AUTOMATED FAULT DETECTION AND DIAGNOSIS FOR ENERGY RECOVERY WHEEL UNITS USING STATISTICAL MACHINE LEARNING METHOD

by

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AUTOMATED FAULT DETECTION AND DIAGNOSIS FOR ENERGY RECOVERY WHEEL UNITS USING STATISTICAL MACHINE LEARNING METHOD

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ABSTRACT: To maintain indoor air quality, there is a need to provide fresh air supply to mechanically conditioned spaces. In tropical climates, supply of fresh air at high temperature increases cooling energy consumption. To reduce the wastage of energy, energy recovery from exhaust air is useful. Energy Recovery Wheel (ERW) can be used to recover both sensible and latent heat from exhaust air at room temperature. If there is a fault in ERW system, it may cause a significant increase in energy consumption compared to the recovered energy. In large commercial buildings with various HVAC equipment installed, faults can remain undetected for hours to months depending on the nature of the fault, results in poor indoor air quality and wastage of energy. In this paper, a method is developed for automating Fault Detection and Diagnosis (FDD) of ERW units. The paper describes the implementation of SVM algorithm on the measured data.

Keywords: Energy Recovery Wheel, Fault Detection and Diagnosis, Support Vector Machine.

INTRODUCTION

According to National Energy Policy, India, about 70% of electricity in India is generated through fossil fuels (NITI Aayog 2017), which are the non-renewable form of energy. Because of the rapidly growing urban sector, the rate at which fossil fuels are consumed is increasing. Buildings consume about 40% of the total annual electrical energy consumption in India (IEA 2015). Thus, for reducing the energy consumption, it is necessary to make the buildings energy efficient. With energy efficiency, indoor air quality is equally important and there are various codes and standards that establish minimum requirements for fresh air (ASHARE 2013), (IGBC 2014), (USGBC 2013). To meet the indoor air quality, generally fresh air is taken from outside which is at higher temperature. This outside air needs to be cooled/heated to supply to occupied conditioned spaces, which leads to wastage of energy. To reduce the wastage of energy one can use energy recovery unit. Energy recovery wheel (ERW) transfers energy from higher energy airstream to the lower energy airstream. In summers, two air streams (supply and exhaust) passes through the wheel, because of the rotation of the wheel, energy from the supply airstream (higher energy) is passed to the exhaust airstream (lower energy). And the vice-versa of this occurs in winters. Here, the energy includes both sensible and latent. Sensible heat transfer occurs because of the difference in the dry-bulb temperatures of the two airstreams and latent heat transfer occurs because of the difference in the vapour pressures of the two airstreams. ERW units are commonly used in commercial, institutional, industrial and multifamily residential buildings to recover energy from exhaust air. So, if there is a fault in ERW units, then it is necessary to diagnose it at the early stage. If not diagnosed early, it may increase the energy consumption instead of reducing it.

LITERATURE SURVEY

According to Annex34 (Dexter and Pakanen 2001), malfunctioning of any of the HVAC equipment can increase the energy consumption of commercial buildings by 10–35%, thus it is necessary to diagnose the fault at early stage. Over the last few decades, many FDD approaches are being proposed for detecting faults in Air Handling Units (AHUs) and chillers. Fault detection and diagnosis methods are generally classified in two categories model-based and data-driven methods (Katipamula and Brambley 2005a, 2005b). Oliveira et al. (2017) proposed a system for detecting and diagnosing faults in dynamic systems using Weightless Neural Networks (WNN). Yan et al. (2018) proposed an algorithm for selecting most important features for FDD in chillers, for making the process of FDD cost effective by selecting the optimum number of sensors. Beghi et al. (2016) used Principal Component Analysis (PCA) for distinguishing between anomalies and fault-free water chillers operation. Li, Hu, and Spanos (2016) adopted Linear Discriminant Analysis (LDA) for detecting and diagnosing faults in water-cooled chillers of building and also determined the severity of faults. Zhu, Jin, and Du (2012) developed combined neural networks by integrating basic neural network and auxiliary neural network for detecting and diagnosing faults in air handling units (AHUs) and also used clustering for classifying the faults. Wang and Xiao (2004) paid attention on developing strategy of FDD for the sensors of AHU using PCA. Later, Du and Jin (2008) further used Principal Component Analysis (PCA) for detecting faults and Fisher Discriminant Analysis (FDA) for diagnosing them in the sensors of AHU. Wang and Qin (2005) proposed PCA for FDD of flow sensors of variable air volume (VAV) box at both system and terminal levels. Lee, House, and Kyong (2004) presented a general regression neural-network (GRNN) for FDD in the AHUs at the subsystem level and demonstrated the effectiveness of the method by showing simulation results. In California, Title 24 code (CEC 2013) requires FDD to be a part of the HVAC system. ERW plays a significant role in reducing energy consumption by recovering considerable amount of the energy from the exhaust airstream (Bartholomew 2004).

