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REVIEW ARTICLE (INVITED ONLY)

Current Progress in the Application of Artificial Intelligence for Nuclear Power Plant Operation

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Abstract
Large-scale infrastructures, such as chemical plants and nuclear power plants (NPPs), are pivotal for modern civilization as they provide vital resources and energy. However, their operation introduces significant risks, as demonstrated by the tragic accidents at Bhopal and Fukushima. While extensive research has been conducted to improve the safety of these safety–critical systems, the human factor remains as a significant concern. In recent years, as artificial intelligence (AI) is being widely adopted in various fields, AI may be a solution for supporting operators and, ultimately, for reducing the overall risk of safety–critical systems such nuclear and chemical plants. This review discusses the application of AI in NPP operations, with a focus on event diagnosis, signal validation, prediction, and autonomous control. Various application examples are presented, highlighting the limitations of classical approaches and the potential for AI overcome such limitations to enhance the safety and efficiency of NPP operations. This work is expected to stimulate further investigation into the application of AI to support operators in not only NPPs but also other safety–critical systems, such as chemical plants.

Keywords Nuclear power plant · Safety–critical system · Artificial intelligence · Human factor · Plant operation · Deep learning

Abbreviations

2D	Two-dimensional
AAKR	Auto-associative kernel regression
A-EOS	Autonomous emergency operation system
AI	Artificial intelligence
ANNs	Artificial neural networks
AOPs	Abnormal operating procedures
APR1400	Advanced Power Reactor with 1400 MW electricity
CDN	Condenser
CNN	Convolutional neural network
DRL	Deep reinforcement learning
EOPs	Emergency operating procedures
eQRNN	Ensemble quantile recurrent neural network
GAT	Gate attention network
GNN	Graph neural network
GRUs	Gated recurrent units
HANARO	High-flux Advanced Neutron Application Reactor
HP	High-pressure
LightGBM	Light gradient boosting machine
LP	Low-pressure
MCR	Main control room
MIMO	Multi-input multi-output
MMIS	Man–machine interface system
NPPs	Nuclear power plants
NRC	Nuclear regulatory commission
PID	Proportional–integral–derivative
PSO	Particle swarm optimization
PZR	Pressurizer
RCP	Reactor coolant pump
RL	Reinforcement learning
RNNs	Recurrent neural networks
SG	Steam generator
SMRs	Small modular reactors
SVMs	Support vector machines
TBN	Turbine
TH	Thermal–hydraulic
TMI	Three Mile Island
VAE	Variational autoencoder

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V&V	Validation and verification
LSTM	Long short-term memory

Introduction

Chemical and nuclear power plants (NPPs) as large-scale infrastructures play a crucial role in meeting the diverse needs of modern civilization. Chemical plants synthesize a variety of substances for use in various industries and by consumers. NPPs, as reliable sources of power, steadily generate electricity for industries and households. Nowadays, the role of nuclear power has been highlighted as an essential component in transitioning toward carbon-free electricity without relying on fossil fuels.

However, the operation of such infrastructure has introduced unprecedented risks to society. In the case of chemical plants, the production and handling of hazardous materials may entail the potential risk of leakage. Accidents occurring in NPPs may cause a large release of radioactive materials [1]. The Bhopal disaster at a pesticide plant and two major accidents at commercial NPPs (i.e., the Chernobyl and Fukushima Daiichi accidents) stand as tragic examples illustrating the catastrophic consequences of such risk [2–5].

In line with this, research and development have been actively conducted to ensure the safe operation of these safety–critical systems. In the case of chemical plants, methods have been proposed to optimize the placement of plant facilities to prevent a 'domino effect', where a single accident causes a chain of accidents in adjacent facilities [6, 7]. Eo et al. proposed a framework for determining safe distances between high-pressure (HP) gas pipelines by considering the probability of a chain accident [8]. Guo et al. utilized fuzzy logic to model the risk of the domino effect in a plant and combined the result with a mathematical programming model to derive the optimal layout with minimized risk levels [9]. Another example is the flare network system, which collects and burn flammable toxic materials to turn them into non-hazardous materials [10]. Kabir et al. evaluated the dynamic reliability of the flare system using fault tree analysis and Bayesian networks [11]. Relatedly, Jo et al. analyzed a dynamic scenario of gas blow-by caused by control valve failure using a process simulator and recommended the use of slow depressurization to prevent vessel failure due to extremely low temperatures [12].

