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MACHINE LEARNING-BASED FAULT DETECTION AND PRELIMINARY DIAGNOSIS FOR TERMINAL AIR-HANDLING UNITS

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Abstract

With the advent of Artificial Intelligence (AI) powered classification techniques, data-driven Fault Detection and Diagnosis (FDD) methods have become increasingly prominent in smart building implementation. Of these, cluster analysis is particularly promising for Building management system (BMS) data. This paper presents an unsupervised learning-based strategy for detecting faults in terminal air handling units as well as the systems serving them. Historical sensor data are pre-processed with PCA to reduce dimensions, followed by OPTICS clustering, which is compared with k-means. OPTICS outperformed the latter, readily identifying noise and had high accuracy across all seasons.

Introduction

In recent years, many efforts have been made to develop and apply various strategies for fault detection and diagnosis (FDD) in HVAC systems, typically at the individual component level. Early fault detection can improve the energy efficiency, reliability, and safety of HVAC systems, while reducing maintenance costs and downtime (Guo et al., 2018; Rosato et al., 2022). Recent research has applied physical model-based methods, rule-based methods, and data-driven methods for HVAC system FDD; for reviews see (Katipamula & Brambley, 2005; Mirnaghi & Haghighat, 2020). Data-driven techniques have been gaining popularity in recent years due to their high accuracy and low level of effort (Mirnaghi & Haghighat, 2020); however, they are limited by their dependence on a large volume of high-quality operational data (Yang et al., 2014). New approaches to extract such data from building management systems (BMSs) mitigates this issue.

This paper proposes a fault detection method using cluster analysis to detect potential faults in fan coil units (FCUs), terminal units providing heating and cooling to rooms served by a dedicated outdoor air system. Data are extracted Time-series data obtained via the BMS is analysed using the Ordering Points to Identify the Clustering Structure (OPTICS) algorithm is used in combination with Principal Component Analysis to differentiate between normal and faulty operations data from time- series data extracted from a BMS. The results were compared with Principal Component Analysis (PCA) and k-means and all data traces were reviewed by a Certified Energy Manager familiar with the building systems to confirm findings and label faults to inform learning.

Background

The early detection and diagnosis of faults in HVAC systems is valuable both to prevent further system or component damage and to avoid loss of service. Several challenges exist for such FDD applications. First, HVAC operation is highly responsive to occupancy and weather, resulting in variable system operation that can make ‘normal’ vs ‘abnormal’ conditions difficult to distinguish (Chen et al., 2022a). Second, HVAC systems are highly interconnected and diverse (Sun et al., 2013). For example, the FCUs considered in this paper contain both heating and cooling coils, tying these systems to the central heating and chilled water plants, respectively. Further, they are provided with tempered outdoor air by an energy recovery ventilator (ERV). Third, interconnections such as these can complicate fault diagnosis, particularly as some faults may balance others, obscuring the problem on the larger system, resulting in complex fault symptoms (Verbert et al., 2017).

As noted previously, data-driven methods are widely used, and of these, cluster analysis has been identified as highly promising for FDD effort (Mirnaghi & Haghighat, 2020). Clustering approaches leverage the statistical differences between ‘normal’ and ‘faulty’ operational data to detect anomalies and identify operational behaviour uncaptured by automated FDD rules such as BMS alarms. Inherent in this strategy is the idea that faulty data and normal data have different features and can be distinguished by identifying their spatial and temporal separation. Cluster analysis is used to separate faulty data from normal data through this method. In order to implement this fault detection strategy, a set of reference data free from errors is needed to identify faults. These reference data are usually obtained during the thorough commissioning process of the HVAC system. Algorithms such as linear discriminant analysis (Li et al., 2016) and k-means (Luo et al., 2019) have both been used for FDD in HVAC systems. Cluster analysis has also been used in semi-supervised learning approaches for FDD (Gunay and Shi, 2020). Of particular interest to this paper are the OPTICS, k-means, and PCA algorithms, discussed in detail in the following sections.

