A Data-driven AFDD Approach Using Acoustic Emission In Building HVAC Systems

Jiajing HUANG[1], Zhiyao YANG[2], Guowen LI[2], Teresa WU[1*], Zheng O'NEILL[2],
Jin WEN[3], K. Selcuk CANDAN[1]

[1]Arizona State University, School of Computing and Augmented Intelligence,
Tempe, AZ, USA
jhuan177@asu.edu; teresa.wu@asu.edu; candan@asu.edu

[2]Texas A&M University, J. Mike Walker '66 Department of Mechanical Engineering,
College Station, TX, USA
z.yang@tamu.edu; guowenli@tamu.edu; zoneill@tamu.edu

[3]Drexel University, Department of Civil, Architectural and Environmental Engineering,
Philadelphia, PA, USA
jw325@drexel.edu

* Corresponding Author

ABSTRACT

Building automatic fault detection and diagnosis (AFDD) technologies have shown great potential for energy savings. Literature on building AFDD research mainly focuses on traditional data available from building automated systems (BAS) or one-time measurements. In this research, we investigate the capability of acoustic emission (AE), a non-traditional data source, to support AFDD in real building heating, ventilation and air-conditioning (HVAC) systems. Experiments were conducted to generate four different AE datasets under different operational scenarios for HVAC systems, where faults were manually injected. The first dataset consists of acoustic data collected from acoustic sensors placed at two different positions (inside/outside) of the same air-cooled chiller under abnormal and normal operations; the second dataset includes acoustic data collected from two identical air-conditioner (AC) outdoor condenser units under abnormal and normal operations; the third one contains acoustic data collected from multiple air diffusers in an experimental residential home under abnormal and normal operations; and the fourth dataset is acoustic data collected under various severity levels of fault conditions occurring in a condenser unit for different time periods. Short-time Fourier Transform (STFT) is used to transform the time series to time-frequency spectrogram, and two different approaches, standard machine learning (ML) and end-to-end deep learning (DL), are used as AFDD strategies to validate the efficacy of AE for the fault detection. For the ML approach, averaged frequency at each time is derived as features fed into random forest classifier; for the DL approach, spectrograms are directly fed into multilayer perceptron. 5-fold cross validation (CV) is repeated 10 times to reduce randomness and avoid overfitting. Experimental results show that AFDD using acoustic data by both the ML and the DL present satisfactory detection performances. For random forest classifier, the averaged fault detection rates are 0.93, 1.00, 1.00 and 0.88 for the four datasets respectively. For multilayer perceptron model, the averaged fault detection rates are 0.97, 1.00, 1.00 and 0.88 respectively. We conclude the use of AE has great potential to support AFDD in the building systems.

1. INTRODUCTION

Buildings are complex and integrated systems consisting of multiple sensors, subsystems, and automatically controlled components. According to International Energy Agency and the United Nations Environment Programme (2018), 36% of global energy use and 39% of energy-related carbon dioxide emission is attributed to building systems. 30% of building energy usage is wasted due to malfunctioning control, operation, and building equipment (Pérez-Lombard et al., 2008; Brambely and Katipamula, 2009). One viable solution for an energy-efficient building system is automatic fault detection and diagnosis (AFDD) (Roth et al., 2004). From building design to the retrofit and commissioning process, understanding the reliability of a building and its energy faults is critical. Faults that degrade the performance of the entire building should be detected, diagnosed, and rectified, while in practice, significant follow-up and technical assistance to correct faults are required once detected and diagnosed. Over the past decades, many AFDD methods have been developed for component level and whole building level. In general, there are two types of AFDD methods (Katipamula and Brambely, 2005): qualitative and quantitative model-based methods (such as rule-based and physics-model based); and process history-based methods (mostly various data-driven and machine learning-based methods). Qualitative and quantitative models are easy to understand and are popular among building engineers and researchers. However, the issues are the high development cost, low scalability due to their needs to be customized for each specific building/project (such as the associated physics-based models, rules, and thresholds). Process history-based methods have therefore received great attention in recent years for their good scalability and low implementation cost. However, the performance of a process history-based method heavily relies on the data that the method is trained from, and it is recognized that the quality of the training data strongly affects the performance of process history-based AFDD tools (Omri et al., 2021). These data usually come from building automated systems (BAS). BAS receives massive sensor readings collected from multiple HVAC components to control and regulate the operational quality of the subsystems (Yuwono et al., 2013), but raw data collected by BAS are usually hard to interpret and in poor qualify since they frequently contain missing values and noise (Simoncicova et al., 2016). Consequently, most literature-reported AFDD methods developed and evaluated based on simulated BAS data (Li and O'Neill, 2018), not only because it is difficult to obtain and analyze real BAS data but also implementing faults and obtaining data that contain fault impacts in real buildings are already challenging. Meanwhile, there are potential limitations using simulated BAS data since AFDD strategy by these data is unable to capture the real fault symptom even though they are validated by building physical domain knowledge (Huang et al., 2022). Given these limitations, building engineers may consider alternative data for AFDD.

