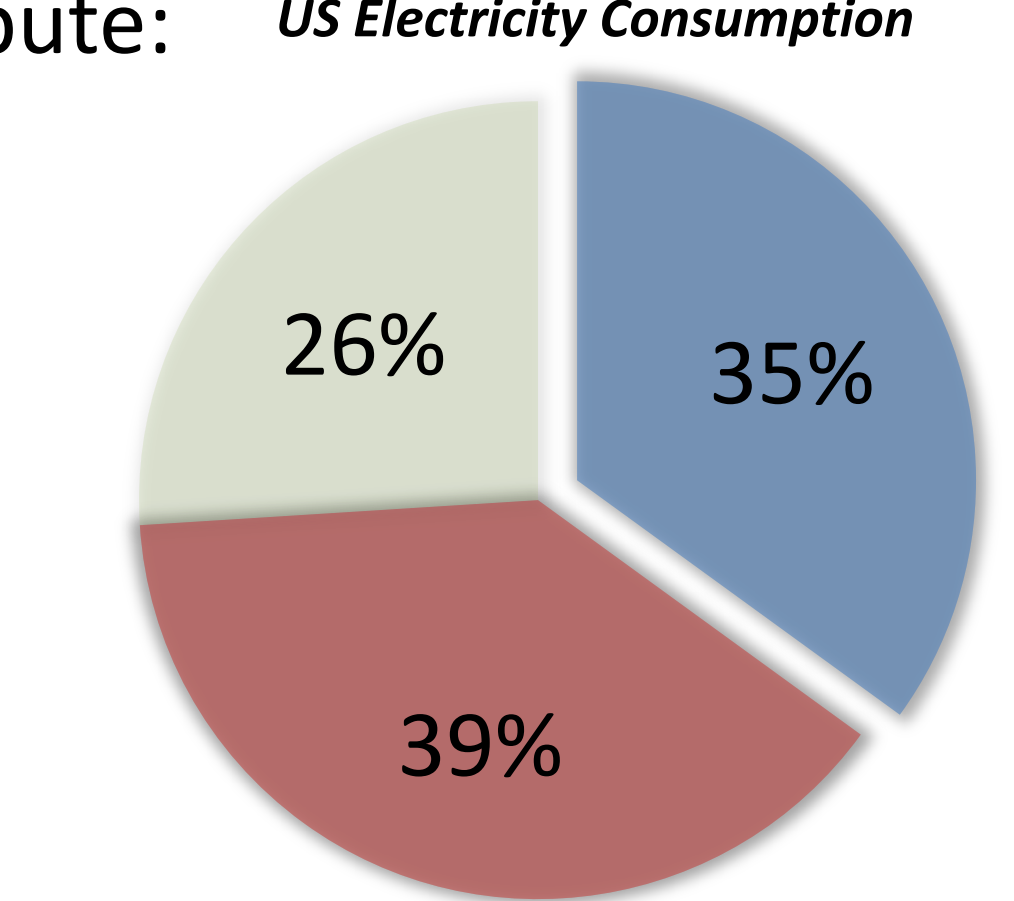


Smart Buildings

- Commercial buildings contribute: *US Electricity Consumption*
 - 19% of primary energy
- HVAC systems contribute:
 - 25%-40% of electricity
 - 50% of primary energy
- People spend 87% of their time indoors.
- Lot of Building sensors
 - UCSD → 180,000 sensor points across 55 buildings
 - How do we exploit sensor information?
- Smart building applications
 - Fault detection
 - Occupancy-based control
 - Smart grid
 - Demand response



