Pacific Northwest NATIONAL LABORATORY

PNNL-29623

Design, Development, and Testing Plan for Energy Efficiency Algorithms Related to Building-Integrated Cooling, Heating, and Power Systems

January 2020

S Katipamula
N Fernandez
AD Smith
AP Rogers

U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
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Performance Monitoring, Real-Time Commissioning Verification and Automated Fault Detection and Diagnostic Algorithms

January 2020

S Katipamula
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Pacific Northwest National Laboratory
Richland, Washington 99354

Summary

Building-integrated cooling, heating, and power (CHP) systems are more efficient than conventional systems at providing local power and thermal energy, and favorable fuel prices are bound to spur their increased adoption. It is estimated that the total CHP technical potential in the commercial building sector is approximately 76 GW, but only a small fraction of that potential is actually deployed. Advanced control and monitoring systems that realize the full potential of these CHP systems can transform this capacity into an asset for both the owner and the electric grid and also accelerate the adoption of these systems in the building sector.

However, to realize the full benefit of the CHP systems, we must ensure persistence of energy efficient operations. Several studies demonstrated that commercial buildings use as much as 30% access energy. Much of the access results from the inability to anticipate load variations (design day vs. non-design day operations; diurnal variation of loads), identify improper operation, and efficiently operate, control, and maintain building systems. Moreover, many buildings, even those with adequate control infrastructure, may lack knowledgeable staff to operate and maintain energy systems. Operators of buildings with CHP systems will constantly need to make tradeoffs (economic dispatch) between onsite power generation and purchasing power, between onsite heat production from distributed generation versus heating/cooling from conventional systems, and different passive and active load management measures.

Much of the inefficiency in the current building operations can be eliminated by use of automated performance monitoring (PM), real-time commissioning verification (CxV) and automated fault detection and diagnostic (AFDD) tools. Automation can help system operators make intelligent decisions. Remote and continuous monitoring of system conditions and performance will enable better management and integration of CHP with existing building systems. Continuous PM, real-time CxV, and AFDD could alleviate burdens for operations staff, enhance operations and maintenance (O&M), and improve reliability of building and CHP systems.

To address the O&M challenges and to provide a means to maximize the rate-of-return of building-integrated CHP systems, the Building Technologies Office (BTO) within the U.S. Department of Energy's (DOE's) Office of Energy Efficiency and Renewable Energy (EERE) initiated a project to design, develop, and field test a VOLTTRON™-based supervisory controller and associated open-source algorithms. These algorithms will ensure real-time optimal operation of a building-integrated CHP system, support electric grid reliability, and lead to achieving the goal of clean, efficient, reliable, and affordable next-generation integrated energy system.

This report lists the components for which PM, real-time CxV, and AFDD algorithms will be developed, how the algorithms will be tested, and the metrics that will be used to validate the algorithms and their ease of deployment. Deployment of these algorithms in the field will result in a reduction in energy consumption of between 10% and 20% (for both CHP and conventional building systems).

Performance Monitoring and Real-Time Commissioning Verification

The goal is to design, develop, and test both component and system-level PM algorithms as well as real-time CxV algorithms for selected CHP and conventional heating, ventilation, and air conditioning (HVAC) systems. Performance monitoring is geared toward trending key variables

or performance indicators that give insight into the functioning of a component within a CHP or HVAC system or a system as a whole. These variables can simply be tracked or monitored in a dashboard for informational purposes, rolled up into more complex time-of-use analytics, or used to alert the user when the performance is degraded for a period of time. In this report, we list the CHP components for which PM and real-time CxV algorithms will be developed, including some additional details of how the algorithms will be implemented. The creation of the PM and real-time CxV algorithms will take place in three phases: initial development, testing, and validation.

Initial development: Initial development involves implementation of the equations and the logic for selected components and systems described in Section 2.1.

Testing: Testing will take place to provide qualitative information as to whether the algorithms are performing as intended, and to guide decisions on what revisions to the algorithms are necessary. While test data from real systems will be used preferentially, we expect to largely rely on simulated data for testing because of lack of easy access to the real CHP system.

Validation: Because both PM and real-time CxV algorithms are either creating a performance metric or comparing the actual operation of the component or system with manufacturer specified performance, no metrics for validating the algorithms are generally needed.

Configuration of algorithms: The goal is to be able to configure the algorithms on a VOLTTRON platform in no more than four hours. Based on our experience, this goal is highly ambitious. However, this can be achieved if the following conditions are met:

- The person configuring the algorithms is well versed in VOLTTRON deployment.
- The person configuring the algorithms is familiar with the BACnet devices and BACnet network that the VOLTTRON node will be connected to.
- There is a standard naming convention already established for various sensor measurements.

For real-time CxV, there is also a need for a lookup table with manufacturers' data for the various components. Creation of lookup tables is not included in the four-hour configuration goal.

Performance Monitoring Algorithms

Component performance metrics are commonly a measure of efficiency, effectiveness, or coefficient of performance – a measure of the ratio between output (useful work) and input energy (fuel). For example, for a prime mover, tracking power generated may also be of interest from a 'dashboard' perspective. Most of these performance metrics rely on quantifying the energy by taking measurements on a fluid in flow (water, air, or fuel). This generally requires installation of sensors capable of measuring temperatures and flow rates. When tracking for the purpose of quantifying degraded performance, other independent variables affecting performance need to be taken into account to properly make a determination of degradation. At the system level, performance metrics are geared toward tracking waste heat and electric power generation as well as some system-level efficiencies that may give insight into the effectiveness of system operations.

As part of this effort, PM algorithms will be developed for the following CHP components:

- Prime movers (fuel cells, microturbines, and reciprocating engines)
- Heat exchanger
- Conventional electrically driven vapor compression chiller
- Waste heat driven absorption chiller
- Boiler
- Battery energy storage system
- Thermal energy storage system
- Photovoltaic system
- Cooling tower.

In addition, we will also develop system-level PM algorithms for the CHP system as a whole.

Real-Time Commissioning Verification Algorithms

Component performance tracking can also be used for real-time CxV of CHP systems. This entails validating that the observed performance of a given component closely matches the expected performance stated by the manufacturer. The variables that can be evaluated for commissioning involve rated efficiency, effectiveness, and coefficient of performance, rated capacity as well as part-load performance. To compare the rated performance with actual performance, actual ambient and operating conditions for certain components need to be approximately equal to rated test conditions or conditions for which manufacturers' data is available. The rated test conditions are typically specified by international or industry standards. Commissioning should be performed soon after installation (within a few months) and can replicate these test conditions either passively (when they happen to occur) or proactively, when possible, through intentional setting of setpoints to match test conditions. In addition to the comparison of rated performance, real-time CxV can also be performed to compare part-load performance of the components, if the manufacturers provide such information.

As part of this effort, we will develop real-time CxV algorithms for the following CHP components:

- Fuel cells
- Conventional electric driven vapor compression chiller
- Waste heat driven absorption chiller
- Boiler
- Battery.

Automated Fault Detection and Diagnostic Algorithms

Automated fault detection and diagnostics extend PM and real-time CxV. It is an automatic process by which faulty (improper) operation, degraded performance, or broken components in a physical system are detected and diagnosed. In this report, we first provide an overview of CHP system and building system components for which AFDD algorithms might be developed, with additional detail on prior related work for the components selected for algorithm development and a description of the basic principles and framework for algorithm development. For each component, a brief history of the state of the art in AFDD work for that device or system is provided. Only one type of equipment had a significantly advanced body of work and corresponding research datasets available: the centrifugal chiller. Automated fault detection and diagnostic algorithms will be developed for:

- Electrically driven vapor compression centrifugal chillers.
- Waste heat driven absorption chillers.
- Boilers.

For other components outside of these three, a brief description is provided on why the component was not ideal for further development at this time. The most advanced algorithms will be created for centrifugal chillers because the development will build on the related prior work.

Four performance metrics will be calculated and used to judge and quantitatively improve the performance of the AFDD algorithms developed: true positive rate (TPR), indicating faults that were correctly identified; false positive rate (FPR), indicating faults that were incorrectly identified, a potentially costly mistake; false negative rate (FNR), indicating designated faults that were missed by the algorithm, also potentially costly; and detection time (DT), indicating the length of time (number of timesteps within the dataset) that a fault was designated as present before detection took place. Other metrics of interest related to the algorithm's success or failure can be directly calculated from TPR, FPR, and FNR, and DT also provides valuable information that can be used to guide algorithm development decisions. For diagnostics, the performance metric will simply be the percentage of faults that are correctly classified from a dataset with specific faults.

The creation of the AFDD algorithms will take place in three major phases: initial development, testing, and validation. The data that is used for algorithm development will be investigated qualitatively and quantitatively with basic statistics, and where sensor performance is not verified, then any faults detected and diagnosed with the proposed algorithms are also coupled with potential sensor faults.

Initial development: The initial development involves implementation of the models and the logic for the three selected components as described in Section 3.2.

Testing: Testing will take place to provide quantitative information as to whether the algorithms are performing as intended, and to guide decisions on what revisions to the algorithms are necessary. While experimental test data will be used preferentially, we expect to largely rely on simulated data for testing the algorithms due to a lack of available datasets with labeled faults. The statistical framework for data creation is presented in Section 3.4.1, and criteria to be used for prioritizing the most valuable and impactful tests to conduct are listed.

Validation: Finally, validation will take place to provide information about whether the results of the algorithms as applied to the test data sets make sense in a real-world context. This stage will begin with data-based validation, a re-testing of the revised algorithms, with the performance metrics calculated. Wherever experimental test data is available, it will be used preferentially. Model-based validation will be conducted, time permitting, using independent models to check the outputs of the algorithms under likely operational conditions. Finally, a qualitative assessment on the datasets, models used, and outcomes will be provided by end user (building operators or energy service providers) interviews for each individual component.

The goal is to show that each of the three algorithms will exhibit the following behavior:

- False positives (calling it a fault when it is not) are less than 20% (realistic) (less than 15% stretch) when the sensitivity of detection is set to low.
- False negatives (not calling it a fault when it is) are less than 20% (realistic) (or less than 15% stretch) when the sensitivity of detection is set to high.

Configuration of algorithms: Like the PM and real-time CxV algorithms, the goal is to be able to configure the AFDD algorithms on a VOLTTRON platform in no more than 4 hours. Based on our experience, this goal is highly ambitious. However, this can be achieved, if the following conditions are met:

- The person configuring the algorithms is well versed in VOLTTRON deployment.
- The person configuring the algorithms is familiar with the BACnet devices and BACnet network that the VOLTTRON node will be connected to.
- There is a standard naming convention already established for various sensor measurements.

Acknowledgments

The authors acknowledge the Buildings Technologies Office (BTO) of the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy for supporting the research and development effort. The authors also acknowledge the valuable guidance from Ms. Erika Gupta, the Sensors and Controls technology development manager at BTO. The authors also acknowledge Ron Underhill for technical review of the document and Colleen Winters for technical editing.

Acronyms and Abbreviations

AFDD	Automated Fault Detection and Diagnostics
AHU	Air Handling Unit
AHP	Analytical Hierarchal Process
AIRx	Automated Identification of Re-tuning™ Measures
ASHRAE	American Society of Heating, Refrigeration and Air-conditioning Engineers
BAS	Building Automation System
BACnet	Building Automation and Controls Network
BTO	Building Technologies Office
CBM	Conditioned Based Maintenance (CBM)
CCR	Correct classification rate
CHP	Cooling, Heating, and Power
Cx	Commissioning
CxV	Commissioning Verification
DOE	Department of Energy
DT	Detection time
EIA	Energy Information Administration
FPR	False positive rate
FNR	False negative rate
HVAC	Heating, Ventilation, and Air Conditioning
HVAC&R	Heating, Ventilation, Air Conditioning and Refrigeration
ILC	Intelligent Load Control
IoT	Internet of Things
NN	Neural Network
O&M	Operations and Maintenance
PM	Performance Monitoring
PNNL	Pacific Northwest National Laboratory
PV	Photovoltaic
RCx	Retro Commissioning
RTU	Rooftop Unit
TPR	True positive rate
VAV	Variable-air-volume

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1.0 Introduction

Building-integrated cooling, heating, and power (CHP) systems are more efficient than conventional systems at providing local power and thermal energy[1,2] and favorable fuel prices are bound to spur their increased adoption. It is estimated that the total CHP technical potential in the commercial building sector is approximately 76 GW[3], but only a small fraction of it is actually deployed. Advanced control and monitoring systems that realize the full potential of these CHP systems can transform this capacity into an asset for both the owner and the grid and also accelerate the adoption of these systems in the building sector. It has been demonstrated by several studies that as much as 30% of building energy use is wasted (Brambley and Katipamula et al. 2009). Much of the waste results from the inability to anticipate load variations (design day vs. non-design day operations; diurnal variation of loads), identify improper operation, and efficiently operate, control, and maintain building systems. Moreover, many buildings, even those with adequate control infrastructure, lack knowledgeable staff to operate and maintain energy systems. Operators of buildings with CHP systems will constantly need to make tradeoffs (economic dispatch) between onsite power generation and purchasing power, between onsite heat production from distributed generation versus heating/cooling from conventional systems, and different passive and active load management measures. In addition, these assets can be used to automatically mitigate variable production of electricity from non-dispatchable distributed renewable energy sources. Furthermore, integrated streamlined control of the individual CHP sub-systems is necessary to ensure efficient, cost-effective operation and maintenance (O&M) of the system as a whole.

Much of the inefficiency in current building operations can be eliminated by use of automated performance monitoring (PM), real-time commissioning verification (CxV), and automated fault detection and diagnostic (AFDD) tools. Automation can help system operators make intelligent decisions. Remote and continuous monitoring of system conditions and performance will enable better management and integration of CHP with existing building systems. Continuous PM, real-time CxV, and AFDD could alleviate burdens for operations staff, enhance O&M, and improve reliability of building and CHP system.

