ Sensor and its working

1. Fan Creates Controlled Airflow
2. Particles travel from inlet to outlet, passing through light source
3. Light scatters as it hits the particles
4. Scattered light is detected by photo diode and converted to a mass concentration output



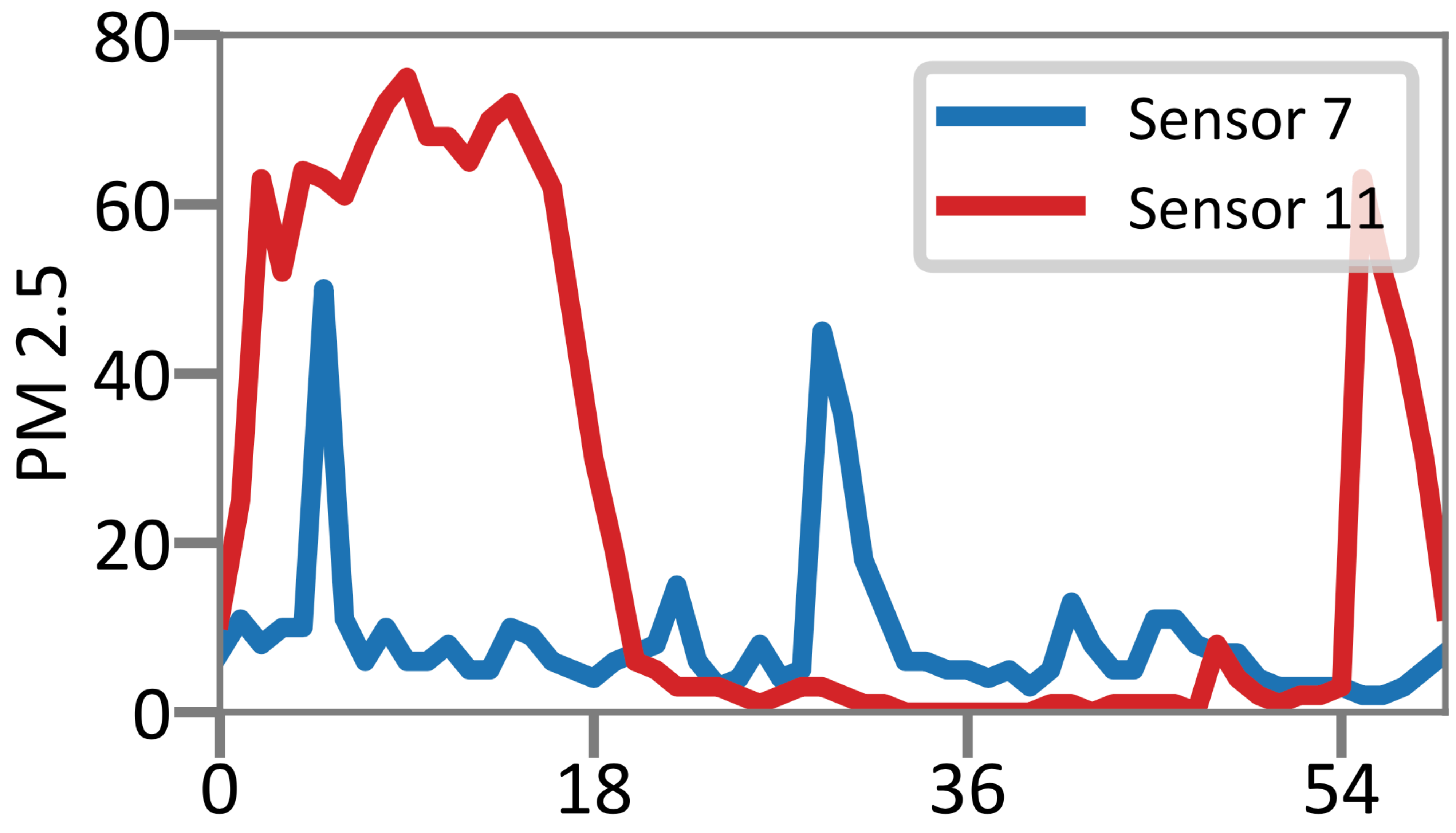
What is a Data Fault?

Catastrophic Faults

ie: Fan stops spinning

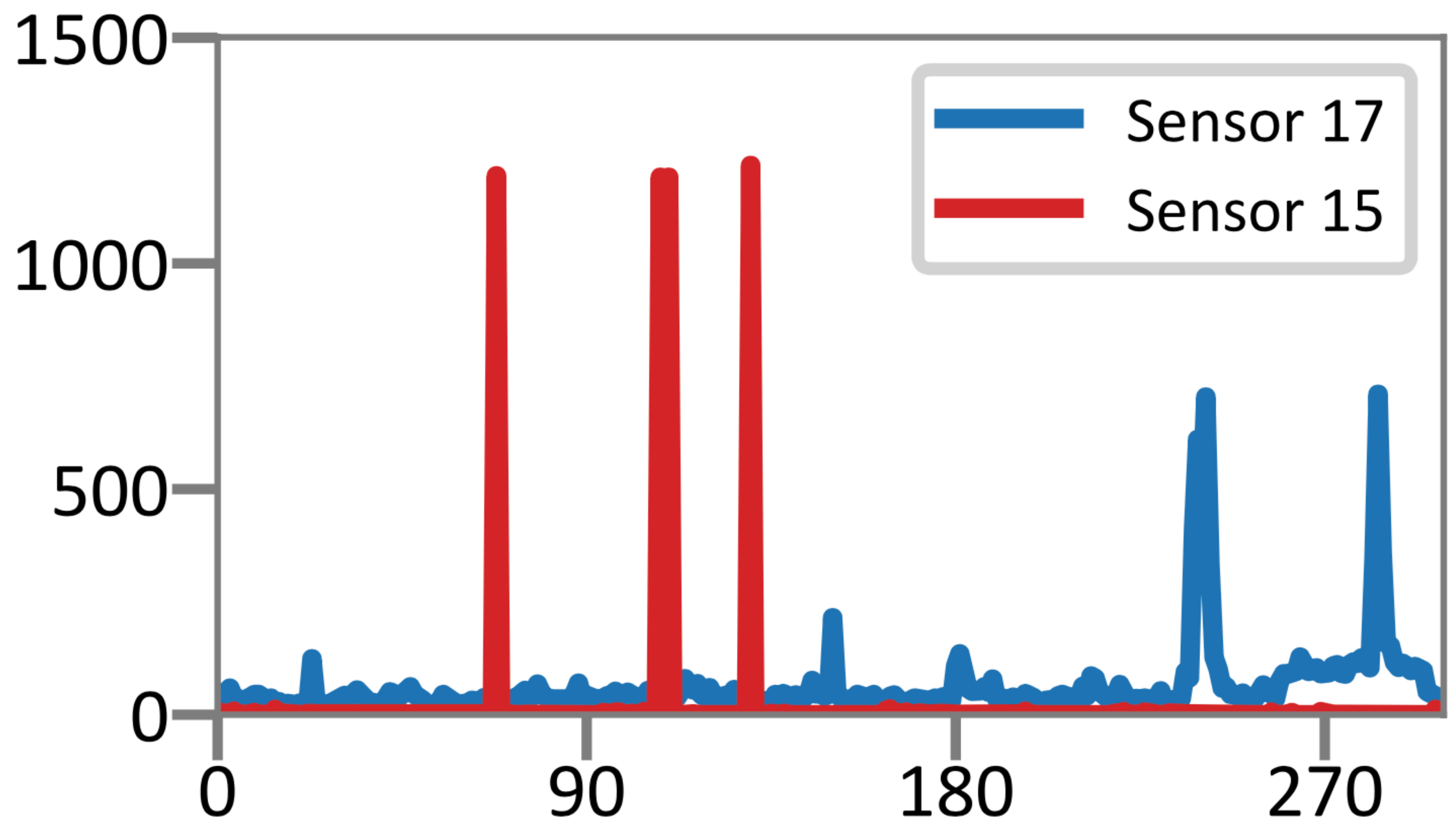
Case 1: Mimicking Data

The **faulty** sensor mimics **working** sensor data.



