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Generative adversarial network for fault detection diagnosis of chillers

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ABSTRACT

Automatic fault detection and diagnosis (AFDD) for chillers has significant impacts on energy saving, indoor environment comfort and systematic building management. Recent works show that the artificial intelligence (AI) enhanced techniques outperform most of the traditional fault detection and diagnosis methods. However, one serious issue has been raised in recent studies, which shows that insufficient number of fault training samples in the training phase of AI techniques can significantly influence the final classification accuracy. The insufficient number of fault samples refers to the imbalanced-class classification problem, which is a hot topic in the field of machine learning. In this study, we re-visit the imbalanced-class problem for fault detection and diagnosis of chiller in the heating, ventilation and air-conditioning (HVAC) system. The generative adversarial network is employed and customized to re-balance the training dataset for chiller AFDD. Experimental results demonstrate the effectiveness of the proposed GAN-integrated framework compared with traditional chiller AFDD methods.

1. Introduction

A sustainable use of total energy consumption with heating, ventilation and air-conditioning (HVAC) is responsible for significant proportions of the energy end-use in a building [1]. For example, about 50% of buildings site energy consumption can be attributed to HVAC in the United States [2]. In countries with a hot and humid climate such as Singapore, this percentage increases to about 60% of the total building energy consumption because of the need address both sensible and latent loads to maintain indoor thermal comfort (Fig. 1) [3]. Furthermore, with the advent of climate change, the amount of cooling required is expected to increase with daily mean temperatures projected to increase by around 2°C (RCP4.5) to 4°C (RCP8.5) for the end-century period (2070–2099) [4]. Therefore, there is an urgent need to aggressively reduce energy use in both new and existing buildings [5].

Chillers account for a large proportion of HVAC energy consumption in the tropics, with the compressor consuming significant amounts of electricity. Therefore, faults in chillers can significantly increase the building's energy consumption. For example, condenser fouling can reduce chiller's coefficient of performance (COP) by 20–30% [7]. However, soft faults such as condenser fouling, high refrigerant charges, as well as faulty sensors and controls are hard to discover through visual observations alone, and thus may remain unnoticed for a long time resulting in prolonged periods of energy wastage. Therefore, Automated Fault Detection and Diagnosis (AFDD) has the potential to greatly improves the operating energy efficiencies of different HVAC systems and components. Poorly maintained, degraded and improperly controlled HVAC components, where chiller is probably the most heavy-loaded equipment, waste an estimated 15%–30% energy wastage in commercial buildings [8]. Therefore, automated fault detection and diagnostics (AFDD) shows promise and has been proven to be an effective method to reducing whole building energy consumptions during (1) commissioning, and (2) Operation and Maintenance (O&M) stages of the building's lifecycle [9,10].

Amongst different AFDD methods, data-driven methods are the most popular because they train models based on historical data without any requirements of prior knowledge of the physical systems [11]. Data-driven AFDD methods adopt the historical chiller operational data and train the supervised classification models, such as support vector machine (SVM), decision trees (DT), Bayesian network (BN) and neural networks (NNs), to distinguish fault conditions from normal operational conditions. The entire AFDD process can be divided into two phase. In the fault detection phase, a binary classification model is trained to separate normal conditional data against fault data. And in the fault diagnosis phase, a multi-class classifier is trained to separate different types of fault data. The classification accuracy obtained by existing works reaches as high as over 80% for most of the cases [12–15].

The above mentioned high classification accuracy of chiller AFDD relies on sufficient number of training data samples and balanced

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Nomenclature

D	Discriminator
$D()$	Discrimination function, outputting discriminative probability
D_loss	Loss value for the discriminator
E	Expectation
F	Real-world fault conditional chiller data
F	Artificially generated fault conditional chiller data
G	Generator
$G()$	Generation function, outputting an generated sample from input
G_loss	Loss value for the generator
L	Severity level of faults
N	Normal conditional chiller data
NoN	Number of normal data samples
NoF	Number of fault data samples
$P_{data(x)}$	Distribution following the real-world data x
$P_z(z)$	Distribution following the random noise z
x	Real-world samples
y	label
z	Random noise

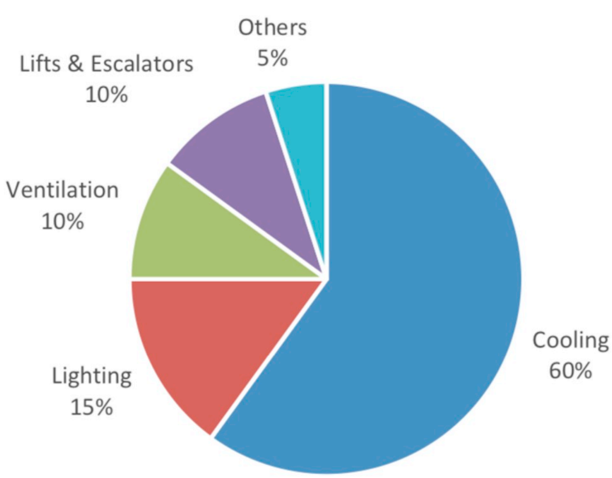

Fig. 1. Typical office building end use energy consumption breakdown in Singapore [6].

training datasets in the training phase [16]. In other words, the classification results become invalid with imbalanced training datasets [17,18]. The insufficient number of fault training samples, as part of the real-world chiller AFDD application scenario, becomes the main obstacle for supervised chiller AFDD methods [19]. To be more specific, the imbalance training dataset of chiller AFDD is naturally formed with the following facts in the real-world scenarios:

- Although remote sensors can collect data in real-time, it is hard in practice to obtain a well-labelled dataset containing incipient faults.
- A chiller failure is an expected event. Usually, a working crew will be sent immediately to fix the failure before sufficient number of fault data was collected by remote sensors.

Generative adversarial network (GAN) is proposed by Goodfellow et al. in 2014, which is developed to generate artificial training samples for minority classes taking the combination of random noises and pieces of original data samples [20]. Compared to traditional data augmentation methods, such as synthetic minority over-sampling technique (SMOTE) [21] and adaptive synthetic sampling approach (ADASYN) [22], GAN employs the concept of function approximator from neural networks to scale-up the minority dataset, which is more suitable re-balancing extremely imbalanced datasets as in the scenarios described above [23]. The 'artificial training samples' are generated in an adversarial way, and proved to be 'very close/similar' to the real-world samples [24]. For chiller AFDD scenarios, as mentioned above, with a large number of normal training samples and a few fault training samples, it is natural to leverage GAN's advantage for enriching the training pool using artificially generated fault samples. Ideally, in the fault detection phase, the imbalanced training dataset is re-balanced by increasing the number of fault training samples. And in the fault diagnosis phase, the multi-class classification accuracy can be improved by enhance the variety of different fault types training data samples.