To address the O&M challenges and to provide a means to maximize the rate-of-return of building-integrated CHP systems, the Building Technologies Office (BTO) within the U.S. Department of Energy's (DOE's) Office of Energy Efficiency and Renewable Energy (EERE) initiated a project to design, develop, and field test a VOLTTRON™-based supervisory controller and associated open-source algorithms. These algorithms will ensure real-time optimal operation of a building-integrated CHP system, support electric grid reliability, and lead to achieving the goal of clean, efficient, reliable, and affordable next-generation integrated energy systems.

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[1] http://www.mckinsey.com/~/media/mckinsey/dotcom/client_service/epng/pdfs/unlocking%20energy%20efficiency/us_energy_efficiency_full_report.ashx: CHP systems can achieve thermal efficiencies greater than 70%, while a combination of conventional power and on-site thermal generation will have net thermal efficiency of 45%

[2] http://www.epa.gov/chp/basic/efficiency.html

[3] https://www.energy.gov/sites/prod/files/2016/04/f30/CHP%20Technical%20Potential%20Study%203-31-2016%20Final.pdf

The initial focus of the project was to develop an automated economic dispatch software that can be deployed on the VOLTTRON platform. That portion of the work concluded in FY19 with a successful field test at a CHP site in upstate New York. The second part of the project is to design, develop, and test PM, real-time CxV, and AFDD algorithms for selected CHP components. This report lists the components for which PM, real-time CxV, and AFDD algorithms will be developed, how the algorithms will be tested, and metrics that will be used to validate the algorithms and ease of deployment.

1.1 Cooling, Heating, and Power System

The Energy Information Administration (EIA) defines a system that is designed to produce both heat (used for both heating as well as cooling) and electricity from a single heat source[4] as a CHP[5] system. The terms "combined heat and power," "cooling, heating, and power" and "CHP" are used synonymously in the literature. All refer to a CHP system as an integrated system (Figure 1.1) "located at or near a building or facility, satisfying at least a portion of the facility's electrical demand, and utilizing the heat generated by the electric (or shaft) power generation equipment to provide heating, cooling, and/or dehumidification to a building and/or industrial processes."[6]

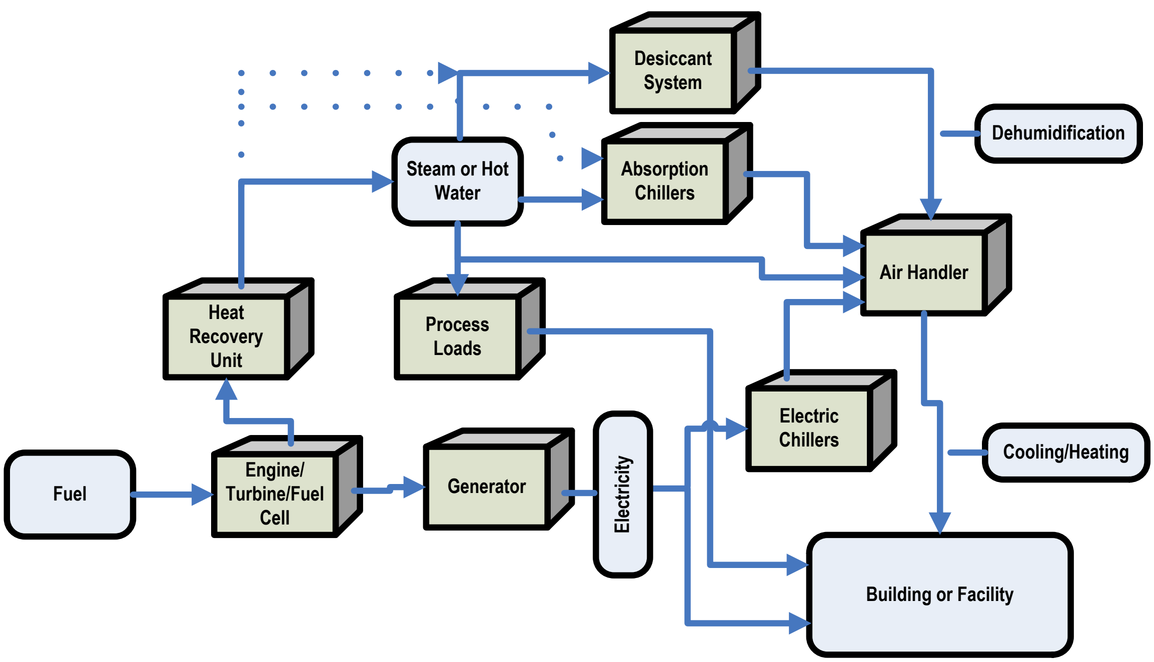

Figure 1.1. Comprehensive schematic diagram of a CHP system (dotted line represents an alternate direct-fired option [6])

[4] According to Energy Information Agency (EIA), the term CHP is being used in place of the term "cogenerator" that was used by EIA in the past. CHP better describes the facilities because some of the plants included do not produce heat and power in a sequential fashion and, as a result, do not meet the legal definition of cogeneration specified in the Public Utility Regulatory Policies Act (PURPA).
[5] Other terms in the literature for CHP systems include building combined heat and power (BCHP), combined cooling, heating and power (CCHP), combined heat and power for buildings, and integrated energy systems.
[6] Midwest CHP Application Center (MAC). 2003. Combined Heat & Power (CHP) Resource Guide, University of Illinois at Chicago, and Avalon Consulting, Inc., Chicago, IL. http://www.chpcentermw.org/pdfs/chp_resource_guide_2003sep.pdf

1.2 VOLTTRON

VOLTTRON is an open-source distributed sensing and control IoT platform (Internet-of-Things-Platform) for buildings, the power grid, and integration of buildings with the grid to support deployment of energy efficiency and transactive energy services. VOLTTRON applications are referred to as agents because VOLTTRON provides an agent-based programming paradigm to ease application development and minimize the lines of code that need to be written by domain experts (such as building engineers). The VOLTTRON platform has four primary roles; it serves as:

- A reference platform for researchers to quickly develop, deploy, and test supervisory control and energy efficiency applications in simulation environment and also real buildings
- A reference platform with flexible data storage support for energy analytics applications, either in academia or in commercial enterprise
- A platform from which commercial enterprise can develop products without license issues and easily integrate them into their product line
- An accelerator to drive industry adoption of energy efficiency, transactive energy, and advanced building energy analytics.

VOLTTRON serves as a single point of contact for interfacing with building devices (rooftop units, air handling units, other building systems, meters, etc.), external resources (weather, utility transactive signals, etc.), and platform services such as data archival and retrieval. VOLTTRON provides a collection of utility and “helper” classes, which simplifies agent development. VOLTTRON connects devices and external signals from the power grid to agents implemented in the platform and/or in the Cloud.

An overview of the VOLTTRON platform components is illustrated in Figure 1.2. The VOLTTRON platform comprises several components and agents that provide services to other agents. Of these components, the Information Exchange Bus (IEB) is central to the platform. All other VOLTTRON components communicate through the IEB using the publish/subscribe paradigm over a variety of topics. For example, the weather agent would publish weather information to a “weather” topic to which interested agents would subscribe. The platform itself publishes platform-related messages to the “platform” topic (such as “shutdown”). Topics are hierarchical following the format “topic/subtopic/sub-subtopic/…/…” and allowing agents to be as general or as specific as desired with their subscriptions. For example, agents could subscribe to “weather/all” and get all weather data for a location or subscribe to “weather/temperature” for only temperature data. VOLTTRON incorporates several open-source projects to build a flexible and powerful platform.

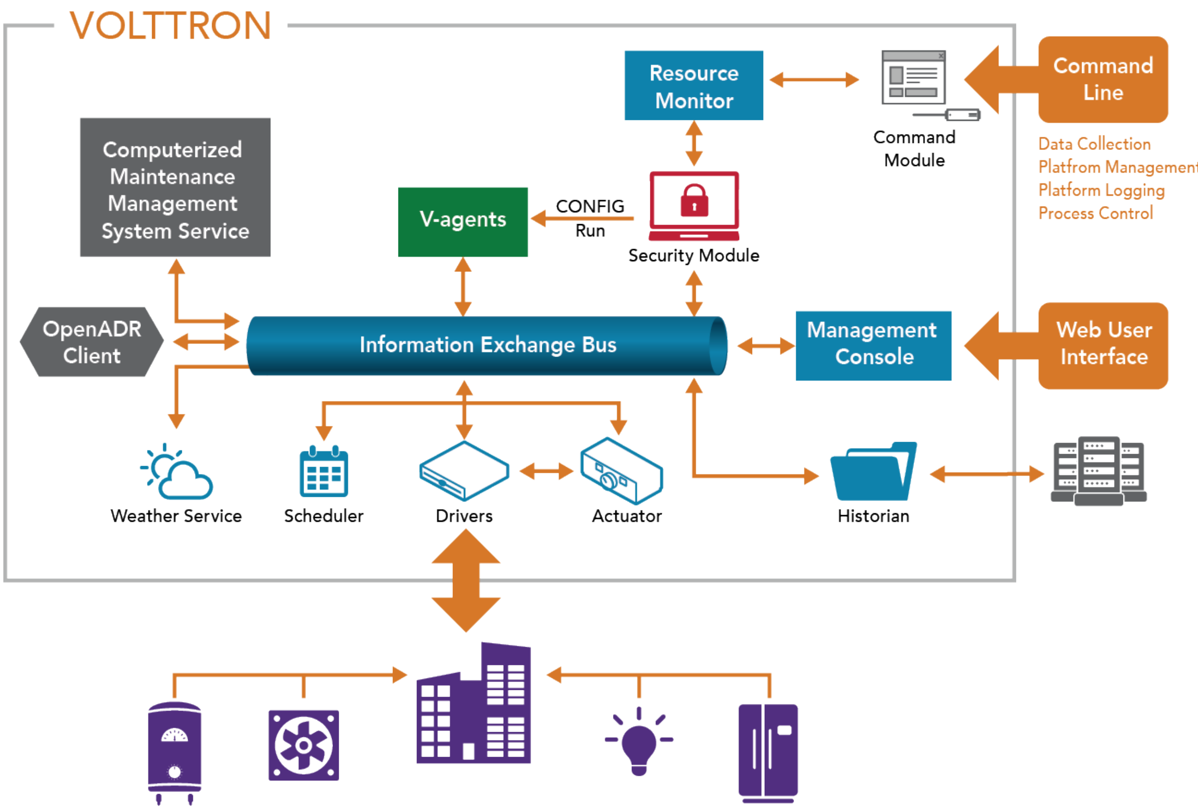

Figure 1.2. Schematic of the VOLTTRON platform

A few of the key services/applications provided by VOLTTRON include the following:

- Actuator agent – manages the control of external devices by agents within the platform.
- Drivers – communicates with devices controlled by the platform. Drivers abstract device-specific protocols from the rest of the platform by publishing device data to and taking commands from the message bus. Although VOLTTRON supports a number of protocols, the two that are relevant to buildings are the BACnet and Modbus protocols.
- Historian – enables the storage of device data obtained by the drivers and application analysis results in a database (currently, SQLlite, CrateDB, MySQL, and MongoDB databases are supported). Multiple historians can run on the platform at the same time.
- Management Interface – A web-based user interface allows the administration of VOLTTRON nodes (and the agent/applications) running on the VOLTTRON nodes on one or more networks.
- Message Bus – All agents and services can publish and subscribe to topics on the message bus. The message bus provides a single and uniform interface that abstracts the details of devices and agents from each other. Agents and components running on the platform produce and consume messages and/or events. The agents decide how agents produce events and how they process received events.

VOLTTRON also provides security against unauthorized access to system data and unauthorized exercise of control functions. VOLTTRON isolates applications running on the platform from each other (if needed) and enforces resource utilization limits on the applications to ensure stability of the computational platform. VOLTTRON uses well-established and widely accepted security mechanisms including elliptic-curve encryption, authentication, and authorization. VOLTTRON agents use authorization to selectively limit which peers can call which methods based on each peer's granted permissions. VOLTTRON authorization gives agent authors and platform owners fine control over who can use their agents and how their agents can be used. Additionally, communications with other VOLTTRON platforms use authentication and authorization functions to ensure that only legitimate transactions are performed. Access to the system through local management interfaces is also protected by similar security measures.

The hardware requirements of the VOLTTRON platform depend on the intended role for each instance. The platform software itself consumes few resources, but the applications deployed into it and the services provided determine where the instance should run. An instance collecting data from a handful of devices could comfortably run on a single-board computer (such as Raspberry Pi or Beagle Bone). However, an instance supporting applications that analyze data from multiple buildings to aggregate grid services or optimize energy use across a campus could require the resources of a server. VOLTTRON's only requirement is that it runs in a Linux environment with needed prerequisites such as Python.

No change to the VOLTTRON platform is necessary for hosting the PM, real-time CxV and AFDD algorithms. In most cases, the deployment can be handled with an Intel® NUC or an equivalent hardware device. These devices typically cost between \$200 and \$300.

1.3 Definition of Performance Monitoring, Real-time Commissioning Verification, and Automated Fault Detection and Diagnostics

In this section generic PM, real-time CxV, and AFDD processes are defined.

1.3.1 Performance Monitoring

The performance of a CHP system can be categorized according to the outcome of primary interest. A CHP system has the objective of providing both electric power and useful heat at the lowest cost possible, while meeting other requirements such as constraints on environmental emissions. Once the physical system is designed and built, operating costs can be controlled by maintaining efficient operation. This involves both operating the system well (ideally optimized) and maintaining the system so that it can perform efficiently. Efficiency should be maximized to minimize fuel use (and fuel cost) subject to external constraints on meeting (but not exceeding) loads and prices, which determine the value of the electricity and the heat produced. Of course, this must be balanced against the cost of each additional maintenance activity.

