ORNL/TM-2022/2810

Connected Loads – Grid Connected Appliances: Deployment IoT Solution for Fault Detection and Diagnostics

Nov. 2022

OAK RIDGE National Laboratory

ORNL/TM-2022/2810

BTO Project 03.02.07.71
FY22 Final Report

CONNECTED LOADS- GRID CONNECTED APPLIANCES: DEPLOYMENT IoT SOULTION FOR FAULT DETECTION AND DIAGNOSTICS

Jian Sun
Teja Kuruganti
Brian Fricke
Yanfei Li
Carlos Cunningham

Nov. 2022

Prepared by
OAK RIDGE NATIONAL LABORATORY
Oak Ridge, TN 37831-6283
managed by
UT-BATTELLE, LLC
for the
US DEPARTMENT OF ENERGY
under contract DE-AC05-00OR22725

CONTENTS

LIST OF FIGURES

LIST OF TABLES

No table of figures entries found.

EXECUTIVE SUMMARY

As one of the most energy-intensive end-uses in the commercial buildings sector, supermarkets consume around 50 kWh/ft^2 (or 537.6 kWh/m^2) of electricity annually, or more than 2 million kWh of electricity per year for a typical store. The biggest consumer of energy in a supermarket is its refrigeration system, which accounts for 40–60% of its total electricity usage and is equivalent to about 2–3% of the total energy consumed by commercial buildings in United States, or around 0.5 quadrillion Btu (or 0.53 quadrillion KJ). Also, the supermarket refrigeration system is one of the biggest consumers of refrigerants. Current supermarket refrigeration systems rely on high global warming potential hydrofluorocarbon refrigerants. Reducing refrigerant usage or using environment friendly alternatives can result in significant climate benefits. Transcritical CO2 refrigeration systems have attracted more attention in recent years because of their zero-carbon emission advantages compared with traditional refrigerants. These systems are widely used in commercial buildings such as supermarkets. The refrigeration system can also be adapted to handle flexible building loads and be integrated into grid response transactive control to balance the supply and demand of the electric grid. Even minor improvements in the efficiency and operational reliability of supermarket refrigeration systems can create significant value in terms of saving energy, improving food quality, protecting the environment, reducing carbon footprint, and enhancing electric grid resilience.

For decarbonization, the new administration has set a target to reduce greenhouse gas emissions by 50–52% by 2030 and targeting a carbon-neutral economy by 2050. For electrification, the goal is to achieve 100% clean electricity by 2035. Such decarbonization and electrification in the building sector require that energy consumption in buildings be reduced significantly. Therefore, the building sector must continuously adopt new technologies to achieve its energy and carbon emission goals. One of the most fundamental technologies is the Internet of Things (IoT). IoT has proven to be an effective solution for the building domain, including building information/energy modeling, smart buildings, etc. Although much progress has been made in the development of IoT-based building energy systems, there is still a lack of reliable, scalable, and affordable IoT-based automated fault and degradation diagnostics (AFDDs) solutions. Such solutions would enable deployment of advanced algorithms into real systems to archive the projected energy benefits. This study reviews existing IoT solutions developed for building energy–related application and developed a simple but effective AFDD IoT deployment solution, including developing a suitable IoT architecture and conducting easy and scalable deployment by leveraging a common cloud-based IoT service.

1. INTRODUCTION

The building sector ranks the highest in terms of energy consumption and carbon emissions among all sectors (U.S. Energy Information Administration (EIA) - Ap 2020). The new US administration has established two critical missions for the building energy sector: decarbonization and electrification. For decarbonization, the new administration has set a target to reduce greenhouse gas emissions by 50–52% by 2030, and ultimately achieving a carbon-neutral economy in 2050. For electrification, the goal is to achieve 100% clean electricity by 2035. For these goals to be met, building energy consumption must be reduced significantly.

In 2020, the residential and commercial building sectors were the main consumers of energy, accounting for 40% (i.e., 22% and 18%, respectively) of the total US energy consumption. Space heating accounted for 43.3% of the total energy in residential buildings in 2015. Moreover, 69.4% of energy for the space heating is provided by natural gas, as such systems are typical in US residential buildings. Only 14.1% of energy for space heating is provided by electricity. This sector must thus continuously adopt new technologies to achieve building energy and carbon emission goals. One of the most fundamental enabling technologies is the Internet of Things (IoT). Based on the work of (Gubbi et al. 2013), IoT is an "interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics and information representation with Cloud computing as the unifying framework." This definition demonstrates IoT's suitability for building applications.

During the past decade, IoT has proven to be an effective solution for the building domain, including building information/energy modeling, smart buildings, etc. IoT is expected to reach $298.26 billion by 2026 in the energy market—from monitoring the temperature of a room using sensors to complex applications that control the energy use of an entire building with cost-cutting and productivity-creating (Mordor Intelligence 2020). Furthermore, it has been reported that IoT has the potential to unlock $1.3 trillion in value for the electricity sector by 2025 (World Economic Forum 2016).

Along with the increasing complexity and scale of building energy systems and integration with other systems (Figure 1) such as renewable energy generation systems (e.g., solar photovoltaics, wind power) and energy storage systems (e.g., battery, thermal storage systems), IoT has attracted great interest and is becoming one of the major applications in building energy systems. Rafsanjani and Ghahramani (2020) utilized an IoT solution to capture the occupant-level energy consumption and integrated with appropriate behavior intervention techniques to influence office buildings' occupant energy use behaviors. Because IoT is capable of connecting billions or trillions of heterogeneous devices, it was considered as a great technology to support potential applications such as smart homes and cities, building management, agricultural automation, and telemedicine (Khajenasiri et al. 2017). Garin et al. (2018) applied IoT with an open-source platform for building a self-developed environment monitoring system. In that work, the IoT solution was used for building energy retrofit via tracking the environmental conditions of the buildings with the goal of making it applicable to other smart environments. IoT technology has been also used for integrating solar photovoltaic power generation technology and building construction (Wu et al. 2022). A building intelligent control architecture based on IoT technology was developed to achieve comprehensive perception of various physical parameters, such as voltage, current, power (Yu et al. 2020). Experiments have been conducted to verify the capability of the proposed platform in a collection of power supply parameters for effectively protecting the safety of the building power system.