Case 2: Anomalous Data

The **faulty** sensor reports anomalous data.



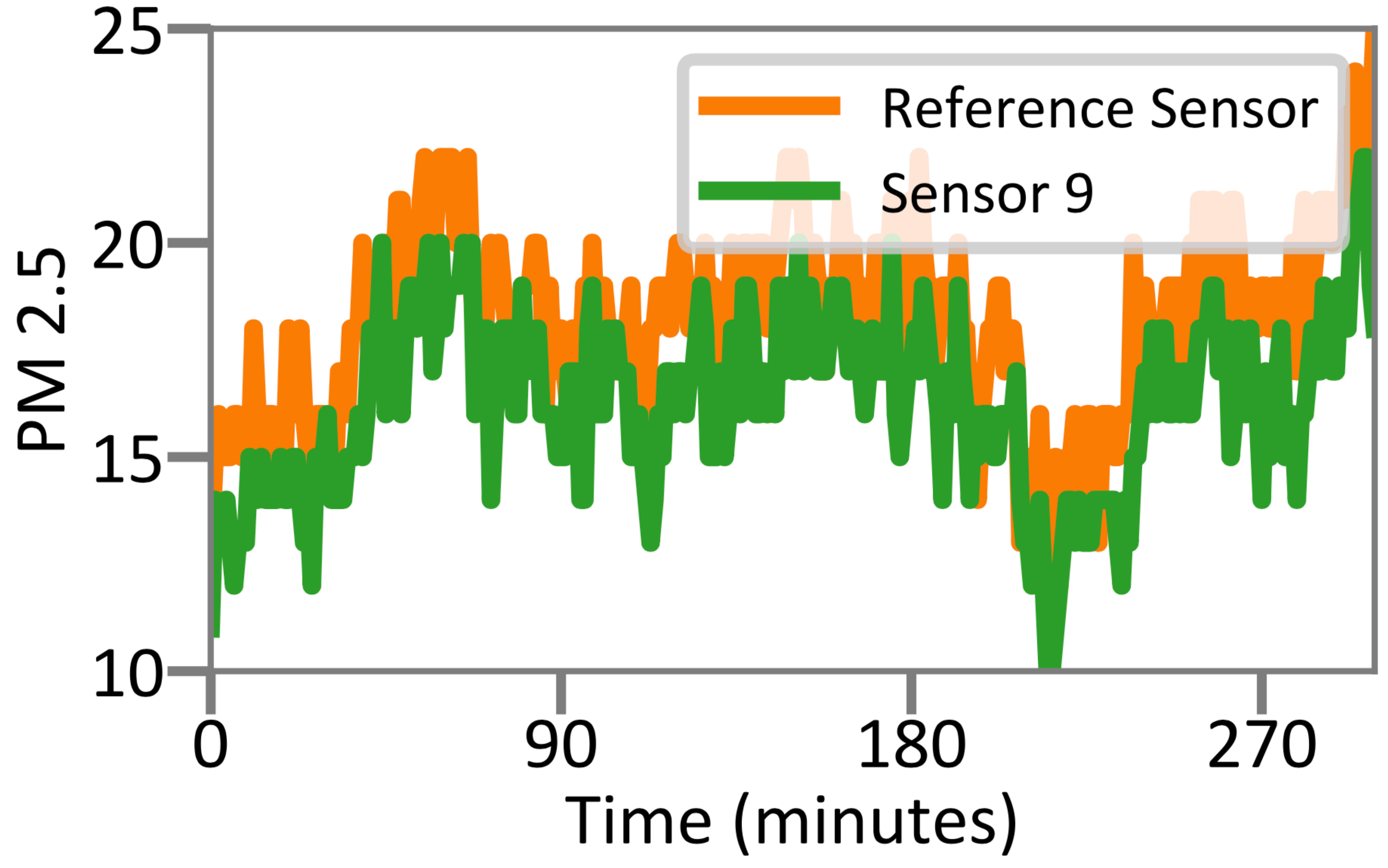
Sensor Drift

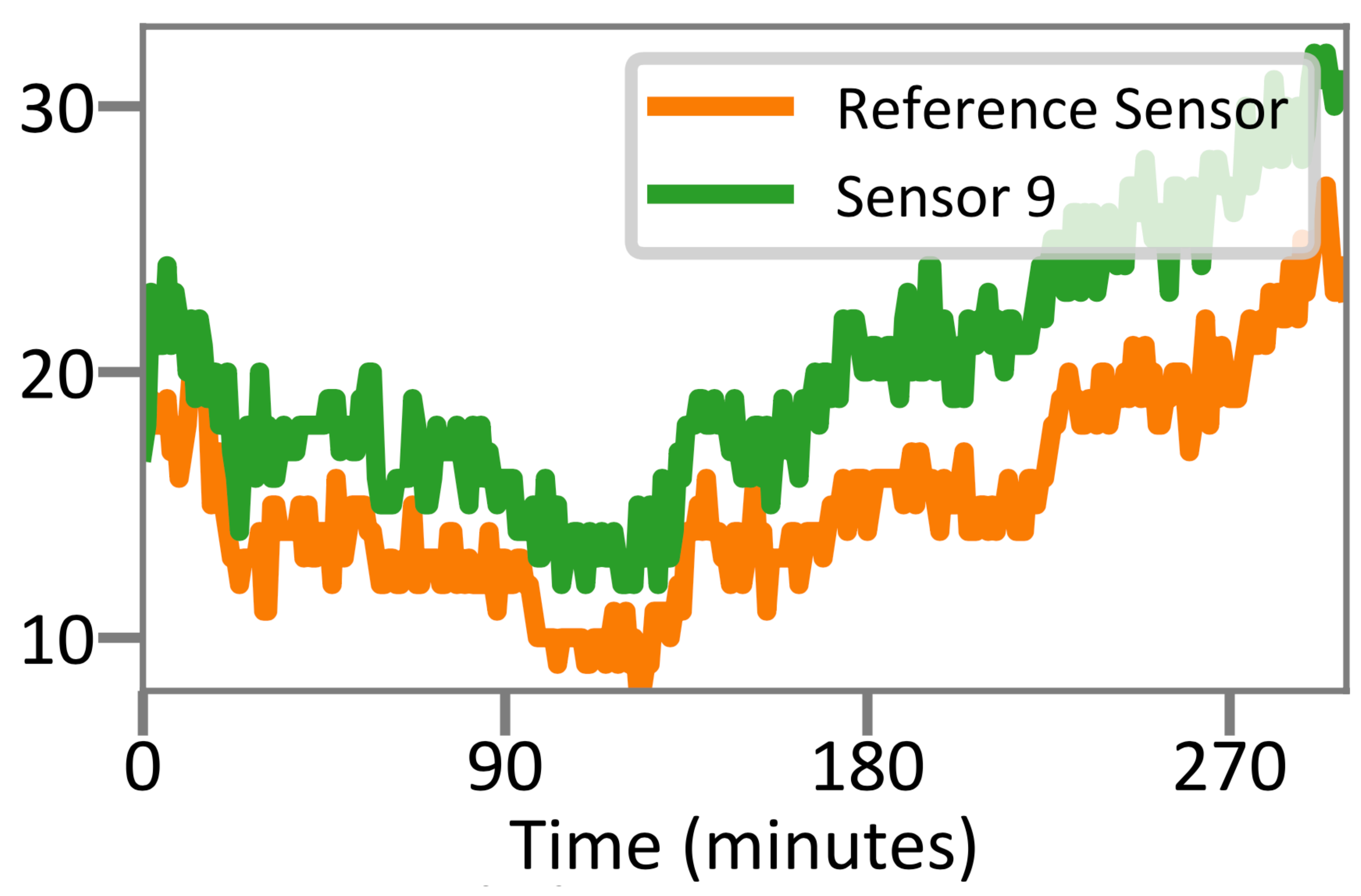
ie: LED Light intensity changes

Low cost $PM_{2.5}$ require calibration to estimate correctly

After deployment, this calibration may not remain valid as sensors wear.