To enable operators to track CHP system performance and detect problems with it, we propose to develop algorithms for monitoring the performance of the overall efficiency of the CHP system and the efficiency of each of the individual components (Figure 1.3). The overall efficiency is an indicator of how well the system is converting fuel into electricity and useful heat. Significant degradations in system efficiency would indicate both a loss in the capacity to generate these useful forms of energy and an increase in fuel use per unit of useful output energy. The latter would lead to increased fuel costs.

Emissions of gaseous pollutants to the atmosphere are controlled by regulation. Exceeding emissions limits can result in fines and the need to shut down the system (decrease emissions to zero by not operating) for a time period necessary to bring the system back into compliance with regulations. While not operating, the capital invested in the CHP system sits idle, providing no return on that investment. This gravely affects the economics of a CHP system. To help operators ensure compliance with emission regulations, algorithms should be developed for tracking environmentally important CHP system emissions as an aid to identify when emission rates increase above normal operation, possibly requiring operational changes or maintenance action, but this is beyond the scope of this project.

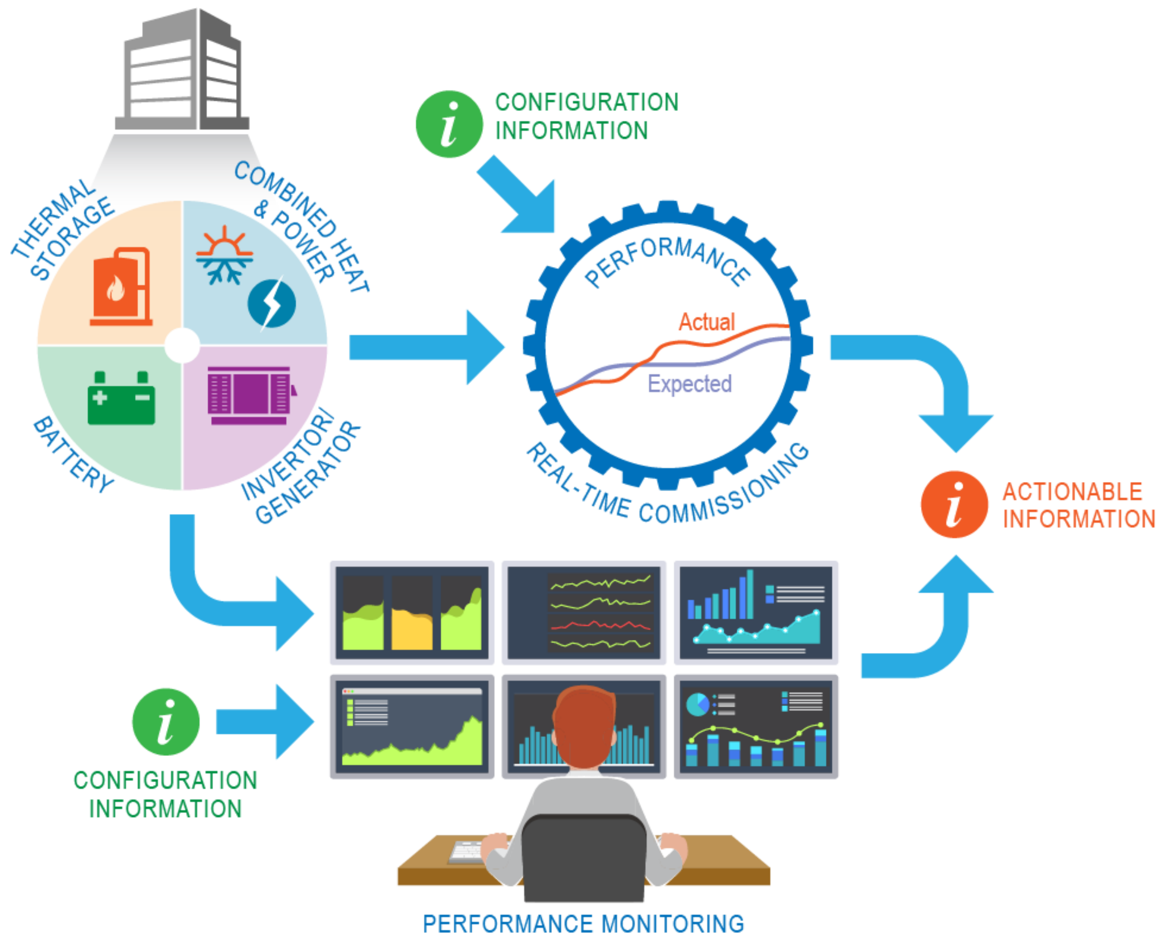

Figure 1.3. Performance monitoring and real-time commissioning verification process

1.3.2 Real-Time Commissioning Verification

Building-integrated CHP system commissioning should involve active testing of components and sub-systems as one of its core activities, including a systematic series of activities, starting in the planning phase, aimed at ensuring correct operation of the CHP system. Commissioning verification is a process by which the actual performance of the individual components in a CHP system and the performance of the CHP system as a whole are verified to comply with the designers' and manufacturers' recommended performance. A goal of this project is to automate parts of the commissioning verification process for CHP systems. This continuous commissioning process is referred to as real-time CxV. Although the real-time CxV process can include active testing of components and sub-systems, in this project the intent is to verify the performance to ensure that the system has been adequately commissioned and to provide indicators that RCx is needed as deficiencies are identified while simultaneously alerting the building operations staff.

The real-time CxV process will rely on the monitoring algorithms described in the preceding subsection (Section 1.3.1). The real-time CxV algorithms will provide the logic by which actual component or system performance is interpreted relative to performance expectations to identify deficiencies in performance during operation of the CHP system and the major individual components. By verifying the performance of the individual components, deficiencies in overall system performance can be isolated so that follow-up efforts can be targeted at the “deficient” components. Some deficiencies may span multiple components of the system. In these cases, controls or other integration issues will be identified as needed. The outputs of the CxV algorithms will include specific alarms, quantitative indicators of deficiencies, and supporting information to help guide corrective actions.

1.3.3 Automated Fault Detection and Diagnostics

Automated fault detection and diagnostics extends PM. It is an automatic process by which faulty (improper) operation, degraded performance, or broken components in a physical system are detected and diagnosed. The AFDD process generally consists of two primary processes: fault detection and fault diagnosis. The first step, fault detection, is the process of determining that some fault has occurred in the system. The second step, fault diagnosis, consists of two sub-processes, fault isolation and fault identification. Fault isolation involves isolating the specific fault that occurred while determining the kind of fault, the location of the fault, the time of detection, and the cause of the fault. Fault identification includes determining the size and time-variant behavior of a fault.

Beyond AFDD, there is the condition-based maintenance (CBM) process, which is a process where the maintenance of engineered systems and equipment are based on their current states, including faults that are present. A generic CBM process can be viewed as having four distinct functional processes, as shown in Figure 1.4. As described previously, the first two steps are the AFDD process. Following diagnosis, fault evaluation assesses the size and significance of the impact on system performance (in terms of energy use, cost, availability, or effects on other performance indicators). Based on the fault evaluation, a decision is then made on how to respond to the fault (e.g., by taking a corrective action or possibly even no action). Together these four steps enable CBM.

If a fault is detected, diagnosed (isolated), and evaluated but not found to cause sufficient risk, that could result in immediate shut down to the operation. The next issue to address is whether the fault can be corrected by changing the control software code or by modifying parameter values such as set points or operating parameters. These faults are sometimes called “soft” faults because they do not require physical repair of the system or they do not cause the system to stop operating. Because they are amenable to correction by changes to parameter values, these faults can usually be automatically corrected. When corrected automatically, the system continues to operate properly without interruption. Controls with this type of reconfiguration capability are also referred to as fault tolerant controls.

The scope of the algorithms that are being developed as part of this effort will only cover the first two steps: fault detection and diagnosis. In the future, the remaining two steps (fault evaluation and decision) can be added to complete the CBM process.

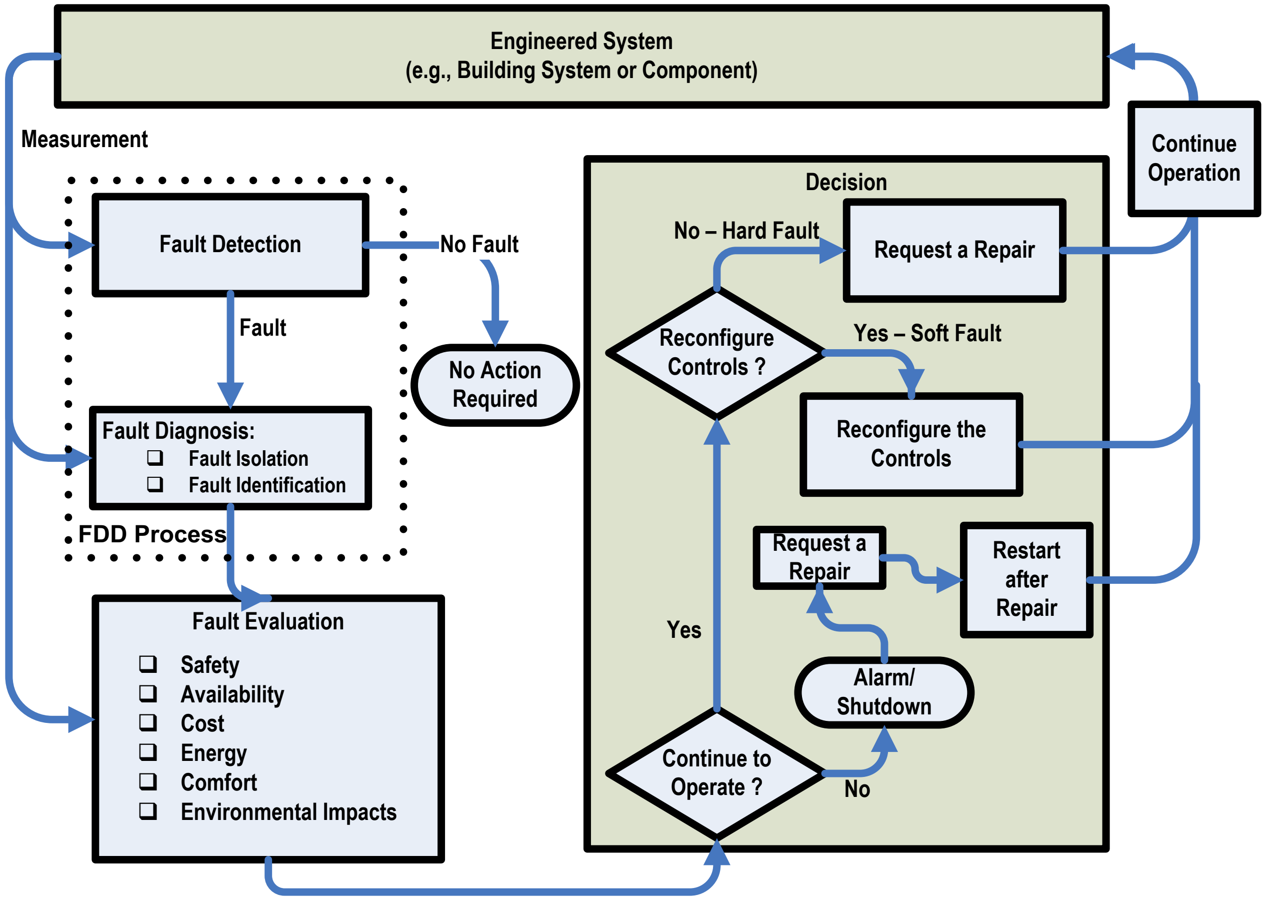

Figure 1.4. Generic application of fault detection and diagnostics to operation and maintenance of engineered systems

1.4 Project Purpose and Scope

The primary goal of the project is to design, develop, test and validate PM, real-time commissioning verification and AFDD algorithms for selected components for building-integrated combined cooling, heating and power systems and conventional heating, ventilation, and air conditioning systems (vapor compression and absorption chillers, cooling towers, and boilers) and energy generation/storage systems, including solar photo voltaic, battery, and thermal storage system and test them with offline data.

As noted previously, in this project, PNNL will use VOLTTRON, an IoT platform that supports distributed sensing and controls and can deliver solutions to an individual building or a network of buildings. The VOLTTRON IoT platform communicates with BACnet/Modbus based building automation systems (BASs) or devices to securely collect data from sensors, meters, and equipment. The data can be processed by the PM, real-time CxV, and AFDD algorithms, which provide automated insights to drive operational changes that result in improved performance.

An IoT-based platform to deliver energy efficiency improvements will have an initial cost and an ongoing operational cost; therefore, it is imperative to maximize the revenue stream to accelerate the rate-of-return on the initial investment and the ongoing operational cost. One way to do this is to simultaneously deliver both energy efficiency and grid services on the same platform. Therefore, the project will also validate peak load management while delivering energy efficiency.

The following approach will be used to execute this project:

1) PNNL will draft a test plan, which will describe how the heating, ventilation, and air conditioning (HVAC) and CHP components PM, real-time CxV, and AFDD algorithms will be developed, how they will be tested, and metrics that will be used for testing (included in this report).

2) Develop PM, real-time CxV. and AFDD algorithms for the selected HVAC and CHP components and convert them to Python using only open-source libraries and integrate them with VOLTTRON for testing and deployment.

3) Test and validate PM, real-time CxV and AFDD algorithms for the selected HVAC and CHP components.

4) Draft a final report, which will include description of algorithms, and testing and validation results.

1.5 Report Content and Organization

The PM, real-time CxV algorithms that will be developed are described Section 2.0 and AFDD algorithms that will be developed are described in Section 3.0. A detailed project timeline is presented in Section 4.0. The list of references is provided in Section 5.0.

2.0 Performance Monitoring and Real-time Commissioning Verification Algorithms

The motivation for developing PM algorithms is two-fold; first, to infer when physical faults may be degrading the performance of an individual component, like a chiller or battery. Such components tend to be self-contained and a simple analysis of inputs to outputs over time is sufficient to infer whether a physical fault is present. Second, PM of a set of components or of the system as a whole can be used to validate whether the control and coordination of the system deviates from established patterns. This could simply indicate a change in control strategy, such as system overrides in the BAS, or this may point to other things, like a component being unexpectedly offline.