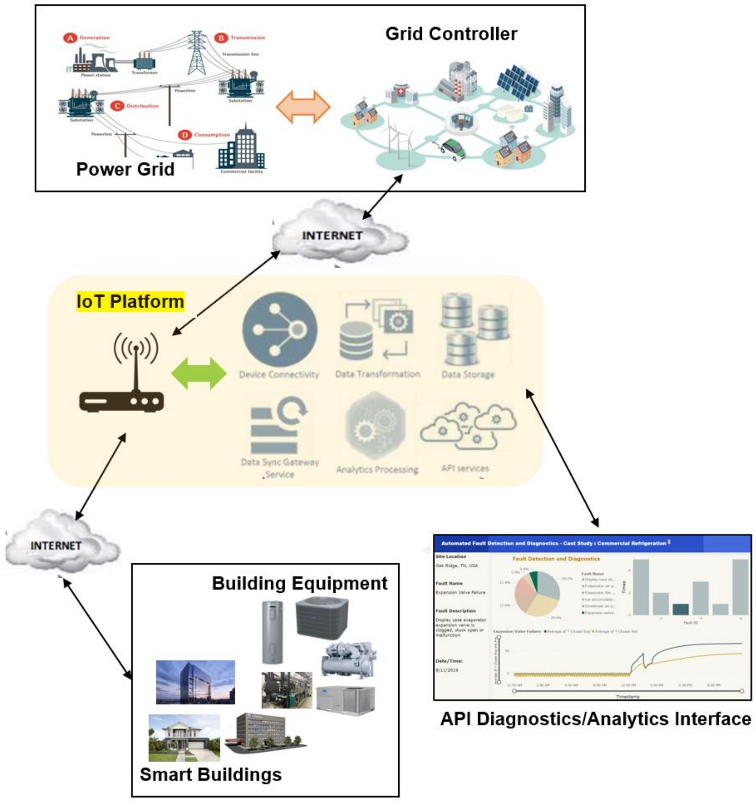

Figure 1: IoT in smart building and smart grid applications

IoT provides a solid foundation to accelerate the utilization of automated fault detection and diagnostics (AFDD) technologies in building energy systems. Before AFDD, there was abundant research on fault detection and diagnostics (FDD) (Katipamula and Brambley 2005; Mirnaghi and Haghighat 2020; B. Yu, Van Paassen, and Riahy 2002; Y. Yu, Woradechjumroen, and Yu 2014). The AFDD workflow (Shi and O'Brien 2019), on the other hand, is composed of four steps. The first step is data collection from sensors; domain knowledge is required to configure and deploy sensors across critical measuring points for buildings and HVAC components /systems. The second step is feature generation. Because of the complexity of HVAC systems and building operations, some faults may share the same symptom, or some faults may have different symptoms at a different stage, especially time-developing faults. There are three modeling methods of feature generation: black-box, grey-box, and white-box. AFDD is more suitable using black-box methods. Because of the limitations of modeling, a new trend has been emerged using the experimental approach (Sun et al. 2021). Another trend is to create fault models (Li and O'Neill 2018, 2019a, 2019b), which generates fault data as the true-baseline, to help better support AFDD. Step three is fault detection, in which the key variables under fault and normal conditions to detect the fault are traditionally compared. (4) The final step is fault diagnostics. This is the ultimate goal.

Although much progress has been made in the development of IoT-based building energy systems, there is still a lack of reliable, scalable, and affordable IoT-based AFDD solutions. Such solutions would enable deployment of advanced algorithms and data analytics methods into real systems to archive the projected energy benefits, including energy consumption reduction or energy cost saving, and enhancing demand flexibility for balancing the power supply. Generally, the IoT platform must acquire and analyze both historic and real-time data of building energy systems, support different applications and functions—including performing energy detection and prediction—and visualize and regulate the analyzed building energy data. To mitigate this gap, this work develops a simple but effective building energy system

AFDD IoT deployment solution—including developing a suitable IoT architecture and conducting easy and scalable deployment by leveraging a common cloud-based IoT service. Also. a low-GWP refrigerant (CO_2) commercial refrigeration system is used as example case to demonstrate the deployment of the developed AFDD IoT solution.

2. IOT ARCHITECTURE

Although there is no single widely accepted IoT architecture in the building energy industry, most of the IoT frameworks developed thus far generally consist of several common modules (Figure 2), including device, sensor, network, gateway, data ingestion, data storage, data analytics, and application. In addition, security is embedded in each of these modules. Different IoT models group them into different layers based on different IoT solution consumers and applications. Patel et al. (2016) used a model to integrate these functions into four layers: smart device/sensor, gateway and network, management service, and application. Minoli et al. (2017) introduced a seven-layer IoT-A architecture model, called the open systems IoT reference model (OSiRM), which includes layers of things, data acquisition, fog networking, data aggregation, data centralization, data analytics and storage, and applications.

Furthermore, cybersecurity has been considered as a general requirement embedded in each of the architecture layers for identifying the IoT device, protecting the information flow, and preventing device hijacking. Martin-Lopo et al. (2020) presented a common cloud-based energy platform architecture that includes three layers: the physical layer, server layer and application layer. The physical layer provides information about the environment, executes user commands, and applies analytical results. The application offers remote control and interaction with human beings or other systems through GUIs. The server layer is the core of the platform and can provide three types of services: software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). Reviewing several IoT system architectures, Lawal et al. (2021) summarized a general four-layer architecture for residential and commercial buildings, including a physical layer, cloud layer, communication layer, and service layer. A building information modeling (BIM)- and IoT-based virtual tool for building enclosures assessment used a three-layer system architecture: a data acquisition layer, middleware layer, and application layer (Shahinmoghadam et al. 2021). The data acquisition layer accumulates and transmits the sources of data to the other two layers. The middleware layer delivers computation/analysis and data storage functionalities. The application layer handles the visualization, immersion, and interaction functionalities. Luo et al. (2019) proposed an IoT data analytics architecture for building load prediction, which is composed of sensitization, storage, analytics support, and service layers, to facilitate the collection, processing, analysis, and presentation of energy data. Similarly, an IoT architecture for smart cities application designed by Moreno et al. (2017) consists of technologies, middleware, management, and services layers. Abdelouahid et al. (2021) proposed a seven-layer IoT platform with a universal interface to improve interoperability between connected objects. This model can ensure object interconnection via smart object.