Nowadays, acoustic emission (AE) technologies have attracted attention for fault detection and diagnosis. AE is defined as a transient elastic wave generated by the rapid release of energy within materials (e.g., a crack occurring inside a material) (Pao et al., 1979). AE technologies have been widely used for anomaly detection and localization in many industrial fields. For example, studies from Tan et al. (2007) compare capabilities of vibration-based technologies with those of AE-based ones for fault diagnosis and prognosis, whose results indicate that AE-based techniques may be more sensitive in detecting and monitoring pitting than vibration. Li et al. (2009) study AE-based techniques for gear damage detection and show that AE-based techniques are able to reach higher classification accuracy than vibration-based techniques. Compared to the most widely used vibration signals, AE signals share certain advantages (Holroyd, 2000): (1) they are not sensitive to typical mechanical background noise and structural resonance but sensitive to activities and location of faults; (2) they provide good trending parameters. These advantages make AE technologies strongly capable of rapid detection, high sensitivity, real-time response and ease of retrofitting (Li and He, 2012).

Motivated by these findings, in this research, we investigate the capability of acoustic emission (AE), a non-traditional data source, to support AFDD in real building heating, ventilation and air-conditioning (HVAC) systems. Experiments were conducted to generate various AE datasets under different operational scenarios for HVAC systems, where faults were manually injected. Short-time Fourier Transform (STFT) is used to transform the time series to time-frequency spectrogram, and two different approaches, standard machine learning (ML) and end-to-end deep learning (DL), are used as AFDD strategies to validate the efficacy of AE for the fault detection.

The paper are organized as follows. Related works on acoustic emission are presented in Section 2, and methodology is described in Section 3. Experiments are presented in Section 4, followed by the results and discussion in Section 5. Conclusions and future work are drawn in Section 6.

2. LITERATURE REVIEW

Data-driven building AFDD methods on BAS data have shown great potential for characterizations on system-level operations and developments of accurate system models mainly because they do not depend on modeling and only rely on the system data (Yang and Rizzoni, 2016). Kim and Katipamula (2018) state that data-driven approaches as history-based AFDD methods are best applied to complicated systems or where the theoretical system behavior of the model is insufficient to clarify the performance of the system.

Data-driven methods on BAS data can be in general categorized into traditional machine learning-based and end-to-end deep learning-based methods. Extensive efforts have been dedicated to investigating machine learning models for building AFDD. For example, Wang et al. (2021) propose a random forest-based self-adaptive model to detect and diagnose multiple simultaneously occurring faults in variable air volume (VAV) systems; Tun et al. (2021) develop a hybrid random forest-support vector machine, which is able to detect faults with insignificant symptoms while reducing the required number of sensors. Recently, deep learning-based methods such as neural networks draw increasing attention mainly because they could provide more accurate results than other supervised machine learning-based methods given a limited number of labeled data available (2019). For example, Fan et al. (2021) applied semi-supervised neural networks for statistical characterization on fault detection and diagnosis of air handling units, which effectively enhance model generalization and provide insightful direction for a data-driven AFDD tools development; Taheri et al. (2021) study various deep recurrent neural networks (DRNNs) and identify the optimal hyperparameters of DRNNs for the HVAC system fault diagnosis.

