2023 European Conference on Computing in Construction
40th International CIB W78 Conference
Heraklion, Crete, Greece
July 10-12, 2023

ADVANCES IN DATA-DRIVEN FAULT DETECTION AND DIAGNOSIS FOR HVAC SYSTEMS: A REVIEW OF RECENT DEVELOPMENTS

Farivar Rajabi[1] and J.J. McArthur[1]
[1]Toronto Metropolitan University, Toronto, ON, Canada

Abstract

Building performance can degrade precipitously after commissioning without adequate maintenance. HVAC system malfunctions can result in excessive energy consumption, associated CO_2 emissions, poor indoor environmental quality, and productivity loss. Fault Detection and Diagnosis (FDD) algorithms using sensor networks and IoT devices are a topic of significant research. This paper presents a comprehensive literature review of HVAC FDD applications using machine learning methods, including supervised classification, unsupervised learning, regression, statistics-based, and hybrid approaches. Each is discussed with respect to their state of development, relative advantages and limitations.

Keywords: Fault Detection and Diagnosis; Machine Learning; Data-driven; HVAC System; Supervised Classification; Unsupervised Learning, Regression and Statistical Approaches, Hybrid Methods

Introduction

Heating, ventilation, and air conditioning (HVAC) systems account for over 40% of the total building energy consumption, making them one of the most critical mechanical systems (DoE, 2011). When an HVAC system malfunctions, it can negatively impact the health and productivity of occupants and adversely affect the quality of thermal comfort in the building (Gärtner et al., 2020). Building HVAC systems can also waste large amounts of energy, reducing the energy efficiency of the building. It has been estimated that faults with HVAC and lighting systems can increase energy consumption by approximately 4% to 18% (Chen et al., 2022). Improper maintenance, malfunctioning components, installation faults, and control errors can significantly degrade HVAC systems. Maintaining fault-free operation of HVAC systems can be challenging because of their many interconnected components and complex interactions with occupants and buildings. To ensure proper functioning of HVAC systems, automated FDD techniques are promising solutions. As building management systems improve with the latest sensors used within buildings as well as advances in computing methods, this process has become more efficient.

Increasing attention is being paid to FDD for HVAC systems due to its importance to building energy efficiency. Several previous reviews summarized and categorized knowledge-based, model-based, and data-driven FDD approaches (Katipamula & Brambley, 2005; Mirnaghi & Haghighat, 2020).

Data-driven FDD approaches have become increasingly promising as building management systems and computational methods advance. While the use of machine learning-based FDD in HVAC systems has been extensively studied over the last decade, there remains lack of comprehensive reviews of such methods. This current paper addresses this research gap, providing a comprehensive review of machine learning-based data-driven fault detection and diagnosis for HVAC systems. This paper compares methods and recommends the best available approaches based on their limitations and advantages. In addition, different building types, systems, and symptoms make the data-driven FDD techniques challenging. In order to address these challenges several approaches have been proposed in recent years. The purpose of this paper is to provide scholars in this domain with a comprehensive review of recent advances in data-driven FDD for HVAC systems.

Background

This paper categorizes FDD methods into three types: knowledge-based approaches, data-driven approaches, and hybrid knowledge-based and data-driven approaches. These approaches as well as current challenges are briefly described in this section.

Knowledge-based approaches

In knowledge-based approaches, a base model is developed using physics or engineering knowledge. This process is known as white-box modeling. In this approach a continuous comparison is conducted between the measured HVAC operation status and the normal operating baselines depicted by the model. Using residual analysis, it is possible to determine the differences (or residuals) between the actual operating state determined from measurements and the expected operating state and values of characteristics determined from the model, thus detecting abnormalities and diagnosing faults at different levels. Even though physical models help detect faults more accurately, their development is time-consuming and tedious, particularly in large HVAC systems.

Data-driven approaches

Data-driven ("black box") approaches rely solely on process data to generate behavioral models that relate input and output data. Data-driven methods have become more widely used for FDD due to advances in communication and computing technology, decreasing device costs (Zhao et al., 2019), and ease of collecting Building Management System data. Further, these methods do not require a deep understanding of physics, nor significant building knowledge. However, data-driven measures are limited by their high dependency on the quantity and quality of the process data (Yang et al., 2014) and are unreliable outside their training domain.

