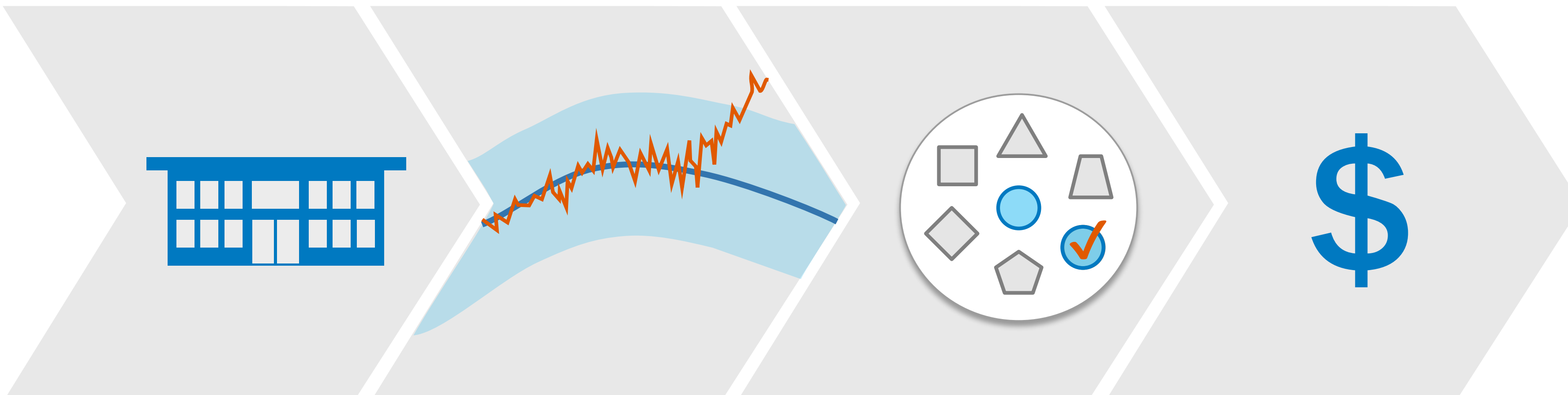
U.S. DEPARTMENT OF
ENERGY
Office of
ENERGY EFFICIENCY &
RENEWABLE ENERGY

An Open, Cloud-Based Platform for Whole-Building Fault Detection and Diagnostics



National Renewable Energy Laboratory, Oak Ridge National Laboratory,
GE Global Research, and Purdue University

PI: Stephen M. Frank, Senior Systems Engineer, NREL (Stephen.Frank@nrel.gov)

Project Summary

Timeline:

Start date: October 1, 2016

Planned end date: September 30, 2019

Key Milestones

1. Fault Models Developed (FY2018 Q1)
2. Fault Models Validated (FY2019 Q1)
3. AFDD Algorithm Completed (FY2019 Q1)
4. Reference Implementation (FY2019 Q4)

Budget:

Total Project $ to Date (Through FY2018 Q2):

- DOE: $734,369
- Cost Share: $92,478

Total Project $:

- DOE: $2,000,000
- Cost Share: $400,000

Key Partners:

Purdue University
GE Global Research Center
Oak Ridge National Laboratory
Lawrence Berkeley National Laboratory
Pacific Northwest National Laboratory

Project Outcome:

This project combines DOE's energy modeling tools with GE's Predix machine learning algorithms to create and validate a model-based automated fault detection and diagnosis (AFDD) platform for small commercial buildings (≤ 10,000 ft^2).

AFDD Project Portfolio

U.S. DEPARTMENT OF ENERGY

Marina Sofos (Emerging Technologies)
Amy Jiron (Commercial Buildings Integration)

← **Technical Advisory Group**

- NREL – National Renewable Energy Laboratory
  - GE
  - Purdue University
  - Oak Ridge National Laboratory
- Berkeley Lab
- Pacific Northwest

Team

Steve Frank
NREL

Xin Jin
NREL

Kim Trenbath
NREL

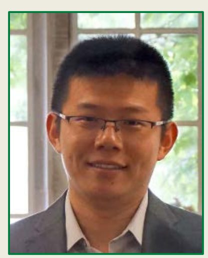
David Goldwasser
NREL

Ry Horsey
NREL

Piljae Im
ORNL

James E. Braun
Purdue

Janghyun Kim
Purdue



Jie Cai
Purdue, University of Oklahoma

Jason Nichols
GE Global Research

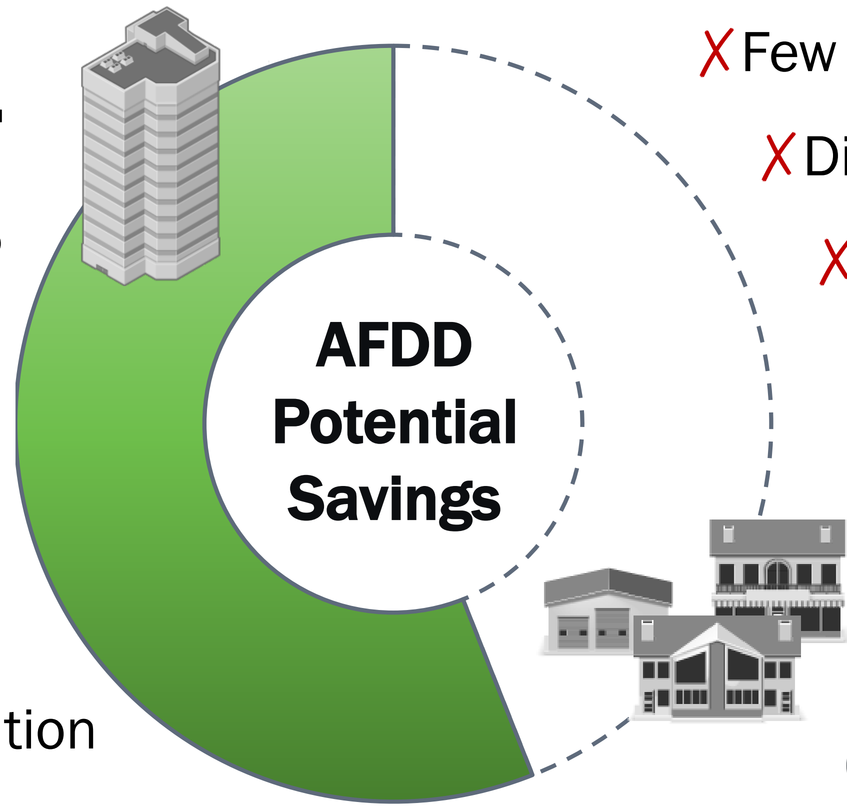
Rui Xu
GE Global Research

Cathy Graichen
GE Global Research

Challenge

Larger Buildings

0.4 Quads



✗ Few Products

✗ Different Equipment

✗ Lack of Data

✗ Too Expensive

Smaller Buildings

0.3 Quads

✓ Many Products

✓ Effective Competition

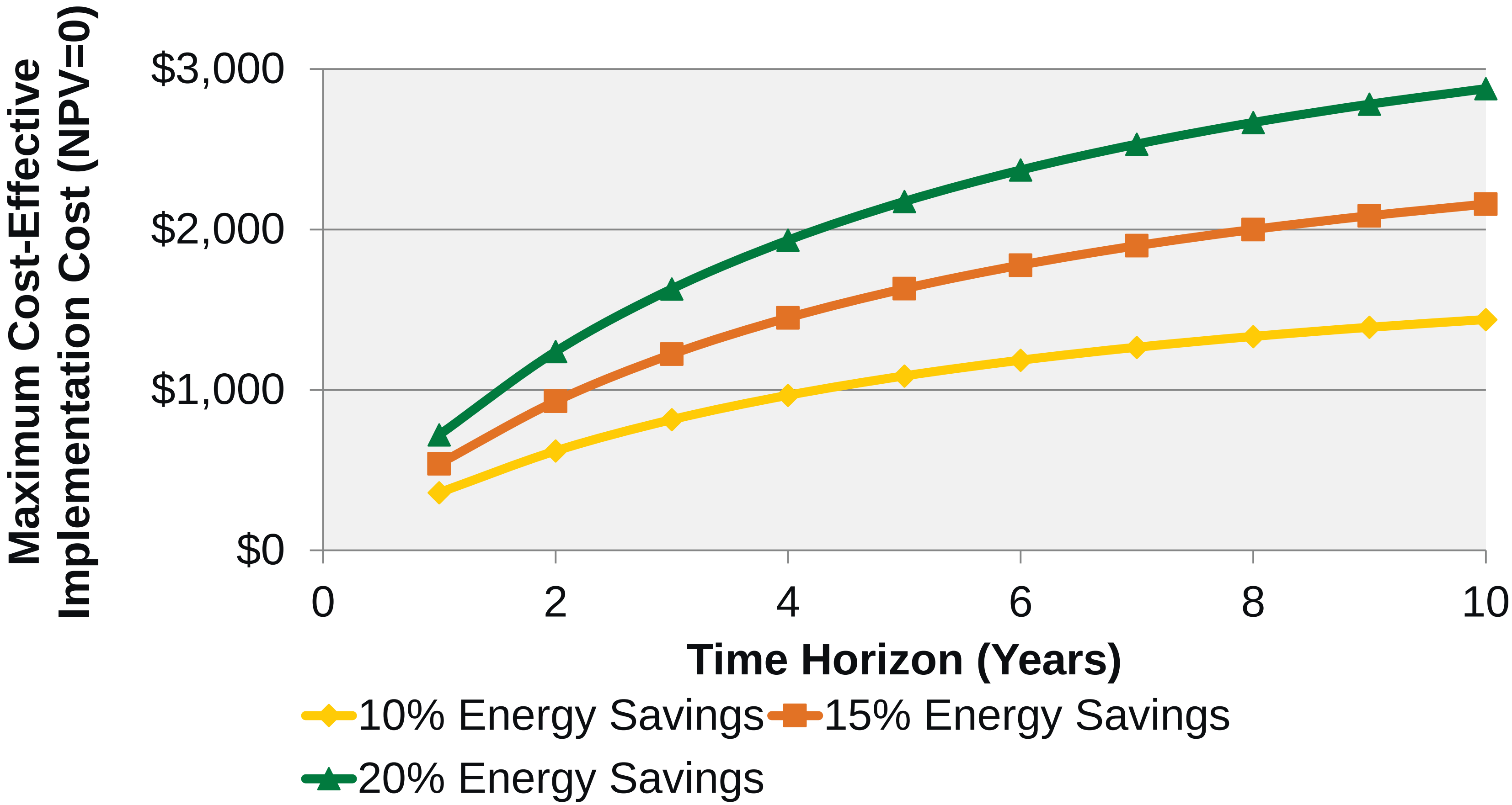
✓ Clear Financial Benefit

Project Goal: Research and develop practical, cost-effective AFDD algorithms for the underserved small commercial buildings sector

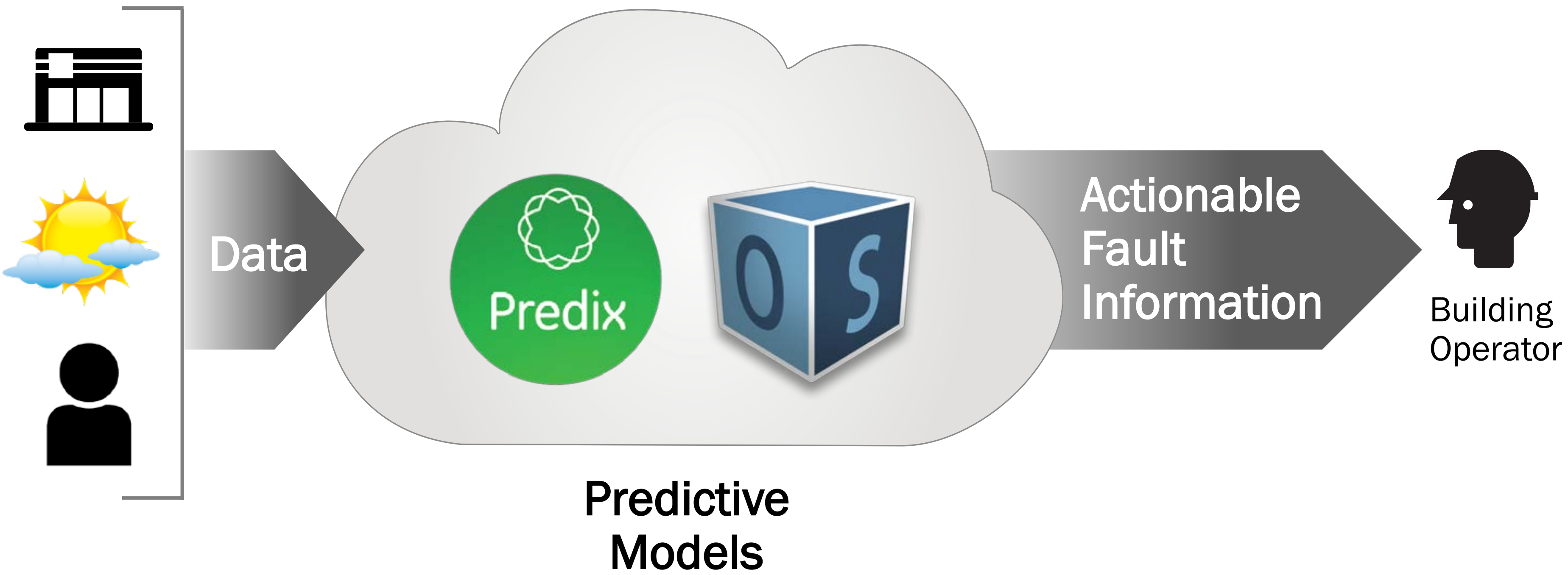
Impact

AFDD Net Present Value Analysis: 5,000 ft² Building

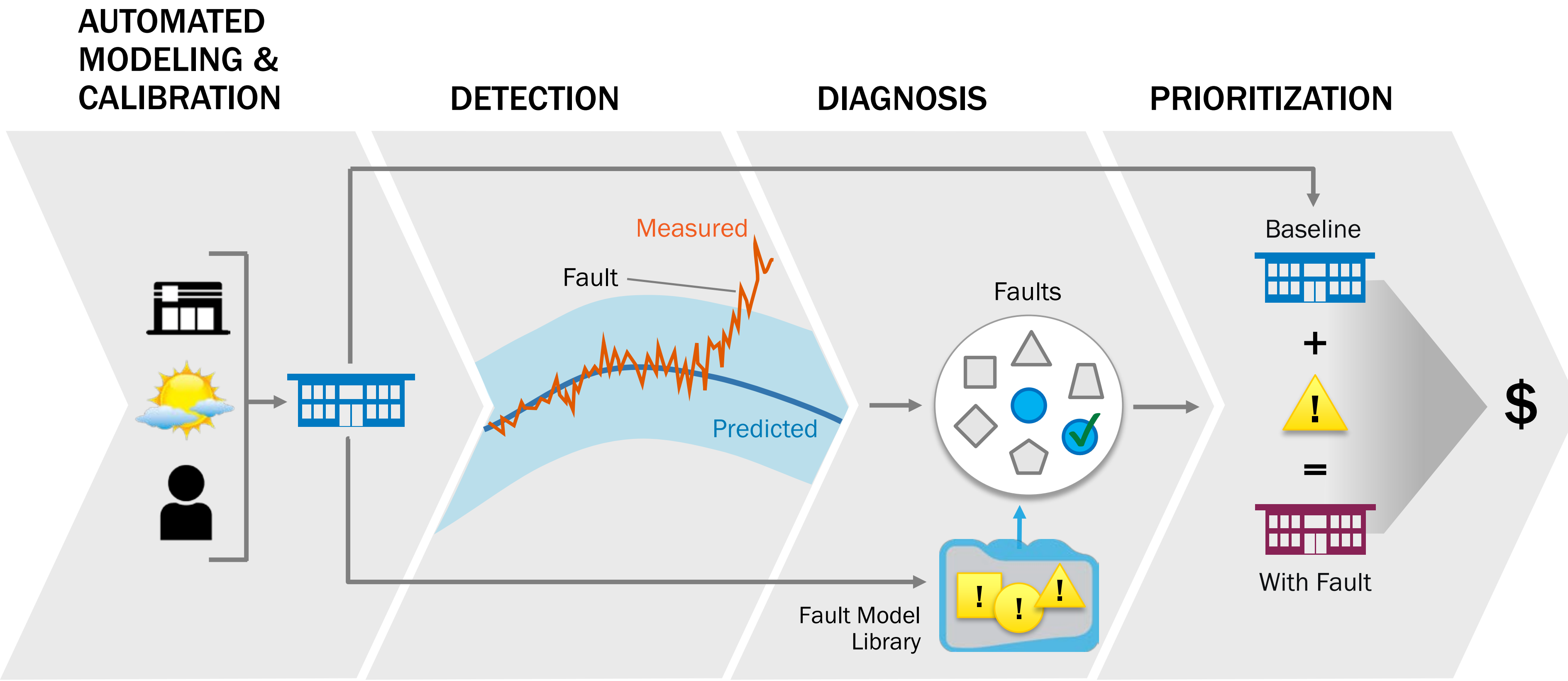
Annual Cost of Capital: 10% | Cost of Energy: $1.80/ft^2 | Annual Subscription Cost: 15% of Purchase Price



