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A Bi-Level Data-Driven Framework for Fault-Detection And Diagnosis of HVAC Systems feature explainability

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Abstract— Machine learning methods have lately received considerable interest for fault detection diagnostic (FDD) analysis of heating, ventilation, and air conditioning (HVAC) systems due to their high detection accuracy. Meanwhile, HVAC malfunctions are regarded as rare occurrences, hence normal operating data samples are much more accessible than data samples in faulty and malfunctioning conditions. The dominating frequency of normal operation in HVAC datasets have also led to heavily biased classification algorithms within the literature. Moreover, the focus of previous literature has been on increasing accuracy of the models while this leads to a high number of false positives (misleading alarms) in the system. To enhance the performance of diagnostic procedures and fill the mentioned gaps, this study proposes a novel data-driven framework. A bi-level machine learning framework is developed for diagnosing faults in air handling units and rooftop units based on principal component analysis (PCA), time series anomaly detection, and random forest (RF). It is shown that PCA can reduce the dataset dimension with one principal component accounting for 95% of data variance. Also, the random forest could classify the faults with 89% precision for single zone AHU, 85% precision for RTU, and 79% for multi-zone AHU.

Keywords— HVAC; Machine learning; Fault Detection, Classification.

I. INTRODUCTION

The energy consumption in building sector is responsible for about 20--40% of the total energy consumption across the globe[1]. Heating, ventilation, and air conditioning (HVAC) systems account for over 50% of the total energy consumed [2]. This makes HVAC systems a source of preventable and unexplored energy waste that can be tackled by incorporating intelligent operations. Meanwhile, malfunctioning of HVAC systems can endanger lifespan of equipment, energy usage, and occupant thermal comfort [3]. Therefore, it is crucial to find solutions that lower the energy consumption of HVAC systems while addressing their malfunctioning problem. Fault detection and diagnosis (FDD) systems have the potential to address the issue by reducing equipment downtime, energy costs, maintenance costs, and improving reliability [4] .

FDD can be generally categorized into conventional rule-based [5] and data-driven methods [6]. For conventional FDD systems, the need for empirical guidelines or mechanical specifications to locate errors has been a recurring difficulty [7]. Likewise, model-based solutions do not promise greater diagnostic precision and simpler implementation. In contrast, advancements in processing power, data collection, and algorithm development have permitted the incorporation of machine learning (ML) technologies into current HVAC systems [8]. Due to its reliance on merely analyzing system data, data-driven approaches have attracted a growing amount of interest in the investigation of system processes and development of complex system models [9]. Furthermore, it is well-established that data-driven techniques are suitable when there is inadequate theoretical system model to clarify the performance of the model [10]. As such, data-driven methods are believed to be more promising approach for FDD in comparison to both model-based and rule-based models.

Montazeri et al [11] presented a data driven method based on artificial neural network approaches including support vector machine (SVM) and radial basis function (RBF) methods. Besides, Principal component analysis (PCA) and kernel PCA were utilized for fault diagnosis. The results showed that by using neural network approaches, 98.7% of the faults were detected and diagnosed. PCA is a statistical method based on least square technique which is widely used for FDD in HVACs. However, the exclusive utilization of PCA is not capable of finding all kinds of HVACs faults unless it is incorporated (combined) with other techniques [12].

In 2018, an associative classifier ML algorithm was suggested by Huang et al. [13] for fault detection in centrifugal chillers. The proposed algorithms effectively identified seven common chiller faults at both low and high severity levels. Also, the correct fault diagnosis ratio was shown to be up to 86.3%. In 2019, Shahnazari et al [14] proposed a recurrent neural network (RNN) for fault detection and isolation in HVAC systems. In this study, plant data were used to shape predictive models and input/output estimators so that it could be embedded within FDD procedure.

Ebrahimifakhar et al [12] developed a statistical ML-based fault detection classification model for packaged rooftop units. Among nine well-known classification methods applied to the dataset to compare their performance, Random Forest (RF) outperformed the other algorithms with the overall accuracy rate of 96.2%. Xu et al [15] investigated a ML-based method for anomaly detection of a HVAC system in a commercial building with a complex cooling system. After detection of abnormal operation data from historical operation data, the identified abnormal energy consumption data is corrected, resulting from a multilevel dynamic energy performance benchmark and a group of energy performance assessment rules for the HVAC system. Li et al proposed a semi-supervised FDD approach based on modified generative adversarial network (modified GAN) to deal with unlabeled data which have a significant impact on fault classification and performance of the system. Authors in [12] applied a hybrid model including principal component analysis (PCA) and statistical models to detect HVAC faults. Similarly, Yun et al, Hosseini et al, Tun et al, and Taheri et al employed supervised, unsupervised, unsupervised, and supervised model for FDD, respectively [16--19].

