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Fault Detection and Diagnosis of Air-Conditioning System using Long Short-Term Memory Recurrent Neural Network

***Abstract**. In this project, a fault detection and diagnosis (FDD) system was developed using Long Short-Term Memory Recurrent Neural Network (LSTM RNN), to detect and classify six common faults in a centralised chilled water air conditioning system. Datasets from a lab-scale centralised chilled water air conditioning system were used in the developed model. Results showed that the classifier model demonstrated a classification accuracy of over 99.3% for all six classes.*

Streszczenie.** W ramach tego projektu opracowano system wykrywania i diagnozowania usterek (FDD) z wykorzystaniem powtarzającej się sieci neuronowej długookresowej pamięci (LSTM RNN) w celu wykrycia i sklasyfikowania sześciu powszechnych usterek w scentralizowanym systemie klimatyzacji wody lodowej. W opracowanym modelu wykorzystano zestawy danych ze scentralizowanego systemu klimatyzacji wody lodowej w skali laboratoryjnej. Wyniki pokazały, że model klasyfikatora wykazał dokładność klasyfikacji na poziomie ponad 99,3% dla wszystkich sześciu klas.* (Wykrywanie usterek i diagnostyka układu klimatyzacji z wykorzystaniem powtarzającej się sieci neuronowej z pamięcią długookresową***)

Keywords: chilled water system; fault detection and diagnosis; LTSM-RNN.
Słowa kluczowe: system wody lodowej; wykrywanie i diagnostyka usterek; LTSM-RNN.

Introduction

The heating, ventilation, and air conditioning (HVAC) system plays important components in many areas such as transportation, building management, and many more. In commercial and office buildings, HVAC consumes about 50% of the overall electricity consumption [1], [2]. Centralised chilled water air conditioning system normally used in commercial and office building is a complex system that consists of various components and interrelated to each other. Therefore, faults from other component may affect the performance of other component as well. For instance, cooling tower fan faulty may increase the temperature of the returned chilled water of the chiller. Consequently, the refrigerant cannot be cooled off completely, thus affecting the supplied air temperature. The untreated faults in one of the air conditioning system components may cause faults to the other components as well. For examples, the untreated cooling tower fan faulty may trigger the chiller compressor to work more in order to cool off the refrigerant. As a result, the chiller may overheat and breakdown. Hence, it is crucial to quickly detect any abnormalities in the system and diagnose the fault correctly to avoid any occupant discomfort, energy wastage, or shorten the equipment lifetime [3].

Due to these issues, a significant number of researchers have focused on studying and implementing fault detection and diagnosis (FDD). FDD provides information that can identify the initial operating performance by inferring the system's state to distinguishes a faulty condition. Supervised FDD methods for building energy systems were successfully diagnosing device faults and sensor faults [4]. The FDD was successfully implemented not only in HVAC fields, but also in other fields as well such as process control and automotive. FDD is particularly crucial in safety-critical and high-cost processes. A successful FDD is not only optimise the energy usage, but it also can expand the system lifespan and reduce the system maintenance costs. The operation performance improved significantly if the detected faults are removed in time. With a successful FDD, it can save 10% - 40% of HVAC energy consumption [5].

Three FDD methods regularly used in HVAC researches which are model-based, rule-based and data driven methods. For instance, Li et al. [6] proposed a model-based method to combine the Hidden Markov process, unscented Kalman filter and dynamic control limit to detect faults and to identify the severity of the faults in chiller system. Likewise, Trothe et al. [7] combined a model-based approach and sensor placement algorithm to improve air handling unit (AHU) fault diagnosability for actual smart building application. Meanwhile, Li et al. [8] implemented a semi-supervised data-driven FDD method at chiller system. They mixed 80 labeled data and 1600 unlabeled data, and the accuracy increased to 84% as compared 65% for supervised data. Yun, Hong and Seo [9] successfully applied a supervised auto-encoder (SAE) for both defined and undefined conditions. The proposed method outperforms support vector machine (SVM) and artificial neural network (ANN) with the precision and recall of 99% and 96.9%, respectively. Similarly, Sulaiman et al. [10] investigated the performance of decision tree, SVM and K-Nearest Neighbours (KNN). All models were successfully detect and diagnose all six common faults in centralised chilled water air conditioning system for more than 97.5% accuracy.

Model-based technique is the most accurate in describing the system, but it is difficult to develop because of the complexity of the air conditiong system itself. Meanwhile, rule-based method did not gain much interest among researchers as complicated systems and faults may not be described correctly using this technique, especially when more rules are required. In contrast, data driven method is easy to implement as it uses fault-free historical operational data to train the system. Furthermore, it does not require verification because the datasets were taken from the actual building. Data driven method such as ANN, SVM, KNN, convolution neural network (CNN) and long short term memory (LSTM) are among the most widely used in FDD.