OPTICS cluster analysis

OPTICS (Ankerst et al., 1999) is a variation of the Density Based Spatial Clustering of Applications with Noise (DBSCAN; Khan et al., 2014) algorithm that uses density-based clustering to identify clusters by searching for areas of high density separated by areas of low density. The core concept of density-based clustering is that each data point in a cluster must have a minimum number of data points (MinPts) within a specified radius (Eps) around it (Ester et al., 1996). Unlike traditional clustering, OPTICS orders data based on reachability-distance (k-distance; the minimum cluster radius to contain the minimum defined number of points), making it valuable for fault detection as it can discover clusters of any shape and are more resistant to noise (Yan et al., 2016). For point p to be directly density-reachable from point q, it must meet the following conditions.

$$p \in N_{Eps}(q) \;\&\; |N_{Eps}(q)| > MinPts$$

where $N_{Eps}(q)$ refers to the set of data points within the radius *Eps* of point q. The reachability-distance between point p and o is expressed as follows.

$$\text{Reachability- distance} = \begin{cases} Undefined,\ if\ |N_{Eps}(o) < MinPts| \\ \max(core - distance(o), distance(o,p)), otherwise \end{cases}$$

While,

$$Core - distance = \begin{cases} Undefined,\ if\ |N_{Eps}(p) < MinPts| \\ MinPts - distance(p), otherwise \end{cases}$$

To tune OPTICS, both a minimum number of cluster points (MinPts) and the cluster distance (Eps) must be determined; this balance is critical as too few points can give false positives for noise in the data while too many can result in false negatives as significant – albeit infrequent – faults are missed. OPTICS has been used with PCA for pre-processing to detect sensor faults (Yan et al., 2016) but there is no published literature demonstrating its application to identify equipment faults.

k-means clustering

k-means clustering is a popular unsupervised machine learning technique that is used to divide an unlabeled data set into a predefined number of clusters, where k represents the number of clusters. The algorithm is centroid-based, meaning that each cluster is associated with a centroid, which is the center point of the cluster. The aim of the algorithm is to minimize the sum of distances between the data points and their respective cluster centroids. Du et al. (2014) proposed a Fault Detection and Diagnosis (FDD) algorithm which combines subtractive clustering analysis and neural networks. They used neural networks to detect faults in the supply air temperature control loop in Heating, Ventilation, and Air Conditioning (HVAC) systems, and the subtractive clustering method to diagnose the faults. This approach has been proven to be effective in identifying and diagnosing faults in HVAC systems. While larger equipment such as Air-handling units (AHUs), chillers, and boilers have been the topic of significant research, for example (Yu et al., 2014; Mirnaghi & Haghighat, 2020), there has been limited research on FDD for terminal units such as fan coil units (Ranade et al., 2020; Chen et al, 2022b). These units have additional complexity because they are highly dependent on the occupancy of the served space as well as the broader weather impacts on the heating and cooling systems that serve them. This paper addresses this gap, presenting a PCA-Clustering method tested across multiple units, seasons, and occupancy conditions.

Methodology

The approach used for fault detection and labeling of FCUs is shown in Figure 1.

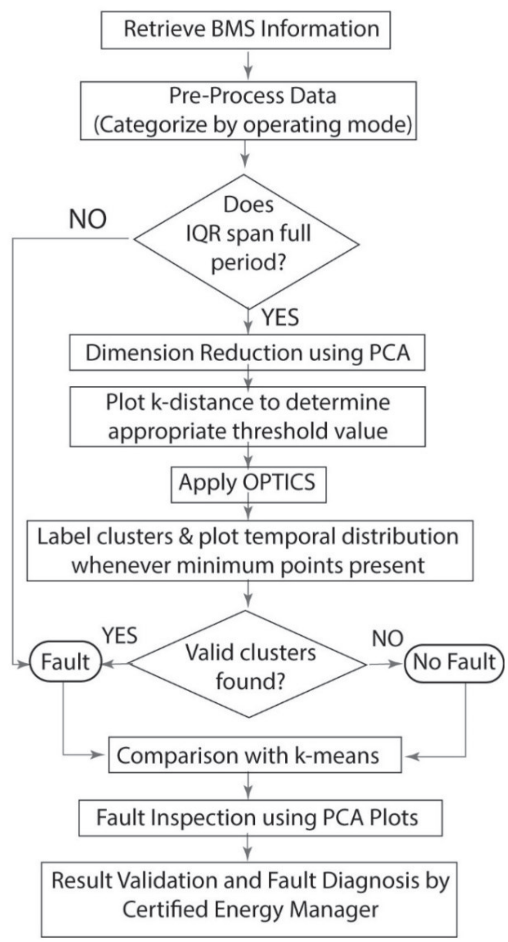

Figure 1: Fault detection and diagnosis methodology for terminal air-handling units, incorporating BMS data, preprocessing, PCA, and OPTICS clustering

