Proceedings of the 8th European Conference of the Prognostics and Health Management Society 2024 - ISBN – 978-1-936263-40-0

Transfer Learning-based Adaptive Diagnosis for Power Plants under Varying Operating Conditions

Jiwoon Han[1], and Daeil Kwon[2]

[1,2]*Department of Industrial Engineering, Sungkyunkwan University, Suwon, Gyeonggi-do, 16419, South Korea*
jiwoon98@g.skku.edu
dikwon@skku.edu

Abstract

Transfer learning is a method that transfers knowledge learned from a source domain to a similar target domain to improve learning. In power plants, obtaining sufficient anomaly data is difficult due to the characteristics of the systems. Transfer learning enables learning with only a small amount of data from the target domain by using a model trained in a similar domain. By applying transfer learning, models developed for one power plant can be expanded and used in other power plants where available data are limited.

Using actual data from an operating combined-cycle power plant, an anomaly diagnosis model was developed and tested. Its applicability to different operating conditions and anomaly cases was evaluated through transfer learning. The fine-tuned pre-trained model was effectively adapted with limited target domain data. Transfer learning was applied despite the limitations of data and distribution differences. The expandability of anomaly diagnosis models to different power plant systems was demonstrated by applying transfer learning.

1. Introduction

The limited anomalous data and labels in power plants are challenges for training anomaly diagnosis models. Due to the requirements for safety and operational stability, inducing failures or obtaining sufficient anomalous data is difficult in power plants (Qian & Liu, 2023). Variations in operating conditions also complicate model training by changing the distribution of data. The operating conditions of power plants change with variations in power demand over time and external factors such as temperature and humidity (Bai, Yang, Liu, Liu, & Yu, 2021). In actual operating power plants, it is difficult to obtain data while operating under the same conditions consistently, as power demands and external factors vary. Differences in operating conditions disrupt the assumption of consistent data distribution between training and testing sets in anomaly diagnosis models (Li, Lin, Li, & Wang, 2022; Zhou, Lei, Zio, Wen, Liu, Su, & Chen, 2023).

Developing diagnosis models for a new power plant system incurs additional costs, even after significant investments have been made to overcome challenges and develop the models. This is because the distribution of data collected varies due to differences in the structure and sensors of the systems in each new power plant. Each new power plant requires a customized approach to model development, involving the redesign of diagnosis models to fit the specific data characteristics of that plant. To develop models for other new power plants, the process should start anew with data collection. Training and validating models with the collected data are essential steps in developing the new model. This process again incurs significant time and costs.

The fact that power plants of the same type share a common domain can be utilized. When applying models to new power plants, it is typically necessary to redesign them due to differences in data distribution. Since the power plants operate on similar principles within the common domain, this can enable the expansion of existing models without a complete redesign. This approach utilizes the commonalities from the same types of plants, reducing development time and costs.

By applying transfer learning, a developed model can be expanded and adaptively used for a new power plant within a similar domain. Transfer learning is a method that transfers knowledge learned from a source domain to a target domain with insufficient data for a similar task (Pan & Yang, 2009). The transfer learning method involves fine-tuning model parameters pre-learned from the source domain using limited data from the target domain. With transfer learning, a model developed in the source domain can be adapted to a new system in the target domain, instead of restarting the entire process. Additionally, it can be applied to the target domain using only a small amount of data, serving as an approach to overcome the challenges of limited data and labels. By applying transfer learning and using the model adaptively, the expandability and practicality of the diagnosis model can be enhanced.

In this paper, an anomaly diagnosis model was developed using data collected from the actual gas turbine of an operating combined-cycle power plant. The developed diagnosis model was tested by applying transfer learning to data with different anomaly features and operating conditions than the training data. Collected data have an emergency shutdown called a "trip", that occurs in the case of anomalies to prevent serious accidents. Cases, where actual data are collected under different operating conditions, have similar situations with other power plants data that have different data distributions. By fine-tuning with limited data from the target domain, this study demonstrated the potential to expand a developed model to different power plant systems. Comparative analysis was conducted by applying transfer learning, even in situations of data imbalance where little anomaly data is available in the target domain.