RESEARCH GAPS

Previous studies mainly focused on the FDD of the air handling units (AHUs), fans, and chillers. It can be observed that very less research has been done in the field of FDD of Energy Recovery Wheel (ERW) units and also there are not many experimental datasets available for developing FDD techniques for ERW units. This paper fills the gap by creating ERW faults dataset that can be used by any researcher in the field and also developed a FDD technique for detecting and diagnosing some of the faults in a typical ERW unit.

METHODOLOGY

Experimental measurements and data-driven methods have been used in the paper to develop techniques for fault detection and diagnosis for ERW units. Experiments are conducted at FDD lab and measurements are stored in central Building Management System (BMS) server. These measured data is used to test and develop the FDD techniques.

Experimental setup

Experiments were performed in FDD lab which consists of two identical test rooms. Both test rooms are thermally insulated with the extruded polystyrene (XPS) of thickness 100 mm and have identical HVAC equipment such as AHUs, Variable Air Volume (VAV) units, ERWs for studying different kinds of faults present in an HVAC system. Chilled water is supplied to AHUs from air-cooled chiller of 10 TR capacity. For our experiment, we used only one test room. Schematic of the ERW unit and sensors placement are shown in Figure 1 and photograph of recovering unit is shown in Figure 2. Also, this lab has a weather tower to measure outside environmental conditions.

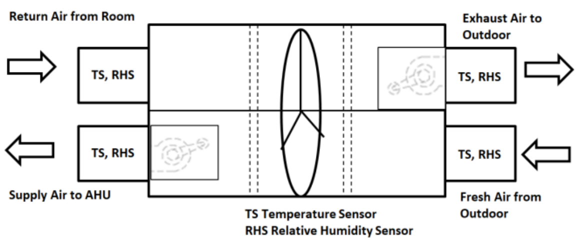

Figure 1 Schematic of Energy Recovery Wheel and Sensor placement

Identification of faults type

There are many sources of information where common faults in parts of HVAC systems are listed for different settings. One of these sources with detailed explanation is a report by IEA Annex 25 (Hyvikinen 1996). But, the report doesn't cover the faults of ERW units. Thus, the faults presented in this paper are found by analyzing the faults found in other HVAC subsystems and also by discussing with the users.

This paper considered five different types of the working conditions and one-off condition of the ERW units. The working conditions considered are:-

1. The normal working condition or the condition with no fault.
2. Fault type 1, an improper working of supply air fan, which is responsible for bringing fresh-air from outside to the system to achieve required outdoor air ventilation rates necessary to meet admissible Indoor Air Quality (IAQ) defined by the ASHRAE Standard 62.
3. Fault type 2, caused by the improper working of exhaust air fan, which is responsible for exhausting room air for maintaining the acceptable CO_2 level in the room.
4. Fault type 3, caused because of improper functioning of rotary wheel. Proper functioning of wheel ensures preconditioning of fresh air, which in turn decreases the load on the compressor.
5. Fault type 4, caused because of improper functioning of both supply and exhaust air fans.

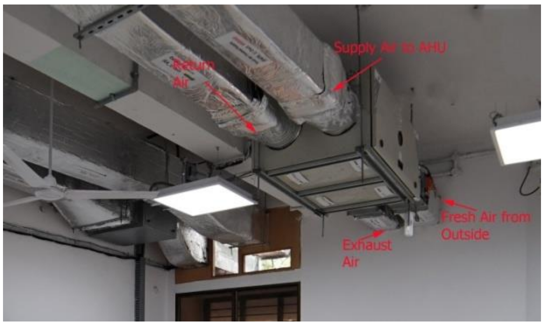

Figure 2 Photograph of Experimental setup

Proposed method detects the fault when the system behavior differs from the expected behavior. As the fault in any component of the ERW unit, instead of saving energy will increase energy consumption and will also affect working and efficiency of the other components. While developing the method, all the combination of major faults in ERW units is considered. Different faults are shown in Figure 5.

Data Collection

Machine learning learns pattern from the given data. For achieving the desired result, set of properties also known as features are recorded or measured from the experiment. Features considered by this paper are Fresh air temperature, supply air temperature, return air temperature, exhaust air temperature, fresh air relative humidity, supply air relative humidity, return air relative humidity and exhaust air relative humidity. Data were logged to BMS server at an interval of one minute.

