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Heat Recovery Unit Failure Detection in Air Handling Unit

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Abstract. Maintenance is a complicated task that encompasses various activities including fault detection, fault diagnosis, and fault reparation. The advancement of Computer Aided Engineering (CAE) has increased challenges in maintenance as modern assets have became complex mixes of systems and sub systems with complex interaction. Among maintenance activities, fault diagnosis is particularly cumbersome as the reason of failures on the system is often neither obvious in terms of their source nor unique. Early detection and diagnosis of such faults is turning to one of the key requirements for economical and functional asset efficiency. Several methods have been investigated to detect machine faults for a number of years that are relevant for many application domains. In this paper, we present the process history-based method adopting nominal efficiency of Air Handling Unit (AHU) to detect heat recovery failure using Principle Component Analysis (PCA) in combination of the logistic regression method.

Keywords: Fault detection · Fault diagnosis · FDD · logistic regression· PCA · Air Handling Unit · heat recovery unit

1 Introduction

Air Handling Unit (AHU) is an integral functionality of any modern buildings that contributes to the well-being of its occupants. As energy prices sore up, operating these devices become costly. As a result of rising energy prices along with environmental concerns, building owners have become more and more interested in reducing the energy consumption of their buildings. In modern AHU, it is common to have Heat Recovery Units (HRU), especially in countries with cold climate like Finland. HRU helps to reduce energy consumption by extracting heat from waste air and employing it to heat the supply air.

Advancement in Computer Aided Engineering (CAE), manufacturing companies are producing complex AHUs with capabilities in computing, sensing, and actuating. Using these capabilities, maintenance of AHU is even more challenging as this equipment became a complex combination of systems and subsystems with complex interactions. Fault diagnosis is considered a complicated maintenance activity since there might be multiple reasons behind each failure and the failure reasons are also often ambiguous in terms of their sources. By identifying and diagnosing the faults to be repaired, building owners can benefit by reducing energy consumption and improving operational performance. However, no matter how reliable the products (or equipment) are, they tend to deteriorate over time and also occasionally fail due to real-world operating conditions under various degrees of stress. In order to make such assets economically and functionally efficient, it is necessary to detect and diagnose such failures at early stages. Several failure detection techniques have been developed to detect different kinds of failure such as cooling coil subsystem and sensor faults, as seen in literature in Section 2. In this paper, we propose a process history-based method to detect HRU failure following the generic principal of nominal efficiency. The novelty of the proposed methodology is application of nominal efficiency to detect faulty HRU hitherto unseen in the literature. The theoretical background and proposed methodology are detailed in Section 3 and Section 4, respectively.

2 Fault Diagnosis in Air Handling Unit

Fault detection and diagnosis is a well-researched area. Several researchers have examined and identified different techniques to detect and diagnose fault condition in AHU. Typically, these techniques have been broadly classified into three categories [1]: quantitative model-based methods, qualitative model-based methods, and process history-based methods. These methods belong to the same generic class—data-driven methods. However, in general, extensive prior knowledge is required to apply quantitative and qualitative model-based methods. They are also often device-specific and are difficult to be applied to other devices. Therefore, process history-based methods are at the core of this study. Process history-based methods are also known as black box models. Unlike model-based methods that are based on physical principles, these methods are based on actual data generated during usage. The relation between input and output are discovered during the learning phase of these methods. Several researchers have worked on such methods for diagnosing failures on AHU.