It is noted most research reviewed above focuses on BAS system. In fact, there exists research investigating machine learning and deep learning algorithm for fault detection and diagnosis in machinery (not building) using acoustic data. For example, Rai et al. (2021) propose a pipeline leakage detection using acoustic emission event features with Kolmogorov-Smirnov (KS) test, which demonstrates outperformances over traditional features such as mean and variance; Jierula et al. (2021) develop a novel detection method for the damage locations in pile foundations based on deep learning using acoustic emission data, and demonstrate the proposed method is capable of continuously detecting and evaluating the severity level of pile foundation damage. To the best of our knowledge, there is limited work on building AFDD using acoustic data. Observing from the reported literature, acoustic data has been used for fault detection and diagnosis on rotational machine in non-building system fields. Considering that many heating, ventilating, and air conditioning systems (HVAC) include rotational machines, such as fans, pumps, and chillers, it is expected that acoustic data can be applied in building AFDD domain. Indeed, commissioning engineers have long used sounds and noises coming from a HVAC equipment as a way to evaluate its health during manual inspection.

3. METHODOLOGY

Given acoustic sensor data, the first step is to extract features for model training and testing. Depending on what kinds of models used for building AFDD, approaches for feature extraction vary from one to another. Therefore, as is shown in Fig. 1, we are exploring two approaches to for acoustic sensor data: (1) transforming temporal acoustic data into multiple frequencies so traditional machine learning models can be applied; (2) transforming acoustic data (1D) into spectrogram (2D) images so deep models can be applied. Both data pre-processing are realized by short-time Fourier transform (STFT). STFT (Mitra, 1997) is a processing technique used to analyze the varying frequency components of a signal over time. It's a powerful tool for understanding how the frequencies in a signal change, which is essential in audio and soundwave processing.

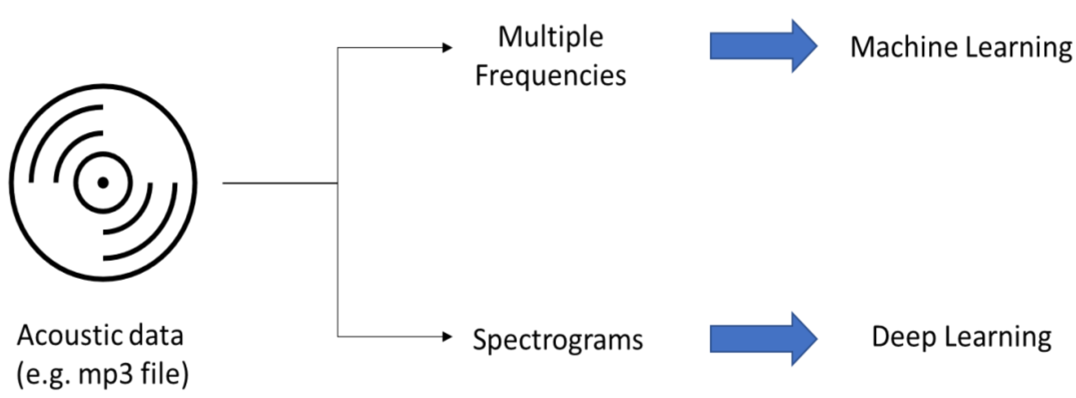

Figure 1: Two approaches for acoustic data learning. (1) Transform acoustic data into multiple frequencies and then apply machine learning methods; (2) Transform acoustic data into spectrograms and then apply deep learning methods.

Consequently, our methods are detailed as shown in Figure 2. We are given two acoustic datasets, one under faulty and another under fault-free conditions. We first do segmentation and divide both data into equal-size time segments. For each acoustic time segment, we may extract multiple frequencies as features for each segment for traditional machine learning (shown in Figure 2 (A)), or obtain spectrograms for deep learning (shown in Figure 2 (B)), both by STFT. Finally, we train corresponding models using these extracted features to observe the fault detection performances.

