SENSELET++: A Low-cost Internet of Things Sensing Platform for Academic Cleanrooms

Beitong Tian, Zhe Yang, Hessam Moeini, Ragini Gupta, Patrick Su, Robert Kaufman, Mark McCollum, John Dallesasse, Klara Nahrstedt

University of Illinois at Urbana Champaign

MASS 2021

Internet of Things is everywhere , however

Smart Home

SmartThings

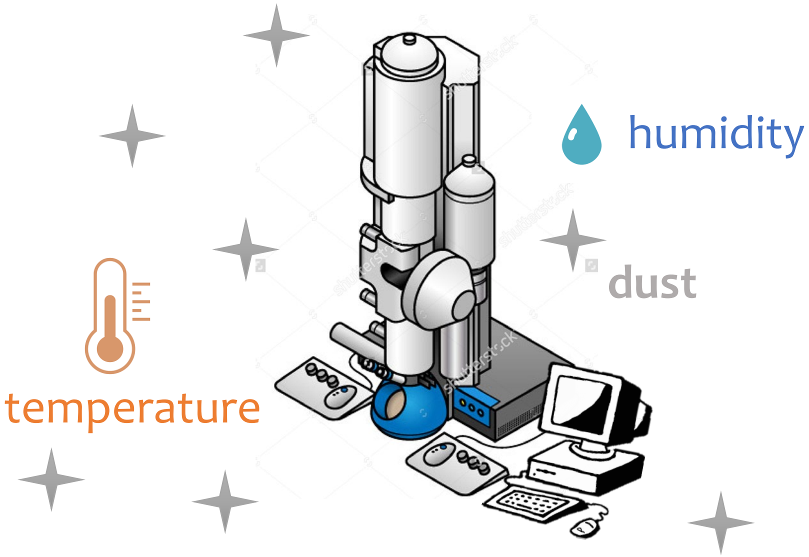
Smart Traffic

Smart Industry

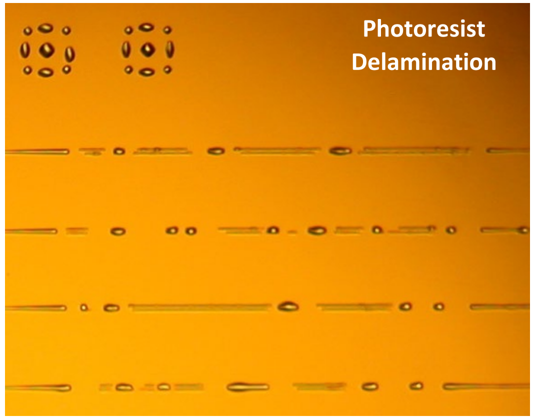
Academic Cleanroom

Why do we need IoT systems in Academic Cleanrooms

- Environmental Monitoring
  - Environmental parameters like humidity, temperature and dust around instruments need to be monitored and controlled to ensure the success of experiment



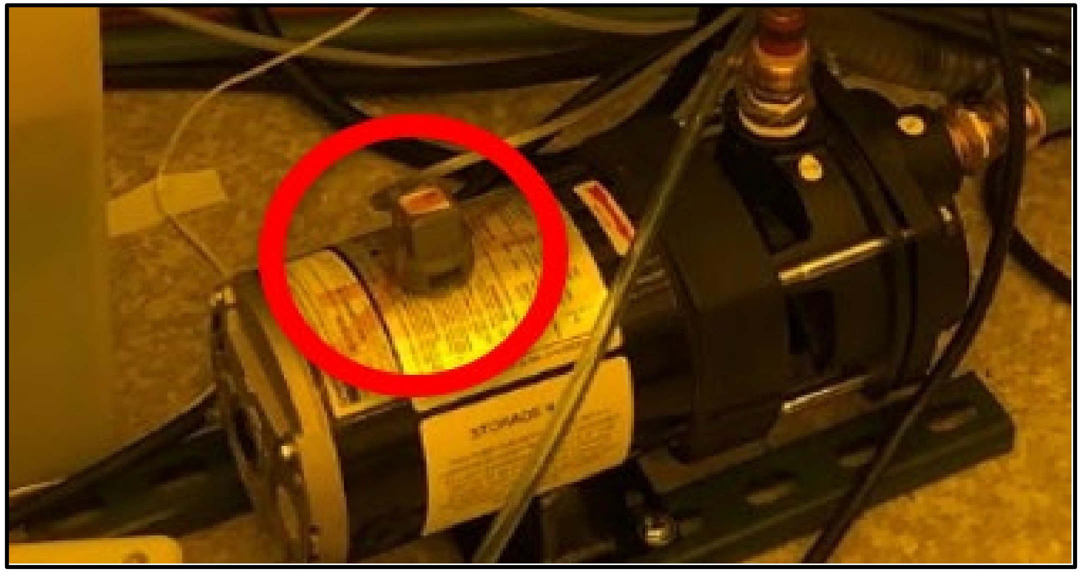
success



fail

Why do we need IoT systems in Academic Cleanrooms

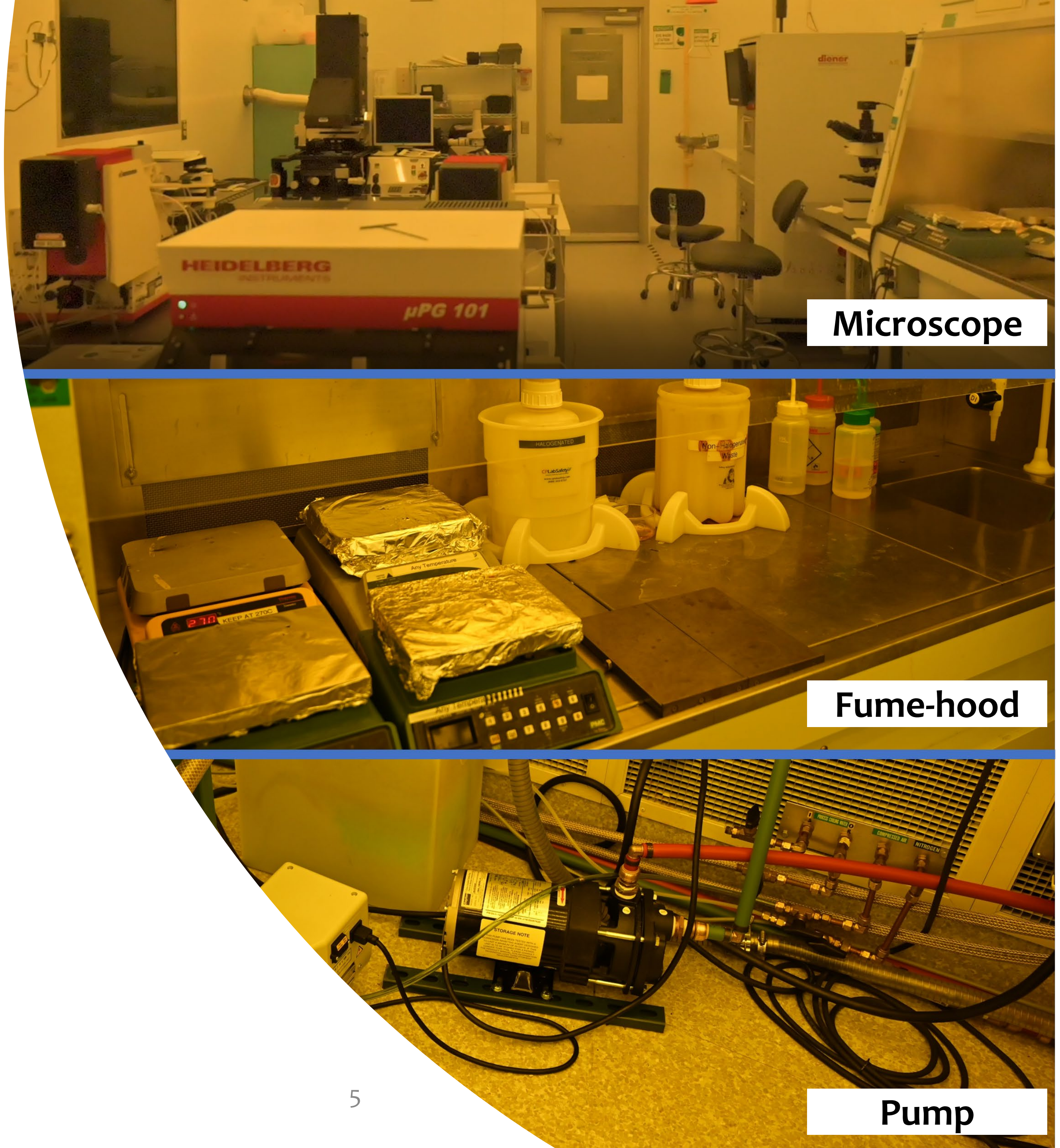
- Instrument Monitoring
  - By monitoring the temperature of the pump, we can determine if the pump is **in a healthy state**.
  - By monitoring the airflow of fume-hood and HVAC systems, we can make sure the toxic gas does not undermine the **safety** of researchers.
- Security Monitoring
  - By monitoring the door at the entrance, we can detect **violated access** to cleanrooms.



