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Development of FDD model for a real-life case using transfer learning with synthetic data

Han-Gyeong Chu[1], Seongkwon Cho[1], Cheol-Soo Park [2*]

1 Department of Architecture and Architectural Engineering, Seoul National University

2 Department of Architecture and Architectural Engineering, Institute of Construction and Environmental Engineering, Institute of Engineering Research, College of Engineering, Seoul National University
(*Corresponding Author: cheolsoo.park@snu.ac.kr)

ABSTRACT

The Air Handling Unit (AHU) system is influenced by various types of errors, which can cause thermal discomfort of occupants and energy waste in building. Therefore, an early and accurate Fault Detection and Diagnosis (FDD) is important for optimal control of building heating/cooling systems and increasing occupant productivity. The data-driven FDD is promising because it is convenient compared to the first principles-based rule set that demands in-depth expertise. However, in order to realize the data-driven FDD for real-life cases, the data imbalance problem in FDD must be solved. In this study, the authors suggest a novel approach that generates synthetic data from an entire building system simulation tool, HVACsim+ and then use them as a source model for applying transfer learning to a target AHU system. For the transfer learning, only the normal operational data from the existing target system was used. It is found that the transfer learning approach is satisfactory, confirming that the proposed method will be effective in mitigating the data imbalance issue in developing the data-driven FDD.

Keywords: building energy, transfer learning, synthetic data, automated fault detection and diagnostics

1. INTRODUCTION

AHU systems are susceptible to various types of errors, such as sensor inaccuracies or equipment malfunctions, which can cause a decline in system performance, thermal discomfort for building occupants and energy waste in building. Therefore, there is a need for early diagnosis and resolution of these issues through the Fault Detection and Diagnosis (FDD) for improvement of building energy system efficiency.

Compared to the physics-based FDD, the data-driven building system FDD requires less physical knowledge about the building or cooling/heating system and can enable the application of high-performance FDD at a relatively low cost. However, one of the key challenges

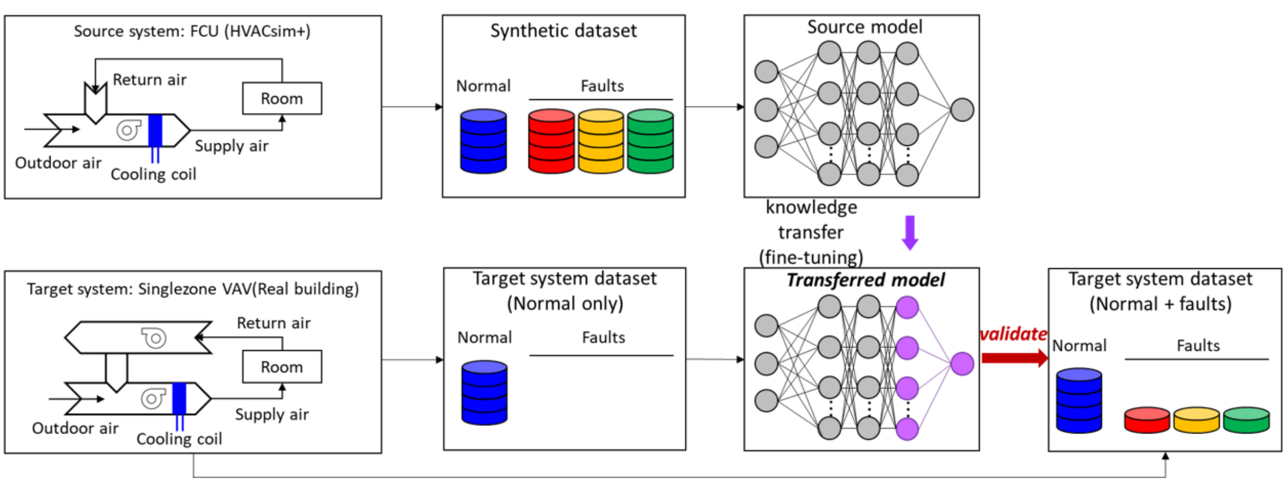

Fig. 1. Workflow of FDD model development via Transfer learning

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in applying the data-driven FDD to real-life cases is the data imbalance problem. Data imbalance refers to an uneven distribution of data among different classes, where certain classes have significantly fewer samples compared to others. This can result in a degradation of the learning performance for error situations and lead to a misconception about the prediction accuracy. For example, in a scenario where 95% of the data collected from an existing building represents normal operating conditions, and only 5% represent error conditions, the FDD model may be evaluated as having a high accuracy of 95% even if it predicts all data as fault-free.