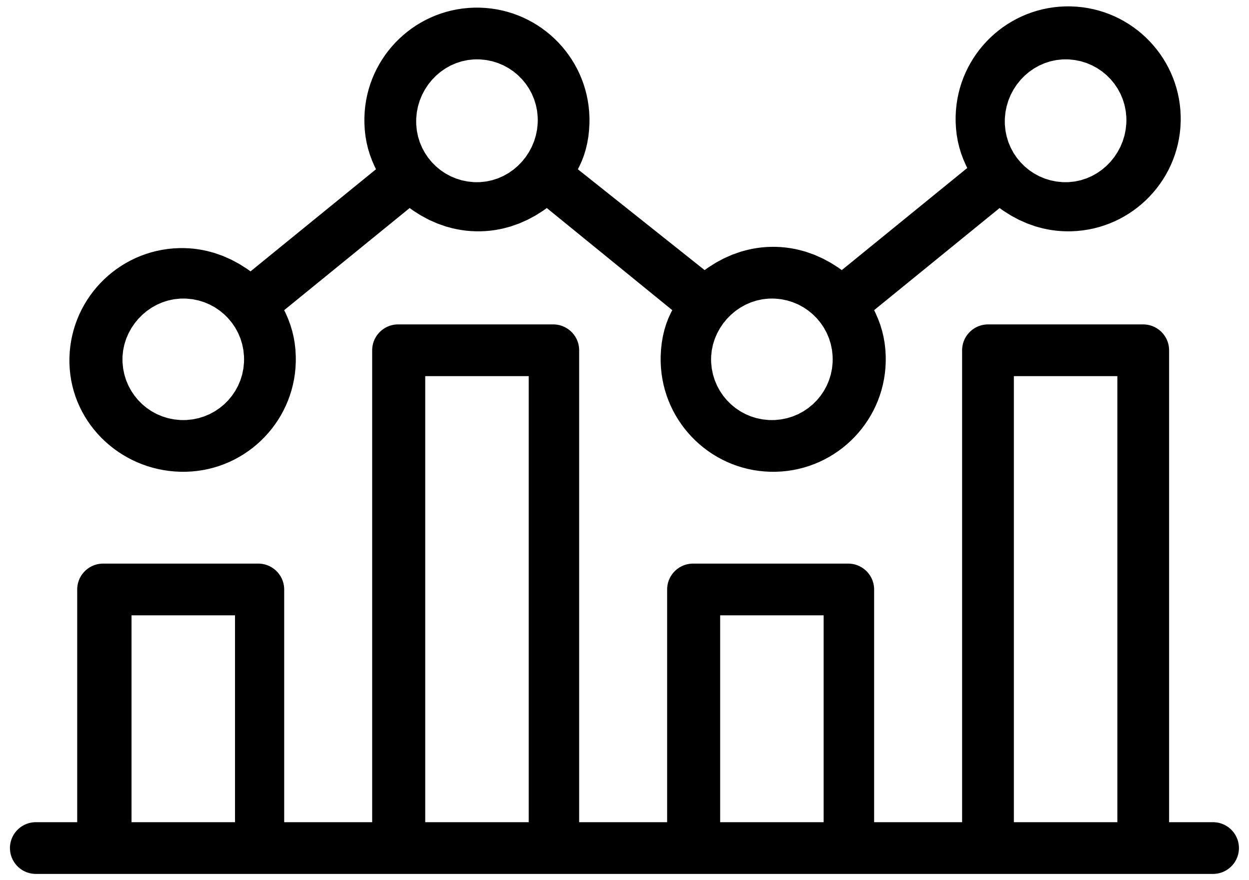
This loss of calibration is very difficult to detect.