Yun et al [16] proposed a data-driven fault detection and diagnosis scheme for AHUs with regard to undefined states. The method considers fault diagnosis if it is of significant inferences on input variables. The results showed that the scheme can distinguish between undefined and defined data precisely (with high precision). Multi-label support vector machine (SVM) was studied by Han et al [20]. Tran et al [21] investigated the least square support vector regression (LSSVR) model to enhance the accuracy of the method for finding fault in a chiller system. Moreover, Bailey et al [22] applied support vector regression (SVR) to detect fault in a chiller system. Also, Zhao et al [23] adopted a rough set (RS) for eliminating redundant attributes and artificial neural network (ANN) for FDD in an air conditioning system. Zhao et al [24] reviewed the utilization of various unsupervised FDD approaches for HVACs, and provided comprehensive review on the utilization of unsupervised data analytics in exploiting massive building operational data.

Although numerous studies have been undertaken on FDD in HVAC systems, the majority of them have focused on the selection of different data-driven methodologies to improve accuracy. Although it is necessary to construct task-specific models that are architecturally optimized, it is no longer necessary to train multiple ML algorithms only to compare their accuracy while the performance difference is negligible in most cases. The argument is that the choice of algorithm may not be all that significant because all of these algorithms can be tuned to achieve high accuracy, despite the fact that the majority of past research has focused on boosting accuracy.

Moreover, some methods to ML-based FDD have produced too aggressive models that exhibit impressive predicting accuracy but produce an excessive number of false positives. False positive alarms are a huge time and expense drain in the FDD setting, as the operational team must establish a response plan for each instance in order to reduce the chance of downtime. False positives lead to negative experiences and impede the deployment of new FDD applications. While the majority of previous literature have focused on improving accuracy, it is important to design FDD applications based on precision to minimize the false positives in order to prevent from getting stuck in misleading alerts and warnings to the operational team.

Furthermore, two important aspects of FDD application are neglected by the majority of previous literature, including having to deal with imbalanced datasets and normal condition monitoring. Nonetheless, classification in supervised ML is usually challenged by the issue of mismatched class sizes. An unequal segmentation of the classes in a classified data will affect the model's predictions. Thus, it is necessary to develop approaches to equalize the frequency of different classes of faults within the dataset, a practice that is neglected by many studies. Meanwhile, HVAC malfunctions are regarded as rare occurrences, hence normal operating data samples are much more accessible than data samples in faulty and malfunctioning conditions. This leads to a significant bias against the normal condition (as a class) in the algorithms proposed in previous papers. To cope with this effect, normal condition monitoring models should be developed to sperate and forecast any deviation from normal condition.

As Can be seen, the previous studies did not consider the aforementioned challenges. Although, some of them may consider false positives, but they do not consider imbalance and normal condition monitoring and vice versa. In this regard, the main contribution of this study can be summarized as follows:

- Proposing a novel framework for FDD in HVAC systems that can minimize the false positives while account for the normal condition monitoring of the system.
- An up-sampling method is introduced to equalize the frequency of each fault category within the dataset.
- A time series anomaly detection is proposed to detect abnormal behavior of HVAC timeseries data. A random forest model is tuned and optimized to process the root cause of each fault once a fault is detected. Both algorithms are discussed in detail with a comprehensive report on hyperparameters, computational time, and network architecture.

II. METHODOLOGY FOR FAULT DIAGNOSIS

This section describes the proposed methodology designed to detect faults in various types of HVAC systems. Here, we first describe the process and its steps. The methodology incorporates a number of algorithms such as PCA, up-sampling, random forest (RF) classifier, and time series anomaly detection. Next, these algorithms are discussed in detail in the following sub-sections. The section is concluded by pointing the challenges and the issues that this methodology might face in different scenarios.