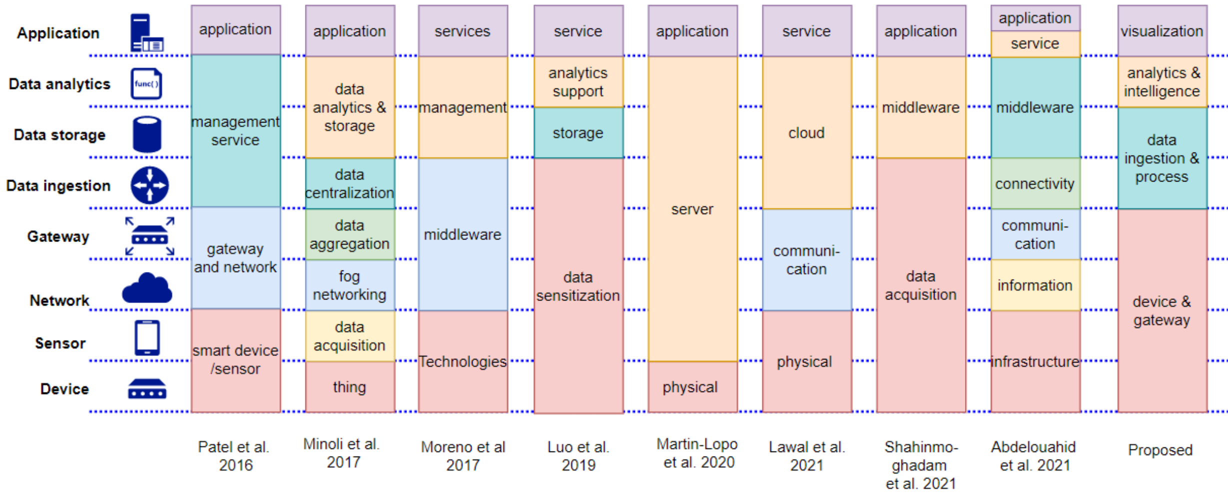

Figure 2: IoT architecture comparison

As one of IoT applications in the building energy industry, IoT-based building energy AFDD refers to reading, connecting, recognizing, addressing, and controlling building energy devices through the internet service for the purpose of detecting, isolating, identifying, and diagnosing the potential faults. According to the characteristics of building energy system IoT-based AFDD, which focuses on the development, implementation, and deployment of advanced algorithms to detect, isolate, verify and diagnose the occurring or potential faults, the proposed IoT architecture (Figure 2) will separate the analytics from other layers as an individual layer called the analytics and intelligence layer, then combine the device sensor, communication and gateway as one layer, called the device and gateway layer. Data ingestion and storage will be integrated into one layer. Application will focus on AFDD results visualization. Figure 3 shows this four-layer IoT-based AFDD architecture deployment in greater detail.

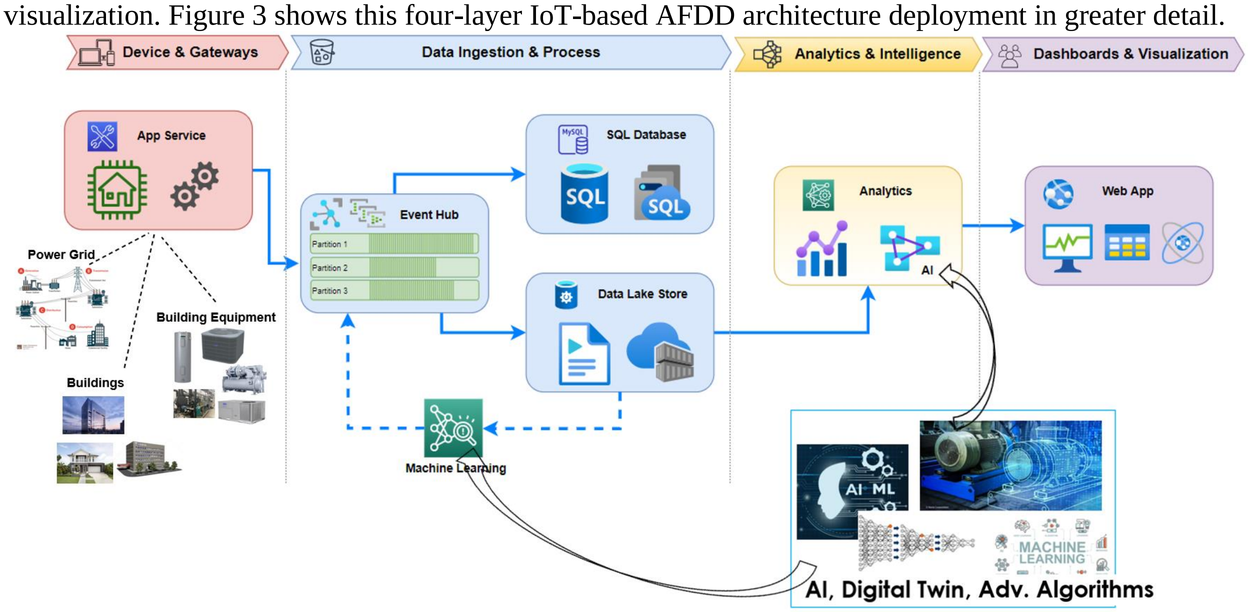

Figure 3: IoT architecture of building energy system AFDD

Layer 1: Device and gateway

Devices are the event generators, which are connected with various sensors to collect telemetry/machine data. Devices include sensors and actuators that gather the information/data for the platform to run algorithms for provided services. Specifically, devices provide two main functions.

- Monitor functions: check and receive the sensor and device performance, including status and performance.
- Control functions: manage device operation for flattening demand and reduce energy cost according to user behavior and external information.

The gateway is the topology that connects the device with the IoT platform. In this topology, the gateway performs the translation between the devices and the server, which can use varying networks or protocols. The gateway device contains the communication hardware module, which includes GSM/WiFi module enabling data transmission over the network. This approach increases the coverage and autonomy of battery-powered devices, and the gateway takes care of IP-based communications. The server benefits in terms of complexity and scalability. If all devices are connected through gateways, the number of simultaneous sockets is drastically reduced, and, in principle, it needs to be able to parse only one protocol. Supporting new devices with different protocols affects the gateway side only.

Layer 2: Data Ingestion, Process, and Storage

Data ingestion is the process of obtaining and importing data for immediate use or storage in a database, filtering unwanted information, and communicating with the cloud. This aspect of IoT is made up of the cloud and wireless communication layer that collects the data from the sensor and analyzes and stores the data. Data ingestion may be continuous or asynchronous depending upon the characteristics of the source and the destination. With the increase in the number of IoT devices, both volume and variance must be accommodated, and often in real time.

Layer 3: Analytics and Intelligence

Analytics and intelligence is designed as a module to implement and verify the fault and degradation self-diagnostics algorithms to address the following challenges.

- Devising methods for domain decomposition and identifying the dependence between operation of physical systems in the building with data generated by these systems. Although correlations can be identified by observations of the data, inference of faults requires a combination of physics-based models and data-driven machine learning (ML) algorithms to robustly identify deviation from expected behavior.
- Addressing spatially and temporally sparse data sets along with information-theoretic approaches to derive the confidence estimates of the fault inference.
- Expanding the use of AI-based approaches in operational building energy management, which requires computational efficiency, creating faults definitions, establishing data quality requirements, selecting modeling and training methods, and developing methods for continuous model calibration.

Artificial intelligence can integrate the data analytics with domain-specific knowledge to create a method or process to develop, verify, and implement fault and degradation diagnostics algorithms for enhancing building performance by optimizing service scheduling, detecting anomalies, and predicting system health status. Several key steps are as follows.

- *Requirement definition*: The requirement of the AFDD algorithm functionality and performance will be established based on domain expertise. Typical algorithm requirements include reliability, robustness, scalability, accuracy, and misdetection rates.
- *Acquiring training data*: Using algorithms defined in the preprocessing module of the proposed data analytics library, the field data quality will be checked to eliminate data of poor quality caused by, for example, malfunctioning sensors and misalignment of data points. To address the challenge of sparse data available in the field, lab experiments will be conducted using the Oak Ridge National Laboratory (ORNL) Flexible Research Platform (FRP) or Yarnell residential test station to generate lab test data, which will combine with sparse field data to composite the training data set.

