Causal 1-D Convolutional Neural Networks Based Chiller Fault Detection and Diagnosis

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ABSTRACT

This paper presents an one-dimensional convolutional neural network (1D-CNN) based fault detection and diagnosis system (FDD) for identifying chiller faults. The 1D-CNN has parallel processing capability against a sequential time-series models that are used in the literature. The 1D-CNN chiller FDD capability is demonstrated on two data sets: RP-1043 and a multi-story building in Singapore. Our experimental results demonstrate the FDD capabilities to identify chiller faults over existing methods. It is shown that the proposed 1D-CNN model achieved superior performance, an average F1 score of 99.48% and 94.62%, respectively, compared to the contemporary data-driven FDD models.

CCS CONCEPTS

• **Computer systems organization → Sensor networks**; • **Computing methodologies → Machine learning**.

KEYWORDS

Smart buildings, Chiller fault-diagnosis, Automated fault-detection and diagnosis, deep learning and convolutional neural networks.

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1 INTRODUCTION

Commercial buildings fitted with heating, ventilation, and air conditioning (HVAC) systems consume significant energy. Consequently, reducing their operating costs assumes significance. While optimizing energy consumption in HVAC systems is exacerbated, maintenance costs towards equipment are often neglected [1]. More importantly, chillers are not only costly equipment but consume significant energy as well. However, energy efficiency and maintenance costs are competing objectives. Reducing maintenance tasks reduces operating costs and increases energy consumption by diminishing equipment performance and vice-versa. Therefore, striking the right maintenance schedules in chillers has assumed significance in commercial buildings as never before [2]. In this context, to detect chiller faults, fault detection and diagnosis (FDD) systems are required to detect faults earlier and judiciously plan maintenance operations.

Legacy building management systems (BMS) are reactive systems with little prediction capabilities (e.g., alarming and trending) and are unsuitable for predicting faults and planning maintenance tasks. A proactive fault detection system helps plan maintenance operations to reduce downtime, component failures, and expensive maintenance tasks. Nevertheless, implementing proactive fault detection techniques requires: data-aggregation, knowledge creation from raw data, predicting impending faults, and providing insights to building operators and maintenance staff.

To this extend, model-based approaches depending on *physics-based* and *data-based*–models have assumed significance [3]. Usually, physics-based models capture chiller or component behaviors using mathematical equations. Although resilient, their scalability is rather difficult for buildings with different operating conditions. Nevertheless, with the advent of communication technologies, data-aggregation capability has increased stupendously, favoring data-driven models [4, 5]. Machine learning approaches such as: support vector machines [6], least squares-SVM [7], self-adaptive principal component analysis [8], linear discriminator analysis [9], and ensemble learning techniques [10] have been used for performing data-based fault detection. More recently, deep-learning approaches have been proposed to improve the performance of the fault detection models for chiller systems [11, 12]. The advantage of deep-learning techniques is their ability to model complex patterns without completely providing the manually extracted features. This is important as discerning faults requires identifying key features contributing to the faults and understanding their causes.

A key aspect in data-based FDD methods is the temporal dependence of the raw data that reveal fault signatures lurking in the data. Among deep-learning approaches, convolution neural network has been known for image processing tasks. However, by embedding causal behaviours within one dimensional convolution neural network (1D-CNN) architecture, data ordering could be preserved [13]. Consequently, our contribution exploits the 1-D CNN advantages in building the chiller FDD systems. We conducted two case studies to evaluate the performance of the 1D-CNN model using real data. Our experimental results showed that the proposed 1D-CNN model achieved superior performance, with an average F1