Approach


Data
Predix
Actionable
Fault
Information
Building
Operator
Predictive
Models

Model-Based AFDD Process



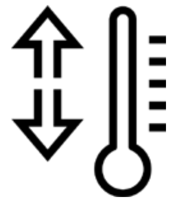
Advantage #1: Fewer Sensors

Rule-Based AFDD


Weather Conditions


Meter Data


Sensor Readings


System Setpoints


Control Commands


Equipment Configuration

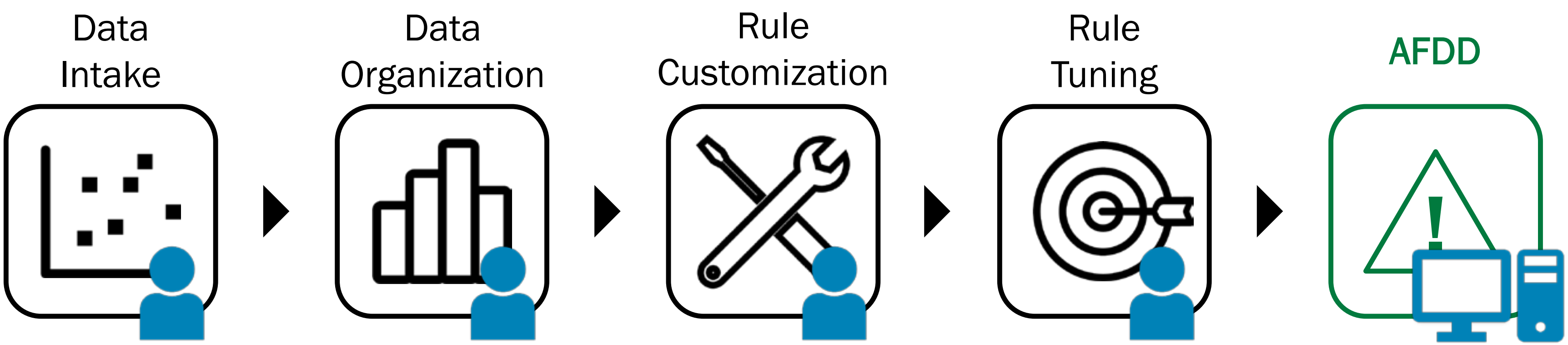
Model-Based AFDD


Weather Conditions

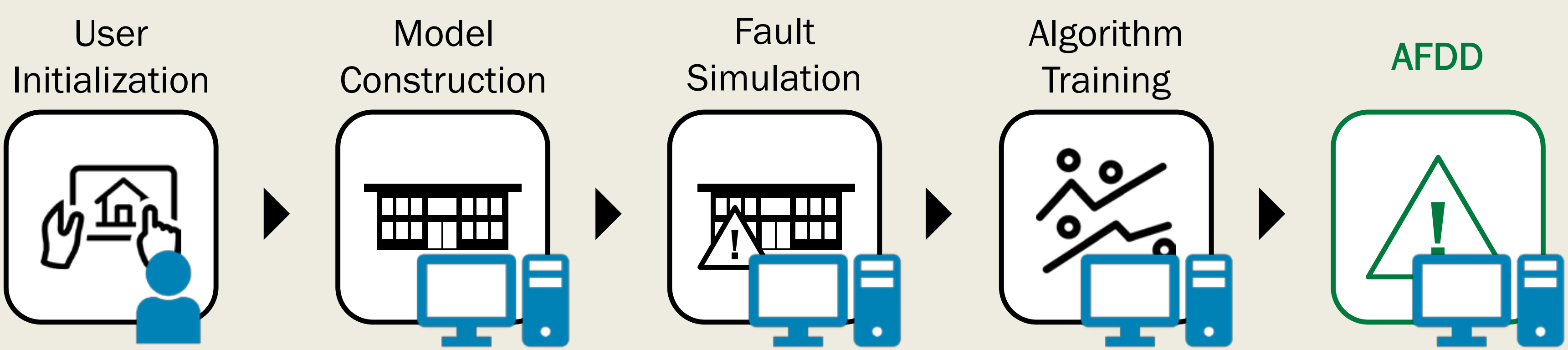

Meter Data

Advantage #2: Automation

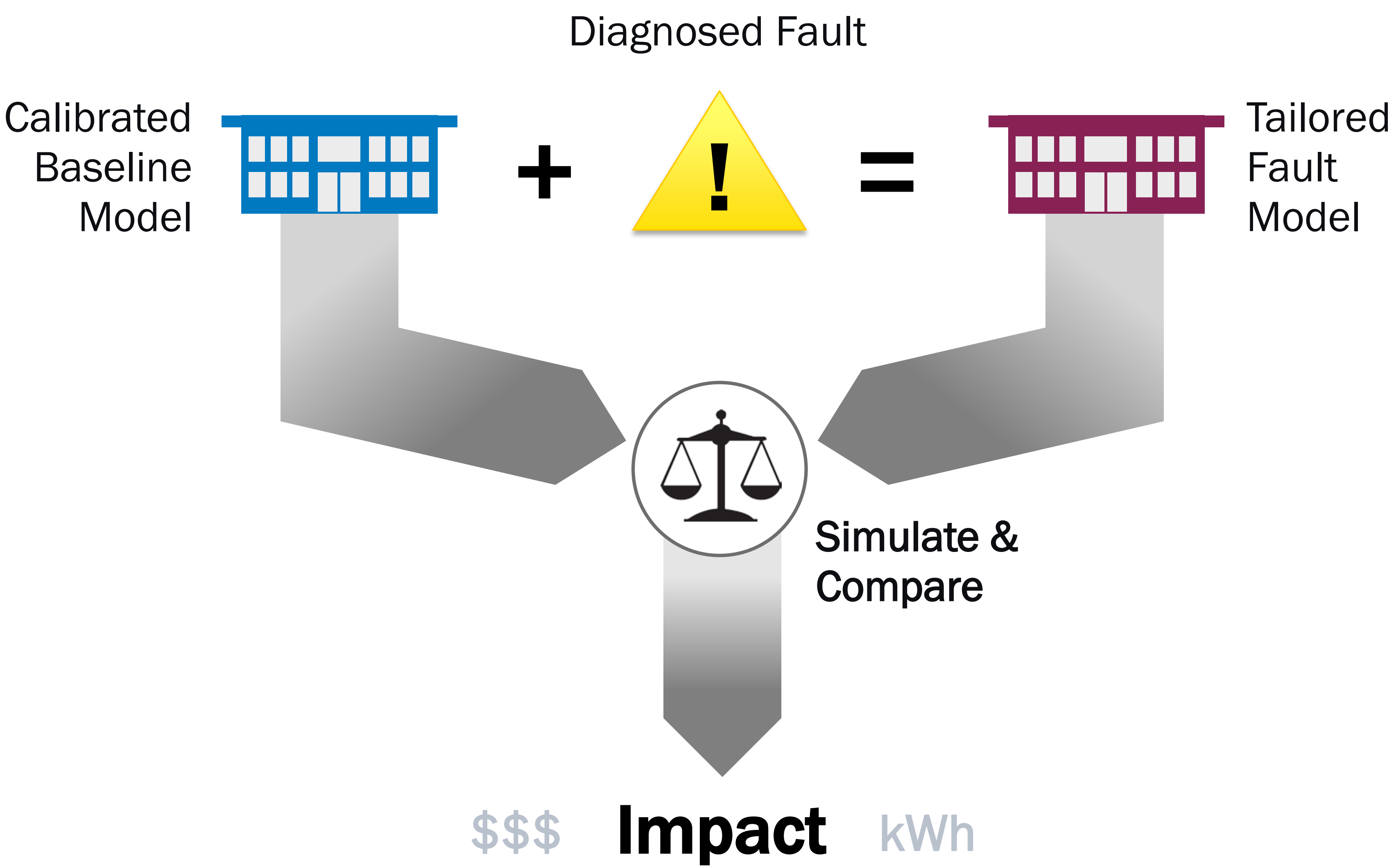
Rule-Based AFDD



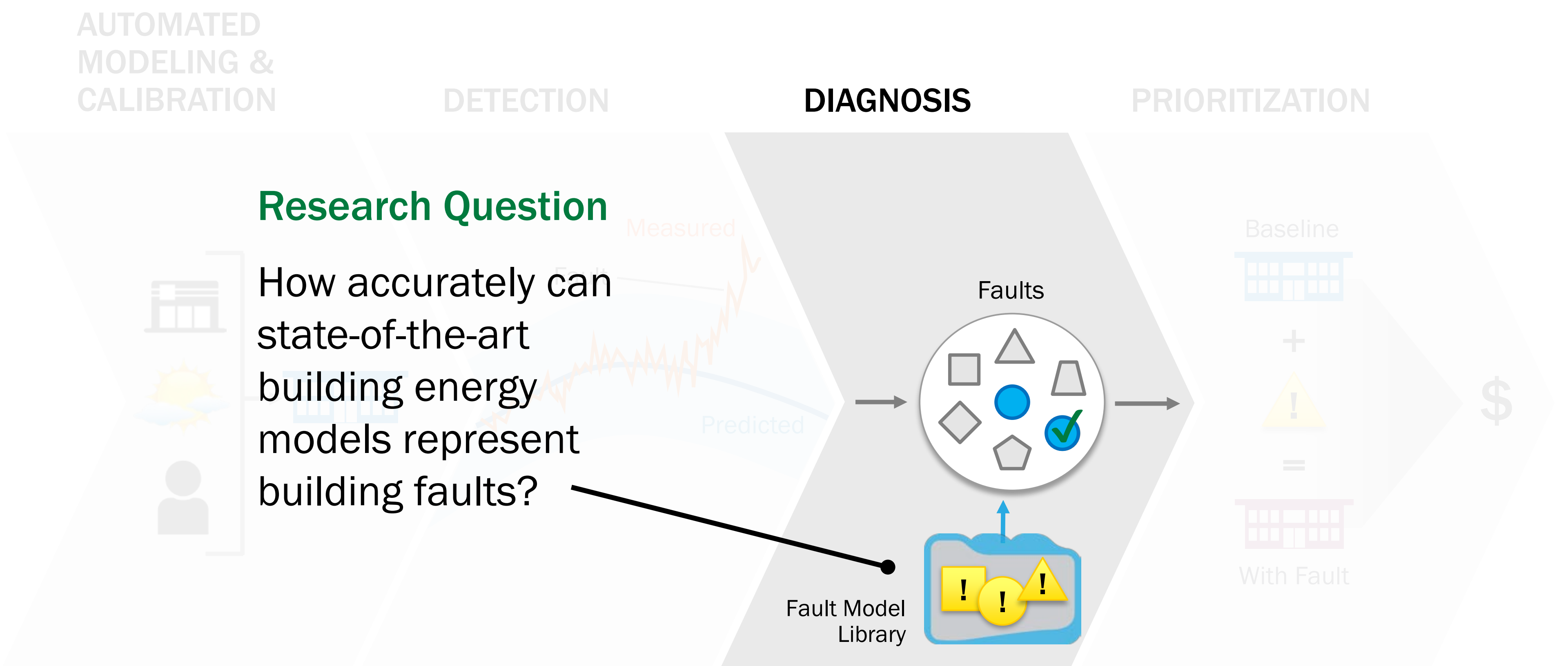
Model-Based AFDD



Advantage #3: Better Prioritization