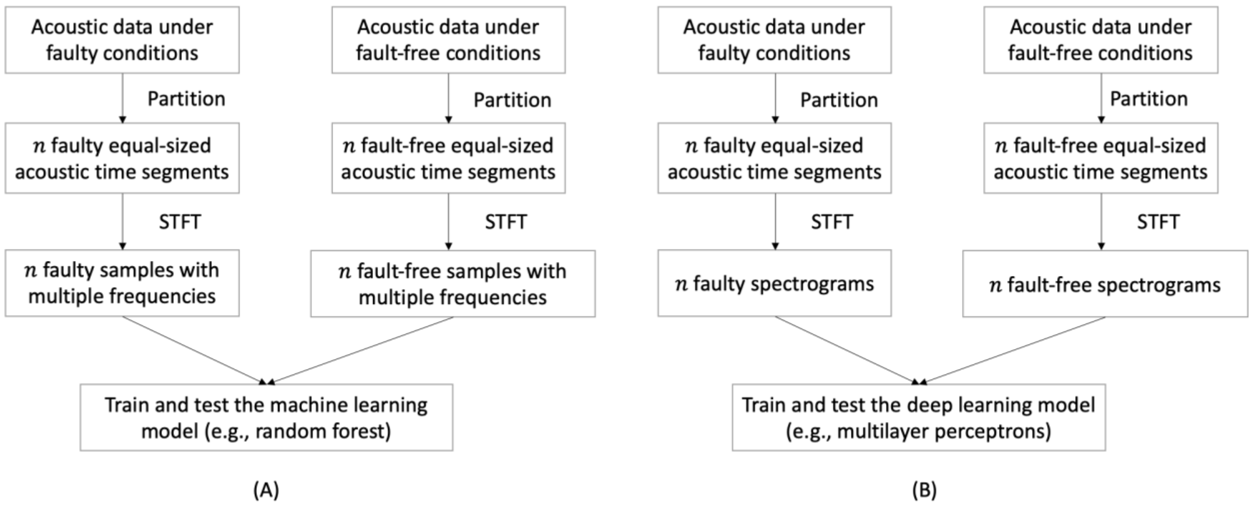

Figure 2: Flowcharts of acoustic data preprocessing and fault detection (A) machine learning methods (B) deep learning methods.

4. EXPERIMENTS

4.1 Experimental datasets

We have conducted our experiments on four sets of acoustic data collected under various settings from different building HVAC subsystems (see Figure 3). The first set of data (DS1) are collected from two different positions of one air-source chiller (Calfa et al., 2023) as shown in Figure 3(A), namely Chiller Inside where the acoustic sensor is placed within the chiller package, and Chiller Outside where the acoustic sensor is placed outside of the chiller package. For each position, there are two types of data: data with noise (the chiller operates under faulty condition), and data with less noise (chiller operates under normal condition).

The second set of data (DS2) are collected from two A/C outdoor units, one in building A (denoted as A/C-A) and another in B (denoted as A/C-B) from the Texas A&M Smart and Connected Homes Testbed (TAM-SCHT) (Firsich et al., 2022). For each unit, there are two acoustic datasets: one under faulty condition and another under fault-free condition. The fault is injected by covering part of the air intake around the A/C outdoor unit to mimic a major fouling in the condenser heat exchanger (see Figure 3(B)).

The third set of data (DS3) are collected from the air handling unit (AHU) and five air diffusers in the TAM-SCHT, as shown in Figure 3(C) , in an experimental residential home under two different operations (faulty and fault-free). Under fault-free conditions, all the air diffusers are opened, while under faulty conditions, they are closed.

The fourth dataset (DS4) is acoustic data collected under various severity levels of fault conditions occurring in a condenser unit for different time periods. The injected fault is covering part of the air intake around the unit to mimic major fouling in the condenser heat exchanger. There are 6 different covering stages, and each covering stage mimicked one different fault stage. At the beginning of operations, the condenser is operating without any interruption. As shown in Figure 3(D), in stage 1, one cardboard is added to cover the side of the condenser, representing the first level of faulty severity; next in stage 2, one more cardboard is added, representing the second level of faulty severity; this process is repeated until stage 6 is reached. Therefore, the collected acoustic data contained seven statuses of operational conditions, saying fault-free (Stage 0), Stage 1, Stage 2, Stage 3, Stage 4, Stage 5, and Stage 6. Detailed information about datasets, including location, operational conditions and corresponding duration can be found in Table 1.

Figure 3: Acoustic data collected under various settings from (A) Air-source chiller; (B) A/C outdoor units; (C) AHU and Air diffusers; and (D) Condenser units.

Table 1. Description of diffuser acoustic data (DS4)

Acoustic datasets		Operational conditions	Duration (in seconds)
DS1	Chiller Inside	Noisy (faulty)	139
		Less noisy (fault-free)	127
	Chiller Outside	Noisy (faulty)	139
		Less noisy (fault-free)	120

DS2	A/C – A	Faulty	668
		Fault-free	634
	A/C – B	Faulty	646
		Fault-free	607
DS3		Faulty	804
		Fault-free	723
DS4		Stage 0 (fault-free)	605
		Stage 1	600
		Stage 2	1115
		Stage 3	615
		Stage 4	595
		Stage 5	620
		Stage 6	640

4.2. Evaluations

Our machine learning model is Random Forest (RF) classifier with max depth = 10, and deep learning model is Multilayer Perceptron (MLP) with 100 epochs, 0.0001 learning rate and 10 hidden layer neuros, respectively. For both models, we apply 5-fold cross validation (CV), each fold with 10 times training to reduce randomness.