LSTM was introduced to overcome the gradient problems in recurrent neural networks (RNN) [11]. Therefore, the learning ability of LSTM has gain interest among researches especially in time series deep learning model. Yan K and Hua J in [12] proposed an LSTM neural network to detect and diagnosis five chiller faults in different severity levels by optimizing and cross- validated the parameters. The proposed method outperforms RNN and GRU frameworks with higher detection and diagnosis accuracy. Park et al. [13] proposed LSTM to classify different type of faults of an auto encoder and compared with deep CNN. The accuracy of LSTM achieved is 91.9%, which much higher than deep CNN with 76.4%. LSTM-RNN classifier successfully detects the attack from intrusion detection system very well with the highest accuracy, 96.93% compared with other classifiers like SVM with 90.4%, KNN with 90.74%, etc. Meanwhile, Abboush et al. [14] combined CNN and LSTM to identify eight types of common sensor faults in the signals of automotive software systems (ASSs). The proposed model successfully achieves average accuracy of 98.85%. LSTM method is also successfully implemented in image recognition as well. For instance, Jebarani and Umadevi [15] proposed one dimensional convolution LSTM (1 DCLSTM) to classify breast ultrasound image into normal, benign, and malignant, respectively. They applied grey wolf optimization GWO) to select the optimal features prior classification. Results show that the proposed method attains 99.43% accuracy, 99.67% specificity and 99.13% sensitivity. In summary, the LSTM RNN is successfully integrated into the fault detection and diagnosis application in various fields.

The objective of this paper is to develop and analyse the performances of LSTM RNN model in detecting and classifying common soft and abrupt faults in centralised chilled water air-conditioning system. In this paper, the model was trained and tested using datasets previously developed in [10], [16]–[19]. The classification performances of the LSTM RNN model were compared with Support Vector Machine (SVM).

This paper was written in four sections. The first section briefs some introduction regarding this paper. The details of the methodology are then explained in Section 2. The results analysis are discussed thoroughly in the following section, whilst in last section concludes the findings of this paper.

Methodology

This sections explains the experimental setup, data collection, data classification, data pre-processing and simulation setup involved in this paper.

Experiment Setup and Data Collection

The dataset was obtained from a lab-scaled chilled water air-conditioning system developed by [10], [16]–[19]. The system is a set of standalone and self-contained equipment. It has a structured platform to accommodate the cooling tower system, water-cooled chiller system, and AHU system. Two rooms were installed next to the structured platform. The developed lab-scale chilled water air conditioning system is shown in Fig.1, while the schematic diagram is shown in Fig.2.

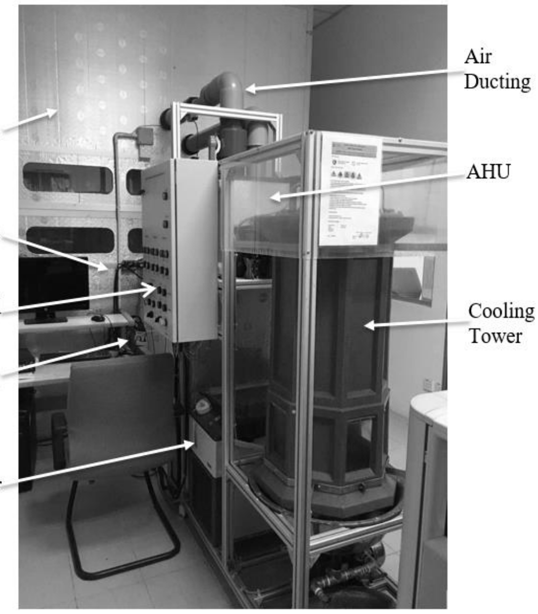

Fig.1 The lab-scale chilled water air conditioning system

Fourteen sensors were installed within the experimental setup, which comprises of one current sensor, two air flowrate sensors, three water flowrate sensors and eight temperature sensors. The system was also equipped with five 100W bulb to mimic heat from occupants and equipment. The system was run from 0800 to 1700 to replicate the air-conditioning usage during office hours. During simulations, two bulbs were turned on to represent heat load from a person and a laptop.