To overcome the aforementioned data imbalance problem, the authors propose a transfer learning approach for developing a building system FDD process following the workflow as shown in Fig.1. (1) Generate synthetic data (or source data) using an entire building system tool, or HVACsim+. (2) Develop a data-driven FDD model (source model) using the source data (FCU). (3) Develop an FDD model for the target system (single-zone VAV) using transfer learning where only normal operational data from the target system was used.

2. DEVELOPMENT OF FDD MODEL

2.1 Source vs. target system

The target system was a single zone variable air volume (VAV) system as shown in Fig. 2. The authors used the AHU data measured from the experimental facility (Granderson, J., & Lin, G. 2019). Internal heat loads that were similar to those in a real commercial building were added in the experiment. Please note that the test cell is served by AHU with a chilled water plant and a hot water plant.

Fig. 2. Target system:F FLEXLAB Test cell X3A (Granderson, J., & Lin, G. (2019))

In contrast, the selected source system is a fan coil unit (FCU) system, while the target system was a single zone VAV system as mentioned above. The synthetic FCU data was generated from HVACsim+ simulations (https://faultdetection.lbl.gov/data/).

The typical fault type of the system is a fully opened cooling coil valve (Mulumba et al, 2015). The synthetic source dataset includes an equal amount of data for both fault-free and fault data.

2.2 Development of source model with synthetic data

Using the synthetic data of the FCU system, an ANN model was developed to classify fault-free and fault scenarios. A total of five variables (room temperature, cooling setpoint temperature, mixed air temperature, supply air temperature, operation status of the supply fan) were selected as input variables for the ANN model. This selection of the five input variables was purposefully designed to investigate the feasibility of the data-driven FDD whether the minimum data that can be easily collected from existing buildings would be sufficiently enough for realizing the data-driven FDD. The ANN model was trained to determine the presence of system errors using input data of one hour. Please note that one hour data consists of four samples with 15 min interval. A total of 5580 synthetic datasets equivalent of 5580 hrs were split into 3906 for training set and 1674 for validation set. The total number of hidden layers is 8, and for the activation functions, ReLU was used for the layers close to the input, while sigmoid was applied the layers closed to the output.

2.3 Transfer learning to fine-tune the source model with real data

The ANN model trained in Section 2.2 was then fine-tuned to be used for the real system by transfer learning. In order to transfer the knowledge acquired from the synthetic data, so the input layer was re-trained. Specifically, fine-tuning was performed using only the fault-free data from the target system owing to the difficulty of collecting fault data from the real building system. In this study, only the first layer was unfrozen (Guo et al, 2019) and re-trained on target system fault-free data with 30 epochs and learning rate is 0.001.

3. RESULTS

3.1 Performance metrics for model accuracy

In this study, the model performance was evaluated using the confusion matrix and the F1-score. The confusion matrix (Fig. 3) shows the relationship between the model's predicted results and the actual labels (Deng et al, 2016). The F1-score is particularly useful for evaluating model performance in situations where the class distribution is uneven, providing a reliable assessment of how well the model correctly identifies all samples. The F1-score can be calculated using the following equation.

$$\mathrm{F1-score} = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$

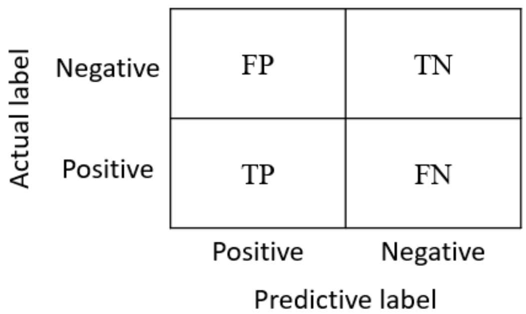

Fig. 3. Components of confusion matrix (True positive (TP), False positive (FP), False negative (FN), True negative (TN))