Suppose we have n samples under faulty conditions. For any faulty sample s_i, let us define an indicator $I(s_i)$, such that:

$$I(s_i) = \begin{cases} 1, & \text{correctly identifed as faulty} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Then our evaluation metric, fault detection rate (FDR), is defined as below:

$$FDR = \frac{\sum_{i=1}^{n} I(s_i)}{n} \tag{2}$$

Finally, we report the averaged fault detection rate for each acoustic data using RF and MLP.

5. RESULTS AND DISCUSSION

In this section, we report experimental results on four sets of acoustic data, including data dimensions, and corresponding fault detection rates for machine learning (RF) and deep learning (MLP) respectively.

5.1. Experimental results by RF on acoustic datasets

Tables 2 summarize our experimental data processed by feature extractions on the chiller acoustic data (DS1), the A/C acoustic data (DS2), the diffuser acoustic data (DS3), and the condenser acoustic data (DS4), respectively. For RF, features are magnitude values generated from STFT, which represent the power density of the acoustic data. Note that durations for data collection vary from one setting to another; Consequently, for each dataset and each individual location, we select the equal time duration and divide into equal size time window for each operational conditions to process the data so that we have the balanced faulty and fault-free samples for model training and testing. Let's take the Chiller Insider from the DS1 as an example. We choose 126-second duration for both noisy and less noisy Chiller Inside acoustic data, and divide them using the time window of 2 seconds into 63 segment (63 samples). Next we apply STFT to extract 129 features on each sample; As a result, we have 63 sample, each with 129 features for both faulty and fault-free data as the RF model input. Specifically, for DS1 or DS2, we report the fault detection performance by taking the average of Chiller Inside/Outside, and both A/C units, respectively.

Table 2. Summary of each processed acoustic data used for RF training

Acoustic datasets	Operational conditions	Input dimension

DS1	Chiller Inside	Noisy (faulty)	63 samples, each sample with 129 features
		Less noisy (fault-free)	
	Chiller Outside	Noisy (faulty)	60 samples, each sample with 129 features
		Less noisy (fault-free)	
DS2	A/C – A	Faulty	63 samples, each sample with 129 features
		Fault-free	
	A/C – B	Faulty	60 samples, each sample with 129 features
		Fault-free	
DS3		Faulty	600 samples, each sample with 129 features
		Fault-free	
DS4		Stage 0 (fault-free)	118 samples, each sample with 129 features
		Stage 1	
		Stage 2	
		Stage 3	
		Stage 4	
		Stage 5	
		Stage 6	

Figure 4 shows the performances by RF on each acoustic data using extracted features. As is observed, using RF, the fault detection rates are 0.93 for DS1, 1.00 for DS2, 1.00 for DS3 and 0.88 for DS4. From the results presented above, we can observe that features extracted by STFT from acoustic data collected from building systems can provide satisfactory fault detectability using traditional machine learning approach (RF), with averaged fault detection rate greater than 0.85.