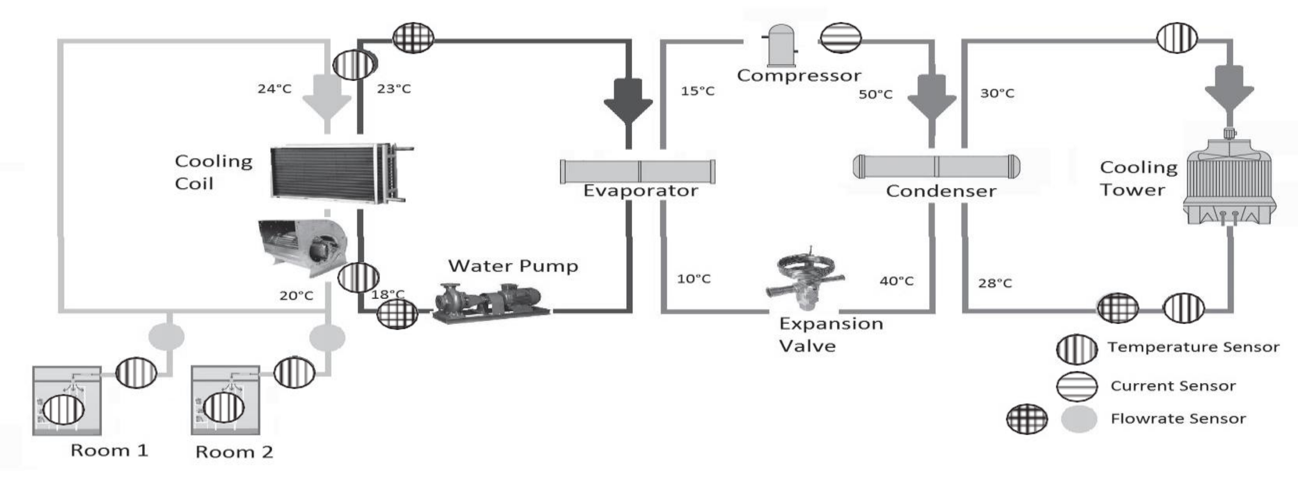

Fig.2. Schematic diagram of sensors located in the prototype system [10], [16]–[19]

Data Classification

Six classes of conditions were simulated in this paper which are five common faults in chilled water air-conditioning system and one normal condition. The details for each class and its fault location were tabulated in Table 1. It consists of soft and abrupt faults. Soft faults are difficult to detect early because they are degraded over the time and only noticeable when the faults have worsenedMeanwhile, the abrupt faults easy to detect because it caused the system to have total breakdown. However, this major breakdown involves big money to repair.

Table 1 Details for each class

Class	Condition	Fault's location
A	Normal	-
B	Cooling Tower Fan Faulty	Cooling Tower
C	Compressor Malfunction	Chiller
D	Supplied Chilled Water Clogging	AHU
E	Damper Stuck	Chiller
F	Air Ducting Leakage	AHU

Data Pre-processing

The collected data was used as the input to train the LSTM RNN model. The process was started by sampling the 133,000 rows of data to 13,166 rows using the Microsoft Excel function. The data was sampled for every 30 seconds interval for every class type. Next, the data were normalised by using the minimum-maximum feature scaling method. The reason was to prevent parameters with a higher range of values affect the training accuracy results. Data normalisation will balance the data range and the flexibility of the data. The next step was to randomly divide the data into 70% of training dataset equivalent to 9216 data and 30% of testing dataset equals 3950 datasets.

Simulation Setup

The LSTM RNN model was built by using MATLAB. The process was started by declaring data's features, training layers, training options, and training network as described in Table 2. The training layers were used to define the deep learning layer and specify optional learnable parameters. The fully connected layers multiply the input by a weight matrix and then add a bias vector for the features and fault class. The LSTM layer then performs additive interactions, improving gradient flow over long sequences of the time series during training. The Rectified Linear Unit (ReLU) layer performs a threshold operation to each input element. After that, the softmax layer applies a softmax function to the input. Lastly the classification layer computes the cross-entropy loss for multiclass classification problems with mutually exclusive classes.

Subsequently, the training options were set for training deep learning neural networks. The mini-batch size specified as a positive integer is used for each training iteration. It is used to evaluate the loss function gradient and update the weights. The gradient threshold was set to 1 so that if the gradient exceeds 1, the gradient is clipped. Shuffle every epoch used to mix up the training data before each training epoch.

Table 2 Parameter setting for LTSM-RNN

Parameters	Setting
Hidden units	10
Training layers (Fully connected)	LSTM ReLu Softmax
Training options	Mini batch size = 16 Gradient threshold = 1 Shuffle = every epoch (30 epochs)

The process also included setup for output confusion matrix and the accuracy for training and testing. The LSTM RNN model was developed for 576 training iterations in one-time processing for forward and backward for an epoch of time series data. The process continued until the iterations reached 30epochs, which accumulated to 17280 iterations. The process took about 5 minutes and 3 seconds to entirely run the classifier model.