Several time-series datasets, including one with a known fault for initial testing, were created by extracting one-week windows for equipment measurement and control points from the BMS. These included both controls {heating (HTG-O) and cooling (CLG-O) coil valve open commands} and sensor measurements {zone temperature (T), discharge air temperature (DA-T), discharge air relative humidity, discharge air flow rate, supply water temperature, and fan speed measurements}. Table 1 lists the sensor names and their descriptions. The purpose of this study is to showcase the efficiency of the proposed fault detection method by analyzing a data set containing HVAC mechanical cooling operation. To achieve this, data from the cooling coil control valves within the interquartile range (IQR), which denotes the range with the most closely grouped observations, is utilized for the subsequent fault detection analysis. Because FCUs typically operate under two normal conditions: cooling and heating, it was necessary to distinguish between them to avoid confounding results. Further, only data when the device was enabled ("ON") was selected. The existence of multiple clusters in the data points is thus not due to different modes of operation, but rather to the presence of a fault so the number of faults can be calculated as the number of clusters minus one.

Table 1. Sensor names and their descriptions

Designation	Description
HTG-O	Heating coil valve
CLG-O	Cooling coil valve
OA-T	Outside air temperature
DA-T	Discharge air temperature
T	Zone temperature
INSLAB-T	In-slab temperature
SF-S	Supply fan status
ST	Supply water temperature
Q	Zone quality

With the assumption of single and non-simultaneous faults, it was anticipated that two clusters of data would be generated, representing normal and faulty system operation. The thresholds for the OPTICS algorithm were thus chosen from the k-distance graph to produce two clusters with MinPts=25. We selected a MinPts value of 25 for the k-distance graph using a trial-and-error approach, with the goal of striking a balance between noise sensitivity and effective cluster formation. In order to verify the robustness of our method, we experimented with different MinPts values and found that the outcome was not particularly sensitive to the specific value selected. As a result, we chose MinPts = 25, which provided satisfactory fault detection and diagnosis performance. It is important to note that the suitability of other values may vary depending on the characteristics of the dataset and the requirements of the specific application. Similarly, the number of clusters in k-means was determined as two. By analyzing the clustering results and observing the system operation data traces, time intervals with faulty operation can be identified as they are grouped under a label distinct from the normal operation. However, the possibility of multiple faults can be explored by using a lower threshold value in the OPTICS algorithm or by using a larger value for k in k-means clustering.

To detect faults, clusters were automatically labeled as 'normal' and 'faulty' operation and non-clusters as 'noise'. PCA plots were created and examined in detail to gain a deeper understanding of the data, which were reviewed by a Certified Energy Manager (CEM) to diagnose the faults. This review served two purposes: it provided expert validation of results beyond the k-means comparison and it allowed for diagnosis of the most likely fault, which was applied as a label to the faulty data to permit diagnosis to be learned in future research.

Result and Discussion

This study evaluated the performance of the proposed fault detection method using data from three FCUs. In this study, we looked at three FCUs (FCU-XX, FCU-YY, and FCU-ZZ) located in office spaces in building at Toronto Metropolitan University. These FCUs were chosen to provide a proof of concept and to illustrate that our methodology can be successfully applied to a larger series of units and the systems that serve them. By choosing FCUs from different locations representing the extremes of room sizes and occupancies, we aimed to show that our approach is versatile and can accommodate varying operational conditions and environmental factors, thus increasing its generalizability to a broader range of installed equipment. Moreover, the scenarios in our study were selected to cover a diverse set of possible fault conditions, enabling us to assess the performance of our method across different fault types and magnitudes. Table 2 outlines the properties of the chosen FCUs, including their spaces served and their associates thermal zones. All are served by the same central air handling unit.