In the case of NPPs, the safety goal is analogous to that of chemical plants, which is to prevent the release of hazardous materials to the public. However, radioactivity is a nuclear property that cannot be removed through any physical or chemical processes. Therefore, the safety goal of NPPs has been typically achieved by containing the radioactive materials in a secure manner. To this end, NPPs are equipped with multiple barriers including a series of physical components such as fuel pellets, fuel cladding, the reactor vessel, linear plates, and containment [13]. Plants in addition utilize a reactor protection system and engineered safety features to terminate nuclear chain reactions and maintain the plant in a safe condition. In recently developed new plants, such as Gen-IV and small modular reactors (SMRs), the reliability of such safety systems is being further enhanced by replacing active power sources with natural forces [14].

While these efforts have improved the mechanical reliability of safety–critical systems, conversely, the contribution of human factors to the risk of these systems has increased [15]. Statistics from several studies suggested that over 80% of failures in chemical and petrochemical industries are related to human error [16–19]. Analysis of operating records for the NPPs in the Republic of Korea (ROK) has revealed that human error was responsible for 14% of unplanned reactor trips over a recent decade [20, 21].

Especially in NPPs, human error is a significant concern as it can have critical consequences when combined with mechanical failures [22]. The accident at the Three Mile Island (TMI) NPP in 1979 serves as a historical demonstration. TMI Unit 2 suffered a loss of coolant accident due to a mechanical stuck-open failure of a pressurizer relief valve. Although several indicators showed related anomalies, such as an unusual decrease in coolant pressure, the operators in the main control room (MCR) were unaware of what had occurred in the plant and took an action that worsened the situation. As a result, the reactor core melted down [4].

Reflecting the lessons learned from this event, significant efforts have been made to support plant operators through advanced systems with enhanced equipment and ergonomic designs of human–machine interfaces [23]. For instance, the MCR of the APR1400 (Advanced Power Reactor with 1400 MW electricity) designed by the Korea Electric Power Corporation adapted personal computers and a large display panel in place of the analog indicators, hand switches, and alarm tiles of classical control rooms and substituted paper-based procedures with a computerized procedure system [24, 25]. Likewise, the chemical industry has investigated the adoption of advanced distributed control systems with automatic control [26], virtual reality and wearable devices [27], and a ubiquitous sensor network [28].

Another promising tool to aid plant operators is artificial intelligence (AI). Deep learning models in particular have gained attention due to their success in a variety of complex cases such as StarCraft II [29], conversational AI (e.g., ChatGPT), and image generation [30]. In the chemical industry, early research with deep learning models was conducted in the 1990s for facility fault detection and autonomous process control [31]. Recent advances in computing power have further stimulated these investigations. Lee et al. proposed a chemical process monitoring system using an autoencoding deep learning model. They improved the system by augmenting the data of rare cases with a variational autoencoder (VAE) [32]. Similarly, Xia et al. developed a fault diagnosis method for a water chiller using a voting-based extreme learning machine with kernel entropy component analysis [33]. In research by Son, long short-term memory (LSTM) networks were utilized for predicting the degradation of adsorbent performance in pressure swing adsorption plants [34]. Wang et al. proposed a control optimization framework for intelligent thermal power plants. The framework employs LSTM networks for plant dynamic modeling and a particle swarm optimization (PSO) algorithm for tuning the parameters of proportional-integral-derivative (PID) controllers [35].

In the nuclear energy field, as in the chemical industry, the potential of AI to serve as an intelligent assistant for plant operators is being actively pursued [36]. Furthermore, next-generation NPPs such as the NuScale SMR require a high degree of automation to reduce operating costs, which is achieved by managing multiple reactors with a minimized number of plant operators while maintaining safety [14, 37]. For this, AI could potentially serve as an autonomous agent, not only as an assistant.

The purpose of this review is to present the current progress in the application of AI to NPP operation, with a focus on four application domains. The first domain is event diagnosis. NPPs are equipped with response procedures for irregular events such as pump malfunctions or station blackouts. However, identifying such events and engaging in the proper procedure can be challenging, even for well-trained plant operators, due to the complexity of NPPs. In this context, AI can identify the events in support of human operators. The second domain is signal validation. Since the status of the plant is primarily understood through sensor signals, abnormal signals can lead to inappropriate operator responses and system malfunctions. In addition, these abnormal signals may be symptoms of abnormal plant conditions. Therefore, the detection of abnormal signals is of paramount importance.

