An Experimental HVAC Faults Data Generation and Detection Using One-dimensional Convolutional Neural Networks

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Abstract— **Heating, ventilation, and air conditioning (HVAC) system contain a number of electrical parts that are susceptible to failure. Defective HVAC system components can lead to false alarms. For the purpose of enhancing HVAC system effectiveness, several fault detection techniques have been developed for use with energy-saving. However, conventional HVAC fault detection systems have low accuracy, requiring artificial feature extraction and selection to improve accuracy. There is no unified framework in place to evaluate and validate faulty conditions of HVAC individual components under various operating conditions. It is critical to create a fault model that covers a wide range of faults across major HVAC components in a reliable fault simulation platform. This study used the dynamic simulation system HVAC SIMulation PLUS (HVACSIM+) to implement an HVAC fault model in a single-story, four-room building to identify ten major HVAC equipment and control system faults using one-dimensional convolution neural network (1D-CNN). Unlike other data-driven fault detection systems, the 1D-CNN uses experimental simulation of HVAC data and does not require pre-processing, feature extraction, or feature selection. The experimental results show 94% accuracy for classifying 10 different HVAC major faults from 194 sensors and achieve the energy-saving goal. The proposed 1D-CNN approach is compared and analysed against previous fault detection systems. Despite the fact that all comparison FDD models correctly classify 10 different types of HVAC faults, the classification accuracy of some faults in each individual approach is less than 75%, which is significantly lower than the proposed 1D-CNN. This clearly shows that the proposed 1D-CNN performs better in HVAC system fault diagnosis, with a better accuracy.**

I. INTRODUCTION

Up to 50% of energy is estimated to be utilised by heating, ventilation, and air conditioning (HVAC) systems in buildings. Poor design installation, equipment wear-related issues can significantly increase energy usage and damage the indoor environment, especially if they go unnoticed for a long time. Failures of the HVAC system, such as those of the equipment and control systems and design defect, reduce the thermal comfort of the occupants. These issues are typically disregarded until they eventually cause an equipment-level alert and lead to complete equipment failure [1]. Fault detection and diagnosis (FDD) in building systems may be used to address this issue and cut down on the expenses associated with building operation and maintenance by efficiently diagnosing, and providing findings on how to address these faults [2]. Applying fault detection diagnosis (FDD) in HVAC results in energy savings of 5% - 30% [3].

Many studies have been done for the implementation of HVAC fault detection and diagnosis systems, especially in three main streams of quantitative model-based, qualitative model-based, and process history-based methods [4][5]. Data-driven approaches were best suited for usage with complex systems like HVAC because they are noise-resistant and may be used to extract an underlying data set while a physical model of the HVAC system is not available. In [6][7], a hybrid technique combining model-based fault detection and diagnosis method with rule-based fault detection was provided as a way to diagnose abrupt faults of variable-air-volume (VAV) air handling units (AHU). However, the rule-base methodology created for one system cannot be simply adapted to another as most HVAC systems are deployed in various buildings/environments. As a result, the challenging process of formulating and establishing rules or creating analytical mathematical models must be customised for each unique building. The rule-based FDD system has a significant risk of malfunction due to its limitation on parameter optimisation and the difficulty of updating the model when the FDD system is deployed in a new HVAC system.

Automated HVAC fault detection and diganosis systems were developed by utilising machine learning (ML) technologies. In [8], an ANN-based FDD system with a two-layer feed-forward neural network (NN) is developed for the purpose of identifying eight typical AHU sensors and mechanical issues. A reconstruction-based error isolation method was suggested in [9] for a data-driven semi-supervised FDD system with principal component analysis (PCA). Additionally, a diagnostic bayesian network (DBN-FDD) framework utilising a probabilistic graphical model [10], an intelligent technique for automatically detecting faults in HVAC systems based on a fuzzy-genetic algorithm (FGA) were developed [11]. In [12], the characteristics of three major faults, including recirculation damper stuck, cooling coil fouling/block, and supply fan speed decreasing, were investigated by combining the model-based FDD method and the Support Vector Machine (SVM) method. A FDD framework the can be augmented through the use of the unsupervised data-driven feature selection algorithm was proposed [13]. While test results showing that the proposed FDD system can efficiently identify HVAC failures, some significant HVAC faults, such as exhaust air dampers trapped in a fully closed position and heating coil valve leakage faults, need to be addressed. It still required the availability of training samples to recognize the faults and it may be

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challenging to apply in real-world operation.