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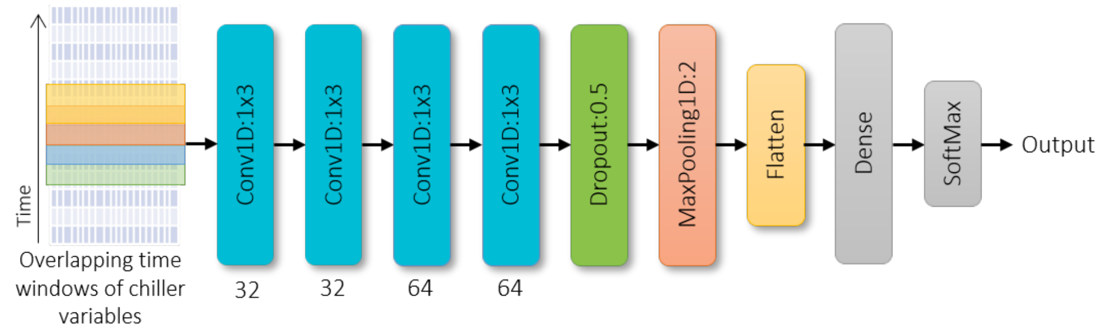

Figure 1: Architecture of the 1D-CNN network for chiller fault detection.

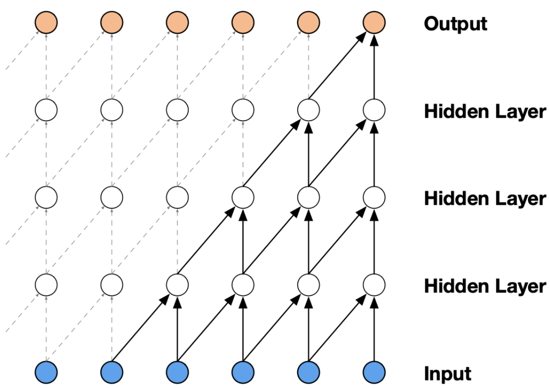

Figure 2: Illustration of causal convolutions from WaveNet [13].

Table 1: List of chiller fault types and severity levels (L1 - L4) from ASHRAE 1043-RP [14]. The percentages in each column indicate the reduction/increase in the corresponding faults and severity levels. For example, -10% for F1 indicates reduced condenser water flow for severity level L1 and so on.

Fault code and description	Fault severity levels			
	L1	L2	L3	L4
F1 - Reduced condenser water flow	-10%	-20%	-30%	-40%
F2 - Reduced evaporator water flow	-10%	-20%	-30%	-40%
F3 - Refrigerant Leak	-10%	-20%	-30%	-40%
F4 - Refrigerant Overcharge	+10%	+20%	+30%	+40%
F5 - Excess Oil	+14%	+32%	+50%	+68%
F6 - Condenser Fouling	-12%	-20%	-30%	-45%
F7 - Non-condensables in refrigerant	1%	2%	3%	5%

score of 99.48% and 94.62%, respectively, compared to the contemporary data-driven FDD models. Furthermore, we also release the reproducible code repository[1].

2 METHODOLOGY

This section presents the details of the causal 1D-CNN model architecture for chiller fault detection. A CNN is an extension of traditional ANN with complex convolutional kernels or filters that are sequentially applied to learn the meaningful patterns in the dataset. One of the unique features of convolutional kernels is that they can learn complex features, also called feature maps, and help perform automatic feature extraction when the number of layers in the model increases. While 2D convolutional kernels are widely applied in image analysis, 1D convolution kernels are applied to model and identify the temporal patterns in time series data. Further, they have parallel processing capability overcoming difficulties with sequential models such as LSTM currently used for fault detection.