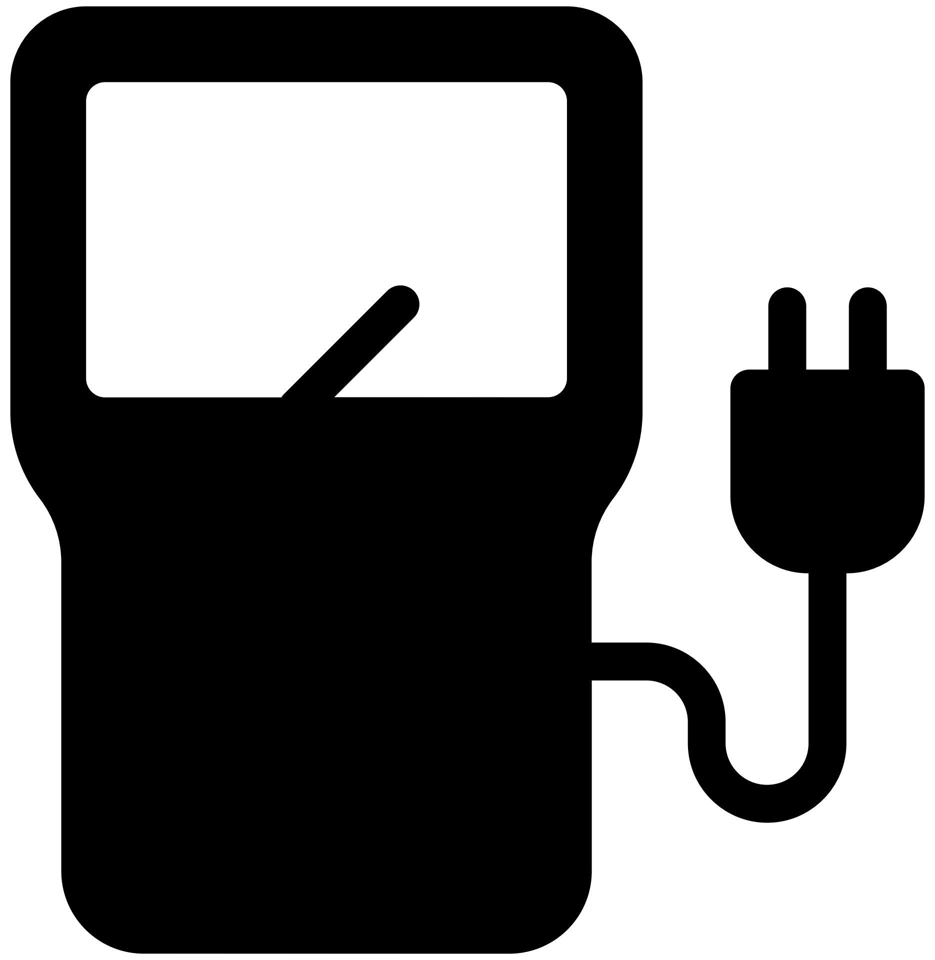


Related Work

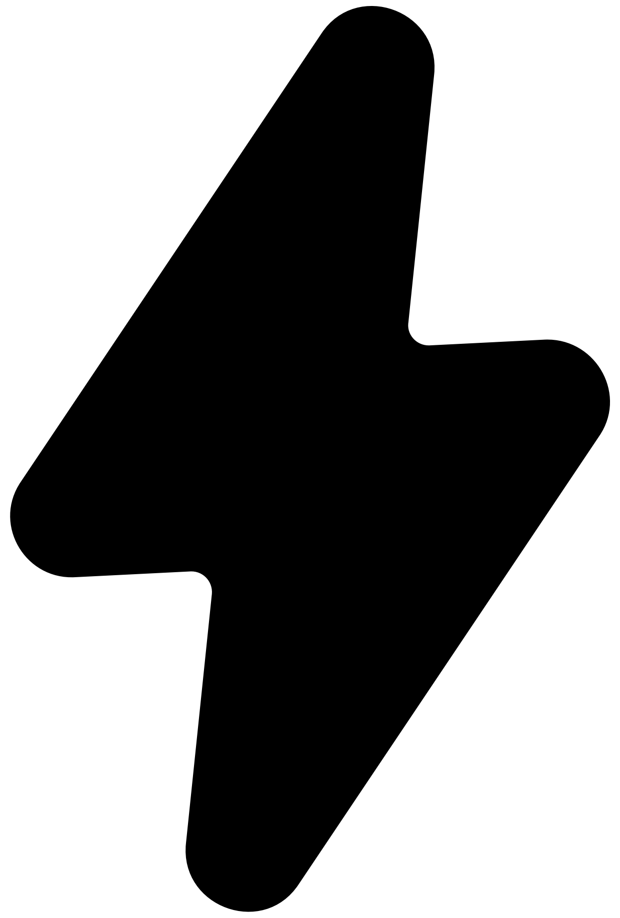
Data-centric efforts



System-centric efforts



Current Signature Analysis



Related Work: Data-centric efforts

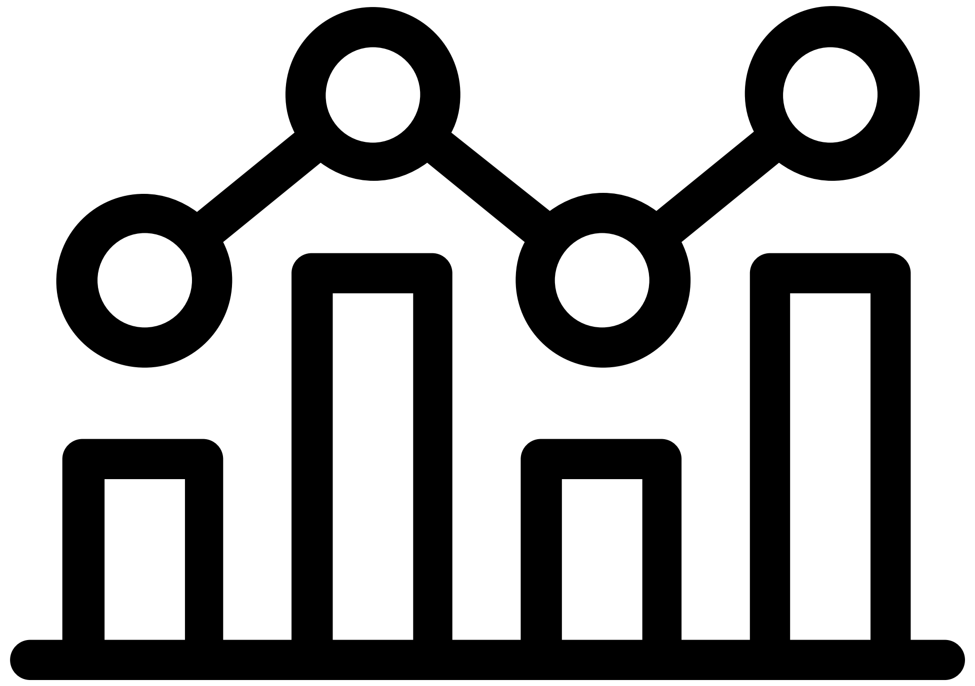
Data of the sensor is analyzed and a fault is identified if the data is out of bounds of the expected behavior.

A faulty sensor can mimic non-faulty data

An anomalous sensor reading need not represent faulty data

Fault Detection in Air Pollution Sensors

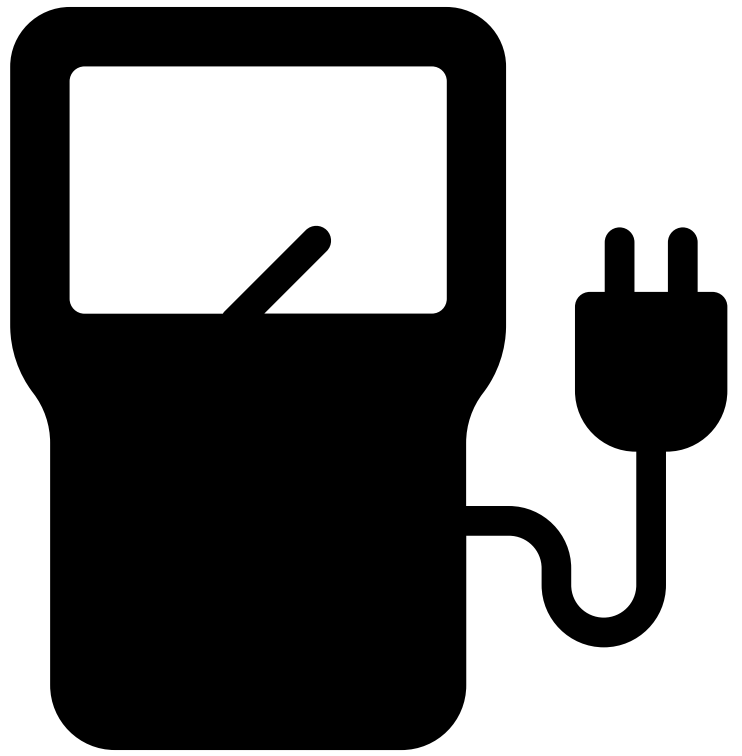
- Use the sensor's placement in time/space to detect anomalies
- Use redundant sensors
- Compare sensor readings to some predicted value



Related Work: System-centric efforts

Use the sensor's voltage response when being turned off to characterize sensor fault.

- ❌ Works only for analog sensors where a sensor's output voltage can be measured directly
- ❌ Fall-curve is designed to only detect faults, and cannot be used to detect and measure sensor drift
- ❌ Fall-curve requires the sensor to be powered down to determine its status



Related Work: Current Signature Analysis

There are other domains in which current signature analysis has been used to detect faults.

Examples

- Motor Current Signature Analysis (MCSA)
- HVAC.
- SocketWatch.

CurrentSense performs
current monitoring
For fault detection and isolation
in low-cost IoT sensors