Table 2. FCUs' Properties

FCU	Feeds	Location
FCU-XX	$50m_2$ entrance lobby	Thermal zone #3 - level 01
FCU-YY	$176m^2$ open-plan student lounge	Thermal zone #3 - level 01
FCU-ZZ	$8m^2$ study room	Thermal zone #3 - level 02

These units are representative of the most common type used in the building and provide heating and cooling to different offices located on first and second floors. Data were sampled from FCU-XX, FCU-YY, and FCU-ZZ year-round during the peak heating (December 2019) and peak cooling (June 2020) seasons.

The first test case, FCU-XX, was specifically chosen to demonstrate the capability of the proposed strategy in detecting faults in FCUs through cluster analysis and its sequential steps. A test scenario was selected as it presented a recognizable fault. The data were initially categorized as cooling or heating operation, and fault detection was solely based on data collected from that specific operation. In this study, the data set that captures the HVAC mechanical cooling operation is employed for further analysis to showcase the efficacy of the suggested fault detection approach. The subsequent step involved determining the number of principal components using a scree plot, and ultimately selecting two PCs (Table 3).

Table 3. Principal Components for FCU-XX

Feature	PC1 Weight	PC2 Weight
T	-0.58	-0.08
INSLAB-T	-0.44	-0.41
Q	0.22	0.58
DA-T	0.34	-0.57
CLG-O	-0.39	-0.02
HTG-O	0.41	-0.43

From this, we note correlations between variables with the same direction of change (e.g., T, INSLAB-T, CLG- O), inverse correlations between those with opposite changes (e.g., T and HTG-O) in one PC, and none when both PCs show opposite changes (e.g., T and Q).

After PCA, we plotted the k-distance diagram and determined Eps, which is the inflection point of the curve (Figure 2); this value was 0.6 for all FCUs considered. Using Eps in OPTICS, we plotted the reachability distance graph and selected a threshold reachability distance that would generate two distinct clusters, representing the faulty and normal operation of the system; in this case 0.5 (Figure 3, bottom). Data were automatically labelled based on this analysis as either 'faulty' and 'normal' operation. When color-coded on time-series charts, the fault time(s) became quickly evident, revealing two distinct periods of faulty operation: June 3, 2020 11:00-17:15 and from 01:10 on June 12, 2020 through 17:15 on June 18.

Cross-checking with known issues validated by the facility engineer confirmed this fault. The application of k-means on the PCA-transformed data showed similar results for the former, with the fault detected from June 3, 2020 11:00-17:25, but only intermittent detection {from 09:20 on June 12, 2020 – 05:30 on June 13, 2020 and from 09:10 on June 13, 2020 through 05:15 on June 14 and from 09:00 on June 14 through 12:50 on June 18} of the latter, showing a decreased sensitivity.

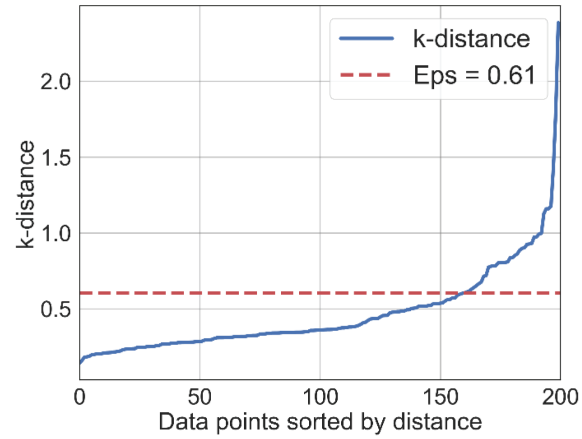

Figure 2. k-distance graph

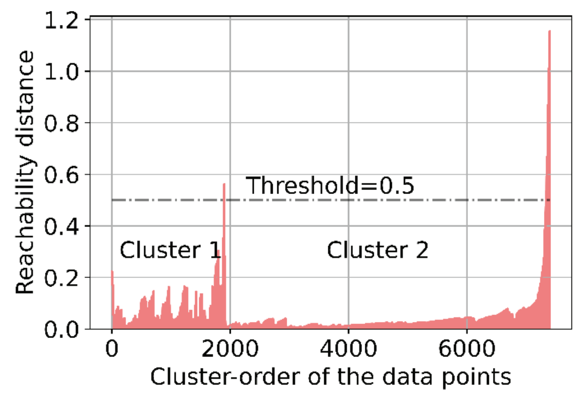

Figure 3: OPTICS Clustering Results and Cluster Identification Using User-Defined Threshold for the FCU-XX Dataset