- *Algorithm development*: In the feature selection process, the methods predefined in the feature engineering module in the proposed data analytics library will be used to down-select a set of variables to capture either key performance or physics of possible faults. A modeling strategy (physics-based or data-driven) will be identified with the support of methods defined in the design module of the proposed data analytics library. This will be carried out by evaluating existing modeling capabilities and developing new modeling capabilities to determine the most suitable models that can predict performance to a degree of accuracy specified by requirements based on identified feature variables. The selected models will be trained by the training data set with corresponding AI algorithms defined in the data analytics library to meet the requirements. Considering the training models and preset performance threshold, the fault detection and diagnostics algorithm will be developed to detect performance degradation and diagnose the root causes.
- *Algorithm verification*: The accuracy of developed AI-based fault and degradation diagnostics algorithms will be verified first through test data from controlled experiments or field conditions. The large-scale algorithm behavior of scalability and robustness will be evaluated with historical field data under wide operation conditions. A continuous-learning mechanism will be studied to improve the algorithm at a large scale and for long-term performance.

Layer 4: Dashboards and Visualization

Data visualization technologies can be powerful as they are easy to use and allow users to quickly and easily understand, articulate, and share insights—as well as create business value by providing underlying trends and the perceived presentation of data after being processed and analyzed for decision-making.

3. DEPLOYMENT IOT SOULTION

In general, there are three approaches to realizing the four-layer AFDD deployment IoT architecture proposed in the previous section:

- Develop the AFDD deployment IoT solution from scratch
- Leverage a common cloud-based IoT service
- Leverage a commercially available energy analytics IoT platform

Developing the AFDD deployment IoT solution from scratch requires developers to construct the IoT infrastructure and deal with many challenging but fundamental issues, such as cybersecurity, protocol translation, data traffic, and real-time data processing; this is impractical and inefficient for most of IoT application solution developers. Thus, it is more effective to leverage an existing IoT service or platform (e.g., a common cloud-based IoT service, commercially available energy analytics platform) and develop the customized deployment IoT solution platform based on it.

This study utilizes the Microsoft Azure IoT service to design an AFDD deployment IoT solution for building energy systems. As shown in Figure 4, the AFDD IoT solution is deployed via the Microsoft Azure service platform to include several key components: IoT Hub, stream analytics, data lake, SQL database, Azure machine learning studio, Power BI, and the app service web site. Among them, IoT Hub, stream analytics, data lake, SQL database, and Azure ML studio belong to the data ingestion and process layer. The analytics and intelligence layer contains the virtual machine component. The Power BI and App service web site realize the visualization functions.

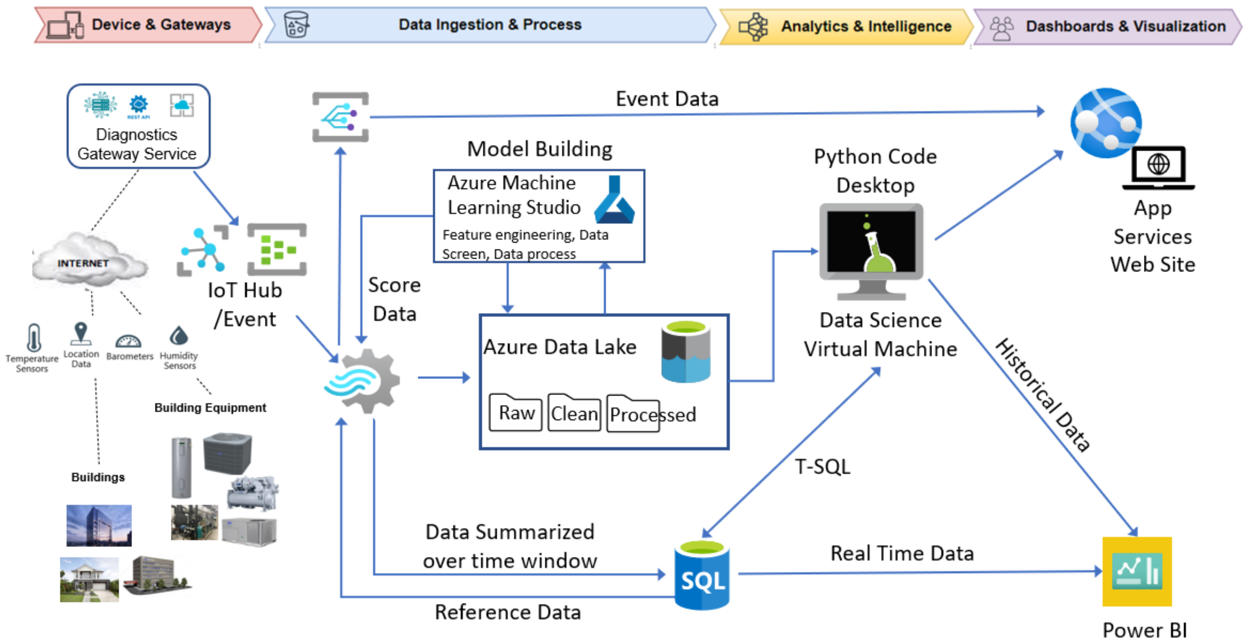

Figure 4: AFDD Deployment IoT Architecture Design in the Microsoft Azure Service Platform

3.1 IoT hub

Azure IoT Hub is a highly secure and reliable communication service between IoT devices and other Azure infrastructure/services. In general, IoT Hub supports device-to-cloud telemetry, file uploading from device, and request–reply methods to control the devices. The data or message received by IoT Hub will generally be saved in a storage account for further processing. In the meantime, IoT Hub can monitor the device status, such as device creation, connection, and failure. Some of key features of IoT Hub include:

- Handling simultaneous connections with devices or sensors through various communication protocols
- Handling incoming data traffic
- Monitoring the device status and activities
- Securing the communication between device and cloud

To set up IoT Hub in Azure, critical steps include creating and initiating IoT Hub, authenticating the device, creating a custom endpoint and storage account, and writing and running the IoT Hub consumer application code.

3.2 Stream analytics

Live data processing deals with real-time incoming data to identify sudden changes, anomalies, patterns through data ingestion, aggregation, and analytics. The main challenges faced by this real-time data ingestion and process include the capability to handle high-volume data ingestion, sufficient processing power to prevent interruptions, sufficient storage, and the ability to act quickly on the output.

To make it easy for IoT solution developers to address these challenges, Azure stream analytics is designed to provide a fully managed, real-time analytics engine for processing fast-moving streams of data. The stream analytics receive the stream data from IoT/event hubs or storage accounts and process the data using tools provided by the Azure ML module. Then, the processed data can be sent to storage accounts or other services, such as bobs storage, the data lake, SQL database, event hub, and Power BI for storage, further processing, or visualization.