Next, the Support Vector Machine (SVM) model was developed using the Classification Learner App in MATLAB. The dataset was imported into the app, and the testing data was held out using holdout validation for 30%. The kernel function used was linear.

Results and Analysis

All results obtained from LSTM-RNN and SVM model are presented and discussed in this section. Both models were developed, trained and tested using MATLAB software.

LSTM-RNN

Fig.3 illustrates the LSTM-RNN training progress developed in MATLAB. The top graph describes the accuracy pattern, meanwhile the bottom graph shows the losses. The accuracy pattern reached towards 100%, while the losses pattern reached towards 0% at the first 2000 iterations. It indicates that the trained model was successfully developed with high accuracy and nearly zero losses.

Meanwhile, Table 3 and Table 4 presents the confusion matrices for training and testing datasets. The matrix represents the accuracy of the machine learning model [20], where it indicates the correlation between the actual and predicted classes. The top row represents the predicted classes, whilst the most left column represents the actual classes. From Table 3 and Table 4, they show that the model was able to successfully classify all six types of conditions even though the data was slightly imbalanced for both training and testing data. The accuracy percentage for all classes were portrayed Fig.4, where LSTM-RNN model has accuracy of more than 98.7% for training datasets and 98.1% for testing accuracy.

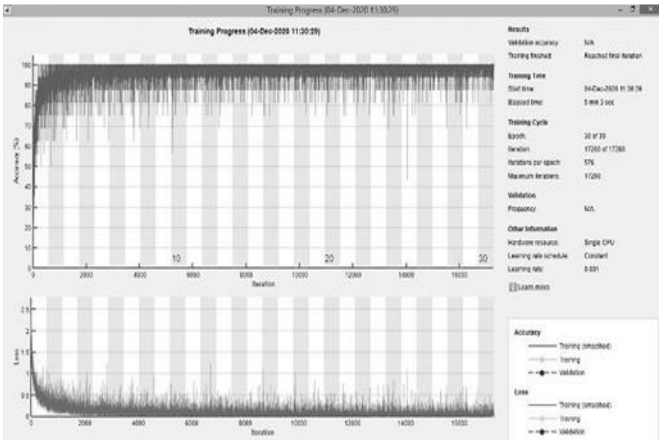

Fig.3. LSTM-RNN Training Progress

Table 3 Confusion matrix for training dataset

Type	A	B	C	D	E	F
A	1754	1	0	2	0	1
B	0	1720	0	7	0	1
C	3	21	1167	2	0	0
D	0	0	6	1733	0	4
E	0	0	0	0	1195	0
F	1	0	0	0	0	1598

Table 4 Confusion matrix for testing dataset

Type	A	B	C	D	E	F
A	757	0	3	4	0	0
B	0	790	10	0	0	0
C	0	1	471	2	0	0
D	4	1	3	770	0	0
E	0	0	0	0	485	0
F	1	0	0	0	0	648

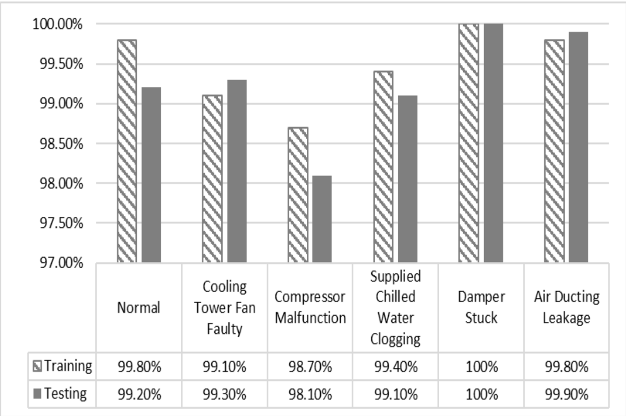

Fig.4. The accuracy of LSTM-RNN

SVM

The SVM model was developed in Classification Learner App in MATLAB as shown in Fig.5. Table 5 and Table 6 show the SVM confusion matrices in classifying all the dataset corresponding to its classes for training and testing data, respectively. 9074 out of 9216 instances training data was correctly classified, whereas the remaining 142 instances data was wrongly classified, which equivalent to a 1.6% loss. Likewise, the percentage losses for testing data was almost similar to the training losses, which was 1.8%. Fig.6 shows the percentage accuracy for each class, which show that SVM model has accuracy of 97.3% - 99.9%, whilst training datasets around 97% - 99.7%.