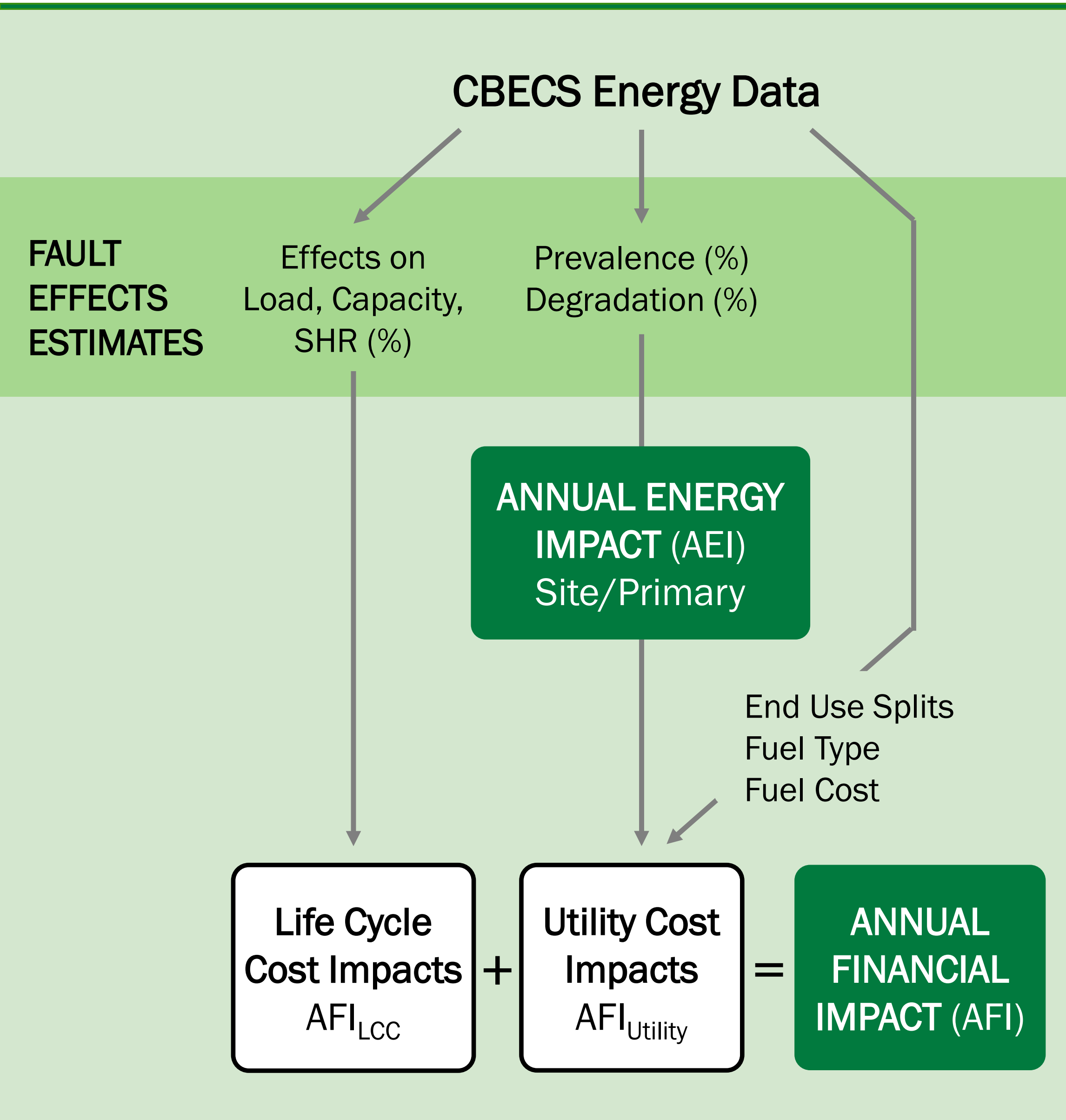
Knowledge Gap: Fault Modeling

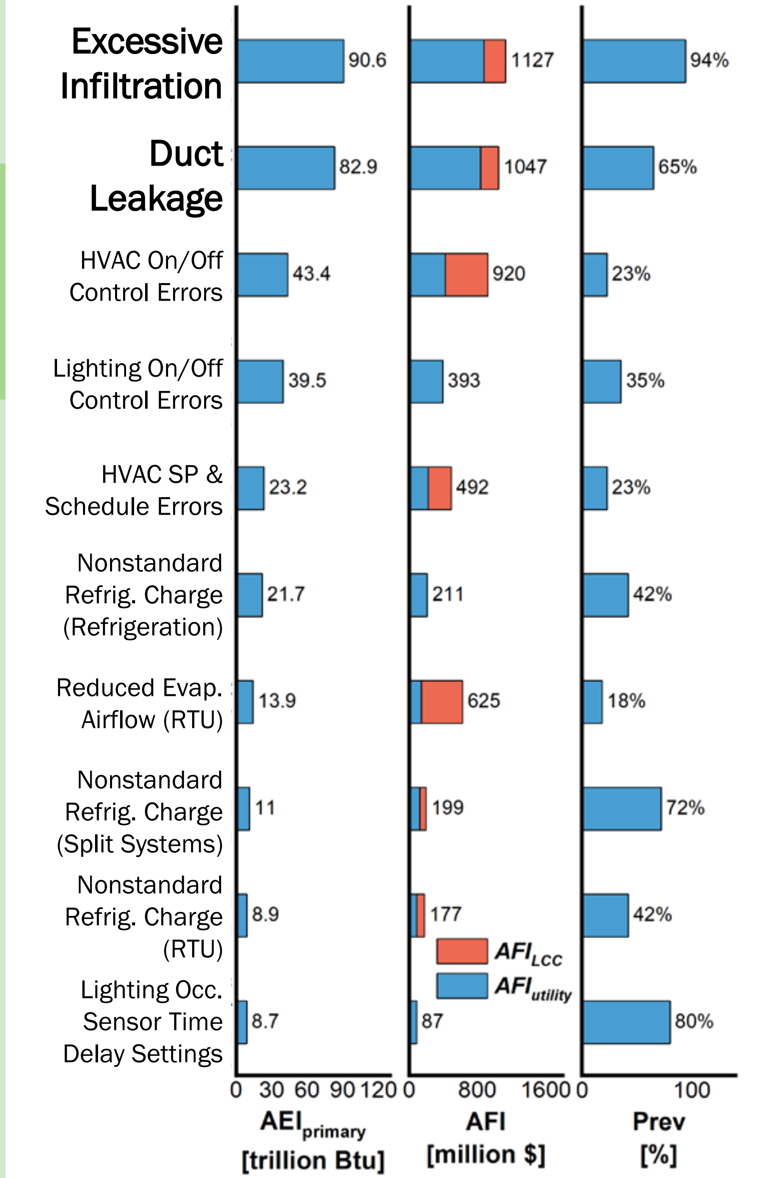


Research Question

How accurately can state-of-the-art building energy models represent building faults?

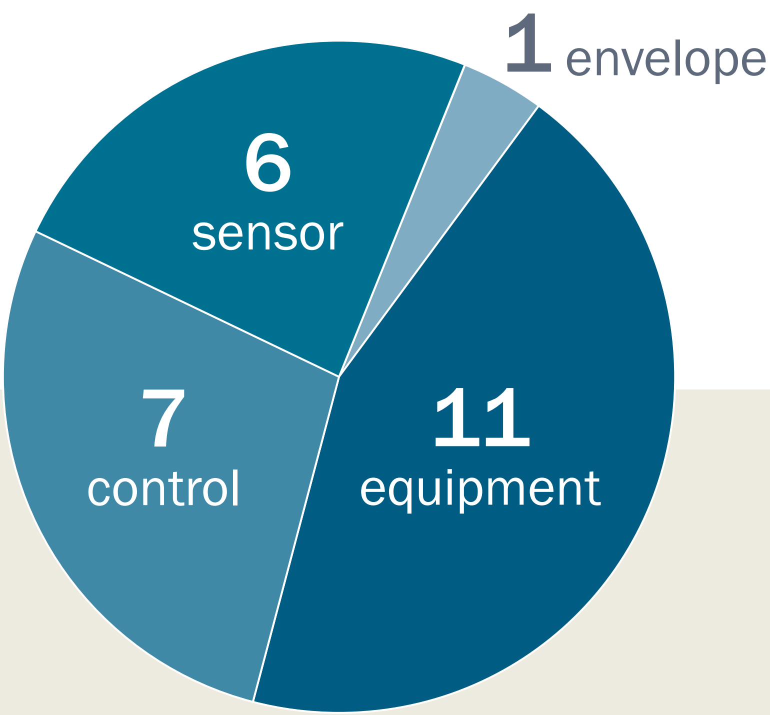
Fault Prioritization





Fault Model Library

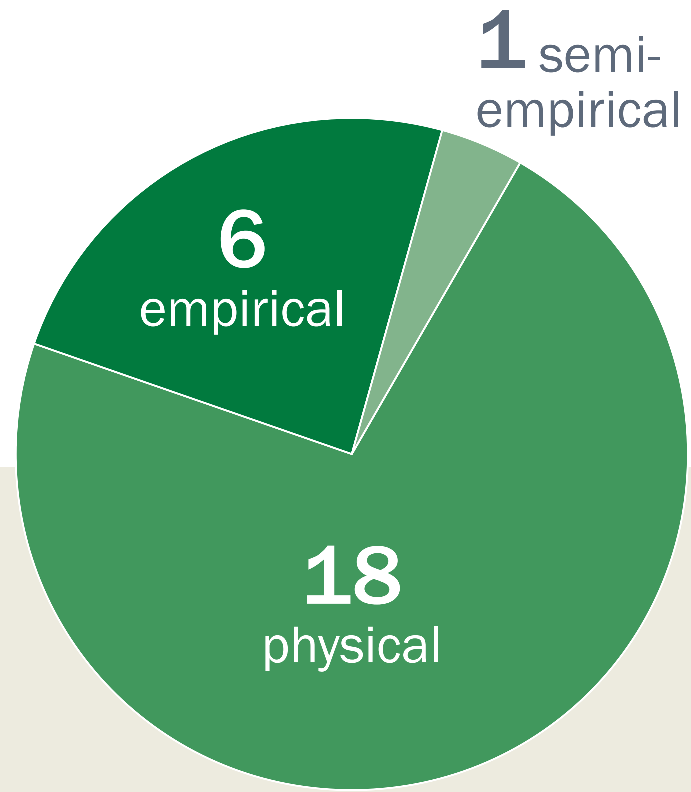
25 Fault Model Measures



Fault Types

95%

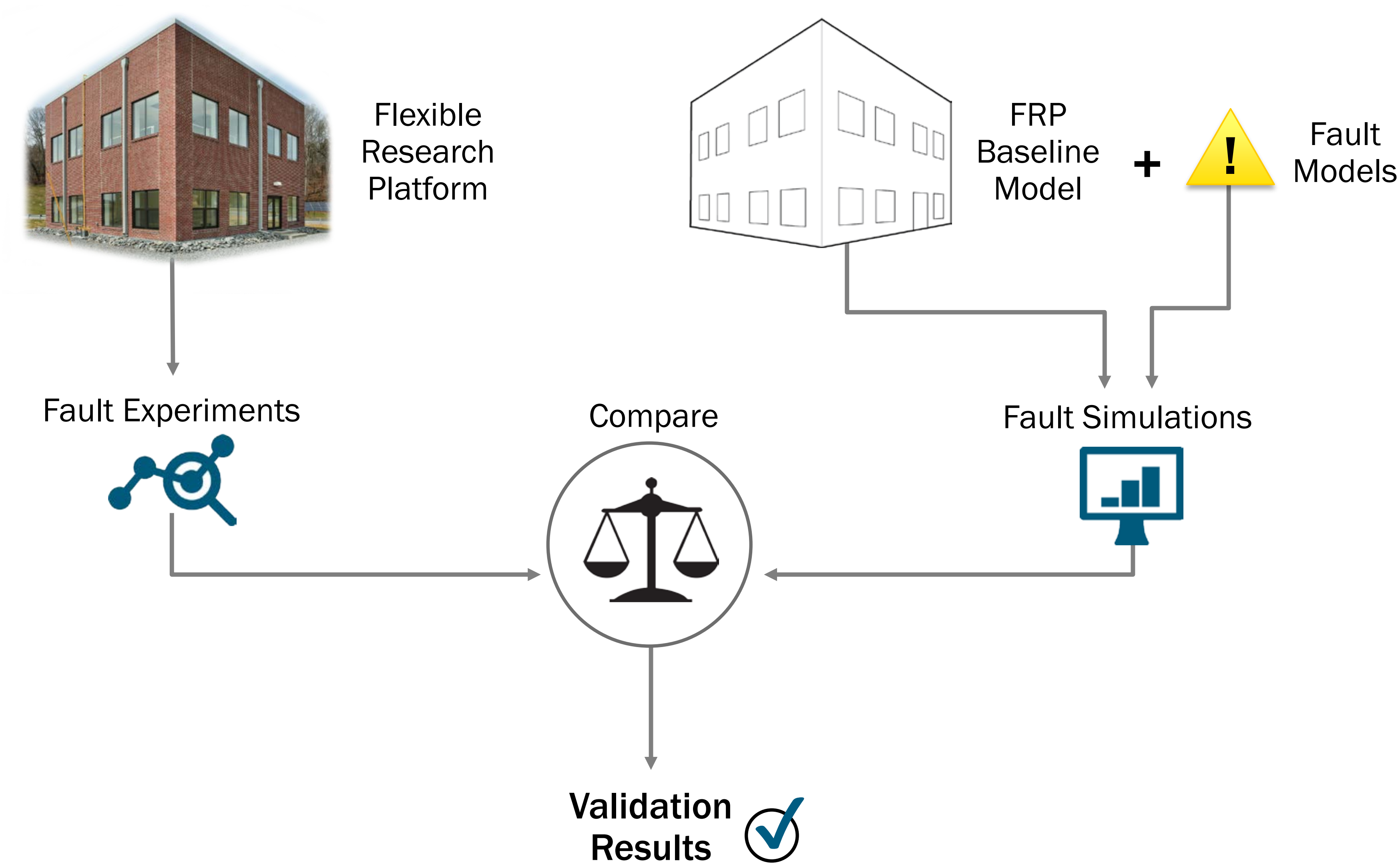
estimated **fault energy impact** from **prioritization**



Model Types

https://github.com/NREL/OpenStudio-fault-models

Fault Model Validation



Fault Experiments

12 of 21 Experiments Completed (as of March 2018)