Performance monitoring of some components and systems may be fairly complex. The metric used to validate performance may vary as a function of several independent system parameters (temperatures, setpoints, flow rates, etc.). There may also be a great deal of noise or variation in the metric of interest due to things like transient behavior as system parameters change or the component is first started up, and measurement uncertainty. Based on these considerations, PM should, in general, include the following features:

1. **Identification of Independent variables affecting performance.** These independent variables can be determined from the literature or from manufacturers' performance data. Regression analysis or machine learning tools can be used to create a map or model of system performance on proper identification and configuration of the independent variables.

2. **Identification of a characteristic time frame for analysis.** For some components, the performance can be measured and evaluated over short time intervals due to the nature of the measurements. In other cases, data may have to be collected and averaged over a longer time window to draw meaningful conclusions.

3. **Identification of appropriate thresholds for "normal" performance.** Performance monitoring is expected to be performed through the collection of a set of representative "baseline" data, then the evaluation of real-time data against the baseline. A decision must be made during the monitoring process of whether or not to characterize the current performance as deviating significantly from expected or baseline performance. This is typically accomplished through the use of thresholds. The choice of threshold can be critical as a tight threshold will induce "false positives" (or characterization of some normal behavior as degradation) and loose thresholds will lead to "false negatives" (or failure to flag degradation).

2.1 Selection of Components and Systems for Performance Monitoring and Real-Time Commissioning Verification Algorithms

Component performance metrics are commonly used as a measure of efficiency, effectiveness, or coefficient of performance – a measure of the ratio between output and input energy. For example, tracking power generated from the prime mover may also be of interest from a "dashboard" perspective. Most of these performance metrics rely on quantifying the energy by taking measurements on fluid streams (water, air, or fuel). This generally requires sensors capable of measuring temperatures and flow rates to be installed. When tracking for the purpose of quantifying degraded performance, other independent variables affecting performance need to be taken into account to properly make a determination of degradation. At the system level, performance metrics are geared toward measuring waste heat and electric power generation as well as some system-level efficiencies that may give insight into the effectiveness of system operations.

As part of this effort, PM algorithms will be developed for the following CHP components:

- Prime movers (fuel cells, microturbines, and reciprocating engines)
- Heat exchanger
- Conventional electrically driven vapor compression chiller
- Waste heat driven absorption chiller
- Boiler
- Battery energy storage system
- Thermal energy storage system
- Photovoltaic system
- Cooling tower.

2.1.1 Prime Mover (Fuel Cell, Microturbine, or Reciprocating Engine)

Metric: Generation efficiency (η_G).

Required sensors: Electric power generated (P_{Elec}), fuel input ($\dot{v}_{Fuel}$).

Equation:

$$\eta_G = \frac{P_{Elec}}{\rho_{Fuel}\dot{v}_{Fuel}LHV_{Fuel}}$$

where $\rho_{Fuel}$is the density of the fuel, in most cases natural gas, and $LHV_{Fuel}$is the lower heating value of the fuel.

Independent variables: Part-load ratio, ambient temperature.

Time frame for performance validation:

1. Wait at least one hour or until the system reaches steady state after equipment start-up.
2. Record real-time performance every minute (not less frequently than five minutes).
3. Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

2.1.2 Electrically Driven Vapor Compression Chiller

Metric: Coefficient of performance (COP).

Required sensors: Chiller power consumption (P_{Ch}), evaporator water inlet temperature ($T_{Ch,w,i}$), evaporator water outlet temperature ($T_{Ch,w,o}$), evaporator water volumetric flow rate ($\dot{v}_{Chw}$).

Equation:

$$COP = \frac{\dot{v}_{Chw}\rho_{Chw}C_{p,Chw}\left(T_{Ch,w,i} - T_{Ch,w,o}\right)}{P_{Ch}}$$

Where ρ_{Chw} is the density of water and $C_{p,Chw}$is the specific heat of water. Both can be approximated as constants.

Independent variables: Chiller part-load ratio, evaporator water outlet temperature, condenser water inlet temperature (cooling tower outlet temperature).

Time frame for performance validation:

1. Wait at least 20 minutes or until the system reaches steady state after chiller start-up.
2. Record real-time performance every minute (not less frequently than five minutes).
3. Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

2.1.3 Heat Exchanger

Metric: Effectiveness (ε_{HRU}).

Required sensors: Heat recovery exhaust inlet temperature ($T_{HRU,ex,i}$), heat recovery exhaust outlet temperature ($T_{HRU,ex,o}$), Heat recovery water inlet temperature ($T_{HRU,w,i}$).

Equation:

$$\varepsilon_{HRU} = \frac{T_{HRU,ex,i} - T_{HRU,ex,o}}{T_{HRU,ex,i} - T_{HRU,w,i}}$$

Independent variables: None.

Time frame for performance validation:

1. Wait at least 20 minutes or until the system reaches steady state after prime mover start-up.
2. Record real-time performance every minute (not less frequently than five minutes).
3. Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

2.1.4 Waste Heat Driven Absorption Chiller

Metric: Coefficient of performance (COP).

Required sensors: Evaporator water inlet temperature ($T_{Ch,w,i}$), evaporator water outlet temperature ($T_{Ch,w,o}$), evaporator water volumetric flow rate ($\dot{v}_w$), generator water inlet temperature ($T_{Gen,w,i}$), generator water outlet temperature ($T_{Gen,w,o}$), generator water volumetric flow rate ($\dot{v}_{Hw}$).

Equation:

$$COP = \frac{\dot{v}_{Chw,}\rho_{Chw}C_{p,Chw}\left(T_{Ch,w,i} - T_{Ch,w,o}\right)}{\dot{v}_{Hw}\rho_{Hw}C_{p,Hw}\left(T_{Gen,w,i} - T_{Gen,w,o}\right)}$$

Where ρ_{Hw} is the density of the hot water in the generator (slightly different from ρ_{Chw}, based on its higher temperature) and $C_{p,Hw}$is the specific heat of the generator water. Both can be approximated as constants.

Independent variables: Part-load ratio, evaporator water outlet temperature, condenser water inlet temperature, generator inlet temperature.

Time frame for performance validation:

1. Wait at least one hour or until the system reaches steady state after absorption chiller start-up.
2. Record real-time performance every minute (not less frequently than five minutes).
3. Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

2.1.5 Boiler

Metric: Boiler efficiency (η_B).

Required sensors: Boiler gas flow rate ($\dot{v}_{B,Fuel}$), boiler hot water inlet temperature ($T_{B,w,i}$), boiler hot water outlet temperature ($T_{B,w,o}$), Boiler water volumetric flow rate ($\dot{v}_{B,w}$).

Equation:

$$\eta_B = \frac{\dot{v}_{B,w}\rho_{Hw}C_{p,Hw}\left(T_{B,w,o} - T_{B,w,i}\right)}{\rho_{Fuel}\dot{v}_{B,Fuel}LHV_{Fuel}}$$

Independent variables: Part-load ratio.

Time frame for performance validation:

1. Wait at least 20 minutes or until the system reaches steady state after boiler start-up.
2. Record real-time performance every minute (not less frequently than five minutes).
3. Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

2.1.6 Battery Energy Storage System

Metric: Charge efficiency (η_{Ch}).

Required sensors: Battery state of charge (SOC), battery charge power meter ($P_{Bat,Ch}$).

Equation:

$$\eta_{Ch} = \frac{\Delta SOC * CAP_R}{\int P_{Bat,Ch}\,dt}$$

where ΔSOC is the change in SOC compared to a previous time and positive indicates an increase in battery charge; CAP_R is the battery's rated capacity. Note that this formulation for charge efficiency relies on the assumption that as the battery's capacity degrades, SOC remains relatively fixed. In other words, the SOC does not get re-scaled to be 100% even as the battery's ability to store charge is degraded. If this is not valid, the roundtrip efficiency metric will identify degradation.

Independent variables: SOC (average), average battery charge power.

Time frame for performance validation:

- Record SOC and P_{Ch} at time intervals (dt) ranging from 10 seconds to 1 minute.
- Evaluate every ten minutes:
  - Over the past 30 minutes, first validate that ΔSOC (SOC at the end of the 30 minutes minus SOC at the beginning of the 30 minutes) is above a minimum threshold for evaluation and that P_{Ch} has always been positive during the entire 30 minutes (battery has not switched from charging to discharging or other scenarios that would invalidate the measurement).
  - Sum across all recording intervals within the 30-minute period: the product of P_{Ch} and dt.

Metric: Discharge efficiency (η_{Dis}).

Required sensors: Battery state of charge (SOC), battery discharge power meter $\left(P_{Bat,Dis}\right)$.

Equation:

$$\eta_{Dis} = \frac{-\Delta SOC * CAP_R}{\int P_{Bat,Dis}\, dt}$$

Independent variables: SOC (average), average battery discharge power.

Time frame for performance validation:

- Record SOC and P_{Dis} at time intervals (dt) ranging from ten seconds to one minute.
- Evaluate every ten minutes:
  - Over the past 30 minutes, first validate that ΔSOC (SOC at the end of the 30 minutes minus SOC at the beginning of the 30 minutes) is below a minimum threshold for evaluation and that P_{Dis} has always been positive during the entire 30 minutes (battery has not switched from charging to discharging or other scenarios that would invalidate the measurement).
  - Sum across all recording intervals within the 30-minute period: the product of P_{Dis} and dt.

Metric: Roundtrip efficiency ($\eta_{Bat,R}$).

Required sensors: Battery state of charge (SOC), battery discharge power meter ($P_{Bat,Dis}$), Battery charge power meter ($P_{Bat,Ch}$).

Equation:

$$\eta_{Bat,R} = \frac{\int P_{Bat,Dis}\, dt}{\int P_{Bat,Ch}\, dt} \text{ (referenced against constant SOC)}$$

Independent variables: Average battery charge power, average battery discharge power

Time frame for performance validation:

- Note the SOC at the current time.
  - Record P_{Ch} and P_{Dis} at a time interval (dt) ranging from ten seconds to one minute. Keep a running total of the product of P_{Ch} and dt as well as a running total of the product of P_{Dis} and dt.
  - Wait for the SOC to change by at least a threshold (either charging or discharging).
  - Evaluate $\eta_{Bat,R}$ when the SOC returns to the original SOC.
  - Determine a threshold fraction of $\eta_{Bat,R}$ readings that are below normal performance by a threshold over a one-week period.

2.1.7 Thermal Energy Storage System

Metric: Thermal storage roundtrip efficiency ($\eta_{TS,R}$).

Required sensors: Thermal storage charge inlet temperature ($T_{TS,ch,in}$), thermal storage charge outlet temperature ($T_{TS,ch,out}$), thermal storage discharge inlet temperature ($T_{TS,dis,in}$), thermal storage discharge outlet temperature ($T_{TS,dis,out}$), thermal storage discharge flow rate ($\dot{v}_{TS,dis}$), thermal storage charge flow rate ($\dot{v}_{TS,ch}$) , thermal storage state of charge (SOC_{TS})

Equation:

$$\eta_{TS,R} = \frac{\int (T_{TS,dis,in} - T_{TS,dis,out})\, \dot{v}_{TS,dis}\, dt}{\int (T_{TS,ch,out} - T_{TS,ch,in})\, \dot{v}_{TS,ch}\, dt} \text{ (referenced against constant SOC}_{TS}\text{)}$$

Independent variables: None.

Time frame for performance validation:

- Note the SOC_{TS} at the current time
  - Record sensor variables at time interval (dt) ranging from 10 seconds to one minute. Keep a running total of the product of $(T_{TS,dis,in} - T_{TS,dis,out}), \dot{v}_{TS,dis}$, and dt as well as a running total of the product of $(T_{TS,ch,out} - T_{TS,ch,in}), \dot{v}_{TS,ch}$, and dt.
  - Wait for the SOC_{TS} to change by at least a threshold (either charging or discharging)
  - Evaluate $\eta_{TS,R}$ when the SOC_{TS} returns to the original SOC_{TS}
  - Determine a threshold fraction of $\eta_{TS,R}$ readings that are below normal performance by a threshold over a one-week period.

2.1.8 Photovoltaics System

Metric: AC power generated (P_{elec}).

Required sensors: Ambient temperature (T_{amb}), tilted surface solar incident radiation (I_T).

Equation: Baseline data can be collected to train the following regression equation (determine constants a, b, and c):

$$P_{elec} = a.I_T.\mathrm{K}_\eta + b.I_T.\mathrm{K}_\eta.T_a + c.(I_T.\mathrm{K}_\eta)^2$$

Where K_η is an angle incidence modifier, defined as

$K_\eta = 1 - 0.1 \times (1/\cos\theta_i - 1)$, where

$\cos\theta_i = \sin\theta_s \sin\theta_p \cos(\phi_s - \phi_p) + \cos\theta_s \cos\theta_p$, and
Θ_p is the tilt of the solar collectors with respect to the horizontal
φ_p is the azimuth of the solar collectors with respect to due South
θ_z is the solar zenith angle
φ_z is the solar azimuth angle

Calculating the solar azimuth and zenith angles is relatively complex and is described in Appendix A.

Time frame for performance validation:

- Collect data over a one-week timeframe.
  - Re-calculate regression coefficients a, b, and c and compare to baseline coefficients.

For better accuracy, baseline values for a, b, and c can be determined monthly.

2.1.9 Cooling Towers

Metric: Cooling tower effectiveness (ε_{CT})

Required sensors: Cooling tower water inlet temperature ($T_{CT,w,i}$), cooling tower water outlet temperature ($T_{Ct,w,o}$), outdoor wet bulb temperature (T_{wb}).

Equation:

$$\eta_{CT} = \frac{T_{CT,w,i} - T_{CT,w,o}}{T_{CT,w,i} - T_{wb}}$$

Independent variables: Cooling tower fan variable frequency drive (VFD) speed, Cooling tower water flow rate (if variable).