In this study, based on the existing dataset collected by the American society of hating, refrigerating and air-conditioning engineers (ASHRAE) with project number 1043-RP, an unsupervised learning AFDD framework is proposed based on a customized GAN algorithm. To the best of our knowledge, we are the first and only research team that explores the application of GAN in the field of chiller AFDD. The internal structure of GAN has been implemented using multi-layer perceptron (MLP) neural networks with stochastic gradient descent (SGD) algorithm and rectified linear unit (ReLU) hidden activation function to best fit chiller AFDD [25,26]. In addition, the original GAN has been extended to Conditional Wasserstein GAN (CWGAN), which has been successfully applied to fault detection in other industrial applications [27,28]. Several questions of using GAN in chiller AFDD are addressed in this study. First, when the number of fault training samples becomes too few, e.g., from 10 to 50, it is challenging to cover the whole feature space using generated fault samples. The GAN uses random noises to increase the diversity of training samples. The minimal required number of the real-world fault training samples remains as a question. In this study, we tested 10, 20, …, 50 real-world fault training samples together with 8400 normal samples in the experiment section. The minimal required number of the real-world fault training samples is concluded. Second, GAN is an unstable machine learning model. The performance of using GAN on the classification accuracy improvement remains as a question. To attack this problem, we repeated all experiments 30 times and took the average to show the classification accuracy improvement. According to the experimental results stated in Section 4, the detection and diagnosis classification accuracy rates are both greatly improved after applying the proposed framework. The main contributions of the current study include:

1. **A chiller AFDD framework integrating unsupervised learning methods.** Most existing chiller AFDD works rely on supervised learning techniques, which neglects the fact that the fault training data is usually limited. In this study, the GAN method, known as an unsupervised learning technique, is employed to fill the gap between theoretical AFDD algorithms and real-world applications. To our knowledge, this is the first work integrating GAN into chiller AFDD.
2. **An extended generative adversarial network for chiller AFDD.** The CWGAN algorithm has been adopted to enhance the performance of chiller AFDD [29,30]. The multi-layer perceptron (MLP) neural networks with stochastic gradient descent (SGD) algorithm and rectified linear unit (ReLU) hidden activation function were employed to implement the proposed extended GAN framework.
3. **A comprehensive comparative study with various initial faulty training datasets.** The effectiveness of the proposed chiller AFDD framework is shown by illustrating the experimental results with/without applying the proposed chiller AFDD framework. With 10, 20, …, 50 fault training samples available for each fault type, the AFDD classification accuracy was shown improved significantly through a comprehensive comparative study. The minimum number requirement of the initial fault training data samples is studied.

2. Related works

AFDD methods can be classified as either (1) quantitative model-based, (2) qualitative model-based, or (3) process history-based [8]. A recent review of 197 AFDD publications [11] revealed that process history-based methods were the most popular, with 62% of the publications employing process history (data-driven) models. This is followed by qualitative model-based methods (26%), and then quantitative model-based methods (12%).

Quantitative model-based methods are first principles physics-based methods and can be further described as either detailed or simplified. The advantages of a physics-based model lies in its ability to characterize the system and thus purports better generalization to conditions beyond the measurements. However, AFDD using detailed physic-based models such as EnergyPlus [31] requires significant *a prior* knowledge of the HVAC system because of the large number of inputs needed to define model [32]. As a result, the models are often difficult to calibrate due to issue of parameter identifiability [33]. To overcome these challenges, an information exchange infrastructure integrating physics-based models with building information models (BIM) and the building energy management system (BEMS) was proposed [34]. A fault-modeling feature was also introduced in EnergyPlus to improve its ability to quantify the impact of faults on building energy consumption and occupant comfort [35]. The use of simplified physics-based models with fewer inputs was also developed and tested on ten buildings (five live tests and five retrospective tests) with over twenty years of combined building energy consumption data [10]. Qualitative model-based methods are usually built upon *a priori* knowledge of the physical system to define a set of if-then rules [36]. An inference mechanism is then employed to search through the rule space to identify faults [8,11]. The advantages of a rule-based model lies in its simplicity (to develop and apply) and its transparency (in reasoning). However, the rules are usually specific to a particular system, thereby limiting the applicability of all rules especially in complex HVAC systems. Since the methodology employed in this study is process history-based (data-driven), other model-based methods will not be discussed further.

Different from quantitative physics-based or qualitative rule-based methods, process history based methods may be classified as either gray-box or black-box models [11]. Gray-box models are formulated based on actual physical parameters. On the contrary, black-box models are data-driven methods that build models purely based on historical sensor data without any *a priori* knowledge about the actual physical system. Therefore, in many cases, the models are hardly interpretable without any physical meaning behind the parameters derived. In principle, all machine learning (ML) methods, including supervised learning and unsupervised learning, belong to data-driven methods.

In the recent five to six years (from 2013 to 2019), while AI technologies become increasingly popular, there are numerous data-driven AFDD methods proposed for HVAC subsystems faults. However, most of these methods are supervised learning approaches. Zhao et al. [14] designed a three-layer Bayesian belief network (BBN) to diagnose various faults in chillers. With the absent or errors in the historical data, BBN can effectively tolerate these problems through probability calculations. Du et al. [37] combined two neural networks with clustering analysis to diagnose various faults in air handling units. The method proposed by Du et al. was demonstrated to be effective in solving the sensor bias problem. Yan et al. [12] proposed a hybrid algorithm combining auto-regressive model with exogenous variables (ARX) model and support vector machine (SVM) to diagnose faults in chillers. The sensor training data is converted into ARX model parameter vectors using mathematical model-based methods. The parameter vectors was then utilized to construct the SVM model. Mulumba et al. [38] compared most available ML methods in the AFDD study of air handling units, including Bayesian networks, neural networks, decision trees, random forests, support vector machines, etc. It was found that since data size of AHU AFDD is relatively small, the results of multi-layer neural network and even deep learning can hardly reach optimal. Traditional ML models, such as decision trees (DTs), random forests (RFs) and SVM, in contrast, are easier and more effective to reach acceptable results. Yan et al. [13] designed a fault diagnosis system for air handling units based on decision tree model. Compared with other ML models, the decision tree model has the advantage of clearly stating the reasonings and evidences for decisions made, allowing maintenance workers to make personal reparation decisions more accurately. Li et al. [39] combined principle component analysis (PCA) and support vector data description (SVDD) methods to detect possible faults in chillers. The SVDD method can be used to detect unknown types of faults (if there is any). However, the detection accuracy is relatively low compared to that of known faults. In 2017, Wang et al. [40] merged Bayesian network with distance rejection (DR) to identify new types of faults in the process of chiller AFDD. Yan et al. [41,42] employed the extended Kalman filtering (EKF) model to process historical data on possible HVAC failures and improved the online AFDD system using hybrid supervised ML methods. Both diagnosis efficiency and accuracy were improved. In 2018, the same group of the researchers proposed an AHU AFDD system based on a semi-supervised learning approach to solve the problem of insufficient fault training data samples in the process of AFDD [43]. The proposed semi-supervised method can temporarily alleviate the insufficient fault training data problem, since any fault type training dataset can only be enriched when the particular fault type happens again. Wang et al. [44] proposed an enhanced chiller fault detection system combining Bayesian network (BN) and principal component analysis (PCA). The BN model provided outstanding performance for detecting chiller faults at slight severity levels. Huang et al. [45] utilized associative classification to perform fault diagnosis for chillers. Shi [46] combined EKF with dynamic Bayesian network (DBN) with leaky noisy-max model simplification to develop a AFDD framework for AHU faults. The proposed model was verified using model-based methods. Wang et al. [15] designed a practical chiller fault diagnosis system based on discrete Bayesian network (DBN). With any assumption about the distributions of the input, the method automatically determined the DBN parameters and diagnose chiller faults effectively. Han et al. [47] implemented a least square support vector machine (LSSVM) trained by eight fault-indicative features extracted from the original 64 features to detect and diagnose faults of chillers. Fan et al. [18] proposed to use Principal component analysis (PCA) and the synthetic minority oversampling technique (SMOTE) were used to oversample the fault sample set principal component analysis (PCA) with synthetic minority oversampling technique (SMOTE) re-balance the original imbalanced training dataset. Support vector machine (SVM) is used for fault diagnosis. Chakraborty and Elzarka [48] employed extreme gradient boosting (XGBoost) to detect possible HVAC faults in the early stage. A dynamic threshold is adopted to improve the XGBoost classification accuracy.