Condenser Fouling, Increased Infiltration, HVAC/Lighting Control Faults

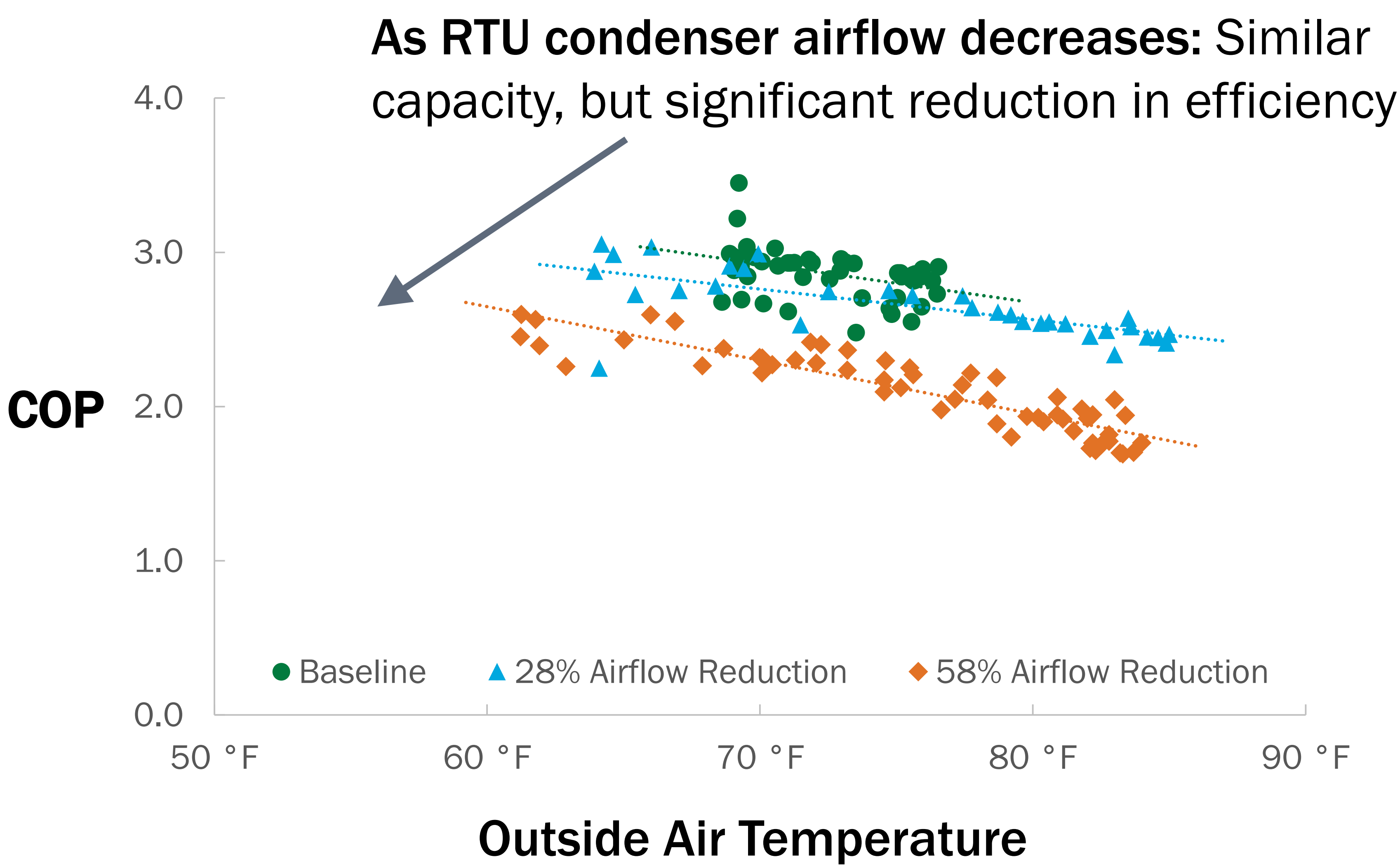
RTU Condenser Fouling Fault

Blower Door Test for Baseline Infiltration

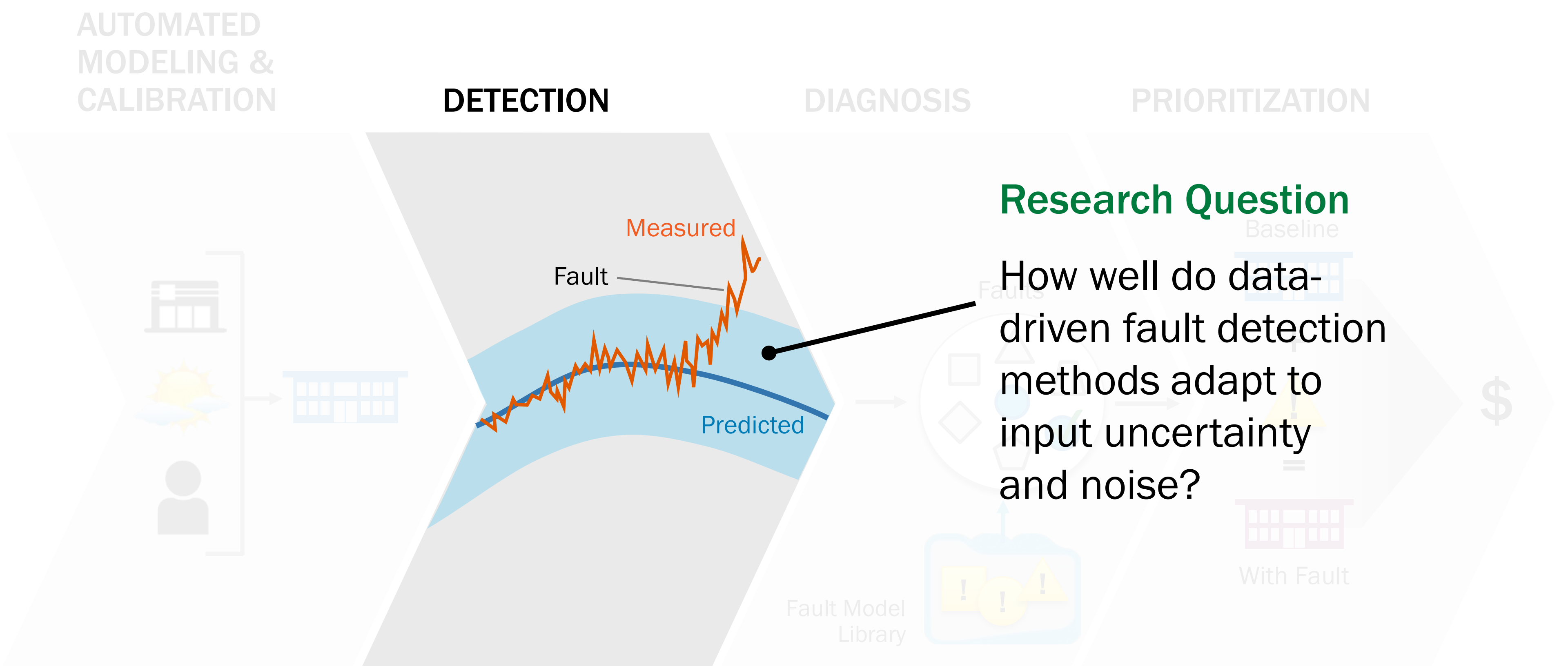
Increased Infiltration Fault

Photo Credit: *Piljae Im, ORNL*

Fault Experiment: Condenser Fouling



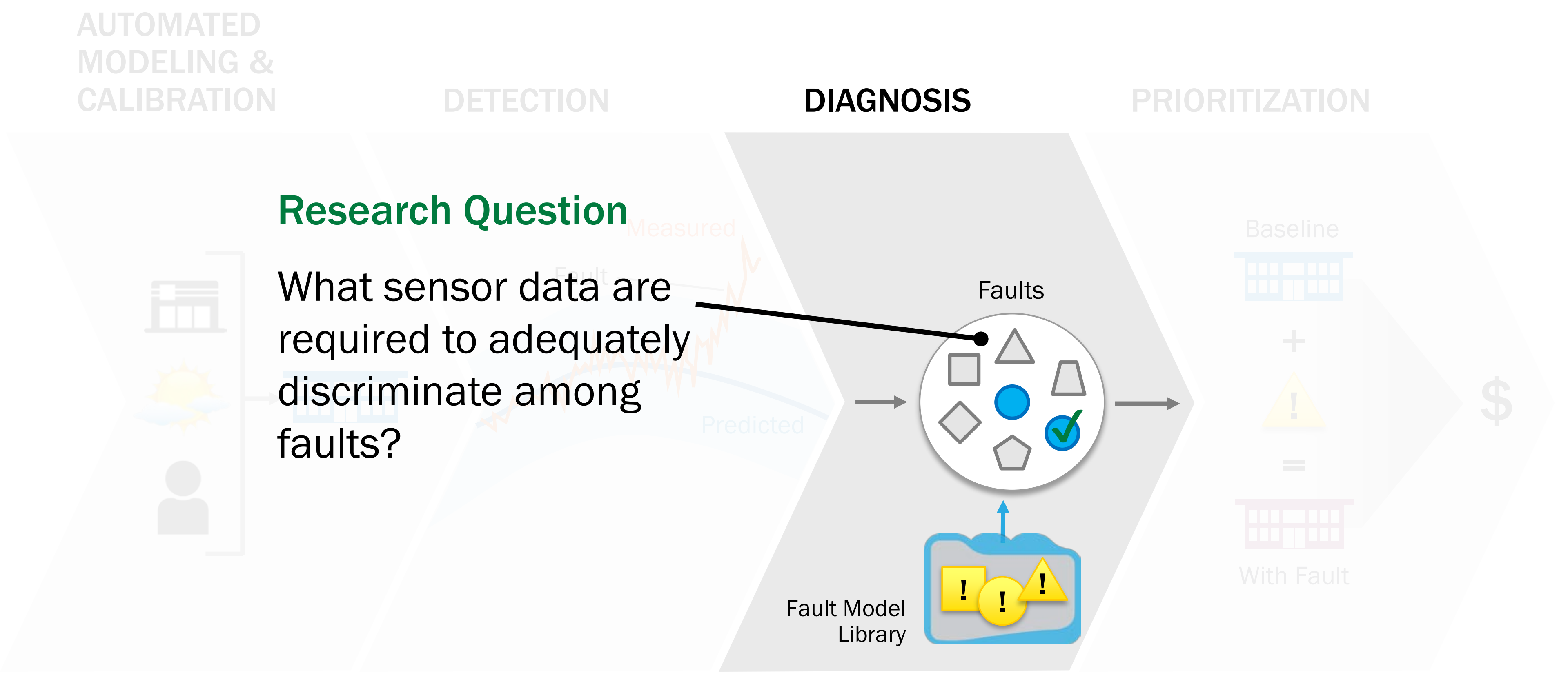
Knowledge Gap: Data-Driven Detection



Research Question

How well do data-driven fault detection methods adapt to input uncertainty and noise?

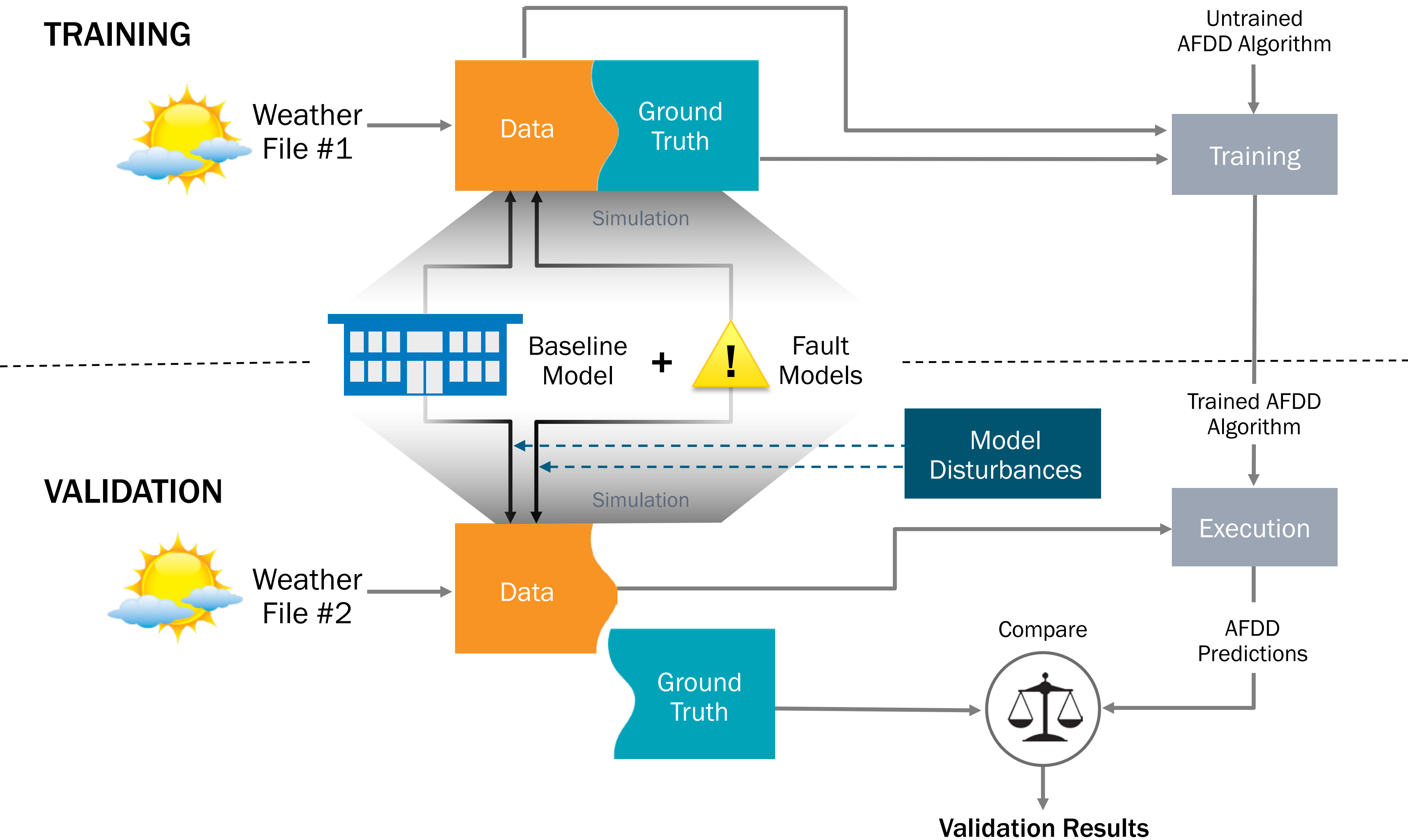
Knowledge Gap: Data-Driven Diagnosis



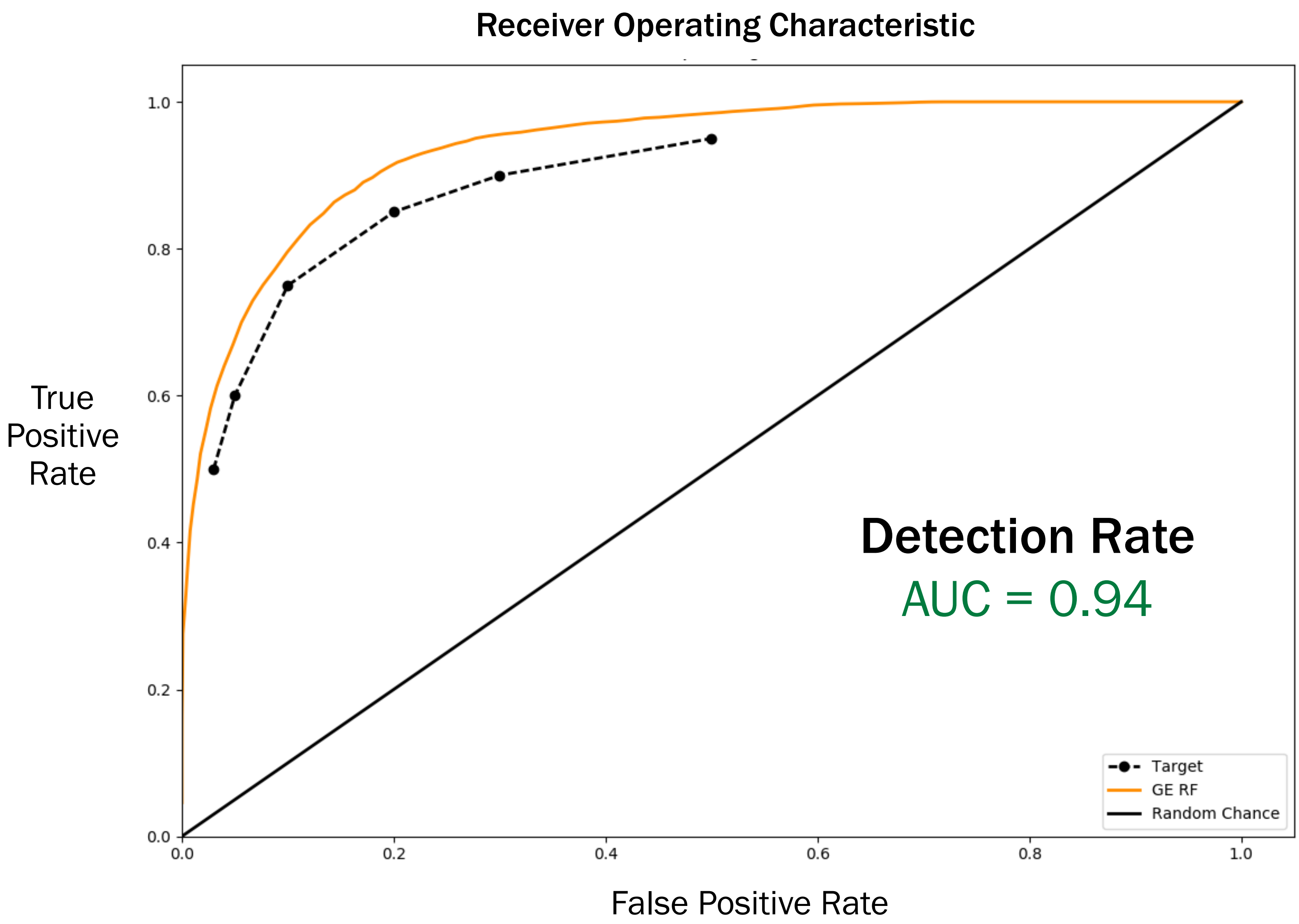
Research Question

What sensor data are required to adequately discriminate among faults?