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Deployment details

51

Devices

8

Months

7

Days between Inspections

Deployment details

51

Devices

33

Working

9

Faulty

9

Drifted

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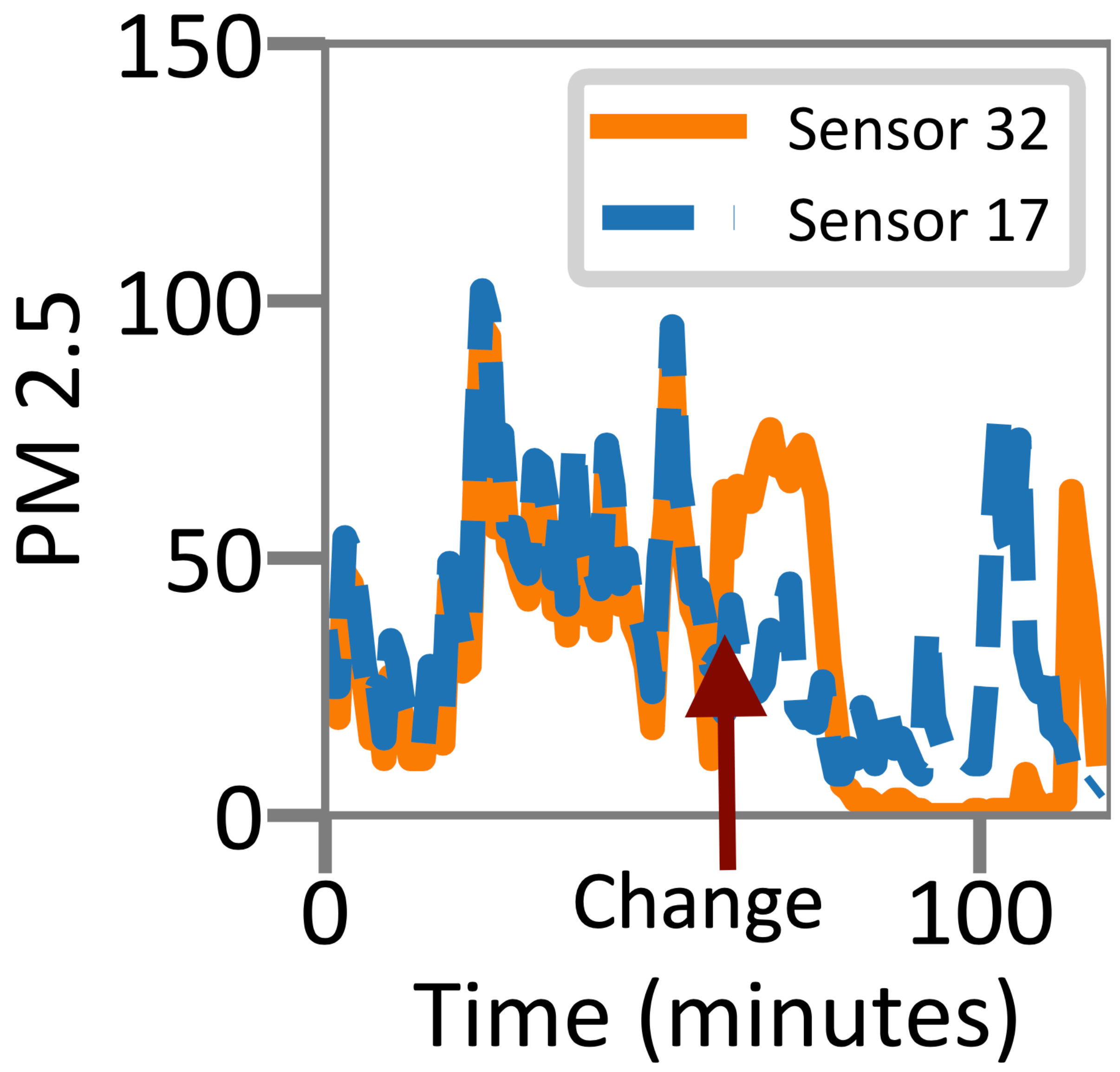
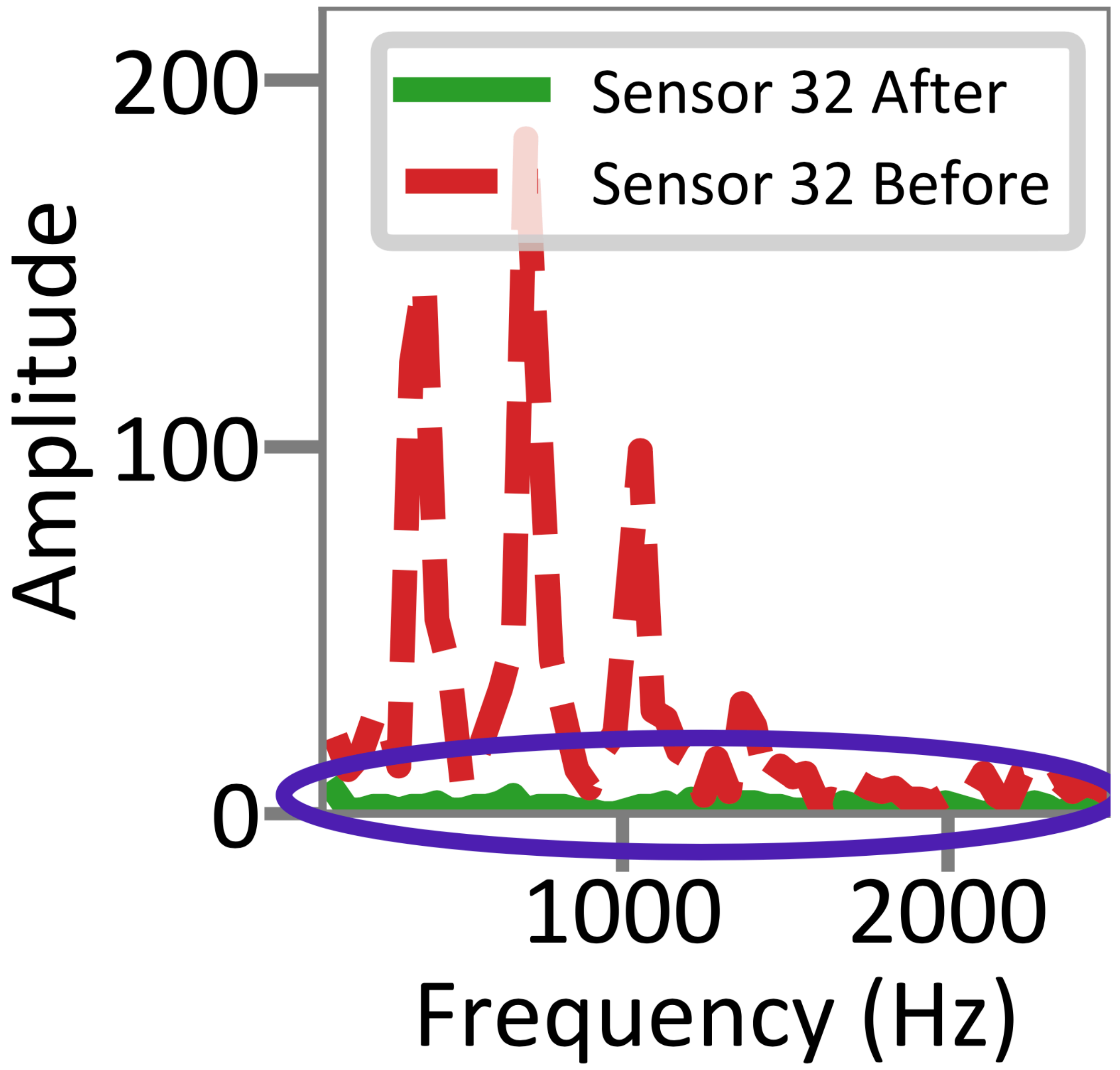
Controlled Experiments