The third area of focus is prediction. While analytical models have been developed for predicting plant-wise behavior or specific phenomena of an NPP, they may face limitations when rapid prediction is required or when computational resources are limited. The last domain is autonomous control. While NPPs have long implemented automated systems using classical methods to improve efficiency and safety, these methods have difficulty in achieving the high level of automation required as the need to reduce human error escalates and as next-generation plants are developed. In this case, AI could be a solution for achieving such high level of automation.

The paper is structured as follows. Sects. "Event Diagnosis" and "Signal Validation" delve into the application of AI for event diagnosis and signal validation, respectively. Sect. "Prediction" explores effective AI approaches to overcome the limitations of predictions using analytical methods. Sect. "Autonomous Control" introduces research on autonomous operation with AI technology at a high automation level. Finally, conclusions and perspectives are presented in Sect. "Conclusion and Perspectives".

Artificial Intelligence for NPP Operations

Event Diagnosis

To ensure both safety and efficiency, NPPs are equipped with operating procedures. In particular, the procedures for accidents and abnormal events provide structured responses that have been established through detailed safety analysis. In general, these procedures can be categorized into two types based on event severity. In cases where the event significantly compromises plant safety and triggers an automatic reactor shutdown, emergency operating procedures (EOPs) are implemented (i.e., emergency operation). For less severe situations, abnormal operating procedures (AOPs) are employed (i.e., abnormal operation) [36].

When such events occur, operators should diagnose them and follow appropriate procedures. However, event diagnosis can be mentally taxing for the plant operators, as it requires rapidly analyzing complex information from alarms, plant parameters, and system statuses [38]. Furthermore, during emergencies, plant and system conditions rapidly change and decisions must be made involving the risk that inaccurate diagnosis could lead to improper responses and potential core damage. In abnormal situations, diagnosis is complicated by a wide range of possibilities. For instance, the APR1400 has of a total of 82 AOPs with 224 sub-procedures with different entry conditions [39], making it even more difficult for operators to select the appropriate procedure. In addition, abnormal situations may result in only minor changes in the plant status, requiring operators to spend more time on diagnosis. Due to these reasons, event diagnosis has been known as a significant challenge even for well-trained operators. In addition, incomplete or intermittent information from sensors can also lead to incorrect diagnosis since sensor information forms the basis of operators' situation awareness. In the TMI accident, inaccurate indication of the status of the relief valves contributed to the operators' misdiagnosis and improper responses [4, 40]. With this backdrop, event diagnosis has emerged as the primary application of AI techniques in NPP operation.

Due to the high complexity of NPPs, analytical approaches for event diagnosis are often considered impractical. Instead, data-driven approaches have been widely investigated [38, 41]. When an event occurs in an NPP, it causes changes in plant parameter trends and equipment and system states, as shown in Fig. 1. Therefore, the purpose of the data-driven approaches is to identify patterns in these changes for each event and the normal state, and to construct a model that understands these patterns and outputs the appropriate class for novel situations. Several diagnostic models have been investigated. For instance, Kwon et al. utilized hidden Markov models that can address temporal patterns in parameter trends for NPP accident diagnosis [42]. Yangping et al. proposed a fault diagnosis process that integrates a genetic algorithm into an expert knowledge basis expressed by event tree and fault tree analyses [43]. Rocco S. et al. implemented one-class and multi-class support vector machines (SVMs) to first identify whether an event was trained or not (i.e., the “known” and “unknown” classes) and then classify the trained one into the most appropriate class [44]. As an intuitive alternative to the above-mentioned diagnosis models, Park et al. suggested a methodology involving a database of simulation results [45]. In this approach, all transient scenarios of the NPP secondary system registered in a simulator are simulated in advance, and the current plant status is compared with the result database. In addition, the authors reduced the number of parameters that should be monitored using a principal component analysis [45].

Artificial neural networks (ANNs) have also been studied extensively for NPP event diagnosis. An ANN is a set of multiple interconnected neurons, inspired by the structure and functioning of the human brain. Within an ANN, each neuron receives input signals from its connected neurons, processes them, and produces an output signal. These networks are capable of learning complex patterns and relationships within data through a training process. During training, the network adjusts its internal parameters to minimize the difference between its predicted output and the desired output, thereby optimizing its performance. ANNs are effective in capturing the nonlinear relationships between input signals, promising outstanding generalization performance. This is especially valuable when the conditions of real applications deviate from those of the training data.

