Explainable AI based Fault Detection and Diagnosis System for Air Handling Units

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Abstract: Fault detection and diagnosis (FDD) methods are designed to determine whether the equipment in buildings is functioning under normal or faulty conditions and aim to identify the type or nature of a fault. Recent years have witnessed an increased interest in the application of machine learning algorithms to FDD problems. Nevertheless, a possible problem is that users may find it difficult to understand the prediction process made by a black-box system that lacks interpretability. This work presents a method that explains the outputs of an XGBoost-based classifier using an eXplainable Artificial Intelligence technique. The proposed approach is validated using real data collected from a commercial facility.

1 INTRODUCTION

The building sector alone is responsible for approximately 36% of the global energy consumption (Abergel et al., 2018). About half of the energy consumed in commercial buildings comes from heating, ventilation, and air conditioning (HVAC) systems, which are used to maintain a certain level of indoor comfort. Meanwhile, common HVAC system faults that are caused by improper maintenance result in 15% of waste in total annual energy consumption (Xiao and Wang, 2009). Faults associated with HVAC systems, such as sensor faults, control errors, component malfunctions, and commissioning flaws, can lead to indoor thermal discomfort, reduced component lifespan, and increased energy consumption.

Recently, a growing number of research studies have focused on the development of automated fault detection and diagnosis (FDD) tools for building HVAC systems (Mirnaghi and Haghighat, 2020). The fault detection system is responsible for determining whether the equipment is functioning under normal or faulty conditions, whereas fault diagnosis aims to identify the type or nature of a fault. Another important component is the fault impact evaluation, which involves estimating the severity and consequences of faults to help human operators to decide on certain actions. The three common techniques for HVAC system FDD problems can be generalized into knowledge (or rule)-based, model-based, and data-driven methods (Mirnaghi and Haghighat, 2020). Modern building management systems generate vast amounts of data, enabling the implementation of more complex data-driven algorithms (Mirnaghi and Haghighat, 2020). Such methods have already become prevalent in the industry due to the ability to leverage lot of raw data (Srinivasan et al., 2021).

Several data-driven methods have been applied to HVAC system fault detection and diagnosis. Works (Wang and Xiao, 2004) and (Du and Jin, 2008) have adopted the principle component analysis method to detect faults in air handling units. Although the

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method is reported to have promising results, it does not retain the original feature relationships, limiting its application to fault diagnosis tasks where important features need to be identified in order to locate the root causes of the faults. Some studies regard FDD tasks as classification problems. Some focus on machine learning methods such as support vector machines (SVM) (Han et al., 2011) and neural networks (NNs) (Du et al., 2014) for solving FDD tasks. Deep learning methods such as convolutional neural networks (CNN) have also received an increased interest for FDD problems due to their high performance, computational efficiency, and ability to perform feature extraction and classification simultaneously (Liao et al., 2021; Li et al., 2021a). In general classification tasks, SVM and other clustering algorithms are also explored (Upadhyay and Nagpal, 2020; Borlea et al., 2021).

While the data-driven FDD models surveyed above clearly have ample potential when applied to complex HVAC systems, they may lack the ability to explain and convince users to take informed actions. This is due to the "black-box" nature of such models, which may hinder users from trusting the system. This work suggests a method that explains the decisions of an eXtreme Gradient Boosting (XGBoost)-based classifier based on the so-called eXplainable AI (XAI) concept, which significantly improves the feedback to the end-user, thus improving the practical usefulness of this method. To this end, first a diagnosis model that is based on XGBoost is proposed to classify the normal operations of an air handling unit from pre-selected four types of faults. A classifier model, trained with fault-free data, is then introduced to filter the faulty data before triggering the diagnosis model. The resulting F1-scores are compared to two baseline models. Then, the classification criteria of the diagnosis model are explained using the SHAP technique, which indicates the importance of each input feature. The obtained results are validated by a certified HVAC engineer, who confirms the correctness of the most important features. The idea is demonstrated using real data from a commercial building.

2 OVERVIEW OF XAI TECHNIQUES IN BUILDING APPLICATIONS

In this section, the application of explainable AI technique (Gunning, 2017; Machlev et al., 2021) to general problems in buildings is first discussed, see (Machlev et al., 2022, Section 4.3) for a more detailed discussion. The focus is then shifted to the specific issues related to fault detection and diagnosis in typical technical units. Based on the literature review, we indicate that the use of XAI for building applications is still new, and only a few studies have been reported so far. Table 1 provides a summary of the XAI concept used in building applications.