Fan fault injected at T = 50



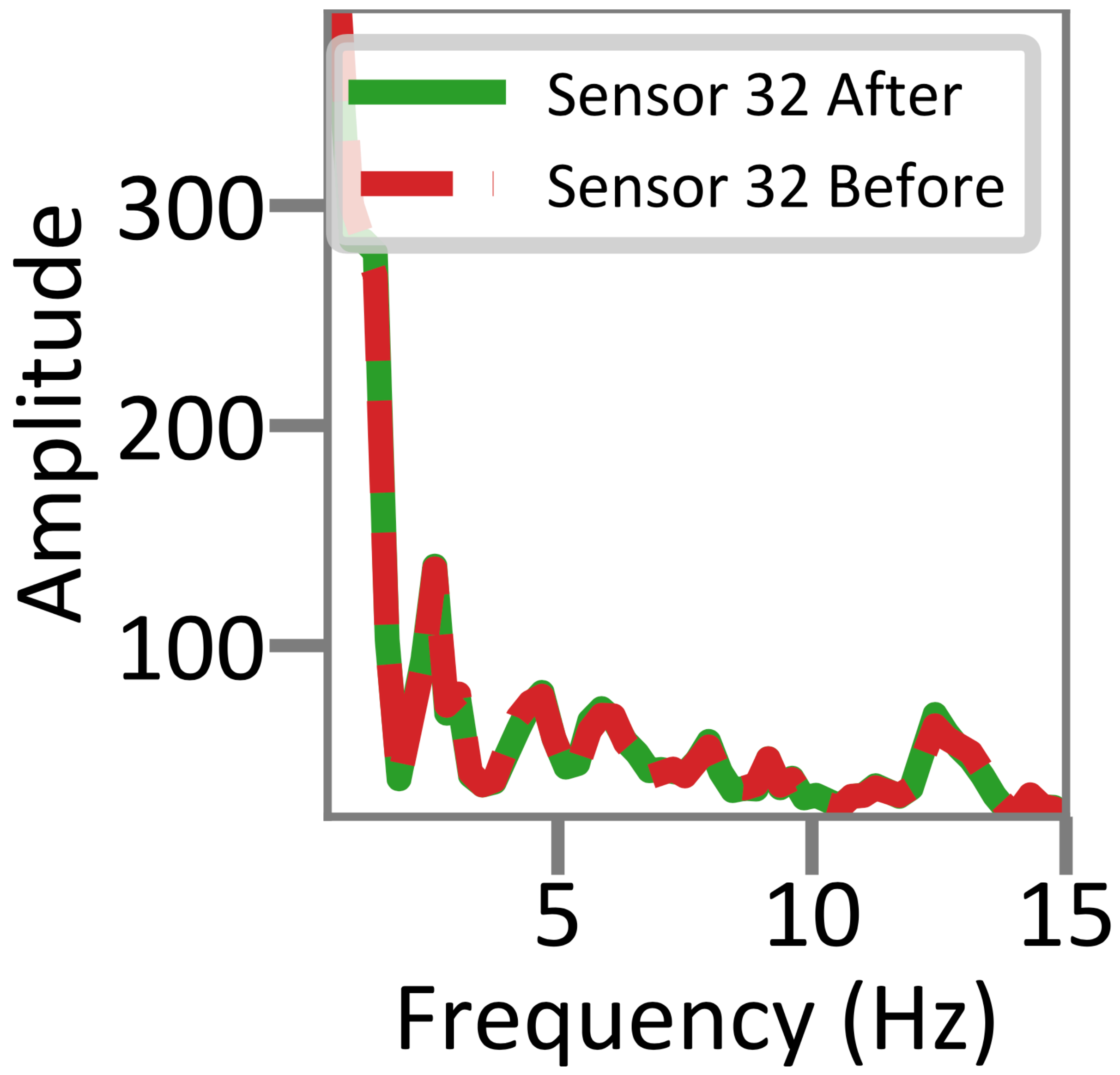
PM data

CurrentSense Features change Dramatically at 5kHz



FFT @ 5kHz

CurrentSense Features do not change at 30Hz



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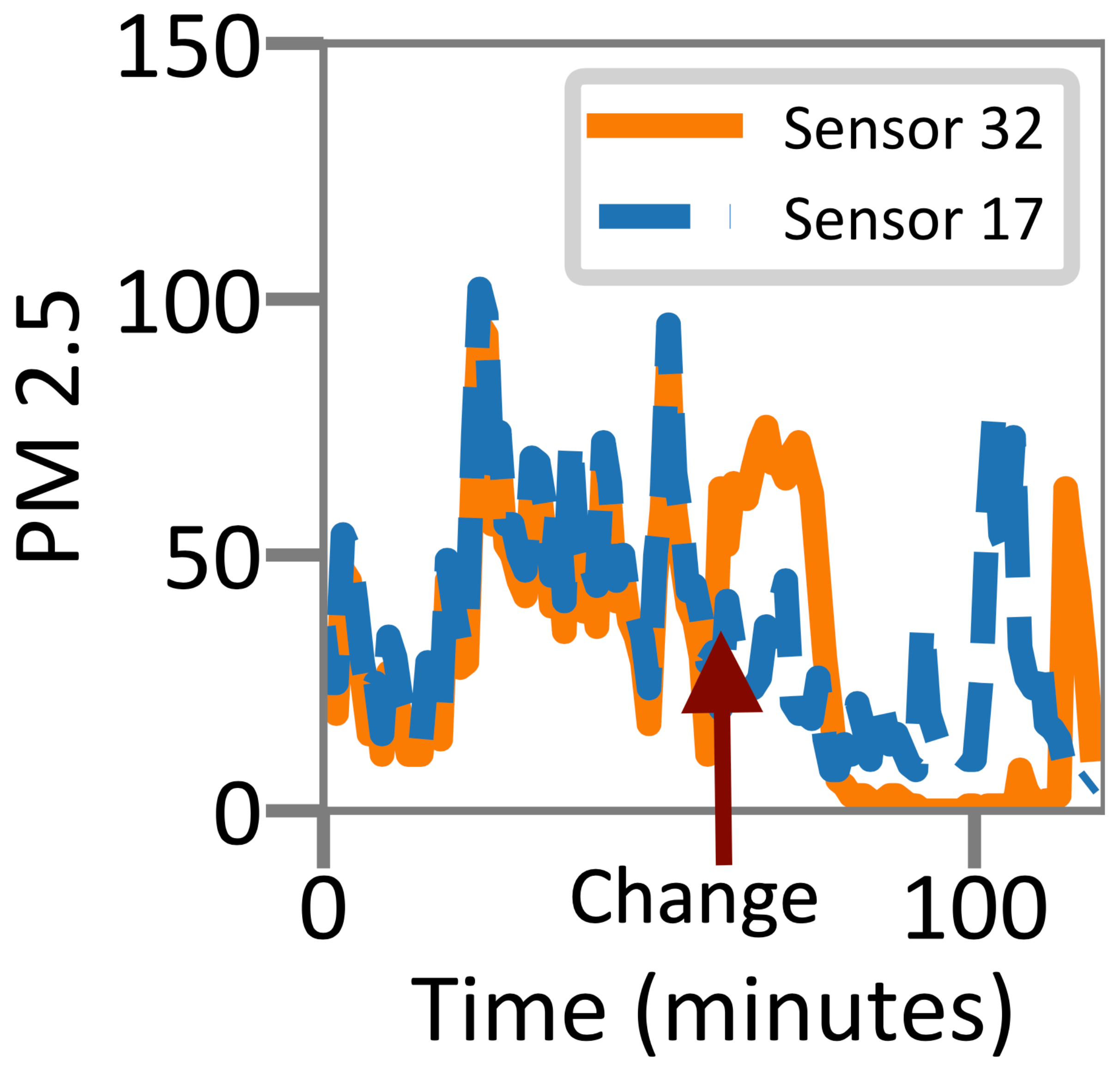