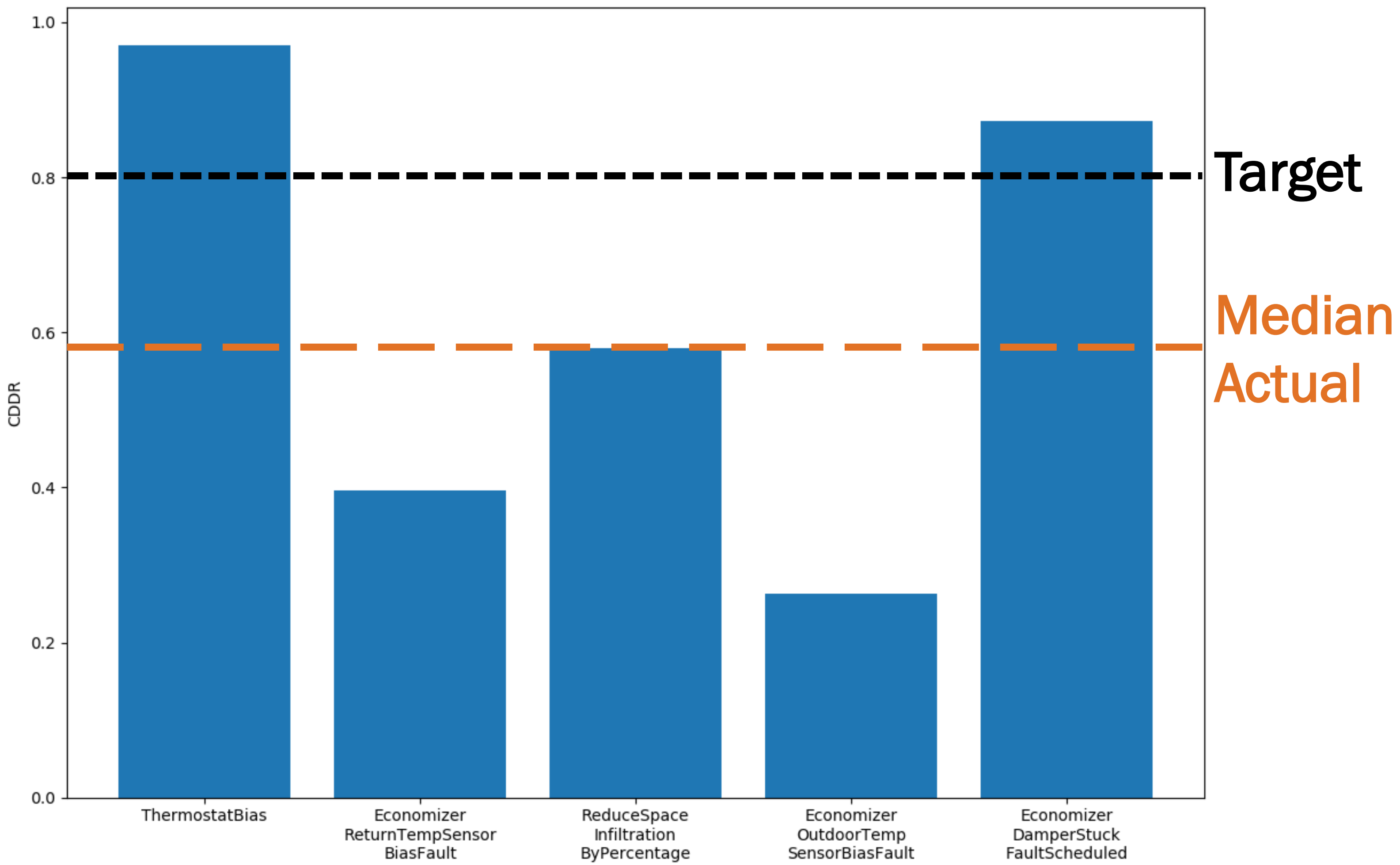
AFDD Performance Evaluation



Initial Performance: Detection



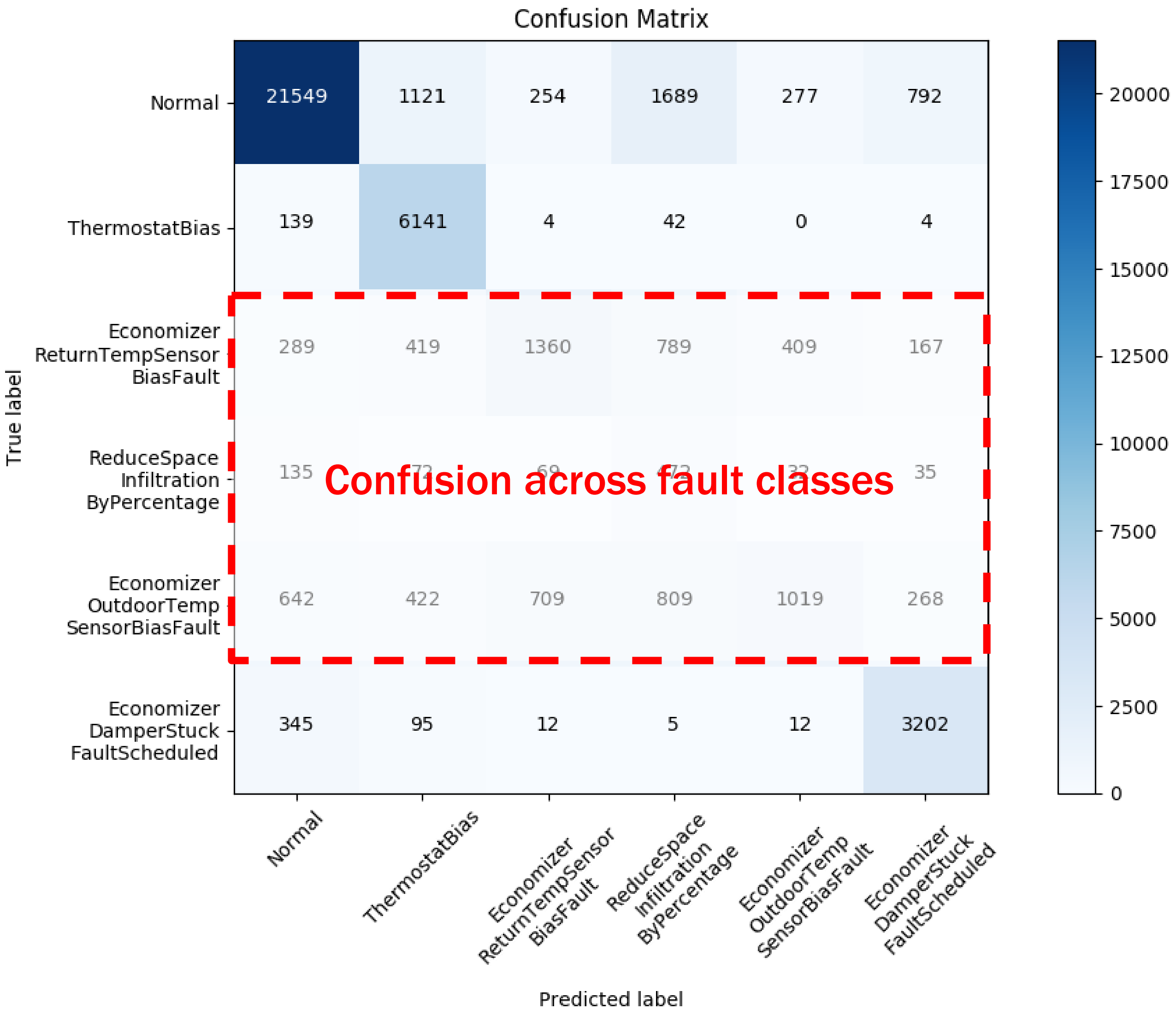
Initial Performance: Diagnosis



Diagnostic Accuracy

median CDDR = 0.6

Initial Performance: Confusion Matrix

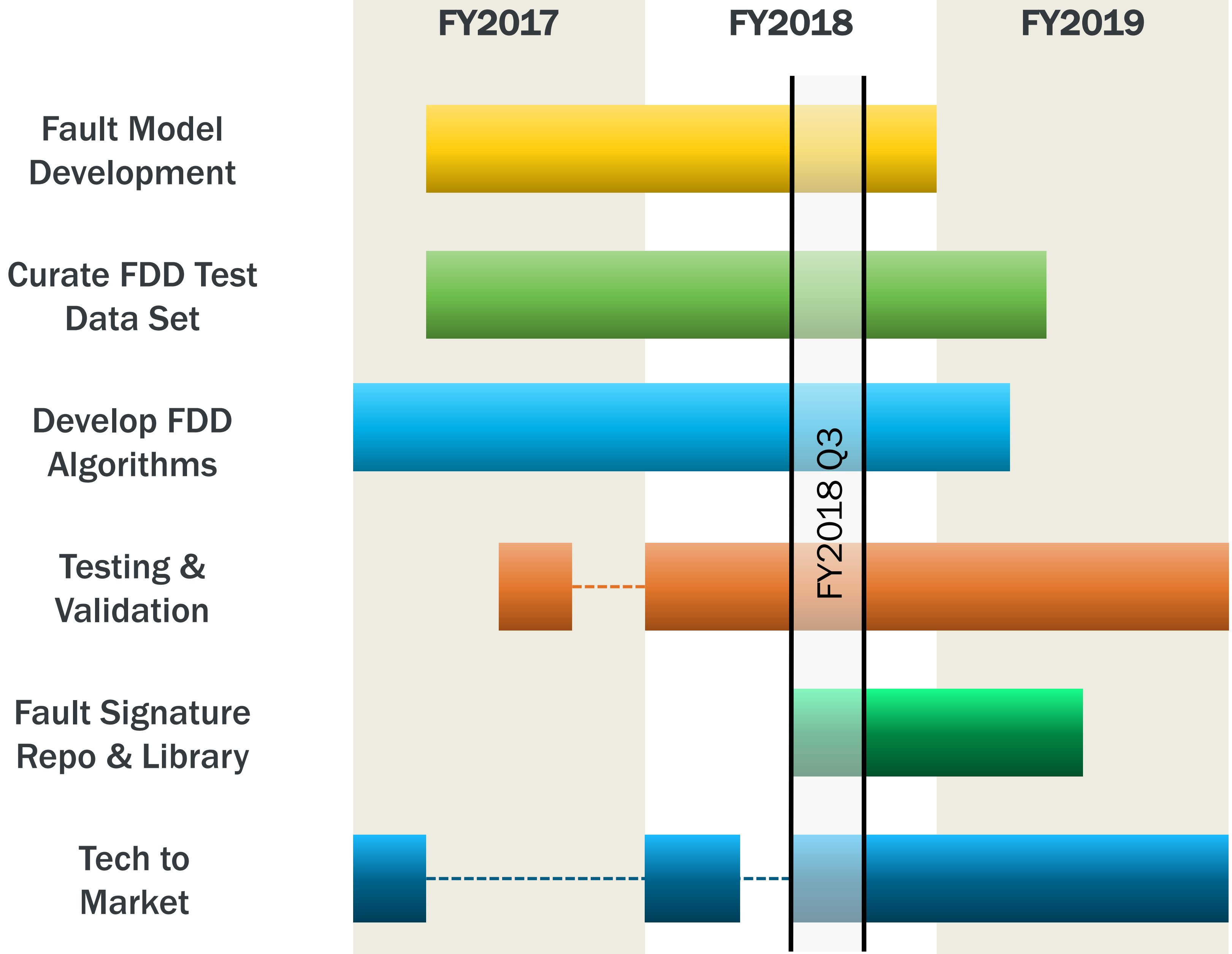


Path Forward

- Establish universal definition of fault
- Normalize fault behavior (capacity vs load)
- Improve automated feature selection
- Improve hierarchical fault class definitions
- Add anomaly detection

Stakeholder Engagement

1. **Technical Advisory Group**
2. **Engage Industry Experts**
3. **Research Industry Needs**
   (Literature, Interviews)
4. **Peer Reviewed Publications**
5. **Presentations at Relevant Conferences**
   e.g., Purdue High Performance Buildings Conf.


FY2017
FY2018
FY2019
Fault Model Development
Curate FDD Test Data Set
Develop FDD Algorithms
Testing & Validation
Fault Signature Repo & Library
Tech to Market
FY2018 Q3

Next Tasks

- Complete Fault Model Validation
- Fault Model Repository & Signature Library
- Final AFDD Algorithm Development
- **Automated Model Generation**

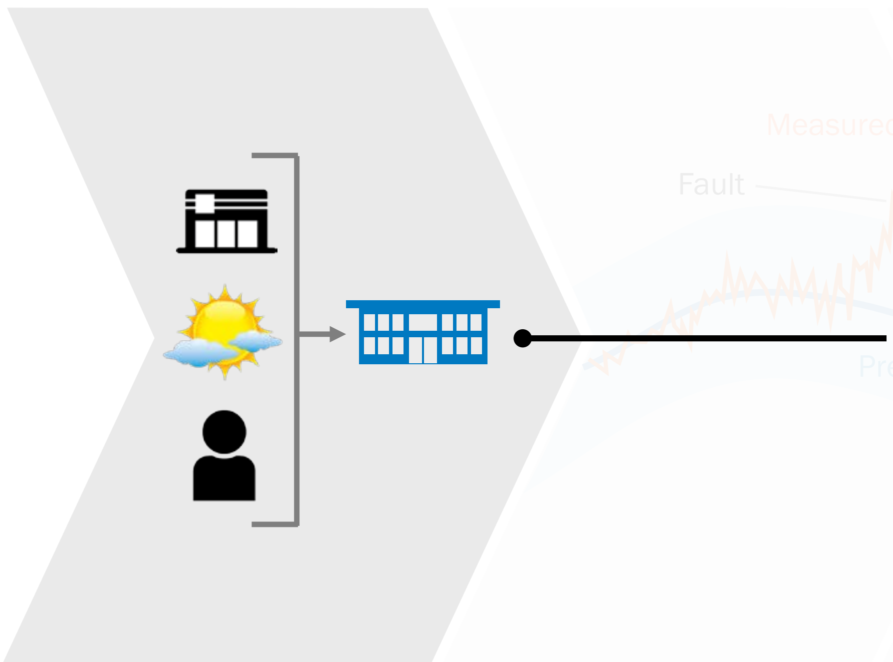
Knowledge Gap: Model Generation

AUTOMATED MODELING & CALIBRATION

DETECTION

DIAGNOSIS

PRIORITIZATION

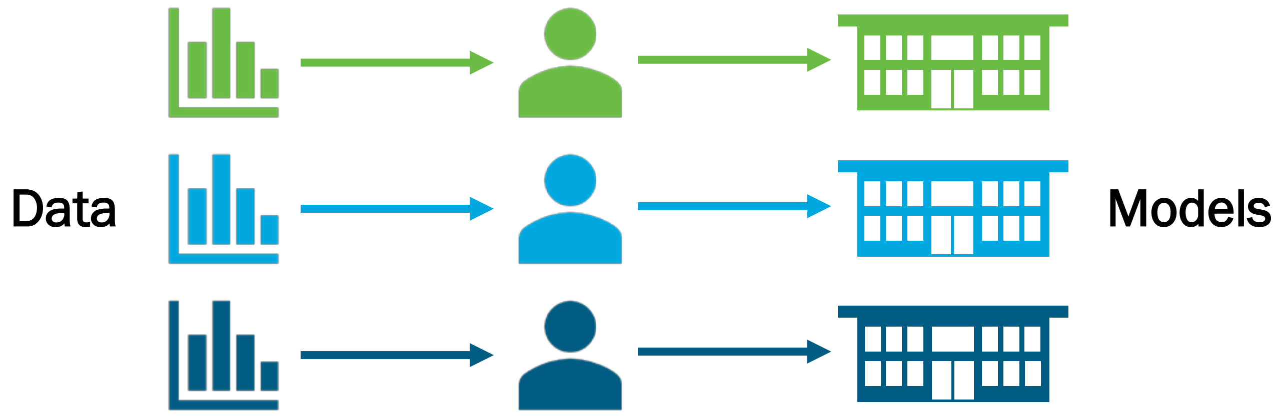


Research Question

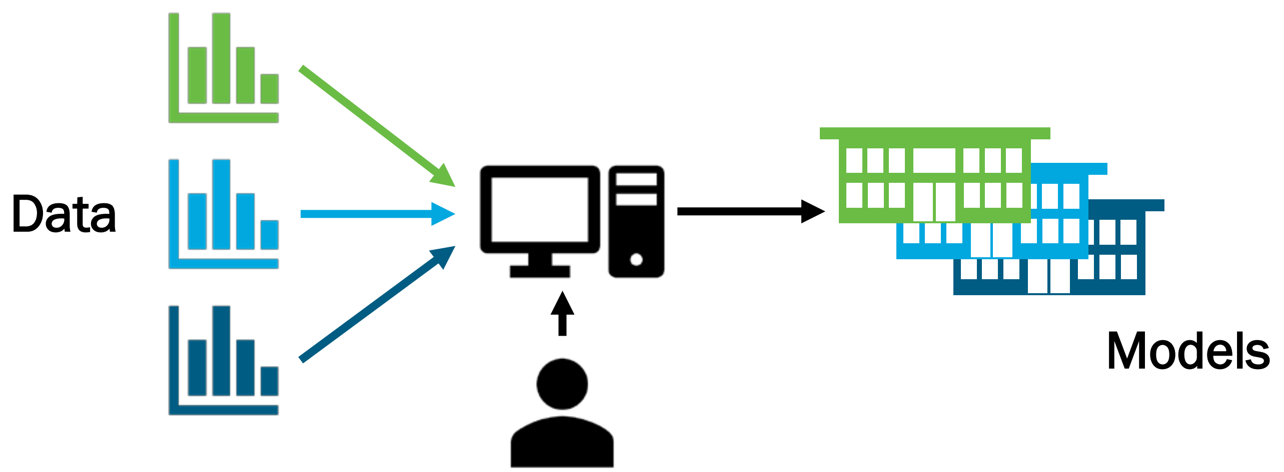
What is the nature of the tradeoff between ease of model generation and model accuracy?