The general applications mostly encompass common problems of evaluating building performance and predicting energy demand. In (Chakraborty et al., 2021) XAI techniques were applied to the XGBoost model for long-term forecasting of the cooling energy consumption of buildings located in different climatic areas. In (Gao and Ruan, 2021), the authors focused on developing attention mechanisms to improve the interpretability of the developed models. The benchmark of buildings using explainable AI was addressed in several recent papers (Arjunan et al., 2020; Miller, 2019; Tsoka et al., 2021). In (Houzé et al., 2021), the use of explainability techniques was proposed in the context of smart home applications.

Several recent papers on fault detection and diagnosis for HVAC systems have focused on explainability for gaining user trust. In (Srinivasan et al., 2021), the LIME (Local Interpretable Model-agnostic Explanations) framework was adopted to explain cases of incipient faults, sensor faults, and false positive results of the diagnosis model for the chiller system, which is based on the XGBoost model. The general XAI-FDD workflow was validated using several real test cases. The proposed approach allowed to reduce fault-detection time, analyze the sources and origins of the problems, and improve maintenance planning. The authors of (Madhikermi et al., 2019) used the LIME method to explain the fault classification results of the support vector machine and neural network models developed for the diagnosis of heat recycler systems. In (Li et al., 2021b), a new Absolute Gradient-weighted Class Activation Mapping (Grad-Absolute-CAM) method was proposed to visualize the fault diagnosis criteria and provide the fault-discriminative information for explainability of the 1D-CNN model, applied to the detection of faults in chiller systems. The developed method was validated using an experimental dataset of an HVAC system, showing diagnosis accuracy of 98.5% for seven chiller faults.

3 TECHNICAL BACKGROUND AND METHODOLOGY

In this section, we provide a brief background on the methods and notions used in the analysis and

Table 1: Recent works on explainable AI methods for building applications.

	Ref.	Application	AI Model	XAI Technique	Year
FDD	This work	Detecting AHU faults	RF, XGBoost	SHAP	2022
	(Srinivasan et al., 2021)	Detecting incipient, sensor, and chiller faults	XGBoost	LIME	2021
	(Li et al., 2021b)	Detecting chiller faults	1D-CNN	Grad-Absolute-CAM	2021
	(Madhikermi et al., 2019)	Detecting heat recycler faults	SVM and NN	LIME	2019
General Applications	(Wenninger et al., 2022)	Predicting long-term building energy performance	QLattice	Permutation feature importance	2022
	(Chakraborty et al., 2021)	Analysis and prediction of climate change impacts on building cooling energy consumption	XGBoost	SHAP	2021
	(Akhlaghi et al., 2021)	Performance forecast of irregular dew point cooler	Deep Neural Network	SHAP	2021
	(Tsoka et al., 2021)	Classification of building energy performance certificate rating levels	ANN	LIME	2021
	(Arjunan et al., 2020)	Benchmarking building energy performance levels	XGBoost	SHAP	2020
	(Fan et al., 2019)	Predicting coefficient of performance of the cooling system	SVM, MLP, XGBoost, RF	LIME	2019

sketch the general methodology. We start with a brief overview of the methods that are considered for the proposed approach.

eXtreme Gradient Boosting: The XGBoost (Chen and Guestrin, 2016) model is an efficient boosting model that is used to solve both regression and classification problems. It integrates several basic classifiers together, which are usually decision tree models, to form a more robust model.

Interpretation of Machine Learning Models: Complex machine learning models such as support vector machines, neural networks, random forest, etc. are black-box in nature. It is therefore crucial to understand the rationale behind the decision making process taking place in the machine in order to invite more human involvement into the loop and obtain more trust along the way. Many methods have been developed for explaining machine learning models, such as LIME (Local interpretable model-agnostic explanations), SHAP, CIU (Contextual Importance and Utility), ELI5, and Grad-CAM (Gradient-weighted class activation mapping), in which the input can be an image, text, etc. (Barredo Arrieta et al., 2020).

SHapley Additive exPlanation: SHAP is a game theory based approach to explain the individual predictions produced by machine learning models (Lundberg and Lee, 2017). It is used to show the contributions of the input features using the computed Shapley values, where each feature works together as an ensemble. The SHAP value is calculated for each feature in the input samples that needs to be explained. Based on the aggregated Shapley values, it can also provide global feature importance and feature interactions. In fault detection tasks, having an estimation of the input feature contribution is useful when visualizing the model decision.