These methods additionally require for signal processing, feature extraction, and feature selection into a selected classifier for faults classification. To achieve accurate FDD system, choosing the proper features is crucial as it reduces redundancies and mutual information across features. No matter how the algorithm is designed, the performance of the FDD model generally depends on the quality of the features. Thus, the selection of the right features for any model-based framework aims to reduce redundancy as much as possible. By dong so, only particular characteristics that behave differently from the rest can be shown to exhibit specific symptoms that are associated with certain HVAC faults [13]. The domain expert previous knowledge and statistical techniques have an impact on the feature extraction and selection process, and the diagnostic model classification accuracy falls short of expectations if insignificant features are chosen.

In practise, the challenge is that the significant features has to be continually observed since they might change dynamically based on the state of the HVAC system under investigation. However, selecting the irrelevant features for the classifier could result in some evident HVAC faults going overlooked. The current approaches do not provide a comprehensive approach for evaluating and testing these FDD algorithms using accurate faulty data, it use the publicly accessible ASHARE data [14]. Although several fault detection and diagnostics (FDD) techniques are available, there is no unified framework to effectively evaluate them across a variety of faulty operating conditions and ensure the fault detection system work as expected. Therefore, it is critical to create a fault model that covers a wide range of faults across major HVAC components in a reliable fault simulation platform.

To overcome the issues of getting reliable faulty data in HVAC systems, this study introduces a novel development of fault-modeling in HVACSIM+ developed by the Institute of Standards and Technology (NIST) [15]. It is a method for dealing with the connectivity of various operational components, the synchronised effect of concurrent faults, and the dynamic nature of fault severity. It is used to model the entire HVAC system because it has capability of performing a distinct hierarchical variable time step technique. For many years, it has been experimentally validated and improved, demonstrating that it is particularly suitable for simulating secondary systems and control schemes [16].

The motivation of this paper is to design a reliable approach for diagnosing HVAC system faults using deep convolutional neural networks (CNN) [17]. More precisely, utilising extensive on-site experimental HVAC data simulated on a single-story, four-room building using the HVAC Simulation PLUS (HVACSIM+), a CNN-based fault detection (FDD) is developed for the accurate detection of 10 various types of major HVAC faults without the need for further data processing or feature engineering process. It has ability to perform feature extraction and fault diagnosis tasks simultaneously. It can replace the conventional fault diagnosis method, which entails processing the signal to extract and choose important features before feeding the data into a final classifier for fault classification. In addition, operational data of HVAC systems are complicated in nature due to component coupling, changing thermodynamics, local and long-term temporal decencies. The developed 1D-CNN approach has shown to be more successful in modelling such complexity and multi-scale temporal-dependencies of HVAC problems.

The next section describes and the theoretical background of Convolutional Neural Network (CNN) in section II-B, and the simulation of the HVAC system on a single-story building using the HVAC Simulation PLUS (HVACSIM +), its parameter settings with 10 different types of HVAC faults and abbreviations are described in section II-A. In addition, the proposed CNN based fault detection and diagnosis methodology was evaluated and discussed in section III. Finally, the proposed 1D-CNN FDD system limitations, conclusions and future work are presented in section IV.

