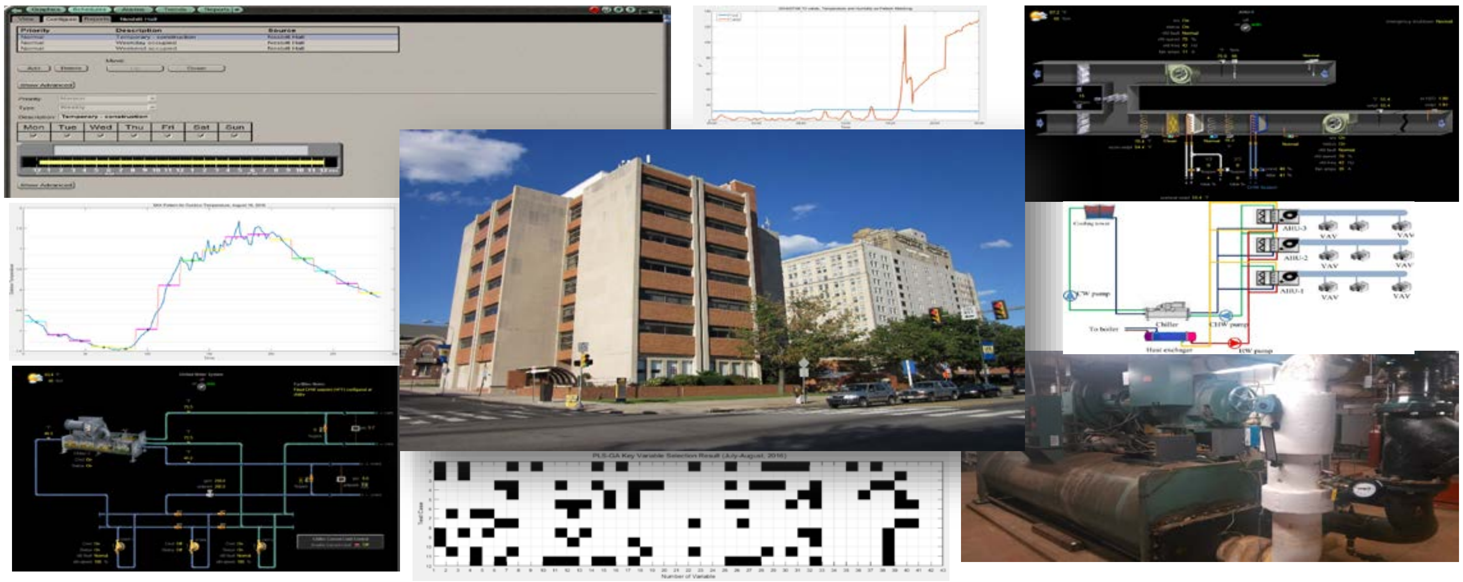
U.S. DEPARTMENT OF
ENERGY
Office of
ENERGY EFFICIENCY &
RENEWABLE ENERGY

VOLTTRON Compatible Whole Building root-Fault Detection and Diagnosis



Drexel University
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Project Summary

Timeline:

Start date: 10/1/2015

Planned end date: 03/30/2018

Key Milestones

1. Data, including whole building test data with artificially injected faults and whole building baseline data collected (by 12/17);
2. Fault detection method developed (by 3/17);
3. Root-fault isolation method developed (by 9/17);
4. Based on the cost and energy impact estimation, the simple payback time is less than 3 years (by 2/18).

Budget:

Total Project $ to Date:

- DOE: $165,876
- Cost Share: $37,636

Total Project $:

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

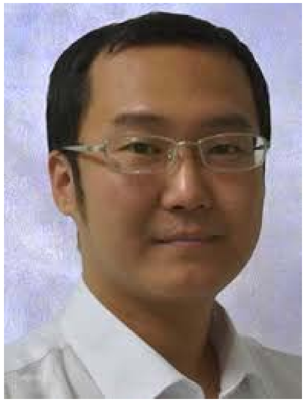
Key Partners:

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

Project Outcome:

- Develop an Automated whole building Fault Detection and Diagnosis (AFDD) tool through statistical process control and machine learning methods. The tool is compatible with a control execution platform;
- Evaluate and demonstrate the cost-effectiveness of the developed whole building AFDD tools using a Drexel campus building; and
- Engage undergraduate students into multi-disciplinary research activities.

Team



Yimin Chen, PhD Student

Consultants

Dr. Zheng O'Neill – HVAC system, whole building faults…

Dr. Teresa Wu – Data mining, Bayesian Network

Industrial Partner

Dr. Nick Gayeski, KGS

PNNL Team

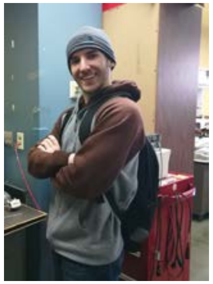
Dr. Srinivas Katipamula
VOLTTRON Team

Undergraduate Students @ Drexel

Taylor Castonguay
AE

Ojas Pradhan
ME

Hans Crompton
AE

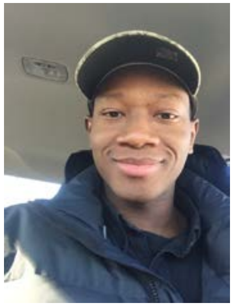


Jaymes Bailey
AE

Noelle Wiggins
Business

Taiyu Chen, IS

Mahamoudou Doumbia
EE



Benjamine Scheinberg, ME
Binbin Fan, ME
Wenjian Yu, ME

Challenge

Problem Definition:

- Malfunctioning control, operation, and building equipment dramatically increase the energy consumption:
  - Estimated to be 1×10^{15} BTU for commercial building primary energy usage[1] and between 0.35 to 1.8 quads of additional energy consumption at a national level[2];
- Existing fault diagnosis solutions
  - mainly focus on component diagnosis;
  - has high engineering hours and installation costs,
    - when calibrated building energy models are needed, or
    - when FDD rules and thresholds need to be manually customized;
  - has limited scalabilities due to the needs to manually customize rules/thresholds, collect data on the field, especially faulty data.