Lee et al. [2] presented Artificial Neural Network (ANN) backward propagation method to detect the fault of cooling coil subsystem of AHU based on dominant residual signature. Similarly, in 2012, Yonghua et al. [3] proposed a method for diagnosing the sensor failure based on the regression neural network with a combination of wavelet and fractal dimensions. In this method, three-level wavelet analysis was applied to decompose the sensor measurement data, and then each frequency band was extracted and used to depict the failure characteristics of the sensors which were then used to train the neural network to diagnose sensor faults. Du et al. [4] introduced a detection method for drifting sensor biases in an AHU using a combination of wavelet analysis along with the neural network. PCA is another technique widely used to detect and diagnose faults in AHU. For instance, Wang et al. [5] could present a PCA-based strategy to detect and diagnose sensor faults in the AHU. This strategy employed squared prediction error as indices of fault detection and the Q-contribution plot to isolate faults in AHU. Similarly, Du et al. [6] employed PCA with Joint Angle Analysis (JAA) to detect and diagnose both fixed and drifting sensor biases in Variable Air Volume (VAV) systems. The Squared Prediction Error (SPE) plot based on PCA was used to detect the sensor fixed and drifting biases. Then, the JAA plot instead of conventional contribution plot was applied to diagnose the faults. Chen et al. [7] also proposed a method using PCA for detecting and identifying sensor bias, drifting, and failure in AHU. In his method, PCA is employed to identify correlation of measured variables in the heating/cooling billing system and reduce the dimension of measured data. SPE statistic was used to detect sensor faults in the system. Xiao et al. in [8] presented an expert-based multivariate coupling method by enhancing capabilities of PCA-based method in fault diagnosis by applying expert knowledge about the process concerned. This method develops unique patterns of typical sensor faults by analysing the physical cause-effect relations among variables, which are compared to fault symptoms reflected by the residual vectors of the PCA models with fault patterns to isolate sensor faults. Similarly, several other researchers such as Yan et al. [9] and Liang et al. [10] used model-based SVM to detect faulty condition in an AHU.

3 Theoretical Background

3.1 System description

A typical AHU with a balanced air ventilation system, as shown in Fig. 1, includes the HRU, supply fan, extract fan, air filters, controllers, and sensors. The system circulates the fresh air from outside to the building by utilising two fans (supply side and extract side) and two ducts (fresh air supply and exhaust vents). Fresh air supply and exhaust vents can be installed in every room, but typically this system is designed to supply fresh air to bedrooms and living rooms, where occupants spend their most of time. A filter is employed to remove dust and pollen from outside air before pushing it into the house. The system also extracts air from rooms where moisture and pollutants are most often generated (e.g. kitchen and bathroom). One of the major components of the AHU is HRU, which is used to decrease energy consumption. The principle behind the HRU is to extract heat from extracted air (before it is removed as waste air) from the house and adopt it to heat the fresh air that is entering the house. HRU is a fundamental component of AHU which helps to recycle extracted heat. The main controllers in the system include the supply air temperature controller, which adjusts the temperature of the supply air entering house and Hru_output, which controls the heat recovery rate. In order to measure HRU efficiency, five temperature sensors are installed in AHU, which measure the temperature of circulating air at different parts of AHU (Table 1). In addition to sensor data, the HRU control state, supply fan speed, and extract fan speed can be collected from the system.

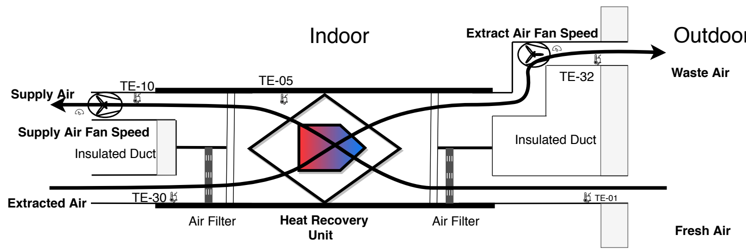


Fig. 1: Schematic diagram of air handling unit

Sensor Name	Sensor Description
T_{frs}(TE-01)	Temperature of fresh incoming air
T_{supH}(TE-05)	Temperature of supply air after HRU
T_{sup}(TE-10)	Temperature of supply air
T_{ext}(TE-30)	Temperature of extracted air
T_{wst}(TE-35)	Temperature of waste air
Hru_Output	State of HRU output controller
Sup_Fan_Speed	The current effective supply-side fan speed
Ext_Fan_Speed	The current effective extract-side fan speed