Research on adopting ANNs for event diagnosis started from the early 1990s [46–49]. In 1992, Bartlett et al. implemented ANNs that distinguished seven accident scenarios and the normal full-power steady-state operation by monitoring 27 plant parameters. However, due to limited computational power at the time, the authors regulated the number of neurons by starting with only a few neurons and adding more until the trained network achieved the desired accuracy [48]. Bartal et al. introduced a probabilistic neural network that can measure the proximity of a given situation to the trained situations and identify novel untrained situations [49]. Following these early attempts, diagnostic frameworks with multiple networks have been proposed. Lee et al. developed an accident diagnosis advisory system using two types of neural networks: a modified dynamic neural network for digital discrete signals, and a dynamic neuro-fuzzy network for continuous analog signals. Both networks perform independent accident diagnosis and provide more informative results to the operator [50]. Mo et al. proposed a diagnostic system that utilizes a level 1 classifier for accident type recognition and a level 2 classifier for predicting the accident severity and location. In particular, the level 2 classifier comprises multiple neural networks, and their results are aggregated to make predictions [51].

In recent years, the advancement of computing power has made it possible to implement ANNs with millions of intrinsic parameters, leading to the emergence of *deep* learning.

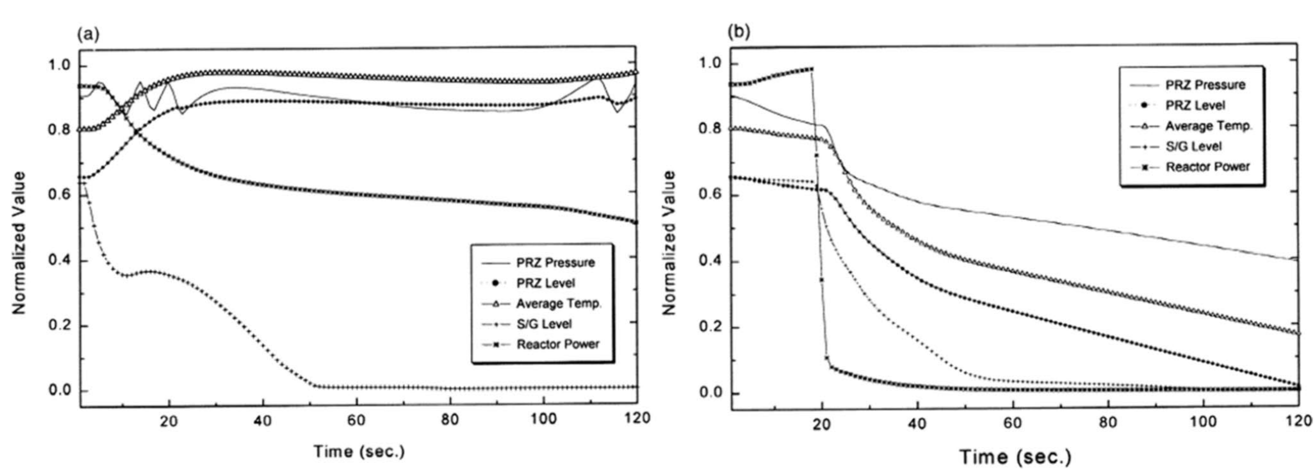


Fig. 1 Example of plant parameter trends following events: **a** anticipated transient without scram, and **b** main steam line break inside containment [42]

Moreover, specialized advanced neural network architectures have been developed. As illustrated in Fig. 1, temporal patterns play a crucial role in event diagnosis. Therefore, recurrent neural networks (RNNs) and their derivatives, including LSTM [52] and gated recurrent units (GRUs) [53], which are ANNs designed specifically for sequential data, have been utilized in event diagnosis tasks. For example, Yang et al. proposed an accident diagnosis algorithm using an LSTM network [54]. Compared to a simple vanilla RNN, where each neuron has a single state updated when each input at a certain time step is given, an LSTM neuron includes an additional cell state that can more effectively retain information from previous time steps. The implemented LSTM network considers a 10-time-step record of 100 plant parameters, which are normalized by min–max scaling, and outputs a real-time diagnosis result, as shown in Fig. 2.

Similarly, GRU, which is an alternative of LSTM, was used by Kim et al. [39]. GRU simplifies its architecture by eliminating the separate cell state of LSTM and merging the state-updating gates found in LSTM. The authors employed GRU networks to tackle the issue of abnormal event diagnosis, a problem recognized as more complex than accident diagnosis primarily because AOPs encompass a larger number of cases compared to EOPs. In addition, symptoms of abnormal events may not be as evident, whereas accidents typically cause a clear deviation in the plant's status. To resolve these challenges, the authors developed a two-stage diagnosis process inspired by the structure of AOPs, as illustrated in Fig. 3. First, the main GRU network predicts the AOP, and subsequently, a GRU network corresponding to each AOP identifies the appropriate sub-procedure. In the case study, which included 20 sub-procedures, the model achieved a diagnosis accuracy of over 99% on datasets generated by a simulator of a generic 1400 MWe pressurized water reactor similar to the APR1400.