→ *False alarm rate when a fault affects multiple components…*

→ *High implementation cost*

→ *High market barriers*

Advice: *Need whole building AFDD strategies that are highly automated and cost-effective, i.e., very low engineering implementation cost, with high accuracy and low false alarm rate.*

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.

Approach - Summary

- **Develop AFDD strategies that are effective at handling whole building datasets with high data dimensionality:**
  - Fault detection: Weather/schedule based Pattern Matching and Feature engineering based Principle Component Analysis strategies (WB PM and FB PCA);
  - Fault diagnosis: Pattern Matching based Bayesian Network.

Data mining and big data analytics based strategies

Self-learning and highly automated AFDD tools

Lower cost and higher accuracy

- **Artificially implement faults at demonstration building:**
  - Implemented 30 fault cases in summer, winter, and transitional seasons;
  - Collected data contain both artificially implemented and naturally occurred faults;
  - Evaluated accuracy, false alarm rate, energy impacts, and cost-effectiveness of the developed strategies using collected data.
- **The developed strategies are VOLTTRON (an open control execution platform) compatible;**
- **Engage undergraduate students from different disciplines through out the course of the project, and develop hardware and software tools for educational purposes.**

Approach – WB PM and FB PCA Fault Detection

Weather/schedule based Pattern Match (PM): Symbolic Aggregate Approximation Method

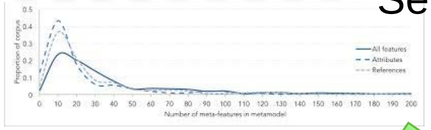
Historical baseline data

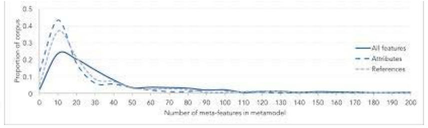
Snapshot of current whole building data

Historical data with similar weather and building use conditions

Feature Selection: Partial Least Square and Genetic Algorithm

PCA Model based on Selected Features





to reduce data dimensionality for efficient PCA modeling

Similar?

Yes

Fault free

No

Faulty

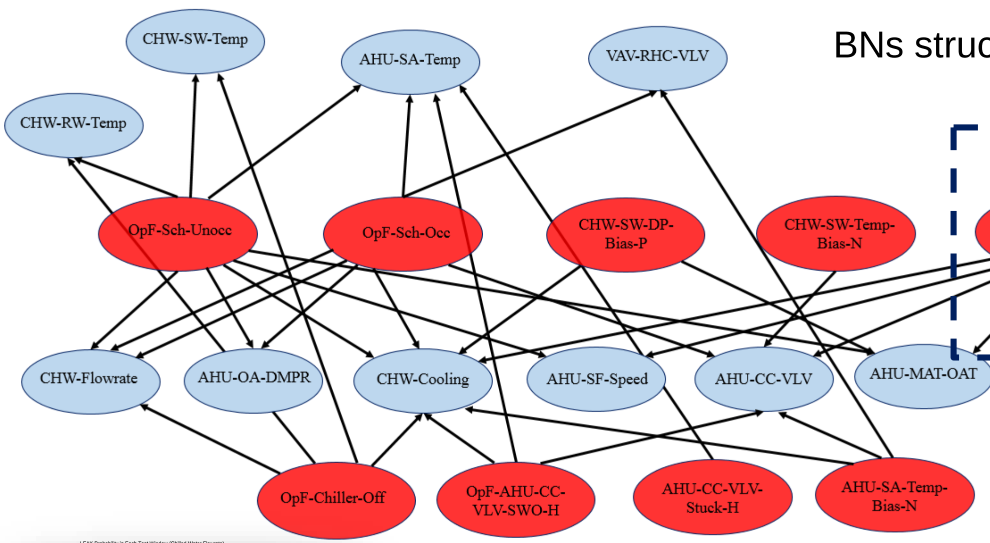
Threshold is automatically generated during the PCA modeling process

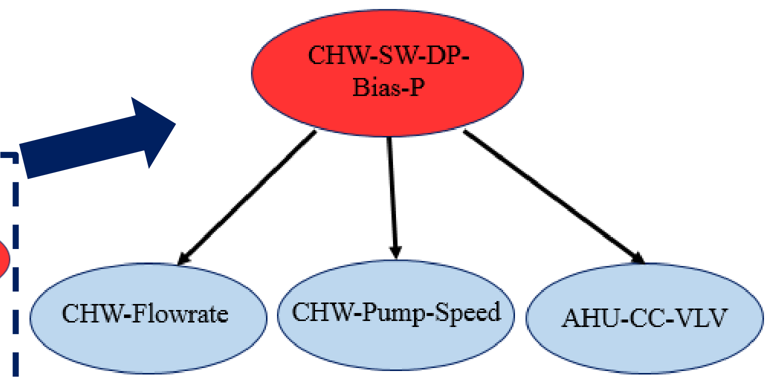
Need for Pattern Matching: Since building systems behave very differently under different weather and operational modes, only similar baseline data (selected using the pattern matching method) should be compared to avoid detecting abnormality caused by other reasons such as weather conditions.