Since the chiller dataset consists of multiple time series representing the physical state of a component or sensor over time, it is intuitive to apply causal 1D-CNN to them to model and isolate the normal operations from faulty conditions. The architecture of the proposed 1D-CNN for chiller fault detection is shown in Figure 1. Firstly, the chiller dataset is converted into a 1D format of fixed time slices to feed them into the 1D-CNN. In this work, we apply a fixed, overlapping time window (w) to each chiller variable to form the training samples. Thus, each training sample will have a vector of $w \times n$ data points where n denotes the number of chiller variables. The first causal 1D convolutional layer consists of 32 kernels of size three that are applied in sequence to the input samples and then transformed using *relu* activation units. Subsequently, to capture the temporal patterns of different lengths, there are three more 1D-CNN layers of sizes 32, 64, and 64, respectively. Note that all four layers are based on causal convolutions (See Figure 2) to ensure our model cannot violate the temporal order of the training samples (inspired from WaveNet [13]). After applying a sequence of 1D convolution filters, a *Dropout* layer is used to randomly reset the input units to 0 to prevent over-fitting of the model. Next, a 1*DMaxPooling* layer is used to downsample the data points by applying the maximum function to a spatial window of size 2. The final layer is a dense or fully connected layer that performs the final fault classification based on the features learned in the previous layers. The final output layer will output the prediction of probability of each each fault class per sample input.

[1]https://github.com/samy101/chiller-fdd-1dcnn

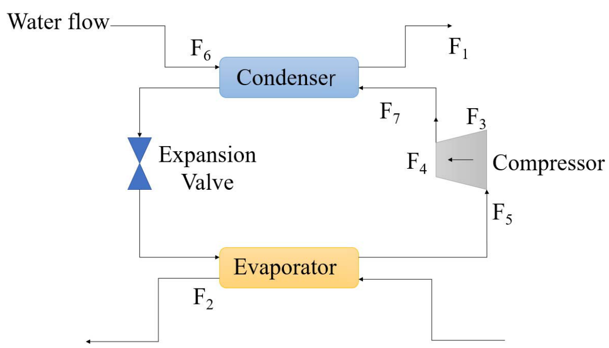

Figure 3: Schematic of the chiller system with the location of the injected faults (F1 to F7) used by ASHRAE 1043-RP [15].

3 DATASET

In this study, we use two datasets with real faults to validate and compare the performance of the proposed 1D-CNN based fault detection method with traditional approaches.

3.1 ASHRAE 1043-RP

This chiller FDD dataset is collected initially by ASHRAE project number 1043-RP, a commonly used data sample [14]. In the 1043-RP dataset, a 90-ton chiller system (See Figure 3) was used to collect samples under normal and faulty conditions. Seven chiller faults are captured in the dataset with four severity levels: L1-L4 (see, Table 1). There are 65 chiller variables reported in the ASHRAE document [14]. Approximately 14.4 hours of data, at 10-second intervals, were collected for each severity level and fault type. In addition, this dataset also contains data samples during normal chiller operations. A subset of the dataset containing 5,191 normal and 36,337 ($7 \times 5{,}191$) faulty samples at each severity level are used during model validation. All 65 variables were used as features after normalizing them.

3.2 A 32-story office building

This chiller dataset is collected from an office building with 32 floors equipped with four chillers. Using the BMS, chiller variables were recorded for data storage and retrieval. These include chiller tonnage, condenser tonnage, chilled water flow, supply and return water temperature of the chiller, approach temperature of the cooling tower, etc. These variables are collected as time-stamped data every 5-minute over seven months. Since the data is recorded from a building management system, there are missing values and outliers in the data. We removed the missing values and outliers using standard statistical and regression analysis.

The fault labels were generated from BMS alarms and validated based on the chiller domain knowledge. Out of 79,979 samples, 3,508 (4.39%) were considered faulty samples. It is to be noted that the assigned fault labels represent system-level faults or degradation, unlike the specific faults injected in the ASHRAE 1043-RP. We advocated this procedure because injecting true faults into the chillers in real buildings is challenging and may be inconvenient to the occupants.

Table 2: F1-score comparison of the proposed 1D-CNN and seven contemporary models for four severity levels (L1-L4) on the ASHRAE 1043-RP dataset. The proposed causal 1D-CNN model achieved the highest average F1-score of 99.48% across four severity levels.