Commercial Residential Industrial

HVAC Background

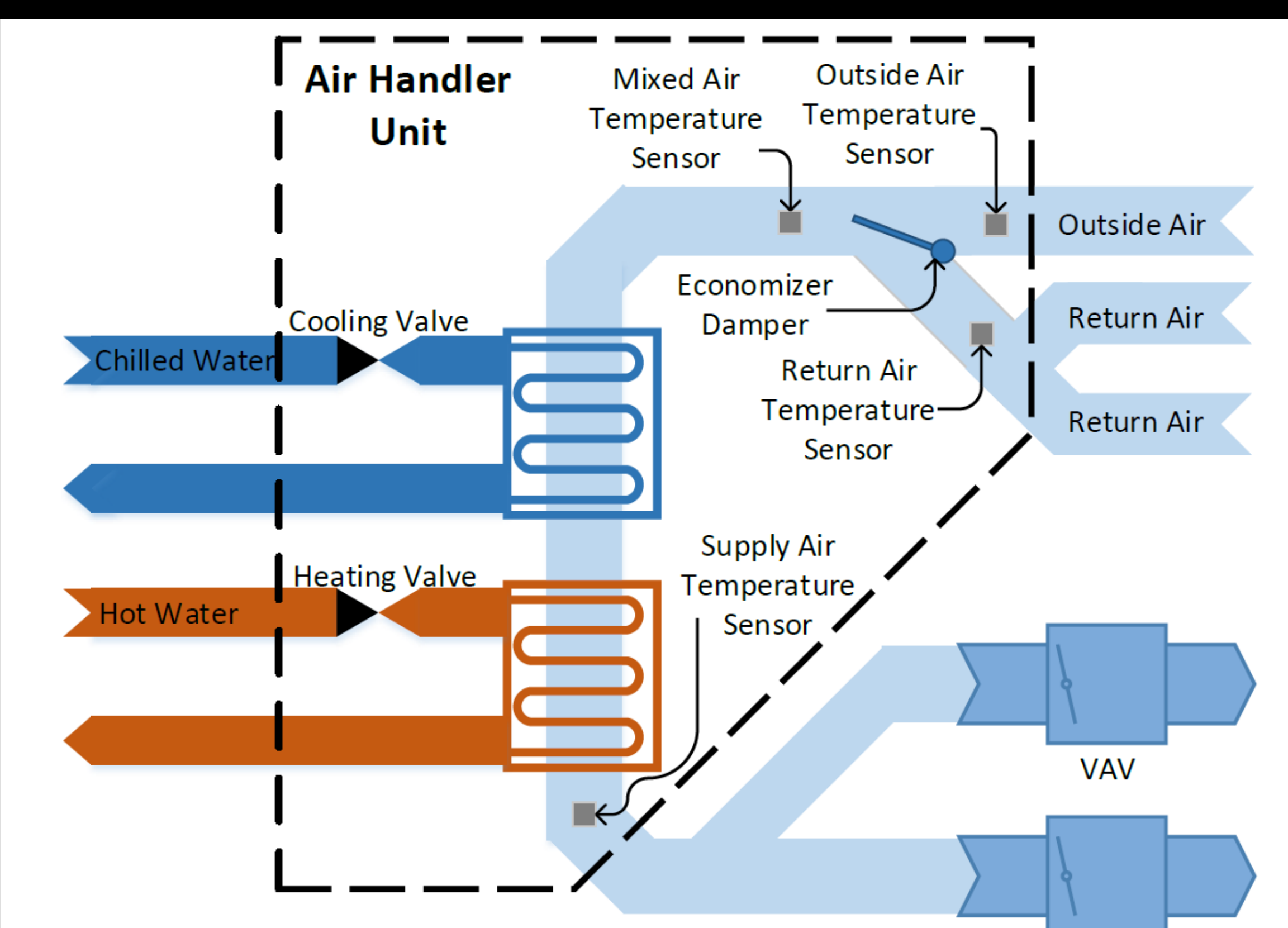


Figure depicture HVAC Air Handler Unit. Sensors monitor equipment and provide feedback to control system

Sensors & Naming

- Each sensor and its metadata is named differently
 - Variation in vendor, equipment, manual input
 - Example: Zone Temperature, Zone Temp, Temp Rm 23, ZN-T
- Commercial Solution: Regular expression
 - It requires domain expertise
 - Fails to exploit additional metadata and sensor data

Vendor Given Name	Description
BLDG2.RM-2819.SUP-FLOW	Supply Air Flow
BLDG3 1stFI RM-111.SUPFLOW	Process Variable