Approach - Bayesian Networks for Fault Diagnosis

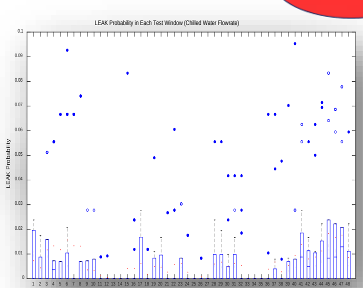
- **Bayesian Network Development**
  - Two Layer BN Structure;
  - Fault symptoms are identified via physical knowledge and experimental data;
  - Parameters are learned from building data (leak probabilities) or estimated based on physical knowledge (conditional and prior probabilities).

BNs structure





Example: Chilled water differential pressure sensor positive bias fault



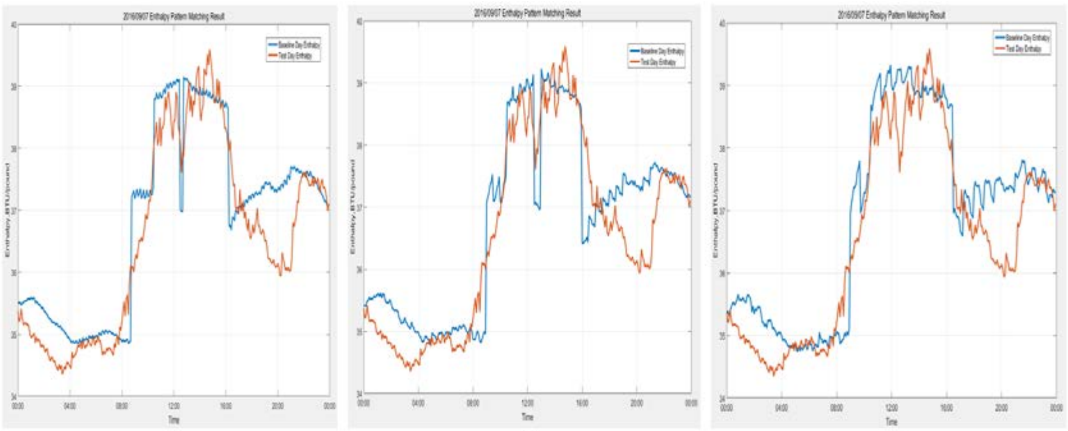
Leak probabilities are found to be less than 4% for all faults tested

Fault Node State	Prior Probability
Fault	0.01
Fault free	0.99

Approach - Sensitivity Tests

Sensitivity tests are performed to determine parameters:

- **Sensitivity test on snapshot window size**
  - ❑ 15-minute, 30-minute and 45-minute are tested.
- **Sensitivity test on data sample searching pool size**
  - ❑ 120-minute, 180-minute and 240-minute are tested.
- **Sensitivity test on the number of baseline day**
  - ❑ 20-day, 30-day are tested.



i Window size 15-minute

ii Window size 30-minute

iii Window size 45-minute

Illustration of snapshot window size sensitivity test

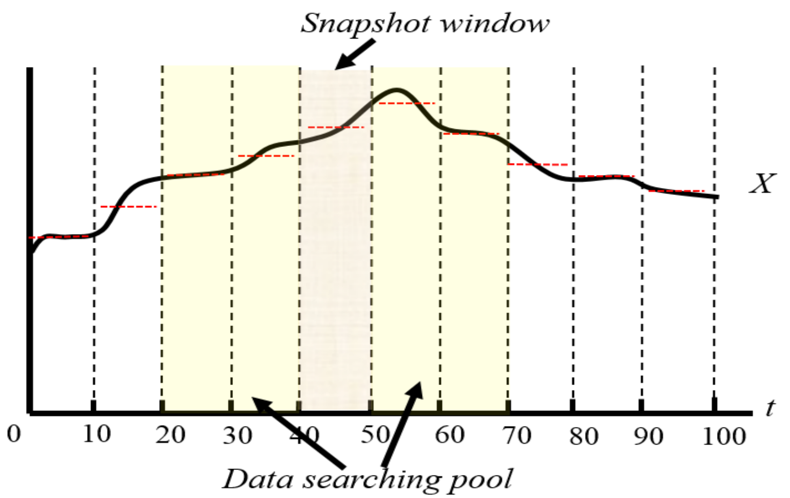


Illustration of data searching pool

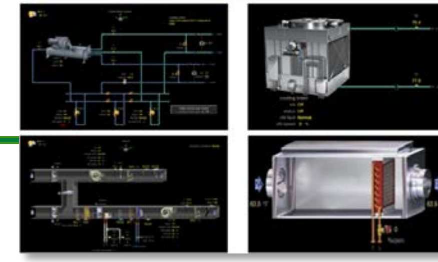
Approach - Evaluation

- **Demo Building – Drexel University Nesbitt Hall**
  - Seven floor mixed use; 78k square-foot; Chiller on site; 3 AHUs; BAS with 500+ measurements; Electricity meter includes some nearby small buildings.
  - Implemented 30+ fault cases.