To process the real-time data, selection of time windows is crucial. Generally, there are four types of time windows: tumbling, hopping, sliding, session windows. A tumbling window uses fixed window size with no overlap between consecutive windows. A hopping window uses fixed window size, but with overlapping between consecutive windows. A sliding window has a fixed window size as well, but new windows are obtained only if new events are happening. For session windows, the window size is not fixed, and consequent windows may not overlap. Also, a session window is created only when there are new events present.

3.3 DATA LAKE

Data lake is a centralized system or repository to allow users to store structured and unstructured data in any scale. The advantage of data lakes over other data storage methods are:

- Versatility: data lakes support both structured and unstructured data. Data from diverse sources are stored in raw format. Processed data can be stored in a structured format.
- Unlimited scalability: data lakes allow users to scale horizontally to fit different needs at a reasonable cost.
- Excellent integration with IoT: data lakes can receive the data from IoT Hub easily to allow users to perform real-time analysis.
- Integration with ML: unlike traditional data warehouse technology that mostly supports only SQL to conduct simple analysis, a data lake supports multiple languages and ML-based, large volumes of data.
- Advanced analytics: unlike a data warehouse, data lakes allow users to apply complex queries and deep learning algorithms to recognize objects or patterns of interest. This helps in real-time decision analytics.

As a general IoT solution platform, it is expected to support different data formats, such as JSON, CSV, XML, and TXT from different energy systems (data acquisition systems) and additional add-on data collectors. Thus, a data lake is the best candidate to store the raw data from building energy systems and processed data from stream analytics. In addition, because it is seamlessly connected with ML and other advanced analytics tools, it meets the need to perform real-time analysis and decision-making, as well as immediately send fault alarms and possible root causes to end users.

3.4 SQL database

In this IoT solution platform, an SQL database is used to store summarized data over time for dashboard and visualization. Although the data lake can also be used to store the same type of data, it is cost effective to use a SQL database to store processed summarized data. The other benefit of using an SQL database to store processed data is its flexibility and suitability for any user. Furthermore, it makes visualization easier for end users to connect databases via Power BI or web app

3.5 Azure ML studio

Azure ML Studio is a solution with associated tools for building ML models and conducting data science experiments, including design, development, training, and evaluation of models. In this case, the ML studio is used for supporting data ingestion and data processing to perform feature engineering, data screening, and preliminary data analytics. Several key steps of using ML studio include data preparation, feature engineering, model generation, model training, and model deployment. The process starts with importing the data—received from IoT Hub through stream analytics and stored in data lake—into ML studio through datastores and datasets and applying several data preparation processes such as exploring, visualizing, and joining. Datastores store the connection information between the storage account and ML studio and provide data connect service. Datasets reference the datastore for use in data analytics. Then, feature engineering is conducted to clean, normalize, transform, group, filter, or rebalance these raw data to identify the predictive features for model development in the next step. Using the supporting modules in ML studio, appropriate supervised or unsupervised ML models—such as regression models, neural networks, decision trees, and support for vector machine models—can be developed and trained. The trained model is applied to the data to perform data analytics, and the results will be saved to SQL database and can be visualized via the Power BI module

3.6 VIRTUAL MACHINE

The virtual machine (VM) is the core module of the analytics and intelligence layer, hosting many widely used data analytics tools for users to jumpstart building data analytics and intelligence. The preinstalled and preconfigured tools in the VM can be categorized into five types:

- Programing languages/packages/tools (e.g., Python, R, Julia, node.js, Jupyter, Anaconda)
- Data storage tools (e.g., SQL database/Server, Azure storage explorer, Blob FUSE driver)
- Artificial intelligence tools/solutions (e.g., NVIDIA driver, TensorFlow, Horovod)
- IDE (e.g., visual studio, notepad++, RStudio desktop, Git, OpenJDK, Azure SDK)
- Visualization tools (e.g., Power BI Desktop, Microsoft 360, Microsoft Teams)

In this case, a dedicated VM will be used as a platform to execute various AFDD algorithms, including data-driven or model-based methods and supervised or unsupervised learning algorithms to retrieve and analyze data. Because of the flexibility and portability, it is a secure and cost-effective way to store and execute your algorithm code or web apps. Microsoft Azure also provides several VM options, such as Windows VM, ML VM, SQL VM, etc.

3.7 POWER BI

As one of main components in the visualizations module, Power BI is an effective and secure tool used to retrieve the data from a variety of data sources and report them in a meaningful, interpretable way. To meet the requirements of different end users, Power BI includes several primary modules: Power BI Desktop for general users, Power BI Services for online users, and Power BI apps for mobile users.

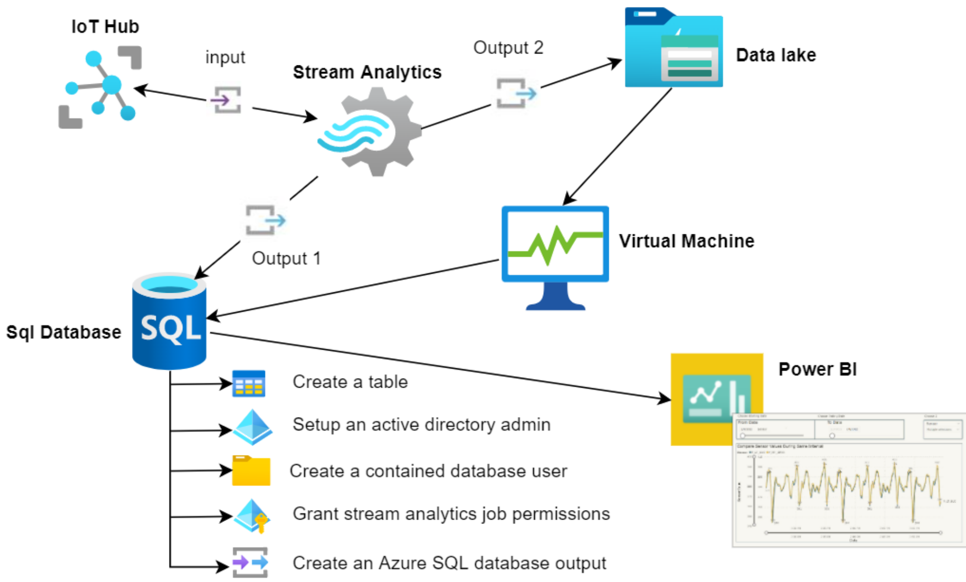

Figure 5: Power BI and data sources

For building an energy systems AFDD application, the data types are generally numerical values, (e.g., temperature, pressure, flow rate, and power) or binary states (e.g., on, off, idle). In this case (Figure 5), Power BI receives data stored in the SQL database that come from two different data sources. One source is the raw data retrieved by the stream analytics job module from devices and sensors through IoT Hub. The other data source is the data analytics results saved in the data lake account after being processed by algorithms residing in the Azure ML module or VM. After receiving these data, Power BI can either directly send a report for visualization or perform further processing with built-in data models, followed by visualization of the analytics results.

