Application of AI methods to NPP: Approach of NICIEL

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1. Introduction

Since a nuclear power plant (NPP) is a safety-critical infrastructure, efforts to improve the safety of the NPP have been steadily conducted. Research on the diagnosis and monitoring of NPPs has been conducted with a model-based approach and a data-based approach.

In the case of a model-based approach, tasks are performed based on a pre-defined set of rules. Because the model-based approach is based on a deep understanding of the system, fast and reasonable inferences are possible. However, a considerable cost is inevitably required to construct a deep understanding of the target system. Furthermore, for a complex system, it is hard to build a model.

Data-based methodologies have been developed to overcome the above shortcomings from the model-based approaches. The data-based methods do not require rules. The method only requires data. Also, the multi-dimensional complex systems can be analyzed using the data. Therefore, using the data-based approach can reduce the cost of understanding the target system.

However, since neither method is perfect, hybrid approaches are being developed to take advantage of each other's strengths and complement each other's weaknesses.

This paper introduces AI-based research conducted in NICIEL (Nuclear Instrumentation and Control and Information Engineering Lab.), and the summary of the progress from the initial data-driven approach to the hybrid approach by using the domain knowledge of the NPP is described.

2. Researches in NICIEL

2.1. Stage 1. Conventional machine learning methods and artificial neural network (ANN) model

Early AI research was mainly conducted using conventional machine learning-based research or a simple ANN model. As a representative study, a study to synthesize the axial power distribution of the core protection calculator system using ANN [1] and a study to predict severe accident using a support vector machine [2] was performed.

A single hidden layer ANN model with 15 neurons is selected to synthesize the axial power distribution. For the input 3-level, ex-core detector signals are provided. Root mean square error is adopted for the error function, and a hyperbolic tangent function is selected for the activation function.

A support vector machine (SVM) algorithm is adopted to predict severe accident occurrence time. Thirteen plant status variables in the main control room with 86 conditions (break size, position) were used to train the SVM. As a result of the training, the SVM algorithm shows around 5% RMS error when estimating break size and predicting the core temperature exceeding 1200 degrees Celsius.

2.2. Stage 2. A data-driven deep learning model

Studies in this stage also did not use prior knowledge and depended only on data, but the difference from the previous stage is that a deep learning model was used.

A study was performed using machine learning and deep learning models to estimate the flow accelerated corrosion (FAC) phenomenon [3]. A study to evaluate the signal's integrity was performed using a variational autoencoder. And also, a reinforcement learning-based fault tree simplification agent was designed. All studies were conducted entirely data-driven without prior knowledge.

Since the FAC phenomenon is affected by various variables (properties of the fluid, the shape of the pipe, etc.), the FAC phenomenon modeling was done by finding a suitable approximation equation through multiple experiments. Therefore, a deep understanding of the phenomenon was essentially required. To predict the FAC phenomenon with the data-driven model, SVM, convolution neural network (CNN), and long-short term memory (LSTM) network-based diagnosis agents were designed. Vibration data from the elbow of the pipe is used to train AI models. Vibration data is vulnerable to disturbance. Therefore, outlier removal was also applied by using cook's distance and several preprocessing (Hilbert enveloping and Fourier transform). As a result, when the degree of pipe thinning was large, SVM, CNN, and RNN were all able to estimate the pipe condition reasonably, but it was confirmed that the LSTM model should be used when the degree of pipe thinning was insignificant.

It can be easily thought as the most crucial thing in data-based methodologies is the amount of data. However, the quality of the data is also essential. Therefore, variational autoencoder-decoder-based signal integrity detect agent was designed to determine the signal's integrity. A variational autoencoder compresses the input signal as a form of latent vector. For instance, the height of people follows the normal distribution. Therefore, we can reconstruct the people's height distribution by using the mean and the standard deviation. The autoencoder's role is similar to finding the mean and standard deviation. The autoencoder finds appropriate representative parameters (latent vector) from the data. And the role of the decoder is to reconstruct data using the compressed latent vector. Therefore, if the model is trained with the normal dataset, then the model's imitated result should be similar to the normal dataset. However, when polluted or abnormal data is provided, the imitated results from the model are not similar to the normal dataset. Therefore, we can detect whether the signal is in normal condition or not.

The binary decision diagram method is an intuitive reliability analysis method. However, the method has a critical deficiency called a variable ordering problem. The complexity of the tree heavily depends on the order of the variable. Therefore, figuring out the optimal order of the variable is a critical problem, but the problem is a non-deterministic polynomial problem. Therefore, a reinforcement learning-based variable ordering agent was suggested [4]. The state, action, and reward should be defined to train the agent with the reinforcement learning method. Therefore, the paper defines the state as the constructed binary decision diagram with specific variable order. And the action was defined as the selection of variable. Finally, the reward was designed as the inverse of the information entropy. As a result, the trained agent constructed a reasonably optimized binary decision diagram with 20 variables.

2.3. Stage 3. Deep learning with indirect prior knowledge

In this stage, prior knowledge was used, but prior knowledge was used in the direction of simply providing additional data without intervention in training in the deep learning model.