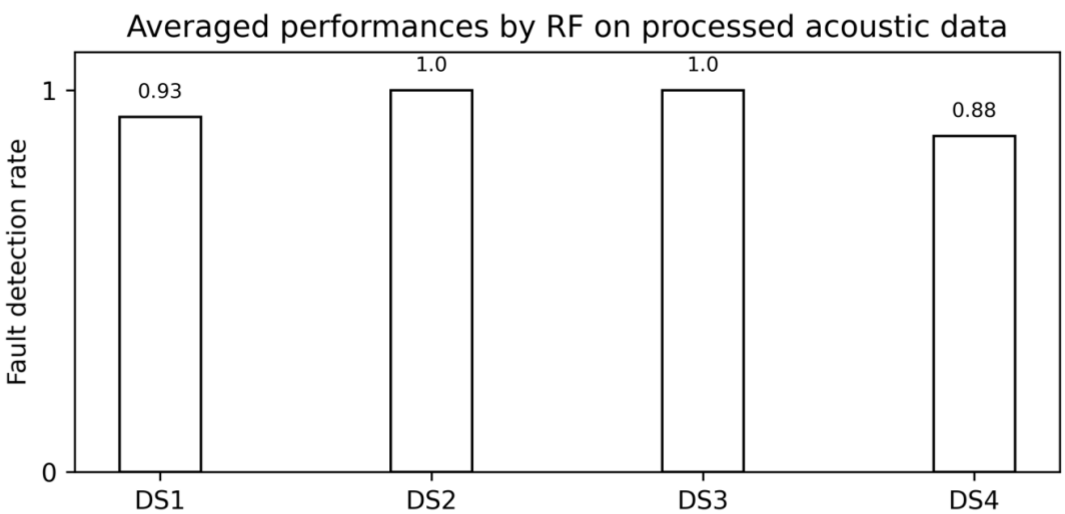

Figure 4: Averaged performances by RF on four processed acoustic data

5.2. Experimental results by MLP on acoustic datasets

Tables 3 summarize our experimental data processed by feature extractions on the chiller acoustic data (DS1), the A/C acoustic data (DS2), the diffuser acoustic data (DS3), and the condenser acoustic data (DS4) for MLP model, respectively. For MLP, features are spectrograms, a visualized representation of the magnitudes. Figure 5 illustrates an example of how spectrograms look like for DS1 (Noise (Faulty) / Less Noise (Fault-free) at Chiller Inside), which are applied to any other acoustic data in this study.

Table 3. Summary of each processed acoustic data used for MLP training

Acoustic datasets	**Operational conditions**	**Input dimension**

DS1	Chiller Inside	Noisy (faulty)	63 samples; each sample is a 129 x 5 image
		Less noisy (fault-free)	
	Chiller Outside	Noisy (faulty)	60 samples; each sample is a 129 x 5 image
		Less noisy (fault-free)	
DS2	A/C – A	Faulty	63 samples; each sample is a 129 x 5 image
		Fault-free	
	A/C – B	Faulty	60 samples; each sample is a 129 x 5 image
		Fault-free	
DS3		Faulty	600 samples; each sample is a 129 x 5 image
		Fault-free	
DS4		Stage 0 (fault-free)	118 samples; each sample is a 129 x 5 image
		Stage 1	
		Stage 2	
		Stage 3	
		Stage 4	
		Stage 5	
		Stage 6	

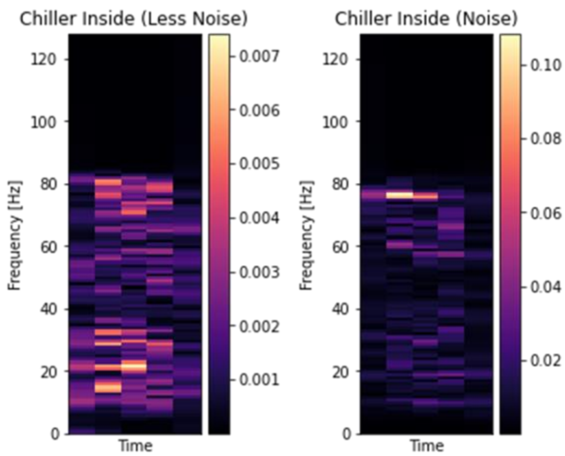

Figure 5: Spectrograms by STFT for Chiller Inside: Noisy data (left), and less noisy data (right)

Figure 6 shows the performances by MLP on acoustic data using spectrogram images. As is observed, using MLP, the fault detection rates are 0.97 for DS1, 1.00 for DS2, 1.00 for DS3 and 0.88 for DS4. From the results presented above, we can observe that spectrogram images extracted by STFT from acoustic data collected from building systems can provide satisfactory fault detectability using end-to-end deep learning approach (MLP), with averaged fault detection rate greater than 0.85.

In summary, the experimental results indicate that the use of acoustic emission has potential support for data-driven building AFDD.