Figure 1 depicts the schematic flow of a general process dedicated to the generation of explanations for AI-based models. Here, an additional "Explainer" layer is used at the later stage to generate explanations by highlighting the main features that are significant for the model output and to present them in a form that is comprehensible by the end user.

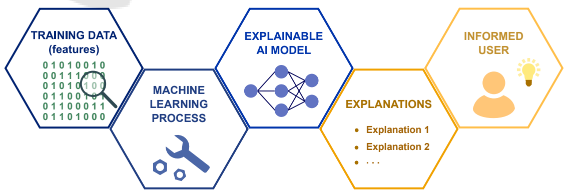


Figure 1: The schematic of a conceptual XAI framework with an additional explanation module, aiming to bridge the gap between decisions made by a model and a user.

This research study, in which the above-described methods are leveraged, is organized as follows: A fault detection and diagnosis model based on XGBoost is implemented and compared with two baseline models. A case study was conducted using real data collected from a commercial building (a shopping mall) located in Estonia. Four different types of faults are selected to provide explanations of the model. The SHAP method is integrated as the explanation algorithm. Explanations are then evaluated by certified HVAC engineers.

Figure 2 outlines the proposed methodology, which can be summarized as follows:

- Data is collected for faulty and fault-free operations and is labeled according to the fault types. Data is preprocessed by removing records with null or non-existing values.
- Two XGBoostClassifier models are implemented for the FDD problem:
  - A binary classification model is used to classify the sample as normal or faulty. The inputs to the model are all the features from the dataset.
  - The second model is a multiclass multi-label classification model, which is used to classify which fault class the sample belongs to. The input uses the same dataset as the fault detection model.
- SHAP method is used to generate explanations for the fault diagnosis model.

Performance metric: We use the F-measure to assess the performance of the classification model. The F-measure (or balanced F_1 score) is the harmonic mean of the *precision* and *recall* measures, defined as (Hripcsak and Rothschild, 2005):

$$F_1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}, \quad (1)$$

where

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad (2)$$

TP is the number of true positives, FP is the number of false positives, and FN is the number of false negatives.

4 NUMERIC RESULTS

4.1 Data Collection and Preparation

In this paper, we consider the data obtained from a shopping mall that was renovated over a decade ago. The facility has three floors that are mostly heated by the group of air handling units. The building is heated with district heating while the cooling is provided by two chillers.

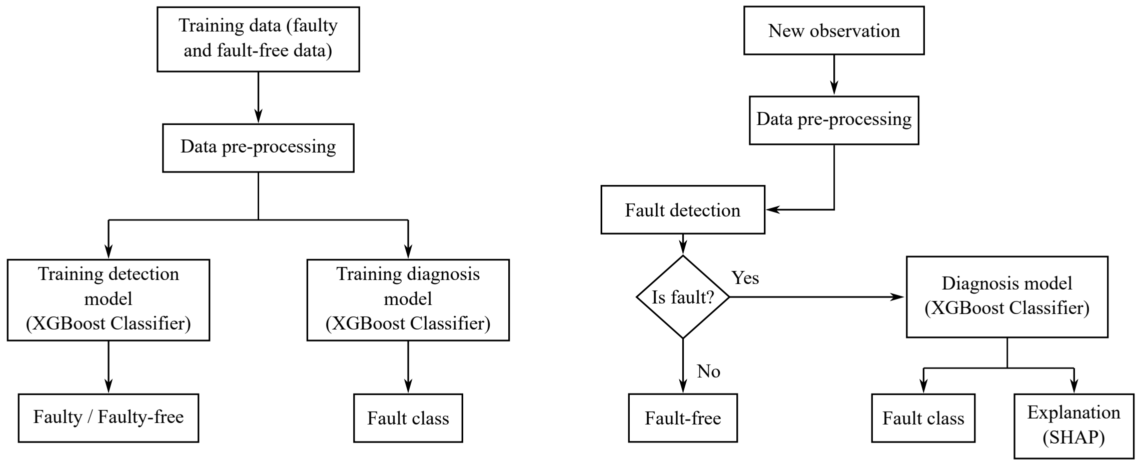
Almost every large commercial building has a building management system (BMS) that contains thousands of data points that are presented through a user interface in real-time. A BMS is usually devoted to information flow and communication with the HVAC equipment. Besides monitoring, it also provides custom reactive alarms to notify the operators at different levels. Data acquisition is accomplished through dedicated BMS in the facilities. The method for data reading and writing is the API connection supported by the BMS. Finally, the data transmission is secured through encrypted VPN tunnels. Data through BMS is read every 15 minutes and was collected for the whole year in the period from February 01, 2020 to March 31, 2021. It includes measurements obtained from an air handling unit during different seasons. Before the analysis, the data is filtered to exclude detected extreme outliers and samples during non-operating periods. It was further processed and the faults were labeled by a dedicated HVAC engineer. The dataset includes 13 input features as shown in Table 2, containing samples of air handling units under normal operating conditions and four types of faults listed in Table 3. The faults are taken from real scenarios and operating conditions.

