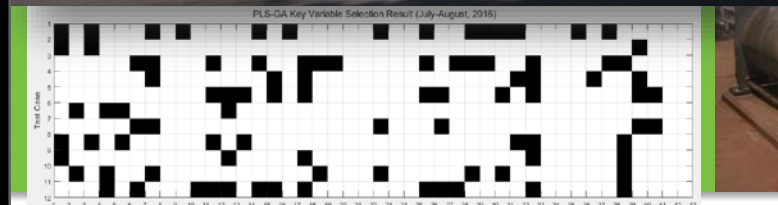
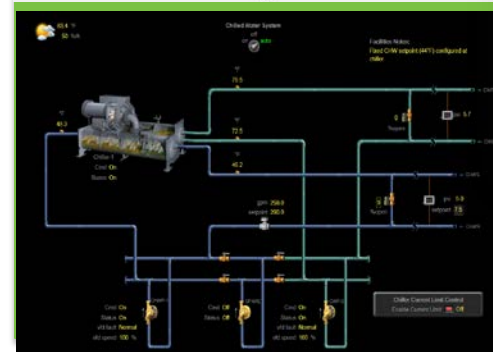
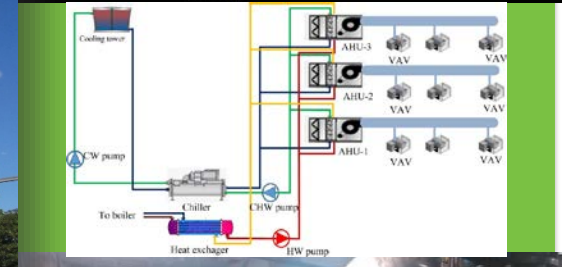
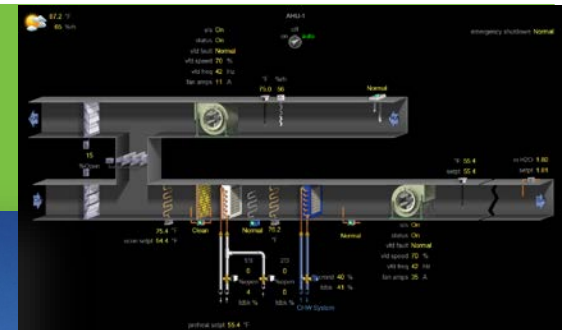
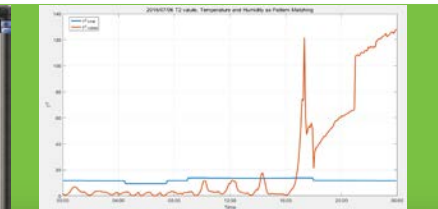
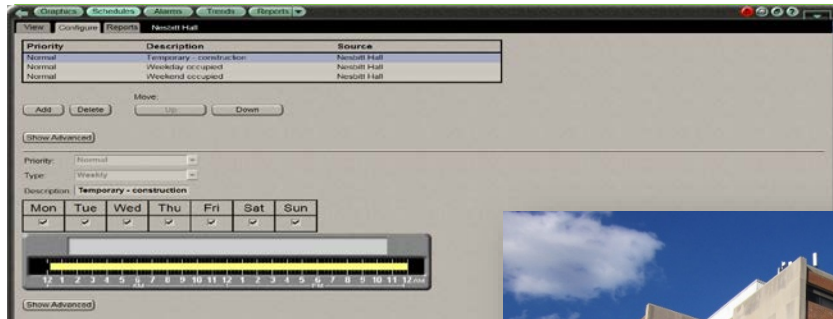


# VOLTRON Compatible Whole Building root-Fault Detection and Diagnosis

2017 Building Technologies Office Peer Review



# Project Summary

## Timeline:

Start date: 10/1/2015

Planned end date: 03/30/2018

## Key Milestones

1. M1 Literature review finished by 12/15
2. M2 Existing building data collected by 3/16
3. M3 Commercialization plan developed by 3/17
4. M4 Fault detection method developed by 3/17
5. M5 Root-fault isolation method developed by 6/17
6. M6 Simple payback time is less than 3 years by 9/17
7. M7 VOLTTRON compatible with GUI by 12/17
8. M8 Educational materials prepared by 3/18

## Budget:

### **Total Project \$ to Date:**

- DOE: \$66,295
- Cost Share: \$22,891

### **Total Project \$:**

- DOE: \$199,997
- Cost Share: \$22,394

## Key Partners:

KGS Buildings	PNNL
Dr. Zheng O’Neill (University of Alabama)	Dr. Teresa Wu (Arizona State University)

## Project Outcome:

- Develop a VOLTTRON compatible, automated, and cost-effective whole building fault detection and diagnosis tool using promising statistical process control and machine learning methods;
- Evaluate and demonstrate the cost-effectiveness of the developed whole building fault diagnosis tools using a Drexel campus building (Nesbitt Hall);
- Create a commercialization plan for the developed automated fault detection and diagnosis (AFDD) solutions; and
- Engage undergraduate students into multi-disciplinary research activities.

# Purpose and Objectives

## Problem Statement:

- Malfunctioning control, operation, and building equipment dramatically increase the energy consumption (estimated to be  $1 \times 10^{15}$  BTU for commercial building primary energy usage<sup>1</sup> and between 0.35 to 17 quads of additional energy consumption caused by key faults at a national level<sup>2</sup>).
- Existing fault diagnosis solutions mainly focus on component diagnosis, which may not lead to overall sustainable and optimally conditioned systems. The few existing whole building fault detection studies use calibrated whole building energy models for abnormality detection, which requires high engineering hours and installation costs.
- Existing solutions often encounter high market barriers because they have limited scalability or high implementation cost due to the needs to manually customize algorithms, collect data on the field, especially faulty data (Page 89 MYPP).

1. TIAX. 2005. Energy Impact of Commercial Building Controls and Performance Diagnostics: Market Characterization, Energy Impact of Building Faults and Energy Savings Potential. Final Report to U.S. Department of Energy.
2. Roth, K.W., D. Westphalen, P. Llana, M. Feng. 2004. "The Energy Impact of Faults in U.S. Commercial Buildings", International Refrigeration and Air Conditioning Conference, Paper 665.

# Purpose and Objectives

## **Target Market and Audience:**

Market - commercial building sector (18 quads of total energy or about 18% of all energy used in the U.S. – BTO MYPP).

Audience – continuous and retro-commissioning company, service company, fault diagnosis (building analytics) company, and control company.

## **Impact of Project:**

Project's outputs: 1) a cost-effective and VOLTTRON compatible whole building AFDD tool (strategies, codes and manuals) based on big data analytics and data mining technologies; 2) collected whole building data (with and without faults); 3) a market study and commercialization plan for the developed strategies; 4) educational materials on whole building fault diagnosis; 5) undergraduate and graduate students training opportunities in the building fault diagnosis and VOLTTRON areas.

# Purpose and Objectives

## Impact of Project (cont.):

Project's contribution: The developed strategies 1) are highly automated, i.e. **plug-n-play, self-learning and self-diagnosis**; 2) will therefore drastically reduce implementation cost (by reducing engineering hours) (**payback time < 3 yrs**); and 3) will help to reduce commercial building sector's (new and existing) energy waste and to help achieve the BTO's key sectoral goal - to reduce the average energy use per square feet of all U.S. buildings by 30% by 2030.