The existing data-driven HVAC AFDD works that have been surveyed in this section are summarized in Table 1. It is evident that most available and popular data-driven HVAC AFDD approaches are still supervised learning methods, including most of the surveyed works published in 2019. Semi-supervised and unsupervised learning methods, such as the generative adversarial networks (GANs), are the minority and highly demanded under this context for bridging the gap between laboratory AFDD experiments and real-world industrial applications.

3. Methodology

The proposed chiller AFDD flowchart is depicted in Fig. 2, where we separate the training and testing processes using different colors. The original training pool contains a small dataset of fault samples (F) and a huge dataset of normal samples (N). Without enhancing the fault dataset in the training pool, it is difficult for traditional chiller AFDD methods to achieve satisfactory classification results. For example, the number of fault training samples can be too small to properly train a multi-class classifier for fault diagnosis.

Table 1
A summary of AFDD works for HVAC sub-systems published in recent five to six years (from 2013 to 2019).

Reference	Target	Methodology	ML Type	Advantage
Zhao et al. (2013) [14]	Chiller Diag.	Three-layer Bayes. belief network	Supervised	Tolerate missing/ error data
Du et al. (2014) [37]	AHU Diag.	Two neural networks & clustering	Supervised	Effective for sensor bias problems
Yan et al. (2014) [12]	Chiller AFDD	ARX model & SVM	Supervised	Improve classification accuracy
Mulumba et al. (2015) [38]	AHU Diag.	Most avail. ML methods	Supervised	Compare ML with DL on AHU AFDD
Yan et al. (2016) [13]	AHU Diag.	Decision trees	Supervised	Reasoning of decision is clearly stated
Li et al. (2016) [39]	Chiller Dete.	PCA-R-SVDD	Supervised	Discover new faults (if any)
Wang et al. (2017) [40]	Chiller Dete.	Bayesian net w. distance rejection	Supervised	Identify new faults w. distance rejection
Yan et al. (2017, 2018) [41,42]	Chiller AHU AFDD	EKF & SVM	Supervised	Real-time AFDD solutions
Yan et al. (2018) [43]	AHU Diag.	Semi-supervised learning & SVM	Semi-supervised	Improve AFDD accuracy
Wang et al. (2018) [44]	Chiller Dete.	Bayesian network & PCA	Supervised	Detect chiller faults at slight severity levels
Huang et al. (2018) [45]	Chiller Diag.	associative classification	Supervised	Association rules were established
Shi et al. (2018) [46]	AHU AFDD	Dynamic Bayesian network & EKF	Supervised	Verification using model-based methods
Wang et al. (2019) [15]	Chiller Diag.	Discrete Bayesian network	Supervised	Automatically determine parameters
Han et al. (2019) [47]	Chiller AFDD	Least square SVM	Supervised	Extracting fault-indicative features
Fan et al. (2019) [18]	Chiller AFDD	PCA-SMOET-SVM	Supervised	Training set re-balancing w. SMOET
Chakraborty (2019) [48]	HVAC AFDD	Extreme gradient boosting	Supervised	Dynamic thresholding

In this study, the conditional Wasserstein GAN (CWGAN) algorithm, which is an extension of the GAN algorithm, introduced in Section 3.3, is employed to generate an additional artificial fault training dataset (F'). The two datasets F and F' are mixed and combined to balance the training pool against N. The binary classifier, e.g., a support vector machine (SVM), is subsequently trained using the re-balanced training pool. In the fault diagnosis phase, considering different types of chiller faults, a multi-class classifier will be trained using only the fault training dataset that contains F and F'. The CWGAN with the 'conditional property' generates artificial samples with fault types (conditions). The samples in F' are therefore valid to be trained with the multi-class classifier, and more importantly, improve the diversity of original fault training dataset, which potentially refines the trained multi-class classifier.

In the testing phase, we use a testing dataset containing equal number of normal and fault data samples. Each data sample is first classified by the binary classifier. If the classification result is fault, the testing data sample is further classified with the multi-class classifier to determine its fault type.

3.1. Data

The chiller operational data used in this study was originally collected by ASHRAE Project numbered 1043-rp [49]. Several common chiller faults were artificially introduced and the resulting operational data was recorded at 10-s and 2-min intervals. We use the 2-min interval data to train and test our AFDD methods.

The project contains both normal and fault data of a 90-ton (316 kW) chiller. Fig. 3 shows the schematic of a typical single stage vapour compression chiller that consists of four components (1) compressor, (2) condenser, (3) expansion valve, and (4) evaporator. To enable efficient heat rejection and absorption, the condenser operates at high pressure (high temperature) while the evaporator operates at low pressure (low temperature). The ideal vapour compression refrigeration cycle comprises of four processes that repeats and can be summarized as follows (with reference to Fig. 3):

1. State 1–2 Isentropic compression (in a compressor)
2. State 2–3 Heat rejection under constant pressure (in a condensor)
3. State 3–4 Isenthalpic expansion (in an expansion valve)
4. State 4-1 Heat absorption under constant pressure (in an evaporator)

Based on the survey results of the most common faults for chillers from the ASHRAE Project 1043-rp [49], seven typical faults were investigated in this study:

1. Reduced condenser water flow (F1)
2. Reduced evaporator water flow (F2)
3. Refrigerant Leak (F3)
4. Refrigerant Overcharge (F4)
5. Excess Oil (F5)
6. Condenser Fouling (F6)
7. Non-condensables in Refrigerant (F7)

All fault locations are also marked in Fig. 3. Each fault mode was monitored one at a time in four severity levels, the details of the severity levels for different faults are shown in Table 2. In ASHRAE project numbered 1043-rp, all seven faults (from F1 to F7) were simulated with manual setup. For example, for the condenser fouling (F6), the tubes in condenser were manually blocked with plugs. A 45% reduction in total tube area approximately results in 5% reduction in condenser water flow rate.

The processed (reduced) dataset provided by the ASHRAE 1043-rp project contains 65 monitored features, including condenser water in/out temperature, evaporator water in/out temperature, oil feed/sump temperature and etc., which are recorded in every 2 min. For each severity level of each fault, an approximately one day dataset containing 864 samples were collected. Therefore, the total number of fault data samples in the original dataset is $864 \times 7 \times 4 = 24{,}192$. The total number of normal operational data samples in the original dataset exceeds 12,000.