Upgrade Academic Cleanrooms is Challenging

Characteristics of Academic Cleanrooms

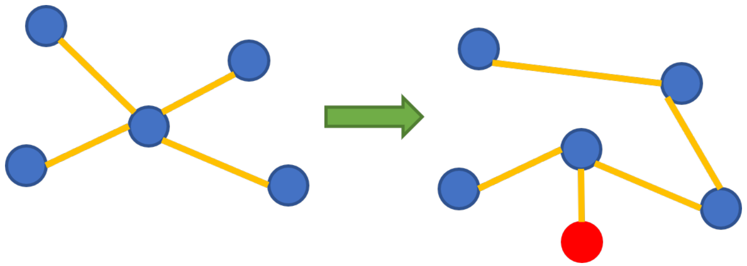
- Highly **diverse research tasks** conducted by researchers
- Highly **diverse scientific**
- Highly **diverse users**
- **Constrained budget** to build and maintain the IoT system in the academic cleanroom

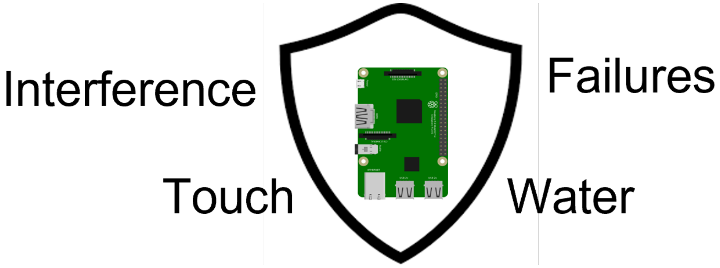


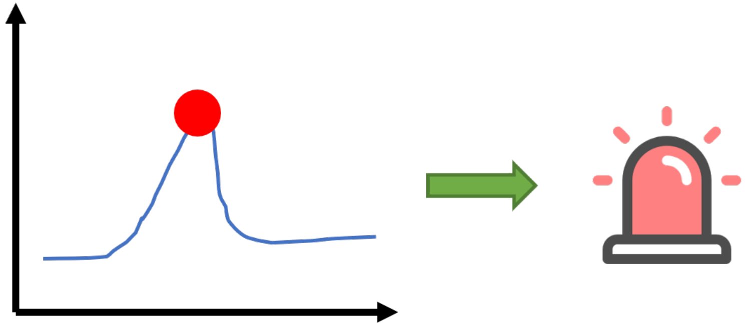
Upgrade Academic Cleanrooms is Challenging

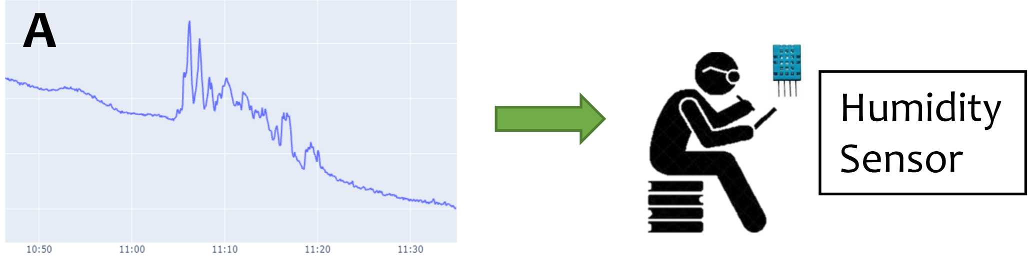
Technical Challenges

- Scalability and Heterogeneity
- Flexibility and Evolvability
- Availability and Reliability
- Effective and Efficient Anomaly Detection