- a. Near-term outcomes: Developed cost-effective whole building AFDD strategies, which satisfy the ET program's goal: By 2020, accelerated technology development will make available cost-effective technologies capable of reducing the energy use of typical buildings by 30% compared to high-efficiency technologies available in 2010.
- b. Intermediate outcomes: 1) Larger scale building demonstration (5-10 buildings) to demonstrate the scalability, accuracy, and cost-effectiveness; 2) Industrial partners start to adopt the strategies into their software.
- c. Long-term outcomes: Developed technologies widely adopted in commercial buildings to achieve substantial energy savings.



# Approach

## Approach (details in later slides):

- Develop self-learning and pattern matching automated fault detection strategies using big data analytics strategies that are effective at handling datasets with high data dimensionality.
- Artificially implement faults in Drexel's demonstration building: Nesbitt Hall. Building data that contain both artificially implemented faults and naturally occurred faults are used to evaluate the developed strategies.
- VOLTTRON platform is utilized for data exchange. The developed strategies are VOLTTRON compatible.
- A market study is performed by our Close School of Entrepreneurship students. A survey study has been implemented to understand the market gap etc.



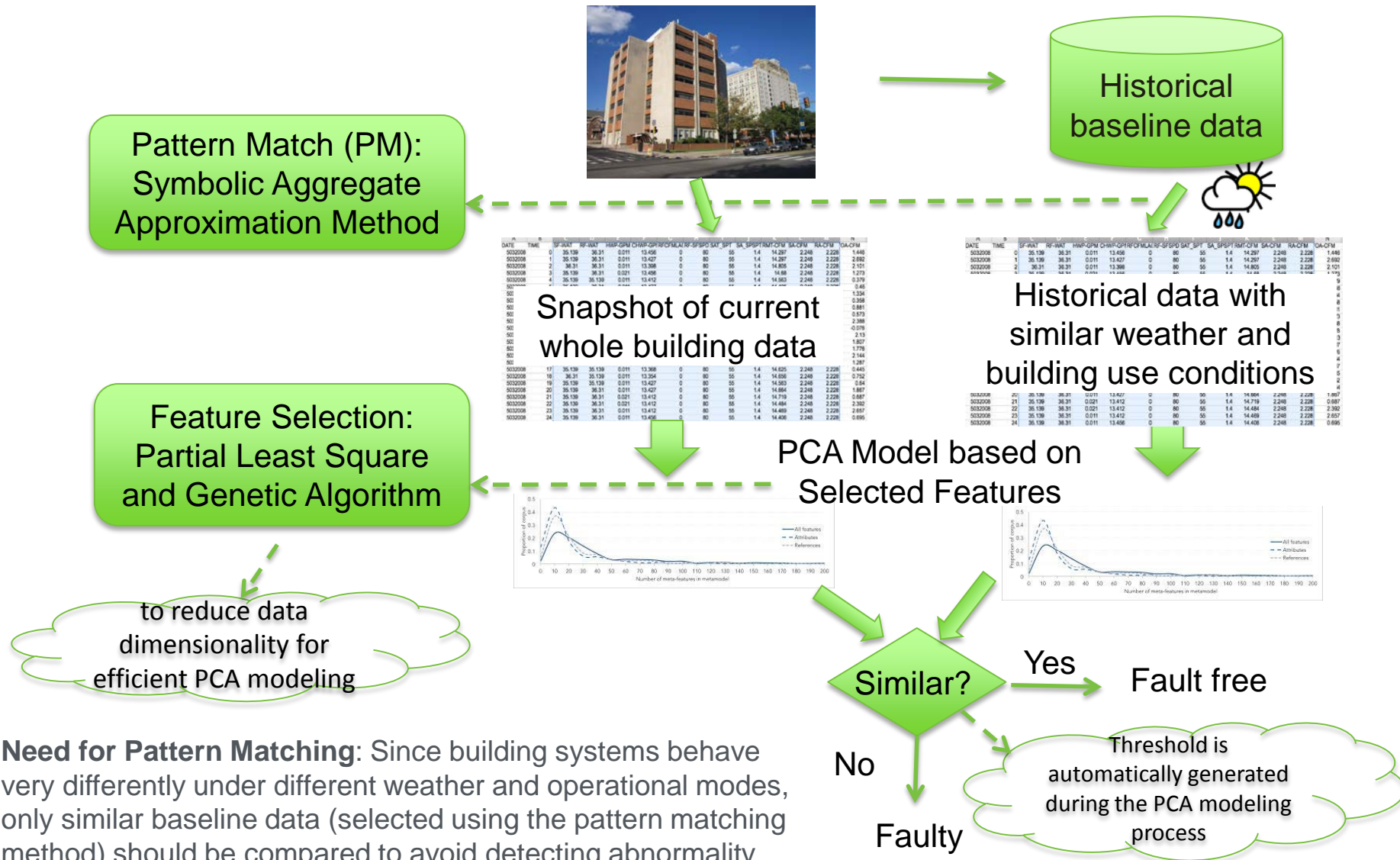
# Approach

**Key Issues:** 1) The high data dimensionality and large data quantity of a whole building dataset greatly challenge conventional data-driven fault detection methods. The Pattern Matching Principle Component Analysis methods which we have successfully developed for air handling units failed to effectively detect abnormalities for a whole building dataset; 2) The developed strategies need to be cost-effective, i.e., very low engineering implementation cost, with high accuracy and low false alarm rate.

## **Distinctive Characteristics:**

- Use big data analytics strategies (time series data pattern matching, feature selection, etc.) to achieve cost-effectiveness and scalability;
- Real building testing and demonstration;
- Engaging undergraduate students from both Engineering and Entrepreneur Colleges;
- Perform market study to develop a commercialization plan.

# Approach – Whole Building Fault Detection Method



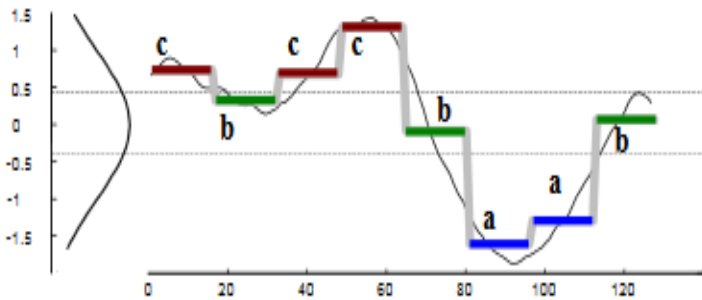
**Need for Pattern Matching:** Since building systems behave very differently under different weather and operational modes, only similar baseline data (selected using the pattern matching method) should be compared to avoid detecting abnormality caused by other reasons such as weather conditions.