Table 1: Air Handling Unit Sensor Details

3.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is the statistical procedure mostly used for dimension reduction and orthogonal decomposition. A Principal Component (PC) is defined as a linear transformation of the original variables which are normally correlated, into a new set uncorrelated variables. If there are n observations with p variables, then the number of distinct PCs is $\min(n-1,p)$. This transformation is defined in such a way that the first PC has the largest possible variance, and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The first PC Y_1 is given by the linear combination of the variables $X_1,\ldots,X_p$ as seen in (1). Collectively, all of these transformations of the original variables to the PCs are given by (2). The rows of matrix A (loading matrix) are called the eigenvectors of matrix S_x derived from (3), the variance-covariance matrix of the original data. The elements of an eigenvector are the weights a_{ij}, known as loadings. The elements in the diagonal of matrix S_y(see (4)), the variance-covariance matrix of the PC, are known as the eigenvalues.

$$Y_1 = a_{11}X_1 + a_{12}X_2 + a_{13}X_3 + \ldots.a_{1p}X_p = A_1X_1 \tag{1}$$

$$Y = AX \tag{2}$$

$$S_x = \frac{X^T X}{(n-1)} \tag{3}$$

$$S_y = A S_x A^T \tag{4}$$

3.3 Logistic Regression (LR)

Logistic Regression (LR) was developed by David Cox in 1958 [11]. It is a statistical method to determine dependent dichotomous variables using one or more independent variables. It is a variation of ordinary regression method that is used when the dependent variable is dichotomous. The goal of LR is to find the best fitting model to describe the relationship between the dichotomous characteristic of the dependent variable and a set of independent variables [12]. LR generates the coefficients, standard errors, and significance levels of a formula to predict a logit transformation of the probability of presence of the characteristic of interest. The logit model of multiple LRs can be shown in (5) and the logit transformation is defined as the logged odds shown in (6).

$$logit(p) = b_o + b_1 X_1 + b_2 X_2 + b_3 X_4 + ...b_k X_k = ln(\frac{p}{1-p}) \tag{5}$$

$$odds = \frac{probability\, of\, presence\, of\, characteristic}{probability\, of\, absence\, of\, characteristic} = \frac{p}{1-p} \tag{6}$$

4 Methodology

The method of detection and diagnosis for HRU failure is shown in Fig. 2. This binary classification method is based on the nominal efficiency of AHU to detect failure of HRU using PCA and LR methods. The rationale behind such methodology is that there is a high number of dimensions and detecting faulty operation (HRU Failure) from normal operation is quite difficult. The nominal efficiency (μ_{nom}) of the HRU is a function of air temperatures in AHU, which is yielded by (7) [13]. To develop this model, the dataset contains 26700 instances of data with two types of information collected using architecture and interfaces described in [14] during “Normal” and “No Heat Recovery” states. One information regards the class label (i.e “Normal”: 18882 instances and “No Heat Recovery”: 7818 instances) and the other contains different kinds of air temperature circulated by AHU (detailed in Table 1). Since Hru_output is set to “max” (i.e. it is a constant parameter) and HRU nominal efficiency is a function of air temperatures associated with AHU (see (7)), only temperature dimensions are considered in this analysis. In other words, these dimensions can be combined to measure the performance of HRU.

$$\mu_{nom} = \frac{T_{ext} - T_{wst}}{T_{ext} - T_{frs}} \tag{7}$$

As the first step, the collected dataset is split into “Train” and “Test” datasets. Second, the PCA model, based on nominal efficiency, is set up through the training dataset with five temperature dimensions. The corresponding matrix is denoted as:

$$X_{26700\times 5} = \begin{pmatrix} T^1_{supH} & T^1_{frs} & T^1_{sup} & T^1_{ext} & T^1_{wst} \\ T^2_{supH} & T^2_{frs} & T^2_{sup} & T^2_{ext} & T^2_{wst} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ T^n_{supH} & T^n_{frs} & T^n_{sup} & T^n_{ext} & T^n_{wst} \end{pmatrix}$$

The primary PCs are identified based on eigenvalue which is calculated based on variance-covariance matrix of PCs (4). Eigenvector is applied to project "Train" and "Test" datasets into principle component subspace. The eigenvectors are computed based on the variance-covariance matrix of original data from (3). Since dependent variables (i.e class) are dichotomous in nature, these data are adopted to train the LR model by merging the associated class with each instance of data. The LR model is trained with different cutoff values in order to improve its predictive performance. The cutoff value is defined as the threshold probability of whether a sample belongs to a particular class or not. Once the optimal cutoff value is selected, the "Test" datasets are used to evaluate the model performance. Different performance metrics and results are presented in the next chapter.