In the experiment section, each severity level will be tested separately. Following the description of the dataset provided by the ASHRAE project 1043-rp, each severity level contains $864 \times 7 = 6048$ fault data samples. Out of the 6048 fault data samples, $10, 20, 30, 40$ or 50 fault data samples of each fault type are randomly selected to form the training set with 8400 normal data samples. And 400 fault data samples of each fault type are randomly selected to form the testing set with 2800 normal data samples. The setup of the training set mimics the real-world scenario where very limited number of fault data samples is available for training. In contrast, the number of available normal data samples is usually enormous. For the testing phase, we purposely set the number of fault data samples (7×400) equivalent to the number of normal data samples (2800). As a result, the experimental results obtained using the balanced testing dataset are meaningful for comparison with other chiller AFDD methods.

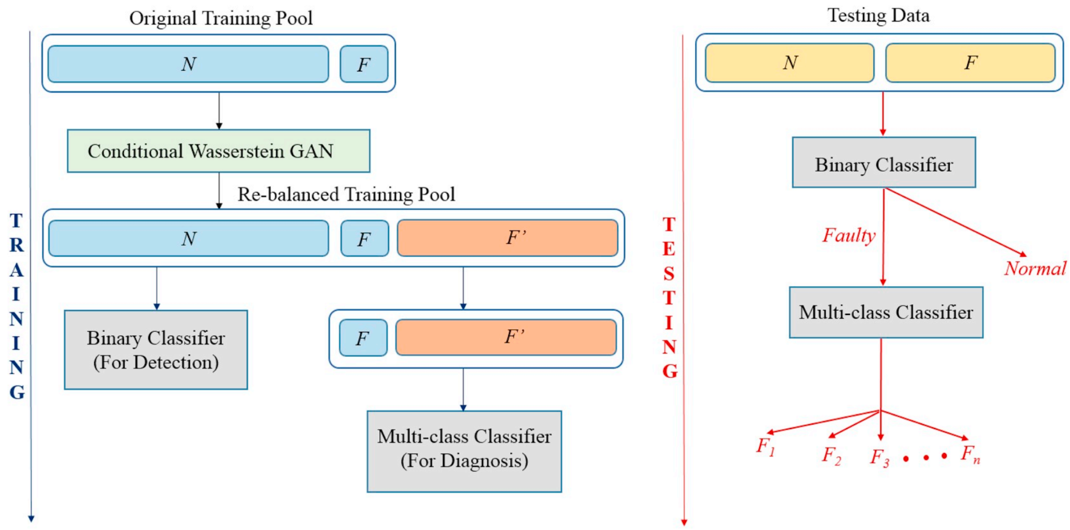

Fig. 2. A simplified illustration of applying conditional Wasserstein GAN (CWGAN) to the traditional supervised chiller FDD. The artificially generated fault samples shown in orange color re-balance the original training pool and improve the diversity of fault training dataset, which potentially help enhance the classification accuracy in both fault detection and fault diagnosis processes. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

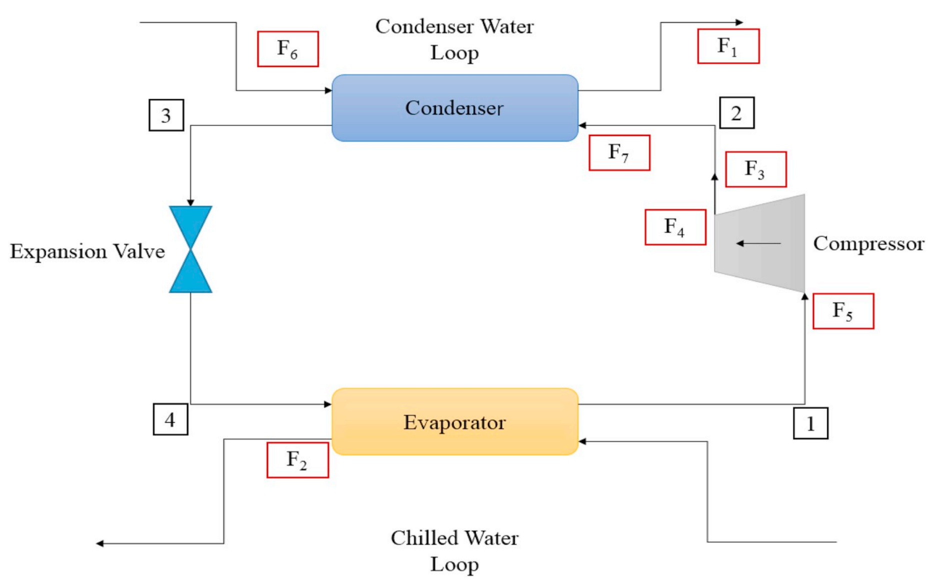

Fig. 3. Schematic of a typical single stage chiller.

Table 2
Details of the severity levels for seven typical chiller faults (from F1 to F7), reported by ASHRAE project number 1043-rp.

Type	Severity Level 1	Severity Level 2	Severity Level 3	Severity Level 4
F1	10% reduced in flow	20% reduced in flow	30% reduced in flow	40% reduced in flow
F2	10% reduced in flow	20% reduced in flow	30% reduced in flow	40% reduced in flow
F3	10% reduced in charge	20% reduced in charge	30% reduced in charge	40% reduced in charge
F4	10% increased in charge	20% increased in charge	30% increased in charge	40% increased in charge
F5	14% increased in charge	32% increased in charge	50% increased in charge	68% increased in charge
F6	12% reduced in tubes	20% reduced in tubes	30% reduced in tubes	45% reduced in tubes
F7	1% by volume Nitrogen	2% by volume Nitrogen	3% by volume Nitrogen	5% by volume Nitrogen

3.2. Feature selection

Feature selection is one of the necessary steps for chiller AFDD, which reduces the number of installed sensors and focuses the monitoring on particular sensor readings. It reduces the financial and computational costs and speeds up the machine learning processes. There exist many feature selection methods in the literature, such as the ReliefF algorithm [12], sensitivity test [50], principal component analysis [51] and genetic algorithm [52]. Most of these feature selection methods do not distinguish the misclassification cost for false positive and false negative.

In 2018, Yan et al. introduced a cost-sensitive sequential feature selection (CSSFS) algorithm particularly designed for chiller AFDD [42]. The proposed algorithm assigns different weights to wrongly classified training samples, distinguishing false positive and false negative classification results. In addition, the selected features are sorted from most important to least important.

In this study, we applied the CSSFS algorithm to the largest training dataset described in Section 3.1, which consists of 50 fault training samples for each severity level of each fault type together with 8400 normal training samples. The misclassification weight ratio between fault and normal training samples is set as 15:1. The misclassification weight ratio was selected considering the extreme imbalance between the two classes in the training dataset, which is obey the real-world scenarios. Another option is to re-balance the training dataset before the feature selection process using generative adversarial networks (GANs), which will be discussed in Section 5. After applying CSSFS algorithm, the top ten selected features are listed in Table 3.

The above ten selected features are selected as the target features for GANs to generate artificial samples. From a long array (e.g., 128 elements) with random attributes, the GANs generate artificial samples that are indeed ten elements arrays. Each array represents a generated fault data sample, mimicking the real-world fault data samples. With the help of conditional GAN (CGAN), the artificially generated samples are labelled with conditions indicating the fault types along with severity levels (refer to Section 3.3). The feature selection is an important process for GANs to shrink the network scale and consequently reduce the number of neural network feedback loops [53].