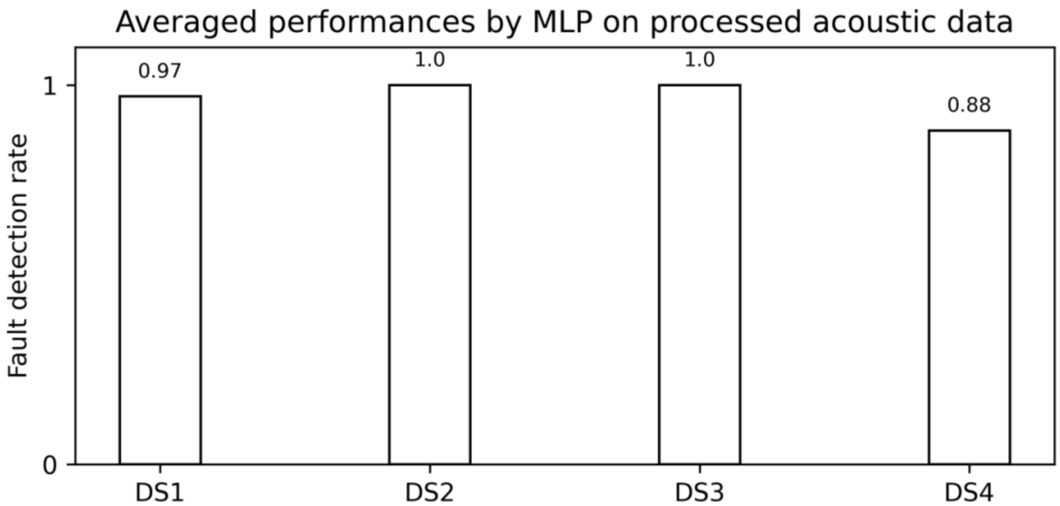

Figure 6: Averaged performances by MLP on four processed acoustic data

6. CONCLUSIONS AND FUTURE WORK

In this research, we investigate the capability of acoustic emission (AE), a non-traditional data source, to support AFDD in real building heating, ventilation and air-conditioning (HVAC) systems. Experiments were conducted to generate four different AE datasets under different operational scenarios for HVAC systems, where faults were manually injected. Short-time Fourier Transform (STFT) is used to transform the time series to time-frequency spectrogram, and two different approaches, standard machine learning (ML) and end-to-end deep learning (DL), are used as AFDD strategies to validate the efficacy of AE for the fault detection. For the ML approach, averaged frequency at each time is derived as features fed into random forest classifier; for the DL approach, spectrograms are directly fed into multilayer perceptron. 5-fold cross validation (CV) is repeated 10 times to reduce randomness and avoid overfitting. Experimental results show that AFDD using acoustic data by both the ML and the DL present satisfactory detection performances. For random forest classifier, the averaged fault detection rates are greater than 0.85 for all four datasets. For multilayer perceptron model, the averaged fault detection rates are greater than 0.85. We can draw our conclusion that the use of AE has great potential to support AFDD in the building systems.

As a starting point, we've conducted research on a certain sets of field acoustic data collected from HVAC equipment, including chillers, A/Cs, diffusers and condensers with very few types of faults. In the future, we are interested in investigating the capacity of acoustic data collected from more complex building systems under multiple fault conditions for fault detections.

REFERENCES

Brambley, M.R., & Katipamula, S. (2009). Commercial building retuning. *ASHRAE Journal*, 51, 12-23.

Calfa, C., Yang, Z., Li, Y., Chen, Z., O'Neill, Z., & Wen, J. (2023). Performance assessment of a real water source heat pump within a hardware-in-the-loop (HIL) testing environment. *Science and Technology for the Built Environment*, 29(10), 1011-1026.

Fan, C., Liu, X., Xue, P., & Wang, J. (2021). Statistical characterization of semi-supervised neural networks for fault detection and diagnosis of air handling units. *Energy and Buildings*, 234, 110733.

Firsich, T., Feng, F., & Zheng O'Neill PhD, P. E. (2022). Texas A&M Smart and Connected Homes Testbed (TAM-SCHT): An Evaluation and Demonstration Platform for Smart & Grid-interactive Technologies. *ASHRAE Transactions*, 128, 274-282.

Holroyd, T. (2000). Acoustic emission and ultrasonics monitoring handbook. Coxmoor Publishing.

Huang, J., Wen, J., Yoon, H., Pradhan, O., Wu, T., O'Neill, Z., & Candan, K.S. (2022). Real vs. simulated: questions on the capability of simulated datasets on building fault detection for energy efficiency from a data-driven perspective. *Energy and Buildings*, 259, 111872.

International Energy Agency & United Nations Environment Programme. (2018). 2018 Global Status Report: Towards a zero-emission, efficient, and resilient buildings and construction sector.

Jierula, A., Oh, T., Wang, S., Lee, J., Kim, H., & Lee, J. (2021). Detection of damage locations and damage steps in pile foundations using acoustic emissions with deep learning technology. *Frontiers in Structural and Civil Engineering*, 15, 318-332.