Hybrid knowledge-based and data-driven approaches

Hybrid approaches, also known as gray box modeling, take advantage of both data-driven and knowledge-based models. A mathematical or rule form is specified using prior knowledge, but parameters are determined from process data. These models are simpler in form, making them easy to use and highly capable of being applied in HVAC equipment for online FDD. In contrast to data-driven models, estimated parameters have physical significance, making them more robust. However, since small uncertainties in data can lead to relatively large changes in physical parameters, minimization of measurement error is essential for meaningful and robust estimates.

Current challenges for FDD

FDD in HVAC systems allows for the early detection and diagnosis of faults in order to prevent further damage to the system or the loss of service. However, in practice, challenges arise due to variable HVAC operation responding to occupancy and weather (Chen et al., 2022), the diversity of interconnected subsystems (Sun et al., 2013), and complex fault symptoms (Verbert et al., 2017). Further, multiple concurrent faults may occur with related or unrelated causes, exhibiting conflicting symptoms.

Comparison of FDD approaches

It is critical for industries to detect and isolate faults early and accurately as part of predictive maintenance. With the advent of sensor networks, huge amounts of data are available for the development of AI-based automated FDD frameworks, permitting sensor data to be analyzed directly using machine learning and statistical techniques. The followings sections summarize the findings of the past 20 years (with emphasis on the last 5) of research on machine learning-based FDD approaches, covering supervised classification, unsupervised learning, regression-based, and hybrid data-driven methods.

Supervised classification

Supervised learning techniques develop a function that maps a set of features to a known label or output. In FDD, supervised classification is used to distinguish between faulty and fault-free operation status by analyzing data characteristics; support vector machine (SVM), artificial neural network (ANN), and ensemble algorithms are frequently used for this purpose.

SVMs have been demonstrated to be an effective machine-learning technique in the field of FDD for HVAC systems. A key challenge with SVM is its high dependence on the quality and quantity of labeled data, which is pushing increased research into hybrid and enhanced SVM derivations in recent studies (Mirnaghi and Haghighat, 2020). Recent studies have focused on either a) combining SVMs with various pre-processing methods such as wavelet analysis and feature selection schemes or b) enhancing SVM to improve its prediction accuracy and computational speed for FDD. For example, in order to improve the quality of collected experimental variable refrigerant flow (VRF) data, Sun et al. (2016) proposed wavelet analysis to increase the prediction accuracy of the SVM-based FDD framework. The recently developed LS-SVM (least squares support vector machine) has been used to improve the convergence speed, using linear equations to reduce the complexity of the algorithm. To investigate faults in centrifugal chillers, Han et al. (2019) developed an LS-SVM model improved by cross-validation finding that it outperforms SVM to solve FDD problems with small data samples.