II. METHOD

The identification of HVAC faults using a one-dimensional convolutional neural network (CNN) is proposed in this section. The proposed model was trained using 10 significant HVAC faults and fault-free experimental data from 195 sensor signals of each HVAC component, generated by HVAC Simulation PLUS (HVACSIM+) on a single-story, four-room building (400 m2 each). It eliminates the influence of the domain expertise for feature extraction and selection process. As presented Fig.1, the proposed framework consists essentially of three major components: (1) generate the reliable HVAC data using the HVACSIM+ simulation model, (2) develop 1D-CNN fault detection system that automatically learns from various degrees of time series sensor signals of each HVAC component, and (3) comparative research was conducted to demonstrate how well the proposed framework worked.

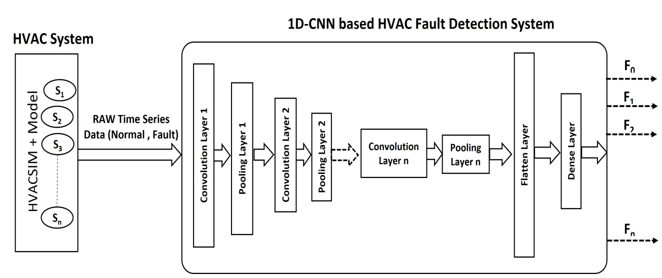

Fig. 1. Process Diagram for Proposed 1D-CNN HVAC Fault Detection System.

A. Experimental HVAC Data using HVACSIM+

To develop the fault detection and diagnosis of the building HVAC system, in this experiment, the normal and faulty operation data were generated using the HVACSIM+ simulation model [18]. A simulation model of a one-story, four-room building was created using HVACSIM+, with roughly equal exposure of each room to the external heat load. Each room in the building has air conditioning thanks to an AHU system with four zones. A variable air volume fan was also included in each room to regulate the temperature in each zone. Figure 2 depicts the building's energy mode setup and the layout of the HVAC system. In this simulation model, the preheating coils, cooling coils, heating coils, heating and cooling coil control valves, outside, air dampers, and conditioned air are the primary components of the AHU. A duct enters the area and exits through it. The simulation model continually monitors the system's operational characteristics using sensors for pressure, temperature, humidity, and airflow. A variable

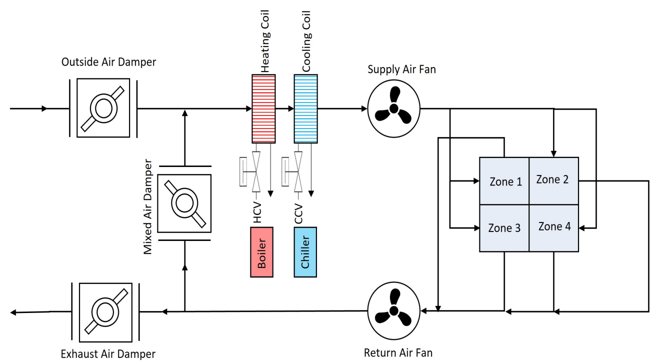

Fig. 2. Block Diagram of HVAC System

air volume (VAV) system, which distributes conditioned air to each terminal unit and zone through a duct system, also regulates the temperature inside the zones. In response to the need for cooling in the zone, a thermostat controls a modulating damper at each terminal. To reach the desired zone temperature set point, the VAV system uses a number of controls, including a supply air temperature controller, fan speed controller, and room temperature controller. The controller activates to regulate the internal VAV box damper, adjusting the air flow volume to attain and maintain suitable indoor thermal conditions, depending on the difference between the current room temperature (TZA) and the current room temperature set-point $(Tset, ZA)$. Table I and II give the related main building and HVAC design configurations.

TABLE I

BUILDING DESIGN PARAMETER.

Description	Design Parameter
Location	Sydney, Australia
L x W of building	20 m x 20 m
Number of floor	Single storey
Floor to ceiling height	3.5 m
Window to floor ratio	35 %
Occupants	0.15 person/sqm
Lighting power	20 W/sqm
Equipment power	12.5 W/sqm
Shade-coefficient and window U values	SC=0.95,U=6.21 W/sqmK
U value of the roof	0.795 W/sqmK
U value of the above grade wall	3.778 W/sqmK

However, several damper modulations in the VAV box cause a change in static pressure inside the supply air duct. As a result, the supply fan controller modifies the supply fan speed in accordance with the difference between the static pressure within the duct (P_{SA}) and the static pressure inside the duct's set point $(P_{set,SA})$. In order to regulate the supply air temperature (T_{SA}) of the AHU in the VAV system, the cooling coil valve controller modifies the cooling coil valve (CCV) in order to modulate the cooling coil water flow rate in accordance with the difference between the supply air temperature (T_{SA}) and the supply air temperature set point $(T_{set,SA})$.