Fault Type	Fault Name	Fault Implementation Season			Total Fault Day Case	Demonstrate Whole Building Level Fault Symptoms
		Winter	Transition	Summer		
Operator Fault	OpF-Sch-Unocc	0	0	1*	1	1
	OpF-Sch-Occ	1	0	2**	3	2
	OpF-Chiller-Off	0	0	2*	2	2
	OpF-CC-VLV-SWO-H	0	0	1	1	1
	OpF-CHW-BPVLV-SWO-H	0	0	2	2	0
	OpF-OA-DMPR-SWO-H	0	1	0	1	0
Supply Air Subsystem Fault	AHU-OA-DMPR-Stuck-H	2	1	3	6	4
	AHU-SA-Temp-Bias-N	1	1	3	5	2
	AHU-SA-DP-Bias-N	0	0	1	1	0
Primary Cooling Subsystem Fault	CHW-SW-Temp-Bias-N	0	0	4***	3	1
	CHW-SDP-Bias-P	0	0	4	4	1
Total		4	3	23	30	14

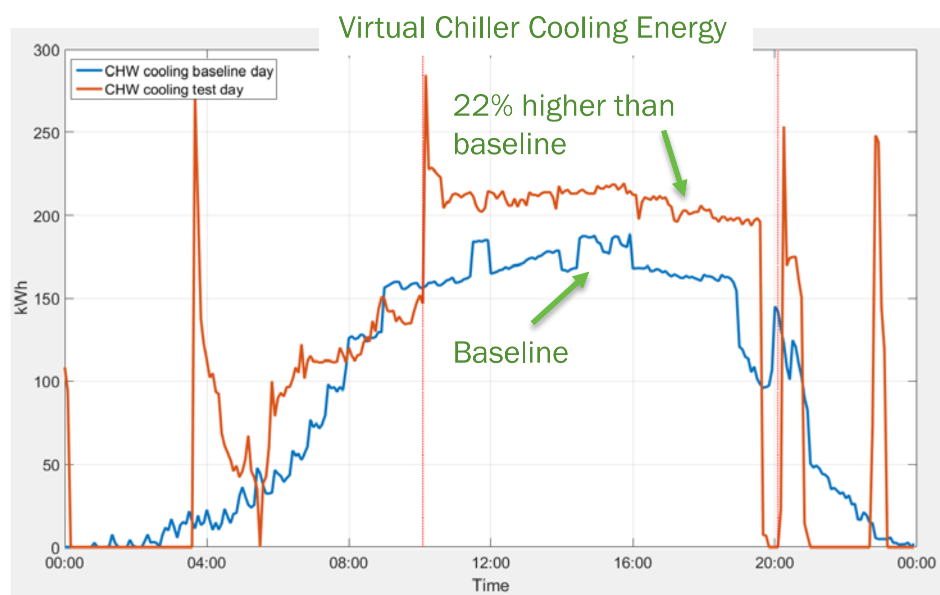
*Naturally occurred fault
**Out of the two cases, one naturally occurred and the other was artificially implemented
***One day is discarded due to missing data

Approach – Evaluation Results



- **Accuracy**
  - WB-PM & FB-PCA Fault detection: 100% (PCA retention rate is 0.95)
    - Even when PCA retention rate is 0.65, the accuracy is 79% (3 mis-detected cases);
      - Retention rate is a parameter that adjusts the PCA model's sensitivity.
    - Fault detection threshold is automatically learned from the baseline data.
  - PM-BN Fault diagnosis: > 90% (only one case mis-diagnosed);
  - False alarm rate: no false alarm!
    - 14 fault free days tested (10 summer, 2 transition, and 2 winter season cases).

- **Energy Impact**
  - Energy impacts of the tested faults vary from 5% to 40% of the HVAC system energy consumption;
  - Virtual HVAC energy meters are used in lieu of whole building or sub-system meters;
  - Baseline energy is automatically generated using our pattern matching method!