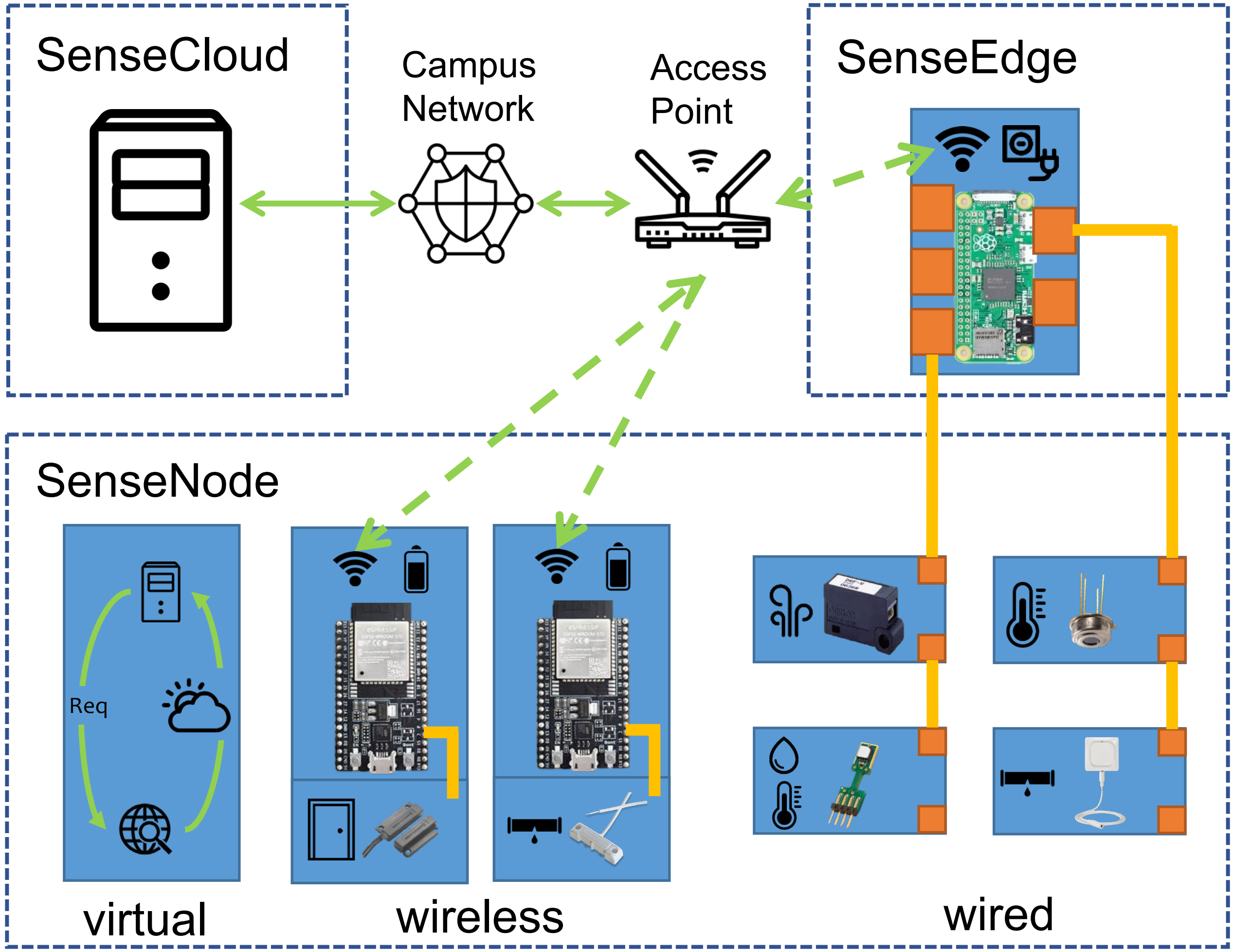




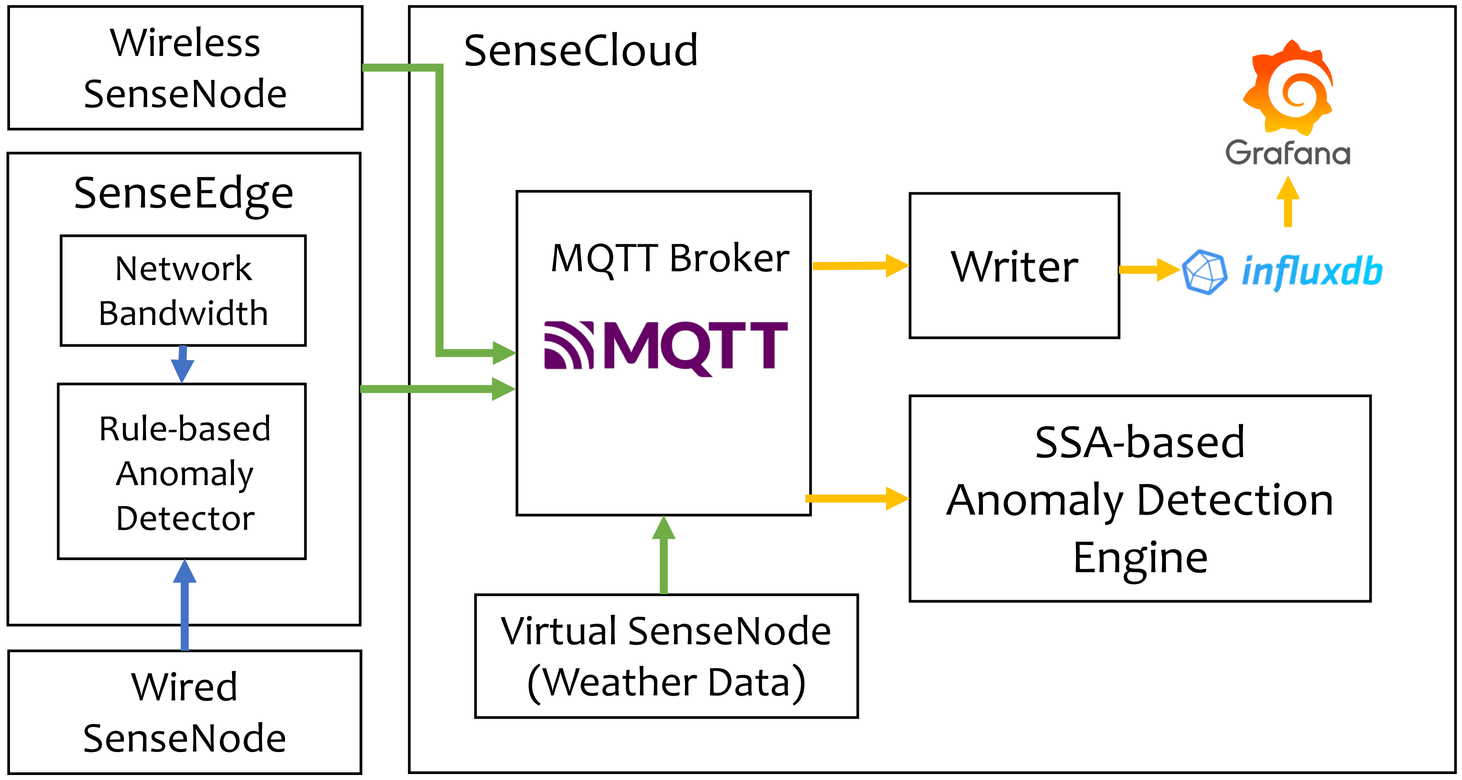




SENSELET++ As The Solution: Hardware and Network



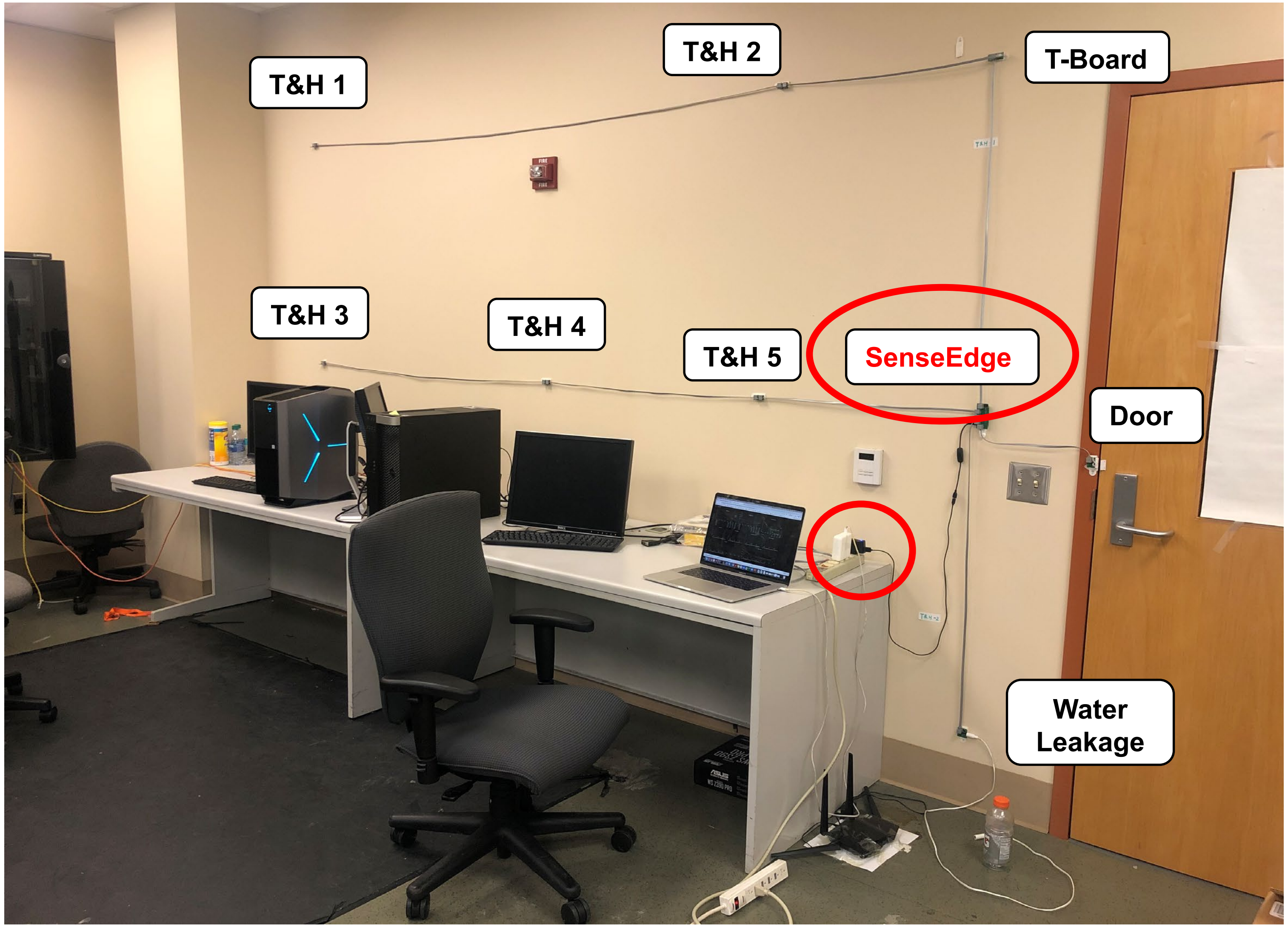
SENSELET++ As The Solution: Data Flow



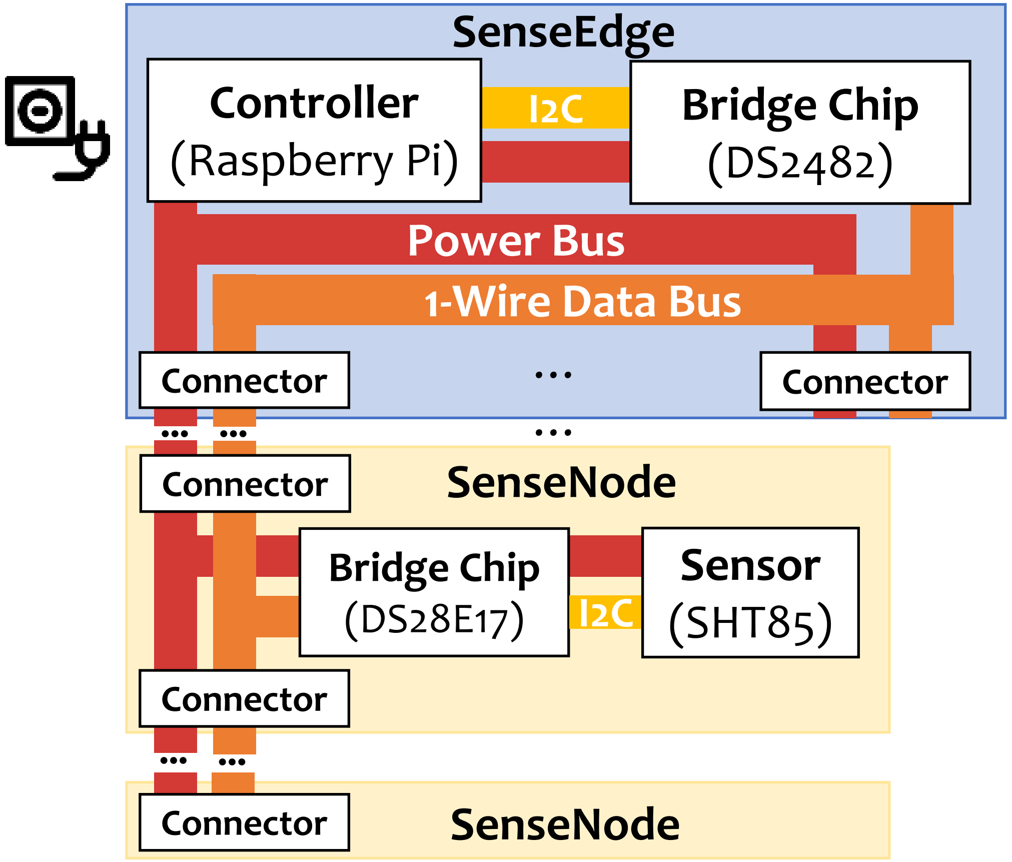
SENSELET++ In Detail

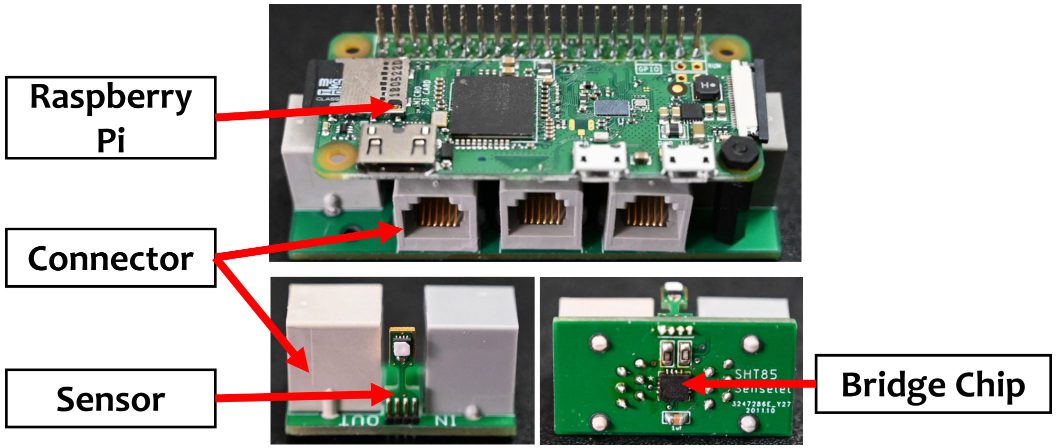
System Design Goal	Solution
Scalability and Flexibility	Customized Interconnection Interface