TABLE II

SYSTEM SET UP FOR HVAC SIMULATION MODEL.

Description	Design Setting
Capacity	Auto Sizing
Chiller coefficient	4.45
Chilled water temperature	7 deg C
Supply/return chilled water temperature different	5 deg C
Supply condensed water temperature30 deg C	35 %
Supply/return condensed water temperature different	5 deg C
AHU fan power	0.000826 W/cfm
Supply air temperature set point	12.77 deg C W/sqm
Zone heating and cooling point	21 deg C and 22 deg C
Control	AHU with VAV, equipped with VSD

The summer season was used to develop the HVAC simulation model, along with several severity levels that simulated both fault-free (normal) and faulty operation circumstances. The summertime settings of the simulation model were divided into three groups: the AHU setting, the zone setting, and the setting for the heating and cooling plants. For each sort of operating condition, the experimenal HVACSIM+ model was supposed to run for 24 hours. The building's occupied hours were from 6 AM to 6 PM, while its unoccupied hours were from 6 PM to 6 AM the next day. To meet the minimum ventilation requirement, the outdoor air damper's minimum opening was set at 40% open. When the supply air temperature was set to 12.77°C and the external air temperature was less than 18°C, it was configured to activate the economiser control. In order to keep the duct static pressure at 1.4 psi, the supply fan speed was adjusted. A speed tracking control device was installed in the return fan, and it was set to keep the supply fan speed at 80%.

For the duration of the occupancy, the room's temperature was set to 21°C. For the exterior and interior zones, the maximum and lowest air flow rates were set at 1000 cfm and 400 cfm and 200 cfm, respectively. The experiment was run for 3 normal days and 9 distinct fault kinds on 9 separate days. Each minute, the data was sampled. In a 24-hour period, 1440 samples from 194 sensor readings were gathered. Among 194 sensors readings, Fig.3 and 4 indicate the time series data from sensors readings of the AHU system under normal operation for temperature and airflow rate. However, the data readings will be varied from

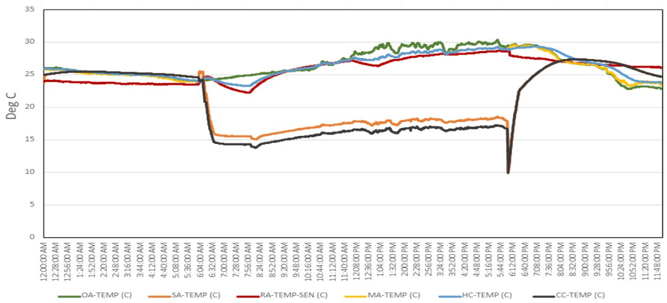

Fig. 3. Temperture Sensors Data

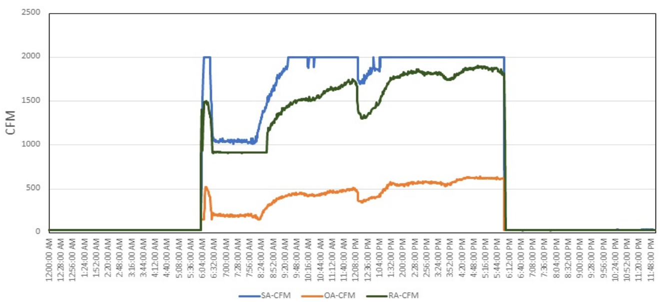

Fig. 4. Air Flow Rate

normal condition while the HVAC system is operating in abnormal conditions, such as malfunctioning of the controls, leakage or stuck of the cooling and heating coil valves, and malfunctioning of the dampers. The information sources and descriptions of the fault types and samples are listed in Table III:

TABLE III
SUMMARY OF AHU FAULTS CONSIDERED IN THE PROPOSED FDD MODEL.