Figure 4 presents the results of both clustering algorithms, demonstrating the discrepancy between the results of the OPTICS and k- means methods. This occurred due to OPTICS's ability to distinguish noise, while k-means falsely identified these as faults. According to the CEM, this indicates a lack of adequate chilled water flow to meet the cooling requirements, which is further validated by the time-series data trace illustrated in Figure 5 (top right). Review by the CEM verified the presence of a fault in the identified intervals as well and confirmed that OPTICS was correct in its identification of noise. However, reviewing the broader dataset, she identified a fault missed by both algorithms during the heating season (from approximately 13:00 December 28, 2019 through 0:30 December 29, 2019). This is evident in in the small negative spike in the DA-T data trace between these times in Figure 5 (top left data series).

To investigate the fault, PCA plots were color-coded and analyzed, adding vectors to indicate the direction of change for each variable. Based on the correlations noted from Figure 4, DA-T and CLG- O should change along a diagonal trajectory, thus, the tail of points extending to the bottom-left indicates an unusual occurrence. While DA-T

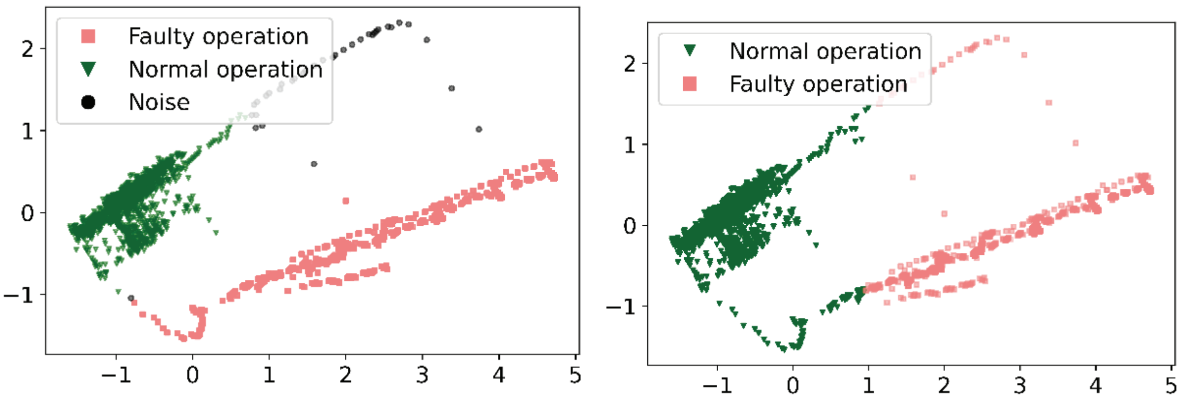

Figure 4: OPTICS (top) vs k-means (bottom) results for FCU-XX plotted against PC1 and PC2.

