A deep neural network based fault diagnosis method for centrifugal chillers

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Abstract. Various types of faults occur in building energy systems throughout their life-cycles. Some faults grow gradually and naturally causing increasingly system energy penalty and performance degradation. Hence, it is crucial to implement an efficient fault diagnosis strategy and maintain optimal operations for systems. Recently, data-driven methods have got increasing interests due to the model flexibility and data availability in modern building energy systems. The fast development in data science has provided new data analytics to tackle classification and prediction problems in a more convenient and efficient way. This paper attempts to investigate the potential of a promising data analysis technique, i.e., deep neural network, in classifying and diagnosing faults in a building energy system, i.e., centrifugal chiller plant. This study exploits the deep neural network based method in both supervised and unsupervised manners, and compares the fault diagnosis accuracy. Centrifugal chiller experimental data from the ASHRAE Research Project 1043(RP-1043) are used to validate the proposed method. Results show that the method can correctly diagnoses the fault data for seven typical chiller faults.

1. Introduction
Various types of faults occur in building energy systems throughout their life-cycles [1,2]. Some faults grow gradually and naturally causing increasingly system energy penalty and performance degradation [3]. As a commonly used building cooling system, chillers are large energy consumers accounting for about 40% of the total energy used in the commercial and industrial buildings for space cooling [4]. Faults can lead to system energy inefficiency, sometimes the efficiency drop can be as much as 30% [5]. Therefore, it is crucial to implement an efficient fault diagnosis strategy and maintain optimal operations for the system.

Over the past two decades, data-driven methods have got increasing interests due to the model flexibility and data availability in modern building energy system [6]. The fast development in data science [7,8] has provided new data analytics to tackle classification and prediction problems in a more convenient and efficient way. Recently, deep learning algorithms [9] have been active in research areas, like energy demand prediction [6,10,11] and anomaly detection [8] in building systems, fault diagnosis in complex industrial and mechanical systems [12,13]. Generally, deep learning architecture has four main types such as deep neural networks, deep belief networks, deep convolution neural networks and recurrent neural networks. And deep learning models can be trained in three
learning manners: supervised, semi-supervised or unsupervised. This study attempts to investigate the potential of a promising data analysis technique, deep neural network [14,15], in diagnosing the fault causes in a typical building energy system, i.e., centrifugal chiller plant. The chiller experimental data from ASHEAR Research Project 1043(RP-1043) [16] are used to analyze the fault diagnosis performance in terms of diagnosis accuracy.

2. Methodology

Deep neural networks (DNNs) have deep architectures containing multiple hidden layers and each hidden layer conducts a non-linear transformation from the previous layer to next one [9,17]. DNNs can be trained in two different learning manners, supervised and unsupervised. The supervised DNNs are just trained in a similar way as the artificial neural network method. As shown in Figure 1, the unsupervised DNN models are trained in a different way consisting of two main steps: (1) Pre-train the DNNs layer by layer with unsupervised techniques, like the autoencoder (AE) in Figure 2. (2) Further fine-tune the DNNs with a softmax classifier for classification.

This study proposes a DNN based fault diagnosis method for the centrifugal chiller system. The proposed method uses an unsupervised autoencoder model to extract deep features from the raw sensor measurements. DNN can distinguish fault-free data and fault data using these learned deep features. The method has three steps as follows:

![Figure 1. Flowchart of the DNN-based classification model.](image)

![Figure 2. Structure of an autoencoder (AEm).](image)
• Data collection and preparation. We first collect and pre-process the chiller sensor measurements under various system operations including both fault-free and faulty operations. The steady-state chiller operational data are selected for model training in the second step.
• DNN model training. A DNN model with multiple hidden layers is trained using operational data prepared in the first step. The number of input units is the dimension of the measured variables. As displayed in Figure 1, the unlabeled training set is adopted to pre-train the DNN layer by layer with autoencoders, where the number of autoencoders refers to the number of hidden layers inside the DNN. The dimension of model output layer is determined according to the total number of the class labels. A softmax classifier is implemented to fine-tune the DNN by minimizing the error between the output and true class labels. Also, deep fault features can be extracted in the hidden layers of the trained model.
• Fault diagnosis. The trained DNN model in the second step is employed to diagnose faults of new testing data samples collected from practical chiller plants.