4.2 Model Development

In this study, the model aims to predict whether the AHU is operating at normal or faulty condition at specific timestamps and which fault type(s) are present. For training the fault detection model, binary labels (0: not fault, 1: fault) are assigned to each sample. For the fault diagnosis, the problem is formulated as a multi-label classification problem, where the labels are binary vectors (value 0 or 1 for each of the four fault classes plus the normal class), and more than one fault type can be present simultaneously. The input data is split into 66% and 34% for the training and test sets, respectively. Random stratified sampling is applied in the data partitioning process to keep the balance of fault classes for both sets.

Table 3 shows that the samples of normal operation (majority class) exceed those of faulty cases (minority class) with a ratio of about 10 to 1. Having imbalanced classes for classification problems can lead to biased predictions towards the majority class. This problem is tackled with random over-sampling and random under-sampling techniques to transform the class distribution in the training set and eliminate the extreme data imbalance.

The training set is used to train three machine learning models, including LogisticRegression, RandomForest, and XGBoost, each for both fault detection and diagnosis tasks. The hyperparameter is tuned as follows: For the fault detection model, the number of estimators is set to 12 for both RandomForest and XGBoost. For the fault diagnosis model, we set the L1 regularization term on weight to 0.1 to reduce



(a) Offline stage (b) Monitoring stage

Figure 2: Proposed fault detection and diagnosis method.

Table 2: Description of the used features.

Feature	Short Description	Unit
AAT	Fresh air intake temperature	°C
ACCVO	Cooling coil valve opening	%
AHCT	Heating coil temperature	°C
AHCVO	Heating coil valve opening	%
AHRS	Heat recovery rotation speed	%
AHRST	Supply air temperature after heat recovery	°C
ARAT	Return air temperature	°C
ARFS	Return fan speed	%
ASAT	Supply air temperature	°C
ASATCSP	Supply air temperature calculated setpoint	°C
ASFPE	Supply fan static pressure	Pa
ASFPECSP	Supply fan static pressure calculated setpoint	Pa
ASFS	Supply fan speed	%

overfitting problem for XGBoost. For RandomForest, we set the minimum number of samples per leaf to 2.

4.3 F1-score Results

The performance is evaluated using the test set for the trained models—LogisticRegression (LR), RandomForest (RF), and XGBoost (XGB). The F_1-scores are displayed in Table 4. The XGBoost method achieves the highest overall performance for most fault types.

Table 3: List of AHU faults used in the analysis.

Title	Fault Type	Component	Sample Size
FPES_M	Fan pressure sensor malfunction	Sensor	1188
HR_NW	Heat recovery not working	Heat recovery	2511
HCV_L	Heating coil valve leakage	Heating coil	1044
CC_C	Cooling coil closed	Controller	279
Normal	–	–	14246

Table 4: F_1-score of the used models in both fault detection and fault diagnosis tasks.

Model	Fault Class	LR	RF	XGB
Fault Detection	Faulty	0.86	0.95	0.97
Fault Diagnosis	FPES_M	1	0.99	0.99
	HR_NW	0.64	0.86	0.90
	HCV_L	0.81	0.92	0.94
	CC_C	0.74	0.88	0.93
	Normal	0.87	0.95	0.97

4.4 The Explanation of Individual Instances

To assess the reliability of the predictions, four individual instances are evaluated based on the calculated Shapley values. As shown in Tables 5-8, the supporting and opposing features are indicated by the red and blue Shapley values, respectively, and the contribution weights are based on the size of the absolute Shapley values.