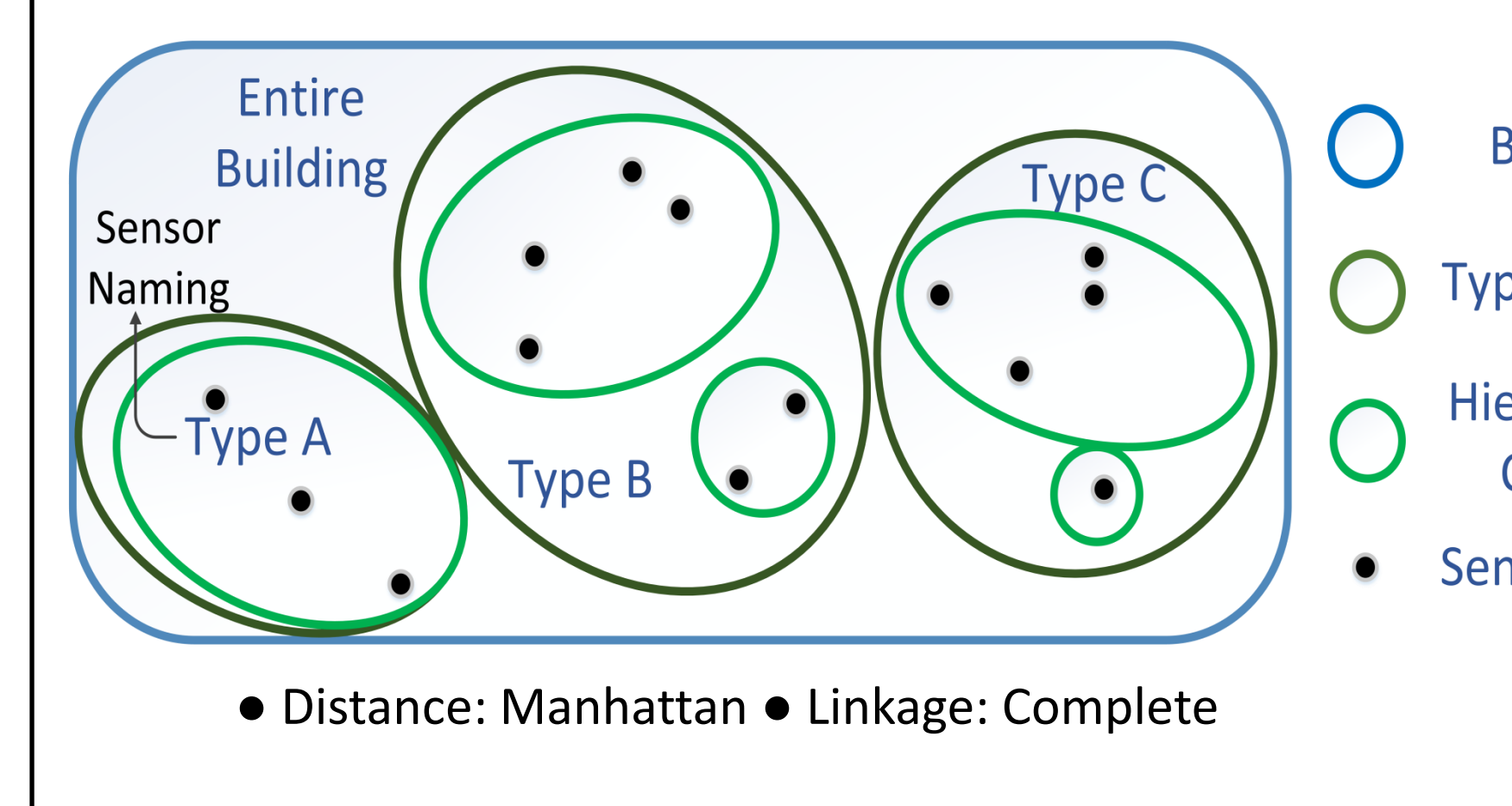
Building # Room # Sensor Type

Identifying Sensor Types

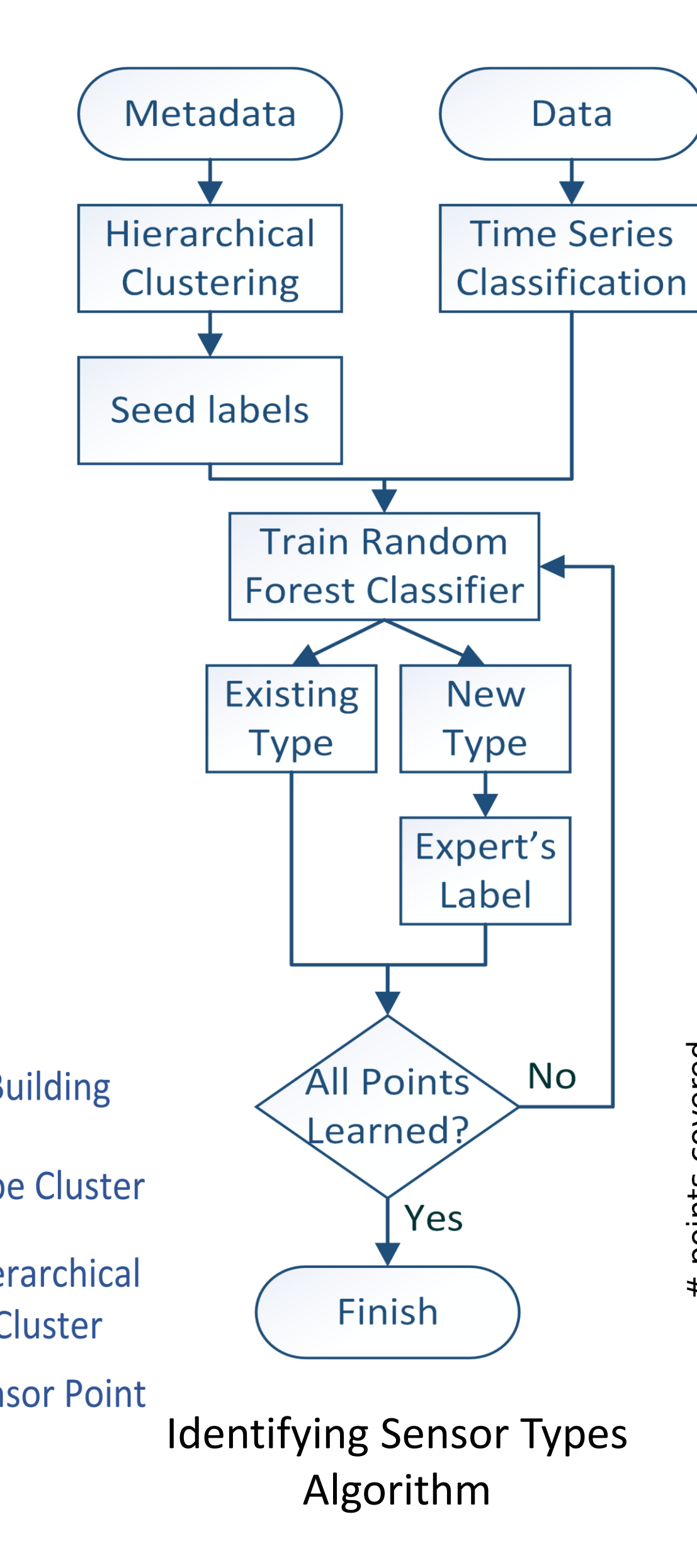
Hierarchical Clustering

- Agglomerative clustering of *bag of words* from tokenization of metadata
- Clusters together sensors of same type
- Advantages of clustering
 - Exploits intrinsic similarities
 - Does not require domain expertise
- For four buildings, accuracy of clustering sensors of same type is 98.7 %

Building	Sensor Points	Unique Sensor Types	Hierarchical Clusters
Bonner Hall	3213	251	300
Biomedical Science	11910	367	1105