A. *Overall Structure of the Proposed Method*

FDD seeks to reduce risk and enhance operations through monitoring, fault detection, and diagnostics. In major commercial structures and building systems, like district cooling facilities, equipment degrades or fails often. In addition, valves, set-points, schedules, and controls are often manually altered for a unique or one-time occurrence and then not restored to regular functioning. In several commercial HVAC systems, suboptimal operations may occur, resulting in unpleasant occupant conditions, equipment damage, and energy waste. FDD has been used effectively in technical domains (e.g., aerospace, automotive, and industrial) for decades, but its application in structures is still expanding and relatively new. Herein, an algorithm is proposed for FDD task in HVAC systems and to fill some of the gaps within this field. Fig. 1 shows the flowchart of this algorithm.

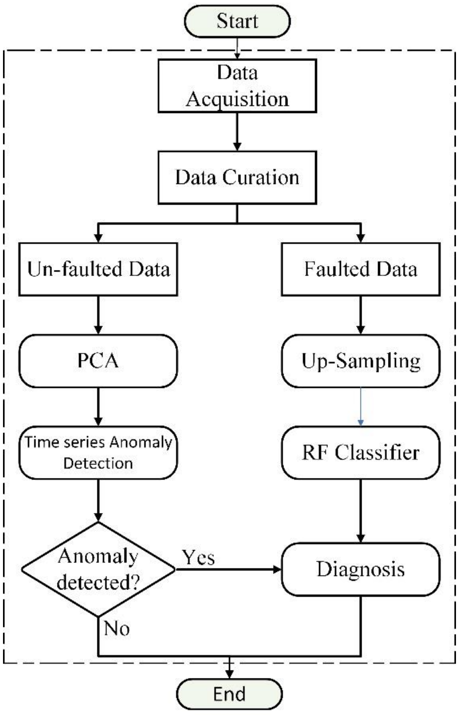

Figure 1. Flowchart representation of the proposed algorithm.

Monitoring must occur prior to implementing FDD, and the quality and type of monitoring might make FDD implementation easier or more complex. Important as data quality is, the accurate portrayal of errors is crucial during this process.

The subsequent phase in FDD is fault detection and identification or determining what the fault is and where it occurred. As the next step, the algorithm expands the concept of faults to include critical deviations from normal condition. As such, the proposed algorithm can help industry to detect and pinpoint anomalies that were previously overlooked and are precursors of larger problems. This is done by using a moving-window PCA Algorithm. PCA is a dimensionality-reduction technique that is often used to decrease the dimensionality of big data sets by reducing a large collection of parameters into a smaller one that retains the majority of the information in the large set. Reducing the number of dimensions in a data collection entails a natural loss of precision, but the key to dimensionality reduction is to sacrifice a little precision for simplicity. Because simpler data sets are easier to examine and interpret and make it simpler and quicker for ML algorithms to analyze data without having to process superfluous factors. The PCA reduces the data dimensionality at a sensor or asset level for the system. This will help reducing the computational time of the overall algorithm and check for principal component trends that are happening within the system.

After dimension reduction with PCA, the time series associated with the principal components should be checked for possible anomalies. A number of reasons make the identification of anomalies in time series more difficult. The first challenge stems from the absence of a coherent and practical definition of anomaly. Anomaly refers to points with abnormally high or low values and unforeseen subsequences (e.g., shape alterations) that arise in a time series. To solve this issued, we suggest using a well-established anomaly detection method that is discussed in Section C.

If something is detected as fault, the next step is to recognize the root cause of that fault to help the operational team to do the maintenance. To do so, the first step is to use a ML model to lean different classes of faults. By employing ML algorithms, businesses may utilize computing power and continuous monitoring to identify anomalies. Here, we suggest using RF as the classification algorithm. Before training the algorithm on different types of faults, it is necessary to account for the data imbalances, resulted by different frequency of various faults within the dataset. An up-sampling method is implemented here to increase the population of faulty samples in different classes. The RF algorithm is then trained on the new dataset to conduct the diagnostic task.

B. Moving Window PCA

Large datasets are becoming more prevalent in numerous areas. In order to analyze such datasets, it is necessary to dramatically decrease their dimensionality in an interpretable manner while preserving the majority of the data's content. PCA is one of the oldest and most extensively used methods for achieving this goal. PCA's concept is straightforward: lower the dimensionality of a dataset while maintaining as much "variability" (i.e. statistical information) as feasible.