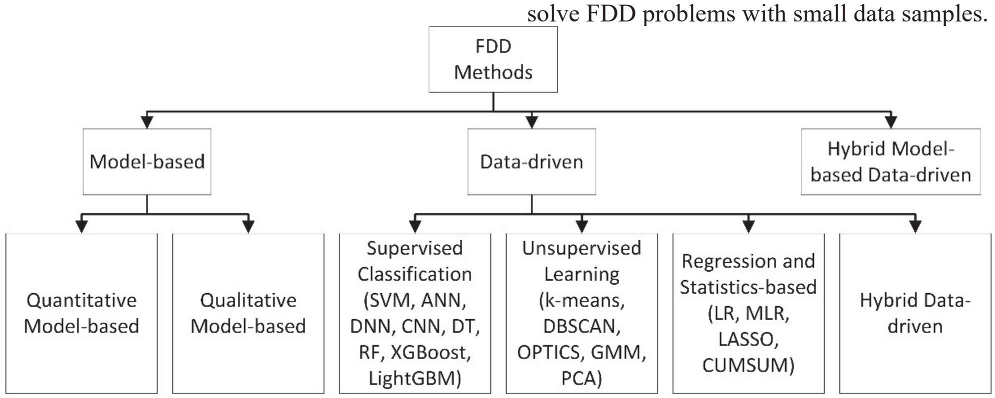

Figure 1. Classification fault detection and diagnostic methods

Artificial neural networks (ANNs) have also been widely applied for FDD since its ability to establish nonlinear decision boundaries makes them ideal for pattern recognition. However, because they cannot reveal the internal data mining mechanisms, diagnosis and root cause analysis become challenging. Newer ANNs using deep learning, have gained a significant amount of attention in recent FDD studies (Zhou et al., 2020; Lee et al., 2019) due to their relatively high accuracy, particularly when labeled data are scarce. Zhou et al. (2020) utilized a deep neural network (DNN) method in VRF system fault diagnosis for single and multiple fault diagnosis, demonstrating that DNN outperformed SVM and shallow neural networks, especially in multiple fault cases. Another study (Lee et al., 2019) applied deep learning for real-time AHU fault diagnostics with 95.16% accuracy. However, efficiently capturing multiscale features is challenging for this algorithm. To address this issue, Cheng et al. (2021) proposed a multiscale convolutional neural networks (CNN) for the fault diagnosis of AHU. By eliminating the requirement for complex feature engineering, this method was shown to be well-suited to multiscale monitoring signals, outperforming previous FDD methods. However, in online fault detection processes, supervised ANNs and deep learning are not accurate enough to diagnose novel faults with low false alarm rates. Furthermore, determining a suitable threshold when using ANN or DNN methods to avoid both false and missed alarms is challenging. This can be addressed by methods such as generative adversarial networks (GANs), which are able to deal with this issue, but their implementation in large HVAC systems is time-consuming.

Recognizing that the proper combination of multiple classifiers can be more effective than a single classifier used alone, ensemble learning-based techniques are increasingly used for HVAC FDD, outperforming weak learners in high-dimensional and complex classification and regression problems (Yao et al., 2022). These have included the combination SVM + KNN + decision tree + logistic regression (Han et al, 2020). Through a comparative study, Yao et al. (2022) proposed an optimal diagnosis method for chillers, comparing the performance of three tree-based ensemble algorithms: random forest, extreme gradient boosting (XGBoost), and light gradient boosting machines (LightGBM); the former reducing training model bias and the latter two reducing its variance. They observe that these outperform SVM-based methods significantly, however its slower implementation speed remains a challenge.

Supervised learning in real-world applications is limited by the high level of effort in creating a labeled dataset, complicating both detection and diagnosis.

Semi-Supervised Learning

Semi-supervised FDD training offers the benefit of only using non-fault class labels and has been widely used for Air Handling Unit (AHU) fault detection. Fan et al. (2021) demonstrated the effectiveness of a neural network-based semi-supervised framework for detecting unknown AHU faults. Another AHU FDD study (Yan et al., 2018) applied an SVM-based semi-supervised FDD for AHU that outperformed four other semi-supervised machine-learning algorithms (CART, KNN, extreme learning machine, and random forest). More recently, Yan et al., (2020) (Yan et al., 2020) (K. Yan et al. 2020) (Yan et al., 2020) (Yan et al., 2020) (Yan et al., 2020) employed GAN to increase the accuracy of semi-supervised FDD. Dey et al. (2018) used a multiclass SVM as a base classifier in a semi-supervised framework for FDD, demonstrating that this method outperformed various KNNs in terms of recall and precision metrics for HVAC terminal units.

Compared with supervised learning, semi-supervised learning works better when fewer faulty samples are available. Every iteration of semi-supervised learning compares an observation with the 'non-faulty' class to identify faulty samples. However, its computational cost exceeds that of supervised learning (Mirnaghi and Haghighat, 2020).

Unsupervised learning

Unsupervised learning facilitates FDD algorithm deployment by avoiding the need to collect and label faulty operation data. Principal component analysis (PCA) and clustering algorithms are both frequently used for HVAC FDD and permit the identification of patterns, underlying structures, and system data distributions.