Availability and Reliability	Separated Design; Customized Closures; Watchdog
Effective and Efficient Anomaly Detection	Fast and Slow Path Anomaly Detection

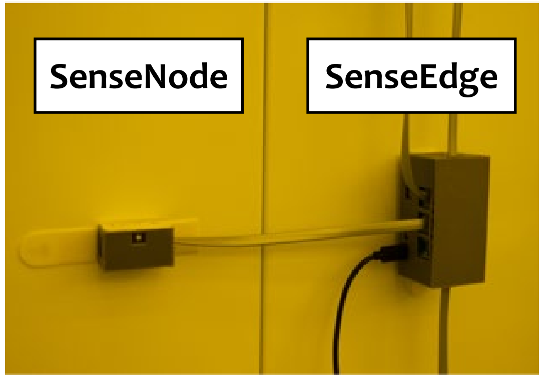
Customized Interconnection Interface



Customized Interconnection Interface







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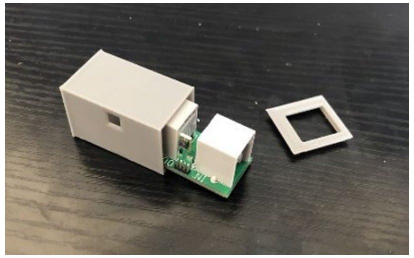