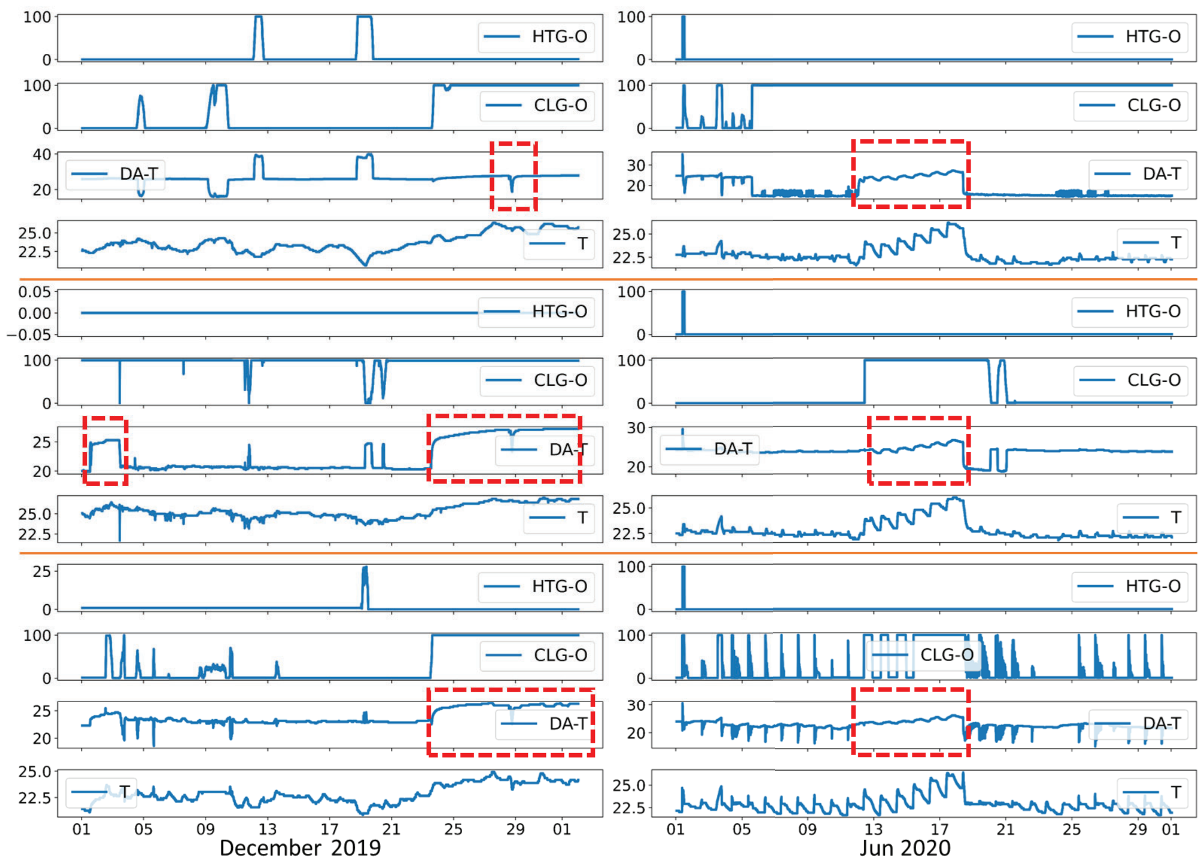

Figure 5: Extracts from time-series data analyzed during peak heating season (left) and cooling season (right) for FCU-XX (top), FCU-YY (middle), and FCU-ZZ (bottom). Solid boxes indicate detected faults while dashed boxes indicate those not detected by either algorithm but confirmed by the CEM.

should decrease towards the right; instead, it is increasing, as illustrated in Figure 6.

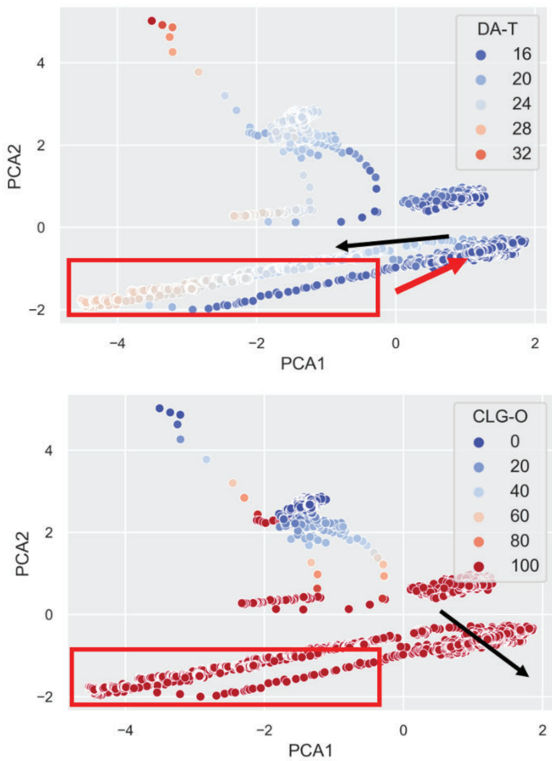

Figure 6: Sample PCA plots with color spectra added

The same process was repeated for the other cases of FCU-YY and FCU-ZZ, identifying an Eps 0.5 and reachability distance thresholds at values of 0.4 for each unit to separate the data into two distinct clusters.