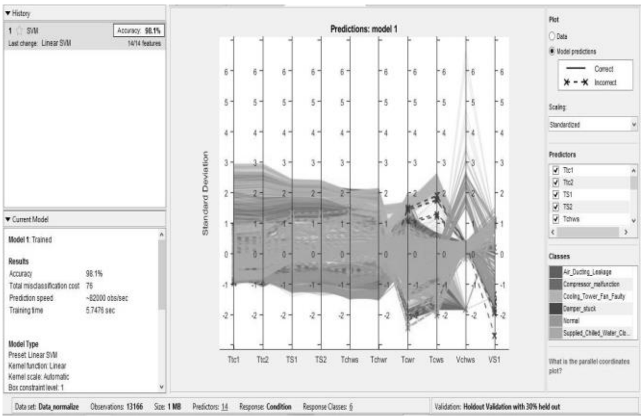

Fig.5. SVM Training Progress

Table 5 Confusion matrix for training dataset

Type	A	B	C	D	E	F
A	1728	1	0	15	0	5
B	15	1693	5	43	7	2
C	3	0	1119	44	0	0
D	0	0	0	1773	0	0
E	0	0	0	0	1173	0
F	1	0	0	0	2	1588

Table 6 Confusion matrix for testing dataset

Type	A	B	C	D	E	F
A	765	0	0	3	0	3
B	7	716	4	21	6	1
C	1	5	487	21	0	0
D	0	0	0	746	0	0
E	0	0	0	1	505	1
F	1	0	0	0	0	655

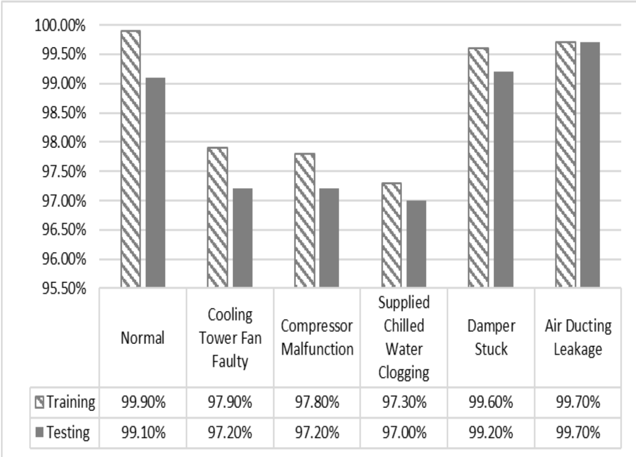

Fig.6. The performance of SVM model

Comparison LSTM RNN and SVM Performance

As shown in Fig.4 and Fig.6, both models were successfully classified all classes for more than 97% of accuracy. Eventhough LTSM-RNN has higher accuracy compared to SVM, but as overall, the accuracy was not much different between these two models. Fig.7 shows the overall performance between LSTM-RNN and SVM. The accuracies of LSTM-RNN was 99.47% for training dataset and 99.27% for testing dataset. Meanwhile, the accuracies of SVM model was 98.7% for training dataset and 98.23% for testing dataset. Thus, it indicates that LSTM-RNN has better performance in classifying the supervised data compared with SVM.

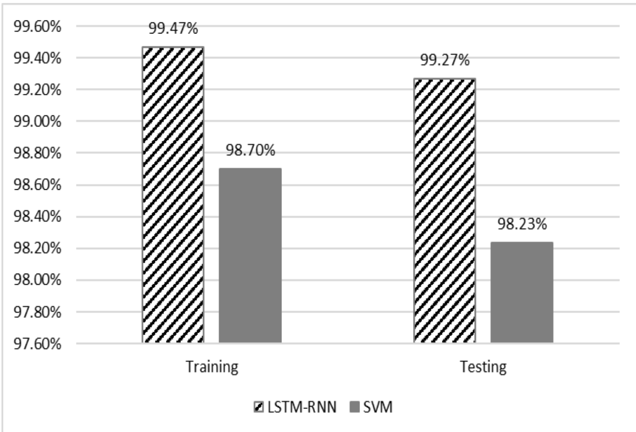

Fig.7. Performance between LSTM RNN and SVM

Conclusions

This paper investigates the performances of machine learning models to detect and diagnose six different faults commonly occurred in centralised chilled water air-conditioning system. Two machine learning models were trained and tested using dataset from the lab-scale prototype centralised chilled water air-conditioning system. The simulation results showed that both machine learning models successfully detected and diagnosed all six classes. Nevertheless, the LSTM-RNN has the highest accuracy up to 99.27% compare to SVM 98.23%. All simulations were conducted in MATLAB software.

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