4. CASE STUDY

To test the developed AFDD deployment IoT solution, a commercial refrigeration system was selected as the case study object. This laboratory-scale commercial refrigeration system (Sun et al. 2021a), as shown in Figure 6, consists of a transcritical CO_2 compressor rack, refrigerated display cases, an air-cooled gas cooler, and auxiliary equipment. The overall cooling capacity of this commercial refrigeration system was approximately 12.2 tons (43 kW), with a low temperature (LT) level cooling capacity of approximately 2.6 tons (9 kW) at an evaporating temperature of −22°F (−30°C) and a medium temperature (MT) level cooling capacity of approximately 9.6 tons (34 kW) at an evaporating temperature of 20°F (−6.7°C). The LT load consisted of one 4-door display case and an LT false load provided by a plate heat exchanger, two electric heaters, and a glycol loop. The MT load consisted of one open display case and an MT false load provided by a plate heat exchanger, nine electric heaters, and a glycol loop.

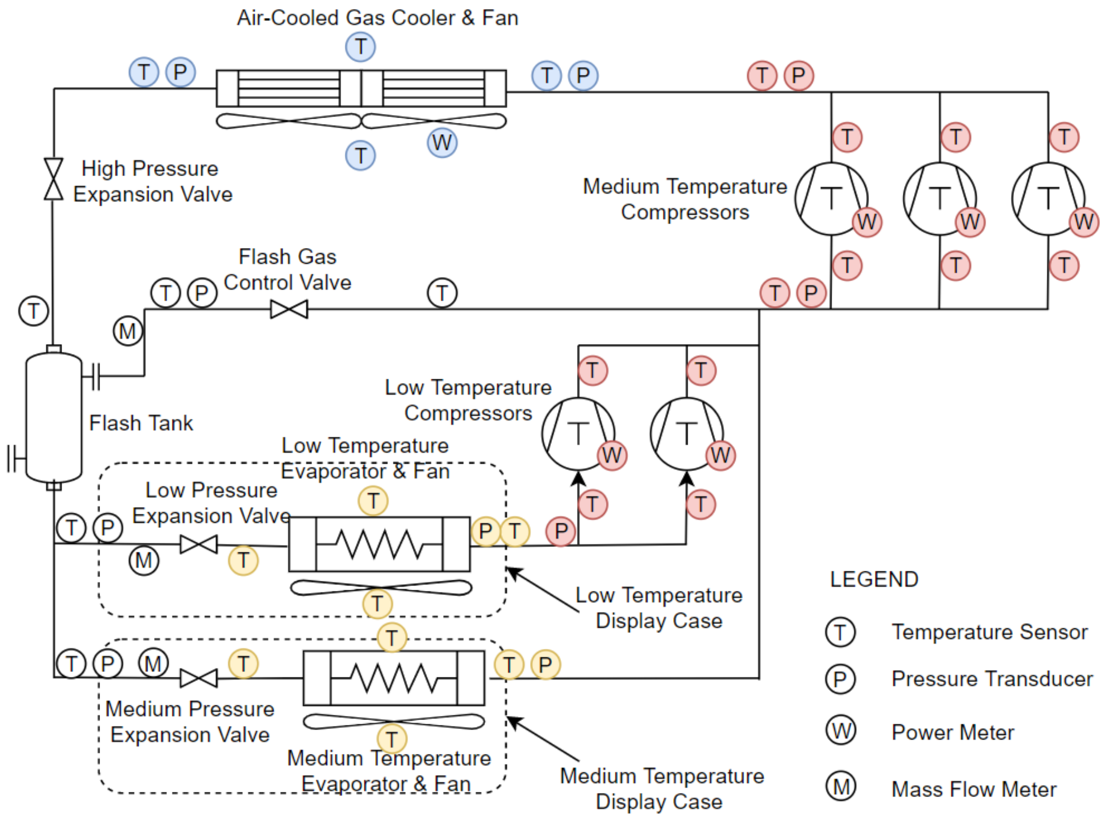

Figure 6: Commercial refrigeration system

The commercial refrigeration system was fully instrumented to measure its performance. The measurements include refrigerant temperature and pressure at the inlet and outlet of major components, such as compressors, display cases, false load heat exchangers, expansion valves, and the gas cooler—as well as refrigerant mass flow rate through the various loads and power consumption of compressors, gas cooler fans, false load heaters, defrost heaters, and display case fans. A detailed list of the measurement points and specifications of the instrumentations is given by Sun et al. (2021b).

The measurement data are recorded and saved in a CSV file in a real-time manner. In this case study, instead of setting up a physical device to submit the data to cloud server directly, a virtual device was created to retrieve the data from the CSV data file through IoT Hub. The data transmission was performed via the C# code shown in Figure 7.

```csharp
int batchctr = 0;
double checkrow = 0;
colCount = maxrowCountNum;
for (int i = 0; i < telemetry_values.Count; i++)
{
    if (String.IsNullOrEmpty(telemetry_names[i]))
    {
        s_logger.LogDebug("*  stopped at value # {0} because of null value name **", i.ToString());
        break;
    }
    using Message msg = PnpHelpers.PnpConvention.CreateMessage(telemetry_names[i], telemetry_values[i], telemetry_components[i]);
    await _deviceClient.SendEventAsync(msg, cancellationToken);

    _logger.LogDebug($"Telemetry: Sent - component=\"{telemetry_components[i]}\", {{ \"{telemetry_names[i]}\": {telemetry_values[i]} }} in {units}.");
    batchctr++;
    int max_column_count = maxrowCountNum;
    if (batchctr == max_column_count)
    {
        batchctr = 0;
        checkrow++;
    }
}
```

Figure 7: Part of the C# code to transmit data to IoT Hub

The stream analytics receives the raw data from IoT Hub ("IotHubInput" in Figure 8) and conducts preliminary data processing such as range checking and outlier removing, then transmits to the SQL database ("AzSql" in Figure 9) and the data lake ("IotHubToDataLake" in Figure 8) to save these data in predefined storage accounts.