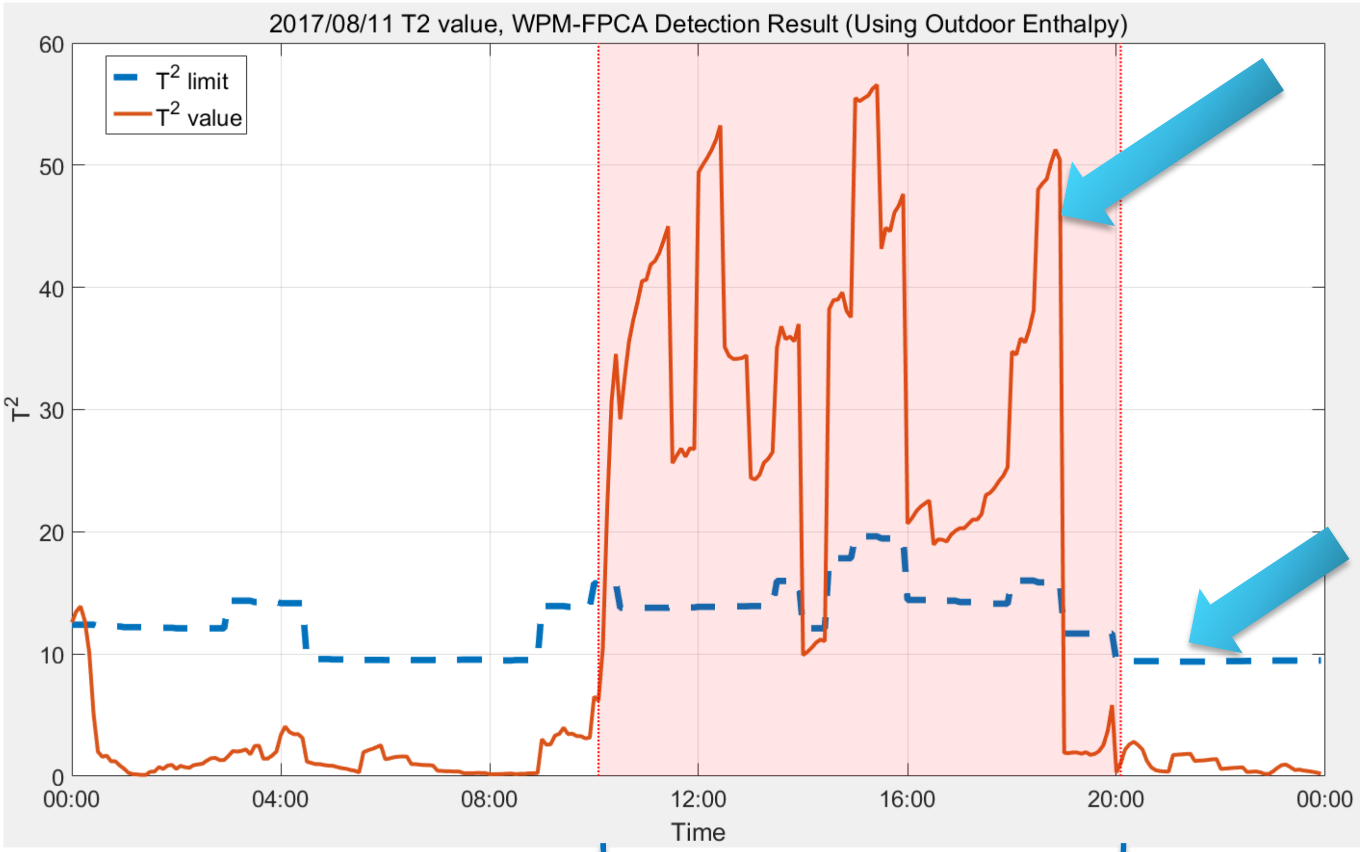


Fault: AHV Cooling Coil Valve SWO at a higher than normal position

Approach – Evaluation Illustration

Successful Case: Fault - AHU-2 cooling coil valve Software Override to be 100% open (position under similar weather is around 60% open), August 11, 2017

Detection Result:



T^2 value of incoming snapshot data

T^2 threshold – automatically generated when generating baseline using Pattern Matching and PCA methods

Fault period

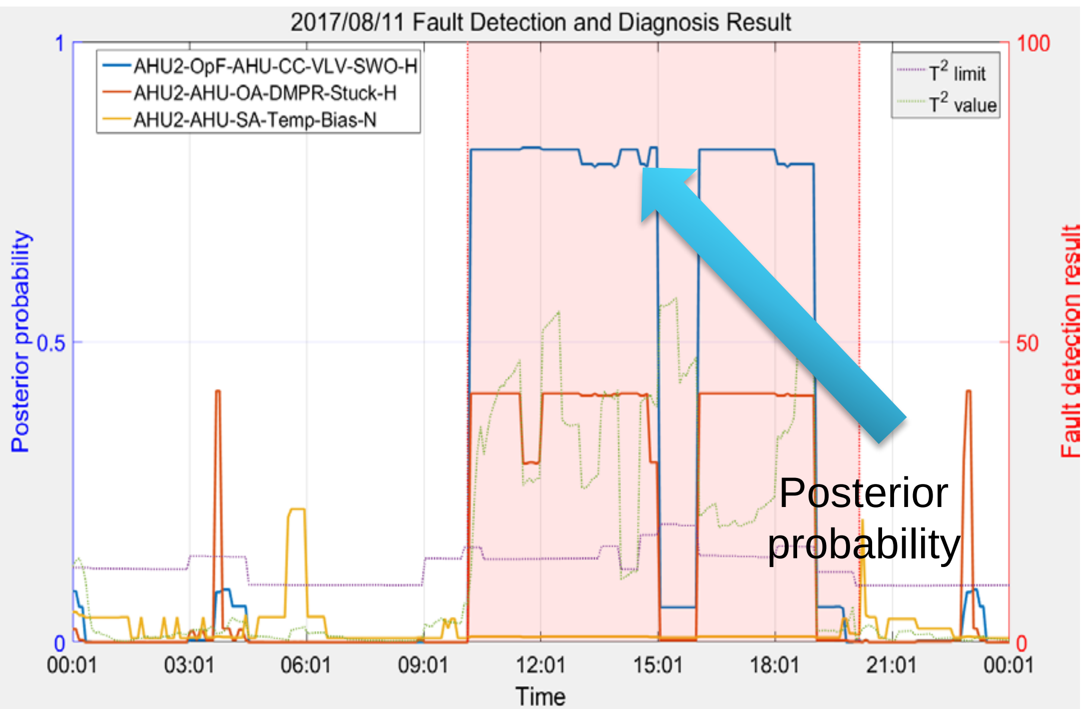
Approach – Evaluation Illustration

Successful Case: Fault - AHU-2 cooling coil valve Software Override to be 100% open (position under similar weather is around 60% open), August 11, 2017