4.4.1 Fan Pressure Sensor Malfunction

The fan differential pressure sensor values correlate with the air volume produced by the fans. If the fan is off, the differential pressure value is expected to be near zero. The sensor value is used to calculate air volume and to verify if the fans are working. If the sensor malfunctions, then the air volume control may fail and even the whole ventilation machine may switch to protective alarm mode.

Figure 3 shows the XGBoost predictions (y-axis) with the supply fan static pressure (ASFPE) sensor value being the main contributing feature. The observation period (x-axis) is taken from 18:30 to 22:00 on November 23, 2021, with the faulty state being evaluated at 20:45. Note that such types of sensor faults can also be easily detected with simple statistical tools to determine the acceptable range of sensor measurements (Liao et al., 2021), eliminating the need for sophisticated machine learning models. However, such complexity is not always the case for arbitrary types of faults, as observed below.

Table 5: Quantitative explanations for XGBoost prediction of the ‘FPES_M’ type of fault.

Feature	XGBoost			
	NOT FPES_M		FPES_M	
	Real	SHAP	Real	SHAP
AAT	6.78	0	5.17	0
ACCVO	0.0	0	0.0	0
AHCT	19.66	0	18.71	0
AHCVO	0.0	0	0.0	0
AHRS	43.24	0	18.35	0
AHRST	17.02	-0.08	10.92	0.03
ARAT	22.01	-0.53	21.79	-0.83
ARFS	75.0	-1.4	30.0	8.35
ASAT	19.21	0	18.20	0
ASATCSP	18	0	18.0	0
ASFPE	**46.43**	-0.66	**3.7**	3.97
ASFPESP	30	0	30	0
ASFS	75.0	-0.03	30	0.04

No faulty state is evaluated at the 0th instance
Faulty state is evaluated at the 9th instance

4.4.2 Heat Recovery Not Working

The heat recovery system recovers heat from return air and uses it to heat up the supply air. There are several different heat recovery systems: rotary, flat plate, run-around loop coil, or return air recirculating damper. The fault detection mechanism tries to estimate if the heat-recovery system is working properly.

Figure 6 shows the individual explanations for predictions made by the XGBoost and RandomForest methods, respectively. The observation period is taken from 20:00 on February 21 until 11:00 on February 22, 2021, with the faulty state being evaluated at 09:00. Note that the non-operating night hours were excluded from the dataset. It can be seen that both methods provide a similar trend picture.

Table 6 shows predictions based on XGBoost and RandomForest methods and provides quantitative explanations. It contains both measured values and calculated SHAP values. According to the domain expert, the main contributing features are AAT, AHRS, AHRST, and ARAT, marked in bold. This is further confirmed by the corresponding Shapley values. Observe that the XGBoost method provides results that better correlate with expert knowledge.

Table 6: Quantitative explanations for XGBoost prediction of the ‘HR_NW’ type of fault.

Feature	XGBoost				Random Forest	
	NOT HR_NW		HR_NW		NOT HR_NW	HR_NW
	Real	SHAP	Real	SHAP	SHAP	SHAP
AAT	**3.85**	-3.37	**5.45**	-0.12	-0.11	-0.02
ACCVO	0.0	0.08	0.0	0.10	0.00	-0.009
AHCT	19.31	-0.03	20.63	0.02	0.00	0.02
AHCVO	0.0	-0.20	49.15	1.59	-0.020	0.26
AHRS	**26.46**	-1.39	**100**	0.06	-0.06	0.03
AHRST	**14.96**	-0.16	**5.55**	5.85	0.003	0.29
ARAT	**22.73**	-0.33	**21.53**	5.85	-0.02	-0.03
ARFS	40.00	-0.57	42.0	1.30	-0.04	0.17
ASAT	18.09	0.04	17.57	0.02	-0.009	0.04
ASATCSP	18.0	0.06	18.5	-0.53	0.01	-0.04
ASFPE	13.22	-0.05	13.63	-0.12	-0.006	-0.005
ASFPESP	14.0	-0.39	14.0	-0.19	-0.006	0.00
ASFS	45.22	0.54	45.64	0.70	0.03	0.02

No faulty state is evaluated at the 0th instance
Faulty state is evaluated at the 9th instance

4.4.3 Heating Coil Valve Leakage

The fault indicates that the heating coil valve is not closing completely when there is a command to close it. Regardless of the fact that the valve should be closed, the hot water flows through the coil and heats up the supply air. This results in the extra heating cost and may even lead to the extra cooling costs and undesired supply air temperature. The leak can be detected by checking the temperature sensors in the supply air channel or comparing the work of the heat recovery and cooling coil with other ventilation machines or this machine’s typical actions.