PCA, a dimensionality reduction algorithm, has commonly been used to diagnose sensor faults (Du et al., 2007). Fault detection is carried out using Hotelling's T^2 and the Q-statistic while fault diagnosis is accomplished using Q-statistics and Q-contribution plots (Singh et al., 2022, Zhao et al., 2019). Because it reduces data complexity and assumes a Gaussian data distribution, PCA can easily generate false alarms or miss small magnitude faults (Xu et al., 2008). To overcome these limitations, PCA is frequently combined with other methods to improve its accuracy for HVAC FDD. Due to its reliance on data quality, PCA can be insensitive to some sensor faults and its ability to isolate sensor faults is also limited, leading researchers to explore performance improvements such as joint angle analysis (JAA) (Wang & Xiao, 2004) and wavelet filters (Li et al., 2016b).

Data pre-processing also greatly influences PCA performance. Wavelet analysis to separate noise dynamics from data and approximate sensor measurements has been shown to detect small sensor errors better than conventional PCA. (Xu et al., 2008). Another study (2012) developed a self-adaptive chiller sensor fault detection strategy based on PCA, removing errors from the original data set through self-adaptive loops to improve fault detection.

Clustering-based unsupervised learning is also widely used for FDD. Because normal and malfunction data are statistically different, they belong to different clusters, allowing them to be readily distinguished and detecting anomalies by identifying patterns of operation uncaptured by automated FDD rules. By using such methods, FDD rules can be better interpreted and advanced machine learning techniques such as active learning and semi-supervised learning can be applied to automated FDD to distinguish between fault-free and fault data (Gunay and Shi, 2020). For example, Li et al. (Li et al., 2016a) used clustering on both faulty and fault-free training datasets of chilled water systems and were able to distinguish between fault types and severity levels based on the closest measurements to the cluster centroids. Similarly, Luo et al. (2019), employed k-means clustering for sensor FDD of the chilled water system using centroid scores characterized via a threshold established using historical data and found this to improve the detection of small and varied sensor faults. Clustering methods can also be useful for analyzing time relationships and interactions between building elements. Data clustering can be used before PCA to facilitate pattern recognition and improve PCA performance. For example, Du et al. (2017) used subtractive clustering to classify and identify known sensor faults before developing PCA models for these conditions. Conversely, Yan et al. (2016a) applied PCA *followed by* clustering, which allowed spatially separated data groups to be isolated to indicate sensor failures.

Use of clustering-based methods is limited by its sensitivity to noise in the data; the need to pre-determine the number of clusters, requiring domain expert input; and the potential to produce large volumes of redundant results requiring post-mining techniques to extract those of value. Further, complex relationships between features in the post-mining step would make clustering more challenging compared to supervised mining (Mirnaghi and Haghighat, 2020).

Regression and statistical approaches

Regression-based and statistical techniques are other data-driven approaches for HVAC FDD and are summarized in Table 1.

Regression-based techniques detect faults by comparing predicted and actual system operation using complex mathematical models. These approaches have high accuracy, but suffer from the dual limitation of the need for a large, high-quality dataset and the challenge of creating the precise mathematical models to support them. Statistical analysis methods avoid this model dependence but also suffer from the need for a large dataset.

Hybrid data-driven approaches

Recently, studies have increasingly used hybrid approaches combining two or more of supervised classification, unsupervised learning, regression, and statistics-based approaches (Yan et al., 2016b). The most common hybrid method in FDD is regression-based approaches combined with either supervised classification, for example (Mulumba et al., 2015, Sun et al., 2019, Yan et al., 2014) or unsupervised learning, for example (Van Every et al., 2017).