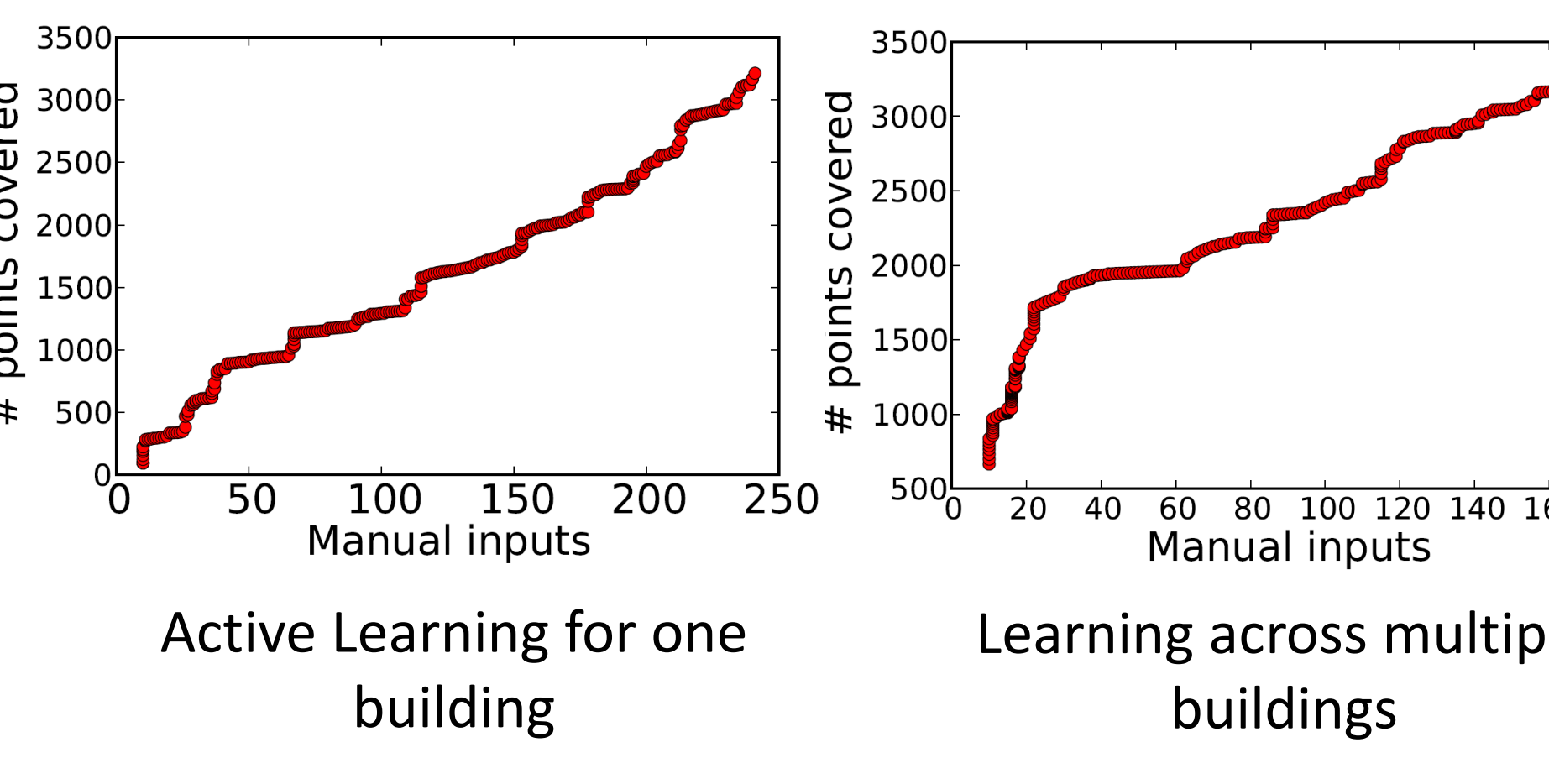
Distance: Manhattan Linkage: Complete



Identifying Sensor Types Algorithm

Active Learning

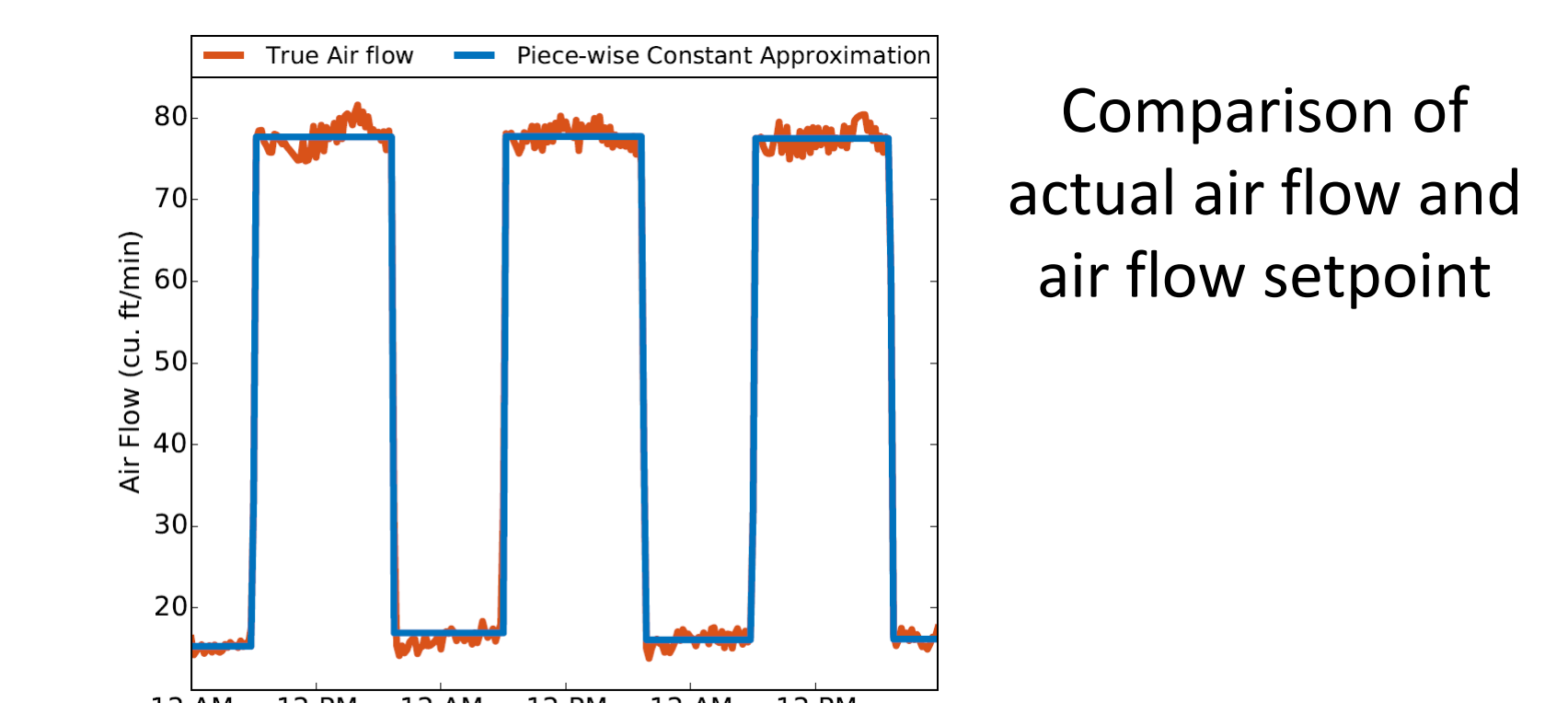
- Some sensor points of same type cannot be clustered together
 - "supply flow", "airflow rate" and "supply flow feedback".
- We use *active learning* for mapping metadata and point type automatically
- Accuracy of labeling a building is 99.3 %
- Manual labeling is reduced by 27%
- Able to learn sensor types across buildings from metadata