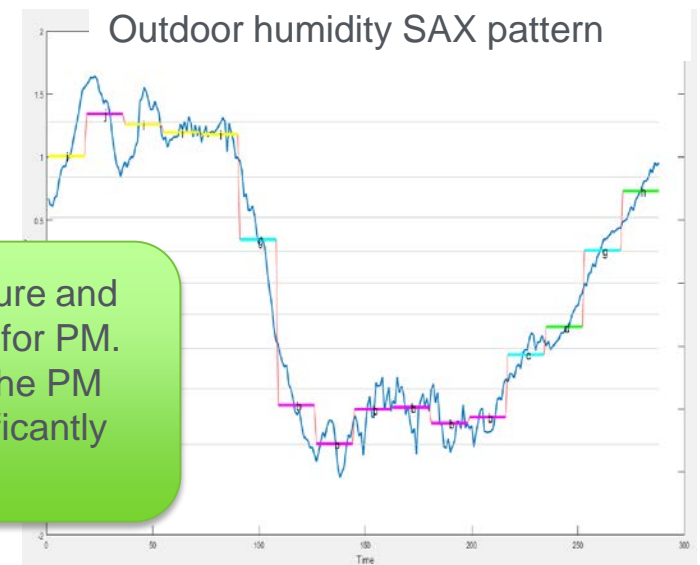
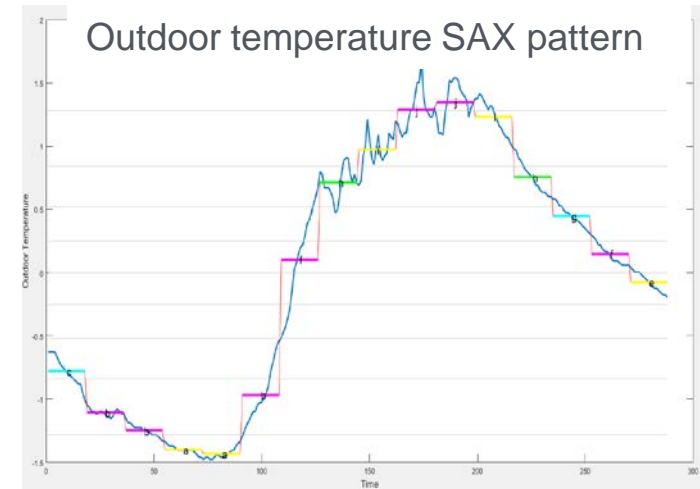
# Approach – Whole Building Fault Detection Method

## Symbolic Aggregate approXimation (SAX)<sup>1</sup>

- Time series data PM – more efficient than conventional PM methods;
- Finding time series data motif and discords:
  - **Motif:** a common subsequence pattern that has the highest number of non-trivial matches;
  - **Discord:** a subsequence of a time series that has the largest distance to its nearest non-self match.



Outdoor temperature and humidity are used for PM. Using SAX PM, the PM efficiency is significantly improved.

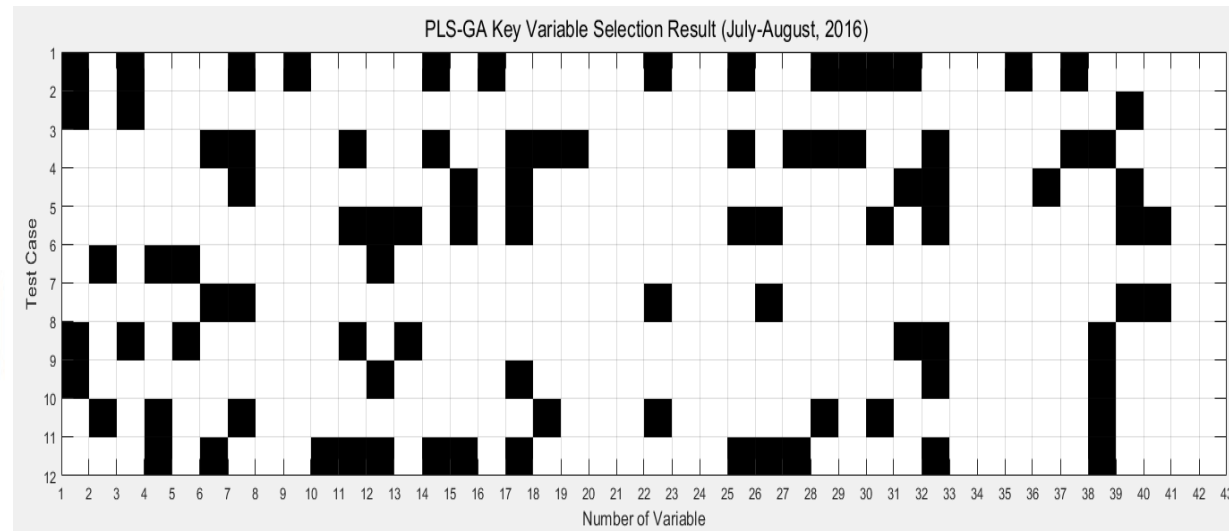
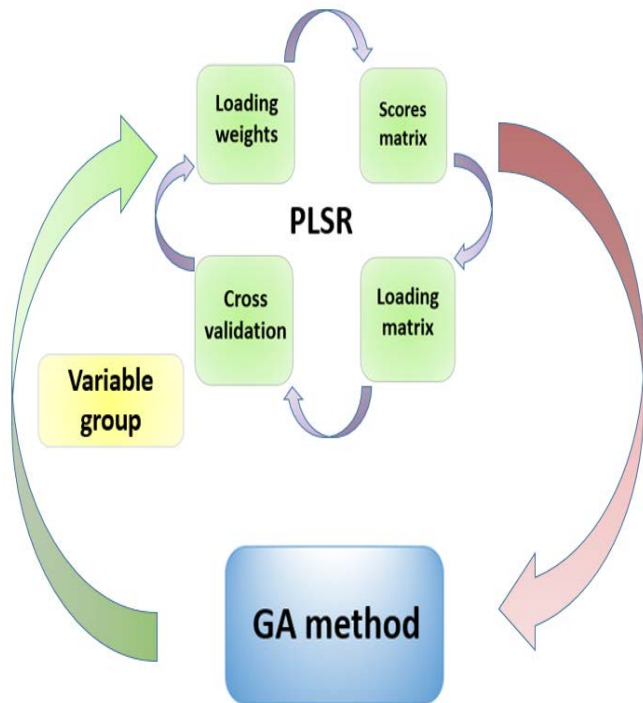


1. Keogh, Eamonn, Jessica Lin, and Ada Fu. "Hot sax: Efficiently finding the most unusual time series subsequence." *Data mining, fifth IEEE international conference*. IEEE, 2005.

# Approach – Whole Building Fault Detection Method

## Dataset dimension reduction and variable selection method – partial least square and genetic algorithm (PLS-GA)<sup>1</sup>

- 20% useful variables are selected for later PCA modeling, significantly increased PCA modeling efficiency and accuracy.
- Features selected can be used for later fault diagnosis.



1. Wise, B. M., Gallagher, N., Bro, R., Shaver, J., Windig, W., and Koch, R. S., PLS Toolbox 4.0. *Eigenvector Research Incorporated*, 3905, 2007.

# Progress and Accomplishments

**Accomplishments:** 1) Literature review revealed a lack of whole building AFDD technologies; 2) Market study further indicated the need for whole building, cost-effective, and accurate AFDD technologies; 3) Identified a demo building and collected baseline data; 4) Implemented **17** fault tests in three seasons; 5) Developed a new PM whole building fault detection method; 6) Supported **4** undergraduate students in both engineering and business disciplines.

## Market Impact:

- Survey study is performed to understand market barrier and technology gap:
  1. Great market opportunities exist;
  2. Cost-effectiveness; accuracy and false alarm rate; difficulty to choose the right product; and the lack of consumer training are the major barriers and gaps.
- Routine meetings and conference presentations to disseminate findings.
- Our industrial partners (KGS Buildings and Kinetic Buildings) are both interested in the developed technologies.