Table 1. Summary of Regression and Statistical Approaches

Approach	Advantages	Limitations	Studies applying to HVAC FDD
Multiple Linear Regression (MLR)	Simple	Cannot capture non-linear behavior	Chillers (Xiao et al., 2011)
Kringing (KRG)	Can approximate both high-order functions and low-dimensional problems; outperforms both MLR & RBF	Sensitive to spatial correlation structure	Chillers (Swider et al., 2001)
Radial Basis Functions (RBF)	Fastest for solving non-linear and high-dimensional problems	Slow convergence for linear and low-dimensional problems	Chillers (Swider et al., 2001)
Process control chart (PCC)	Can identify sharp and sudden changes in variable values	Compromised when data is correlated	Chillers (Yao et al., 2022)
Exponentially-weighted moving average (EWMA)	Permit more recent data to be prioritized in analysis	Sensitivity to noise and short-term fluctuations, Poor accuracy	Chillers (Zhao et al., 2013)
Cumulative sum (CUSUM)	Widely used; useful for monitoring impact of small changes over time; sensitive to incipient faults	Parameter choice critical, Poor accuracy	Air-Conditioning (Li et al., 2012)
Residual-based EWMA & CUSUM	Serial correlations are eliminated, improving FDD performance and reliability	Cannot isolate multiple faults with intense interactions; poor accuracy	Variable-air-volume (Wang and Chen, 2016) Variable-air-volume (Wang et al., 2011)
MLR+EWMA	Outperformed KRG-EWMA & RBF-EWMA	Limited model adaptability, may struggle with complex or non-linear faults	Chillers (Tran et al., 2016b)
Least-Squares Support Vector Regression + EWMA	Model parameters optimized with differential evolution and outperformed RBF-EWMA	Requires sufficient training data, Sensitivity to hyperparameter selection	Chillers (Chen et al., 2016a)

In such methods, regression is used to build a baseline model for predicting system operation and either supervised or unsupervised techniques are employed for fault detection and isolation. Supervised classification and unsupervised learning can also be combined, for example (Fan et al., 2019; Li et al, 2017).

Presently, hybrid approaches are considered as a preferred methodology for online FDD processes. It is anticipated that these methodologies will predominate in future real-world applications because they allow complementary methods mitigate each other's limitations.

Discussion

Data-driven machine learning techniques have been extensively applied to detecting and diagnosing faults in building HVAC systems. Data-driven approaches offer an advantage over white-box modeling with their ability to perform calculations and generate FDD models automatically, thus being applicable to a variety of building types and systems without the creation of an explicit model. However, such approaches are often difficult to interpret and understand for facility managers and engineers due to the intrinsic nature of black-box models. This can be mitigated through the use of decision trees, regression models, and control charts, which are easier to interpret in comparison with other approaches.

For HVAC FDD to be practical, it is essential to choose the proper machine-learning technique. Table 2 summarizes the highest-performing FDD approaches from the literature, along with their key advantages and limitations.

While recent studies show a variety of approaches providing high accuracy, the type of available data will limit method choice. A supervised classification method or a hybrid method incorporating supervised learning always needs sufficient labeled data of faulty or normal operation of the system to be trained. Due to the time and effort required to gather sufficient amounts of labeled data in real buildings, the use of supervised classification-based FDD methods has generally been limited to simulation data (e.g. from TRNSYS and Modelica) as well as experimental data, like ASHRAE RP 1043 (ASHRAE, 2006) and RP 1312 (Wen and Li, 2012) projects. Moreover, due to the lack of sufficient labeled data and the complexity of interacting faults, diagnosing the source of faults is quite challenging in supervised-based FDD. In contrast, FDD methods based on unsupervised learning, regression, and statistical methods rely solely on fault-free data, making them useful for real-world building applications.

Two anticipated future directions for FDD research within HVAC are improving data quality to and methodological development. A major barrier to developing effective FDD schemes is the difficulty of collecting data from the faulty operation of the system in practice; this is of critical concern as it affects the effectiveness of all FDD methods.