Model name	Fault severity levels L1	L2	L3	L4	Average
1D-CNN	99.60	99.62	98.74	99.96	99.48
SVC	87.81	94.22	97.15	98.41	94.40
LR	82.04	90.73	96.10	97.74	91.65
XGB	82.75	83.24	93.85	95.15	88.75
RF	74.80	81.78	90.50	95.38	85.61
DT	70.35	72.11	84.78	87.18	78.61
kNN	63.37	66.34	76.84	84.33	72.72
MLP	75.12	71.28	56.72	79.22	70.58

4 EXPERIMENTAL SETUP AND RESULTS

Evaluation Metrics: In this work, we have used precision, recall, and F1 score to have a fair understanding of the distribution of false positives and false negatives to evaluate the fault detection performance. The formulas are:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{1}$$

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{2}$$

$$F_1score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3}$$

Baseline models: We compare the performance of the proposed causal 1D-CNN performance with several existing machine learning models previously used in the literature [1, 4–7, 10]. These include Decision Tree (DT), k-Nearest Neighbours (kNN), Logistic Regression (LR), Multilayer Perceptron (MLP), Random Forest (RF), Support Vector Machine (SVC), and XGBoost (XGB).

Experimental setup: We use a stratified five-fold cross-validation strategy to validate the model performance robustly. In each fold, 80% of the total samples were used for training, and the remaining 20% samples were used for testing. The scores from all folds are averaged to get the final score. There were four subsets, one per severity level, in the ASHRAE dataset and another four subsets, one per chiller, in the office building dataset. The five-fold cross-validation is applied to each subset independently. All models were implemented using Python 3 with standard libraries. The experiment environment includes a laptop computer with a CPU of Intel Core i7-8750h, a graphics card of NVIDIA GTX 1050Ti, 32GB RAM, and a 512GB SSD hard disk.

The F1 score of all models on the ASHRAE 1043-RP dataset is compared in Table 2. The causal 1D-CNN model achieved the highest average F1 score of 99.48%, across all four fault types followed by SVC (94.40%). The MLP based model yielded the lowest performance with an average F1 score of 70.58%. Similarly, the F1 score of all models on the office building dataset is compared in Table 3. We can observe that the proposed causal 1D-CNN model achieved the highest average F1 score of 94.62% across all four chillers. This

Table 3: Comparison of F1-score of the proposed causal 1D-CNN with seven contemporary fault detection models for four chillers on the multi-story office building dataset. The proposed 1D-CNN model achieved the highest average F1-score of 94.62% across all four chillers.

Model	Chiller1	Chiller2	Chiller4	Chiller5	Average
1D-CNN	97.92	95.26	96.74	88.54	94.62
XGB	84.21	94.24	98.54	97.22	93.56
SVC	89.68	86.93	98.84	97.32	93.19
LR	90.38	87.39	98.84	95.94	93.14
MLP	91.21	92.17	93.36	93.04	92.44
RF	87.49	80.41	98.80	96.15	90.71
DT	86.77	78.64	99.04	97.18	90.41
kNN	83.88	79.82	99.02	95.89	89.65

is followed by XGBoost, which achieved an average F1 score of 93.56%. The KNN yielded the lowest performance with an average F1 score of 89.65%. Additional comparisons of all models using various metrics are provided in the code repository. To conclude, the proposed 1D-CNN model achieved superior performance across different fault types and chiller systems on both datasets. The higher accuracy is attributed to the model's capability to capture better the temporal patterns of faulty and normal conditions in the given chiller variables.

5 CONCLUSION AND FUTURE WORK

This paper presented a fault detection and diagnosis (FDD) methodology for chillers in commercial buildings that used data-driven models against rule-based ones in existing works. The main contribution is the causal one-dimensional convolution neural network that achieved improved performance in identifying chiller faults on two data sets with real faults. Further, exploiting the deep-learning framework manual feature engineering is avoided. Extending to explainability aspects is the future course of this investigation.

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