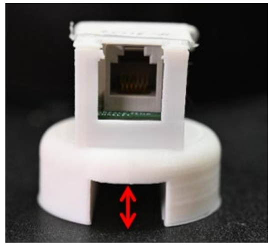

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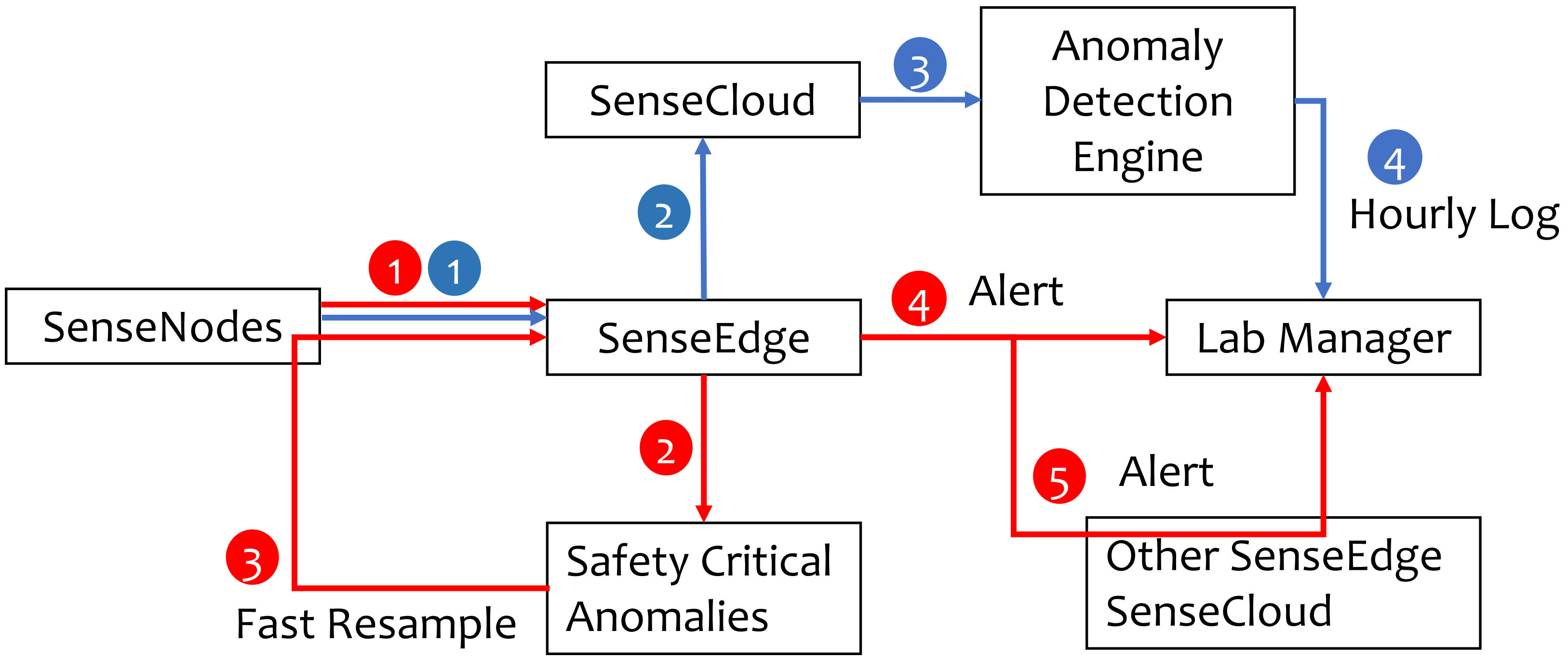
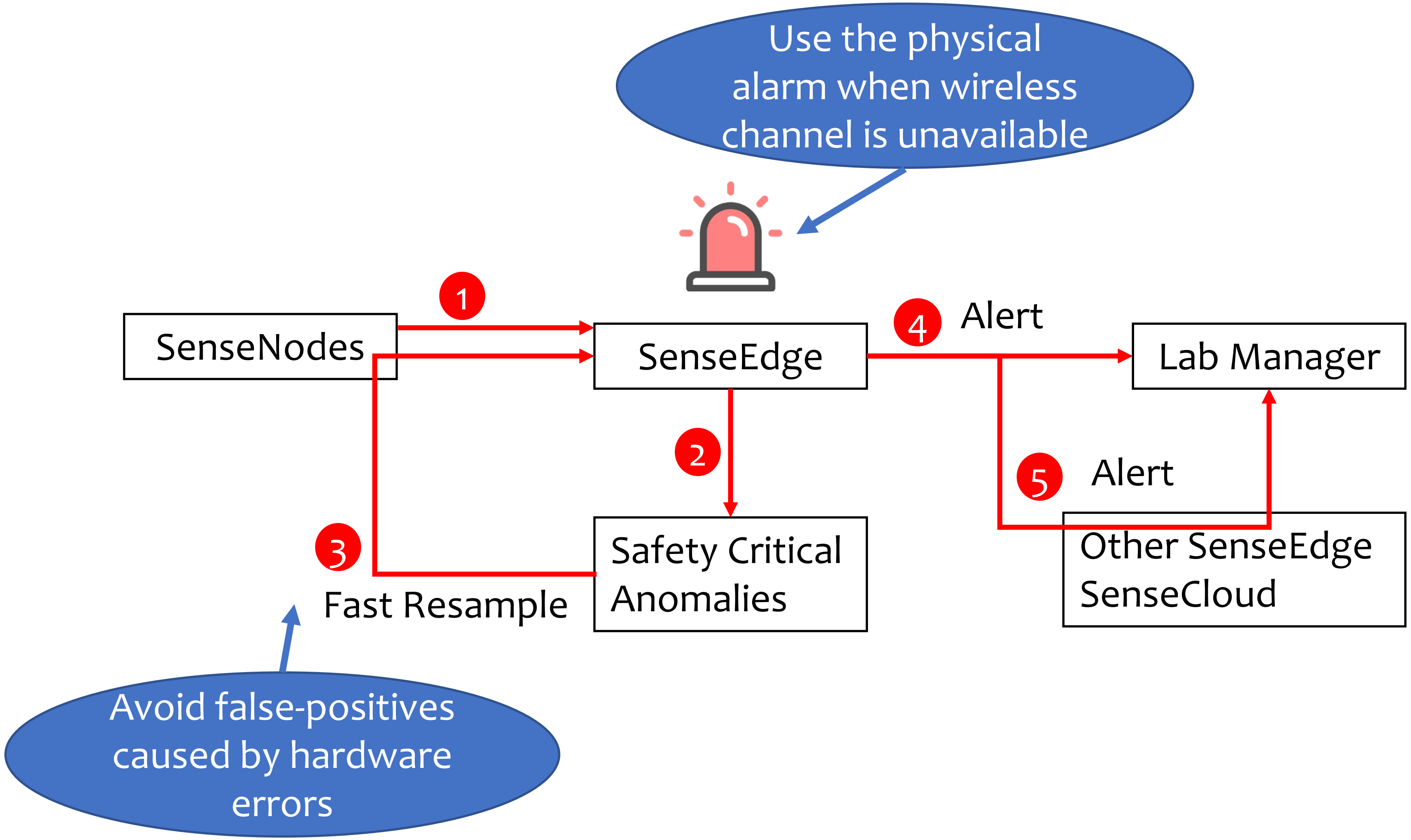
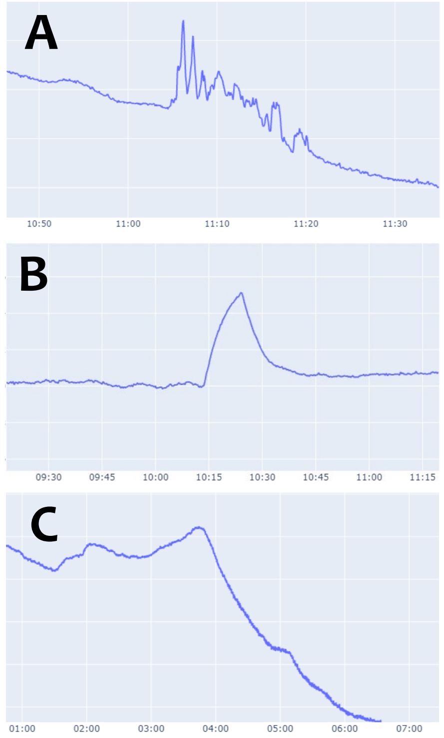
Anomaly Detection