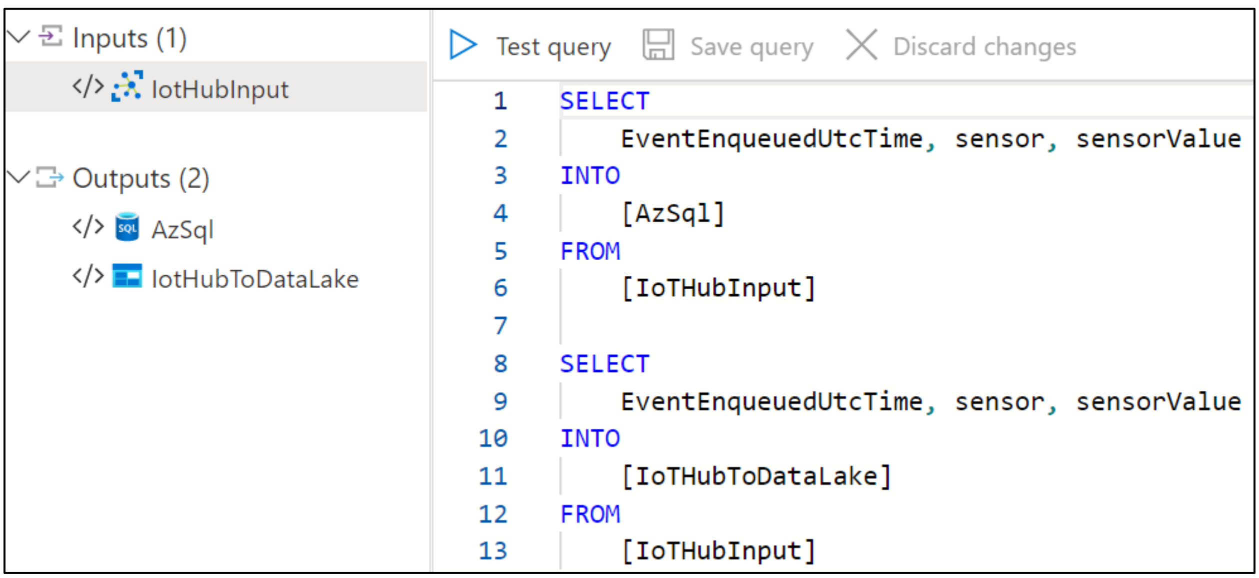

Figure 8: Configuring inputs and output in stream analytics

The stored data can be further processed through two modules: Azure ML Studio and VM. In this case, Azure ML Studio is used for assessing the system operation health status to identify potential faults and recommend predictive maintenance. ML Studio hosts various applications, such as Jupiter, VS code, and RStudio for users to implement analytics algorithm models. The operation healthy status assessment in this case is coded with Python program. The assessment results are saved to the SQL database and displayed through the Power BI module. For example, the compressor operation status is shown in Figure 9.

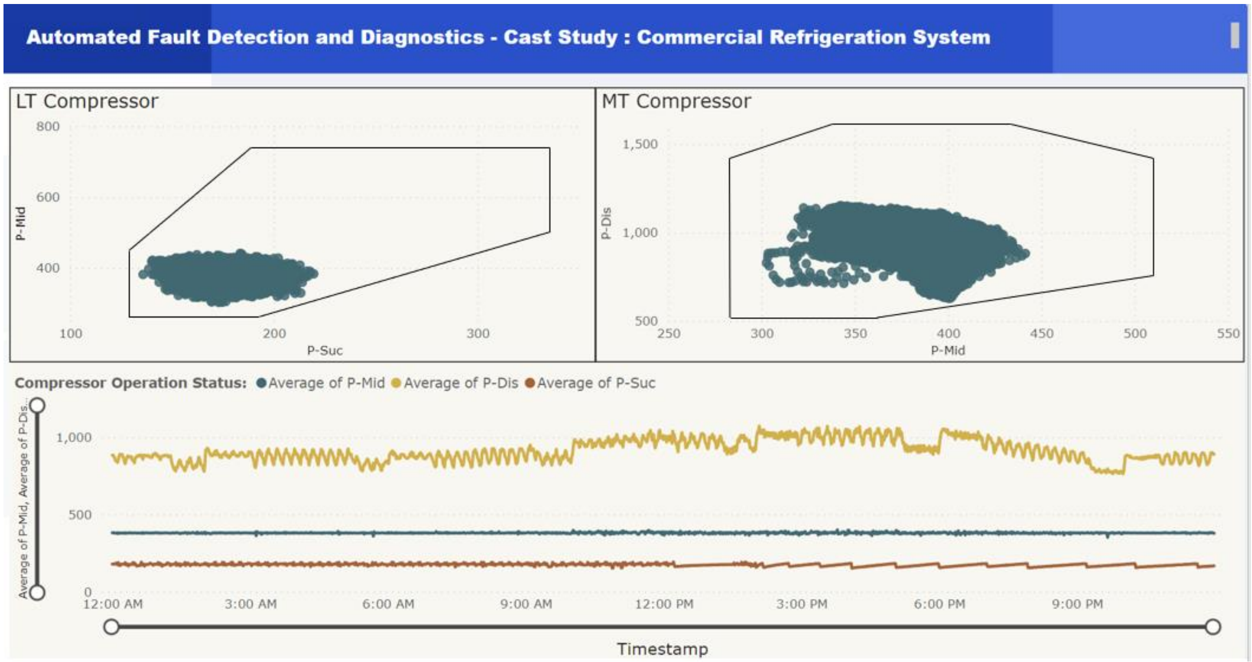

Figure 9: Compressor operation healthy status: compressor suction/discharge pressure in operational envelope, and compressor suction/middle/discharge pressure time series changes