Section 2 introduces the related works that developed a diagnosis model for the power plant and applied transfer learning to the model. Section 3 describes the data, model, and transfer learning methods used in this study. Section 4 presents the results, Section 5 discusses these results, and Section 6 presents the conclusions and future work.

2. RELATED WORKS

Related studies on anomaly diagnosis in power plants have been conducted across various subjects and domains. Diagnosis using the Gaussian Process (GP) algorithm and model ensemble techniques were conducted at an actual coal-fired thermal power plant (Zhang, Dong, Kong, & Meng, 2019). They identified relationships between variables to reflect temporal dependencies and cross-variable associations, using combinational data relationships to develop the diagnosis model. Lee et al. (2021) collected data from a full-scope simulator for abnormality diagnosis in a nuclear power plant and developed a Convolutional Neural Network (CNN) algorithm model. To manage the 1004 sensor variable data, they converted it into two-channel 2D images with a data size of 32*32.

As mentioned in the introduction, power plants have challenges due to the limited anomaly data and differences in operating conditions. To address these challenges, transfer learning methods have actively been researched for diagnosing power plants. Studies have been conducted to apply transfer learning for fault diagnosis at different power levels in nuclear power plants. Data were collected at several power levels using a simulator, and a CNN algorithm was developed to handle numerous sensor variables. Maximum Mean Discrepancy (MMD) was used to develop the model to adapt to differences in distributions when power levels vary. With these approaches, Li et al. (2022) divided domains based on power levels and applied transfer learning across different power levels. They also analyzed the effects of various kernel functions used to calculate MMD. Wang et al. (2022) utilized Transfer Local MMD (TLMMD) combined with the ResNet-18 algorithm to develop a diagnosis model. Li, Lin, Li, and Wang, (2022) applied transfer learning to construct models for each power level. They proposed a framework that determines the current power level during actual operation and matches data to the model trained at each power level.

The CNN algorithm and transfer learning were also applied for fault detection in the gas turbine combustion chambers of power plant systems (Bai et al., 2021). Exhaust Gas Temperature (EGT) data collected from two gas turbines were used. The turbine with more data was used as the source domain for training, and transfer learning was then applied to the other turbine, which had limited data. The performance of the transfer learning approach was evaluated and compared with various other diagnosis methods.

3. APPROACH

A diagnosis model was developed for the gas turbine of an operating combined-cycle power plant. Training and testing were conducted using data from collected anomaly cases, and transfer learning was applied. The model's performance was evaluated, observing changes in performance based on the data used for training and the application of transfer learning.

3.1. Data

The operating data were collected from sensors related to the gas turbine equipment of a combined-cycle power plant A, located in region B of Korea. The power plant data were provided by KEPRI (Korea Electric Power Corporation Research Institute). A total of eight anomaly cases related to trips were detected. Data for each case were collected on the dates when the anomaly occurred for four years. Each case has different operating conditions, resulting in different characteristics.

Table 1. Collection of Data.

Collection period	4 years	
Number of sensors	118	
Number of Cases	8	
Data instance per cases	Total	256
	Normal	128
	Anomaly	128

Data were collected from 118 sensors of the plant's gas turbine system. Sensors collected data on flow rate, pressure, and temperature, such as EGT. Each sensor was related to the control and flow of fuel gas in the gas turbine.

Within each of the eight anomaly cases, there are 128 instances of both normal and anomaly data, labeled by domain experts based on the investigation reports conducted for each case. The data format consists of 60-minute windows for the 118 collected sensor data points.

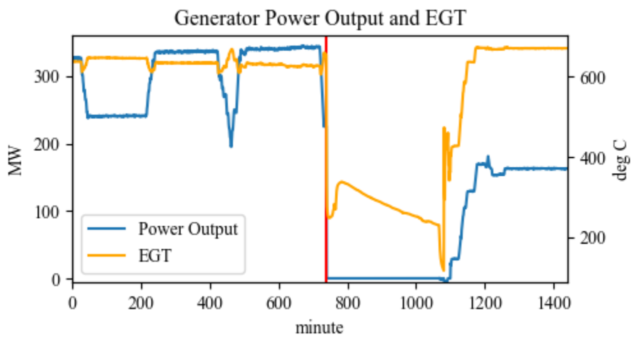

Figure 1. Example of collected data with a trip.