3.3. Customized GAN for chiller AFDD

In this subsection, the original GAN has been re-implemented and customized to best suit the chiller AFDD. In particular, two multi-layer perceptron (MLP) neural networks with stochastic gradient descent (SGD) algorithm and rectified linear unit (ReLU) hidden activation function were used to replace the original internal neural networks in GAN [25,26]. In addition, the concepts of conditional GAN (CGAN) and Wasserstein GAN (WGAN) were adopted to form the CWGAN algorithm, enhancing the performance of chiller AFDD.

Generative adversarial network (GAN), introduced by Goodfellow et al. [20], originally intends to solve the main bottleneck problem of many machine learning and data mining application, which is the lack of data. The GAN structure proposed in Ref. [20] consists of two neural networks. One is called generator and the other is called discriminator. The generator randomly generates desired samples that initially can be in bad quality. The discriminator provides feedbacks to the generator by comparing the artificial samples generated by the generator and real-world data samples. The two neural networks adjust the hyper-parameters through a series of iterations to improve the quality of artificially generated samples until they are very close to the real-world samples, i.e., the discriminator can hardly distinguish between real or artificial samples. The ultimate purpose of GAN is to solve the conflict between generator G and discriminator D using the equation shown in Eq. (2):

$$\min_{G}\max_{D} V(D,G) = E_{x\sim P_{data(x)}}[\log D(x)] + E_{z\sim P_z(z)}[\log(1-D(G(z)))], \quad (1)$$

where x is a real-world sample. $G(z)$ creates artificial samples using random noise z. And $D(x)$ calculates the probability if x is real. Eq. (2) is also called the loss function. The value of the right hand side of Eq. (2) is called the loss value. For the generator, the loss value (G_loss) has to be minimized to fool the discriminator. For the discriminator, the loss value (D_loss) has to be large enough to distinguish between real or artificial samples. In the convergence process of GAN, G_loss and D_loss are converged through a series of iterations.

Table 3
Ten most important features selected by cost-sensitive sequential feature selection (CSSFS) algorithm [42].

Feature	Description
TCI	Temperature of Condenser Water In
TEO	Temperature of Evaporator Water Out
kW/ton	Chiller efficiency
TCO	Temperature of Condenser Water Out
PO_feed	Pressure of Oil Feed
TEI	Temperature of Evaporator Water In
PRC	Pressure of Condenser
EvapTons	Evaporator Cooling Rate
TCA	Condenser Approach Temperature
TRC_sub	Subcooling Temperature

It is evident that the original GAN proposed by Goodfellow et al. cannot be directly applied to chiller AFDD. For example, the first and most commonly visited application of GAN is image processing [54–56], where most of the generators use convolutional neural networks (CNNs) to up-sample the random noises into an image. However, for chiller AFDD, each sample only consists of limited number of features, e.g., ten features in the current case. In fact, instead of up-sampling, the generator for chiller AFDD down-samples a 128-element array into a 10-element array. Therefore, CNN is not suitable for implementing generator in the chiller AFDD case.

In addition, two bottlenecks exist for applying the traditional GAN directly to chiller AFDD. First, the traditional GAN as an unsupervised technique, generates artificial samples belonging to the same class. For multi-class problem, for example, in the fault diagnosis phase, there are seven different types of faults with different severity levels. The original GAN has to be trained multiple times for different classes, which is inefficient in practice. The conditional GAN (CGAN) [29] adds one more feature indicating the conditions in the discriminator, which allows the real-world data samples bringing labels (Fig. 4). The target equation of CGAN adds label variable y to both the generator and discriminator:

$$\min_{G}\max_{D} V(D,G) = E_{x\sim P_{data(x)}}[\log D(x|y)] + E_{z\sim P_z(z)}[\log(1-D(G(z|y)))]. \quad (2)$$

CGAN is therefore capable of generating different types of artificial samples simultaneously without been trained multiple times.

Another bottleneck of the original GAN is that the log functions in the target equation slow down the convergence process between the losses of generator and discriminator according to experimental practices. In 2017, Arjovsky et al. suggests to remove the two logs in the target equation and approximate the losses of generator and discriminator using Wasserstein distance [30]. The improved WGAN increases the convergence speed of the original GAN.

In this study, we combine the concepts of CGAN and WGAN to the original GAN structure to enhance the performance of chiller AFDD. The customized CWGAN structure for chiller AFDD is shown in Fig. 4. We employ the MLP to implement both generator and discriminator. The generator has five layers and the discriminator has six. For each layer, the generator contains 128, 64, 32, 16 and 10 neurons, respectively. And the discriminator contains 64, 128, 64, 32, 16 and 1 neurons for each layer, respectively. The stochastic gradient descent (SGD) algorithm and rectified linear unit (ReLU) hidden activation function are employed to update the hyperparameters. The maximum number of loops shown in Fig. 4 is set as 20,000. An example of the accelerated convergence process between G_loss and D_loss is shown in Fig. 5, where the target of the CWGAN method is to converge G_loss and D_loss.

4. Experimental results

4.1. Initial setup

The lab workstation used for AFDD experiments of this study is with the following configuration: Intel Core(TM) i7-7700HQ CPU @ 2.8 GHZ, NVIDIA, GeForce GTX1070Ti graphics card, Python 3.6.5 (64-bit), Tensorflow with version 1.8.0 and Keras 2.6.1.

As explained in Section 3.1, the training dataset contains 8400 real-world normal training data samples with selected numbers of fault training samples, mimicking the real-world scenario where the number of fault training samples is much less than the number of normal training samples. The experiment of each severity level was performed

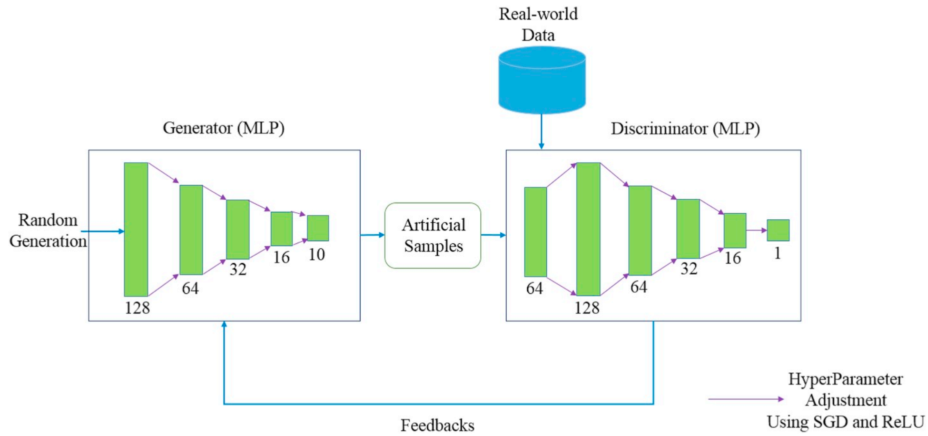

Fig. 4. The customized generative adversarial network (GAN) framework for chiller AFDD.