To evaluate the performance improvement enhanced by the transfer learning, two baseline cases and the proposed approach were defined as follows:

- Baseline case #1 (Source Model): The source model was trained on the synthetic source dataset. It serves as the base model for transfer learning.
- Baseline case #2 (Target Model, Fig. 2): A model trained using the measured dataset from the target system (Fig. 2). This model is a stand-alone model trained specifically for the target system.
- Transfer Model: The source model's weights were transferred and then fine-tuned using only the normal operation data from the target system. This transfer model is developed to employ the knowledge learned from the source model for the target system.

3.2 Source model's accuracy with synthetic data

Fig.4 shows the confusion matrix results of the source model with the synthetic data. Please note that 1,674 validation data consist of 824 fault-free and 850 fault data. Both of the F1-scores for fault-free fault data are 1.0, which indicates that the faults of 'the cooling valve fully opened' can be accurately detected without errors. However, please note that the F1-scores of 1.0 were obtained based on the synthetic data. In other words, sufficient knowledge about the cooling coil faults can be acquired through the synthetic data.

3.3 Development of source model with synthetic data

Fig.5 shows the results of the source model on the measured data from the target system, and the F1-scores are 0.71 for fault-free and 0.51 for fault data. In the case of fault-free samples, only 30 out of 53 predictions match the actual fault-free instances. For fault cases, out of 15 actual fault cases, 13 were correctly predicted as faults, but there were many cases where fault-free data were incorrectly predicted as faults, leading to a lower F1-score. This suggests that a lack of knowledge is remained as a bottleneck for describing the dynamic behavior of the real building system (Fig. 2).

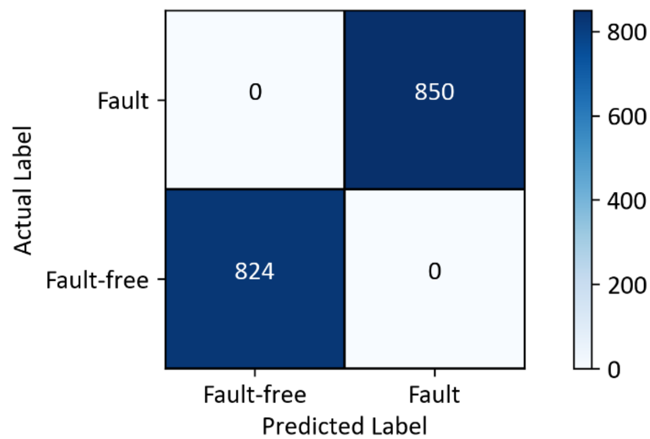

Fig. 4. Result of source model on synthetic data

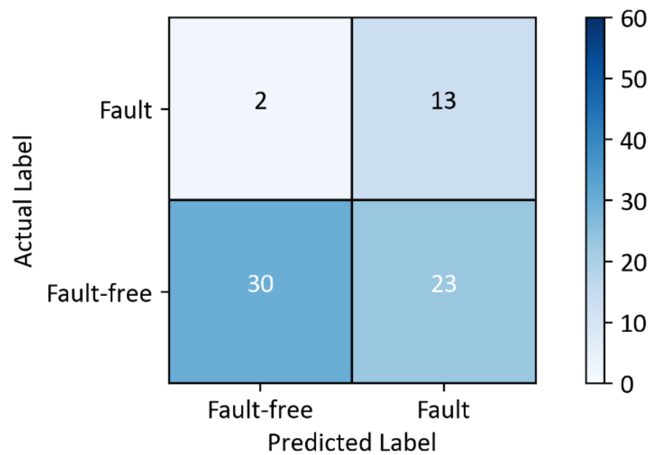

Fig. 5. Result of source model on measured data from the target system

Fig.6 illustrates the prediction results of the target model with the measured data from the target system. The target model detected the fault of the target VAV system with F1-scores of 0.88 for fault-free and 0 for fault cases. Unfortunately, the target model predicts all instances as fault-free, indicating that it has been biased towards the fault-free class due to the data imbalance. This shows that the target model learned to prioritize the majority class (fault-free) during training, resulting in a complete failure to detect faults (the F1-score of 0).