For measuring relative humidity and temperature, total eight sensors are used. Four SHT21 sensors (Datasheet-SHT21 2014) are used for measuring relative humidity with the typical accuracy tolerance of ±2%RH. For measuring temperature four PT-100 platinum resistance thermometer sensors are used as frontend component with Cypress PSoC 5 microcontroller which has 20-Bit Delta-Sigma ADC is used as the core controller to acquire the temperature data.

Preprocessing of data

Pre-processing is a crucial step before classification as real-world data is generally incomplete, noisy and inconsistent. It converts raw data to an understandable format. As raw data has some missing, out of range and inconsistent values which affect the results, so they are removed. Data is also normalized so that one feature does not dominate other features.

Relative humidity of return air before pre-processing step is shown in Figure 3. It can be observed that it has five missing value which is removed in pre-processing step as shown in Figure 4.

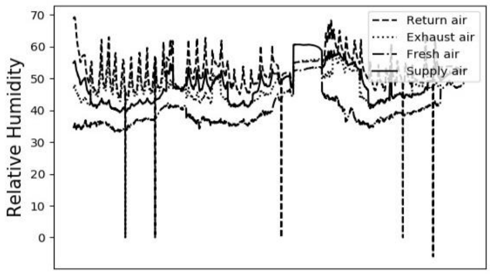

Figure 3 Data before preprocessing

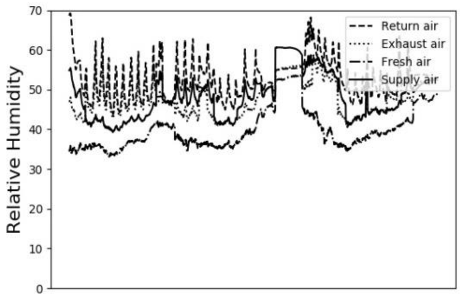

Figure 4 Data after preprocessing

Learning techniques

Machine learning algorithms are used for making the system intelligent and automatic for detecting and diagnosing faults in real-time. They mainly belong to the following categories: Supervised Learning, Unsupervised Learning, Semi-supervised learning or Reinforcement Learning.

Supervised learning algorithm aims to make an adaptive model which learns from the input data and depending upon the algorithm used for training; it picks the function which best describes the training data. The end function f(x) makes the best estimation of output variable y given the input feature vector x such that the error is minimal.

$$y = f(x)$$

For supervised learning algorithms human acts as a teacher for feeding the training data to the system. Training data contains both input (features) and also the correct output (label) corresponding to that input. The system task is to learn the patterns from the given input and output. Supervised Algorithms try to model the dependencies between the input features and the output such that the output can be predicted for the new data features.

The majority of real-life machine uses supervised learning algorithms for making the predictions. The trained system will predict the outcome of the new features and will help in detecting faults and diagnosing which in turn helps in minimizing energy consumption, maximizing occupant comfort, and improve system commissioning.

Supervised learning problems can be divided into two groups, regression and classification. In classification problems, we predict the category or the label y. The classification can be both binary and multi-class. In binary classification, there are two classes to predict from and in Multi-class classification, there are more than two class labels to predict from. One of the popular examples of supervised machine learning algorithm is Support vector machines (SVMs) for classification problems and is used in many practical machine learning problems.

Support Vector Machine algorithm

Support Vector Machines (SVM) is a machine learning algorithm (Vapnik 1998). The present work uses SVM for classifying the features obtained through pre-processing. One-against-all classification is used for classifying the features (Liu and Zheng 2005). The resultant class of the feature helps in identifying if there is a fault present in the system and if presents, then what type of the fault, which in turn helps in diagnosing the fault.

Supervised Support Vector Machine (SVM) allows machine or system to learn from the training data, that is, the classifier is taught what it should expect under normal and faulty conditions. It works well in high dimensional spaces and even when the number of features is greater than the number of samples. It requires less memory as it only uses support vectors in the decision function.

For linearly separable data, n-dimensional data points are separated by a $n-1$ dimensional hyperplane. Though there can be many hyperplanes classifying the data but the best hyperplane is the one that has the largest separation or margin from the classes. So the hyperplane chosen by the SVM is such that its distance from the nearest or closest data points of each class is maximum. Margin from the classes is maximized to minimize the generalization error of the model.