### Service Providers Survey

[https://drexel.qualtrics.com/SE/?SID=SV\\_6ujZWI0IPOJf4r3](https://drexel.qualtrics.com/SE/?SID=SV_6ujZWI0IPOJf4r3)

### Building Owner/Operator Survey

[https://drexel.qualtrics.com/SE/?SID=SV\\_78rH3vujFJ5PIKB](https://drexel.qualtrics.com/SE/?SID=SV_78rH3vujFJ5PIKB)



Have you considered improvements to your current software offerings in the past year?

- Yes  
 No

Which of the following characteristics are most important to you in diagnostic software?

- Low Cost  
 Diagnostic Accuracy/ Low False Alarm Rates  
 Data Visualization  
 Easy Installation  
 Other (please specify)

Rank the following diagnostic software characteristics as most important (1) and least important (3). Drag and drop the numbers into order.

U.S. DEPARTMENT OF  
**ENERGY**

Energy Efficiency &  
Renewable Energy

# Accomplishments: PM Whole Building Fault Detection Method Preliminary Evaluation

Data from five manually implemented faults and one naturally occurred fault are used to evaluate the detection accuracy

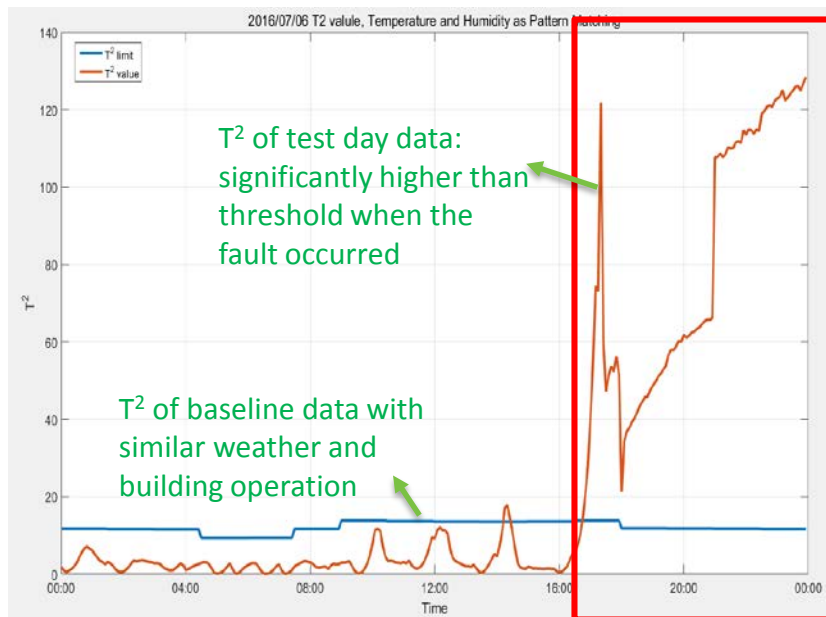
Date	Start	End	Fault Description	Implementation Method	Detection Results
07/06/16	16:00	24:00	Chiller stops working	Naturally occurred	Yes
08/01/16	15:59	21:30	AHU-1 supply air pressure sensor has a negative bias (0.2 in.w.g)	Override in BAS	No
08/08/16	10:22	21:16	AHU-1 supply air temperature sensor has a positive bias (4 °F)	Override in BAS	No
08/13/16	19:30	22:00	Schedule faults (change to unoccupied mode 2.5 hrs earlier)	Override in BAS	Yes
08/16/16	11:28	21:41	Chilled water differential pressure sensor has a negative bias (0.5 psi)	Override in BAS	Yes
08/18/16	09:30	19:17	AHU-1 outdoor air damper stuck at 30% open	Override in BAS	Yes

For mis-detected days (August 1 and 8), we found no obvious symptoms (only a few component variables are affected) regarding to the whole building behavior (details in backup slides).

# Accomplishments: PM Whole Building Fault Detection Method Preliminary Evaluation

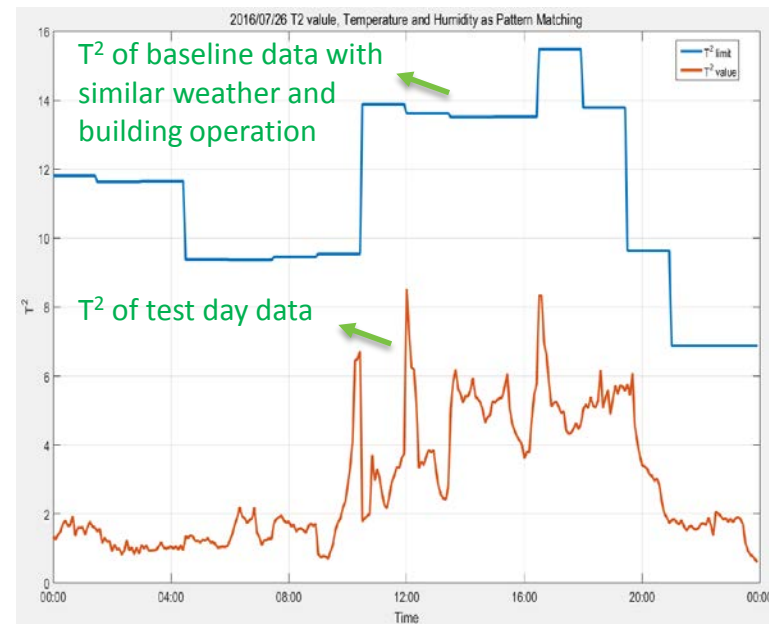
Data from five fault free days (07/26/16;08/26/16 to 08/29/16) are used to evaluate the false alarm rate. The method does not generate any false alarm.

$T^2$  for a fault day (chiller stopped working):  
July 06, 2016



Fault period:  
chiller stopped

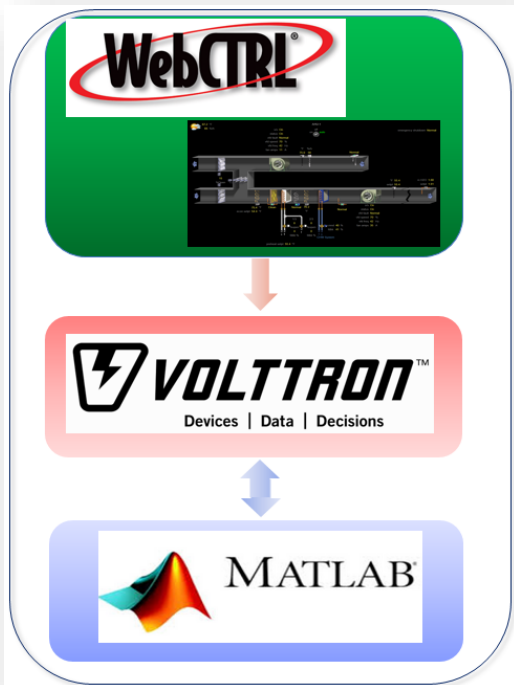
$T^2$  for a fault free day: July 26, 2016





