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Application Status of Artificial Intelligence to Nuclear Power R&D

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1. Introduction

Artificial intelligence (AI) is actively being researched across industries because it can solve problem solving that are either complex for conventional methods or need to complicated computation. In particular, AI is being used in the field of nuclear power plants, where conventional methods can't be problem solving. However, no papers or reports have been published in Republic of Korea that provide a comprehensive overview of the current status of AI's application in nuclear power plants. This lack of information makes it difficult for researchers who wish to apply AI in this field.

This paper analyzes and summarizes current domestic and international research on the application of AI to nuclear power generation. The analysis is classified into three categories: the field of nuclear power generation, training data, and learning algorithms. The purpose of categorizing into three categories is to examine the relationship among the categories.

2. What is artificial intelligence?

For researchers new to AI, this chapter provides a brief overview about AI.

2.1 AI Overview

Artificial intelligence is the implementation of human intelligence into machines or computer programs. To do this, computer systems are designed to mimic human learning and judgement, such as analyzing data and patterns to solve problems, making inferences and decisions [1].

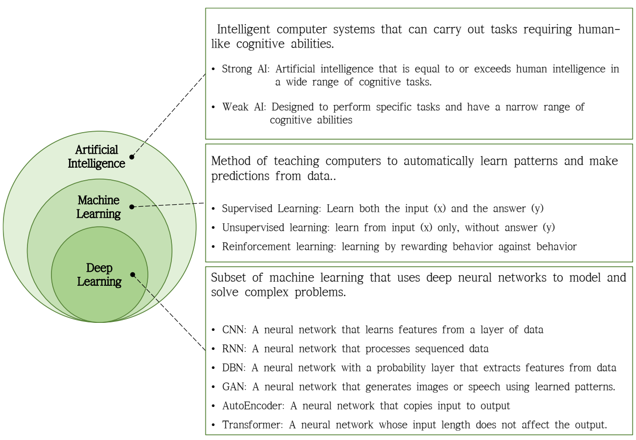

Fig. 1. The classification of AI[1]

AI is generally classified into two categories: Strong AI and Weak AI[2]. Strong AI refers to AI that completely mimics human learning, reasoning, and judgement, and is defined as the level at which an artificially created being can behave as an intelligent life form, much like a human. Weak AI, on the other hand, refers to AI that has been created for a specific purpose and can solve the belongs to problems within a limited scope. To date, most AI programs corresponds to the latter category.

Machine learning (ML) is also a critical component of AI. It is the technology that builds artificial intelligence models using algorithms that can learn on their own, based on data rather than human-defined rules. These models can identify patterns based on training data and make predictions or classifications on new data. Deep learning is a branch of machine learning that uses artificial neural networks to automatically learn from large amounts of data. Deep learning is widely used to build artificial intelligence models in various fields, including computer vision, speech recognition, and natural language processing.

3. Classification of AI applied to nuclear R&D

In this chapter, AI research cases applied to the nuclear power R&D are classified in three different ways to evaluate their relevance. The first classification is based on the nuclear power plant field, which provides insight into the specific applications of AI in this domain. The second classification is based on the type of training data used, which helps to identify the types of data that are most useful for training AI models in this field. Finally, the third classification is based on the learning algorithm used, which provides a better understanding of the different approaches to AI modeling in the nuclear power field. Through these three classifications, we can gain a comprehensive understanding of the current state of AI research in the nuclear power field and identify potential areas for future research and development.

3.1 The classification by nuclear power generation field

First, the field of nuclear power generation is typically categorized into four categories: diagnosis, prediction, response, and process. Diagnosis is mainly applied to the detection of abnormalities in nuclear power plant equipment. Prediction is used to prevent accidents by predicting transient conditions or severe accidents in nuclear power plants. Response is applied to real-time risk assessment and emergency response in the event of a severe accident at nuclear power plant. Process is used to optimize the design and operation of nuclear power plants.

By classifying AI research cases in this manner, we can better understand the specific applications of AI in the nuclear power field and identify areas for further research and development.