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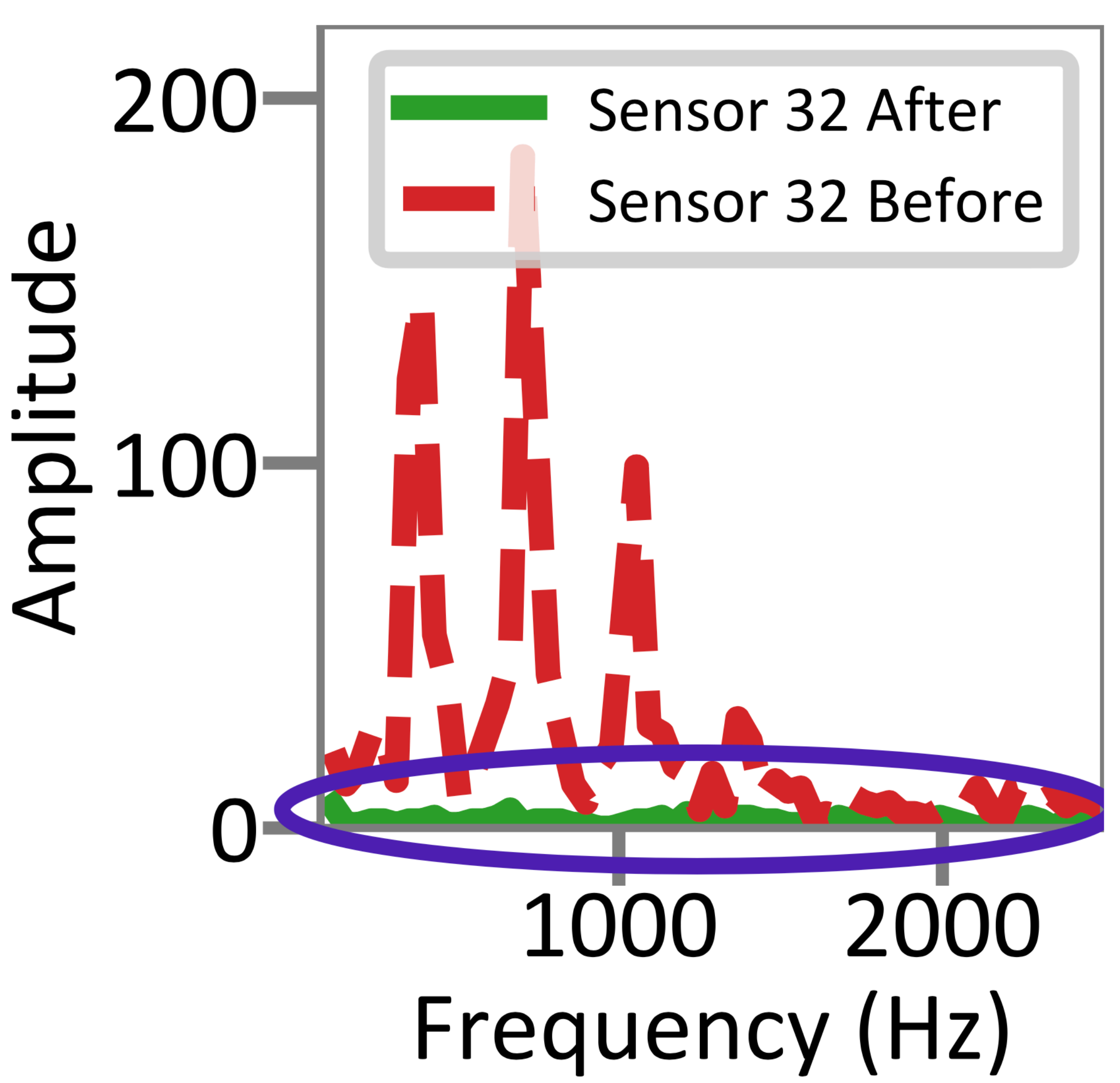

FFT @ 5kHz

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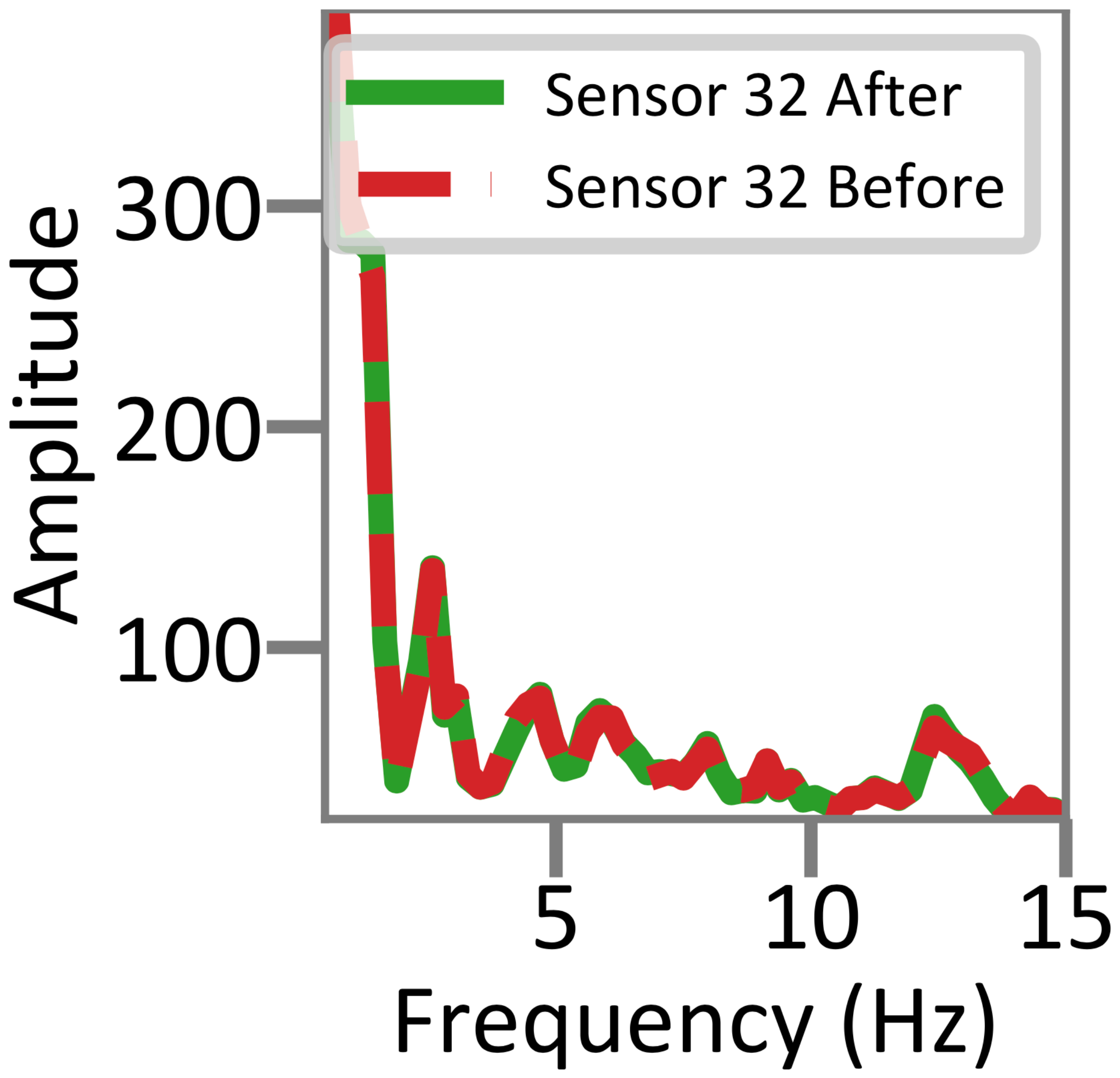

FFT @ 30Hz

Conclusion: We can accurately detect and isolate faults by analyzing CurrentSense fingerprints.