# Accomplishments: VOLTTRON Integration with Nesbitt BAS

Integrate VOLTTRON Platform with MATLAB Environment and Drexel Building Automation System (BAS)



```

# Subtract one second from start time so it gets the first value:
tov, ddy, tdy = create_datetime_vector(stime, etime, dt)
stime_shift = shift_time(stime)
maxRecords = 500000

# Fill data and time columns:
dat_out = [[None for x in range(len(trendLogPath)+2)] for x in range(len(ddv))]
for rNo in range(0, len(ddv)):
    dat_out[rNo][0] = ddy[rNo]
    dat_out[rNo][1] = tdy[rNo]
print ""
print dat_out

# Loop through the rest of the points, and fill the data:
missing_points = []
col_no = 1

for ptNo in trendLogPath:
    try:
        col_no += 1
        soap_data = call_webctrl_trend(trend_w1, ptNo, stime_shift, etime, maxRecords, session)
        tov_start = 0
        for tNo in xrange(0, len(soap_data), 2):
            tov_no = tov_start
            fill_time = datetime.strptime(soap_data[tNo], "%a/%d/%Y %H:%M:%S.%p")
            if (fill_time.minute % 5 > 0) or (fill_time.second > 0):
                rem_time = timedelta(minutes=fill_time.minute % 5, seconds=fill_time.second, microseconds=fill_time.microsecond)
                fill_time -= rem_time
                if rem_time := timedelta(minutes=5):
                    fill_time += timedelta(minutes=5)
            while tov_no < len(tov):
                if tov[tov_no] == fill_time:
                    dat_out[tov_no][col_no] = soap_data[tNo+1]
                    tov_start = tov_no
                    break
                tov_no += 1
            except:
                missing_points.append(ptNo)
    print ""

```

VOLTTRON WebCTRL Driver

```

%% Calculate Training Day SAK Pattern
Training_symbolic_data_list_temper = [];
Training_symbolic_data_list_humid = [];
Training_Date = datenum(Training_Start_Date);

for i = 1:No_Train_Date
    % Collect Training Date Data and Scale Data
    Date_ix = datestr(Training_Date, 'yyyy/mm/dd');
    [Training_data] = Data_collection_0(file_path, Date_ix);
    % [Training_data_scaled] = Data_scale(Training_data, scale_parameter);
    [Training_symbolic_data_temp, Training_symbolic_data_humid] = SAK_PM_T1(Training_data, N, n, alphabet_size, OA_temperature_ix, OA_humidity_ix);
    Training_symbolic_data_list_temper = [Training_symbolic_data_list_temper; Training_symbolic_data_temp];
    Training_symbolic_data_list_humid = [Training_symbolic_data_list_humid; Training_symbolic_data_humid];
    Fault_free_data(i) = Training_data;
    Training_Date = Training_Date + 1;
end

%% Extract Historical Baseline Data
[temper_baseline_day_ix, humid_baseline_day_ix, ...
temper_baseline_day_ix_FWD, humid_baseline_day_ix_FWD, ...
temper_baseline_day_ix_BCK, humid_baseline_day_ix_BCK] = Weather_day_extract_Ext_VI(Training_symbolic_data_list_temper, Training_symbolic_data_list_humid, Training_symbolic_data_list_temper, Training_symbolic_data_list_humid);

% [temper_baseline_day_ix, humid_baseline_day_ix] = Weather_day_extract_VI(Training_symbolic_data_list_temper, Training_symbolic_data_list_humid, Training_symbolic_data_list_temper, Training_symbolic_data_list_humid);

%% Pattern Matching --- Baseline Day
[Nov_baseline_day_ix, FWD_baseline_day_ix, BCK_baseline_day_ix] = Generate_baseline_day_Ext(Training_symbolic_data_list_temper, Training_symbolic_data_list_humid, Training_symbolic_data_list_temper, Training_symbolic_data_list_humid, Training_symbolic_data_list_temper, Training_symbolic_data_list_humid);

```

AFDD Application in MATLAB

# Progress and Accomplishments

## Project Integration and Collaboration

**Awards/Recognition:** None.

**Student Training:** 4 undergraduate students : 1) two engineering seniors: one now works for a design firm and one works for a FDD service provider; 2) two business students conducted the market study and developed a commercialization plan. The Ph.D. student, Yimin Chen, is currently a Ph.D. candidate. We are also hiring 2 more engineering students for interface development and data analysis.

**Lessons Learned:** 1) Challenges when data dimension dramatically increased; 2) Real building testing often brings uncertainties caused by weather/systems and other unforeseen challenges; 3) Survey challenges.

**Project Integration:** Weekly face to face meetings among Drexel team members. Monthly and Bi-monthly meetings among collaborators.

**Partners, Subcontractors, and Collaborators:**

Consultants: Dr. O'Neill from The Univ. of Alabama; Dr. Wu from Arizona State University. Industrial Partners: KGS Buildings and Kinetic Buildings.

# Next Steps and Future Plans

**Next Steps and Future Plans:** 1) Further evaluate the developed fault detection strategy with more building data, especially those that contain faults with a whole building impact; 2) Develop a whole building fault diagnosis strategy to isolate fault causes; 3) Develop educational materials to be adopted in Drexel's existing architectural and mechanical engineering courses (MEM 414; AE 430; AE 552).

## Communications:

- Regnier, A. and Wen, J., "Automated Fault Diagnostics for AHU-VAV Systems: A Bayesian Network Approach," 2016 Purdue High Performance Buildings Intelligent Building Operation Session, West Lafayette, IN, July 2016.
- Wen, J., "From Big Data to Big Energy Saving - Improving Building Energy Efficiency and Building-Human interactions through Advanced Control, Operation and Data Analytics," Invited Seminar, Beijing University of Civil Engineering and Architecture, Beijing, China, August, 2016.
- Wen, J., "From Big Data to Big Energy Saving - Improving Building Energy Efficiency and Building-Human interactions through Advanced Control, Operation and Data Analytics," Invited Presentation, ASHRAE Philly Chapter, Philadelphia, PA, November, 2016.
- Chen, Y., J. Wen, and Rgenier, A., "Using Pattern Matching and Principal Component Analysis Method for Whole Building Fault Detection", ASHRAE 2017 Summer Conference, Conference Paper Accepted, Long Beach, CA, June, 2017.

---

# REFERENCE SLIDES

# Fault experiments in Nesbitt Hall

17 whole building level faults were implemented in Nesbitt Hall in summer, fall and winter 2016

Date	Day	Start Time	End Time	Fault Description	Implementation
08/01/16	Monday	15:59	21:30	AHU-1 supply air static pressure negative bias 0.2 in.WC	Override SP setpoint to 2.0 in.WC
08/08/16	Monday	10:22	21:16	AHU-1 supply air temperature sensor positive bias 4 °F	Override BAS software point "DEM adj" by 2
08/13/16	Saturday	6:30	8:00	First floor schedule fault	Occupied from 8:00AM to 6:30PM
08/16/16	Tuesday	11:28	21:41	Chiller differential pressure sensor negative bias fault (0.5 psi)	Override DP setpoint to 8 psi
08/18/16	Thursday	9:30	19:17	AHU-1 supply air outdoor air damper stuck	Override OA damper at 30% Open
08/30/16	Tuesday	11:20	19:00	Chiller differential pressure sensor positive bias fault (0.5 psi)	Override DP setpoint to 7 psi
09/07/16	Tuesday	10:30	22:09	AHU-2 supply air temperature sensor negative bias 4 °F	Override BAS software point "DEM adj" by 2
09/11/16	Sunday	18:30	20:30	Second and third floor schedule fault	Occupied from 6:30 PM to 8:30PM
09/12/16	Monday	11:02	21:01	AHU-1 supply air temperature sensor negative bias 6°F	Override BAS software point "DEM adj" by 3
10/18/16	Tuesday	12:05	22:00	CHWS Negative Bias 2°F	Manually insert the value to chiller control panel +2°F
10/19/16	Wednesday	10:48	21:06	CHWS Negative Bias 4°F	Manually insert the value to chiller control panel +4°F
11/18/16	Friday	10:00	20:30	AHU-1 OA damper stuck at too high (70%)	Override OA damper at 70% Open
11/22/16	Tuesday	10:00	20:30	AHU-1 OA damper stuck at too high (90%)	Override OA damper at 90% Open
11/29/16	Tuesday	10:00	20:30	AHU-2 OA damper stuck at too high (90%)	Override OA damper at 90% Open
12/05/16	Monday	10:00	20:30	AHU-2 OA damper stuck at too high (80%)	Override OA damper at 80% Open
12/17/16 to 12/19/16	Saturday	4:00	9:45	Occupancy schedule fault	Occupied from 8:00 AM to 4:00 AM
12/26/16	Monday	10:00	20:30	AHU-2 SA temperature sensor bias positive 4°F	Override BAS software point "DEM adj" by 2