To utilize the overall 118 sensor data, the collected time series data can be concatenated in parallel to form a two-dimensional matrix. Each row is composed of a time series, and the patterns of the sensors contain information about anomalies. The data from 118 sensors have variations in units and ranges of values, depending on their measurement targets. To address this, min-max normalization was applied to each sensor. The matrix collected from 118 sensors over a 60-minute window is represented as an image as follows.

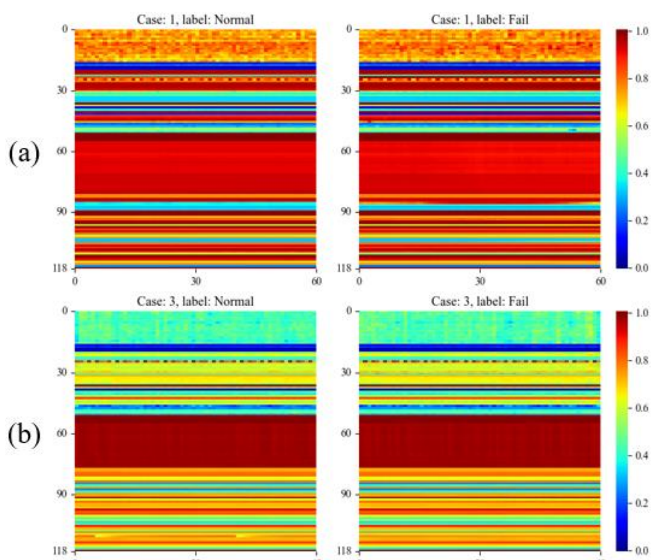

Figure 2. Example image of data. (a) Case 1, (b) Case 3.

3.2. Transfer Learning

Transfer learning was applied by taking a model trained in the source domain and fine-tuning it with a limited dataset from the target domain, with some weights of the convolutional layer fixed. The model was constructed using a Convolutional Neural Network (CNN) architecture, with 1D kernels utilized to detect patterns in the data from 118 sensors over a 60-minute window. The model's structure includes convolutional layers, max-pooling layers, batch-normalization layers, and fully connected layers. It is designed to learn features from the data and perform classification.

In the CNN model, the initial convolutional layers extract general features, while the fully connected layers extract specific features (Zhu, Peng, Chen, & Gao, 2019). This characteristic enables the use of general features validated in the source domain while adapting specific features for classification in the target domain when applying transfer learning. The model was trained using all available data in the source domain, and fine-tuning was conducted with only 60 data instances from the target domain.

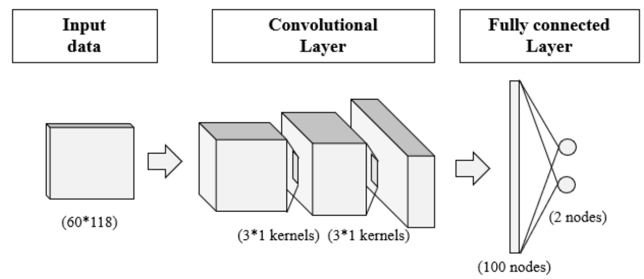

Figure 3. Outline for Structure of CNN model

3.3. Evaluation

Eight cases were used as different source domains, with each dataset being used to train a CNN model individually. Each trained source case model was evaluated using the validation data from that case and tested using the remaining seven cases as test data. Thus, there are eight evaluation results for one case model and a total of 64 results for all eight cases. The average of the calculated performance metrics was used to evaluate how each method applies. This average performance metric was compared based on the application of transfer learning and depending on the case used for training.