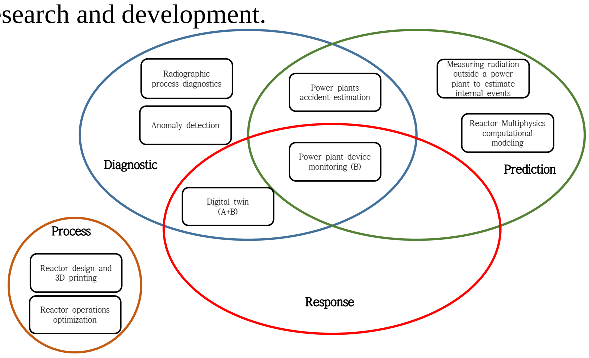

Fig. 2. The classification of nuclear power generation fields

3.1.1 Diagnosis

J. Ma [3] categorized six types of faults in nuclear power plants: instrument degradation, measurement channel dynamic degradation, equipment fault detection, reactor coolant system components, reactor core abnormalities, and power plant transient detection. Table I illustrates the application of artificial intelligence in nuclear power plants, categorizing the faults into two main categories: instrument fault detection (including instrument performance degradation, measurement channel dynamic degradation, equipment fault detection, reactor coolant system component defects, and reactor core abnormalities) and power plant fault detection (specifically power plant transient detection). As demonstrated in Table I, the selection of an appropriate AI algorithm is dependent on both the type of data being analyzed and the characteristics of the system.

Table I. An example of AI applications in diagnostics

Classification	Purpose	AI	Performance / limit	Reference
Instrument fault detection	Learning from sensor errors that can lead to human error	LSTM	Learn sensor performance diagnostics / Multiple faults are not diagnosable	[4]
	Drift estimation for reactor coolant sensors	SVM Random Forest	Estimating anomalous sensors by training on healthy sensor data	[5]
	Diagnose multiple faults in a sensor	K-NN	Drift diagnostics for sensors	[6]
	Diagnosing crack defects in rotary machines	Decision Tree	Power plant turbine fault diagnostics	[7]
	Diagnosing a steam generator tube rupture	Logistic Regression ANN SVM Random Forest	Diagnosing SGTR	[8]
	Crack detection in concrete	CNN	Works without utilizing image processing techniques for feature extraction	[9]
Power plant fault detection	Create a collision database to detect foreign objects in cooling systems and compare them using artificial intelligence learning methods	SVM GP ANN CNN	Metal fragment location mass diagnostics comparison	[10]
	Estimate the mass of a metal fragment that hits a pipe or wall with HMM and ANN methods	ANN	Estimate the location and mass of a fragment using training data	[11]
	Detect foreign object collisions with noise cancellation	SVM	Detect impact only / no location & mass	[12]
	Detecting anomalies in pressure tube ultrasonic inspection data of CANDU-type reactor fuel	CNN	Pressure tube anomaly detection	[13]
	A Convolutional Neural Network Model for Nuclear Abnormalities Diagnosis is proposed	CNN	Two-channel CNN models outperform other classification models in terms of accuracy and reliability	[14]
	The problem of choosing among the several measured plant parameters those to be used for efficient, early transient diagnosis is tackled by means of genetic algorithms.	GA	Diagnostics using transient key parameters	[15]
	Multi-Incident Diagnostic System with Limited Measurement Parameters	GNN	Nuclear accident diagnosis through key parameters of nuclear power plants	[16]

Long short-term memory (LSTM), Support vector machine (SVM), K-nearest neighbor (KNN), Deep Q-network (DQN), Gaussian process (GP), Radial basis function network (RBFN), Artificial neural network (ANN), Hidden Markov model (HMM), Convolutional neural network (CNN), Graph neural network (GNN)

3.1.2 Prediction

In the field of nuclear power, prediction refers to the prediction of transients or critical accidents in nuclear power plants. For instance, artificial intelligence can be used to predict the progression of a Loss of Coolant

Accident (LOCA) faster than a RELAP5 (Reactor Excursion and Leak Analysis Program) accident simulation by applying AI learning to the LOCA accident progression [47]. Additionally, AI can be used to predict severe accidents, such as performing uncertainty analysis of nuclear power plants by learning key parameters of accidents from MELCOR(Methods for Estimation of Leakages and Consequences of Releases) data [2, 23]. Table II illustrates examples of AI applications in the field of prediction in nuclear power.