Time frame for performance validation:

- Record real-time performance every five-ten minutes
  - Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

Metric: Cooling tower electric efficiency ($\eta_{CT,elec}$).

Required sensors: Cooling tower water inlet temperature ($T_{CT,w,i}$), cooling tower water outlet temperature ($T_{Ct,w,o}$), outdoor wet bulb temperature (T_{wb}), cooling tower water flow rate ($\dot{v}_{CT,w}$) and cooling tower electricity consumption ($P_{CT,elec}$).

Equation:

$$\eta_{CT,elec} = \frac{\rho_w \, C_{p,w} \, \dot{v}_{CT,w}(T_{CT,w,i} - T_{CT,w,o})}{P_{CT,elec}}$$

Note that this "efficiency" is expected to be much greater than one.

Independent variables: Cooling tower fan VFD speed, cooling tower water flow rate (if variable).

Time frame for performance validation:

- Record real-time performance every minute (not less frequently than five minutes).
    - Determine a threshold fraction of real-time performance readings that are below normal performance by a threshold over a one-day window.

2.1.10 System-Level Validation

The following metrics can be used to perform validations of how the CHP system as a whole is performing. While component level validation typically indicates a degradation in performance likely related to a fault or degradation in intrinsic capabilities, system-level validation is more likely to uncover issues related to control or dispatch of the components, unless the system-level performance degradation is paired with component level performance problems.

Metric: Fuel utilization factor[7] (η_F).

This metric quantifies what fraction of the fuel used in the facility is used for productive purposes (rather than rejected as waste heat). Because the prime movers can generate heat that feeds into a building's hot water loop, the boilers are considered in this equation as well. Generated power may be used directly (productively) or may be stored in the battery temporarily. Thus, battery flows are considered as well.

Required sensors: Prime mover electric power generated (P_{Elec}), prime mover fuel flow ($\dot{v}_{Fuel,pm}$) boiler fuel flow ($\dot{v}_{Fuel,boiler}$), battery charge power ($P_{Bat,Ch}$), battery discharge power ($P_{Bat,Dis}$), building hot water loop volumetric flow ($\dot{v}_{hw,bldg}$), building hot water loop supply temperature ($T_{HW,S}$), building hot water loop return temperature ($T_{HW,R}$).

Equation:

$$\eta_F = \frac{P_{Elec} + P_{Bat,Dis} - P_{Bat,Ch} + \rho_w \dot{v}_{hw,bldg} C_p (T_{HW,S} - T_{HW,R})}{\rho_{Fuel}(\dot{v}_{Fuel,pm} + \dot{v}_{Fuel,boiler}) LHV_{Fuel}}$$

η_F is not very informative as an instantaneous value; a time-averaged value is more useful. By summing the product of the efficiency and the timestep, divided by the total elapsed time, the average fuel utilization factor can be determined:

$$\overline{\eta_F} = \frac{\sum \eta_F dt}{\Delta t}$$

Time frame for performance validation:
Evaluate $\overline{\eta_F}$ as a daily or weekly average.

Metric: Value-weighted energy utilization factor (EUF_{VW}).

This metric helps to refine the fuel utilization factor by applying value weights ($V_{elec}, V_{HW}, V_{fuel}$) to the energy streams. While assigning values to electricity and natural gas may be straightforward (equal to current prices for electricity and natural gas from the utility), assigning a value to hot water requires a more subjective judgment/process.

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[7] During the design stage, we will make a decision whether the control boundary will include boilers and conventional chillers.

Required sensors: Prime mover electric power generated (P_{Elec}), prime mover fuel flow ($\dot{v}_{Fuel,pm}$), boiler fuel flow ($\dot{v}_{Fuel,boiler}$), battery charge power ($P_{Bat,Ch}$), battery discharge power ($P_{Bat,Dis}$), building hot water loop volumetric flow ($\dot{v}_{hw,bldg}$), building hot water loop supply temperature ($T_{HW,S}$), Building hot water loop return temperature ($T_{HW,R}$).

Equation:

$$EUF_{VW} = \frac{\left[P_{Elec} + P_{Bat,Dis} - P_{Bat,Ch}\right]V_{elec} + \rho_w \dot{v}_{hw,bldg} C_p (T_{HW,S-}T_{HW,R})V_{HW}}{\rho_{Fuel}(\dot{v}_{Fuel,pm}+\dot{v}_{Fuel,boiler})LHV_{Fuel}V_{Fuel}}$$

EUF_{VW} is not very informative as an instantaneous value; a time-averaged value is more useful:

$$\overline{EUF_{VW}} = \frac{\sum EUF_{VW}dt}{\Delta t}$$

Time frame for performance validation:
Evaluate $\overline{EUF_{VW}}$ as a daily or weekly average.

Metric: Absorption chiller utilization fraction (Ab_F).

This metric helps to determine how effectively waste heat is being used for cooling, as opposed to conventional chiller operation. The metric determines the total fraction of generated chilled water-cooling energy provided by the absorption chiller.

Required sensors: Absorption chiller evaporator water outlet temperature ($T_{ab,w,o}$), absorption chiller evaporator water inlet temperature ($T_{ab,w,i}$), absorption chiller evaporator water flow rate ($\dot{v}_{ab,w}$), chiller water inlet temperature ($T_{Ch,w,i}$), chiller water outlet temperature ($T_{Ch,w,o}$), chiller volumetric flow rate – all chillers($\dot{v}_{Ch}$).

Equation:

$$Ab_F = \frac{\rho_w \dot{v}_{ab,w} C_p (T_{ab,w,i} - T_{ab,w,o})}{\rho_w \dot{v}_{ab,w} C_p \left(T_{ab,w,i} - T_{ab,w,o}\right) + \rho_w \dot{v}_{Ch} C_p \left(T_{Ch,w,i} - T_{Ch,w,o}\right)}$$

Ab_F is not very informative as an instantaneous value; a time-averaged value is more useful:

$$\overline{Ab_F} = \frac{\sum Ab_F dt}{\Delta t}$$

Independent Variables: Total chilled water load.

Time frame for performance validation:
Evaluate $\overline{Ab_F}$ as a daily or weekly average.

Metric: Current rate of useful thermal output (Q_{th}).

This metric indicates the rate of useful thermal output for heating or cooling by the CHP system.

Required sensors: Heat recovery outlet water temperature ($T_{hr,w,o}$), heat recovery water inlet temperature ($T_{hr,w,i}$), heat recovery water flow rate ($\dot{v}_{hr,w}$).

Equation:

$Q_{th} = \rho_w \dot{v}_{hr,w} C_p (T_{hr,w,o} - T_{hr,w,i})$

Independent Variables: Total hot water load.

Time frame for performance validation:

Instantaneous, for real-time monitoring. Alert operator if $Q_{th}$is below normal thresholds if the total hot water load is greater than Q_{th} and the boilers are running.

Metric: Current Electric Power Output (W_{elec}).

This metric indicates the net electric power output from the CHP system.

Required sensors: Prime mover electric power output (P_{pm}).

Time frame for performance validation:
Instantaneous, for real-time monitoring/dashboard.

Metric: Current electric power output (Q_{fuel}).

This metric indicates the net electric power output from the CHP system.

Equation:
$Q_{fuel} = \rho_{Fuel} \dot{v}_{Fuel,pm} LHV_{Fuel}$

Required sensors: Prime mover fuel flow rate ($\dot{v}_{Fuel,pm}$).

Time frame for performance validation:
Instantaneous, for real-time monitoring/dashboard.

Metric: Current expenditure rate for fuel ($Cost_{Fuel}$).

This metric indicates the rate of expenditure of funds on fuel for the CHP plant.

Equation:
$Q_{fuel} = \rho_{Fuel} \dot{v}_{Fuel,pm} LHV_{Fuel} \mathrm{Price}_{\mathrm{Fuel}}$

Required sensors: Prime mover fuel flow rate ($\dot{v}_{Fuel,pm}$).

Time frame for performance validation:
Instantaneous, for real-time monitoring/dashboard.

2.2 Performance Monitoring and Real-Time Commissioning Verification Algorithms Performance Metrics

Real-time commissioning refers to a validation of the rated or expected performance of a component or system from manufacturers' data. Real-time commissioning is an exercise that should be performed in the first few months after the device or system is installed and running. This time frame allows for validation of the performance of the system while it is new enough to rule out any performance degradation that may occur over time. The set of validation metrics that can be used for real-time commissioning is likely to be a subset of those used for PM because it necessarily relies on metrics that are likely to be specified by the manufacturer. An important difference between real-time CxV and PM is that the real-time CxV has to replicate any rated conditions to be valid. This may be done passively, by waiting until conditions that are sufficiently close to rated conditions, or it may be done proactively, for example, by controlling the component or system to setpoints that actively reproduce the rated conditions. If part-load performance data is available from the manufacturer, that information can also be used to compare to the actual part-load performance. Table 2.1 lists all real-time CxV metrics that can be deployed for CHP system components, the rated test conditions that should be replicated as closely as possible, and any other considerations (that could negatively impact accurate conclusions/increase uncertainty).

Table 2.1. Real-time commissioning metrics and rated test conditions

Component	Metric	Rated Conditions	Other Considerations
Microturbine	Rated efficiency (η_G at rated conditions)	ISO Conditions: Ambient Temperature (59°F), 14.696 psia ambient pressure, full (rated) power, ambient relative humidity (60%)	Installations at high elevation will not be able to meet the rated ambient pressure conditions. A correction factor may be required. Performance is also affected by inlet and exhaust back pressure (e.g., presence of heat recovery HX)[8]. Only passive commissioning possible
	Rated Capacity (P_{Elec} at rated conditions and full power output)	ISO Conditions: Ambient Temperature (59°F), 14.696 psia ambient pressure, full (rated) power, ambient relative humidity (60%)	Installations at high elevation will not be able to meet the rated ambient pressure conditions
Fuel Cell	Rated efficiency (η_G at rated conditions)	ISO conditions: 0.987 atmosphere ambient pressure, 77°F ambient temperature	Only passive commissioning possible. Installations at high elevation will not be able to meet the rated ambient pressure conditions
	Rated Capacity (P_{Elec} at rated conditions and full power output)	ISO conditions: 0.987 atmosphere ambient pressure, 77°F ambient temperature	Only passive commissioning possible. Installations at high elevation will not be

[8] https://www.epa.gov/sites/production/files/2015-07/documents/catalog_of_chp_technologies_section_5._characterization_-_microturbines.pdf

Component	Metric	Rated Conditions	Other Considerations
			able to meet the rated ambient pressure conditions
Conventional Chiller	Rated COP (COP at rated conditions)	ASHRAE/ANSI/AHRI/ISO Standard 13256, 100% part-load ratio, 7°C leaving evaporator water temperature, 30°C entering condenser water temperature	Can be performed passively or proactively
	Rated Capacity (Cooling energy provided at rated conditions and full power output) $\dot{v}_{Chw}\rho_{Chw}C_{p,Chw}\left(T_{Ch,w,i} - T_{Ch,w,o}\right)$	100% part-load ratio, 7°C leaving evaporator water temperature, 30°C entering condenser water temperature	Can be performed passively or proactively
Absorption Chiller	Rated COP (COP at rated conditions)	AHRI Standard 560-2000: Condenser water entering temperature: 85°F; Evaporator leaving water temperature: 44°F, hot water (generator) entering temperatures manufacturer specified	Can be performed passively or proactively
	Rated Capacity (Cooling energy provided at rated conditions and full power output) $\dot{v}_{Chw,}\rho_{Chw}C_{p,Chw}\left(T_{Ch,w,i} - T_{Ch,w,o}\right)$	Condenser water entering temperature: 85°F; Evaporator leaving water temperature: 44°F, hot water (generator) entering temperatures manufacturer specified	Can be performed passively or proactively
Boiler	Rated Efficiency ($\eta_B$at rated conditions)	(AHRI) Standard 1500. Full rated capacity, 180°F hot water temperature (non-condensing boilers), 120°F hot water temperature (condensing boilers)	Can be performed passively or proactively
	Rated Capacity (Heating energy provided at rated conditions and full power output) $\dot{v}_{B,w}\rho_{Hw}C_{p,Hw}\left(T_{B,w,o} - T_{B,w,i}\right)$	Full rated capacity, 180°F hot water temperature (non-condensing boilers), 120°F hot water temperature (condensing boilers)	Can be performed passively or proactively
Battery	Roundtrip Efficiency	Average charge/discharge power, likely manufacturer provided	Should be performed proactively

2.3 Performance Monitoring and Real-Time Commissioning Verification Algorithms Test and Validation Plan

In general, there are two ways to test and validate the proposed PM and real-time CxV algorithms. The first and most compelling option is to implement the monitoring on real systems. This can be done for a limited set of components, such as boilers, chillers, and cooling towers, using real systems on the PNNL campus. Note that this will only be possible if the required set of sensors is available. PNNL will identify candidate systems, trend baseline data for one month, then deploy the PM and real-time CxV algorithms where possible, collecting and monitoring performance data for another month. The performance metrics will be validated by:

- Confirming that they are within expected ranges (for example, boiler efficiencies 70-90%, chiller COPs mostly in the range of 3 to 8)
- Determining the stability of each metric
    - Standard deviation of data within hourly monitoring frames
    - Minimum and maximum values for each day
- Appropriate thresholds for detection of performance degradation, given observed variation in the data.

For other CHP components – and for the system-level metrics, PNNL does not have access to data on physical systems that could be used for validation. In these cases, PNNL will use a building energy model in EnergyPlus with a complete CHP system specified. The following validation can be performed:

- Baseline data and evaluation data extracted from the same annual dataset (fault-free)
    - Validate that each metric produces values in expected ranges
    - Validate that the proposed timeframes for performance validation are appropriate (do not lead to false positives)
- Evaluation data is run with a separate model with induced performance degradation or change in system dispatch
    - Validate that the proposed timeframes for performance validation are appropriate (do not lead to false negatives)
    - Determine appropriate thresholds for detection of performance degradation.