Fast path – For Critical Anomalies

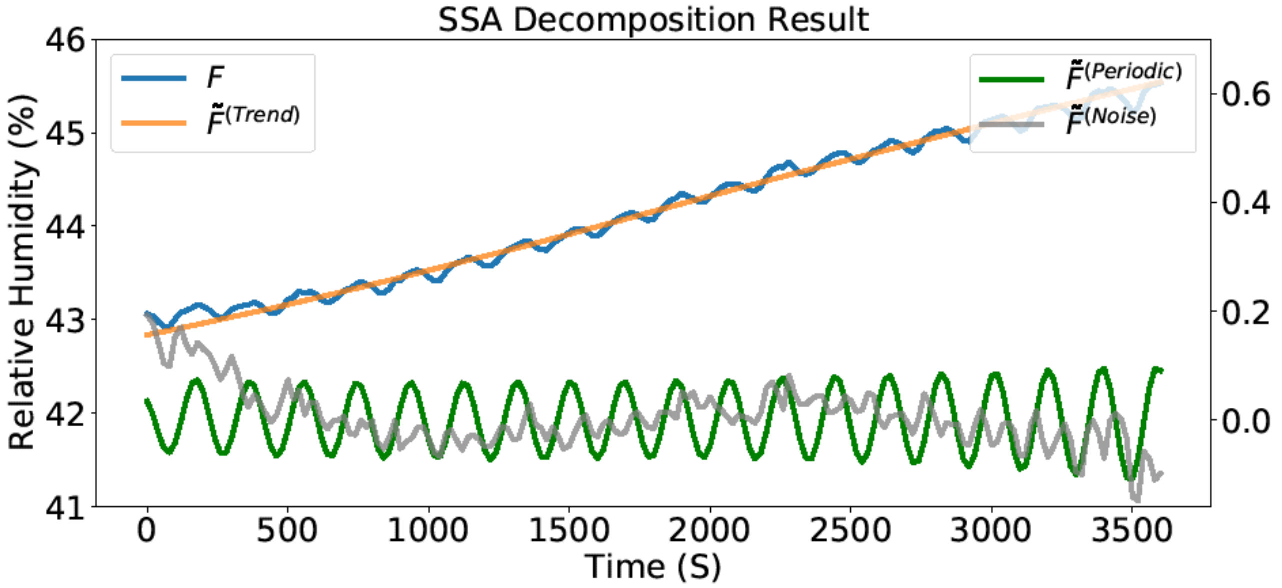


Slow Path – SSA based Anomaly Detection

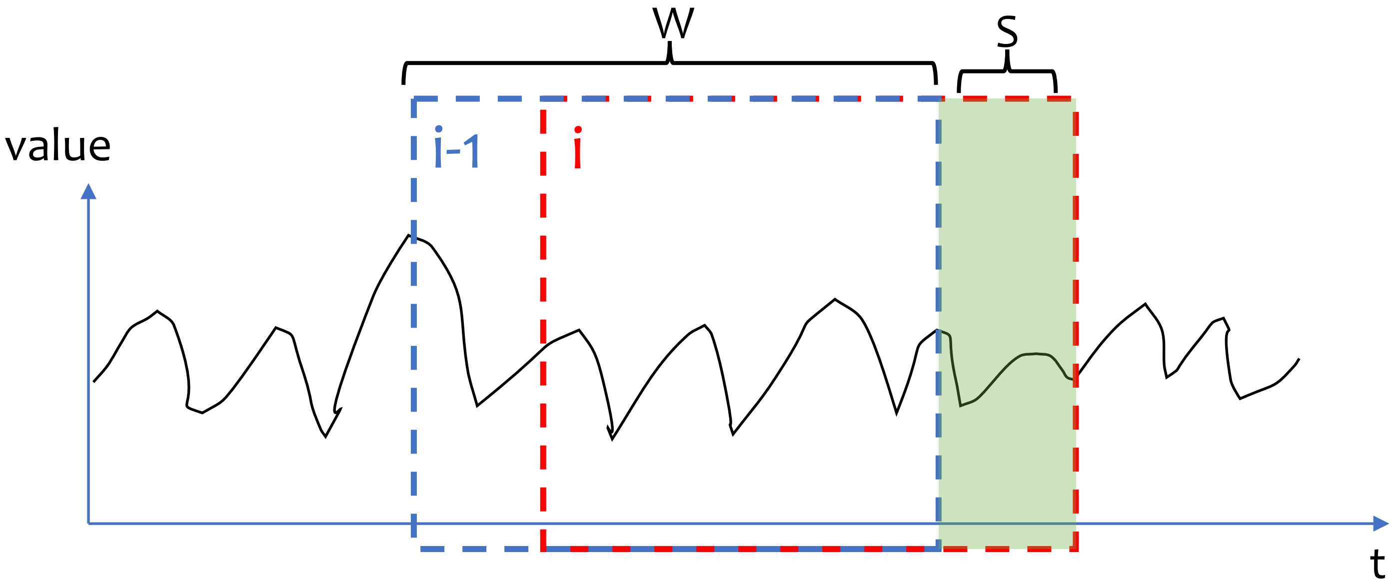


Singular spectrum analysis (SSA) is used to decompose a time series into **Trend, Periodicity** and **Noise** three parts.

$$F \approx \tilde{F}^{(Trend)} + \tilde{F}^{(Periodicity)} + \tilde{F}^{(Noise)}$$



Slow Path – SSA based Anomaly Detection



$\text{Trend}_i, Periodicity_i, Noise_i$

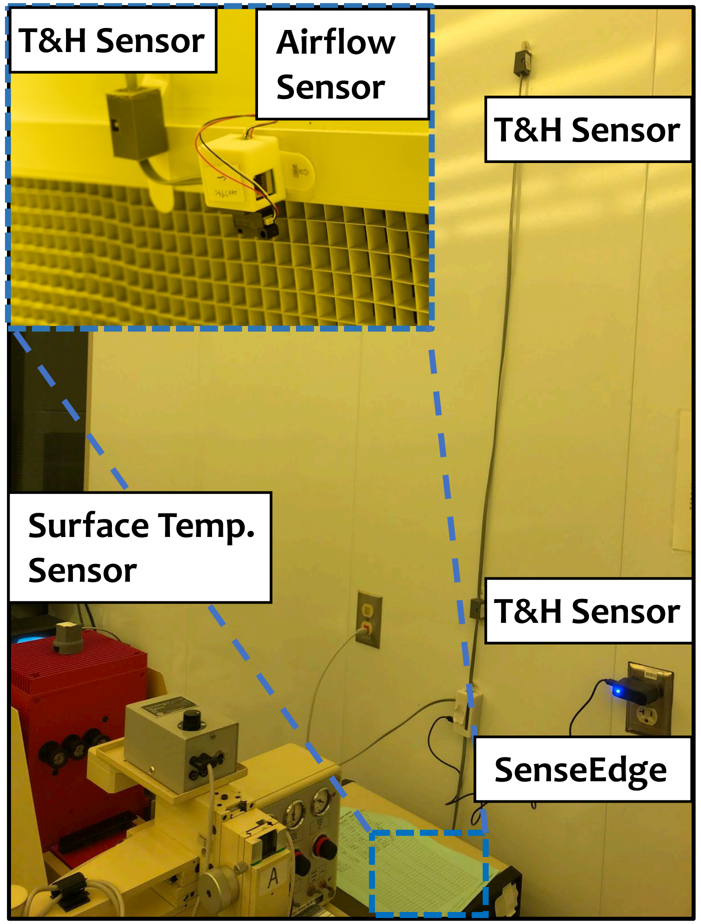
$\text{Trend}_{i-1}, Periodicity_{i-1}, Noise_{i-1}$

$$AS_1 = ||Noise_i[W - S : W]||_2 \quad (1)$$

$$AS_2 = normalize(||Trend_i - Trend_{i-1}||_2) \quad (2)$$

Experimental Validation: Deployment

- We deployed 16 sensors and 4 edge devices in Holonyak Micro and Nanotechnology Laboratory (HMNTL) in UIUC.
- We deployed the SenseCloud in a computer science lab. The server uses i7-2600 CPU with 3.40GHz and 4 GB memory running Ubuntu 16.04.
- The system has run 8 months
- The system generated **new and useful** findings of the cleanroom.



Name	*Count*	*Price ($)*
Temp. & Humidity	8	35
Airflow	3	30
Surface Temp.	2	20
Magnetic Door	2	5
Water Leakage	1	25
SenseEdge	4	25

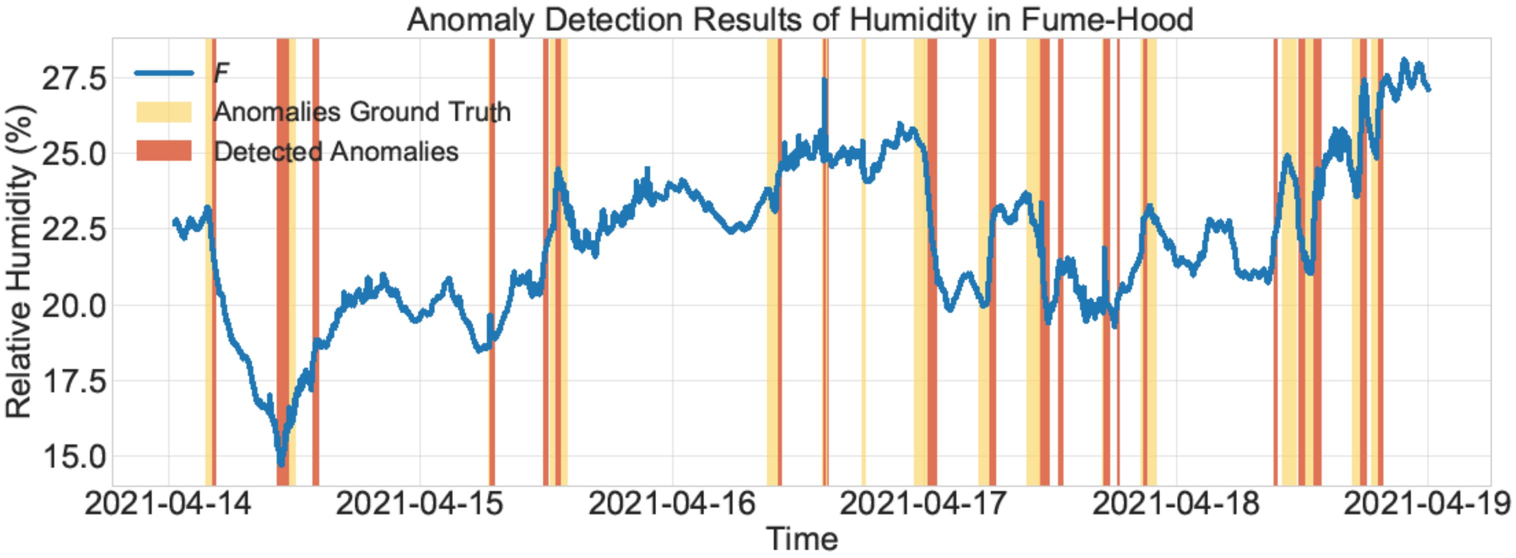
Critical Anomaly Detection Results

- We emulate **four** events for **four** different kinds of sensors
- We repeat each events **ten** times to verify the effectiveness of the anomaly detection system
- We measure the time between the SenseEdge **invokes a sensor reading** to the **alert arrives at the user's server** as the alert latency