Automated Model Generation

Current Workflow: Manual



Desired Workflow: Automated



Thank You!

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REFERENCE SLIDES

Upcoming Publications

Ball, Brian, David Goldwasser, Piljae Im, Amanda Farthing, and Stephen Frank. 2018. "Advances in Calibration of Building Energy Models to Time Series Data." In *2018 Building Performance Analysis Conference and SimBuild*. Chicago, IL: ASHRAE and IBPSA-USA. To be published.

Frank, Stephen, Xin Jin, Daniel Studer, and Amanda Farthing. 2018. "Automated Fault Detection and Diagnosis Technology for Small Commercial Buildings: An Overview." Manuscript submitted for publication.

Kim, Janghyun, Jie Cai, and James E. Braun. 2018. "Common Faults and Their Prioritization in Small Commercial Buildings." In *2018 Purdue University High Performance Buildings Conference.* West Lafayette, IN: Purdue University. To be published.

Lin, Guanjing, Jessica Granderson, Rupam Singla, Stephen Frank, Xin Jin, and Amanda Farthing. 2018. "A Performance Evaluation Framework for Automated Fault Detection and Diagnosis Protocols for Buildings." Manuscript in preparation.

Project Budget

Project Budget:

Total Budget:	$2,400,000	(By Year: $750K, $950K, $700K)
DOE Portion:	$2,000,000	(By Year: $600K, $800K, $600K)
Cost Share:	$400,000	(By Year: $150K, $150K, $100K)

Variances:

Original (proposed) budget $2.75M	(DOE: $2,250K, Cost Share: $500K)
At project inception, adjusted down to $2.2M	(DOE: $1,800K, Cost Share: $400K)
Received $200K plus-up funding in FY2018	(DOE: $2,000K, Cost Share: $400K)

Spend to Date (through FY2018 Q2): $734,369*

*Does not reflect uninvoiced FY2018 Q2 subtier partner costs

Additional Funding: Price Match Cost Share from GE Global Research ($400K)

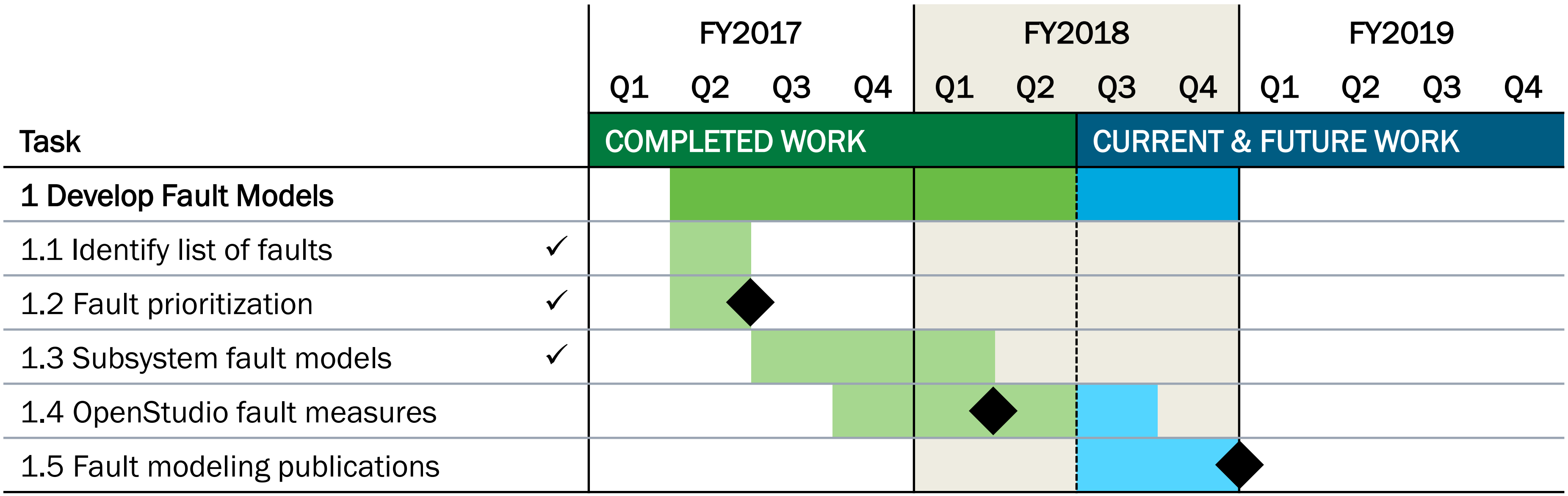
Budget History

FY2017 (past, actuals)		FY2018 (current + projected)		FY2019 (planned)	
DOE	Cost-share	DOE	Cost-share	DOE	Cost-share
$437,219	$92,478	$962,781	$163,099	$600,000	$145,950

Project Plan and Schedule

Project Start: October 1, 2016

Project End: September 30, 2019



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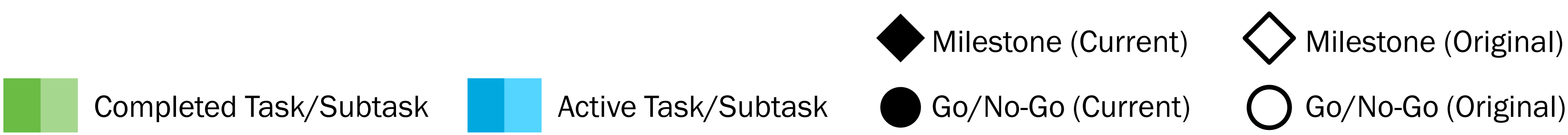
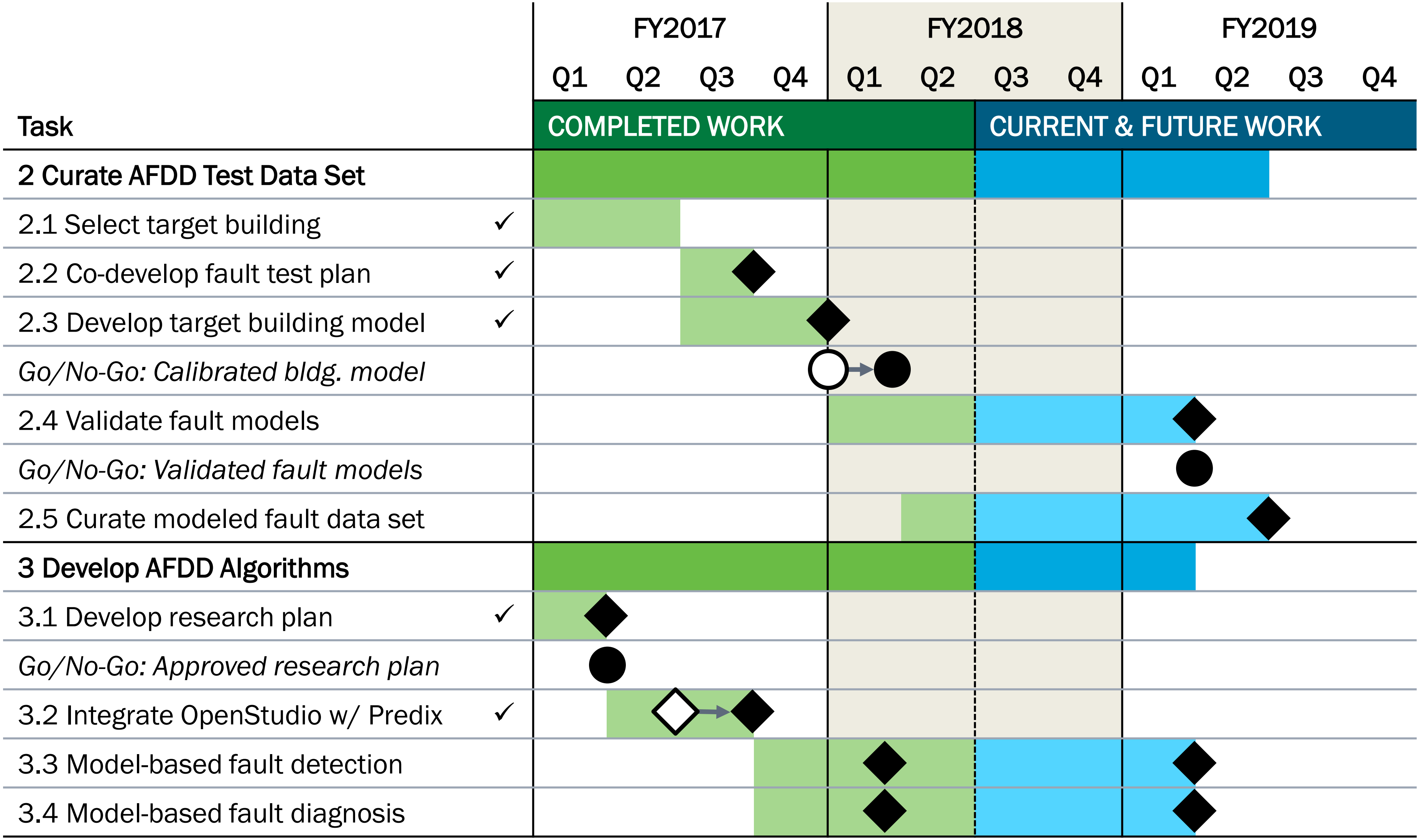


Project Plan and Schedule (Cont.)



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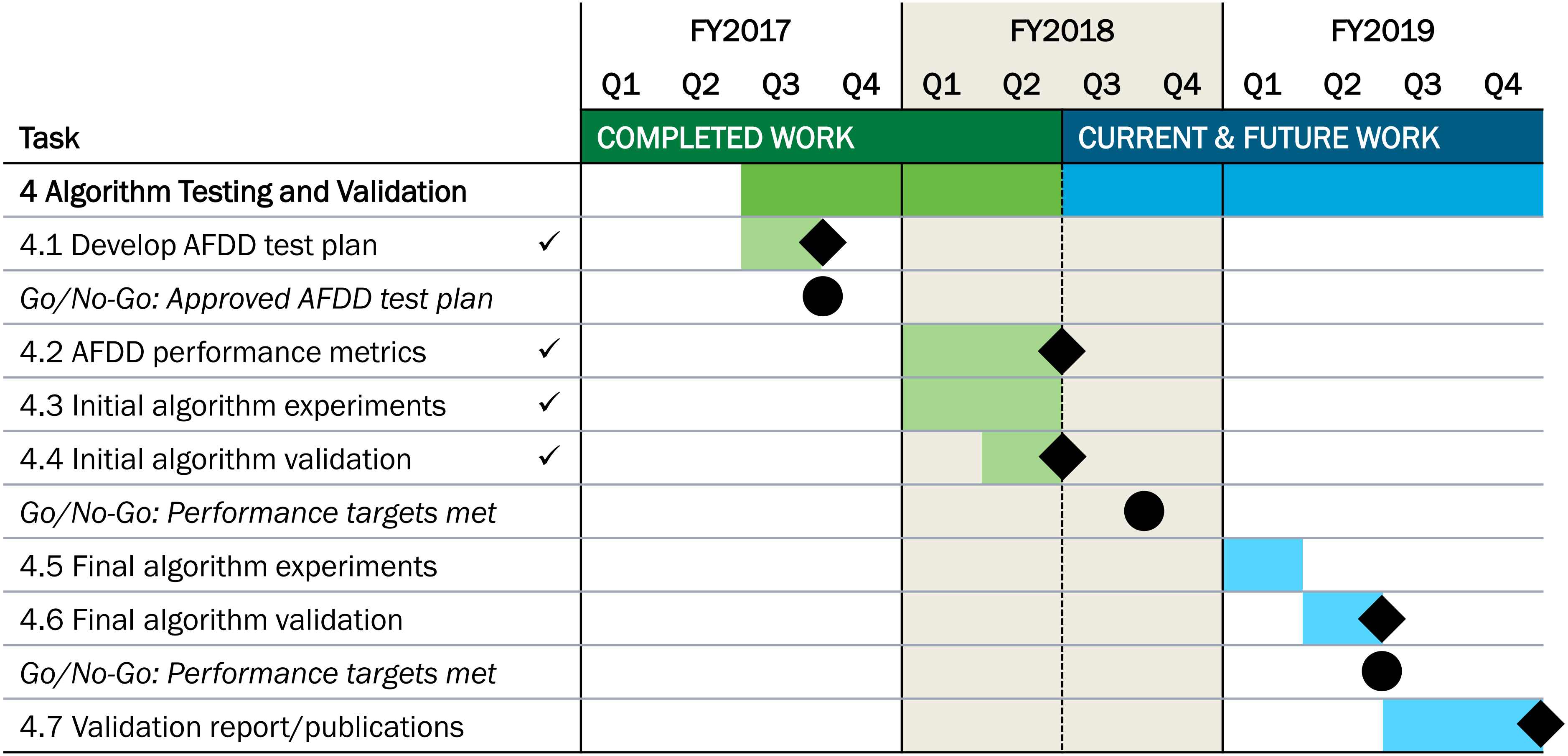
Project Plan and Schedule (Cont.)



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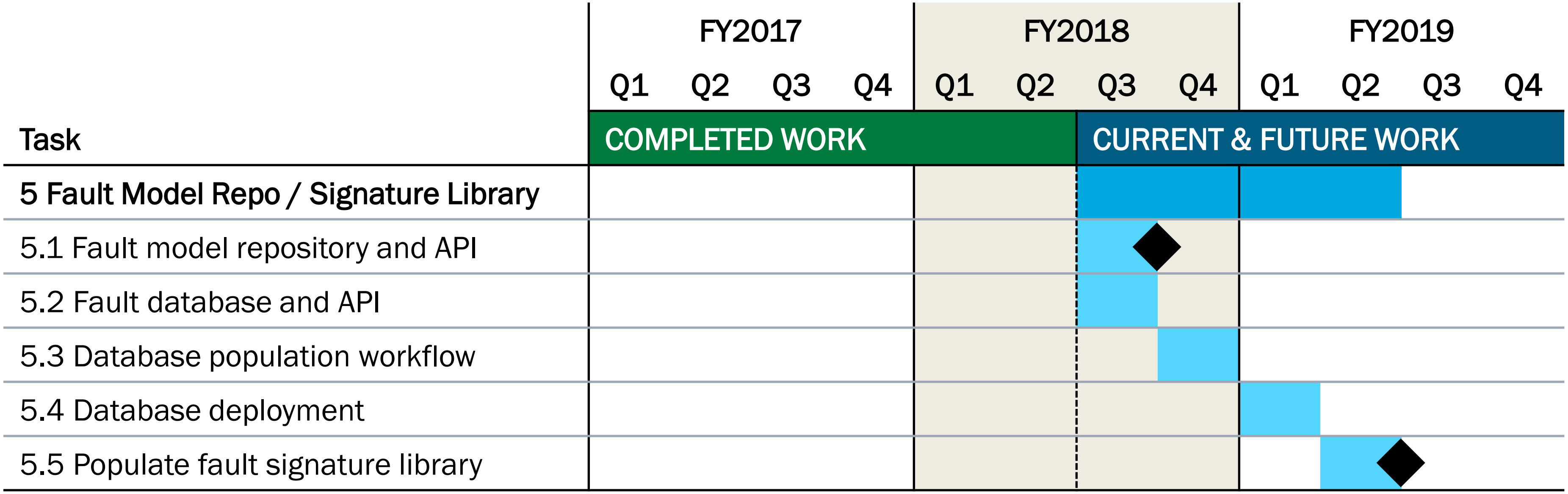
Project Plan and Schedule (Cont.)