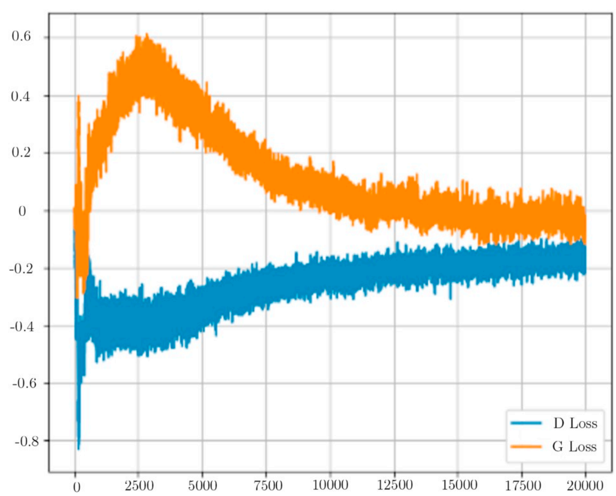

Fig. 5. An example of the loss value difference between the generator *GLoss* and discriminator *D Loss* during the convergence process.

separately. For each severity level, a training set is formed with *NoN* normal data samples and *NoF* fault data samples. $NoN = 8400$. And we select five different numbers for *NoF* to test different scenarios. Specifically, we randomly select 10, 20, …, 50 fault training samples from each fault type in the original ASHRAE 1043-rp dataset as the fault data part in the training set. As a result, *NoF* is $7 \times 10 = 70$, $7 \times 20 = 140$, $7 \times 30 = 210$, $7 \times 40 = 280$ or $7 \times 50 = 350$.

The testing dataset is a balanced dataset, containing 2800 normal data samples and 2800 mixed-type fault data samples (400 from each fault type) for each severity level.

In the fault detection phase, the customized CWGAN framework is used to generated $NoN - NoF$ artificial fault training samples using the *NoF* fault training samples available in the original training dataset to re-balance the training dataset. The training set contains 8400 normal data samples and 8400 fault data samples after applying CWGAN. In the fault diagnosis phase, we re-form the training dataset using only *NoF* fault training samples in each severity level. For each severity level, it is a seven-class classification problem. For each fault type, we increase the number of fault training samples from 10, 20, …, 50 to 1200 using artificially generated fault training samples using the proposed CWGAN framework. The training set in the fault diagnosis phase contains 8400 fault data samples. And the testing set contains 2800 real-world fault data samples.

4.2. Selection of classifiers

In the overall algorithm description shown in Section 3, we missed out some important details, which is the choice of the base classifier for the binary and multi-class classification. In this subsection, we evaluate and compare most available machine learning methods in the literature, including support vector machine (SVM) [57], random forest (RF) [58], decision tree (DT) [59], Bayesian network (BN) [60], k-nearest-neighbor (KNN) [61] and logistic regression (LR) [62]. After apply the customized CWGAN to the original training dataset, the fault detection (binary) and fault diagnosis (multi-class) classification accuracy rates are listed in Tables 4 and 5. It is noted that the classification accuracy rates shown in 4 and 5 are collected by taking the average of 30 repeated experiments for each base classifier. All compared methods can finish the training process within 2 min time, given the hardware configuration listed in Section 4.1 and the size of the training dataset. The highest classification accuracy rate among all tested classifiers is highlighted in bold font.

From the classification accuracy rates collected from Tables 4 and 5, although the accuracy difference becomes smaller when the number of fault training samples increases, SVM outperforms all other compared base classifiers. Consequently, SVM is selected to be the base classifier for both fault detection and fault diagnosis in the following comparative studies (Sections 4.3 and 4.4).

4.3. Results of fault detection

To show the advantage of the proposed GAN-integrated framework, a comparative study was conducted between the traditional chiller AFDD approach (Fig. 6) and the proposed GAN-integrated chiller AFDD framework (Fig. 2). In Fig. 6, symbol '*F*' denotes fault data samples and symbol '*N*' denotes normal data samples. The traditional chiller AFDD approach directly trains the classifiers using the imbalanced training set and applies the trained classifiers to the testing phase. The fault detection results of the traditional approach, denoted as 'original', and the proposed approach, denoted as 'proposed' are shown in Table 6. It is noted that the statistics shown in Table 6 are collected by taking the average of 30 repeated trials. In each trial, a random selection of initial fault training samples was performed.

In Fig. 7, we shows the significant improvement of the fault detection classification accuracy before and after applying CWGAN. Every pair of the vertical bars shows the classification improvement after applying CWGAN and the traditional AFDD approach. The four subfigures show the performance improvements using initial training samples 10, 20, …, 50 for levels 1, 2, 3 and 4, respectively. From both Fig. 7 and Table 6, it is noted that when the number of fault training samples increases, the classification accuracy difference between the proposed method and the traditional approach becomes smaller. The proposed CWGAN method is

Table 4
Fault detection binary classification accuracy rates using different classifiers. Horizontally, we record the classification accuracy using different numbers of fault training samples for each fault type (10, 20, 30 and 40) with different severity levels (L1, L2, L3 and L4). Vertically, we show the binary classification accuracy based on support vector machine (SVM), random forest (RF), decision tree (DT), Bayesian network (BN), k-nearest-neighbor (KNN) and logistic regression (LR). The highest classification accuracy rate is highlighted in bold font.

Detec.	10				20				30				40			
Acc.%	L1	L2	L3	L4	L1	L2	L3	L4	L1	L2	L3	L4	L1	L2	L3	L4
SVM	**78.06**	**92.02**	**92.63**	**93.96**	**77.99**	**92.08**	**94.46**	**92.94**	**83.40**	**92.44**	**95.60**	**99.17**	**86.65**	**92.74**	**95.77**	**99.99**
RF	72.92	87.90	92.08	93.25	72.94	88.11	89.87	92.82	83.02	91.32	94.93	95.12	86.34	91.21	95.18	99.61
DT	76.57	80.25	83.14	92.87	71.78	83.12	87.62	90.10	81.13	87.04	93.05	96.18	72.39	87.36	92.92	97.31
BN	53.80	58.92	69.15	83.91	52.07	76.45	78.47	89.04	61.73	65.99	76.19	95.95	63.01	81.41	92.93	93.26
KNN	72.01	85.29	88.34	87.13	64.66	78.03	79.89	90.25	76.26	84.53	88.16	90.56	60.23	61.07	79.21	91.42
LR	75.13	84.06	91.69	93.30	75.74	86.06	89.16	91.90	81.22	84.94	93.99	98.25	82.78	90.13	92.48	97.77

Table 5
Fault diagnosis multi-class classification accuracy rates using different classifiers. Horizontally, we record the classification accuracy using different numbers of fault training samples for each fault type (10, 20, 30 and 40) with different severity levels (L1, L2, L3 and L4). Vertically, we show the binary classification accuracy based on support vector machine (SVM), random forest (RF), decision tree (DT), Bayesian network (BN), k-nearest-neighbor (KNN) and logistic regression (LR). The highest classification accuracy rate is highlighted in bold font.