The performance metric used is the Matthews Correlation Coefficient (MCC), which represents performance through the correlation between actual and predicted labels, among metrics for binary classification (Chicco, Tötsch, & Jurman, 2021). MCC values range from [-1, 1], as it is a correlation coefficient. Accuracy, the commonly used performance metric, cannot represent cases of class imbalance and cases where predictions are made with only one label. The MCC metric can effectively show the relationship between actual and predicted labels. It is considered to perform well even in cases of class imbalance, indicating a value of 0 when predictions are made with only one label.

4. Result

The comparison of the average MCC for the three cases is shown in the figure below. CNN models were trained using data from eight different anomaly cases. The models for each case were trained and validated in an 8:2 ratio, and data from different cases, which were not used in training, were utilized for testing.

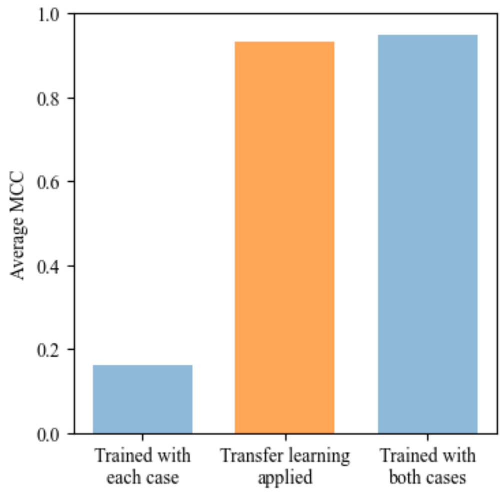

Figure 4. Comparison of the average MCC

The performance of the model significantly improved when transfer learning was applied, compared to using data from only one case. Additionally, although the best performance was in the case that used data from both domains, the performance with transfer learning exhibited similar levels of effectiveness.

Each anomaly case has different operating conditions and anomalies. While the models exhibit high performance in validation for each specific case, most exhibit low MCC scores when applied to other cases. Most test cases with low MCC scores are cases where predictions are made with only one label, either normal or anomaly. Figure 4 shows that the diagnosis models are well-trained for each specific case. Additionally, it indicates that the models cannot predict accurately in tests for other anomaly cases due to different operating conditions and anomalies.

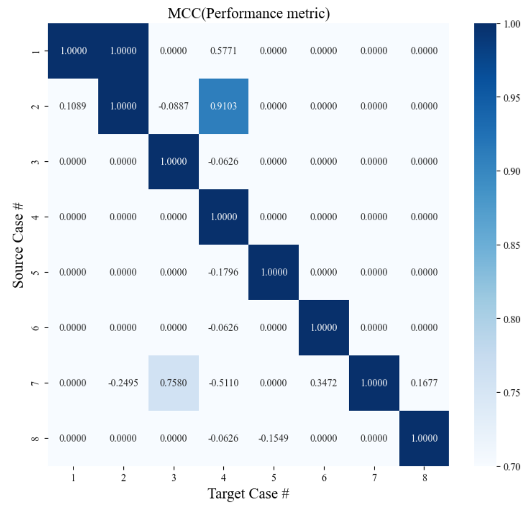

Figure 5. Performance of models trained with each case.

The performance of each case was evaluated by applying transfer learning. To evaluate the effectiveness of transfer learning, a comparison was made between models that applied transfer learning and those that used all the data from both the source and target domains without transfer learning. Initially, each case was fine-tuned with limited data from the target domain, based on the model trained in the source domain. The performance metrics were evaluated using test data that were not used in the fine-tuning of the target domain. Transfer learning was applied as described in Section 3.2.

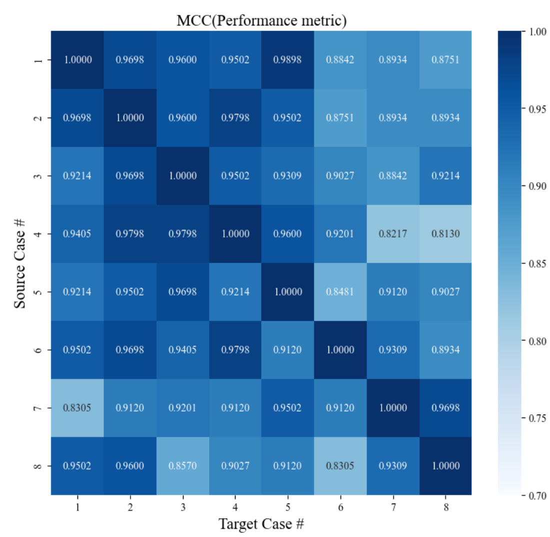

Figure 6. Performance of models applied transfer learning.