Table 2. Summary of comparison between data-driven FDD methods

System	Technique	Performance	Key Advantages	Key Limitations	Reference
AHUs	CNN	F1-score: 0.989	Good at handling spatial data, robust feature extraction	Requires large data, computationally expensive	Cheng et al., 2021
	DNN	Accuracy: 95.16%	High accuracy, feature extraction capabilities	Requires large data, computationally expensive	Lee et al., 2019
	Semi-supervised ANN	Recall: 92.74%	Utilizes both labeled and unlabeled data, improved generalization	Sensitive to training data	Fan et al., 2021
	Semi-supervised SVM	Accuracy: 92.53%	Utilizes both labeled and unlabeled data, improved generalization	Challenging parameter selection	Yan et al., 2018
AHU sensors	Clustering	Accuracy: Up to 100%	No labeled data required, scalable	Assumes specific cluster shapes, sensitive to noise	Yan et al., 2016
Chillers	Tree-based ensemble	Accuracy: 88.71%	Robust, reduced overfitting, improved accuracy	Robust, reduced overfitting, improved accuracy	Yao et al., 2022
	Regression	R-square: 0.98	Simplicity, easy interpretation	Assumes linear relationships, limited generalization	Tran et al., 2016
Chiller sensors	PCA	Accuracy: 77.7% -100%	Dimensionality reduction, data compression	Linear assumptions, limited fault isolation	Hu et al., 2012
Variable Air Volume	Statistic-based	Detection rate: 5 of 8 fault types	No training required, easy to implement	Assumes normal distribution, limited fault isolation	Li et al., 2012
Variable Refrigerant Flow	SVM	Accuracy: Up to 98.73%	Robust to noise, strong generalization	Challenging parameter selection	Sun et al., 2016

While pre-processing (e.g. outlier removal) is helpful, HVAC operation mode(s) identification, steady-state detection, and/or feature selection, as well as dataset enrichment through simulation also offer value. Creating simulated datasets using validated empirical models, for example (Li and O'Neill, 2018; Shohet et al., 2020) is a low-cost approach to generating fault data for model training.

Methodologically, future development could include improving the reliability of current data-driven approaches, specifically for unknown system faults or system operation status. In such cases, machine-learning algorithms, specifically supervised classification, are faced with the challenge of extrapolation, making false alarms more likely. Fault data is labeled according to domain knowledge and known faults. The accuracy and generality of labeled data determine the reliability of supervised learning-based FDD. Therefore, training labeled data may be insufficient to support novel faults. Furthermore, data-driven methods typically analyze historical data obtained from older systems. This data set may not contain novel faults, so false alarms may occur when a novel fault is found in the system. On the other hand, there is a vast amount of data that must be processed with from unsupervised learning methods, as they often produce many redundant results. In order to automatically extract interesting results and mine correlations from these massive sets of results, post-mining methods such as active methods are required. Additionally, the complex relationships among multiple features would make clustering more challenging in the post-mining step, as opposed to supervised methods. As a result, the use of a hybrid approach that combines both supervised and unsupervised approaches seem to show more promise as a method for FDD processes in HVAC systems.

Moreover, the adaptability of the FDD framework can be further improved for dynamic operation of the building and outdoor environment. In order to accomplish this, recursive algorithms that make use of streamlined data can be employed to update a model's parameters. Finally, there is an opportunity to improve current data-driven methods through the development of FDD models that are capable of detecting and diagnosing multiple faults that occur simultaneously. The problem can be addressed by adopting hybrid methods that combine data-driven methods with knowledge-based approaches. Knowledge-based approaches are more reliable and perform better in extrapolation, so hybrid approaches combining data-driven methods and knowledge-based models can be adopted to resolve the problem.

Conclusion

This paper has presented a comprehensive review of over 50 recent papers regarding data-driven methods for detecting and diagnosing faults. The key findings are as-follows:

First, detection or diagnosis methods should be selected based on the type of fault to be identified. Faults can present themselves in different ways at different times, so diagnosing them can be more challenging than detecting them. Multiple faults occurring concurrently make it more difficult to diagnose faults.

Second, detection and diagnosis are both influenced by the measurement of data. A lack of sufficient data means that the detection process will rely more on detailed physical models. It may, however, be necessary to provide more physical information about a system, including its characteristics and design details to construct a physical model. On the other hand, the diagnosis and detection of faults in unitary HVAC systems can be accomplished using a wide range of data-driven methods. In the future, hybrid FDD methods will have enormous potential in real-world applications as an improvement over FDD.

Third, data-driven approaches have been found to be more promising than model-based and knowledge-based approaches for FDD in large-scale and complex HVAC systems where creating physical models or developing mathematical functions is challenging.

Fourth, existing data-driven methods are classified into four categories: supervised classification, unsupervised learning, regression and statistical approaches, and hybrid data-driven strategies. Essentially, all methods rely on a common set of sensors in FDD for data collection and these approaches typically utilize similar training data sizes.