C. Time Series Anomaly Detection

As a prerequisite for detecting anomalies in a time series, we must have an understanding of the normal condition. Given the historical raw data in a series for a certain sensor, it is challenging to determine the location of the anomaly within the time series. When dealing with sequential data, it is preferable to have a baseline to use as a comparison point. For instance, it is known that the supply air temperature sensor can have a daily or weekly pattern since its results are significantly correlated with ambient temperature. Therefore, we can calculate a baseline by averaging the numbers throughout that time, and by comparing those values to the baseline, we may begin to determine which of these anomalies (noises, persistent rise, sustained decline, and density change as depicted in Fig. 2) is representing real faults.

From domain expertise, we care about sustained temperature increase and do not wish to identify outliers, noises, and density changes as abnormal situations that represent a system fault. Meantime, we have the baseline (orange line in Fig. 2) for the specific sensor time series data, followed by the observation data (blue line in Fig. 2). These lines could be PCA angles or merely sensor-specific raw data. This chart contains three sources of abnormality, each of which might be interpreted as faults or as normal conditions.

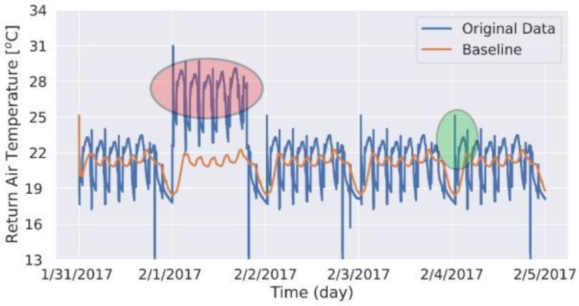

Figure 2. Time series noise and sustained value increase as potential anomalies.

The green circle denotes a single or a small number of locations with extreme deviation from the baseline. This anomaly is not reflective of a fault because its consequences are not sustained and cannot be observed in later time stamps. The red circle represents a prolonged temperature increase within the system, which we consider to be a system fault. Notice that a significant fraction of the points inside this window deviate from the baseline, and that the disparity between the baseline and the sensor readings is substantial. As a result, we know that the scenario is faulty if the observation is consistently greater than the baseline. We express this in a more quantifiable manner by employing the simple idea that, given a time window, how many points for the observation are above the baseline. If the percentage is near to 50%, for example, this indicates the presence of random noise. However, if the percentage is far above 50%, a fault has been identified. To get the most out of this strategy, we conducted a hypothesis test using this approach. In our case, the optimal hyperparameter for FDD of HVACs was 78%.

D. Up-sampling Different Fault Classes

Classification in supervised ML is often hindered by the problem of unequal class sizes. Given binary categorized data, an unbalanced segregation of the classes will influence the model's predictions. There are several solutions to the problem of unequal class sizes. An effective strategy is to collect more information and data. This is not always achievable, though. Another method involves manually balancing the classes. Using re-sampling or bootstrapping procedures, it is usual to over-sample the minority class or under-sample the majority class.

If a deterministic dynamic governs the mobility of the time series, then the time gap between data points must be narrow enough to identify the system dynamics. For this reason, the fault classes were oversampled to provide a smooth phase space for system dynamics identification. The process for up-sampling is dependent on the frequency content. Using Fourier transform (FT), the signals were converted to the frequency domain, and then zeros were added to the frequency signal. After adding zero, the new frequency signal was converted to the time domain using inverse Fourier transform (IFT). In this method, time-related signals are up-sampled without any modification to their frequency content. Table I lists the specifics of up-sampling, whereas Fig.3 depicts the up-sampling procedure.

TABLE I. UP-SAMPLING DETAILS FOR DIFFERENT FAULT CLASSES

Data Class (Fault)	**Frequency of instances prior to up-sampling**	**Factor of Up-sampling**	**Frequency of instances after up-sampling**
F1	25.7	9.5	243
F2	16.4	15.0	248
F3	9.3	25.8	240
F4	11.1	21.5	239
F5	12.8	19.0	244
F6	13.9	17.9	249
F7	6.6	38.0	251
F8	4.2	58.3	245

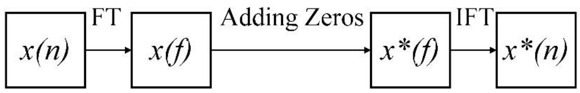

Figure 3. Up-sampling procedure of time series data.

E. Random Forest Model

Random forest (RF) as an ensemble learning algorithm has drawn increasing attention due to its better capability of identifying noise compared to single classifier. RF was firstly suggested by Beirman [26] as a new and promising classifier in 2001. RF can deal with the thousands of input variables without elimination and estimates the importance of variables in the classification. RF approach can significantly reduce the generalization error since it utilizes a random subset of input features or predictive variables in the division of every node instead of using the best variables [19].