For comparison, a scenario was assumed in which data were collected and available from both domains. The model was trained using all the data from both the source and target domains without the use of transfer learning. The results are as follows.

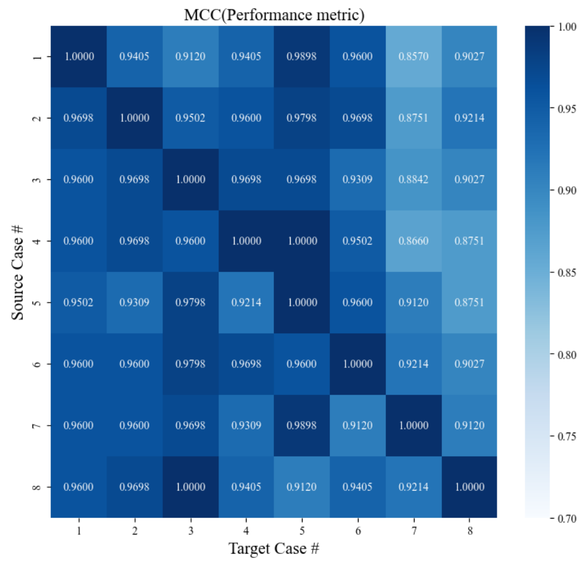

Figure 7. Performance of models trained with both domains.

When trained using data from both domains, the data for training and validation was the same as when only one domain was trained and validated, but the trained model was not completely accurate. This is because each domain has different operating conditions, making it challenging to treat and learn from them as a single domain.

It can be observed that diagnoses performed with transfer learning are effective. The difference in the effectiveness is due to the different distributions of data from each anomaly case under different operating conditions. When using models trained with a single case, the features identified during training differ from those in the test, leading to poor performance of the model. In contrast, the application of transfer learning has shown that fine-tuning the model with a limited amount of data can enhance performance. When compared to cases where data from both the source and target domains are available, similar performance metrics were observed. This indicates the effectiveness of transfer learning in cases with different data distributions. When expanding the model to different new power plant systems, data newly collected under different operating conditions or anomaly cases differ from the previously trained data. Previous results demonstrate the expandability of the diagnosis model through transfer learning, which has been effective despite these differences.

5. Discussion

In real-world situations, collecting anomaly data is more challenging compared to normal data, resulting in a data imbalance. Additional analysis was conducted to monitor changes in the training models by applying transfer learning. A sensitivity analysis was performed on the ratio of normal to anomaly data used in fine-tuning the target domain. To address this, the performance of transfer learning was evaluated by gradually increasing the proportion of normal data. Figure 8 shows the results of the average MCC according to the ratio of normal to anomaly data used in fine-tuning. The results indicate a significant decrease in performance when no anomaly data were included.

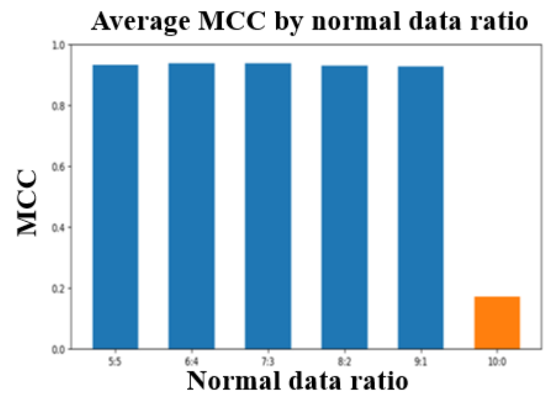

Figure 8. Average MCC according to the ratio of normal to anomaly data.