The results of the OPTICS and k-means clustering process for FCU-YY is presented in Figure 7. As observed in this figure, both clustering algorithms revealed two instances of system malfunction during the heating season, extending beyond the period identified by the CEM.

To better understand these faults, once again a PCA plot (Figure 8) was consulted, indicating a group of points on the left revealing an unexpected system behavior. Despite CLG- O being at 100% open, DA-T is high, once again indicating a lack of adequate chilled water. Because FCU-XX and FCU-YY are located on the same level and hydronic zone, this indicates a system fault at either the zone or full-building level.

Review by the CEM verified the presence of a fault in the identified intervals as well and confirmed that OPTICS was correct in its identification of noise. However, reviewing the broader dataset, she identified that the same fault period identified by OPTICS and k-means in June for FCU-XX was also evident in the FCU-YY data but missed by both algorithms (box on Figure 5, middle right data series).

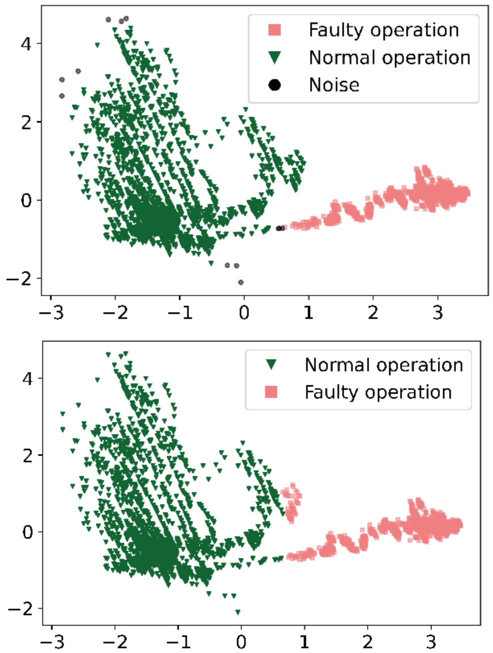

Figure 7: OPTICS (top) & k-means (bottom) (FCU-YY)

FCU-ZZ showed similar results. Figure 9 displays the results of the OPTICS and k-means analysis, revealing the presence of faults in the time frames of 2019-12-23 13:40 to 2020-01-01 23:50. OPTICS also detected a fault from 2019-12-02 12:55 to 20:05 of the same day. As in previous cases, OPTICS outperformed k-means both detecting a fault missed by the latter and by avoiding misclassifying noise as faults. This was confirmed by the PCA results, which indicated that DA-T did not respond correctly to CLG-O at certain times in December. This is indicated on the figure by the red arrows showing the actual change in direction for DA-T compared with the expected (black arrow): despite CLG-O being at 100%, DA-T was still high. Further input from the CEM noted that this same issue occurred in FCUs on multiple levels, suggesting a central plant fault, rather than a local one, as evidenced in Figure 5. This is was similarly visible in the PCA plots, which displayed similar fault trends as those of FCU-YY.

Review by the CEM again verified the presence of a fault in the identified intervals and confirmed that OPTICS was correct in its identification of noise. However, reviewing the broader dataset, she once again identified that the same fault period identified by OPTICS and k-means in June for FCU-XX was also evident in the FCU-ZZ data and again missed by both algorithms (box on Figure 5, bottom right data series).