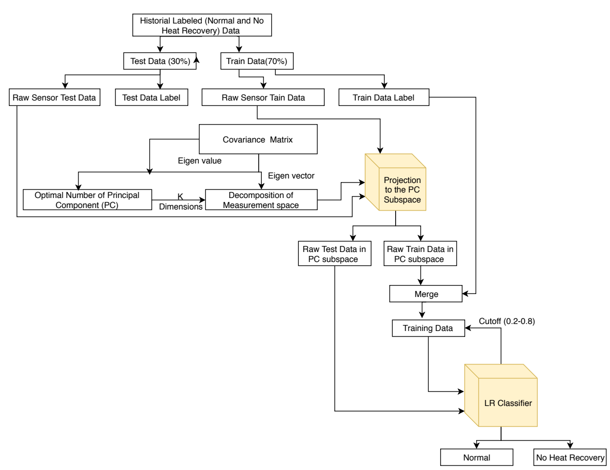
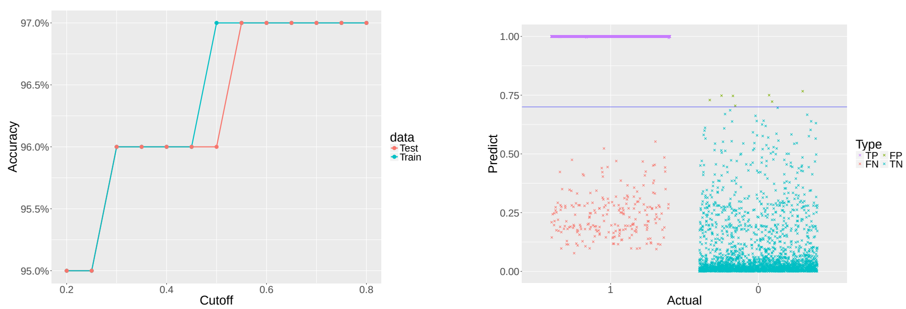


Fig. 2: Heat recovery failure detection methodology

5 Result and Conclusion

As stated, detection and diagnosis of HRU failure is performed by adopting the "Test" dataset. The accuracy of our proposed method for "Train" and "Test" at different cutoff values is shown in Fig. 3 (a). It is clearly seen that the model accuracy is increased from 95% to 97% when the cutoff is changed from 0.3 to 0.8. Detailed performance metrics such as methods Sensitivity and Specificity are presented in Table 2. It is worth noticing that the change in the cutoff value has effects on Sensitivity and Specificity.



(a) Accuracy at different cutoff (b) Confusion matrix with cutoff at 0.7

Fig. 3: Model Results

Fig. 3 (b) depicts the tradeoff between False Negative (FN) and False Positive (FP) for choosing a reasonable cutoff. If we increase the cutoff value, the number of True Negative (TN) increases and the number of True Positive (TP) decreases or in other words, if we increase the cutoff value, the number of FP is lowered, while the number of FN rises. Our main objective is to effectively detect HRU failure for immediate maintenance, thus we chose 0.7 as the final cutoff where the faulty HRU can be detected with 97% accuracy while maintaining perfect specificity of 100% along with 91% sensitivity.

Cut-off value	**Accuracy**	**Sensitivity**	**Specificity**
0.2	0.95	0.95	0.95
0.4	0.96	0.91	0.98
0.6	0.97	0.91	0.99
0.8	0.97	0.91	1.00

Table 2: Performance metrics of proposed methodology to detect HRU failure

In this paper, we presented the application of PCA in combination with LR to detect the HRU failure of the AHU based on nominal efficiency parameters. This method helps quick detection of faulty HRU, which aids to take quick action (such as maintenance of AHU) to avoid further damage. If such faults remain undetected, it may result in unwanted consequences such as wasting of energy and establishing an unhealthy living space. This study focuses on fault detection of a single component (i.e. HRU) of AHU using nominal efficiency. In future, we plan to extend this study to detect other types of fault that might occur in other components during the operation of AHU.

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