Detec.	10				20				30				40			
Acc.%	L1	L2	L3	L4	L1	L2	L3	L4	L1	L2	L3	L4	L1	L2	L3	L4
SVM	**74.14**	**86.29**	**94.19**	**96.71**	**81.43**	**86.38**	**92.16**	**98.57**	**82.58**	**89.74**	**97.52**	**98.65**	**86.57**	**96.21**	**97.93**	**98.66**
RF	67.05	76.48	81.81	93.19	72.83	81.24	88.88	94.69	74.80	82.16	89.06	96.23	76.75	86.80	92.25	97.38
DT	69.43	72.67	77.26	91.90	71.71	77.45	85.33	92.33	72.49	79.02	87.73	93.81	75.18	82.00	88.49	94.02
BN	38.48	53.81	62.29	76.95	38.67	58.48	76.19	77.98	49.11	63.70	84.29	91.03	55.30	67.98	86.72	95.98
KNN	49.14	61.90	71.67	78.52	53.71	64.76	72.98	80.71	60.57	71.76	74.38	91.59	63.96	75.19	83.76	93.64
LR	70.90	75.81	85.14	89.95	71.71	77.40	87.14	92.90	76.89	80.65	87.48	93.07	80.13	85.89	89.08	96.81

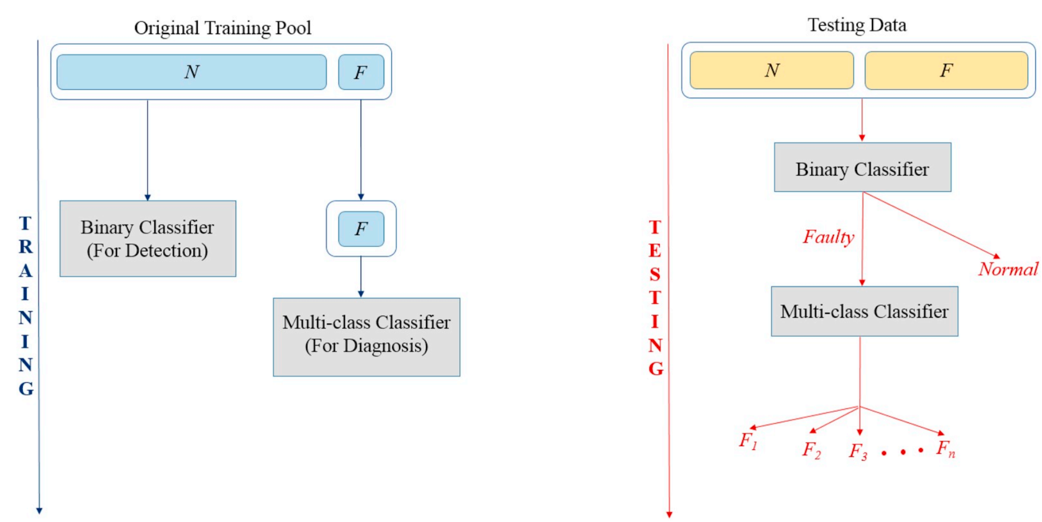

Fig. 6. The conventional chiller AFDD framework without applying the CWGAN method.

Table 6
The fault detection binary classification accuracy rates before (original) and after (proposed) re-balancing the training dataset using SVM as the base classifier. Horizontally, we record the classification accuracy using different numbers of fault training samples for each fault type (10, 20, …, 50). Vertically, we show the classification accuracy on different severity levels (from level 1 to level 4).

Detection	10		20		30		40		50	
Accu.(%)	proposed	original	proposed	original	proposed	original	proposed	original	proposed	original
Average	**89.39**	56.02	**90.00**	61.25	**92.54**	60.02	**93.78**	67.30	**94.91**	78.69
Level 1	**78.06**	64.60	**77.99**	50.62	**83.40**	51.08	**86.65**	71.64	**86.89**	61.50
Level 2	**92.02**	51.51	**92.08**	61.88	**92.44**	60.24	**92.74**	78.92	**92.80**	83.71
Level 3	**92.63**	54.92	**94.46**	69.40	**95.60**	65.53	**95.77**	62.92	**99.96**	84.20
Level 4	**93.96**	53.03	**92.94**	63.06	**99.17**	63.24	**99.99**	55.72	**100.0**	85.38

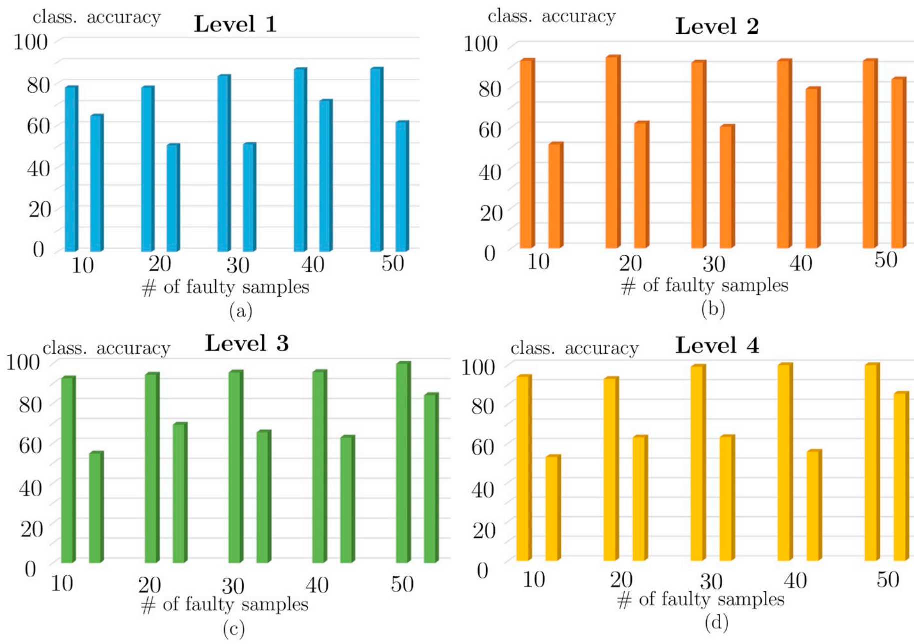

Fig. 7. The chart shows the significant improvement of the fault detection classification accuracy after and before applying the proposed framework. Subfigure 7.a shows the detection classification accuracy improvement for severity level 1 with initial training samples 10, 20, …, 50. Every pair of the vertical bars shows the classification improvement after and before applying the proposed framework. Subfigure 7.b shows the classification accuracy improvement for severity level 2. Subfigure 7.c shows the classification accuracy improvement for severity level 3. And subfigure 7.d shows the classification accuracy improvement for severity level 4.

effective when the training dataset is extremely imbalanced.

Since the original training dataset is extremely imbalanced (consisting of 10–40 fault samples for each fault type and 8400 normal samples), without the proposed customized GAN framework, the traditional AFDD approach always tends to classify the fault samples as normal samples, since the normal samples have dominated the training pool. The classification accuracy is around 50%. According to Table 6 and Fig. 7, after the training dataset is re-balanced using the proposed customized GAN method, fault detection accuracy reaches 90% in average with randomly selecting 20 fault samples from each fault type.

4.4. Results of fault diagnosis

In the fault diagnosis phase, the training dataset contains 8400 fault training data samples, with 1200 samples for each fault type. A multi-class SVM is used to verify the classification performance using the customized CWGAN framework. The testing dataset contains 400 real-world data samples from each fault type. The multi-class classification (fault diagnosis) accuracy without ('original') and with ('proposed') applying the customized CWGAN framework is shown in Table 7. It is noted that the statistics shown in Table 7 are collected by taking the average of 30 repeated trials. In each trial, a random selection of initial fault training samples was performed.

In Fig. 8, we shows the significant improvement of the fault diagnosis classification accuracy applying the proposed GAN-integrated framework. Every pair of the vertical bars shows the classification accuracy difference between the proposed framework and the traditional approach. The four subfigures show the performance improvements using initial training samples 10, 20, …, 50 for levels 1, 2, 3 and 4, respectively.