Figure 5 shows the individual explanations for predictions based on XGBoost method. The observation period is taken from 20:30 on February 14 to 10:00 on February 15, 2020, with the fault be-

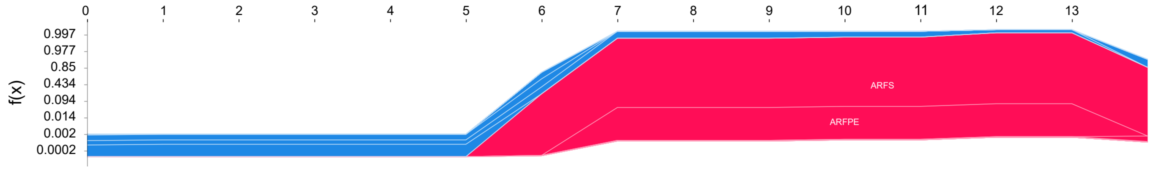
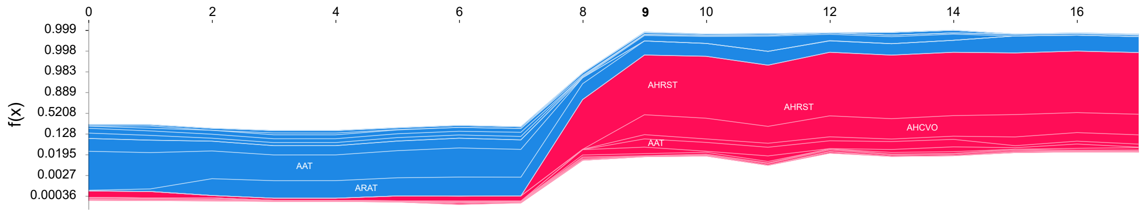
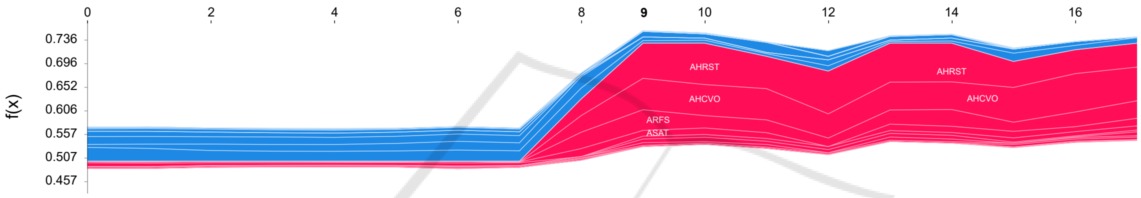


Figure 3: ‘Fan Pressure Sensor Malfunction’ type of the fault: Simulation results using XGBoost based models with SHAP explanation method.



(a) XGBoost



(b) Random Forest

Figure 4: ‘Heat Recovery not Working’ type of the fault: Simulation results using XGBoost (top plot) and Random Forest (bottom plot) based models with SHAP explanation method.

ing evaluated at 09:15. Table 7 describes predictions using only the XGBoost method. According to the domain expert, the top contributing features include AAT, AHCVO, AHRST, and ASAT. The top three corresponding Shapley values confirm these observations.

4.4.4 Cooling Coil Closed

The problem means that the controller for the ventilation unit is not sending a command to use all of the cooling capacity.

Figure 6 shows the individual explanations for predictions based on the XGBoost method for the fault type ‘Cooling Coil Closed’. The time period is taken from 20:00 to 22:45 on July 15, with the fault being evaluated at 20:45. Table 8 presents the individual explanations obtained for predictions generated using the XGBoost model. According to the domain expert, ACCVO, AHRST, and ASATCSP are the most important features that help to explain the fault in this sample. From the corresponding Shaley values, ACCVO has the largest impact on the fault. AHRST and ASATCSP also have positive effects on the fault CC_C although they are not among the top three contributing features. For comparison, in the NOT CC_C sample, ACCVO has 0%, which significantly reduces the total Shapley value for CC_C. Parameters AHRST and ASATCSP also have low effects in this case.

Table 7: Quantitative explanations for XGBoost prediction of the ‘AHCV_L’ type of fault.