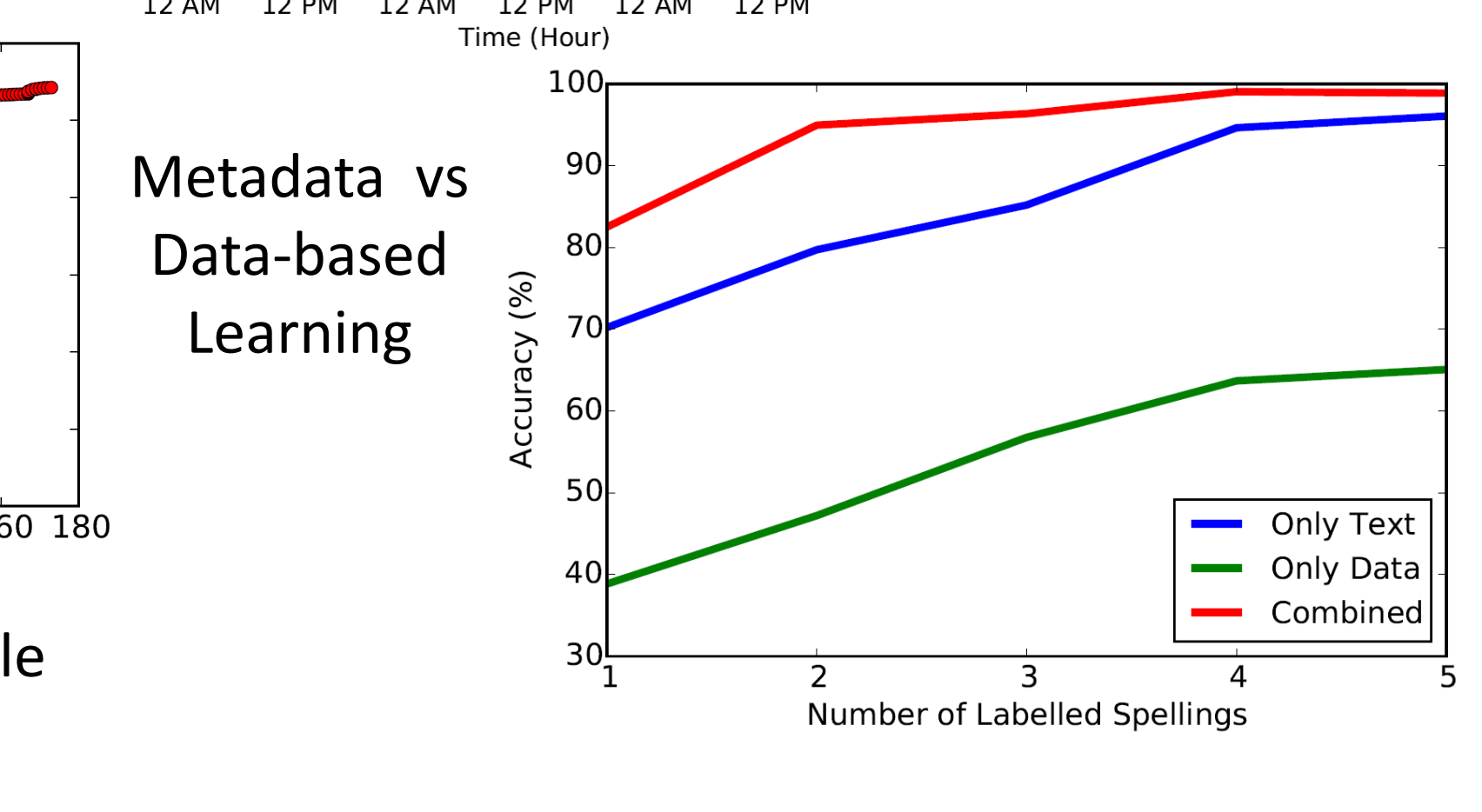
Active Learning for one building Learning across multiple buildings

Exploiting Sensor Data

- Extract feature from sensor data:
 - Scale-based
 - Pattern-based
 - Texture-based
 - Shape-based
- Flow sensor and flow setpoint have same shape, but different texture.