Fault Description	Fault Code	Sample
Normal Condition	NORMAL	2160
Control Coil Valve stuck at fully opened	CCV100%OP	720
Control Coil Valve stuck at fully closed	CCV100%CL	720
Cooling Coil Valve Reverse Action	CCVREV	720
Duct Leaf After Supply Fan	DLAFTSF	720
Exhaust Air Damper stuck at opened	EADAMPOP	720
Exhaust Air Damper stuck at closed	EADAMPCL	720
Outside Air Damper stuck at closed	OADAMPCL	720
Outside Air Damper stuck at 45% opened	OADAMP45%OP	720
Heating Coil Valve Leak	HCVLSTG2	720

B. Deep Convolution Neural Network

The classification of HVACV faulty and normal time series generated by HVACSIM+ in section II-A is carried out using the one-dimensional convolution neural network (1D-CNN) [19], which is described in this section along with its training process. As shown in Fig.5, the typical architecture is split into two parts: the first uses convolution operations to create a feature map of the raw input signal with the proper kernel size, and the second employs multi layer perception (MLP) to identify faults characteristics. The first input layer has $N \times k$ input dimensions, where k is the variate number of input time series and N is the length of each univariate series. The convolution layer, which is the second layer, executes convolution operations using m numbers of filters, convolution stride s and the $y \times y$ filter size. In addition, a non-linear transformation function f also needs to be considered in this layer.

The next stage is the pooling procedure, which involves splitting a feature map into N equal-length segments and representing each segment by its average or maximum value. By downsampling the output bands of the convolutions, the pooling procedure has the advantage of reducing the hidden activation's variability. A set of feature mappings that link to final output layers with n classes after various convolution and pooling processes represent the initial time series. A sequence of training examples which is used to perform is given by: $(x_1, y_1), (x_2, y_2), .., (x_{Nsample}, y_{Nsample})$ with $(x_t \in R^{N \times k}, y_t \in R^n for 1 \leq t \leq N_{sample}$. The multivariate or uni-variate time series x_t is given as input to the network, while the vector y_t denotes the target output. The network is trained using the multiple steps as detailed in [19].

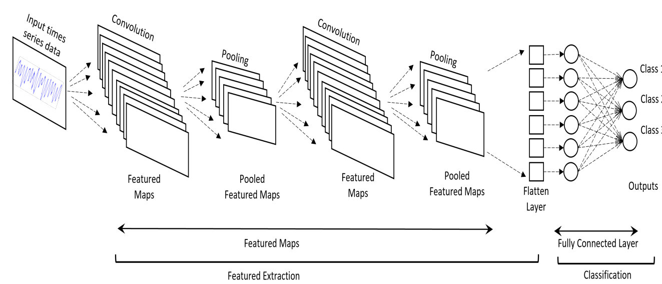

Fig. 5. 1D-CNN architecture: convolution, pooling, and fully connected layers.

III. RESULT AND DISCUSSION

The proposed 1D-CNN HVAC fault detection system was validated through data collecting during the occupancy period, resulting in 720 data points over 12 hours. Sensor readings did not vary significantly outside the cutoff period, but they were not suitable for use in modeling and decision making. Table III shows the number of normal samples collected during 3 fault-free days and the number of fault samples collected for each fault type. Section II-A of this study looked at the nine different types of operational HVAC faults and normal conditions. Using the data samples as indicated in Table III, the training and testing of the proposed model were conducted using 6912 and 1728 samples, respectively.