In SVM, data with n-features (n is the number of features) is plotted as a point in an n-dimensional space and the value of each feature is the value of a particular coordinate. Then the algorithm proceeds by finding the set of hyperplanes which are segregating or differentiating the classes very well. SVM not only works well with linear classification but performs efficiently well for non-linear classification as well with the help of kernel-trick which make the classes easily linearly separable by mapping the input features into higher dimensional feature space. Kernel function K is defined as:-

$$K(x, y) = \Phi(x) \cdot \Phi(y)$$

where $\Phi(x)$ and $\Phi(y)$ are representing points x and y respectively in higher dimensional space. We can save on the computational cost a lot by not explicitly computing the dot product of the mapping of the features in higher dimensional space. This is achieved by designing mapping such that the dot product of the mapping of the features in higher dimensional space can be computed easily in terms of the features in the original space.

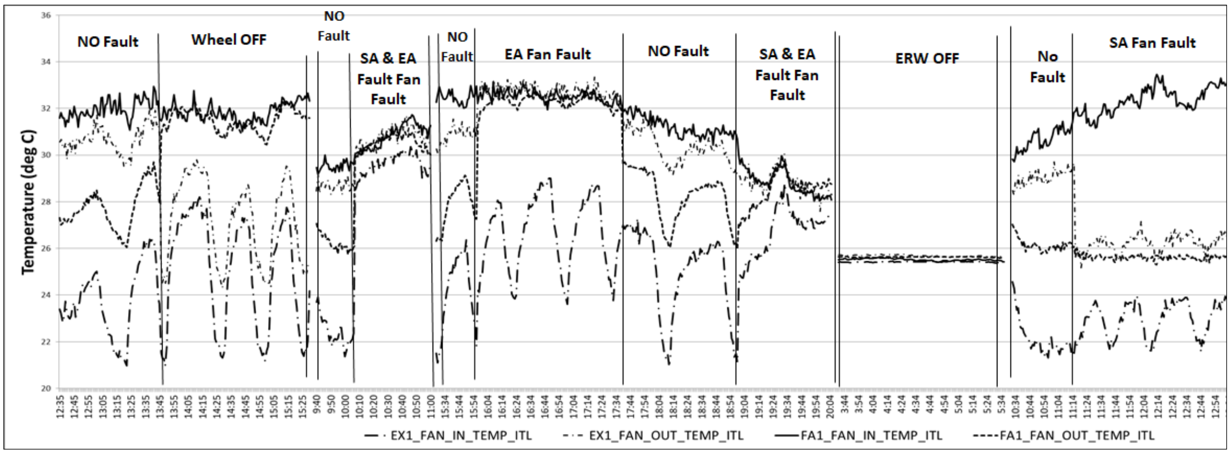

Figure 5 Plot of measured temperature data with different working conditions

Formulation of the SVM for the fault detection

Dataset is shuffled and randomly split into 70% for training and 30% for testing. In training phase, six class data is classified using "One-against-all" method. This method constructs six binary SVM models for the six classes. And, each binary SVM is trained by labeling a class corresponding to it as '1' and rest of the classes as '0'. In the testing phase, a testing sample is classified by all the six binary SVMs. And, each binary SVM classifier gives the probability of that data sample to belong to the class corresponding to it. Finally, the sample is assigned to a class for which it got the highest probability (Hsu and Lin 2002).

Parameter Tuning

Parameter tuning plays a vital role in finding the best model for fault detection and diagnosis. For SVM classifier, three hyper-parameters c, γ and kernel need to be optimized to avoid underfitting and overfitting of the model. This paper chose Grid Search and 10-fold Cross-Validation for finding the best hyperparameters.

Table 1 Confusion Matrix for the RBF kernel without noise

Actual class \ Predicted class	No Fault	Wheel Fault	SA Fan Fault	SA and EA Fans Fault	EA Fan Fault	ERW OFF
No Fault	136	0	0	0	0	0
Wheel Fault	0	112	0	0	0	0
SA Fan Fault	0	0	44	0	0	0
SA and EA Fans Fault	0	0	0	42	0	0
EA Fan Fault	1	0	0	0	81	0
ERW OFF	0	0	0	0	0	67

Table 2 Accuracy of different Kernels without noise

S.No.	SVM Kernal Function	Accuracy of detection (%)	Precision	Recall	F1-score
1	Linear	99.172	99.181	99.172	99.177
2	RBF	99.793	99.794	99.793	99.794
3	Polynomial	99.796	99.794	99.795	99.796
4	Sigmoid	99.792	99.794	99.793	99.793