Jin, B., Li, D., Srinivasan, S., Ng, S., Poolla, K., & Sangiovanni-Vincentelli, A. (2019). Detecting and diagnosing incipient building faults using uncertainty information from deep neural networks. *In Proceedings of the 2019 IEEE International Conference on Prognostics and Health Management (ICPHM)* (pp. 1–8).

Katipamula, S., & Brambley, M.R. (2005). Methods for fault detection, diagnostics, and prognostics for building systems—a review, part I. *HVAC&R Research*, 11(1), 3-25.

Kim, W., & Katipamula, S. (2018). A review of fault detection and diagnostics methods for building systems. *Science and Technology for the Built Environment*, 24(1), 3–21.

Li, R., & He, D. (2012). Rotational machine health monitoring and fault detection using EMD-based acoustic emission feature quantification. *IEEE Transactions on Instrumentation and Measurement*, 61(4), 990-1001.

Li, R., He, D., & Bechhoefe, E. (2009). Investigation on fault detection for split torque gearbox using acoustic emission and vibration signals. *In Proceedings of the Annual Conference of Prognostics and Health Management Society* (pp. 1–11). San Diego, CA.

Li, Y., & O'Neill, Z. (2018). A critical review of fault modeling of HVAC systems in buildings. *Building Simulation*, 11(5), 953-975.

Mitra, S. K. (1997). Digital signal processing: A computer-based approach. McGraw-Hill.

Omri, N., Al Masry, Z., Mairot, N., Giampiccolo, S., & Zerhouni, N. (2021). Towards an adapted PHM approach: Data quality requirements methodology for fault detection applications. *Computers in Industry*, 127, 103414.

Pao, Y., Gajewski, R., & Ceranoglu, A. (1979). Acoustic emission and transient waves in an elastic plate. *Journal of the Acoustical Society of America*, 65(1), 96–105.

Pérez-Lombard, L., Ortiz, J., & Pout, C. (2008). A review on buildings energy consumption information. *Energy and Buildings*, 40(3), 394–398.

Rai, A., Ahmad, Z., Hasan, M., & Kim, J. (2021). A novel pipeline leak detection technique based on acoustic emission features and two-sample Kolmogorov-Smirnov test. *Sensors*, 21, 8247.

Roth, K.W., Westphalen, D., Llana, P., & Feng, M. (2004). The energy impact of faults in US commercial buildings. *In Proceedings of the International Refrigeration and Air Conditioning Conference* (pp. 665). West Lafayette, IN.

Simoncicova, V., Hrcka, L., Tadanai, O., Tanuska, P., & Vazan, P. (2016). Data preprocessing from production processes for analysis in automotive industry. *In Proceedings of the 27th Central European Conference on Information and Intelligent Systems* (pp. 17–21). Zagreb, Croatia.

Taheri, S., Ahmadi, A., Mohammadi-Ivatloo, B., Asadi, S. (2021). Fault detection diagnostic for HVAC systems via deep learning algorithms. *Energy and Buildings*, 250, 111275.

Tan, C., Irving, P., & Mba, D. (2007). A comparative experimental study on the diagnostic and prognostic capabilities of acoustics emission, vibration and spectrometric oil analysis for spur gears. *Mechanical Systems and Signal Processing*, 21(1), 208–233.

Tun, W., Wong, J., & Ling, S. (2021). Hybrid random forest and support vector machine modeling for HVAC fault detection and diagnosis. *Sensors*, 21, 8163.

Wang, H., Feng, D., & Liu, K. (2021). Fault detection and diagnosis for multiple faults of VAV terminals using self-adaptive model and layered random forest. *Building and Environment*, 193, 107667.

Yang, R., & Rizzoni, G. (2016). Comparison of model-based vs. data-driven methods for fault detection and isolation in engine idle speed control system. *In Proceedings of the Annual Conference of the Prognostics and Health Management Society* (pp. 1–9).

Yuwono, M., Su, S.W., Guo, Y., Li, J., West, S., & Wall, J. (2013). Automatic feature selection using multiobjective cluster optimization for fault detection in a heating ventilation and air conditioning system. *In Proceedings of the 1st International Conference on Artificial Intelligence, Modelling and Simulation* (pp. 171-176).

ACKNOWLEDGMENT

This study was funded by the U.S. Department of Energy through the CYDRES Project (Securing Grid-interactive Efficient Buildings (GEB) through Cyber Defense and Resilient System (CYDRES)).