Table II. An example of AI applications in prediction

Classification	Purpose	AI	Performance / limit	Reference
Anomaly prediction	Predicting NPP parameter trends based on device control, comparing different algorithms	LSTM, RNN	LSTM with MIMO strategy achieves 90%accuracy on average	[17]
	Distinguish between SBLOCA and SGTR by predicting safe stops in SGTR scenarios	Transformer	Distinguish between SBLOCA and SGTR by predicting safe stops in SGTR scenarios	[18]
	Predicting steam/water stratified flow's characteristics.	LSTM SVM MLP	The predicted pressure shows a trend similar to the values obtained from the thermal-hydraulic modelling	[19]
	Predicting integrity of the vessel	LSTM	Train the ASTM PLOTTER database to predict the integrity of a vessel	[20]
	A new method based on Recurrent Neural Networks for calculating the Critical Heat Flux (CHF) in fuel assemblies	RNN	the neural network model can reasonably well predict both the value of the CHF and its location without the need of any additional correction factors.	[21]
	A new method based on Recurrent Neural Networks for calculating the Critical Heat Flux (CHF) in fuel assemblies	LSTM	the neural network model can reasonably well predict both the value of the CHF and its location without the need of any additional correction factors.	[22]
	Predicting decomposition by neutron irradiation of reactor pressure vessels	SVM Random Forest XGB Decision Tree	Predicting Pressure Vessel Anomalies with Neutron Metrics	[23]
Predicting severe accident	Predict Critical Heat Flux for Fuel Bunches with Non-Uniform Heat Fluxes	RNN	Training EPRI CHF data to predict CHF	[24]
	Predicting Failure Thresholds for Nuclear Power Plant Gate Valves	RNN	ON OFF Valve life prediction	[25]
	Predicting accidents by changing parameters in drywells	LSTM	Using Fukushima accident data	[26]

Extreme gradient boosting (XGB)

3.1.3 Response

Table III. shows an example of AI applications in response. In the field of nuclear power plants, response has been actively studied to date, but compared to the previous cases, it is an area that requires more research. When a Design Basis Accident (DBA) occurs in a nuclear power plant, AI can learn the internal data of the nuclear power plant to respond quickly to the DBA [27]. However, in the case of an isolated power failure, such as the Fukushima accident, the internal data of the nuclear power plant cannot be utilized if the connection between the nuclear power plant and the outside world is cut off. To address this issue, it is necessary to measure the radiation dose from outside the plant to determine the extent of the accident [29].

In addition, there is also active research on digital twins [30-32]. This technology enables the comprehensive reproduction of the intricate infrastructure of nuclear power plants in digital form, allowing for not only visual representation but also precise simulation of the physical and mechanical properties between components. For instance, by creating a virtual replica of an actual power plant and integrating real-time measurement data, computer-based operation becomes possible to replicate the exact conditions of the real power plant.

Table III. An example of AI applications in response

Classification	Purpose	AI	Performance/ limit	Reference
Incident estimation	Real-time accident estimation using internal nuclear data	Transformer	Estimate incidents using on- and off-site data	[27]
	Identifying nuclide types in water	DGNN	Estimating the concentration of radioactive material in water during an accident	[28]
	Accident Prediction Using External Radiation Dose in Nuclear Accidents	Decision Tree	Estimation using only marginalized radiation data	[29]
Digital twins	Digital twin model to predict power distribution in nuclear reactors	SVM AE	Predicting output distributions	[30]

	Suggestions for self- calibration of digital twin models	BPNN	Autonomous calibration of key parameters prevents power plants from going into transients or severe accident	[31]
	Nuclear power plant startup and output operation automation	A3C LSTM	Implementing only part of the nuclear power plant	[32]

Depp graph neural network(DGNN), Auto encoder(AE), Back propagation neural network (BPNN), Asynchronous advantage actor-critic (A3C)

3.1.4 Process

The process of a nuclear power plant can be divided into two areas: control and design. In the control field, researchers are studying ways to reduce human reliability analysis (HRA) during plant startup and shutdown operations using AI [33], using genetic algorithms to prolong the equilibrium cycle and use fuel more efficiently [34], and developing control models for autonomous operation [35]. Additionally, research is underway to automatically recognize and classify documents created inside nuclear power plants for operation efficiently [36].

In the design field, the introduction of AI can lead to optimized designs of nuclear power plants [35] and the efficient design of nuclear power plants [37]. Table IV shows the examples of AI applications in the process field.

Table IV. An example of AI applications in process

Classification	Purpose	AI	Performance / Limit	Reference
Nuclear Power Control	Quantifying HEP to reduce HRA in nuclear plant startup and shutdown operations	BBN	Create a BBN model and compare it to existing practices	[33]
	Using genetic algorithms to prolong the core equilibrium cycle of PWRs	GA	Maintain an equilibrium cycle with optimized fuel placement	[34]
	Developing Fuel Management Tools for the Advanced Heavy Water Reactor	CARS-ANN	Streamline fuel management	[35]
	Simple Model Predictive Control for Nuclear Power Plant Autonomous Operation	SVR GRU LSTM	Predict and control nuclear power plant key parameters	[36]
	Automatic recognition system for document digitization in nuclear power plants	Cascade R-CNN	Auto categorizing documents	[37]
Reactor Design	Calculating the coefficient of friction of sump filters and pipelines for long-term cooling of a pipe break scenario at the ACP100 nuclear power plant.	Random Forest	Using limited scope and calculated algorithms	[38]
	Predict core parameters for core design	Decision Tree SVM Random Forest ANN	Performance comparison of the four algorithms for the reactor design confirms the relative superiority of the DLP method	[39]
	Evaluating seismic effects on the core design of an advanced gas-cooled reactor	CNN DNN	Design more time-efficiently than traditional methods	[40]