Many signals may be lost in a severe accident, such as the Fukushima accident. In this case, it is difficult to estimate the state of the NPP, and as a result of the signal loss, it is impossible to respond to an accident efficiently. Therefore, a generative adversarial network-based (GAN) signal reconstructing agent is designed [5]. In order to sufficiently consider the specificity of the nuclear power plant signal, the generator is configured in the form of a recurrent GAN that is easy to process time series data. Moreover, conditional GAN and manifold-guided GAN concepts were used to solve the mode collapse problem. Moreover, the steam generator signals (pressure, flow) was excluded when training the algorithm using the prior knowledge that the measurement deviation of the steam generator signal is inevitably large due to the characteristics of the steam generator. As a result, it was confirmed that the signal was reconstructed with a lower error level when the steam generator variables were excluded.

In the case of a single accident that may occur in an NPP, it is relatively easy to diagnose, but in the case of a complex accident, it is difficult to diagnose it unless the accident diagnosis resolution is sufficiently high. Furthermore, as mentioned in the study above, it is difficult to assume that all measurements of the power plant can be used in severe accident situations. Therefore, the diagnosis agent must have a high accident diagnosis resolution based on as little data as possible. In order to achieve sufficient accident diagnosis resolution with only a small number of data, additional information should be provided to compensate for the data. Therefore, a graph neural network (GNN) based accident diagnosis agent was designed [6]. Existing data-based diagnostic methodologies used only measured values. However, graph neural networks can receive graph-type data as input. Therefore, not only the measured values but the correlations of the components were graphed and provided to the learning. In the design of the diagnostic agent using GNN, the prior knowledge of the NPP components configuration was utilized in the learning to perform efficient learning. As a result, it was confirmed that the diagnostic agent could use the information on the correlation of the device for training so that even using a small number of data (19 measurement data), a higher level of diagnostic accuracy than CNN can be obtained (CNN Acc.: 40%, GNN Acc.: 95%).

2.4. Stage 4. Deep learning with direct prior knowledge

In this stage, prior knowledge with explicit form (a form of the equation) was used. And also, prior knowledge was used in training the deep learning model as a form of loss.

For the analysis codes to accurately calculate the NPP status, the node should be divided into small pieces, which inevitably increases the time required for the calculation. Moreover, if the analysis result is different from the actual data, it is difficult to correct the code. Therefore, if the analysis can be performed quickly and accurately, and the analysis code can be updated based on the actual data, then the method can contribute to the analysis of the NPP and the construction of digital twins. Therefore, the physics-informed neural network (PINN) based analysis module and PINN-based physics update module were developed [7]. The PINN-based analysis module is trained from the data and the physics, which is provided based on prior knowledge. For instance, continuity, momentum, and energy loss will be provided to analyze the thermal-hydraulic phenomenon. The Kolmogorov-Chapman differential equation will be provided as prior knowledge to analyze the reliability of two elements with one recovery. Various analyses could be conducted by substituting the physics module, which is based on prior knowledge. Moreover, the PINN-based update module can be attached to update the physics module based on acquired real-world data. The update module intakes the real-world data and selects the most appropriate governing equation that reflects acquired data.

This approach provides explicit prior knowledge, which is a form of the equation, to train the neural network.

3. Conclusion

Data-based research requires a large number of data because it uses only data. To overcome the limitation, the guided training method of artificial neural networks using prior knowledge can be used. In this paper, AI research conducted in NICIEL Lab. was arranged and introduced. The paper introduced research from fully data-driven to data-driven with prior knowledge. In fact, by changing from fully data-driven to prior knowledge added data-driven, the uncertainty of the experiment decreased, and the reproducibility increased.

If those who study data-based methodologies in the nuclear field can properly reflect their strength, which is called domain knowledge in learning artificial neural networks, they will be able to design more advanced and more efficient data-driven methods.

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REFERENCES

[1] 최영재. "Application of artificial neural networks to CPCS axial power distribution synthesis." Master thesis KAIST (2015).

[2] Kim, Seung Geun, Young Gyu No, and Poong Hyun Seong. "Prediction of severe accident occurrence time using support vector machines." Nuclear Engineering and Technology 47.1 (2015): 74-84.

[3] Chae, Young Ho, et al. "A methodology for diagnosing FAC induced pipe thinning using accelerometers and deep learning models." Annals of Nuclear Energy 143 (2020): 107501.

[4] Chae, Young Ho, and Poong Hyun Seong. "Optimization of binary decision diagram: Heuristics from reinforcement learning." (2021).

[5] Kim, Seung Geun, Young Ho Chae, and Poong Hyun Seong. "Development of a generative-adversarial-network-based signal reconstruction method for nuclear power plants." Annals of Nuclear Energy 142 (2020): 107410.

[6] Chae, Young Ho, et al. "Graph neural network based multiple accident diagnosis in nuclear power plants: Data optimization to represent the system configuration." Nuclear Engineering and Technology (2022).

[7] Chae, Young Ho, et al. "Development of a Physics Informed Neural Network based Simulation Methodology for Dynamic-PSA."