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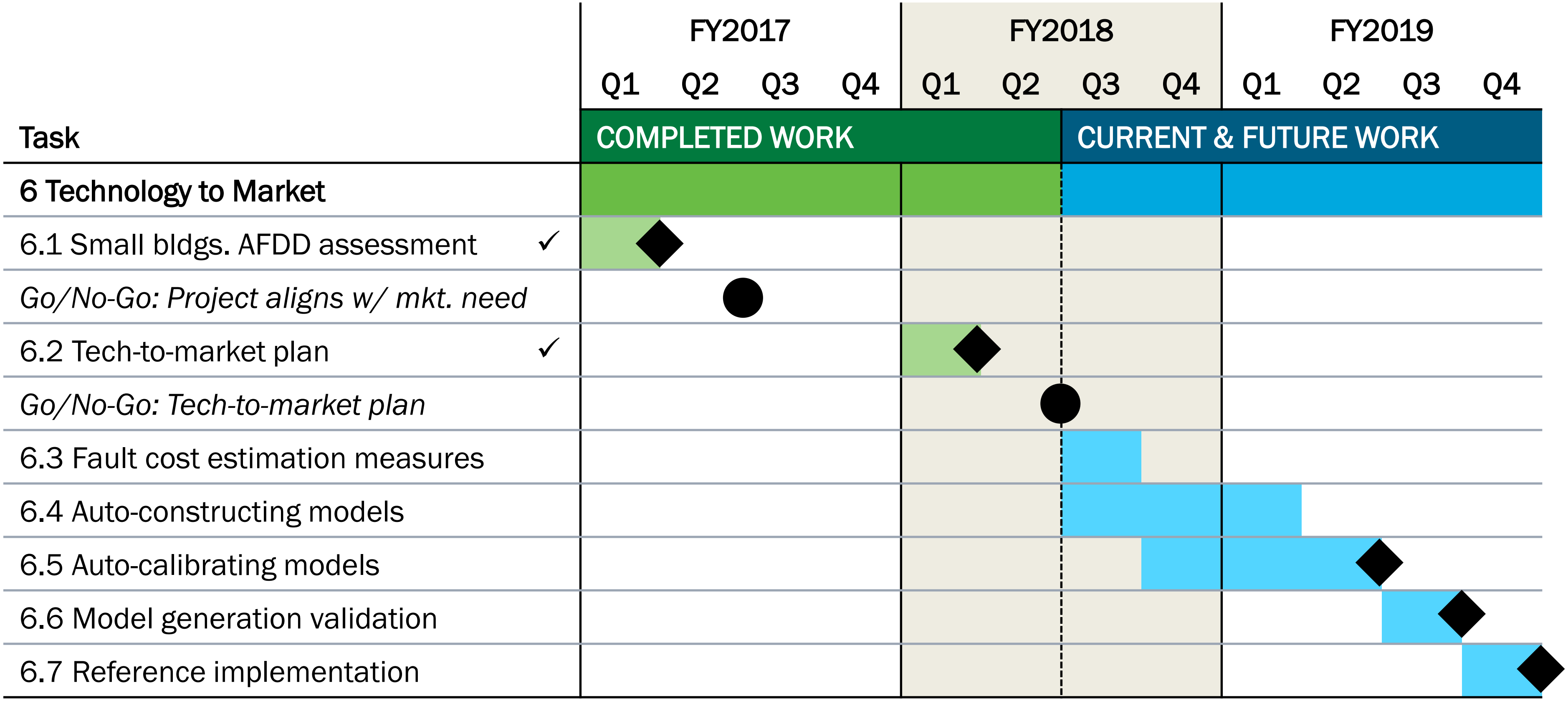
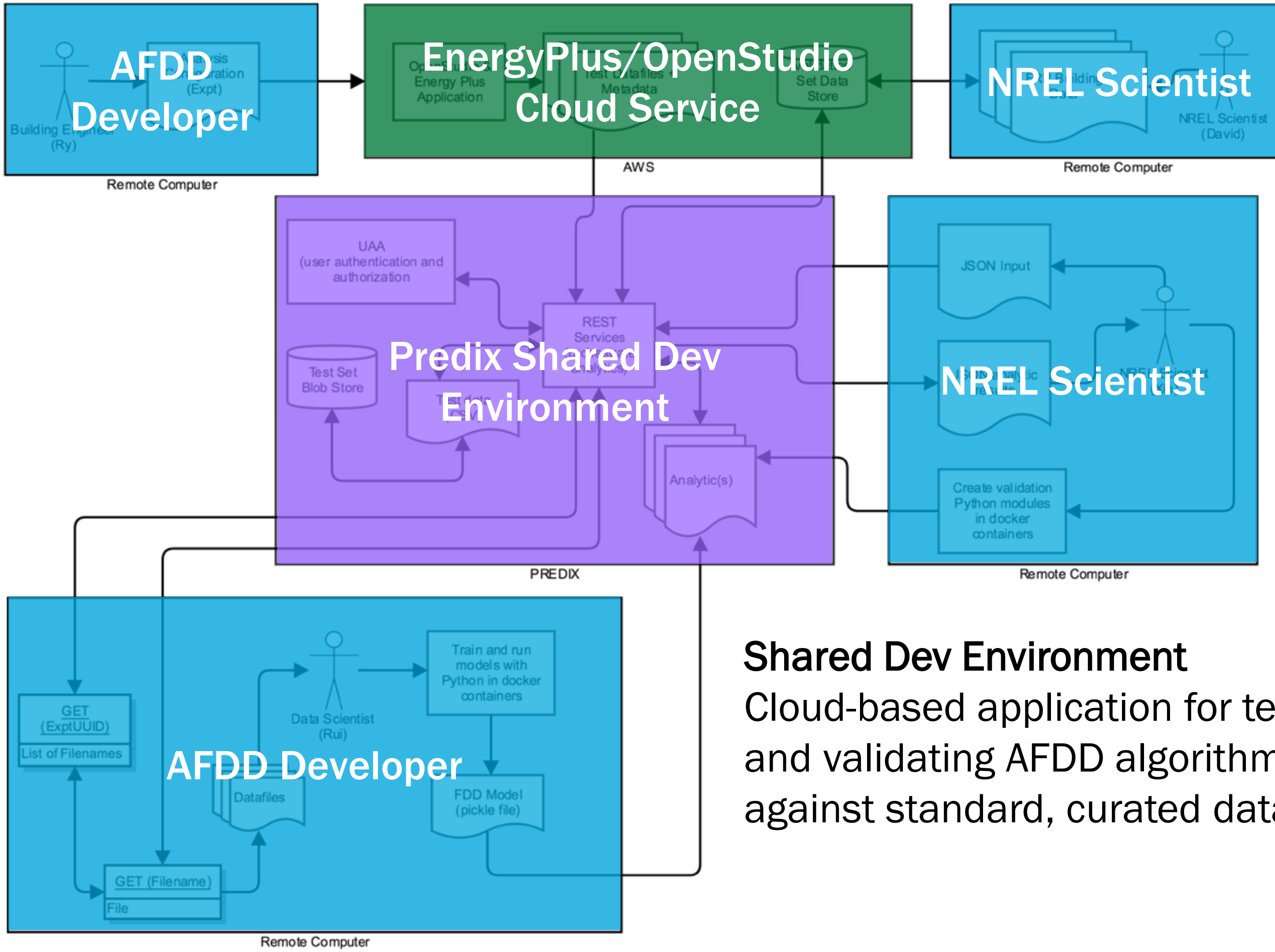
Project Plan and Schedule (Cont.)



AFDD Platform

Architecture and Implementation

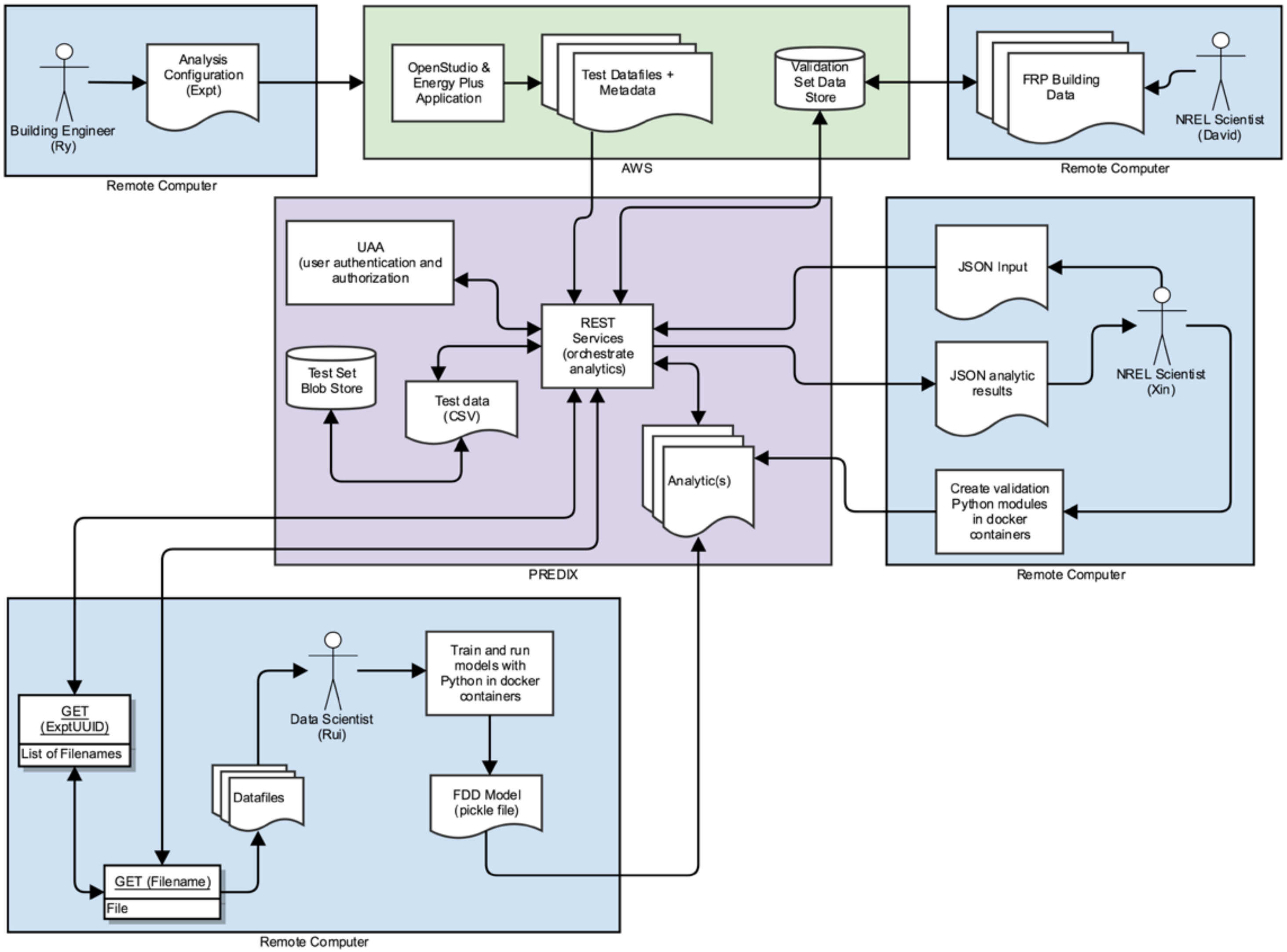
Predix Shared Development Environment



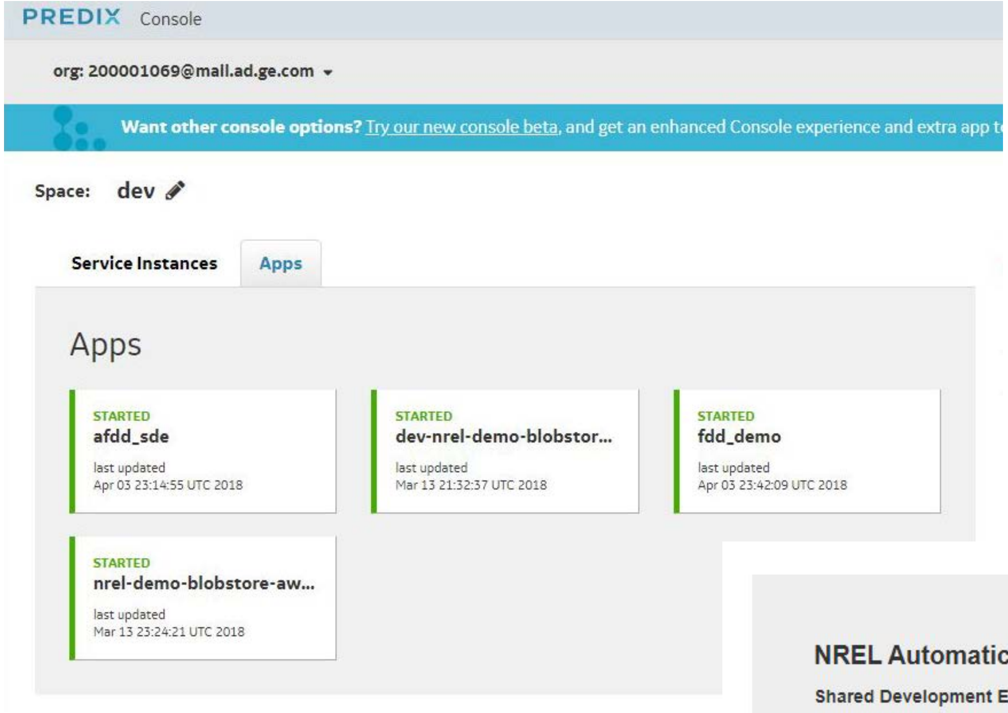
Shared Dev Environment

Cloud-based application for testing and validating AFDD algorithms against standard, curated data sets

Platform Architecture

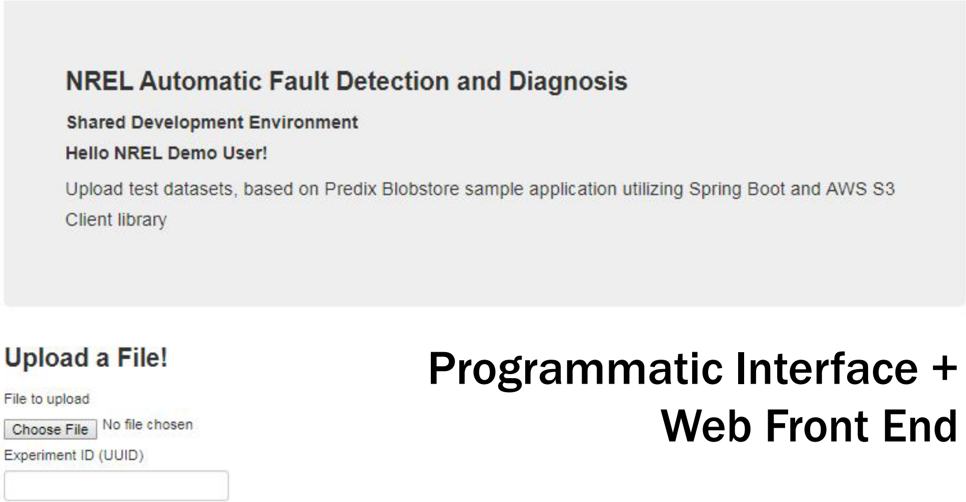


Predix Shared Development Environment



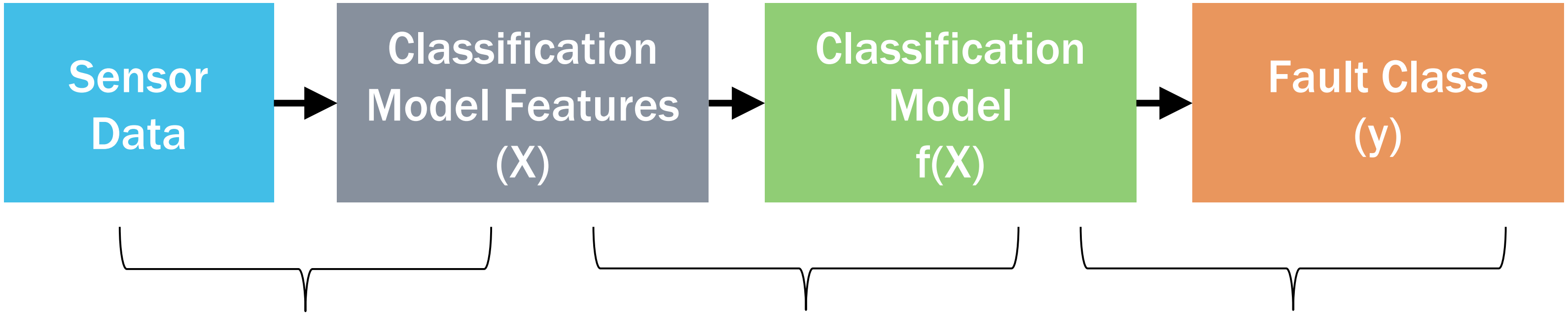
Predix Cloud Environment

- Secured timeseries & file datastores
- Analytics Runtime
- Application Frontend