3.0 Automated Fault Detection Diagnostic Algorithms

As stated previously, AFDD extends PM and real-time CxV. It is an automatic process by which faulty (improper) operation, degraded performance, or broken components in a physical system are detected and diagnosed. The AFDD process generally consists of two primary processes: fault detection and fault diagnosis (Figure 1.4). Because there are a number of CHP and conventional HVAC system components that are typically used with a building-integrated CHP system, the time and resources required to develop AFDD algorithms for all components would be significant. Therefore, AFDD algorithms will be developed for selected components.

In this section, we summarize the available AFDD literature relevant to our study, then we list the components for which we will develop AFDD algorithms, the performance metrics that will be used to validate the algorithms, and the validation process plan.

3.1 Summary of the Automated Fault Detection Diagnostic Literature

Close to 200 AFDD studies related to building HVAC systems have been published over the past three decades. These studies have made significant contributions to the advancement of AFDD in the building sector; however, there are significant gaps as well. In 2004, Katipamula and Brambley (2005a, 2005b) conducted a detailed review of AFDD studies of building systems and published a two-part review that summarized the AFDD and prognostics methods. The review of over 120 articles, of which about 90 focused on building systems, was completed in 2004. The first part of the review focused on generic AFDD and prognostics, provided a framework for categorizing methods, described them, and identified their primary strengths and weaknesses. The second part of the review focused on research and applications specific to the fields of heating, ventilation, air conditioning and refrigeration (HVAC&R) systems. In 2017, Kim and Katipamula (2017) updated the previous review paper by reviewing AFDD papers published after 2004 that are relevant to commercial building sector.

Automated Fault Detection and Diagnostics focused on the HVAC&R systems increased in number since 2004—an additional 118 new studies were identified and were reviewed in the most recent review paper (Kim and Katipamula 2017). The paper classified the studies into one of three types of AFDD method: process history-based, qualitative model-based, or quantitative model-based and also classified the studies based on building system. The paper also noted that many studies did not include energy and cost impacts of faults. Of the 197 studies, 42% were associated with variable-air-volume (VAV) air handling units (AHUs), 17% were for chillers and cooling towers, 16% for rooftop units (RTUs), 12% for overall building (whole building application), 4% for water heaters, 3% each for commercial refrigerators and lighting, and 2% each for other HVAC and fan coil units. Based on the review, 87% of the current research is focused on the development of AFDD methods for a handful of building systems: VAV-AHUs, chillers and cooling towers, RTUs, and the overall building.

A vapor compression chiller system is a critical component of conventional HVAC systems and provides supplemental cooling source in a building-integrated CHP system. Automated fault detection and diagnostics methods for vapor compression chillers and cooling towers were popular (Bonvini et al. 2014; Han et al. 2011a, 2011b; Magoules et al. 2013; Navarro-Esbri et al. 2006; Rueda et al. 2005; Xu et al. 2008). Of the 34 studies related to the chillers and cooling towers, 79% used a process history-based method followed by studies that used quantitative model-based (15%) and qualitative model-based (6%) methods. These studies were further sub-classified based on the AFDD method used: 50% of the studies used black box, 18% used a combination of black box and gray box (18%), 12% used detailed physical models, 12% used gray box, 6% used rule-based, and 3% used simplified physical models. Because there is significant available literature for vapor compression chillers, this component would be a good target for AFDD software development.

Commercial building CHP and HVAC systems may include three water distribution loops: chilled water, condenser water, and hot water. The number of water loops present depends on the type of system. For example, air-cooled chillers will not include a condenser water loop, direct expansion systems will not include a chilled water or a condenser water loop, and systems with electric heat will not have a hot water loop. Each water loop includes one or more pumps that are subject to several faults. Detection and diagnosis methods for pumps may include specific and detailed faults such as obstructions, cavitation, and bearing failure (Kallesoe et al. 2006; Wolfram et al. 2001). While this level of detail may be needed in some applications, a high-level approach would be appropriate for HVAC applications. For example, the pump efficiency and flow rate could be used to analyze overall performance.

Due to their ability to generate chilled water from recovered heat, absorption chillers are part of many CHP system installations. However, there has been relatively little effort to develop AFDD methods for absorption chillers. One reason for this lack of development is that there are significantly fewer operating data available for these systems (especially operating data with known faults). Studies have detected chiller degradation using a model for normal operation (Gordon and Ng 1995, Labus et al. 2013, Tsutsui et al. 1994) or used a simulation of basic faults (e.g., reduced water flow rates) to develop AFDD methods (Han et al. 2015). Further development of AFDD for absorption chillers should focus on the most common faults in these systems, which were reported by Hyvärinen and Kärki (1996) to include loss of vacuum and clogging of condenser and evaporator tubes.

A review of commercial absorption chiller systems (Carrier 2005; Trane 2001) revealed an existing method for loss of vacuum faults that involves the purge system. American Society of Heating, Refrigeration and Air-conditioning Engineers (ASHRAE) Standard 147 requires that a purge system be used with refrigerant systems with (a) refrigerant charge greater than 50 lbs, and (b) a portion of the cycle that operates at sub-atmospheric pressures (ANSI/ASHRAE 2019). The purpose of the purge system is to separate non-condensable gasses such as hydrogen, nitrogen, and oxygen from the refrigerant and vent them out of the refrigeration system. The standard further requires that the purge system include an alarm to indicate when purging exceeds the manufacturer's threshold. This existing alarm provides a foundation on which AFDD algorithms may continue to build, and there is opportunity to improve this method. The alarm will only detect a leak once it has reached a certain size, but it will not detect the onset of vacuum leak. Furthermore, hydrogen is generated in small quantities within the absorption chiller during normal operation (Brotzu et al. 2015, Carrier 2005b) and therefore the purge system will operate periodically during normal operation in order to remove the hydrogen generated during the absorption process.

A gas-fired boiler is often a supplemental heat source when combined with a CHP system, providing thermal energy beyond that recovered from the CHP prime mover, so that a degraded or failed boiler could result in insufficient water or steam being available for hot water, process heat, or space heating. A steam boiler may also be used to run a steam turbine generator that provides power for the CHP system (Darrow et al. 2017), in which case a boiler that is not functioning or that functions inefficiently could severely impact the CHP system's utilization factor. Although AFDD studies associated with boilers are significantly fewer than studies associated with vapor compression chillers, there is sufficient literature to support development of a boiler AFDD algorithm (Patan and Korbicz 2009, Xue et al. 2005, Mavromatidis et al. 2013, Wang and Hong 2013, Fernandez et al. 2017).

A gas turbine is considered a conventional or industrial-scale turbine in the size range of 500 kW to 300 MW. It is usually the prime mover, a primary source of electrical energy, and a significant source of thermal energy, when it is part of a CHP system, so that its performance will directly reduce the CHP's utilization factor or eliminate the use of CHP altogether if it is not functioning properly.

A gas turbine has potential faults including (Li 2002, Wong et al. 2014, Palade et al. 2002, and Jinfu et al. 2017) reduced compression efficiency, reduced expansion efficiency, reduced nozzle area at the turbine inlet or exhaust area, fuel nozzle malfunction, gearbox faults (gear failures), structural failures (loose or misaligned components), thermal failures or "hot component faults" (Liu et al. 2017 and 2018), actuator faults, and sensor faults. These faults can result in a turbine shutdown or in a turbine operating with reduced efficiency/higher heat rate or at a lower power (and thermal) output than desired.

Gas turbine maintenance costs can vary significantly, and turbines are often sold with a service contract that covers scheduled maintenance and overhauls, and optionally unscheduled events as well. Gas turbine diagnostics have been developed using a variety of common statistical methods, with a straightforward and common one being the decision tree model (Wang et al. 2014). Because industrial-scale gas turbines are often developed and sold with on-board diagnostics in a proprietary integrated software package from the manufacturer, AFDD algorithm development for gas turbines is not a selected focus for this work, at this time.

A microturbine may be the central prime mover for a CHP system or it may be used in conjunction with another power source such as a fuel cell power generation unit. Its performance will directly reduce the CHP system's utilization factor if it is not functioning properly.

A microturbine has similar high-level potential fault classes to those of the conventional gas turbine. The machinery is similar to the conventional or industrial-scale gas turbine, generally with lower compression ratios, single-stage radial flow, heat recuperation, high rotational speeds, and power output in the range of 25 to 500 kW. Microturbine faults can also result in shutdown of power generation, reduced operational efficiency, or may result in a lower power (and thermal) output than desired.

Microturbines will tend to have a great deal of variance in performance, even for the same engine type and size (Rahman et al. 2018), and AFDD algorithms may need to be customized for a specific engine in mind and may be less transferrable than algorithms developed for more conventional large-scale turbines and other engines. Because the focus of this project is the development of general algorithms and not customized to a particular site and a specific microturbine generator, AFDD algorithm development for microturbines is not selected for this work, at this time.

3.2 Automated Fault Detection and Diagnostics Algorithms

Based on the literature search of selected CHP components, PNNL has decided to design, develop, and test AFDD algorithms for the following three components:

- Electrically driven vapor compression centrifugal chillers

- Waste heat driven absorption chillers
- Boilers.

3.2.1 Vapor Compression Chillers

Centrifugal chillers typically account for more electrical energy and demand than any other individual component within a commercial building. As a result, these systems are well-instrumented for PM, and, as previously stated, significant effort has been expended on developing AFDD methods for this system.

Much of the AFDD research work for centrifugal chillers has been supported by the ASHRAE. The first phase of this research (research project 1043-RP) included a review of existing methods, comprehensive experiments to understand fault-free and faulty operating behavior, and data-driven modeling of chiller operation (Bendapudi and Braun 2002, Comstock and Braun 1999a and 1999b). The second phase (research project 1275-RP) included the development of AFDD algorithm evaluation methods and the selection and comparison of four potential AFDD methods using the experimental data generated during phase one (Reddy 2006 and 2007). The third and final phase (research project 1486-RP) further refined and tested the AFDD algorithms (Zhao et al. 2011). The AFDD methods proposed in the 2nd and 3rd phases of the ASRHAE-supported research provide a foundation on which to build AFDD algorithms for this project, and the data generated in the 1st phase provides a means to validate the algorithms.

Faults considered in the ASHRAE development of AFDD for centrifugal chillers include:

1. Reduced condenser water flow rate
2. Reduced evaporator water flow rate
3. Condenser fouling
4. Low refrigerant charge
5. High refrigerant charge
6. Presence of non-condensable gas in the system.

For many of these faults, there exists a direct measurement that would provide an ideal indicator of the fault level. For example, the condenser or evaporator water flow could be measured directly using a flow meter. Unfortunately, these direct measurements are either impractical or expensive. As a result, the proposed AFDD algorithm will use an indirect method to detect and diagnose these faults, and these features are typically derived from common temperature and pressure measurements.

The third phase of ASHRAE research included the development and application of “decoupling-based” AFDD methods using the fault-free and faulty operating data generated in 1043-RP. The premise of the decoupling-based methods is that each feature should correspond to a given fault and deviation of that feature from the expected value indicates that the corresponding fault is present. This approach essentially performs fault *detection* and fault *diagnosis* in a single step. Similar methods were developed earlier for direct expansion air conditioning systems (Li and Braun 2007). Table 3.1 presents the features and fault diagnosis rules used for one of the most successful methods in phase 2 (Reddy 2006 and 2007), and Table 3.2 lists the decoupling features proposed in phase 3 (Li and Braun 2007 and Zhao et al. 2011).

Table 3.1. Fault diagnosis rules using features derived from raw measurements. Reported in (Reddy 2007)

Fault	Drop in Evaporator Water Temperature ΔTE	Rise in Condenser Water Temperature ΔTC	Subcooling at Condenser Exit TSC	Condenser Approach Temperature TCA	Condenser Overall Heat Transfer Coefficient UAC
Condenser Water Flow		+			
Evaporator Water Flow	+				
Condenser Fouling					–
Low Refrigerant Charge			–	–	+
High Refrigerant Charge			+	+	–
Non-Condensable Gas			+	+	–

Table 3.2. Decoupling features used to perform AFDD for centrifugal chillers. Refer to (Zhao et al. 2011 and Li and Braun 2007) for detailed derivation and implementation

Fault	Decoupling Feature
Condenser Water Flow	$\dot{m}_{cond} = \dfrac{\dot{m}_r \times (h_{dis} - h_{ll})}{c_p \times (T_{cdo} - T_{cdi})}$
Evaporator Water Flow	$\dot{m}_{evap} = \dfrac{\dot{m}_r \times (h_{suc} - h_{ll})}{c_p \times (T_{evi} - T_{evo})}$
Condenser Fouling	$UA^* = \dot{m}_{cond} \times \ln\left(1 + \dfrac{T_{cdo} - T_{cdi}}{TCA - TCA_{ref}}\right)$
Refrigerant Charge (Low and High)	$\Delta T_{sc-sh} = \left(T_{sc} - T^*_{sc,rated}\right) - \dfrac{K_{sh}}{K_{sc}}\left(T_{sh} - T^*_{sh,rated}\right)$
Non-Condensable Gas	$\Delta T_{cond} = T_{cond,pr} - T_{cond}(P_{cond})$

Although Table 3.1 and Table 3.2 outline the core of two promising AFDD approaches, these methods were developed using filtered steady state data from a 90-ton centrifugal chiller operating in a laboratory setting. Implementing these methods on a field-operating system will require preprocessing methods to identify the steady state conditions and will require an understanding of the measurement error in order to establish effective thresholds. Furthermore, these methods may need to be modified if all of the required sensors are not available in the BAS. Table 3.3 lists the required sensors for detecting chiller faults based on methods developed by Reddy (2007) and Zhao et al. (2011) and the sensors typically found in chillers.

In some applications, the water flow of the condenser and/or chilled water may be measured directly. However, diagnosing water flow faults at the chiller is still valuable because some water may bypass the chiller such that the measured water flow is not representative of the chiller water flow. Furthermore, even when no water is bypassed, the chiller AFDD methods may be used to validate the data from a water flow meter.