3. Results
This study validates the proposed method using the ASHRAE RP-1043 chiller experimental dataset including one group of normal data and seven groups of fault data from the Reduced Data Set [16]. The normal2 dataset is selected as the Normal class for model training and validation. Table 1 shows the seven faults. Each fault has 4 severity levels labeled with SL1 to SL4 in an ascending order. SL1 is the least severe fault while SL4 is the most severe level. The Reduced Data Set has totally 64 variables and 433 data samples for each SL. A slope based steady-state filter was adopted to remove the transient data in each SL [18]. After the data pre-processing process, 257 of the 433 data samples were eliminated for each SL. To avoid class imbalance problem, the steady-state Normal class is duplicated for three times and inputted to develop the DNN model, so the entire steady-state dataset has 176*(1*4+7*4)=5632 samples.

| Fault (class label)         | Descriptions                        | SL1 | SL2 | SL3 | SL4 |
|-----------------------------|-------------------------------------|-----|-----|-----|-----|
| Normal operation (Normal)   | Operating at fault-free conditions  | -   | -   | -   | -   |
| Condenser fouling (CF)      | Plugging tubes                       | 10% | 20% | 30% | 40% |
| Refrigerant overcharge (RO) | Overcharging refrigerant weight      | 10% | 20% | 30% | 40% |
| Refrigerant undercharge (RL)| Discharging refrigerant weight       | 10% | 20% | 30% | 40% |
| Non-condensable gas in refrigerant (NC) | Adding nitrogen volume | 1.0% | 1.7% | 2.4% | 5.7% |
| Reduced evaporator water flow (FWE) | Reducing water flow rate | 10% | 20% | 30% | 40% |
| Reduced condenser water flow (FWC) | Reducing water flow rate | 10% | 20% | 30% | 40% |
| Excessive oil (EO)          | Increasing lubricant charge          | 14% | 32% | 50% | 68% |

3.1. DNN model training and parameter tuning
The designed DNN model has seven layers consisting of five hidden layers. The unit number of the input layer is determined by the dimension of the input variables while the unit number of the output layer is determined by the number of fault classes. The unit number of the first to the fifth hidden layer are 64, 16, 2, 16 and 64 respectively. The unit number of the third hidden layer is designed to be only 2 since we want to explore the features in a least two dimensional space. Also, we try principal component analysis(PCA) projection method to get the visualization of the deep feature data in other hidden layers. The entire steady-state dataset is divided into three parts randomly: 40% of samples are selected as the training set, the other 30% are chosen as the validation set and the remaining 30% are
left to test the fault diagnosis performance. The DNN is trained in the RStudio environment. Some parameters are set to the default values, i.e. the weights are initialized randomly, the biases are initialized to zero, the maximum training epoch is 150, the learning rate is 0.05 and the momentum is 0. A grid search method is used to find an optimal combination of three model parameters such as activation function, L1 regularization and L2 regularization. To reduce computation cost, a random searching strategy is used to search all the combinations of the three parameters. The early stopping criterion is adopted the maximum runtime should be less than 600 seconds. After parameters tuning, the training DNN model selected hyperbolic tangent functions as activation and both L1 and L2 regularization values to be 0.0001. For each fault type, at least 25 trials were conducted for fault diagnosis.