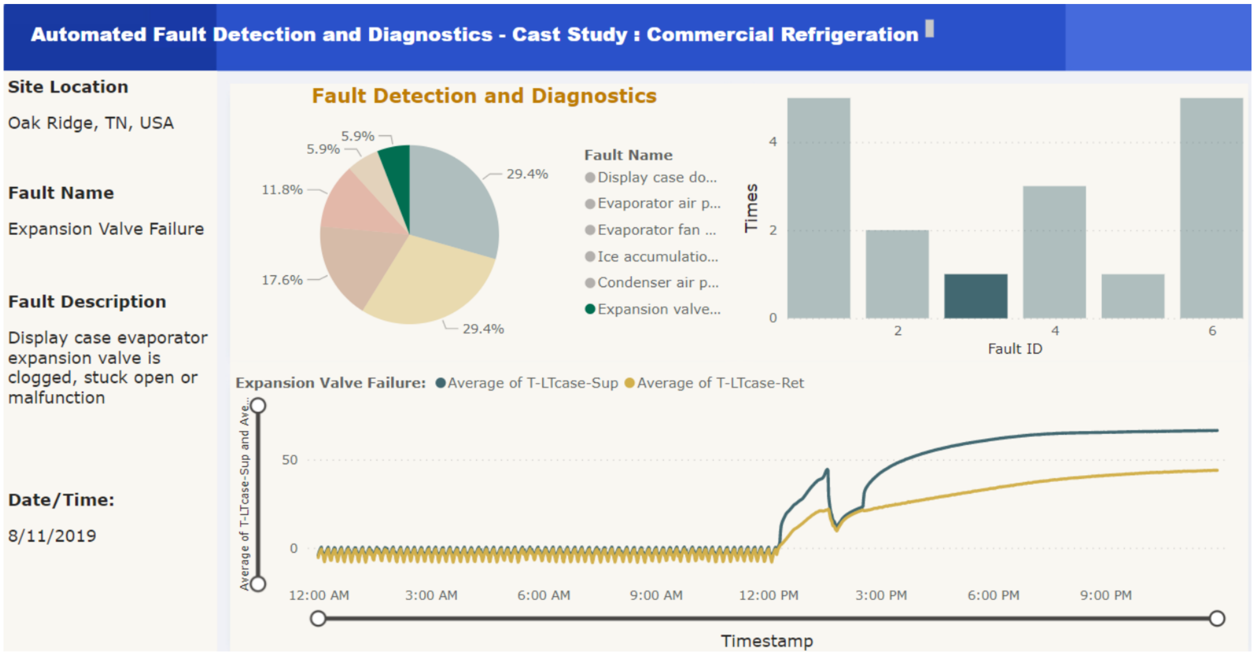

Figure 10: Summary of AFDD results for a commercial refrigeration system

The VM will host and apply the AFDD algorithms to the real-time data for identifying and isolating the operational faults. In this case, the AFDD algorithms developed for several common commercial refrigeration system faults—including display case door open, evaporator fan failure, evaporator air path blockage, condenser air path blockage, ice accumulation, expansion valve failure—have been implemented the VM for real-time receiving of data. The AFDD analytics results are saved to the SQL databased for publishing in a Power BI report; an example is shown in Figure 10.

5. CONCLUSIONS

IoT technology is being increasingly adopted in the building sector, including in such applications as smart buildings, building energy management, and building energy systems, to achieve building energy savings and carbon emission reduction goals. To accelerate the broader utilization of AFDD technologies in building energy systems, a reliable, scalable, and affordable IoT-based AFDD solution is necessary for deploying advanced algorithms and data analytics methods into real systems. This will enable archiving the projected energy benefits, including energy savings or energy cost savings and enhancement of demand flexibility for balancing power supply. This study reviews existing building energy system IoT platforms and proposes a AFDD-oriented four-layer IoT architecture that leverages a common cloud-based IoT service to implement the proposed IoT framework based on the Microsoft Azure platform. A commercial refrigeration system is used as example case to demonstrate the deployment of the developed AFDD IoT solution. To further enhance this developed AFDD IoT solution, future work will include integrating the IoT platform with the actual sensor network and retrieving the sensor measurements directly, scaling up the capabilities of the developed IoT framework to handle multiple systems simultaneously, and continuing to develop a cost-effective and high-accuracy AFDD algorithm using model-based and data-driven approaches

6. ACKNOWLEDGMENTS

Funding for this research was provided by the US Department of Energy, Office of Energy Efficiency and Renewable Energy. The authors would like to thank Antonio Bouza, Brian Walker, and Samuel Petty Program Managers of Building Technologies Office, for their support of this work.

7. REFERENCES

1. Abdelouahid , R. A., Debauche O., Marzak, A., Internet of Things: a new Interoperable IoT Platform. Application to a Smart Building, Procedia Computer Science, Volume 191, 2021, Pages 511-517,
2. Gubbi, Jayavardhana, Rajkumar Buyya, Slaven Marusic, and Marimuthu Palaniswami. 2013. “Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions.” Future Generation Computer Systems 29(7): 1645–60.
3. Katipamula, Srinivas, and Michael R. Brambley. 2005. “Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems - A Review, Part I.” HVAC&R Research 11(1): 3–25.
4. Keyur K Patel, Sunil M Patel, PG Scholar, 2016, Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges, International Journal of Engineering Science and Computing, Vol 6 Issue No.5
5. Khajenasiri, I., Estebsari, A., Verhelst, M., Gielen, G., A Review on Internet of Things Solutions for Intelligent Energy Control in Buildings for Smart City Applications, Energy Procedia, Volume 111, 2017, Pages 770-779,
6. Li, Yanfei, and Zheng O’Neill. 2018. “A Critical Review of Fault Modeling of HVAC Systems in Buildings.” In Building Simulation, Springer, 953–75.
7. Li, Yanfei, and Zheng O’Neill. 2019a. “An Innovative Fault Impact Analysis Framework for Enhancing Building Operations.” Energy and Buildings 199: 311–31.
8. Li, Yanfei, and Zheng O’Neill. 2019b. “Simulation Based Fault Impact Analysis for the Secondary School in the US.” ASHRAE Transactions 125(2).

9. Mirnaghi, Maryam Sadat, and Fariborz Haghighat. 2020. "Fault Detection and Diagnosis of Large-Scale HVAC Systems in Buildings Using Data-Driven Methods: A Comprehensive Review." Energy and Buildings 229: 110492.
10. Mordor Intelligence, Internet of Things in energy market – growth, trends, Covid-19 impact, and forecasts (2020-2027), 2020, Industry report
11. Rafsanjani , H. N., Ghahramani, A., 2020, Towards utilizing internet of things (IoT) devices for understanding individual occupants' energy usage of personal and shared appliances in office buildings, Journal of Building Engineering, Volume 27, 100948.
12. Shi, Zixiao, and William O'Brien. 2019. "Development and Implementation of Automated Fault Detection and Diagnostics for Building Systems: A Review." Automation in Construction 104: 215–29.
13. Sun, J., Kuruganti, T., Munk, J., Dong, J., Cui, B., 2021b, Low global warming potential (GWP) refrigerant supermarket refrigeration system modeling and its application, International Journal of Refrigeration, Volume 126, 2021, Pages 195-209
14. Sun, J., et al. 2021. "Fault Detection of Low Global Warming Potential Refrigerant Supermarket Refrigeration System: Experimental Investigation." Case Studies in Thermal Engineering 26: 101–200.
15. Sun, J., Im, P., Bae, Y. *et al.* 2021a, Dataset of low global warming potential refrigerant refrigeration system for fault detection and diagnostics. *Sci Data* 8, 144 (2021).
16. "U.S. Energy Information Administration (EIA) - Ap." 2020. https://www.eia.gov/environment/emissions/carbon/ (January 14, 2022).
17. World Economic Forum: Electricity: Uncovering value through digital transformation, 2016, http://reports.weforum.org/digital-transformation/electricity-an-industry-ready-for-digitization/
18. Wu, X., Yang, C.Y., Han, W.C., Pan, Z.R., Integrated design of solar photovoltaic power generation technology and building construction based on the Internet of Things, Alexandria Engineering Journal, Volume 61, Issue 4, 2022, Pages 2775-2786,
19. Yu, Bing, Dolf HC Van Paassen, and Siamak Riahy. 2002. "General Modeling for Model-Based FDD on Building HVAC System." Simulation Practice and Theory 9(6–8): 387–97.
20. Yu, L., Nazir, B., Wang,Y., Intelligent power monitoring of building equipment based on Internet of Things technology, Computer Communications, Volume 157, 2020, Pages 76-84
21. Yu, Yuebin, Denchai Woradechjumroen, and Daihong Yu. 2014. "A Review of Fault Detection and Diagnosis Methodologies on Air-Handling Units." Energy and Buildings 82: 550–62.