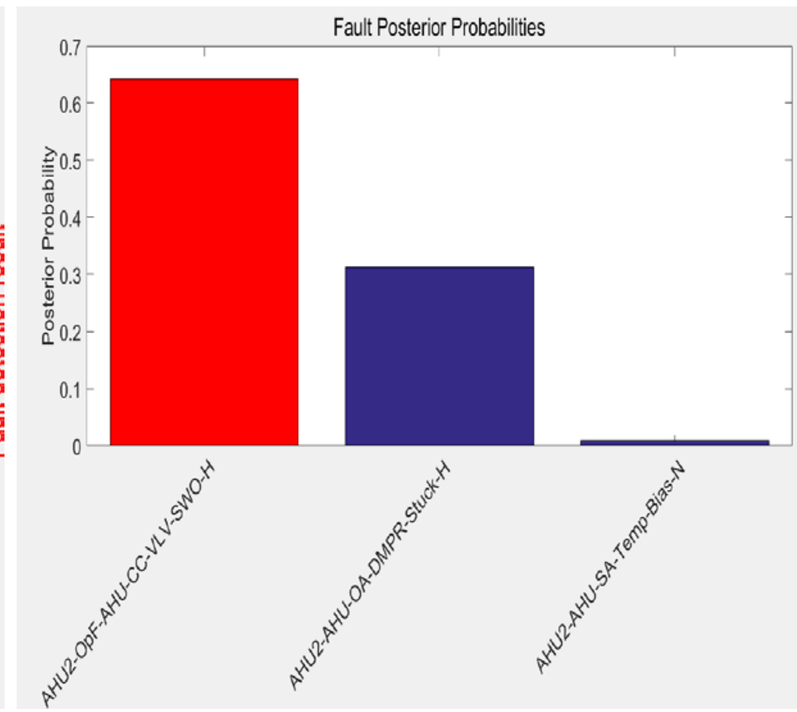
A fault is considered successfully diagnosed if

1) This fault's highest posterior probability is greater than a threshold (0.3);
2) This fault's averaged posterior probability during the fault period is greater than a threshold (0.1);
3) The difference between this fault's posterior probability (highest) and the second-highest one is greater than a threshold (0.1).

Diagnosis Result:



Fault posterior probabilities

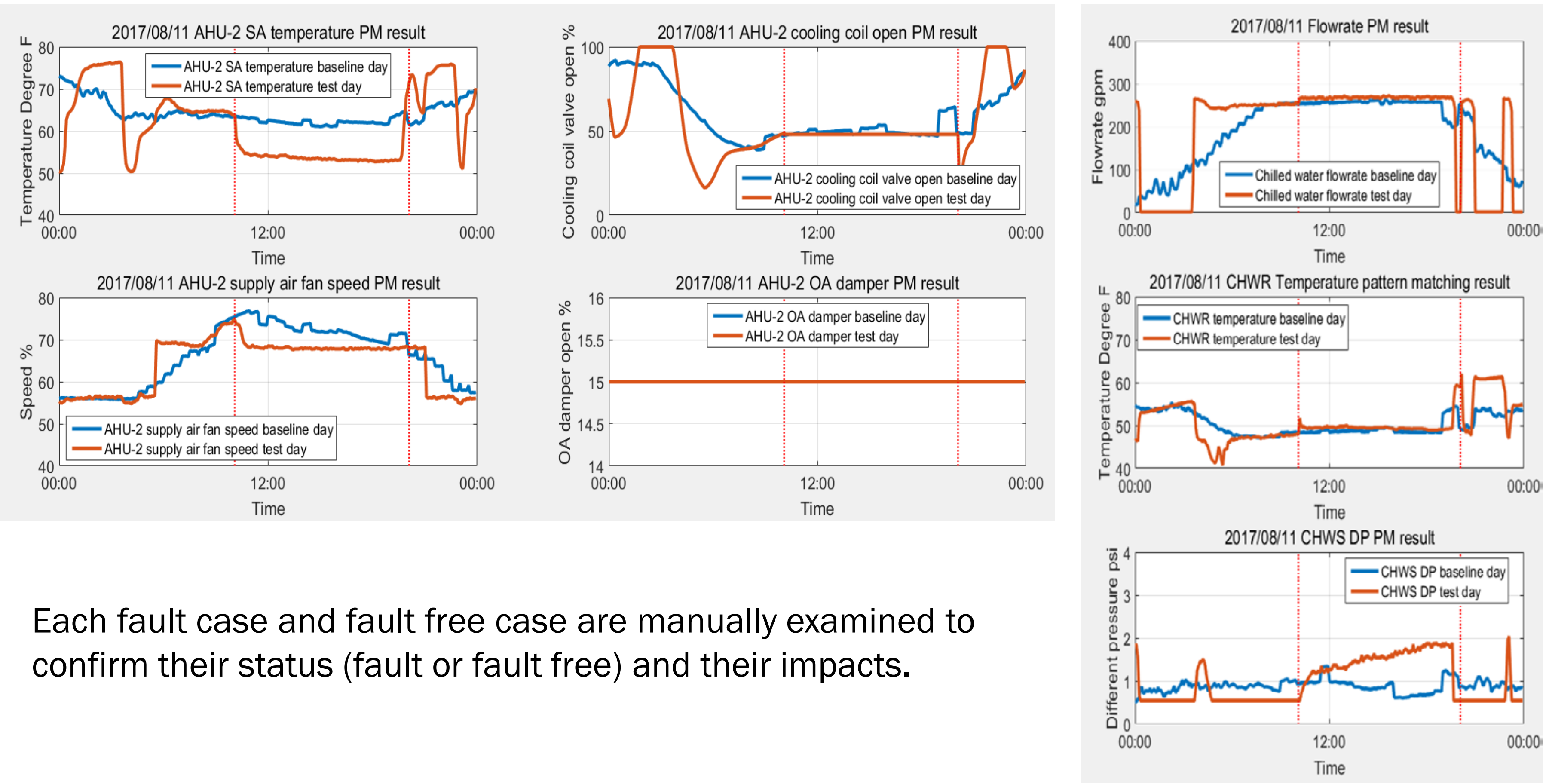


Fault posterior probability ranking

Approach – Evaluation Illustration

Successful Case: Fault - AHU-2 cooling coil valve Software Override to be 100% open (position under similar weather is around 60% open), August 11, 2017