3.2. Results of chiller fault diagnosis and deep features

This study compares the fault diagnosis performance of three DNN models including the unsupervised DNN model, the supervised DNN models with and without parameter optimization. To make it brief, this study uses abbreviations DNN(S), DNN(S,Opt) and DNN(U) to denote the three models. DNN(S) refers to the supervised DNN model without parameter optimization. DNN(S,Opt) refers to the supervised DNN model with parameter optimization. DNN(U) refers to the unsupervised DNN model. Figure 3 illustrates the fault diagnosis results of the three DNN models in terms of the average overall fault diagnosis accuracy of all ten trials. The overall diagnosis accuracy denotes to the ratio between the number of data samples that are correctly diagnosed by the model and total number of given data samples. In these trials, the overall diagnosis accuracies are over 90%, which indicates that the DNN method is able to distinguish the chiller faulty classes from the Normal class. After parameter tuning, the diagnosis accuracy of supervised model DNN(S,Opt) increased by about 1%, which can correctly identify the fault class labels for about 97% of three datasets including training, validation and testing sets. Clearly, the unsupervised model DNN(U) shows slightly better fault diagnosis results. The diagnosis accuracy of DNN(U) is around 98%. For each of the seven faults, Figure 4 depicts the average diagnosis results of the testing set. It can be found that the three models show relatively high model accuracy for the Normal class. DNN(S,Opt) shows the least accuracy, which is also larger than 89% although it may leads to false alarms during system operations. DNN(S,Opt) seems confused with some Normal and RL data.

![Figure 3](image1.png)

Figure 3. Fault diagnosis results of three datasets: training, validation and testing sets.

![Figure 4](image2.png)

Figure 4. Fault diagnosis results of each fault type in the testing dataset.

We take one trial as an example. In Figure 5 (b), PCA is used to project the deep feature data of hidden layer 4 (16 neural units) into the first two dimensions (Dim1 and Dim2 account for 51.7% + 47.7% of the total data variance information) in the PC subspace. From the data distribution illustration, it can be seen an obvious overlapping area of the deep fault feature data between RL class and Normal class. While for DNN(S) and DNN(U), the accuracies of the Normal data are 97% and 94%, respectively. From Figure 5 (a) and (c), it can be observed that the overlapping areas are reduced for deep fault features of DNN(S) and DNN(U). Obviously, the three DNN models can almost identify...
nearly all the fault data samples for four faults including CF, FWC, FWE and NC. But for the refrigerant charge faults, the DNN(S) model seems hard to distinguish some RL data from the EO data. As can be seen in Figure 5 (a), the RL class and the EO class are overlapped in their contact regions. The diagnosis accuracy of RL fault is only 83%. For the EO fault, DNN(S) can successfully diagnose 91% of the fault data. On the contrary, both DNN(S,Opt) and DNN(U) can at least 98% of the EO data and 90% of the RL data.

![DNN(S) model](image1)

![DNN(S,Opt) model](image2)

![DNN(U) model](image3)

Figure 5. Data visualizations of the forth layer deep fault features in PC subspace.

4. Conclusions
This paper presents a deep neural network based fault diagnosis method for centrifugal chillers. The ASHEAR Research Project 1043 experimental data including one normal and seven faulty groups of chiller data are used to validate the proposed method. The fault diagnosis performance is briefly analyzed. Main conclusions are as follows:

- The deep neural network method developed in both supervised and unsupervised manners shows good fault diagnosis performance for seven chiller faults including condenser fouling, refrigerant undercharge and overcharge, non-condensable gas in refrigerant, reduced evaporator water flow, reduced condenser water flow and excessive oil.

- The unsupervised deep neural network with autoencoder can be used to extract deep fault features. The feature extraction process is less dependent on human labor and prior knowledge about feature selection techniques. The deep fault features show good distinguishing ability even if the raw data dimensionality is reduced to only two dimensions. Using these fault features, the unsupervised deep neural network method obtains slightly higher chiller fault diagnosis accuracy than the supervised.

Future work should try to explore how to interpret the deep features and evaluate the feature importance. The optimization of the deep neural network structure and parameters, i.e., number of unit and layer should be studied. The model stability of the deep neural network method should be investigated. Comparisons with other machine learning methods also should be studied.
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