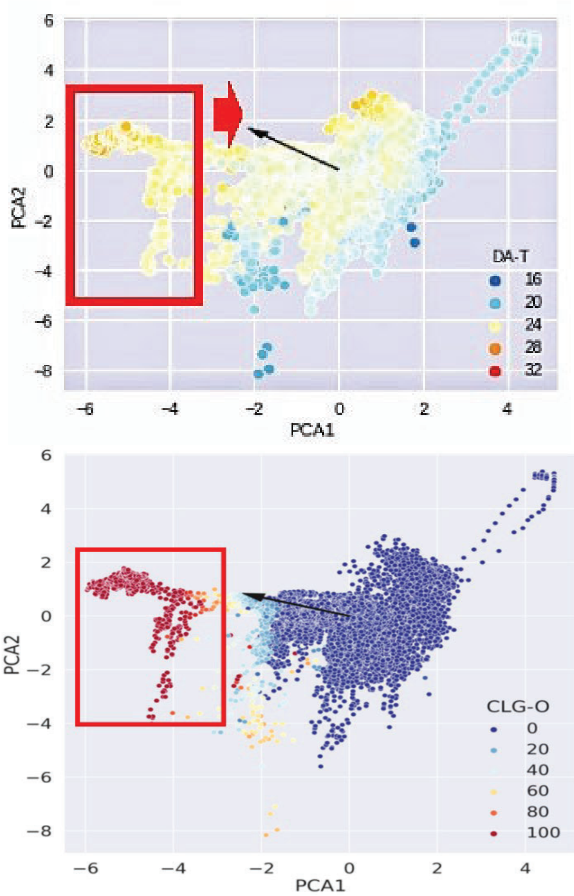

Figure 8: PCA Plot for diagnosing fault in FCU-YY

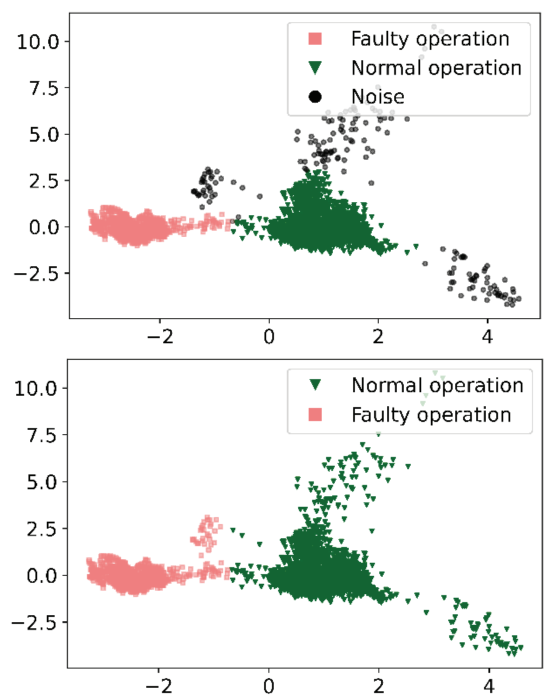

Figure 9: OPTICS (top) vs k-means (bottom) (FCU- ZZ)

Table 2 presents a summary of the results to compare the OPTIC and k-means approaches. To contextualize this, the null accuracy was calculated as 0.751 (1846 actual fault and 5554 normal data points out of 7400 total).

Table 4: Results Summary

Measure	PCA + OPTICS	PCA + k-means
Sensitivity	0.989	0.869
Specificity	0.986	0.978
Precision	0.959	0.928
Accuracy	0.986	0.951

These results demonstrate that PCA and OPTICS outperform PCA and k-means in all aspects and that the approach presented is valid for mechanical fault detection as well as the sensor fault detection previously demonstrated by Yan et al (2016). This high accuracy supports the use of PCA + OPTICS for automated fault detection in terminal air handling units.

Conclusions

The series of cases presented has demonstrated that OPTICS provides excellent results for fault detection. While the current research is limited to manual confirmation and diagnosis of the nature of the faults, the extent of the fault can be automatically diagnosed by comparing fault ranges across FCUs; this is extremely valuable to aid root cause analysis. There is also a significant level of effort reduction for the manual labelling because PCA + OPTICS allows only fault data to be reviewed. The availability of maintenance records to cross-validate could further reduce using Natural Language Processing to automate classification, similar to the work presented by McArthur et al. (2018).

Other limitations of this research are the relatively small sample size (three pieces of equipment in one building) and limitation to cooling operation only.

Several areas of future research are identified. First, we will expand OPTICS analysis to the full set of FCUs in the target building and label detected faults to create a training dataset that can be used to train a fault diagnosis classifier; this will be repeated for heating operation. The fault range comparison across units will then be automated to support autonomous detection of system issues, indicated by multiple simultaneous equipment faults. To support this, we will undertake sensitivity analysis to determine if reachability distance thresholds can be improved and whether this can be generalized for each equipment type. Finally, we will investigate the use of online learning to permit autonomous operation, requiring only new faults that cannot be classified using learned rules to be manually labeled, resulting in an online semi-supervised FDD algorithm.

Acknowledgments

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