**Abbreviation:**

SA: supply air; OA : outdoor air; CHWS: chilled water supply; DEM adj: demand adjustment



Energy Efficiency & Renewable Energy



# Project Budget

**Project Budget:** \$199,997

**Variances:** None

**Cost to Date:** \$66,295

**Additional Funding:** DOE BIRD Fellowship (a PHD student, Yimin Chen, is partially sponsored by this fellowship)

## Budget History

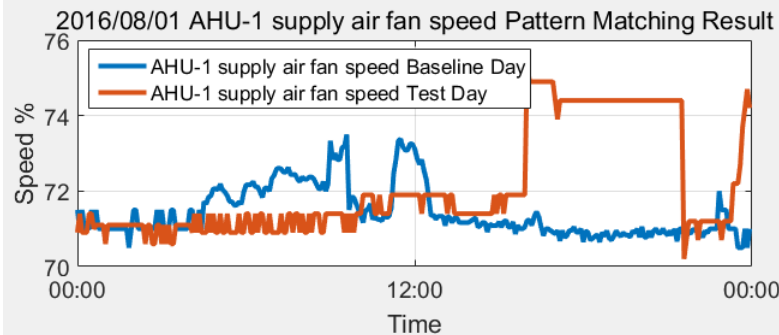
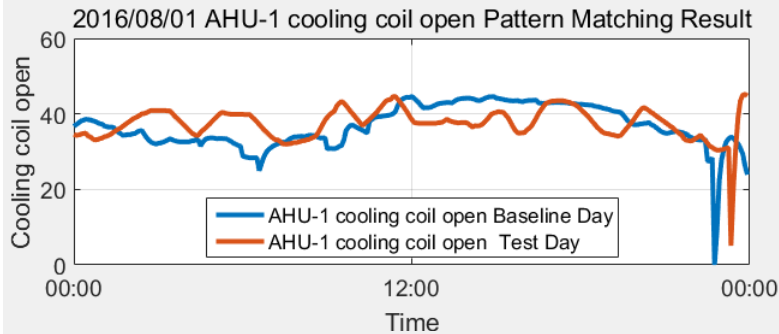
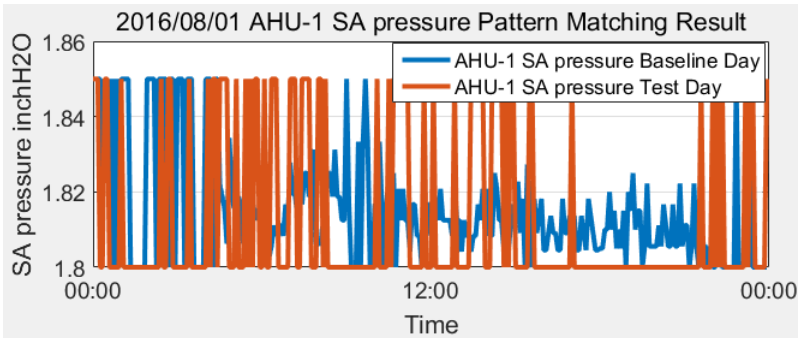
10/1/15 – FY 2016 (past)		FY 2017 (current)		FY 2018 – 3/31/18 (planned)	
DOE	Cost-share	DOE	Cost-share	DOE	Cost-share
\$66,295.00	\$22,890.78	\$2,000.00	\$0.00	\$199,997.00	\$22,394.00

# Project Plan and Schedule

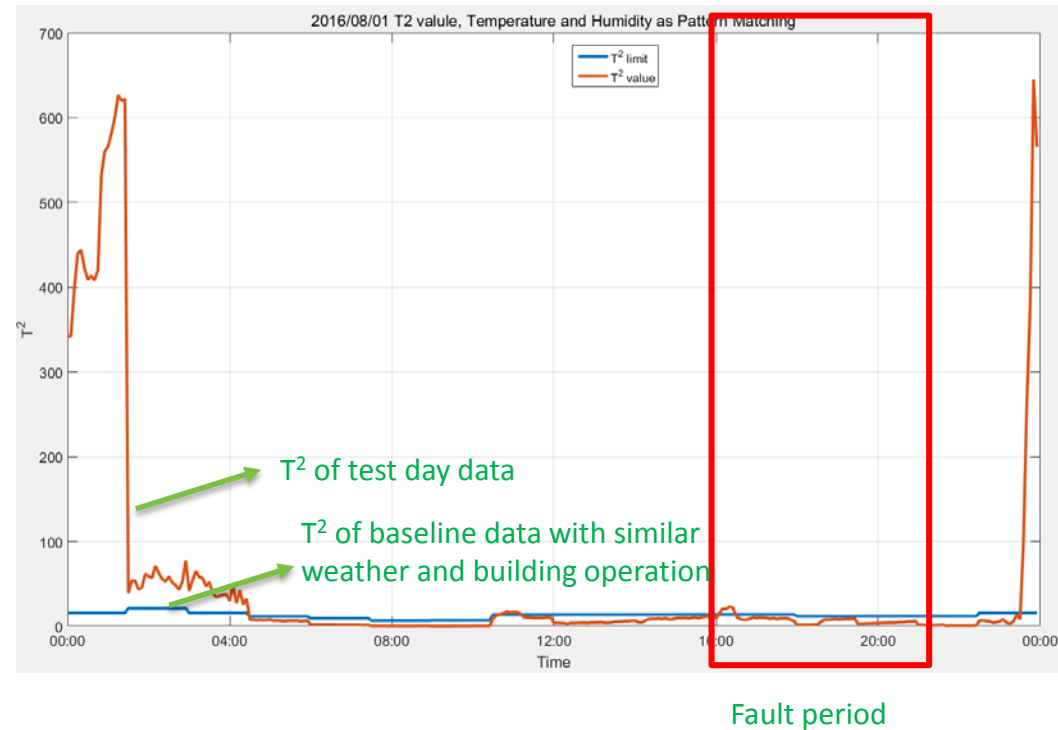
Project Schedule										
		Completed work								
Project Start: 10/1/2015		Active task								
Project End: 3/31/2018		Milestone/Deliverable (Originally Planned)								
		Milestone/Deliverable (Actual)								
	FY15	FY 16				FY 17				FY18
Task	Q1 (Oct-Dec)	Q2 (Jan-Mar)	Q3 (Apr-Jun)	Q4 (Jul-Sep)	Q1 (Oct-Dec)	Q2 (Jan-Mar)	Q3 (Apr-Jun)	Q4 (Jul-Sep)	Q1 (Oct-Dec)	Q2 (Jan-Mar)
<b>Past Work</b>										
Q1 MS: Literature review finished	◆									
Q2 MS: Existing whole building data collected		◆								
Q3 MS: Comprehensive commercialization plan developed				◆		◆				
Q4 MS: Fault detection method developed				◆		◆				
<b>Current/Future Work</b>										
Q5 MS: Root fault isolation method developed					◆		◆			
Q6 MS: Based on the cost and energy impact estimation, the simple payback time is less than 3yrs						◆		◆		
Q7 MS: Developed tools are VOLTTRON compatible and GUI is developed							◆		◆	
Q8 MS: Course and training materials are developed								◆		◆

# Details about the Mis-detected Faults

August 1, 2016: AHU-1 supply air static pressure sensor was implemented with a negative bias (0.2 in.w.) from 15:59 to 21:30.