Finally, it is necessary to have fault data for FDD development- based supervised learning methods, but it is not necessary for methods such as unsupervised learning, regression and statistical analysis. However, the capabilities of these methods can still be improved by sufficient fault data. In real buildings, supervised learning-based methods cannot be applied due to the lack of fault data. It is important to note that when these methods are used solely, they are only applicable to data obtained from simulations and experiments. However, it is possible to use and validate other FDD algorithms including unsupervised learning, regression and statistical approaches with simulation, experiments, and real building data. After data collection, data pre-processing is typically performed to ensure the performance of FDD.

The current data-driven FDD methods have some limitations. There is still an insufficient number of data-driven FDD methods to cope with complex fault situations, such as multiple faults occurring simultaneously. Furthermore, the lack of fault data remains a critical obstacle to improving algorithm performance and making FDD practical in real-world settings, especially for supervised learning algorithms. Data-driven approaches also require a greater degree of interpretability of models to be credible for facility managers and engineers. To further improve the performance of data-driven methods for FDD of HVAC systems employing fault modeling methods, improving the capability of handling simultaneous faults, and developing adaptability models for different buildings and environments are among the issues that may need to be addressed in the future.

Finally, challenges in FDD were discussed as well as future research directions to further improve it in practice.

Acknowledgments

This research was funded by the Natural Science and Engineering Research Council of Canada [ALLRP-544569-2019] and FuseForward Solutions Group.

References

ASHRAE (2006) RP 1043—Fault Detection and Diagnostic (FDD) Requirements and Evaluation Tools for Chillers. Ashrae, Atlanta.

ASHRAE (2012) RP-1312–Tools for evaluating fault detection and diagnostic methods for air-handling units. Ashrae. Atlanta.

Chen, J., Zhang, L., Li, Y., Shi, Y., Gao, X. & Hu, Y. (2022). A review of computing-based automated fault detection and diagnosis of heating, ventilation and air conditioning systems. Renewable and Sustainable Energy Reviews, 161, 112395.

Cheng, F., Cai, W., Zhang, X., Liao, H. & Cui, C. (2021). Fault detection and diagnosis for Air Handling Unit based on multiscale convolutional neural networks. Energy and Buildings, 236, 110795.

Dey, M., Rana, S. P. & Dudley, S. Semi-supervised learning techniques for automated fault detection and diagnosis of hvac systems. 2018 IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI), 2018. IEEE, 872-877.

Doe (2011). Buildings energy data book. Energy Efficiency & Renewable Energy Department, 286.

Fan, C., Liu, Y., Liu, X., Sun, Y. & Wang, J. (2021). A study on semi-supervised learning in enhancing performance of AHU unseen fault detection with limited labeled data. Sustainable Cities and Society, 70, 102874.

Gärtner, J. A., Gray, F. M. & Auer, T. (2020). Assessment of the impact of HVAC system configuration and control zoning on thermal comfort and energy efficiency in flexible office spaces. Energy and Buildings, 212, 109785.

Gunay, H. B. & Shi, Z. (2020). Cluster analysis-based anomaly detection in building automation systems. Energy and Buildings, 228, 110445.

Hu, Y., Chen, H., Xie, J., Yang, X. & Zhou, C. (2012). Chiller sensor fault detection using a self-adaptive principal component analysis method. Energy and buildings, 54, 252-258.

Li, D., Hu, G. & Spanos, C. J. (2016a). A data-driven strategy for detection and diagnosis of building chiller faults using linear discriminant analysis. Energy and Buildings, 128, 519-529.

Li, G., Hu, Y., Chen, H., Li, H., Hu, M., Guo, Y., Shi, S. & Hu, W. (2016b). A sensor fault detection and diagnosis strategy for screw chiller system using support vector data description-based D-statistic and DV-contribution plots. Energy and Buildings, 133, 230-245.

Luo, X., Fong, K., Sun, Y. & Leung, M. (2019). Development of clustering-based sensor fault detection and diagnosis strategy for chilled water system. Energy and Buildings, 186, 17-36.

Mirnaghi, M. S. & Haghighat, F. (2020). Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review. Energy and Buildings, 229, 110492.