Illustration of key measurements compared with their baseline values:

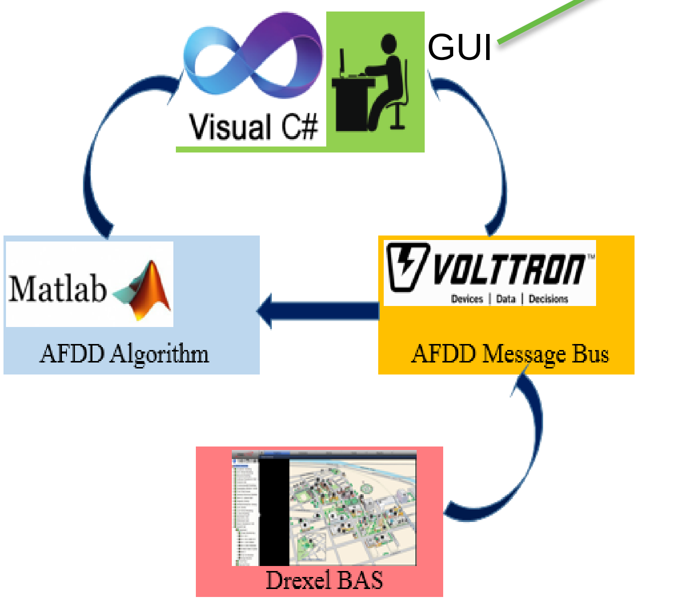


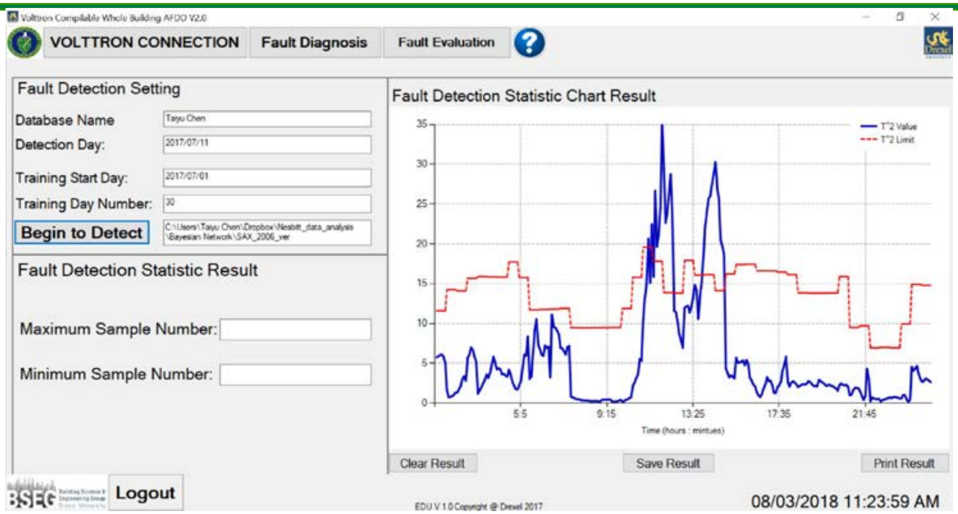
Each fault case and fault free case are manually examined to confirm their status (fault or fault free) and their impacts.

Approach - VOLTTRON Compatible and GUI

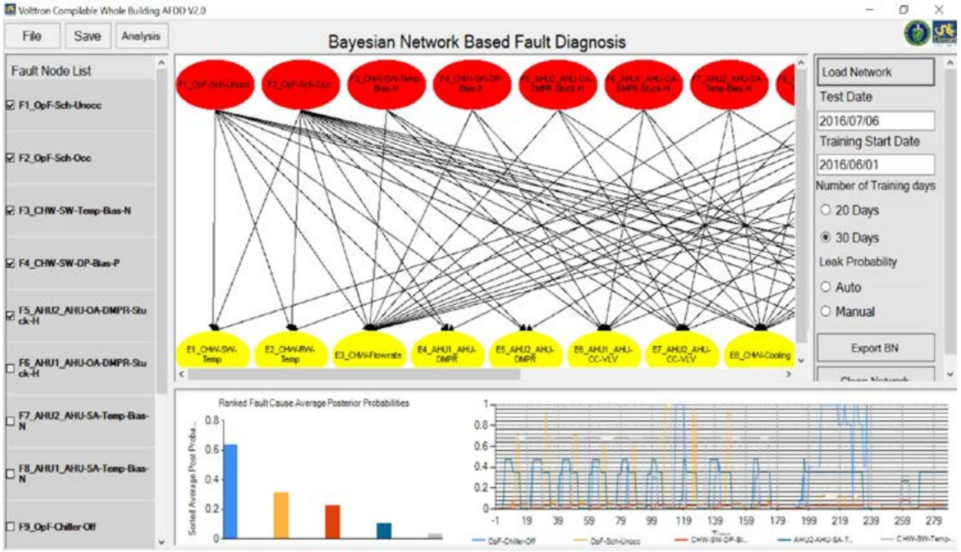
- Developed whole building AFDD strategies that are compatible with open execution controls platform, VOLTTRON
- A user-friendly GUI is developed