$T^2$  of the whole building dataset is not significantly different from the baseline one

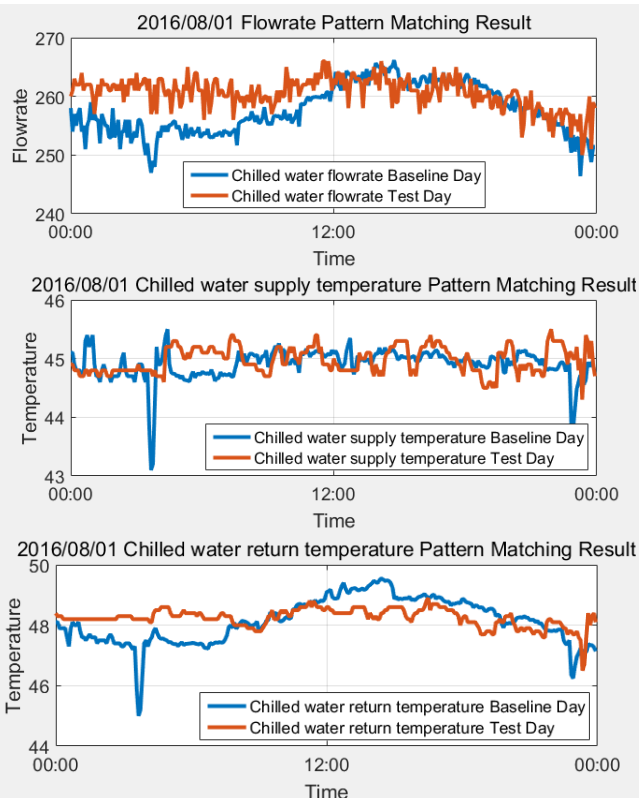


AHU variables: 2 variables show abnormality

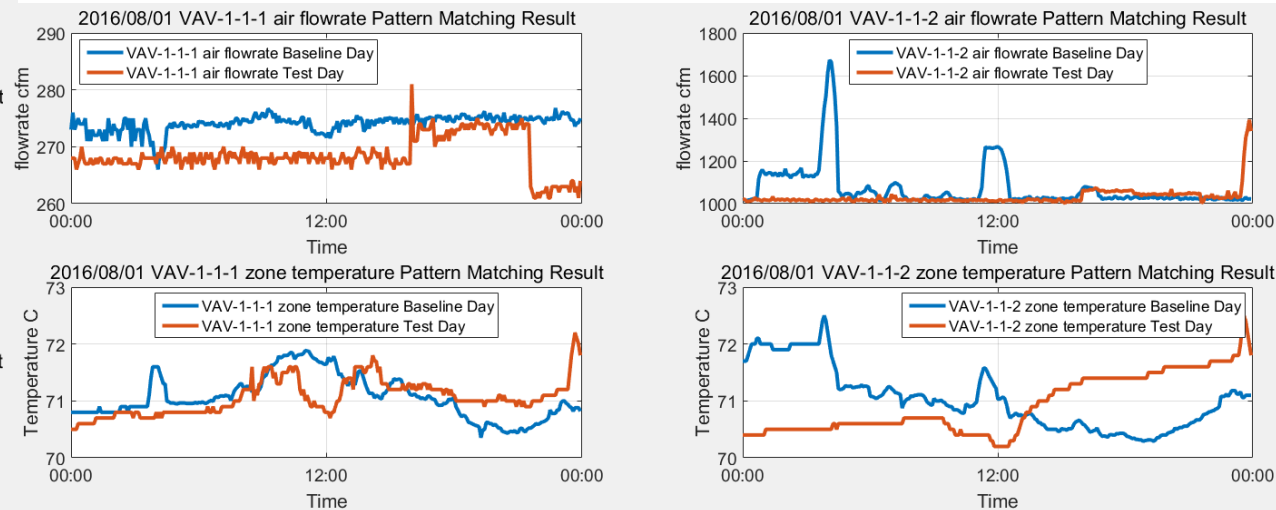
# Details about the Mis-detected Faults

August 1, 2016: AHU-1 supply air static pressure sensor was implemented with a negative bias (0.2 in.w.) from 15:59 to 21:30 (cont.).

Chiller variables: no significant differences



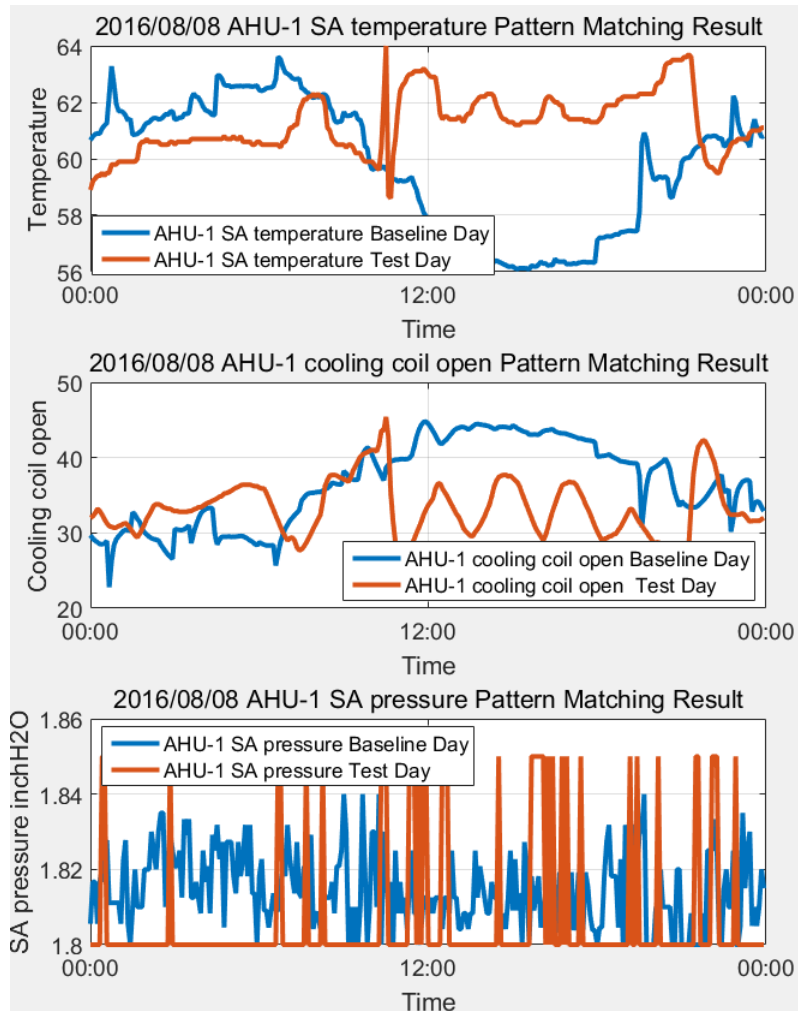
VAV variables (selected from many more units): no significant differences – only 1-2 variables affected