Table 3.3. Sensors required to calculate the features used for AFDD and sensors included on commercial chillers

	Features in (Reddy 2007)					Features in (Zhao et al. 2011)					Currently available chillers		
Sensors:	ΔTE	ΔTC	TSC	TCA	UAC	$\dot{m}_{cond}$	$\dot{m}_{evap}$	UA^*	ΔT_{sc-sh}	ΔT_{cond}	York (2019) model YK	Carrier (2019) model 19DV	Daikin (2016) model WSC
Chilled water entering temperature	×						×				×	×	×
Chilled water leaving temperature	×						×				×	×	×
Condenser water entering temperature		×			×	×		×			×	×	×
Condenser water leaving temperature		×			×	×		×		×	×	×	×
Refrigerant Liquid Line Temperature			×	×	×	×	×	×	×	×		×	×
Condensing temperature OR pressure*			×		×	×	×	×	×	P	?	P	?
Evaporating temperature OR pressure*				×	×	×	×	×	×	×	?	P	?
Compressor suction temperature					×	×	×	×	×	×			×
Compressor discharge temperature					×	×	×	×		×	×	×	×
Compressor electrical current					×	×	×	×		×	×	×	×

* For the saturation properties, "×" indicates that either a pressure or temperature sensor is sufficient. "P" indicates (a) that the feature requires a pressure sensor, or (b) that the commercial chiller specifically has a pressure sensor installed. "?" indicates that the commercial chiller has at least one saturation sensor installed, but the documentation is unclear regarding whether the sensor is a temperature or pressure sensor.

3.2.2 Absorption Chiller

The absorption chiller faults that will be focused on include (1) low condenser water flow, (2) low evaporator water flow, and (3) a vacuum leak (Hyvärinen & Kärki, 1996). Han et al. (2015) provided fault diagnosis rules for low water flow faults in absorption chillers (Table 3.4). However, these rules were derived using raw measurements as features and did not consider the advantage that other features could provide. For example, (Reddy, 2007) found that the change in water temperature through either the condenser or evaporator greatly simplified the diagnosis of low water flow faults in centrifugal chillers. These features may also simplify the diagnosis of low water flow faults in absorption chiller systems and will be investigated further.

Table 3.4. Fault diagnosis rules for low water flow in absorption chillers (Han et al. 2015)

Fault	Chilled Water Inlet Temperature Tchwi	Condensing Temperature Tc	Evaporating Temperature Te	Absorber Temperature Ta	Generator Temperature Tg
Low Condenser Water Flow		+	+	+	+
Low Evaporator Water Flow	+	+	+	+	+

Current ASHRAE standards require that an alarm be raised if the chiller purge rate exceeds a threshold. This alarm provides an indication that a vacuum leak is allowing non-condensable gasses to enter the refrigeration cycle thus requiring a purge more often. Left untreated, the leak will become larger and cause corrosion throughout the absorption chiller. The process of detecting a leak using the purge rate can be improved by making the threshold adaptive to a specific application thereby detecting a leak as soon as possible. However, developing this algorithm requires data from an absorption chiller operating in the field because the purge process will not be captured in most simulation models. However, the condensing and evaporating temperatures may also be used to gain insight to changes in pressure within the system and these features are easier to simulate. Changes in the condensing temperature, evaporating temperature, and purge rate form a fault diagnosis rule for loss of vacuum as shown in Table 3.5.

Table 3.5. Proposed fault diagnosis rule for loss of vacuum in absorption chillers

Fault	Condensing Temperature Tc	Evaporating Temperature Te	Purge Rate Rp
Loss of Vacuum	-/+	+	+

3.2.3 Boiler

Boiler faults include water leakage from the central boiler or from the connected piping, valve-related faults, pump-related faults, fouling, and sensor faults. These faults can result in a non-functioning boiler or in a boiler that operates with reduced efficiency or at a set point other than desired (e.g., decreased flow rate or insufficient exit temperature for the water or steam).

The AFDD algorithms can be developed using a recurrent neural network-based system model and a neural network-based fault approximator, using the basic framework provided by Patan and Korbicz (2009). The fault approximator can ideally be trained on labeled real data representing specific boiler faults (Xue et al. 2005). Prior work indicates that it is likely that the radial basis function will be useful in this context, but multiple common activation functions can be tested on the same data set and compared. Basic mass balance and enthalpy-based First Law control volume models can be created and used as a baseline for comparison of the performance model, and to provide a bounding function that restricts the results of the neural network model to states that are thermodynamically possible.

If real data are not available or are insufficient for training and testing the algorithms, it is possible to do fault detection based on energy use data alone (Mavromatidis et al. 2013) but options for fault detection will then be limited. Fault detection may be based on simulated fault data only, but there is a lack of experimental studies connecting simulated fault data to the real values of observed variables with similar faults. The specific fault of boiler fouling has been simulated by applying a “degradation factor” which is a simple multiplier that changes the inputs to an EnergyPlus model that are used to calculate boiler efficiency (Wang and Hong 2013). Leakage faults are difficult to model with EnergyPlus as the piping is not physically described and the thermal physics are typically neglected in building energy models (Fernandez et al. 2017).

The specific faults to be detected and diagnosed in this project are at a high level and focus on identifying faults that affect the water side of the boiler system. Water-side faults are most likely to be impactful to the overall performance of the CHP system and building systems, and this is consistent with the focus of a concurrent project that will provide synthetic fault data which will be used for training the algorithm to detect short cycling and sensor faults. Model-based or model-augmented fault detection is more difficult on the combustion side or “fire side” of the boiler; e.g., for leak detection, Widarsson and Dotzauer (2008) point out that precision is lower using a mass balance on the combustion side compared with the water side, although if data are available for both, leakage faults on either side can be successfully predicted at lower leakage rates by using the two mass balances together in conjunction with a Bayesian network for diagnostics. If this particular type of fault is found to be highly represented in the experimental data, a Bayesian network can be constructed and compared with the performance of a simple water-side mass balance model.

Faulty scenarios considered in this project may include:

- Fouling or scaling of heat transfer surfaces (Wang and Hong 2013)
- Water leak (Patan and Korbicz 2012) or boiler tube rupture/failure (Navaseelan and Bhuvaneswari 2017)
- Pump performance reduction (Patan and Korbicz 2009)
- Boiler short cycling that causes a boiler efficiency reduction
- Sensor faults that introduce bias into the readings used to control equipment, e.g., water level sensor failure (Patan and Korbicz 2009).

The desired measurements for including these faults for detection and diagnosis are shown in Table 3.6.

Table 3.6. Boiler faults with related measurements for detection and diagnosis

Fault:	Hot Water Temp. Entering Boiler (HWRT)	Hot Water Pressure Entering Boiler (need for HWDP)	Hot Water Temp. Leaving Boiler (HWST)	Hot Water Pressure Leaving Boiler (need for HWDP)	Water Volumetric Flow Rate through Boiler (HWGPM)	Water Level Reading	Pump Power Use	Gas Flow Rate Entering Boiler
Fouling of water-side heat transfer surfaces	x	x	x	x				x
Water leak	x	x	x	x		x		
Pump performance reduction	x	x	x	x	x	x	x	
Short cycling	x	x	x	x			x	x
Sensor bias or failure	x	x	x	x	x	x	x	

The raw data needs for performing fault detection in this way are:

- Hot water inlet temperature and outlet temperature ($T_{B,w,i}$ and $T_{B,w,o}$)
- Hot water inlet pressure and outlet pressure ($P_{B,w,i}$ and $P_{B,w,o}$)
- Water volumetric flow rate ($\dot{v}_{B,w}$)
- Water level reading ($l_{B,w}$)
- Pump power ($\dot{W}_{B,Pump}$)
- Boiler gas volumetric flow rate ($\dot{v}_{B,Fuel}$).

The additional metrics to be calculated using these data in order to perform fault detection in this way are:

- Boiler efficiency (η_B)
- Pump efficiency (η_P).

Before algorithm development takes place, the team will identify the specific type(s) of boilers that are appropriate for this application. The selection of boilers will include broad classifications such as hot water boilers only (not steam boilers); a distinction between fire-tube and water-tube boilers; and possibly pressure criteria. The restriction to specific boiler types will be based on the following criteria:

Commonly used boilers in CHP, campus, or commercial building applications

- Those that are consistent with the chosen performance metrics
- Those that are likely to have the appropriate measurements available for use in the algorithm
- Those that are consistent with boilers observed or modeled in comparable or related work.

Two white-box (physics-based) models based on these First Law principles will be constructed based on the expectations of:

- Conservation of mass of water within the boiler
- Conservation of energy for the water side of the boiler.

The neural-network-based system model will be used to make time series predictions for output (exiting) conditions and for pump power consumption and boiler efficiency after training on historical data from the same device. The historical data will also be analyzed to identify the expected variance in each of the measured values and performance metrics, so that the appropriate tuning parameters can be selected as described in Section 3.3.

The residuals between both the white-box and black box models will be monitored, and deviations will be flagged as potential faults based on the user's desired level of sensitivity. After identification, the fault will be diagnosed using rule-based logic to test its likeliness of belonging to one of the fault categories above.

Table 3.7 shows a list of specific faults that could be diagnosed with the appropriate data provided. If the residual values indicate a likely fault but it cannot be categorized using the rule-based guidance, it will be classified as Other, resulting in a detected fault with no diagnosis.

To diagnose additional faults (e.g., combustion-side faults) or perform more specific or reliable fault diagnosis, additional information needed would include:

- Values of control variables used to control combustion or water flow rate
- Inlet air flow rate
- Inlet air temperature
- Flue gas flow rate
- Flue gas temperature
- Flue gas analysis.

Table 3.7.Rule-based guidance for diagnosing boiler faults according to deviations in key measurements and calculated metrics

Fault:	Hot Water Temp. Entering Boiler (HWRT)	Hot Water Pressure Entering Boiler (need for HWDP)	Hot Water Temp. Leaving Boiler (HWST)	Hot Water Pressure Leaving Boiler (need for HWDP)	Water Volumetric Flow Rate through Boiler (HWGPM)	Water Level Read-ing	Pump Efficiency	Boiler Efficiency
Fouling of water-side heat transfer surfaces			**-**	**+**				**-**
Water leak				**-**	**-**	**-**		
Pump performance reduction				**-**	**-**		**-**	
Short cycling					**Many step changes per relevant time unit**			**-**
Water Level sensor fault						**-/+**		
Hot Water Supply Temp sensor fault			**-/+**					
Hot Water Return Temp sensor fault	**-/+**							
Hot Water Pressure Differential sensor fault		**-/+**		**-/+**				
Hot Water Gallons Per Minute sensor fault					**-/+**			

3.3 Performance Metrics of Automated Fault Detection and Diagnostics Algorithms

The possible outcomes of the AFDD algorithms are considered here, adapted from the categories used by Yuill and Braun (2016) in their study on AFDD tools for air conditioning equipment:

1. No Response: The algorithm is not able to provide a response; e.g., it has insufficient data, or the calculations violate laws of physics.

2. Correct: The algorithm correctly identifies a fault where one is present or correctly does not identify a fault where one is not present at a significant level.

3. False Alarm: The algorithm provides a false positive, identifying a fault where one is not present at a significant level.

4. Misdiagnosis: The algorithm correctly identifies a fault where one is present but incorrectly diagnoses the fault.

5. Missed Detection: The algorithm fails to identify a fault where one is present.

6. No Diagnosis: The algorithm correctly identifies a fault where one is present but is not able to provide a diagnosis for the fault.

For fault detection, we will adopt key performance metrics as described by Shi and O'Brien in a generalized study on AFDD methods for building systems (Shi and O'Brien 2019):

1. **True Positive Rate:** Percentage of designated faults that were detected

$$TPR = \frac{TP}{FN + TP}$$

   where $TP = TruePositive$, $FN = FalseNegative$.

2. **False Positive Rate:** Percentage of detected faults that were *not* actually designated faults

$$FPR = \frac{FP}{FP + TN}$$

   where $FP = FalsePositive$, $TN = TrueNegative$.

3. **False Negative Rate:** Percentage of designated faults that were not detected

$$FNR = 1 - TPR$$

4. **Detection Time:** Length of time for a correct fault detection to take place

$$DT = t_{FirstTruePositive} - t_{FaultDetectionStart}$$

   where $t = time$.

The abbreviation for each metric is indicated in Figure 3.1 to illustrate in which cases that particular indicator would be used. FPR and FNR provide quantitative information on mistakes that can be potentially costly, either in terms of wasted labor or inadvisable replacement for false positives, or in terms of additional energy use, suboptimal performance, or equipment degradation or failure for false negatives. TPR and FNR can, of course, be obtained from each other, but both provide unique information that can be used to describe either the algorithm's success or the costs of the algorithm's mistakes. The algorithm's precision, another metric for good performance that gives the fraction of total fault identifications that are indeed faults, can easily be obtained from TPR and FPR. DT also provides valuable information indicating whether costly faults are persisting for a significant time period before detection, which can also be used to inform algorithm development efforts; that is, to quantify the potential benefit in increasing the algorithm's speed of computation or access to computational resources.

For fault diagnosis, we will calculate:

1. **Correct Classification Rate:** Percentage of correctly identified designated faults that were then classified into the correct diagnostic category for that fault.

For each component, the historical data (or simulated equivalent) will be analyzed for the typical variance in its operating parameters and standard deviation, σ, will be calculated for each variable that will be predicted by a model or otherwise used within the AFDD algorithms. There will be a sensitivity tuning parameter, whose value can be adjusted by the user, that is based on a multiplier with the standard deviation. For example, if 3 was selected as the tuning parameter value (as in Patan and Korbicz 2009), only values that had a magnitude of 3 σ or more would be flagged for investigation as potential faults. It is important to note that the performance metrics will vary as the tuning parameter changes, and if time and resources permit, we may conduct a study on the sensitivity of the AFDD algorithm's performance to specific tuning parameters values so that we can provide guidance on appropriate selection of these values in real-world implementations.