Due to the fact that the CNN model in this experiment was developed layer by layer during training, a sequential model was used in Keras to generate it. An architecture consisting of five convolutional layers, followed by pooling layers and a fully connected final classification layer. A seven layer 1-D CNN was developed to extract features and classify HVAC faults. The network has a 32-32-64-64-128-128-10 design, whereas every layer was made up of kernel filters with a stride of 1 and a size of $[6 \times 6]$. Table IV contains information on the number of optimised parameters for the proposed 1D-CNN HVAC fault detection system. Regarding other parameters in the network, SoftMax was used for final classification, whereas a rectified linear unit (ReLU) was employed as an activation unit for all the convolution layers. The adaptive moment estimation (Adam) [19] optimizer was used for best optimised parameters.

TABLE IV
1D-CNN HVAV FAULT DETECTION SYSTEM: NETWORK ARCHITECTURE AND PARAMETERS

Layer	Filters	Kernel	Output	Parameters
Input Layer	-	-	(194,1)	-
Conv1D	32	6×6	(194,32)	224
Batch Normalization	-	-	194,32	128
ReLU	-	-	194,32	-
Conv1D	32	6×6	194,32	6176
Batch Normalization	-	-	194,32	128
ReLU	-	-	194,32	-
Conv1D	64	6×6	194, 64	12352
Batch Normalization	-	-	194, 64	256
ReLU	-	-	194,64	-
Conv1D	64	6×6	194, 64	24640
Batch Normalization	-	-	194, 64	256
ReLU	-	-	194,64	-
Conv1D	128	6×6	194, 128	49280
Batch Normalization	-	-	194, 128	512
ReLU	-	-	194,128	-
Global Average Pooling	-	-	128	-
Classification	-	-	10	1290

The proposed 1D-CNN can identify 10 different types of summer HVAC faults with better accuracy at 94%. The confusion matrix in Fig.6 indicates that the diagnosis accuracy of the proposed 1D-CNN for every single fault type is higher than 89% except for heating coil valve leak (HCVSTG2L) of 82% accuracy. In addition, the proposed method achieves above 95% accuracy in the classification of cooling coil valve faults and outside air damper faults which considered as the most significant faults in HVAC system. The exhaust air damper stuck opened faults (EADAMPOP) are successfully classified with 96%, whereas 3% fo these faults are misclassified to normal conditions due to minimal effect to the system. Furthermore, fault free conditions (NORMAL) and are successfully classified with 96% accuracy, whereas $1-2\%$ of normal conditions are mis-classified to other faults which are insignificant to the system.

Table V shows the detail experimental results for the proposed 1D-CNN approach. Aside from the precision rate of DLBFSF at 82%, the precision rates of others range from 91% to 100%, while recall rates average around 94%. In this experiment, the $F1-score$ is used to assess how well the model handles unbalanced data, a high $F1-score$ frequently indicates that the model handles uneven data well. The $F1-score$ details in Table VI results show how well the developed 1D-CNN handles an unbalanced input data set.