Mulumba, T., Afshari, A., Yan, K., Shen, W. & Norford, L. K. (2015). Robust model-based fault diagnosis for air handling units. Energy and Buildings, 86, 698-707.

Singh, V., Mathur, J. & Bhatia, A. (2022). A Comprehensive Review: Fault Detection, Diagnostics, Prognostics, and Fault Modelling in HVAC Systems. International Journal of Refrigeration.

Sun, B., Luh, P. B., Jia, Q.-S., O'neill, Z. & Song, F. (2013). Building energy doctors: An SPC and Kalman filter-based method for system-level fault detection in HVAC systems. IEEE Transactions on Automation Science and Engineering, 11, 215-229.

Sun, Z., Jin, H., Gu, J., Huang, Y., Wang, X. & Shen, X. (2019). Gradual fault early stage diagnosis for air source heat pump system using deep learning techniques. International Journal of Refrigeration, 107, 63-72.

Swider, D., Browne, M., Bansal, P. & Kecman, V. (2001). Modelling of vapour-compression liquid chillers with neural networks. Applied thermal engineering, 21, 311-329.

Verbert, K., Babuška, R. & De Schutter, B. (2017). Combining knowledge and historical data for system-level fault diagnosis of HVAC systems. Engineering Applications of Artificial Intelligence, 59, 260-273.

Wang, H. & Chen, Y. (2016). A robust fault detection and diagnosis strategy for multiple faults of VAV air handling units. Energy and Buildings, 127, 442-451.

Wang, H., Chen, Y., Chan, C. W. & Qin, J. (2011). A robust fault detection and diagnosis strategy for pressure-independent VAV terminals of real office buildings. Energy and Buildings, 43, 1774-1783.

Wen, J. & Li, S. (2012). RP-1312–Tools for evaluating fault detection and diagnostic methods for air-handling units. ASHRAE, Tech. Rep, Tech. Rep.

Xiao, F., Zheng, C. & Wang, S. (2011). A fault detection and diagnosis strategy with enhanced sensitivity for centrifugal chillers. Applied thermal engineering, 31, 3963-3970.

Xu, X., Xiao, F. & Wang, S. (2008). Enhanced chiller sensor fault detection, diagnosis and estimation using wavelet analysis and principal component analysis methods. Applied Thermal Engineering, 28, 226-237.

Yan, K., Huang, J., Shen, W. & Ji, Z. (2020). Unsupervised learning for fault detection and diagnosis of air handling units. Energy and Buildings, 210, 109689.

Yan, K., Shen, W., Mulumba, T. & Afshari, A. (2014). ARX model based fault detection and diagnosis for chillers using support vector machines. Energy and Buildings, 81, 287-295.

Yan, R., Ma, Z., Kokogiannakis, G. & Zhao, Y. (2016a). A sensor fault detection strategy for air handling units using cluster analysis. Automation in Construction, 70, 77-88.

Yan, R., Ma, Z., Zhao, Y. & Kokogiannakis, G. (2016b). A decision tree based data-driven diagnostic strategy for air handling units. Energy and Buildings, 133, 37-45.

Yang, H., Zhang, T., Li, H., Woradechjumroen, D. & Liu, X. 2014. HVAC equipment, unitary: fault detection and diagnosis. Encyclopedia of Energy Engineering and Technology, Second Edition. CRC Press.

Yao, W., Li, D. & Gao, L. (2022). Fault detection and diagnosis using tree-based ensemble learning methods and multivariate control charts for centrifugal chillers. Journal of Building Engineering, 51, 104243.

Zhao, Y., Li, T., Zhang, X. & Zhang, C. (2019). Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future. Renewable and Sustainable Energy Reviews, 109, 85-101.

Zhao, Y., Wang, S. & Xiao, F. (2013). A system-level incipient fault-detection method for HVAC systems. HVAC&R Research, 19, 593-601.

Zhou, Z., Li, G., Wang, J., Chen, H., Zhong, H. & Cao, Z. (2020). A comparison study of basic data-driven fault diagnosis methods for variable refrigerant flow system. Energy and Buildings, 224, 110232.