Using transfer learning, the ratio of normal to anomaly data used for fine-tuning was changed to analyze factors that influence its effectiveness. It was observed that even a small amount of anomaly data could yield good results when the overall proportion of anomaly data was reduced. In real-world application scenarios, normal data is generally more prevalent. The model could identify anomalies well even in imbalanced situations where the ratio of anomaly data was 9 to 1. However, the performance significantly decreased when there was no anomaly data at all. This decrease occurs because fine-tuning without any information about anomalies makes it difficult to adaptively use the identified anomaly features through transfer learning.

6. Conclusion and Future Work

In this study, an anomaly diagnosis model was developed using data from an actual combined-cycle power plant. Diagnosis models were developed for each case, and it was observed that the operating conditions and anomaly features varied according to each case. To use the diagnosis models adaptively, transfer learning was applied to fine-tune the models and evaluate their performance. Using transfer learning, the ratio of normal to anomaly data used in the fine-tuning of the target domain was varied to analyze changes in performance. This process demonstrated that transfer learning could be effectively applied even in imbalanced situations with a predominance of normal data, and it also highlighted the importance of collecting anomaly data.

Next, Research could be conducted to validate the expandability of the model through transfer learning using data collected from different new power plants. Research could be conducted on applying the model in real-time scenarios at actual power plants using transfer learning. In actual power plant operations, the occurrence of an anomaly is already critical. There is a need for an approach that allows for fine-tuning without information about anomalies and adaptively uses the model under different operating conditions. Additionally, considering that data are collected in a sequential time series, there is a need for a transfer learning framework that fine-tunes the model using only initial data and adaptively detects anomalies.

ACKNOWLEDGEMENT

This work was partly supported by Korea Institute of Energy Technology Evaluation and Planing(KETEP) grant funded by the Korea government(MOTIE) (20217010100020, Development of Intelligent O&M Technologies for Standard Combined Cycle Power Plant).

REFERENCES

Bai, M., Yang, X., Liu, J., Liu, J., & Yu, D. (2021). Convolutional neural network-based deep transfer learning for fault detection of gas turbine combustion chambers. Applied Energy, 302, 117509.

Chicco, D., Tötsch, N., & Jurman, G. (2021). The Matthews correlation coefficient (MCC) is more reliable than balanced accuracy, bookmaker informedness, and markedness in two-class confusion matrix evaluation. BioData mining, 14, 1-22.

Lee, G., Lee, S. J., & Lee, C. (2021). A convolutional neural network model for abnormality diagnosis in a nuclear power plant. Applied Soft Computing, 99, 106874.

Li, J., Lin, M., Li, Y., & Wang, X. (2022). Transfer learning network for nuclear power plant fault diagnosis with unlabeled data under varying operating conditions. Energy, 254, 124358.

Li, J., Lin, M., Li, Y., & Wang, X. (2022). Transfer learning with limited labeled data for fault diagnosis in nuclear power plants. Nuclear Engineering and Design, 390, 111690.

Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), 1345-1359.

Qian, G., & Liu, J. (2023). Fault diagnosis based on gated recurrent unit network with attention mechanism and transfer learning under few samples in nuclear power plants. Progress in Nuclear Energy, 155, 104502.

Wang, Z., Xia, H., Zhang, J., Annor-Nyarko, M., Zhu, S., Jiang, Y., & Yin, W. (2022). A deep transfer learning method for system-level fault diagnosis of nuclear power plants under different power levels. Annals of Nuclear Energy, 166, 108771.

Zhang, Y., Dong, Z. Y., Kong, W., & Meng, K. (2019). A composite anomaly detection system for data-driven power plant condition monitoring. IEEE Transactions on Industrial Informatics, 16(7), 4390-4402.

Zhou, H., Lei, Z., Zio, E., Wen, G., Liu, Z., Su, Y., & Chen, X. (2023). Conditional feature disentanglement learning for anomaly detection in machines operating under time-varying conditions. Mechanical Systems and Signal Processing, 191, 110139.

Zhu, Z., Peng, G., Chen, Y., & Gao, H. (2019). A convolutional neural network based on a capsule network with strong generalization for bearing fault diagnosis. Neurocomputing, 323, 62-75.