Comparison of actual air flow and air flow setpoint

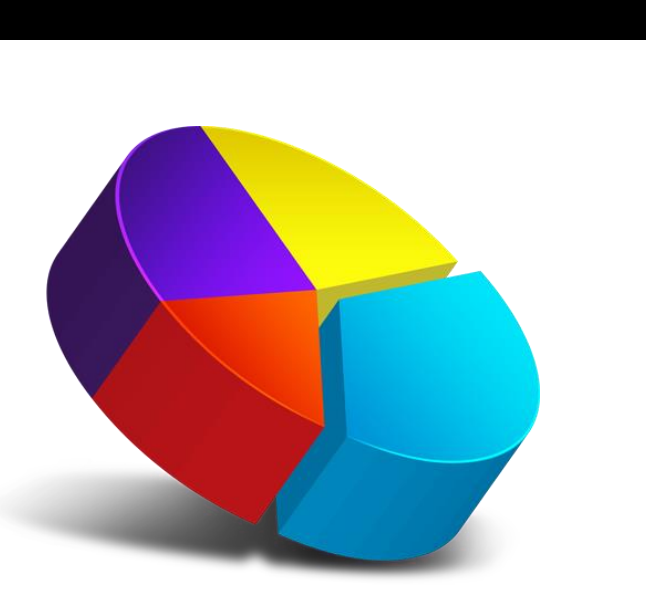


Metadata vs Data-based Learning

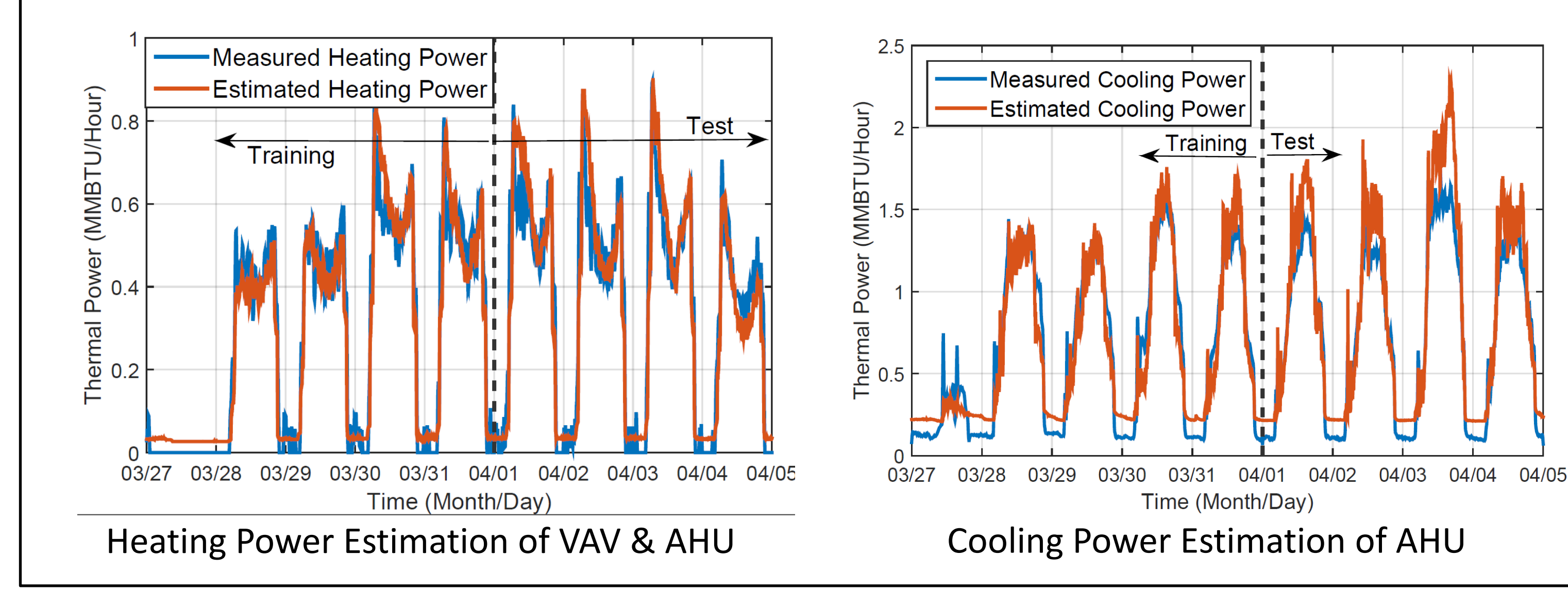
HVAC Working & Energy Analysis



- Installed power meters only provide building level consumption
- Cannot breakdown power by individual equipment and rooms



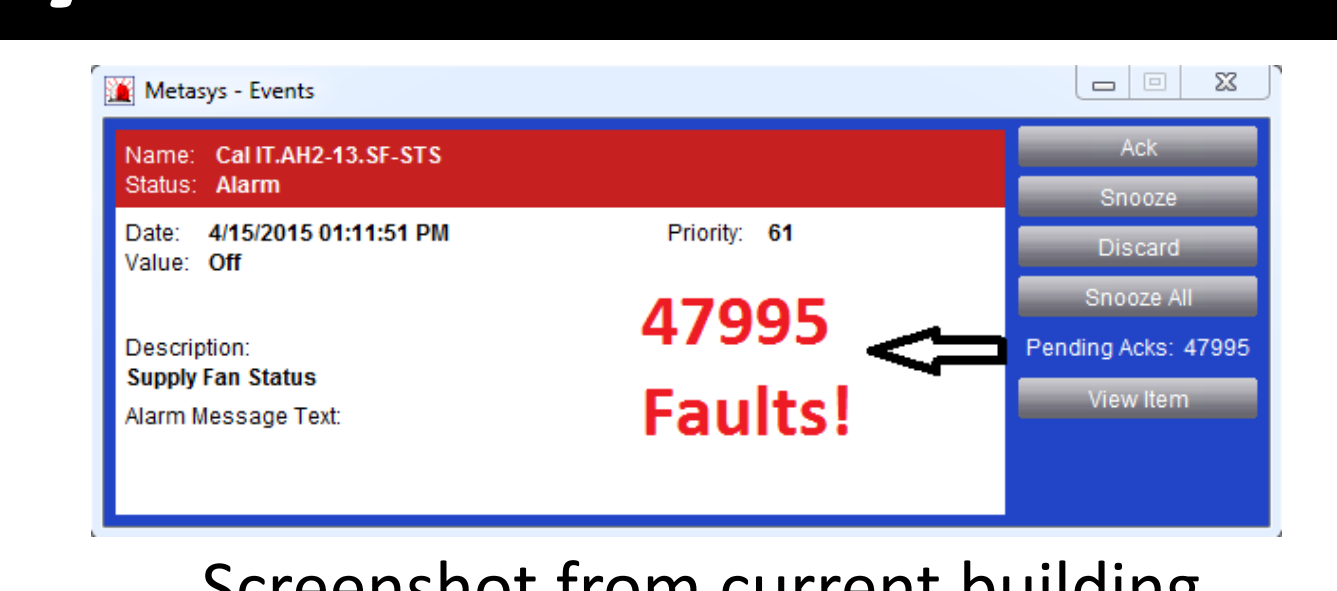
- We use simple power estimation model using heat transfer equations
 - Cooling power = $C_1 * (T_{mixed\ air} - T_{supply\ air}) * \sum air\ flow_{vav}$
 - Heating power = $C_2 * (T_{supply\ water} - T_{supply\ air}) * air\ flow_{vav} * H_{valve}$
- T = Temperature, H = Heating Valve, VAV = Variable Air Volume Box
- Learn constants C_1 , C_2 using linear regression
- Linear correlation of estimation and measurement is 89.2% in average