From the statistics shown in Table 7 and Fig. 8, with less or equals to 30 data samples of each fault type, it is difficult to perform fully automated fault diagnosis using traditional chiller AFDD approach. The averaged classification accuracy is less than 70%. In contrast, after enriching the training dataset using artificially generated training samples from the customized CWGAN, all classification accuracy rates are significantly improved. The averaged multi-class classification accuracy reaches 90.40% for 30 data samples from each fault type, which is fairly acceptable for real-world application usage.

5. Conclusion, limitations and future works

Targeting at the problem of insufficient number of fault training samples in the chiller AFDD process, this study proposes a CWGAN unsupervised learning framework to generate artificial fault training samples to diversify and re-balance the training dataset. A practical implementation of the original GAN is proposed to fit the chiller AFDD application. In particular, the up-sampling in the generator has been revised using a down-sampling structure (Fig. 4), since the chiller data sample has only limited number of features. In addition, the adoption of multi-layer perceptrons (MLPs) for both generator and discriminator accelerates the convergence speed in the training phase.

The real-world chiller AFDD data collected from ASHRAE project 1043-RP is re-visited to verify the effectiveness of the proposed algorithm. In the fault detection phase, we randomly select 10, 20, …, 50 fault training samples from each fault type and combine with 8400

Table 7
The fault diagnosis multi-class classification accuracy rates before (original) and after (proposed) applying the customized CWGAN method. Horizontally, we record the classification accuracy using different numbers of real-world fault training samples for each fault type (10, 20, …, 50). Vertically, we show the classification accuracy on different severity levels (from level 1 to level 4).

Diagnosis	10		20		30		40		50	
Accu.(%)	proposed	original	proposed	original	proposed	original	proposed	original	proposed	original
Average	**87.83**	58.98	**89.64**	65.31	**90.40**	68.04	**92.12**	79.03	**94.84**	83.02
Level 1	**74.14**	38.48	**81.43**	49.14	**81.76**	53.71	**82.58**	66.63	**86.57**	67.67
Level 2	**86.29**	53.81	**86.38**	61.90	**87.60**	64.76	**89.74**	77.49	**96.21**	85.29
Level 3	**94.19**	66.95	**92.16**	71.67	**93.63**	72.98	**97.52**	81.40	**97.93**	87.75
Level 4	**96.71**	76.67	**98.57**	78.52	**98.60**	80.71	**98.65**	90.62	**98.66**	91.36

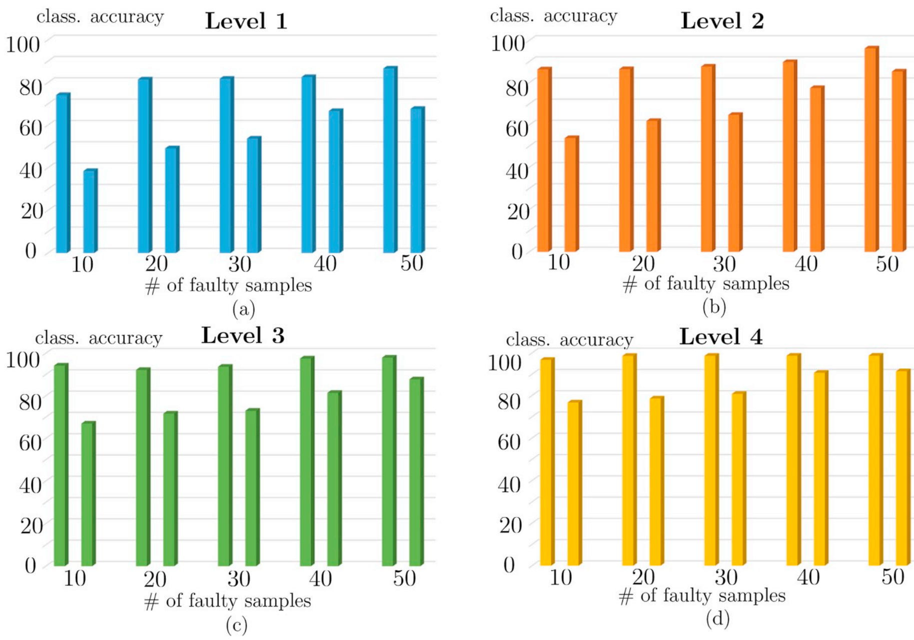

Fig. 8. The chart shows the significant improvement of the fault diagnosis classification accuracy after and before applying the proposed framework. Subfigure 8.a shows the diagnosis classification accuracy improvement for severity level 1 with initial training samples 10, 20, …, 50. Every pair of the vertical bars shows the classification improvement after and before applying the proposed framework. Subfigure 8.b shows the diagnosis classification accuracy improvement for severity level 2. Subfigure 8.c shows the diagnosis classification accuracy improvement for severity level 3. And subfigure 8. d shows the diagnosis classification accuracy improvement for severity level 4.

normal data samples to form the training dataset. Additional fault training samples were generated by the customized CWGAN to re-balance the training dataset. As a result, the fault detection classification accuracy rates are significantly improved for all severity levels according to Table 6 using a balanced testing dataset containing 2800 fault and normal samples, respectively. In the fault diagnosis phase, the training dataset contains only the 10, 20, …, 50 fault training samples from each fault type. The insufficient diversity limits the classification performance for conventional data-driven AFDD methods. the customized CWGAN algorithm diversifies the original training dataset using randomly generated high-quality fault samples. The fault diagnosis classification accuracy rates are improved more than 10% in average compared with conventional AFDD methods.

This study addresses two important questions while GAN and its extensions are applied in the field of AFDD. First, we address the question about the level of diversity increment using the customized CWGAN when the number of real-world training samples is less than 50 for each fault type. According to the experimental results listed in Tables 6 and 7, with 20 real-world samples of each fault type, the fault detection classification accuracy reaches 90% in average. And with 30 real-world samples of each fault type, the fault diagnosis classification accuracy reaches 90.4% in average. Hence, an effective chiller AFDD system with the customized CWGAN framework requires at least 30 real-world fault samples to reach acceptable detection and diagnosis accuracy. Without CWGAN, the classification accuracy can hardly achieve 90%, since the diversity of the original training dataset is low. CWGAN increases the diversity level by introduce random noises in the artificial samples generation process. Second, we address the unstable performance property of GAN in the process of chiller AFDD. With 30 repeated experiments using different training dataset, the averaged classification accuracy rates listed in Tables 6 and 7 are more reliable. From the comparative experimental results, it is noted that the proposed customized CWGAN method effectively improves the chiller AFDD performance when the training dataset is extremely imbalanced.

The limitation of this study is that it is difficult in practice to obtain a dataset consisting of faults occurring over a wide range of operating conditions. The future work of this study includes to.

- Extend the current GAN structure using more diverse deep learning techniques, such as a convolutional neural network (CNN) and long short term memory (LSTM) neural networks.
- Use building energy simulation software EnergyPlus to generate synthetic fault data [31], which is expected to more closely emulate real-world fault data. The original input data of GAN, which is the random noise, is replaced by the synthetic fault data generated by EnergyPlus to improve the classification accuracy of the proposed method.

Declaration of competing interest

The authors declare that they have no competing interests.

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