Feature	**XGBoost**			
	AHCV_L		NOT AHCV_L	
	Real	SHAP	Real	SHAP
AAT	**0.45**	5.09	**1.27**	3.41
ACCVO	0.0	0.0	0.0	0.0
AHCT	19.49	-0.05	19.98	0.15
AHCVO	**0.0**	1.96	**0.0**	1.28
AHRS	21.01	1.49	51.64	0.73
AHRST	**12.11**	1.61	**14.88**	0.29
ARAT	22.50	-0.01	21.59	0.35
ARFS	40.4	0.17	40.0	-0.08
ASAT	**17.959**	-0.25	**18.84**	0.32
ASATCSP	18.0	-0.02	18.0	-0.12
ASFPE	14.03	0.01	12.68	0.12
ASFPESP	14.0	0.34	14.0	0.28
ASFS	44.84	0.75	43.78	-1.85

No faulty state is evaluated at the 0th instance
Faulty state is evaluated at the 8th instance

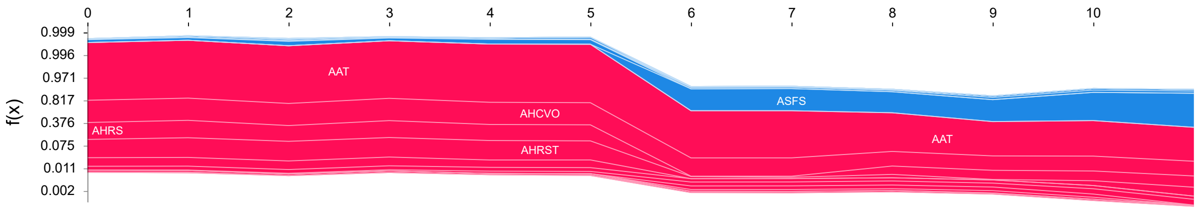


Figure 5: ‘Heating Coil Valve Leakage’ type of fault: Simulation results using XGBoost model with SHAP explanation method.

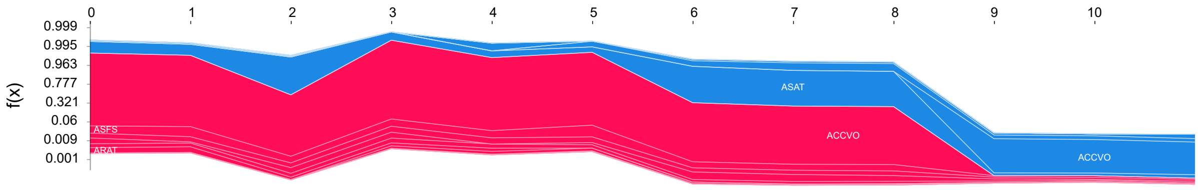


Figure 6: ‘Cooling Coil Closed’ type of fault: Simulation results using the XGBoost model with SHAP explanation method.

Table 8: Quantitative explanations for XGBoost prediction of the ‘CC_C’ type of fault.

Feature	**XGBoost**			
	CC_C		NOT CC_C	
	Real	SHAP	Real	SHAP
AAT	19.42	-0.11	18.39	-0.20
ACCVO	**84.30**	7.73	**0.0**	-3.55
AHCT	20.93	-0.03	20.06	0.04
AHCVO	0.0	0.0	0.0	0.0
AHRS	0.0	0.0	0.0	0.06
AHRST	**19.30**	0.03	**18.21**	0.03
ARAT	25.25	0.57	24.48	-0.39
ARFS	40.00	0.41	40.0	0.13
ASAT	18.61	-1.22	18.72	-0.28
ASATCSP	**18.0**	0.51	**18.0**	0.19
ASFPE	13.22	0.61	12.54	0.08
ASFPESP	13.0	0.0	13.0	0.0
ASFS	43.44	0.76	43.44	0.192

Faulty state is evaluated at the 0th instance
No faulty state is evaluated at the 10th instance

5 CONCLUSIONS

Advanced machine learning techniques have recently demonstrated excellent performance in fault detection and diagnosis problems. Nevertheless, building personnel may find it hard to evaluate and understand the reasoning behind the produced outputs. In this way, we propose a method that uses a XAI technique to explain the decisions of an XGBoost-based classifier to the end user in a simple and trustworthy way. The obtained results are validated by the certified HVAC engineer. This idea is demonstrated using real data collected from a commercial building.

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