Design of an Anomaly Detection System for Research Reactor based on Data-driven Approach

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1. Introduction

Recent development in artificial intelligence affected various industrial fields, including nuclear engineering. Specifically, based on the massive amount of data collected by multiple sensors, data-driven methods are adopted to solve various tasks of nuclear engineering, for example, time-series forecasting [1, 2], and accident identification [3].

In this study, we introduce an anomaly detection system utilizing a data-driven approach. Specifically, the deep neural network (DNN) model is used for detecting anomalies from multi-variate sensor data of HANARO. HANARO is firmly protected by the safety systems and undergoes an automatic shutdown process according to the reactor regulating system (RRS) and reactor protection system (RPS). These safety systems monitor the key reactor variables and consider them as an anomaly if the measured value exceeds its operational threshold. On the other hand, the data-driven approach differs in a way of considering abnormal behavior. Instead of focusing on specific variables based on the prior knowledge, we train a model using all available data. Then the model overlooks the relations between variables according to the knowledge learned from historical data and may detect anomalies that is not considered by the existing system. In doing this, we designed a modularized anomaly detection system, and the prototype of a deep learning-based anomaly detection system (DAS) is implemented to research reactor HANARO.

2. Methodology and System Design

In this section, we describe deep learning-based anomaly detection methods and overall structure of DAS.

2.1 Anomaly detection via deep learning

Anomaly detection is a binary classification problem based on an anomaly score that quantifies the degree of abnormality of a given sample. Data-driven anomaly detection calculates anomaly scores based on the relation between the data. For example, the k nearest neighbor method derives the anomaly score by the distance to the nearest points of the given sample. Therefore, learning relations that distinguish normal and abnormal is the key point in data-driven anomaly detection. For doing this, DNN, which is a universal function approximator, can be used to exploit the internal relations of data. One of the simple and effective methods for deep learning-based anomaly detection is using an autoencoder. For doing this, an autoencoder is trained to minimize the reconstruction error of normal data (D_{train}). Reconstruction error is the distance between input x and reconstruction after encoding $\hat{x} = g(f(x))$, $d(x, \hat{x})$. When a new sample is given, the autoencoder calculates the reconstruction error and classify to normal if the error is low, otherwise to an anomaly. For anomaly detection, the deep learning model is operated in two different stages, namely the training stage and the inference stage. In the training stage, DNN is trained on normal data and learns latent features for normality. In the inference stage, DNN computes anomaly scores based on learned results from the training stage. In this regard, deploying the deep learning model in a real system requires a function of feeding new data and an interface to transmit the anomaly detection information to human operators.

2.2 Anomaly detection system

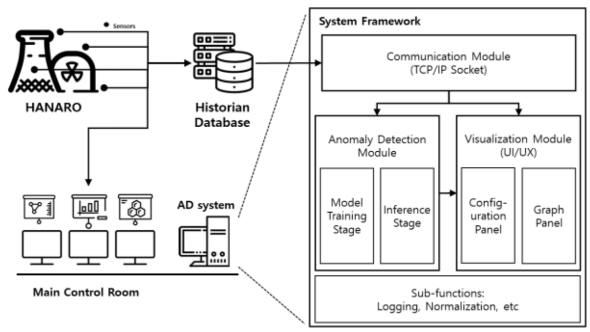

Fig. 1. Framework of data-driven anomaly detection system.

Based on the previous problem formulation, DAS composes three modules considering the legacy system of HANARO: a communication module, an anomaly detection module, and a visualization module. The communication module (CM) manages the data flow of the system. Multiple sensors are deployed in HANARO, and measured sensor data is stored in a secured database server in real-time. CM receives measured sensor data from the database server by establishing TCP/IP socket connection. Raw packets from the database server are obtained at 2 s intervals and stored in a data queue object. The raw packet from the server consists of input variables for the deep learning model. Raw packets are preprocessed to an input vector of the anomaly detection model and passed to the anomaly detection module (AM). Multiple deep learning models can be implemented to AM; autoencoder is considered in the prototype of DAS. Deep learning models are trained independently to DAS operation; thus, DAS loads the trained model and performs inference for anomaly detection. According to the type of neural network, the output of the neural network can be directly used as an anomaly score or used as a source for anomaly score computation. For the latter, AM has a separate function for anomaly score calculation. In the case of the autoencoder, the neural network outputs reconstruction of the original input. Therefore, the anomaly score can be derived based on the error between the input and its reconstruction. Then anomaly scoring function could calculate different anomaly scores, for example, mean squared error (MSE), Mahalanobis distance, and top-k score. After the anomaly score is derived, AM classifies the anomaly according to the predefined anomaly score threshold. Finally, the visualization module (VM) provides a user interface of DAS and manages the monitoring panel. The panel consists of several graphs, including a plot of main variables and an anomaly score graph. In addition, VM sets an alarm signal according to the detection results from AM.

3. Implementation

The prototype of DAS is deployed in the main control room of HANARO in 2021. It is successfully linked with the existing database server and visualizes related information.

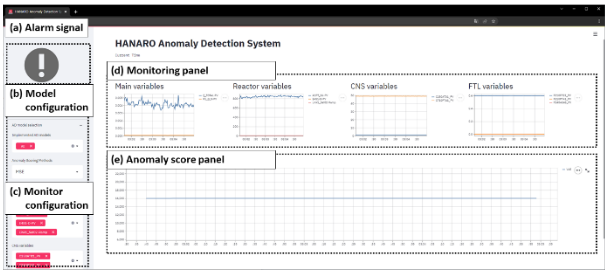

Fig. 2. Example of display panel of prototype implementation.

After the test operation of the prototype model, the following issues are considered for future investigation. First, the implementation of various deep learning anomaly detection models is required; currently, only an autoencoder network is implemented. This also includes hyperparameter optimization and designing a loss function for anomaly detection. Second, upgrades in the anomaly score calculation is considered. This includes setting the optimal anomaly score threshold and developing a method to utilize anomaly scores from multiple models for ensemble. Finally, the implementation of an online training mechanism is required to cope with the changes in the status of the facility.

4. Conclusion

In this study, we design a deep learning-based anomaly detection system to utilize data-driven approach for research reactor HANARO. Autoencoder-based anomaly detection model is trained with historical data and the prototype of anomaly detection system is implemented at HANARO. Based on the established prototype system, we are planning to investigate various intelligent technologies and upgrade the system based on the opinions of operators.

ACKNOWLEDGEMENTS

This research was supported by a grant from the Korea Atomic Energy Research Institute (KAERI) R&D Program (No. KAERI-524450-22)

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