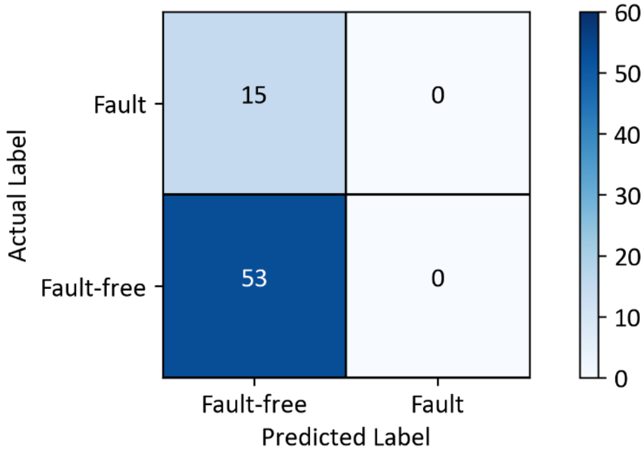

Fig. 6. Result of target model on measured data from the

Fig.7 shows the prediction results of the transfer model, and the F1-scores for each type are 0.93 for fault-free and 0.71 for fault cases. Compared to the source model on the measured data from the target system (Fig. 5), a significant improvement was made in the F1-scores for fault-free predictions, increasing from 0.71 to 0.93, and also for fault predictions increasing from 0.51 to 0.71. This indicates the need for the transfer learning when the obtained data form the target system is not sufficient or imbalanced.

The number of instances where actual faults match predicted faults decreased from 13 to 10, but there was a substantial decrease in misclassifying actual fault-free instances as faults, reducing from 23 to 3, resulting in an overall increase in fault detection accuracy.

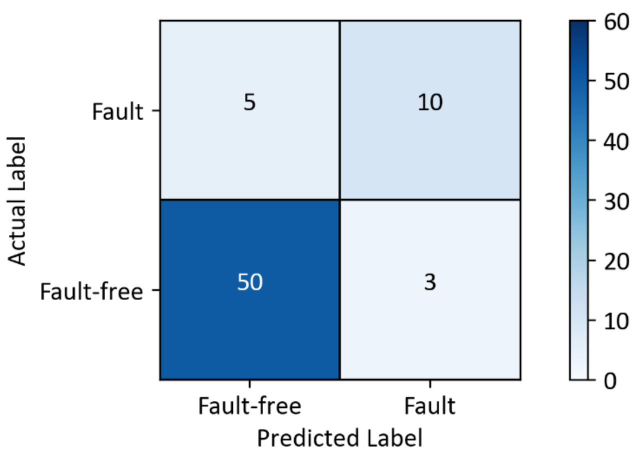

Fig. 7. Result of transfer model on measured data from the

4. CONCLUSION

In this study, the authors presented an application of the transfer learning for the data-driven FDD for a real-life case. Firstly, we developed a source model with the synthetic data consisting of fault-free and fault data. Then, the source model was fine-tuned using only normal operation data from the target system, called the transfer model. Finally, the prediction accuracies of the three models including the source model, target model and transfer model (defined in section 3.1) were cross-compared.

As a result, the source model that was trained with the synthetic data proved to be not good enough for the target system's FDD as illustrated in Fig. 5. The target model that was trained with the measured data from the target system performed even worse than the source model because of the data imbalance problem (Fig. 6). In other words, the measured data collected from the existing target system did not include an even distribution of fault-free and fault data. Please note that it is common that most existing system's data do not include sufficient fault data, which is the case in this study. In contrast, the transfer model performs best because it inherits the knowledge extracted from the synthetic data and then is fine-tuned with the measured data from the target system (Fig. 7).

This study exemplifies how the transfer learning can be beneficially used for the FDD for the real-life case. In other words, the transfer learning can be a promising candidate to overcome the data imbalance issue in the FDD of existing buildings. As a further study, the authors will apply the transfer learning to many different building systems including chiller, boiler, and cooling tower. In addition, applicability/reliability of the ANN black-box model under different conditions will be investigated.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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