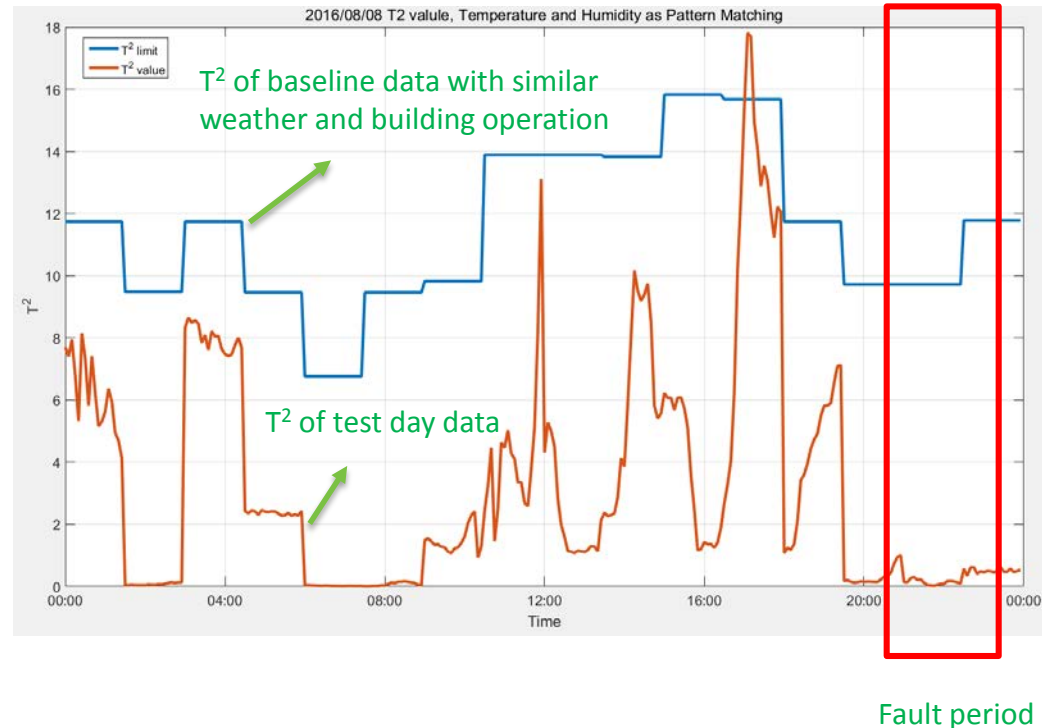
In summary, this fault caused a very small amount of variables to show abnormality. It can be detected using a component AFDD tool. It is not a good representation of whole building faults.

# Details about the Mis-detected Faults

August 8, 2016: AHU-1 supply air temperature sensor was implemented with a positive bias (4 °F) from 10:22 to 21:16.



$T^2$  of the whole building dataset is not significantly different from the baseline one



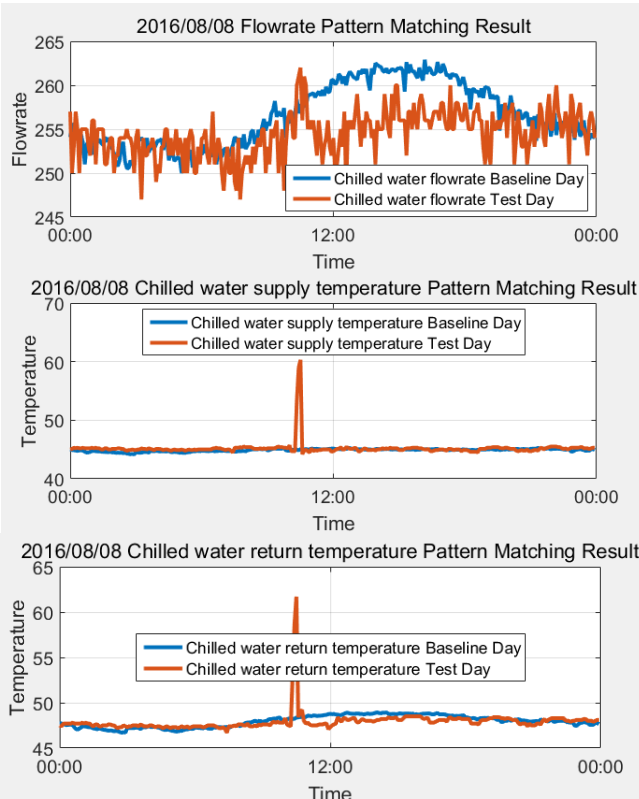
AHU variables: 2 variables show abnormality



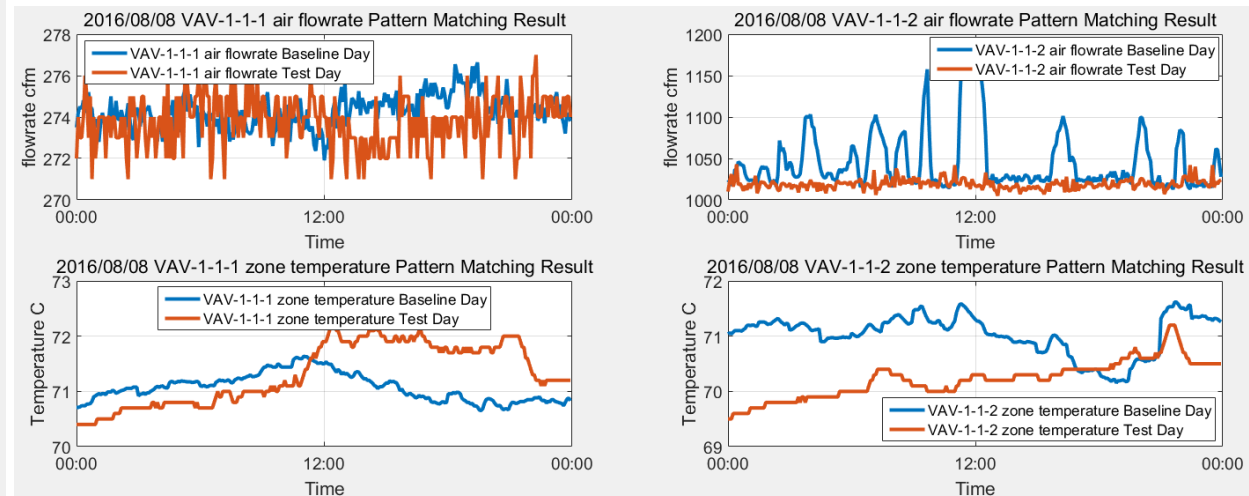
# Details about the Mis-detected Faults

August 8, 2016: AHU-1 supply air temperature sensor was implemented with a positive bias (4 °F) from 10:22 to 21:16 (cont.).

Chiller variables: no significant differences



VAV variables (selected from many more units): no significant differences – only 1-2 variables affected



In summary, this fault caused a very small amount of variables to show abnormality. It can be detected using a component AFDD tool. It is not a good representation of whole building faults.