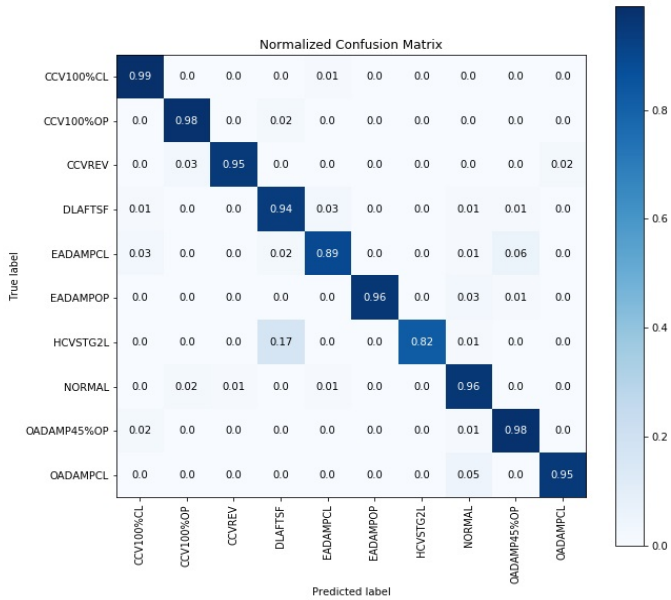

Fig. 6. FDD-CNN Confusion Matrix

TABLE V
PERFORMANCE EVALUATION OF PROPOSED 1D-CNN USING HVACSIM+ SIMULATED DATA

Fault Code	Precision (%)	Recall(%)	F1-score (%)
NORMAL	96	96	96
CCV100%CL	95	99	97
CCV100%OP	92	98	95
CCVREV	98	95	96
DLAFTSF	82	94	88
EADAMPCL	91	89	90
EADAMPOP	100	96	98
HCVSTG2L	99	82	90
OADAMP45%OP	91	98	95
OADAMPCL	98	95	97
Overall Model Accuracy	94	94	94

The efficiency of the proposed 1D-CNN approach is compared and analysed in Table VI results with previous FDD (RF and SVM) models for summer fault patterns using 10 classes (1 normal and 9 faults). For the RF classifier, the model evaluates a raw sensor signal with 194 features to compare the performance of the models. In spite 88% model accuracy, the experimental result, as shown in Table VI, indicates that the RF performed well for detecting HVAC's faults, which given overall accuracy of 88%. It provides promising results in detection of cooling coil valve reverse action (CCVREV), exhaust air damper stuck closed faults (EADAMPCL) and cooling coil val faults (CCV100%CL, CCV100%OP).

However, the RF classifier performed considerably lower than the proposed 1D-CNN approach in classifying fault free conditions (NORMAL), exhaust air damper stuck opened faults (EADAMPOP) and outside air damper faults

TABLE VI

COMPARISON STUDIES WITH OTHER STATE-OF-THE-ART FDD ALGORITHMS

Fault Code	**1D-CNN** (%)	**RF** (%)	**SVM** (%)
NORMAL	96	73	91
CCV100%CL	99	96	69
CCV100%OP	98	97	92
CCVREV	95	100	85
DLAFTSF	94	93	73
EADAMPCL	89	100	69
EADAMPOP	96	80	94
HCVSTG2L	82	88	94
OADAMP45%OP	98	93	64
OADAMPCL	95	93	69
Model Accuracy	94	88	82

(OADAMP45%OP, OADAMPCL). For the SVM based model, the model evaluates with the same input dataset to compare the performance with other approaches. With the 82% of model accuracy, the SVNM based model can detect the NORMAL with 91% accuracy, CCV100%OP with 92 % accuracy, EADAMPCL & HCVSTG2L with 94% accuracy respectively. However, it performs significantly low accuracy in classifying some faults types such as OADAMP45%OP, OADAMPCL, CCV100%CL, EADAMPCL, DLAFTSF faults. Despite the fact that all comparison FDD models successfully classify 10 different types of HVAC faults, the classification accuracy of some faults is less than 75% in each individual approach, which is significantly lower than the proposed 1D-CNN. This clearly indicates that the proposed 1D-CNN performs better in the fault diagnosis of HVAC systems, with an improved accuracy of 94%.

IV. CONCLUSION

Experimental HVAC fault data simulated from a building energy model (HVACSIM+) was used to develop a new fault diagnostic system using 1D Convolutional Neural Networks to accurately detect 10 types of HVAC faults (CNN). High-level useful features are extracted from the raw HAVC sensor signal using optimised parameters in the proposed CNN-based FDD system. The CNN framework with unsupervised feature extraction and softmax classification to mutually improve both feature extraction and classification processes and improve the performance of the FDD system with 94% accuracy. Studies comparing the proposed method to existing data-driven FDD methods (RF and SVM). The developed fault detection system allows for real-time fault detection and maintenance of HVAC systems, improves the accuracy, reliability of system, and meets energy-saving targets. It enables locals and maintenance staff to troubleshoot HVAC systems quickly and efficiently and return them to regular functioning after identifying fault events. Despite the fact that the proposed technique produced promising results, it has potential limitations for large-scale computations in real-time implementation. Future research should concentrate on improving real-time effectiveness and accelerating deployment.

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