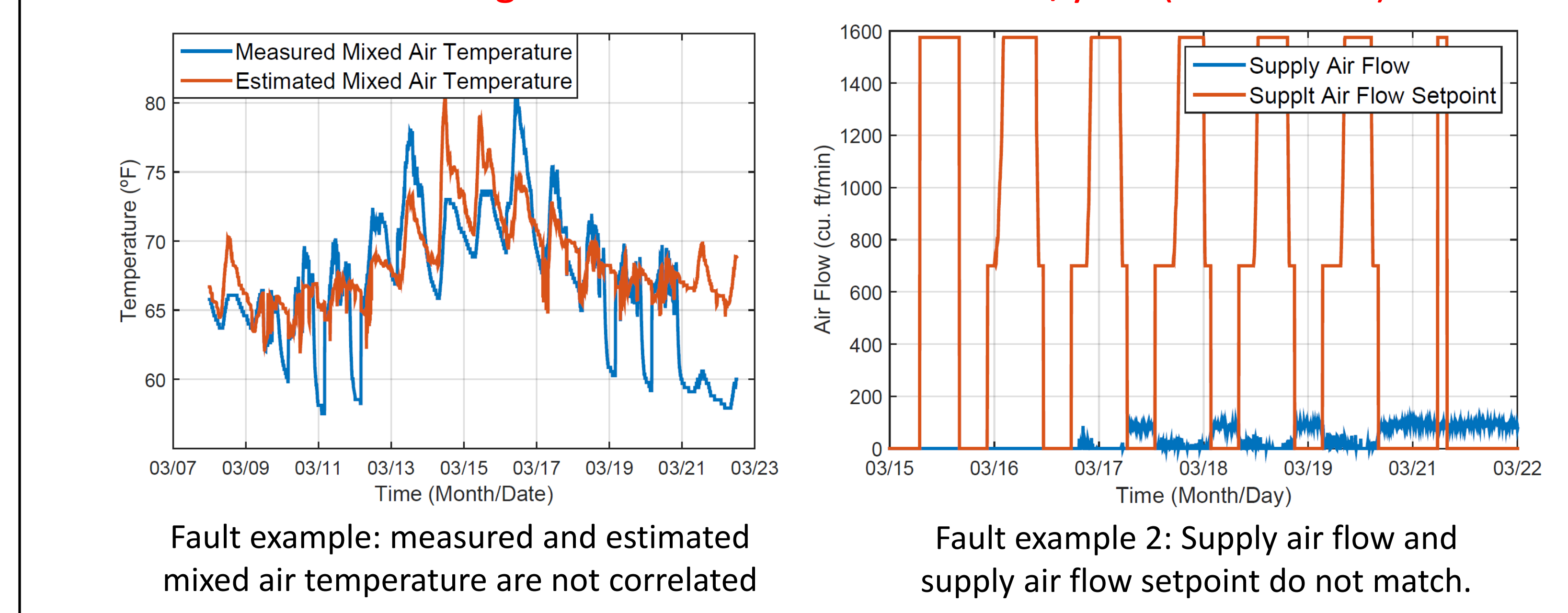
Heating Power Estimation of VAV & AHU Cooling Power Estimation of AHU

Fault Analysis

- Current system reports *too many* faults, so building managers ignore them
- We give priorities to faults by their impact on energy consumption
- We use rule based fault detection method
- Example of rules
 - Estimated and measured mixed air temperature should be correlated
 - Supply and mixed air temperature are equal when cooling is off
- Our platform detects 135 faults across seven buildings with 83 % accuracy.
- Faults of three building contribute to 127.2 MMBTU/year (293.3 kWh)



Screenshot from current building management system shows too many faults to manage



Fault example: measured and estimated mixed air temperature are not correlated

Fault example 2: Supply air flow and supply air flow setpoint do not match.