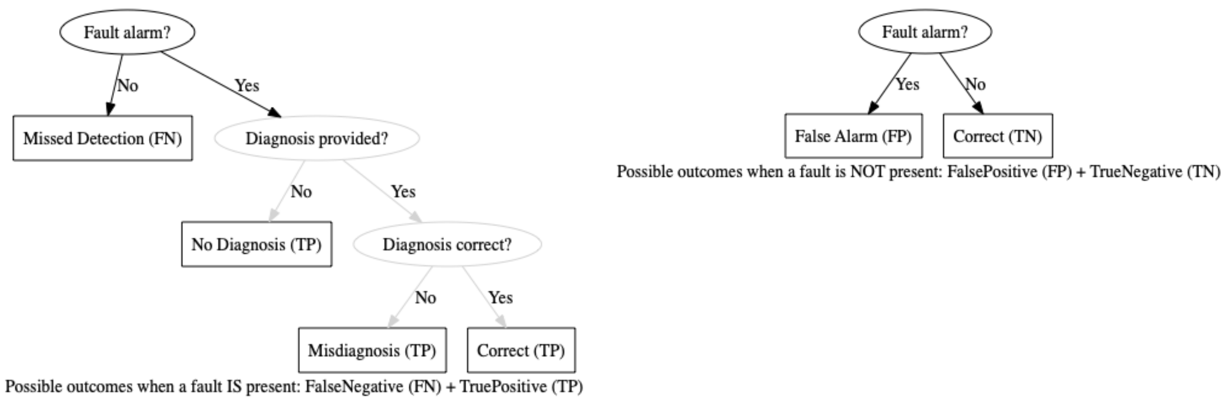

Figure 3.1. Possible outcomes of applying AFDD algorithms: (Left) when a fault has been designated as present, and (Right) when a fault has not been designated as present. Parentheses indicate the performance metric that will be affected by a given outcome

The first two performance metrics provide measures of accuracy for fault detection. Performance metrics 1 and 2 will involve tradeoffs, such that increasing the TPR (beneficial in catching faults) can also increase the false positive rate (potentially costly in dealing with faults that are not present). The sensitivity parameter will affect this trade-off, and other factors that are found to affect the ratio of false negatives to true positives will be documented. Each of the performance metrics should change in accordance with the tunable sensitivity rate that is chosen for implementation with the AFDD algorithms.

In determining whether a fault is present, this project will use the following standard for designated faults: A fault is present for a simulated fault when the simulator is provided with data that has been designated faulty. An experimental fault that has been noted as a potential fault is considered a designated fault when it has been verified through means other than the automated detection algorithm, which could include confirmation through a vendor, building manager or technician.

In determining how a fault should be properly classified, this project will use the following standard for designation of fault classifications: For simulated data, this is simply based on the type of fault that was introduced into the simulation data. An experimental fault that has been designated as a fault must be classified through means other than the automated diagnosis algorithm.

The performance metrics and the use of the variable sensitivity tuning will be revisited in Task 3 and Task 4 of the project and adjusted as needed based on the data that are available and whether the research team and facility managers find the metrics provided to be useful. The selection of metrics and tunability thresholds will be based on the following criteria:

- Commonly used thresholds or a selection that can be easily defined and explained
- Those that are consistent with values that are relevant for decision making, for operational control, or for maintenance
- Those that are consistent with metrics used in comparable or related work.

Because an algorithm that is used for diagnosis is more likely to be sensitive to the input data than an algorithm that is used for detection, we expect that the AFDD algorithms will have better performance on metrics related to detection only (TPR, FPR, FNR, and DT) when compared with its success at diagnosing faults (CCR). A detection algorithm tends to be more robust to differences in input data (Yuill and Braun 2016), but if the diagnosis portion is equally important the accuracy of the diagnostic algorithm could be improved with additional data and algorithmic improvements on a fault-by-fault basis.

3.4 Automated Fault Detection and Diagnostics Algorithms Test Plan

The algorithm test plan below describes the work needed to test whether the algorithms are operating as intended, and whether additional tuning or revisions to the algorithms are necessary. There are substantial data requirements needed for training and testing the algorithms for the components and faults described above. Experimental data is always preferable to modeled or synthetic data and will be used preferentially whenever possible. However, modeled or synthetic data may be used to supplement or replace real data when the desired measurements are not available or are found not to be reliable. The acquisition of new experimental data is outside the scope of this project and the use of existing data, when available, may require extensive labor for data cleaning and preparation.

The priority given to items in the testing plan will therefore need to prioritize tests that are most likely to yield results that provide critical information toward improving the performance of the algorithms on metrics described in Section 3.3. Therefore, the testing phase will include the use of modeled or synthetic data as described below in Section 3.4.1. The steps taken for testing will be prioritized based on whether they are:

- Applicable to real-world systems
- Applicable to more than one specific component within the CHP system
- Likely to result in necessary or desirable changes to the algorithms
- Possible within the allocated engineering time and with the data available to the team.

The testing plan will only include one fault at a time, unless the team identifies an experimental data set with multiple labeled faults which can be used for testing. If multiple faults are encountered in testing, the metrics for successful detection and diagnosis will be counted favorably if either fault is correctly identified or correctly identified and correctly classified. The evaluation and separation of multiple co-occurring faults within a building system is an advanced endeavor with even higher data requirements than the single-fault conditions, and the current state of AFDD research for these components is not yet sufficiently advanced that this may be done reliably.

3.4.1 Synthetic Data Testing

To provide the algorithms with adequate data for training and testing the models and the logic encoded within, synthetic data will be created using simple statistical models. Faulty data points will be assigned a range of possible values, bounded by physical limits according to the physical limits of the equipment and the First Law physics-based models developed for individual components. A probability distribution will be assigned for each of the significantly affected variables, according to the significant variables as identified in Section 3.2. Operational data points may also be created using the same method; values will take a smaller range of appropriate operational states and the probability distribution should be more narrowly defined. Some variables may only allow a small set of discrete values (e.g., on/off or measurement series that result in step functions) and for those only a probability of falling within a given bin for each value will be necessary. Where appropriate, a unique distribution will be assigned for each season and an annual simulation will be conducted to test the algorithms.

The probability distribution indicates the values that a particular variable is likely to take under specific operational conditions identified as either normal or a designated fault condition, which will be based on a survey of literature for information related to the particular fault, or engineering judgment in certain areas where prior research is sparse. The data creation will then be conducted by sampling from the identified sample space using a Monte Carlo method and creating new sets of operational data by fault, by component, and by season where appropriate.

For some specific faults, a synthetic data set is already in development for another BTO project lead by PNNL. This data will be used for testing the algorithms created here, provided that the data sets are available by June 2020.

Where synthetic data is needed for training the algorithm (e.g., historical data used to train a neural network), a training/test split will be decided beforehand based on the quantity of data available, such as 90/10, and the smaller fraction of these datasets will be reserved for use in the testing phase only.

Each algorithm will be trained and configured for the type of data it will be receiving, and then it will be tested by receiving data and attempting to detect and diagnose faults. In addition to calculating the AFDD performance metrics for each algorithm test, the computational time required for each algorithm's performance on each test will be recorded.

The remainder of the time spent in the testing phase will be used to revise the algorithms based on the per-fault and per-component performance, and if possible, to re-run the test using different sensitivity tuning parameters.

3.5 Automated Fault Detection and Diagnostics Algorithms Validation Plan

The algorithm validation plan below describes the work needed to test whether the algorithms are operating in a way that is consistent with known physical characteristics of these systems, and whether their results are likely to be useful in future practical implementations. This corresponds to a verification step for the computer models used in this work, and additional checks with real-world data and/or system operators for the output provided by the algorithm. To reach a scientific validation of the models and of the fault detection and diagnosis outcomes will require obtaining operating data with labeled faulty behavior for real-world components. A literature review has not revealed any such data sources for many of the components considered here, and additional experiments would be beyond the time and financial resources allocated to this project. The project team will provide in the final report an assessment of the future work that would be most helpful toward further developing these algorithms.

The algorithm test plan will be adjusted based on availability of data and personnel as needed. Experimental data is always preferable to modeled or synthetic data, but modeled or synthetic data may be used for validation when experimental validation is not possible. The validation plan will prioritize components for validation based on the availability of data within the project period. Ideally, validation will take place with more than one real-world system so that the results are more likely to be generalizable without being applicable to only one specific device.

3.5.1 Data-Based Validation

The first stage of the validation process is similar to the data testing protocol described in Section 3.4.1; however, the algorithms tested will be the versions that have been revised based on the results of the algorithm testing plan. If experimental field data can be obtained and there are greater than 12 months represented in the dataset, then at least 12 months of data will be used in the testing phase and the remainder of the data will be held until the validation phase, given that no major equipment or operational changes have occurred over that time period.

After the outputs have been thus compared against the known data sets, final statistics will be computed for the success of the algorithms according to the performance metrics described in Section 3.3.

3.5.2 Potential End User Feedback

Because measured data from actual systems will not be available for all components and faults covered by the algorithms, the team will reach out to real-world operators of systems related to those evaluated by the algorithms for a subjective perspective on whether the output is quantitatively reasonable based on their experience and potentially useful to an operator in terms of the fault information that they provide. This will include one interview with an engineer or operator from a partnering organization who is familiar with each of the major components for which algorithms have been developed. A PNNL team member will provide a brief presentation with the basis for the algorithm and the results obtained using simulated data and record any comments, concerns, or suggestions that arise. This end user feedback will be used to inform the next steps for modification of the algorithms toward adoption by the greater community.

4.0 Development and Testing Timeline

1. Design of PM and real-time CxV algorithms for CHP system components complete – 4/30/2020.

2. Design of AFDD algorithms for CHP system components complete – 6/30/2020.

3. Coding and testing of PM and real-time CxV algorithms for CHP components and CHP system as a whole complete – 9/30/2020.

4. Coding and testing of AFDD algorithms complete for CHP system components – 9/30/2020.

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Appendix A – Solar Angle Calculation

The sun's position in the sky can be defined by two angles:

1. zenith angle (θ_s)

$$\cos\theta_s = \cos\lambda\cos\delta\cos\omega + \sin\lambda\sin\delta \qquad 5.1$$

2. azimuth angle (ϕ_s)

$$\sin\phi_s = \frac{\cos\delta\sin\omega}{\sin\theta_s} \qquad 5.2$$

where λ= latitude of location and δ = solar declination, which can be calculated according to Equation 2.18. ω is the solar hour angle, defined according to Equation 2.18, where n is the day of the year, counting from January 1 and t_{sol} is the solar time.

$$\sin\delta = -\sin 23.45^\circ \times \cos\frac{360^\circ \times (n+10)}{365.25} \qquad 5.3$$

$$\omega = (t_{\mathrm{sol}} - 12\,\mathrm{h}) \times 15^\circ \qquad 5.4$$

A flat plane is specified in terms of the zenith angle (or tilt angle from the horizontal) θ_p and azimuth ϕ_p of the surface normal (positive for orientations west of south). The Solar incidence angle, θ_i (equal to the angle between normal of plane and line to sun) for **stationary planes** is defined as

$$\cos\theta_i = \sin\theta_s\sin\theta_p\cos(\phi_s - \phi_p) + \cos\theta_s\cos\theta_p \qquad 5.5$$

Expressions for different types of trackers requiring periodic or continuous adjustments can be found in the literature (see for example, Duffie and Beckman, 2006). In the case of horizontal **N-S one-axis trackers** with continuous adjustment (a rather common mounting type):

$$\cos\theta_i = (\cos^2\theta_s + \cos^2\delta.\sin\omega)^{1/2} \qquad 5.6$$

All solar angles calculations should be based on solar time. Three quantities are relevant when specifying time of the day at a specified location:

a. Standard time t_{std} of the time zone of the specified location is defined by the reference value of the longitude. For instance, in the contiguous United States, the reference meridians for the time zones are 75°W for Eastern, 90°W for Central, 105°W for Mountain, and 120°W for Pacific standard times. The standard time is the watch time when daylight savings is not followed.

b. Local civil time $t_{civ,loc}$ is the time at the specific location in question. A constant correction is needed which accounts for the difference in longitude between the reference meridian and the local meridian. Since one full cycle of a day corresponds to 360° longitude, each degree corresponds to $(\frac{24\text{ h x }60\text{ min}}{360^0}) = \frac{1}{15}\text{ h} = 4\text{ min}$. In most parts of the world, clocks are set to the same time within a time zone covering approximately 15° of longitude (although the boundaries may be quite irregular).

c. Daylight savings time (DST) needs to be corrected for when appropriate.

d. Equation of time

Another source of deviation between solar time and local civil time is due the *equation of time* E_t. It is a function of the time of year and can be approximated by

$$E_t = 9.87\times\sin 2B - 7.53\times\cos B - 1.5\times\sin B \quad (\text{min}) \tag{5.7}$$

with

$$B = 360^\circ \times \frac{n-81}{364} \quad \text{for } n\text{th day of year} \tag{5.8}$$

Solar time t_{sol} is related to standard time t_{std}:

In hours: $$t_{sol} = t_{std} \pm \frac{L_{std} - L_{loc}}{15^\circ/\text{h}} + \frac{E_t}{60\text{ min/h}} \tag{5.9}$$

In minutes: $$t_{sol} = t_{std} \pm 4' \times (L_{std} - L_{loc}) + E_t \tag{5.10}$$

where L_{std} and L_{loc} designate the longitudes (in degrees) of the time zone and the location, respectively. The plus (+) sign is to be used for locations west of Greenwich and the negative (-) sign for locations east of Greenwich. In regions with daylight saving time, one has to subtract 1 h from daylight saving time to obtain t_{std} during the summer half of the year.

Pacific Northwest National Laboratory

902 Battelle Boulevard
P.O. Box 999
Richland, WA 99354
1-888-375-PNNL (7665)

www.pnnl.gov