III. CASE STUDY AND RESULTS

In this section, we first describe the data characteristics with all the associated features. Then, the case studies are introduced, and the results obtained from applying the proposed framework on the introduced case studies are discussed.

A. Data characteristics

There are sixteen different variables involved for assessing the FDD in this system. To seek the most influential variables for construction of our model, a correlation analysis can be conducted over Pearson correlation index, that is, Pearson correlation calculates the expression of possible linearity relationship between variables. It is given by the sum of the products of the standardized scores of the two variables, divided by the number of subjects. As can be extracted from the correlations between different features, the FDGT has a negative correlation with Supply Air Fan Status (SAFS), Return Air Fan Status (RAFS), Cooling Coil Valve Control Signal (CCVCS), Supply Air Duct Static Pressure (SADSP), and Occupancy Mode Indicator (OMI). On the other hand, FDGT has a positive correlation with Supply Air Temperature (SAT), Outdoor Air Temperature (OAT), Mixed Air Temperature (MAT), Return Air Temperature (RAT), Supply Air Fan Speed Control Signal (SAFSCS), Return Air Fan Speed Control Signal (RAFSCS), Outdoor Air Damper Control Signal (OADCS), Return Air Damper Control Signal (RADCS), and Heating Coil Valve Control Signal (HCVCS).

Moreover, supply air temperature (SAT) and return air temperature (RAT) are the variables that have the highest correlation with FDGT. SADSPS is highly correlated with SAFSCS and RAFSCS. Also, SAFS is highly correlated with RAFSCS and SAFSCS. The same pattern can be observed between RAFS and RAFSCS, and RAFS and SAFSCS.

B. Case Studies

Three case studies are investigated in this study which are single-zone constant air volume (CAV) and variable air volume (VAV) air handling unit (AHU) system, multi-zone VAV AHU, and rooftop unit (RTU). Interested readers are invited to see [25] for a full description of those cases.

C. Hyperparameter Optimization

Parameters and hyperparameters are essential part of any machine learning model. Parameters are the portion of the model that has been trained using previous data. In traditional machine learning literature, the model may be seen as the hypothesis and the parameters as the data-specific adaptation of the hypothesis. While model parameters, such as the intercept and slope in a linear regression, are learnt during training, the data scientist must select the hyperparameters beforehand. In the case of a RF, hyperparameters consist of the quantity of decision trees in the forest and the number of characteristics examined by each tree when splitting a node (The parameters of a random forest are the parameters and thresholds used during training to divide each node into two). Scikit-Learn provides a decent set of default hyperparameters for all algorithms, although they are not guaranteed to be best for a particular situation. Tuning a model is when machine learning transforms from a science to an engineering based on trial-and-error. The ideal hyperparameters are frequently hard to know in advance.

Tuning hyperparameters depends more on experimentation than on theory; thus, the best way to identify the ideal settings is to attempt a variety of configurations and assess the performance of each model. Typically, we have only a rough notion of the optimal hyperparameters; hence, the most effective method for narrowing our search is to test a broad range of values for each hyperparameter. Using “Scikit-RandomizedSearchCV” method, we constructed a grid of hyperparameter ranges and then randomly selected from the grid, executing K-Fold CV on each combination of values. The returns of the various performance enhancement strategies have been compared in a brief analysis. Table II illustrates the final outcomes of all the enhancements we made.

TABLE II RF OPTIMIZED HYPERPARAMETER AND ASSOCIATED COMPUTATIONAL TIME

Hyperparameter	SZ-AHU	MZ-AHU	RTU	Average
bootstrap	True	True	True	-
max_depth	70	130	70	90
max_features	auto	auto	auto	-
min_samples_leaf	4	8	6	9
min_samples_split	10	15	10	11.7
n_estimators	400	650	380	476.7
Time per epoch (s)	18.3	21.5	19.0	19.6

D. Model Performance

This section describes the performance of the suggested FDD model. As previously described, the proposed FDD strategy is to first establish the normal condition using moving window PCA, and then use historical PCA trends to determine whether anything deviates from the normal situation. Then, RF is applied to increase the accuracy of fault detection findings, anticipate the underlying causes of failures, and perform predictive maintenance. The first question to answer is how effective PCA is at reducing the data dimensions. We had a 16 by 16 covariance matrix and sixteen possible main components, each of which corresponded to a share of the data's variance. Fig. 3's scree plot demonstrates that the first principal component may account for about 95% of data volatility. This means that we can only utilize the first PCA to monitor the HVAC systems' conditions.