Programmatic Interface + Web Front End

Data-Driven Algorithm Workflow



Auto feature generation
Genetic Algorithm
TBD

Multiclass Classification
Random Forest
TBD
Anomaly Detection
TBD

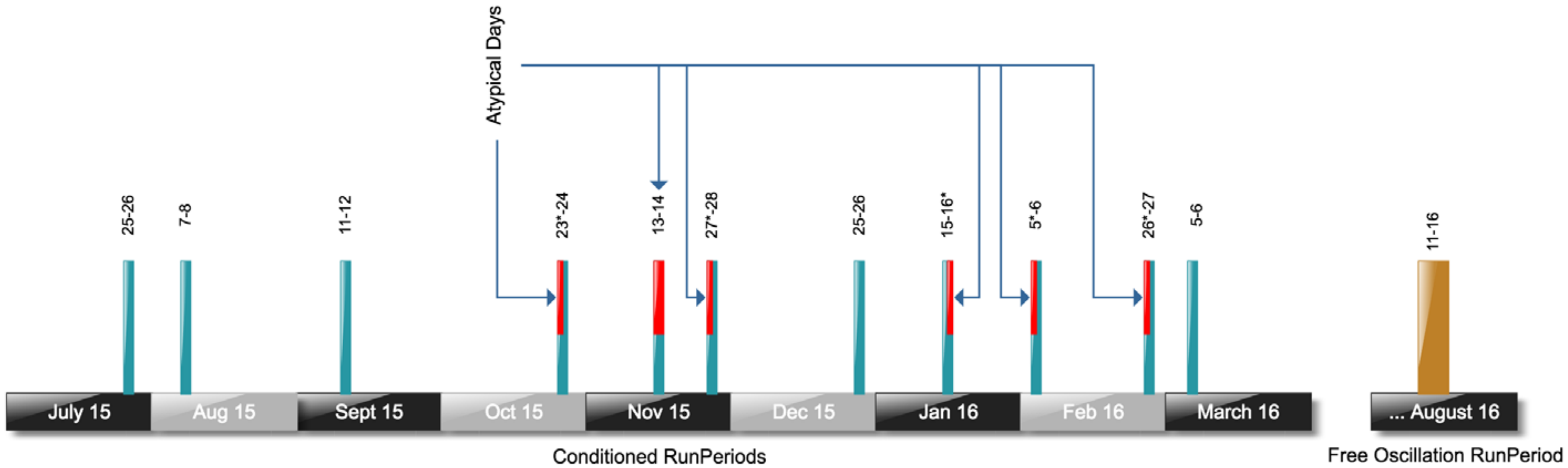
Performance Metrics
Detection Rate (AUC)
Diagnostic Accuracy (CDDR)
Time-to-detect
Etc.

Goal: Robust, general pipeline generating AFDD algorithms from EnergyPlus/OpenStudio data

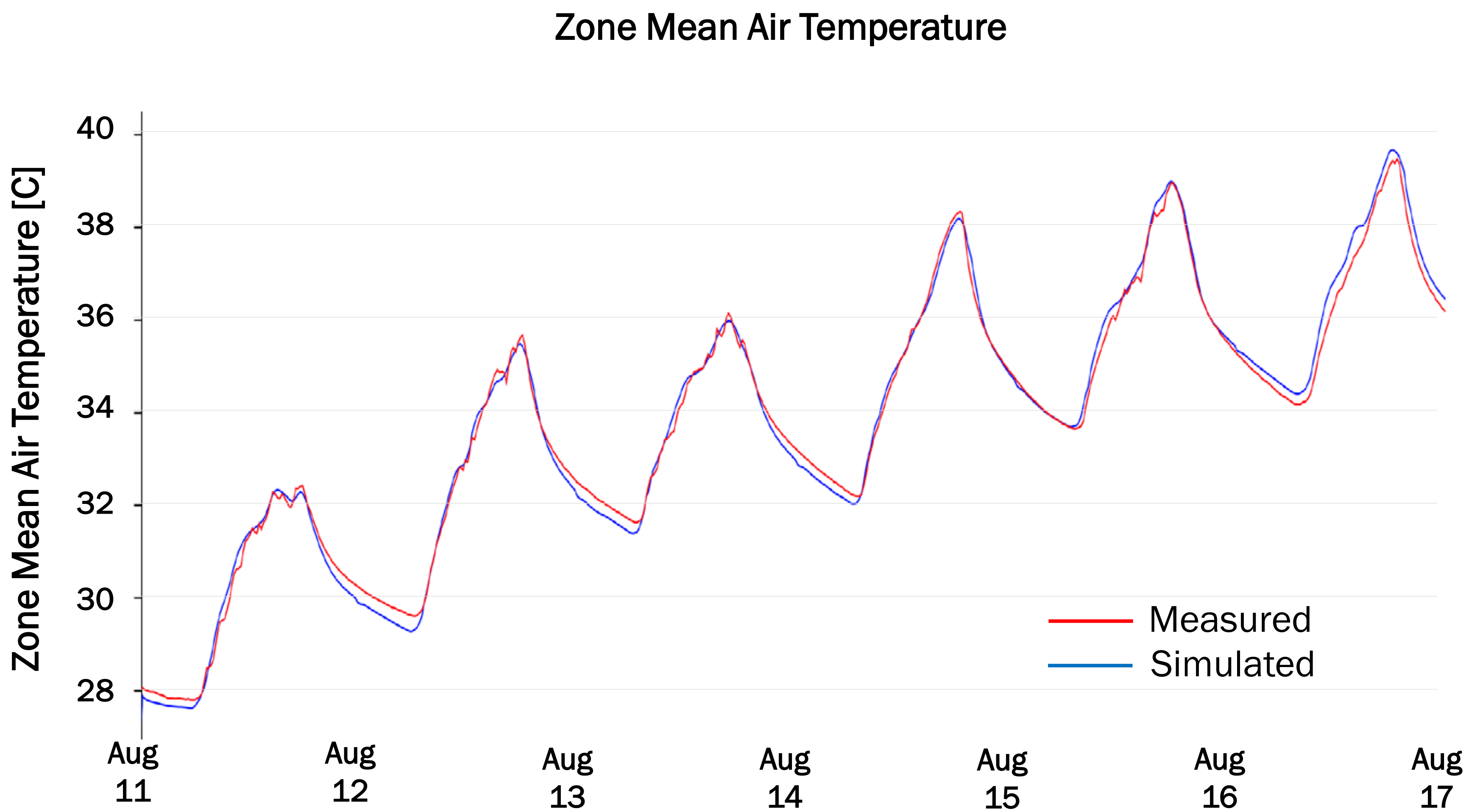
FRP Model

Calibration Results

Calibration Run Periods

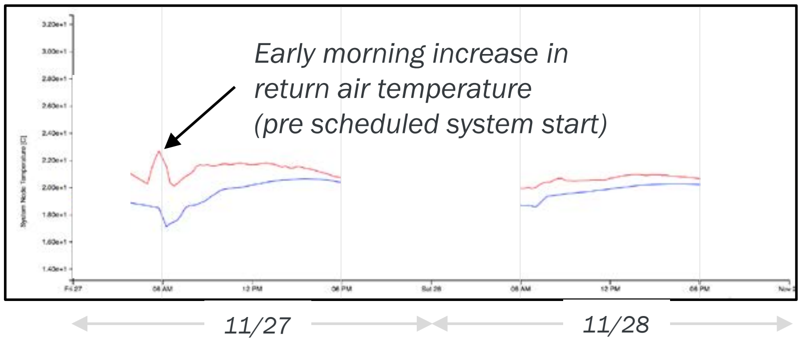


Free Oscillation Period

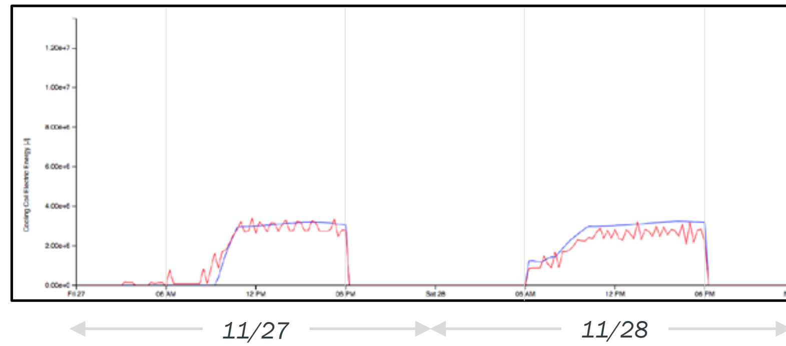


Building Conditions Throughout Air Loop

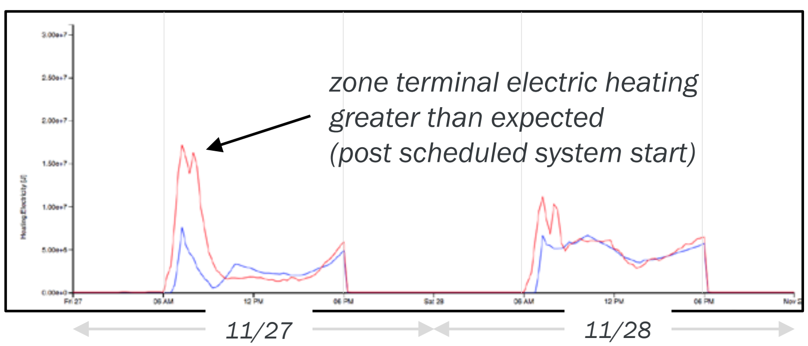
RTU Entering Air Temperature



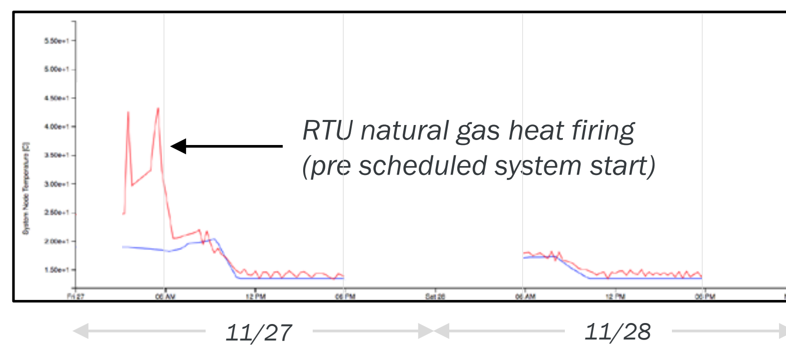
RTU Cooling Electric Consumption



Zone Terminal Heating Electric Consumption



RTU Leaving Air Temperature



Arrows show direction of Airflow through RTU and Building Zones (November 27 and 28, 2015)

Measured
Simulated

Calibration Metrics

		All Days			Typical Days		
Component	Type	Consumption (GJ) *	CVRMSE	NMBE	CVRMSE	NMBE	Notes
Target			≤ 30%	≤ 10%	≤ 30%	≤ 10%	
Whole Building	Electricity	17.4	26.2%	5.7%	14.7%	0.81%	
Cooling (RTU)	Electricity	3.0	44.5%	4.2%	40.6%	0.03%	
Heating (zone terminals)	Electricity	3.5	120.9%	24.4%	69.2%	5.2%	
Fan	Electricity	1.7	15.5%	4.0%	14.6%	4.0%	
Lights	Electricity	2.7	3.3%	0.23%	3.8%	0.28%	Controlled
Electric Equipment	Electricity	6.6	3.9%	0.20%	4.5%	0.24%	Controlled
RTU Entering Air	Temperature		9.9%	7.9%	6.9%	7.0%	
RTU Exiting Air	Temperature		21.2%	5.7%	20.1%	6.8%	
No HVAC Avg. Bldg. Air	Temperature		0.68%	0.04%	0.68%	0.04%	No days removed

** Measured consumption during conditioned run periods*

ASHRAE Guideline 14 Targets:

Coefficient of Variation of Root Mean Squared Error (CVRMSE) ≤ 30%

Normalized Mean Bias Error (NMBE) ≤ 10%

Fault Model Development

List of Fault Models

Fault Models

25 OpenStudio Fault Measures Available (https://github.com/NREL/OpenStudio-fault-models/tree/master/fault_measures_2017**)**

Fault Measures	Fault Location	Fault Stage	Fault Type	Model Type	Fault Priority	Dynamic or Static Model
Excessive infiltration around the building envelope	Envelope	Operation	Building	Physical	1	Static
Supply air duct leakages	RTU	Operation	Equipment	Physical	2	Static
Return air duct leakages	RTU	Operation	Equipment	Physical	2	Dynamic
HVAC setback error: delayed onset	HVAC	Operation	Control	Physical	3, 6	Static
HVAC setback error: early termination	HVAC	Operation	Control	Physical	3, 6	Static
HVAC setback error: no overnight setback	HVAC	Operation	Control	Physical	3, 6	Static
Nonstandard refrigerant charging	Refrigeration Split RTU	Operation	Equipment	Empirical	4	Dynamic
Lighting setback error: delayed onset	Lighting w/o occ sensor	Operation	Control	Physical	5	Static
Lighting setback error: early termination	Lighting w/o occ sensor	Operation	Control	Physical	5	Static
Lighting setback error: no overnight setback	Lighting w/o occ sensor	Operation	Control	Physical	5	Static
Evaporator fouling (Duct fouling)	RTU Split	Operation	Equipment	Empirical	8	Static
Condenser fouling	Split Refrigeration RTU	Operation	Equipment	Empirical	7	Dynamic
Oversized equipment at design	RTU	Design	Equipment	Physical	11	Static
Improper time delay setting in occupancy sensors	Lighting w/o occ sensor	Operation	Control	Physical	20	Static
Air handling unit fan motor degradation	Ventilation	Operation	Equipment	Semiempirical	13	Static
Refrigerant liquid-line restriction	Refrigeration RTU Split	Operation	Equipment	Empirical	15	Dynamic
Thermostat measurement bias	HVAC	Operation	Sensor	Physical	14	Static
Economizer opening stuck at certain position	RTU	Operation	Equipment	Physical	17	Static
Condenser fan degradation	Refrigeration RTU	Operation	Equipment	Empirical	18	Dynamic
Presence of noncondensable in refrigerant	Refrigeration RTU Split	Operation	Equipment	Empirical	16	Dynamic
Biased economizer sensor: outdoor RH	RTU	Operation	Sensor	Physical	19	Dynamic
Biased economizer sensor: outdoor temperature	RTU	Operation	Sensor	Physical	19	Dynamic
Biased economizer sensor: mixed temperature	RTU	Operation	Sensor	Physical	19	Static
Biased economizer sensor: return RH	RTU	Operation	Sensor	Physical	19	Dynamic
Biased economizer sensor: return temperature	RTU	Operation	Sensor	Physical	19	Dynamic