Event	*Alert Rule*	*Success Rate*	*Latency* **Mean ± Std. (s)**
Fire	$> 30°C$	10 / 10	0.23 ± 0.09
Overheat	$> 70°C$	10 / 10	0.14 ± 0.04
Water Leak	if True	10 / 10	0.29 ± 0.04
Door Open	if True	10 / 10	0.09 ± 0.03

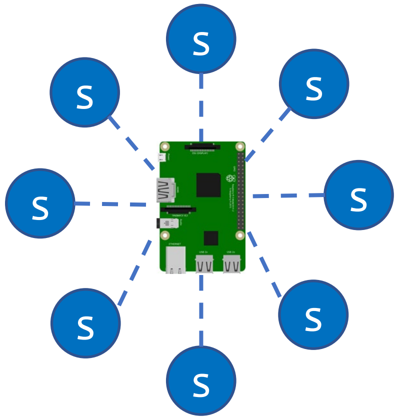
SSA-Based Anomaly Detection Results

- We randomly choose **5-days** data to test the SSA-based anomaly detection system
- We **manually** labelled the anomalies in the chosen dataset.
- We use the number of **false negatives and false positives** as our metrics.

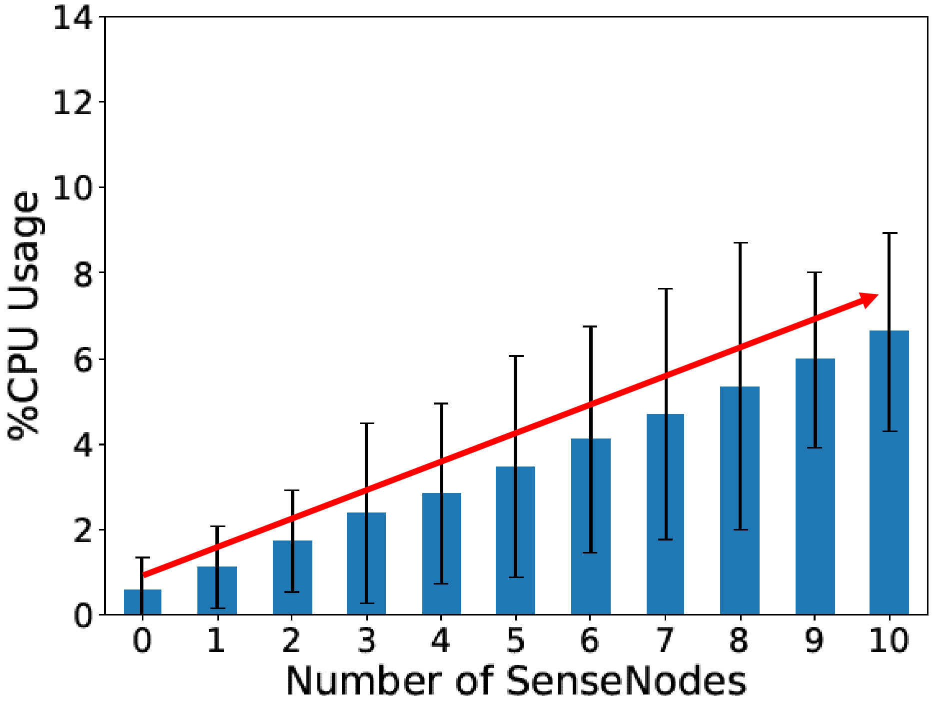


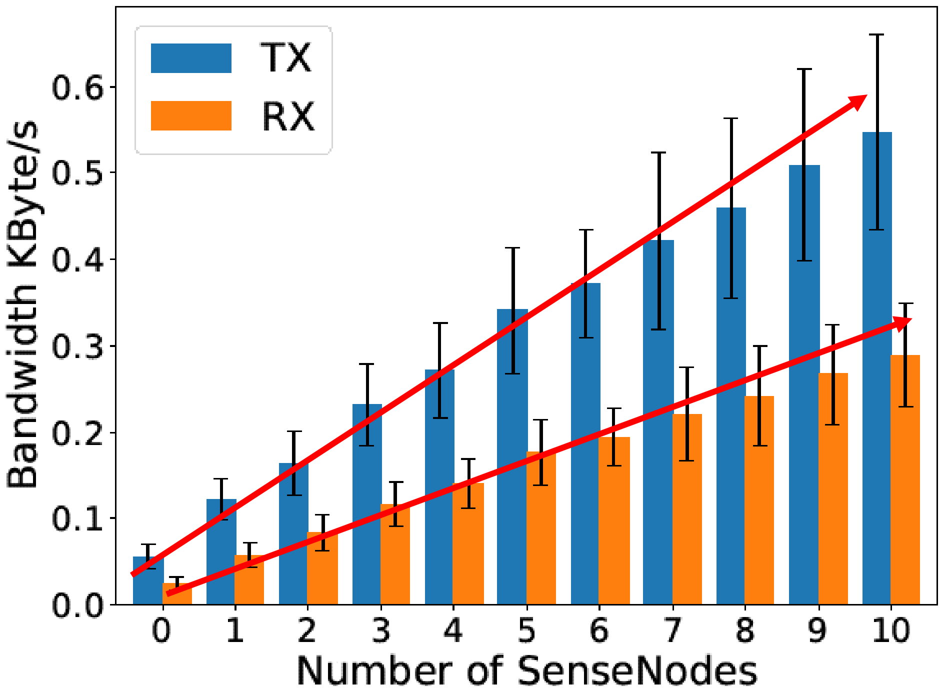
Data Stream	*Shape Anomaly*	*Trend Anomaly*	*False Positive*
Humidity 1	5/6	11/11	2
Humidity 2	1/2	9/11	1
Temperature 1	0/0	7/8	8
Temperature 2	14/14	4/4	1
Total	20/22	31/34	12