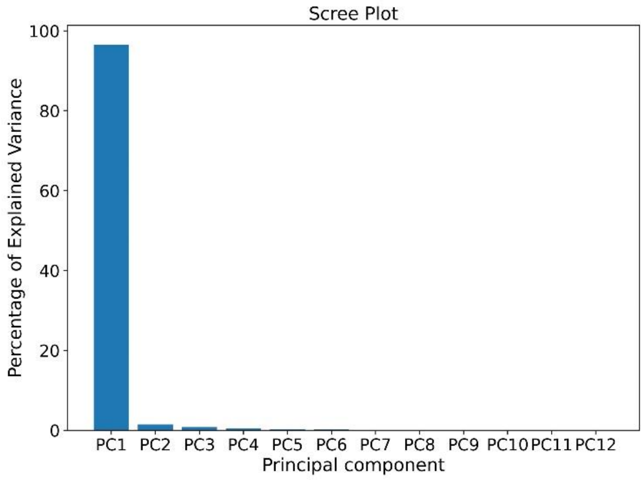

Figure 3. Scree plot of the percentage of explained variance by different components.

In general, classifiers may be evaluated in several ways since there are numerous performance metrics. Table III displays the assessment ratings for the various FDD classification systems. Cross-entropy (CE) is a frequently used loss function for classifier algorithms and is a metric of the difference between two probability distributions for a series of events. Precision is measured by dividing the number of actual positives by the number of expected positives. Recall is computed by measuring the proportion of cases that were successfully recognized as relevant by the model from the total number of relevant occurrences. The MCC and accuracy metrics are also reported.

TABLE III FORECASTING PERFORMANCE OF THE PROPOSED MODEL FOR DIFFERENT CASES

Performance Metric	SZ-AHU	RTU	MZ-AHU
CE	1.13	1.16	1.22
Precision	0.89	0.83	0.78
Recall	0.93	0.88	0.82
Accuracy	0.90	0.82	0.79
MCC	0.83	0.81	0.77

Fig. 4 depicts the receiver operating characteristic (ROC) curve to further illustrate the models' capabilities. The ROC is a typical tool for comparing classification algorithms that plots the true positive against false positive rates. In ROC graphics, a dashed line represents the worst-case situation in which we have a completely random classifier. A better classifier prefers to travel toward the upper-left corner and as far away from the black line with dots as possible. Due to the fact that ROC can only display one class per plot, we chose the F2 class for improper operation since categorizing this category was quite challenging for all three models.

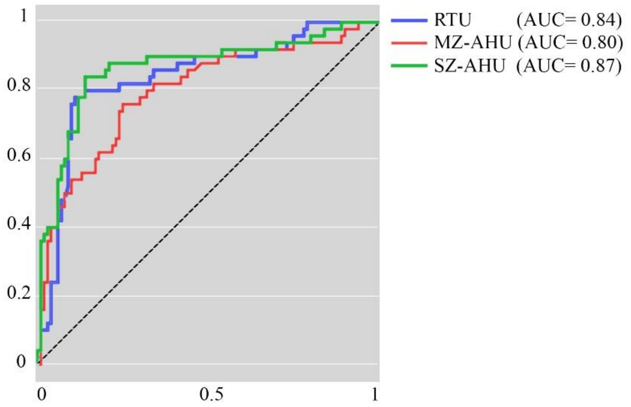

Figure 4. ROC curve plotted for heating coil stuck in SZ-AHU, RTU, and MZ-AHU.

IV. Conclusion

This research describes a novel method for defect identification and diagnostics in HVAC systems. Developing such a framework was motivated by a desire to address some of the persistent issues in this sector, including (I) the inability to account for data imbalance, (II) the ignoring of the effects of false positives, and (III) the exploitation of the normal condition data information. Each component of the proposed framework—a PCA technique, a time series anomaly detection model, and a random forest classifier—is described in depth. The results demonstrate that the model detects eight types of problems for a single-zone AHU, a rooftop unit, and a multi-zone AHU with significant accuracy. It is demonstrated that PCA can minimize the dimension of a dataset by accounting for 95% of the variation with a single principal component. In addition, the random forest was able to classify faults with an accuracy of 90% for single zone AHU, 82% for RTU, and 79% for multi-zone AHU.

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