Overall Software Structure





Fault detection interface



Fault diagnosis interface

Impact

Impact of Project:

- Increase HVAC AFDD tools' market adoption by overcoming key barriers to implementation:
  - Barrier 1 - *Difficult to install and tune AFDD tool*: the developed strategies are highly automated, i.e. **plug-n-play, self-learning and self-diagnosis**;
  - Barrier 2 – *High implementation and operation cost:* the developed strategies will drastically reduce implementation cost (by reducing engineering hours) with a payback time that is less than 3 years;
  - Barrier 3 - *Lack of useful fault information:* the developed strategies provide energy impact and fault root-cause information.
- Help to achieve BTO's goal of achieving 30% energy savings by 2030 from HVAC-based AFDD in the commercial sector;
- Has trained 10+ undergraduate and graduate students in the area of building AFDD. The developed educational/demonstration materials will have long-term impacts on the building industry and its workforce.

Progress and Remain Work

- **Project successfully completed last month with the following accomplishments achieved:**
  - Developed Weather/schedule based Pattern Matching and Feature engineering based PCA fault detection strategy and BN based fault diagnosis strategy for whole building level faults.
  - Demonstrated that the developed strategies have an accuracy that is over **90%** and a false alarm rate that is less than **5%** by implementing faults into a real, operational buildings.
  - Demonstrated compatibility with the VOLTTRON platform for executing control functions with input from improved whole building fault detection and diagnosis data.
  - These strategies are highly automated, computational efficient and do not require special training with an estimated implementation cost of **~$0.12** per square foot. The simple payback time is less than 3 years.
  - An estimated 5-40% of HVAC system energy can be saved by diagnosing and correcting the faults investigated.
  - Eleven undergraduate students from different disciplines were engaged and exposed to AFDD in the building industry.

Stakeholder Engagement

- Market and survey studies are performed by undergraduate students from the Drexel Close Entrepreneurship School to understand the challenges and gaps in the whole building AFDD area;
- Routine meetings with industrial partner and other collaborators to solicit feedback;
- Presented our progresses in various conferences/events to expose engineers and stake holders to 1) the significance of FDD, and 2) potential cost-effective data-driven FDD solutions.
  - Yimin Chen, Jin Wen. "A Whole Building Fault Detection Using Weather Based Pattern Matching and Feature Based PCA Method", 2017 IEEE International Conference on Big Data (IEEE Big Data 2017) Boston, MA, USA. December 11-14, 2017
  - Yimin Chen, Jin Wen. "Whole Building System Fault Detection Based on Weather Pattern Matching and PCA Method", 2017 3rd International Conference on Control Science and Systems Engineering (ICCSSE 2017). Beijing, China. August 18-19, 2017
  - Yimin Chen, Jin Wen, Adam Reigner. "Using Pattern Matching and Principal Component Analysis Method for Whole Building Fault Detection". 2017 ASHRAE Annual Conference. Long Beach, CA, USA. June 25-28, 2017
  - 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
  - Wen, J., A. Regnier, and Y. Chen, "Automated Diagnostic Developments & Case Studies - VOLTTRON-Compatible AHU Diagnostic System,", 2016 Purdue High Performance Buildings Intelligent Building Operation Session, West Lafayette, IN, July.

Thank You

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REFERENCE SLIDES

Project Budget

Project Budget: See Table below
Variances: None
Cost to Date: $165,876
Additional Funding: None

Budget History					
October 2015– FY 2017 (past)		FY 2018 (current)		FY 2019 – N/A (planned)	
DOE	Cost-share	DOE	Cost-share	DOE	Cost-share
132,956.89	37,636	67,039	0	N/A	N/A

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-De	Q2 (Jan-M	Q3 (Apr-Ju	Q4 (Jul-Se	Q1 (Oct-De	Q2 (Jan-M	Q3 (Apr-Ju	Q4 (Jul-Se	Q1 (Oct-De	Q2 (Jan-M	Q3 (Apr-Ju	
Past Work												
Q1 MS: Literature review finished												
Q2 MS: Existing whole building data collected												
Q3 MS: Comprehensive commercialization plan developed												
Q4 MS: Fault detection method developed												
Q5 MS: Root fault isolaiton method developed												
Q6 MS:Based on the cost and energy impact estimation, the payback time is less than 3yrs												
Q7 MS: Developed tools are VOLTTRON compatible and GU developed												
Q8 MS: Course and training materials are developed												
Current/Future Work												
Final report and data preparation												

Approach - Development of BN

- **Development of BN parameter model**
  - *Prior* Probability
    - ❑ *Represents the frequency of a fault event may happen, needs to be assigned to the fault nodes*
  - *Conditional* Probability
    - ❑ *Measure the probability of a symptom event under the occurrence of a fault event*
    - ❑ *Three severity levels are defined in CPT*
    - ❑ *Conditional Probabilities are tested from BN based component-level fault diagnosis tool*

Evidence Symptom Level	Description	Conditional Probability Under Fault
Serious	Very Serious (S_V_S)	0.45
	Serious (SS)	0.45
	Serious Reminder (SR)	0.1
Medium	Very Large (M_V_L)	0.25
	Large (M_L)	0.25
	Medium Reminder (MR)	0.5
Light	Light (LV)	0.05
	Very Light (L_V_L)	0.05
	Light Reminder (LR)	0.9