Scalability of SenseEdge

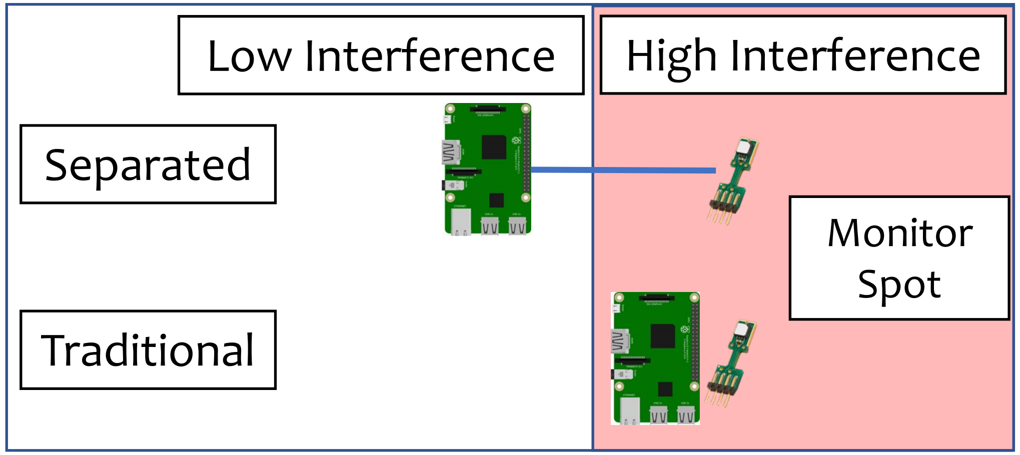


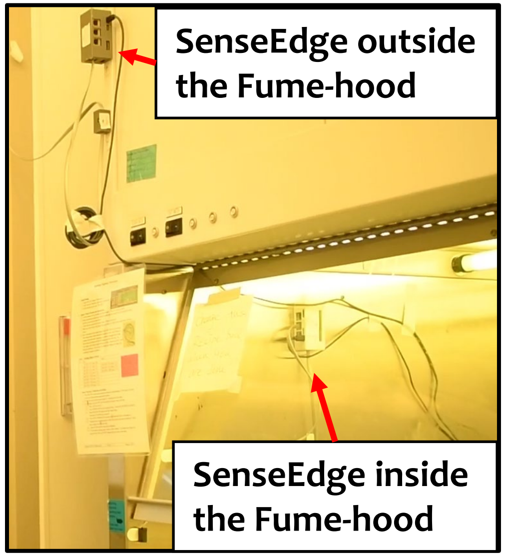
Sampling
frequency: 0.5 Hz

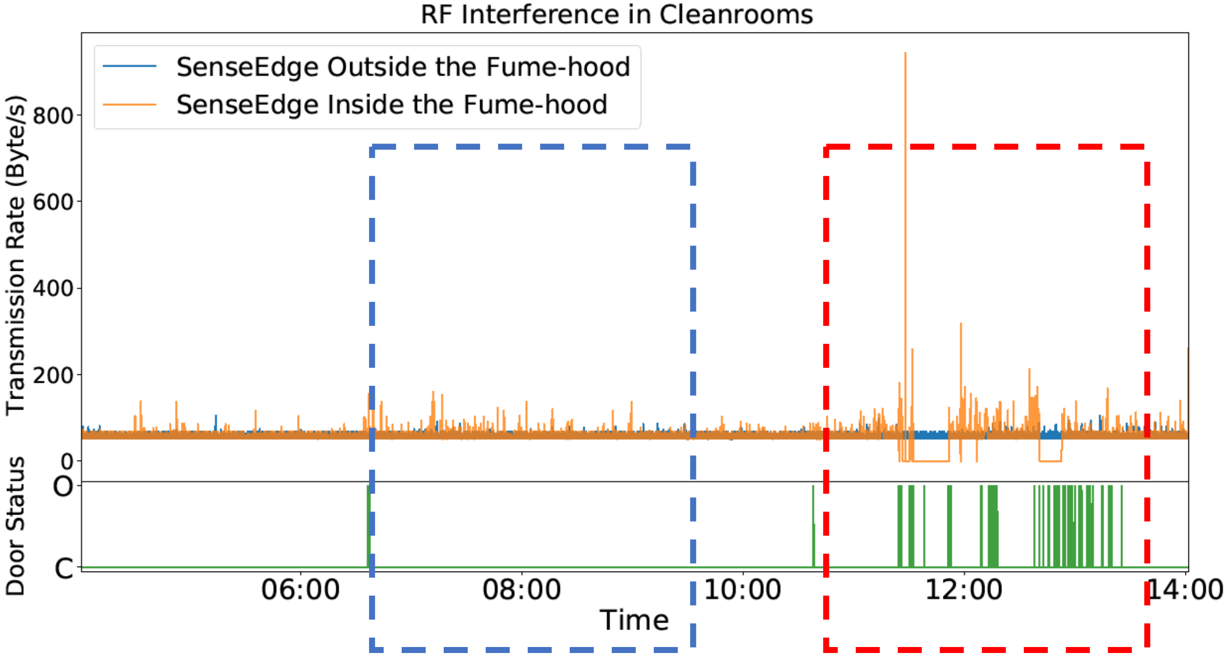




Robustness to the Wireless Interference







Conclusion

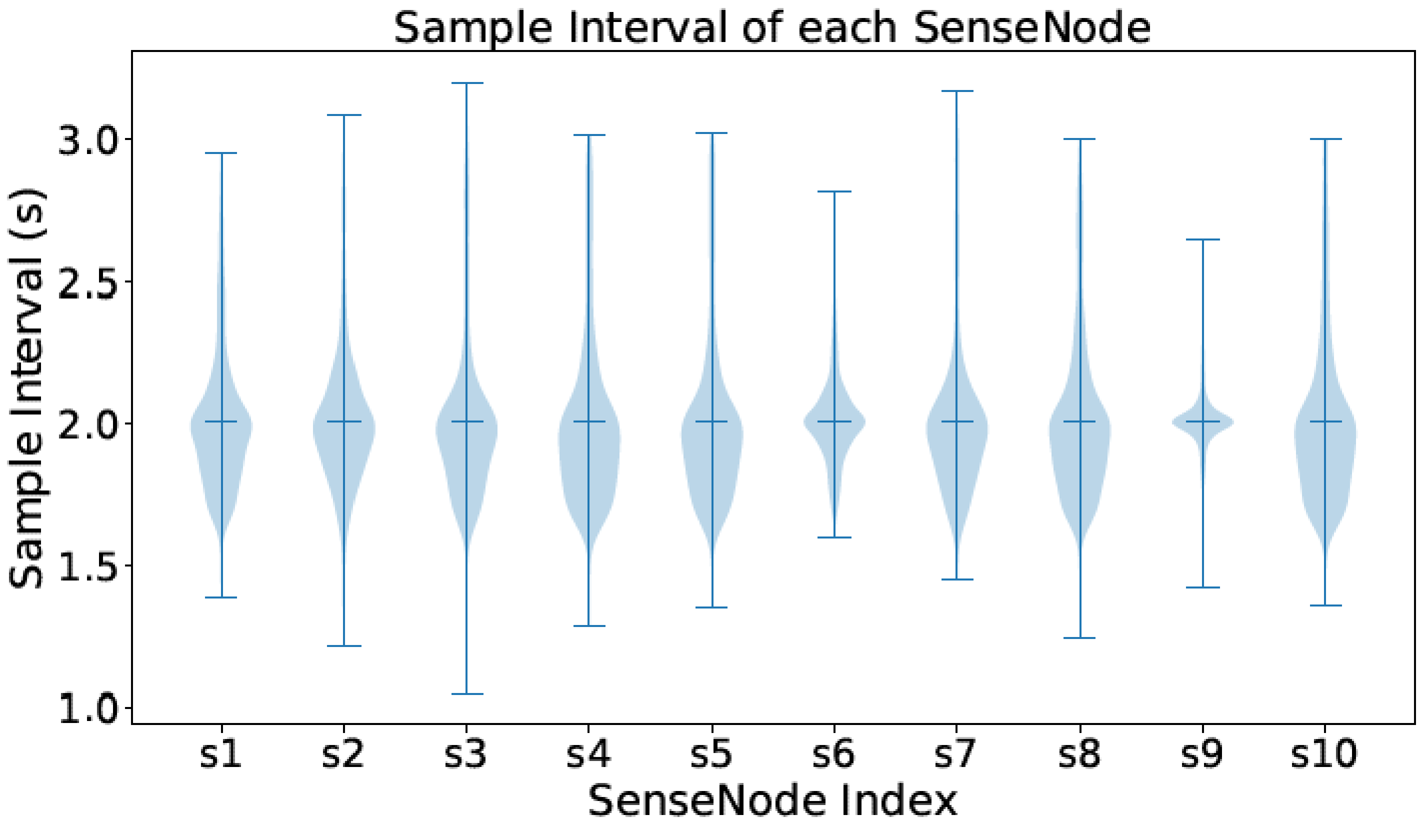
- We present design of **SENSELET++**, an IoT system for academic cleanrooms.
- We validate our system in a **real academic cleanroom**.
- The proposed system can also be used by academic community in other scenarios for **long-term data collection**.

Thank you!

(beitong2@illinois.edu)

Backup

Real Sample Interval



Critical Anomaly Detection Results

TABLE II
CRITICAL ANOMALY DETECTION RESULTS

Event	*Alert Rule*	*Success Rate*	*Latency* **Mean ± Std. (s)**
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Parameters used in SSA-Based Anomaly Detection

TABLE III
SSA-BASED ANOMALY DETECTOR SETTING

Parameter Name & Symbol	*Value*
Sliding Window Width W	180 samples (30 minutes)
Sliding Window Step S	30 samples (5 minutes)
Trajectory Matrix Size L	60 samples (10 minutes)
Anomaly Shape Threshold	1.5 (humidity); 0.125 (temperature)
Trend Change Threshold	0.15 (humidity); 0.08 (temperature)

TABLE IV
SSA-BASED ANOMALY DETECTION RESULT

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