Bilateral-branch network(BBN), Genetic algorithm(GA), Gated recurrent unit (GRU)

3.2 The classification by training data type

The second classification is to classify the training data by type. The types of data are generally divided into structured data, unstructured data, and time series data. The structured data in nuclear power plants refers to data generated during their normal operation, such as the data measured from power plant equipment and radiation instruments. Structured data has a fixed format, making it relatively easy to analyze. In contrast, The unstructured data, such as text, voice, video, and images, does not have a fixed format. An example of unstructured data in nuclear power plants is Closed-Circuit Television (CCTV) data during plant operation, which needs to be transformed into structured data to apply AI. The time series data in nuclear power plants is data that has chronological order, such as analogue data generated by simulation programs like MAAP (Modular Accident Analysis Program) [41] and MELCOR [42], and data measured during a severe accident in an analogue manner.
Table V shows the classification of research cases according to data types. Most of the data is made up of time series data

Table V. The classification by training data type

Data Type	Reference	Classification of nuclear power generation fields
Structured data	[4,5], [8-16], [19-28], [32-34], [36-40]	diagnostic, prediction, prediction
Unstructured data	[6], [7], [17,18], [29-31], [35]	diagnostic, response, prediction, process
Time series data	[4-8],[10],[12-19].[21-26],[28-40]	diagnostic, response, prediction

3.3 The classification based on learning algorithms.

The third classifications based on learning algorithms include supervised learning, unsupervised learning, and reinforcement learning. The supervised learning is a method of inferring the correct answer to real data by learning training data with correct answers. A typical example is regression analysis to predict or classify the correct answer. The unsupervised learning infers the correct answer from training data that does not have a correct answer. It is a method of inferring patterns or rules from data to obtain structure. A typical example is learning the consumption patterns of shopping mall users and recommending the products that the customers are needed. The reinforcement learning infers the correct answer without data, through behaviors that maximizes rewards in the current state. Typical examples include Deep blue in chess and AlphaGo in Go.

A typical example of supervised learning in the field of nuclear power generation is the detection of abnormal vibration of pumps in the primary coolant. To detect abnormal vibrations, vibration data is learned, and the actual data is used to determine whether the pump is abnormal or not. A typical example of unsupervised learning is learning key parameters of transients in nuclear power plants to predict the trend of future transients or critical accidents. A typical example of reinforcement learning is the autonomous calibration of key parameters of nuclear power plants using digital twins. Through digital twins, a virtual power plant like a real nuclear power plant is created and various key parameters are learned. When the learned virtual power plant receives the key parameters, it corrects the key parameters of the nuclear power plant to prevent transient conditions or severe accidents from occurring.

Table VI shows that researchers interested in studying the diagnosis, prediction, and process fields of nuclear power plants should use supervised learning algorithms. CNN, which is strong in image data analysis, and RNN and LSTM, which excel in time series analysis, are the most active algorithms in this category. Unsupervised learning algorithms are recommended for studying the diagnosis, response, and process fields, with the GAN algorithm being efficient for learning with limited data and the Transformer algorithm attracting attention for its excellent learning performance. For researchers studying the diagnosis and response fields, reinforcement learning algorithms such as DQN algorithms, which excel in sequential decision processing in high-dimensional spaces, and Trust region policy optimization(TRPO) algorithms, which can directly determine behavior, are recommended.

Table VI. The classification of learning algorithms and nuclear power generation fields

	Reference	Classification of nuclear power generation fields	Learning algorithms
Supervised Leaning	[4,5], [8-16], [19-28], [32-34], [36-40]	diagnostic, prediction, process	SVM, XGBoost, CNN, RNN, LSTM
Unsupervised Leaning	[6], [7], [17,18], [29-31], [35]	diagnostic, response, process	Transformer, GAN,
Reinforcement Leaning	[7], [32]	diagnostic, response	Q-Learning, DQN, A3C, TRPO

4. Conclusions

In conclusion, the application of AI in the field of nuclear power plants has great potential to improve safety, efficiency, and productivity. Through the integration and summary of existing AI research in this field, we have provided a guide for researchers who want to apply AI to nuclear power plants. In particular, supervised learning algorithms are recommended for diagnostics, prediction, and processes, while unsupervised learning algorithms are recommended for diagnosis and prediction, and reinforcement learning algorithms are recommended for response and process.

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