Real-world deployment results

1 Measurement Per Minute

10 Fingerprints Per Week Subsampled

since ground truth was taken weekly

$$10 \times 34 \times 51 = 17340$$

Fingerprints · Weeks · Devices · Total Fingerprints

Real-world deployment results

	Working	Fan Fault	LED Fault	Complete Fault
Working	1.00	0.00	0.00	0.00
Fan Fault	0.04	0.96	0.00	0.00
LED Fault	0.05	0.00	0.95	0.00
Complete Fault	0.03	0.00	0.00	0.97

97.4
% Precision

99.8
% Recall

98.5
% F_1

Real-world deployment results

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Conclusion: A model trained with data collected in the lab can still accurately detect and isolate faults in real-world with an overall F_1 score of 98% across all classes

Comparison with data-centric algorithms

CurrentSense

VS

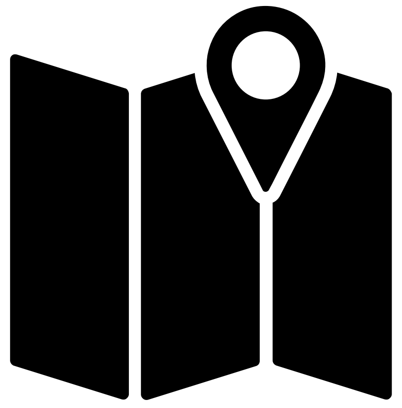
ADF

An Anomaly Detection Framework for Large-Scale $PM_{2.5}$ Sensing Systems

Comparison with data-centric algorithms

Spacial Anomaly

Hyper-local variations in the pollution levels



$F_1 = 77.8\%$

Temporal Anomaly

Distribution of particle matters is generally non-stationary

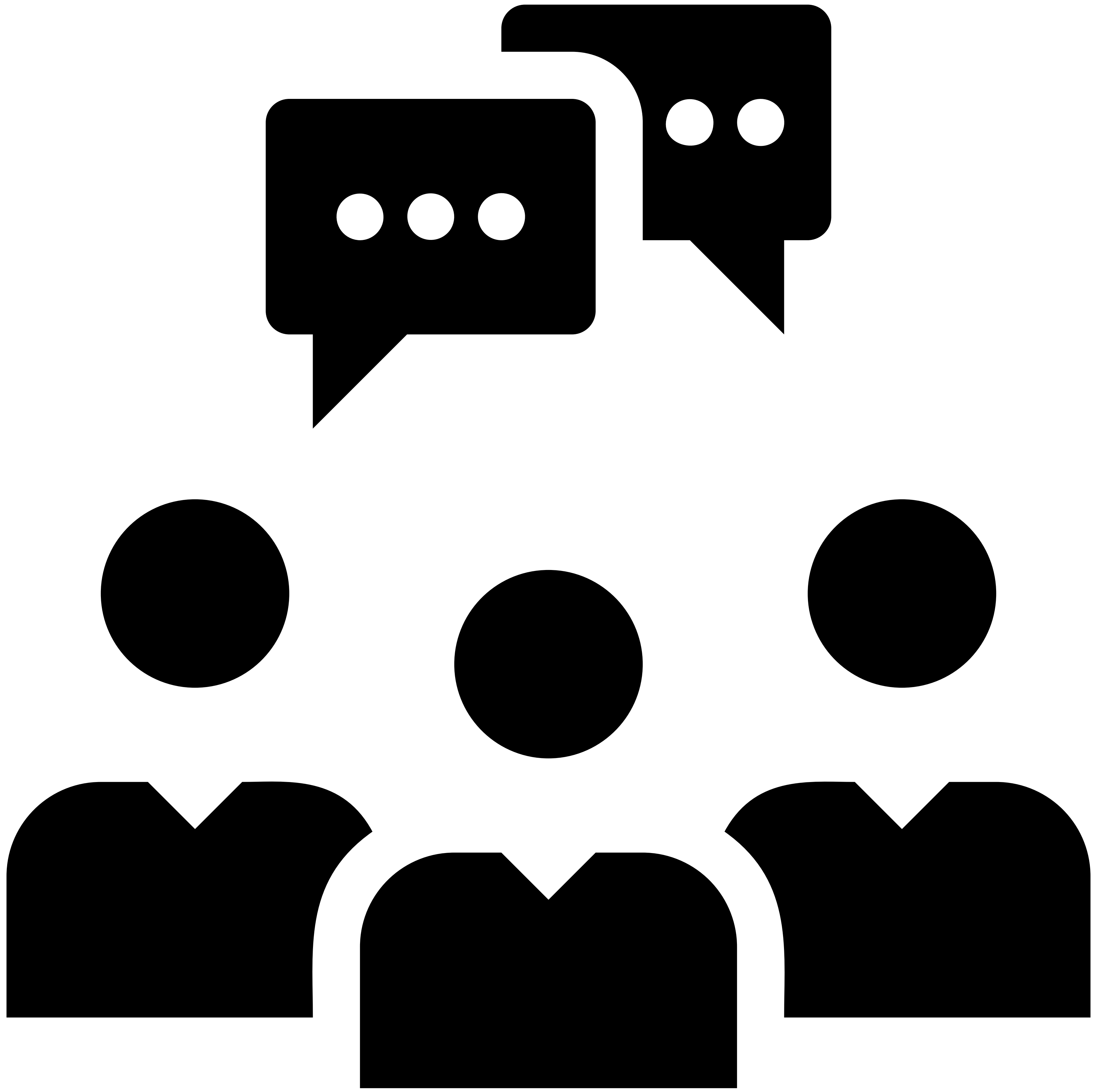
$F_1 = 67.2\%$

Spatio-temporal Anomaly

$F_1 = 33.0\%$

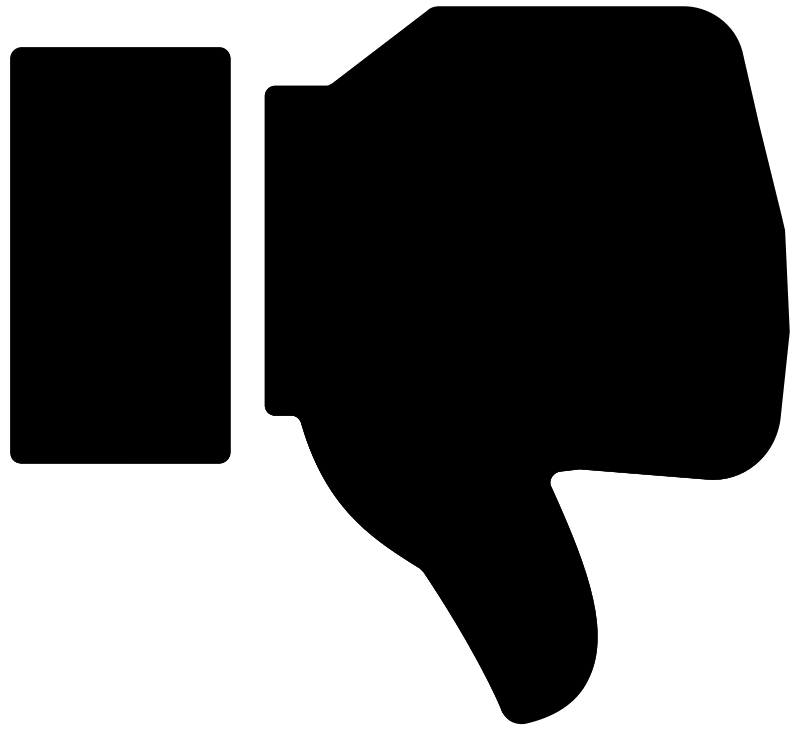
CurrentSense

Discussion



- **Flexible.** Applies to a wide variety of sensors.
- **Rigorously Tested.** Example of thorough experimentation.
- **Relevant.** This could feasibly be rolled out in the near future.

- **Limited.** Cannot detect faults due to environmental factors
- **Costly.** Current amplifiers are expensive relative to the cost of pollution sensors



Any Questions?

What benefits/challenges would there be if a device manufacturer wanted to ship devices with CurrentSense already loaded?

What other applications are there for this “electrical fingerprint”?

In what contexts is drift correction appropriate? Are there any it is not appropriate in?

Are there any digital sensors this approach would not work well for?