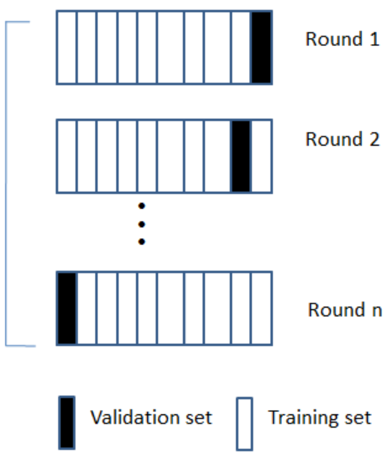

Figure 6 Cross Validation approach

First, data is shuffled and split using Stratified ShuffleSplit cross-validator which provides train and test indices such that data of each class type is present in both the training and testing sets. Training dataset is further divided into ten disjoint subsets and then one by one each subset is used as a validation set as shown in Figure 6 and remaining as training to search the best orderly hyperparameters.

RESULTS AND DISCUSSIONS

SVM is selected as it has given high classification accuracy in many existing works done in FDD (Han et al. 2011). It also works well when the number of features is large which gives Building Management System (BMS) the flexibility of selecting a large number of sensors for predicting the state of the system more accurately. Table 2 shows the maximum accuracy obtained through different kernels on testing data. A training dataset of 1128 data points is used for training and an entirely different dataset of 483 points is used for testing the model.

In Practice, the temperature and relative humidity values measured by the sensors may differ from the actual value and the noise can be present because of many factors like the response time of sensors, calibration uncertainty, sampling issues or may be because of the external heat provided by Infrared radiations due to which temperature sensor may record higher value. Thus, it is necessary to check the performance of the model in the presence of the noises. Table 3 shows the performance of the kernels when the different percentage of continuous random noises are added to the test data. The magnitude of noises added are in the range of ±10%, ±20%, ±30%, ±40%, ±50% and ±60% of the value of the testing data. It can be observed from the table that addition of noises only affect the performance of the RBF kernel.

Table 1 shows the confusion matrix obtained for RBF kernel when no noise is added to the testing data.

CONCLUSIONS

The purpose of this paper is to detect and diagnose faults in Energy recovery Wheel (ERW) units, for this SVM machine learning algorithm is used. Experiments were performed in an FDD test lab specifically designed for air conditioning systems, located in Hyderabad. Real data is collected with a sample rate of one minute.

NOMENCLATURE

Greek letters

γ Width of Gaussian kernel function

Acronyms

AHU	Air Handling Unit
BMS	Building Management System
ERW	Energy recovery Wheel
FDD	Fault Detection and Diagnosis
HVAC	Heating Ventilation and Air Conditioning
IAQ	Indoor Air Quality
LDA	Linear Discriminant Analysis
PCA	PCA Principal Component Analysis
RBF	Radial Bias Function
SVM	Support Vector Machine
VAV	VAV Variable Air Volume
WNN	WNN Weightless Neural Network
XPS	Extruded polystyrene
SA	Supply Air
EA	Exhaust Air
c	Penalty width

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Table 3 Accuracy of different Kernels with noise

Percentage of noise	Kernel	Accuracy	Precision	Recall	F1-score
10	RBF	0.997	0.998	0.997	0.997
20	RBF	0.998	0.998	0.998	0.998
30	RBF	0.988	0.988	0.988	0.988
40	RBF	0.942	0.952	0.942	0.947
50	RBF	0.928	0.945	0.928	0.936
60	RBF	0.874	0.910	0.874	0.892
10	Sigmoid	0.994	0.994	0.994	0.994
20	Sigmoid	0.994	0.994	0.994	0.994
30	Sigmoid	0.992	0.992	0.992	0.992
40	Sigmoid	0.985	0.985	0.985	0.985
50	Sigmoid	0.972	0.972	0.972	0.972
60	Sigmoid	0.964	0.965	0.964	0.964
10	Linear	0.996	0.996	0.996	0.996
20	Linear	0.995	0.995	0.995	0.995
30	Linear	0.993	0.993	0.993	0.993
40	Linear	0.981	0.981	0.981	0.981
50	Linear	0.973	0.973	0.973	0.973
60	Linear	0.954	0.956	0.954	0.955
10	Polynomial	0.997	0.997	0.997	0.997
20	Polynomial	0.994	0.995	0.994	0.994
30	Polynomial	0.993	0.993	0.992	0.993
40	Polynomial	0.986	0.986	0.986	0.986
50	Polynomial	0.969	0.970	0.969	0.970
60	Polynomial	0.953	0.956	0.953	0.954