Lee et al. addressed the abnormal event diagnosis problem using a convolutional neural network (CNN) [55]. A CNN consists of convolutional layers responsible for extracting features from the input data. Each convolutional layer applies convolution operations between the input data and a set of learnable filters. These filters are small-sized matrices that slide across the input data, computing element-wise multiplications and summations to produce feature maps. Since the convolution operations can effectively capture spatial patterns between adjacent data points, a CNN is typically used with image input data. The authors converted the records of plant parameters into a set of square two-dimensional (2D) images to incorporate into the CNN, as shown in Fig. 4. To account for temporal patterns, they computed the deviation of plant parameters over a specified time period and transformed it into a 2D image using the same method as above. Both of these 2D images were then supplied to each input channel of the CNN. In an experiment, the two-channel 2D CNN outperformed a simple ANN, GRU, and SVM in terms of diagnosis accuracy.

Chae et al. proposed an accident diagnosis algorithm using a graph neural network (GNN) [56]. A GNN is designed for graph data, where nodes are interconnected by edges, representing spatial relationships between input parameters [57]. Leveraging the physical relationships

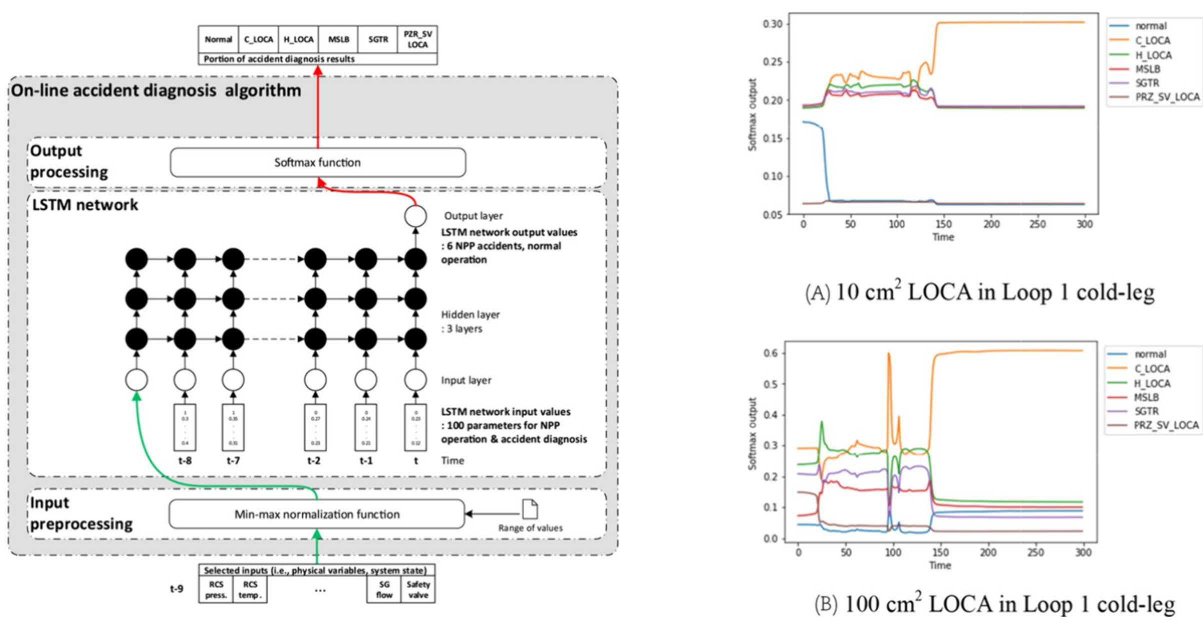


Fig. 2 Accident diagnosis algorithm using an LSTM network proposed by Yang et al. and real-time diagnosis result for a malfunction injected at 30 s [54]

between plant parameters, the authors structured the graph data, as illustrated in Fig. 5, and used it to train the GNN. The performance of accident identification was compared with a CNN, and the results demonstrated that the GNN outperformed the CNN in accuracy, especially for scenarios in which two accidents occurred simultaneously.

Building upon past work aimed at mitigating the risk of incorrect diagnoses when given situations differ significantly from the training data [49], Yang et al. and

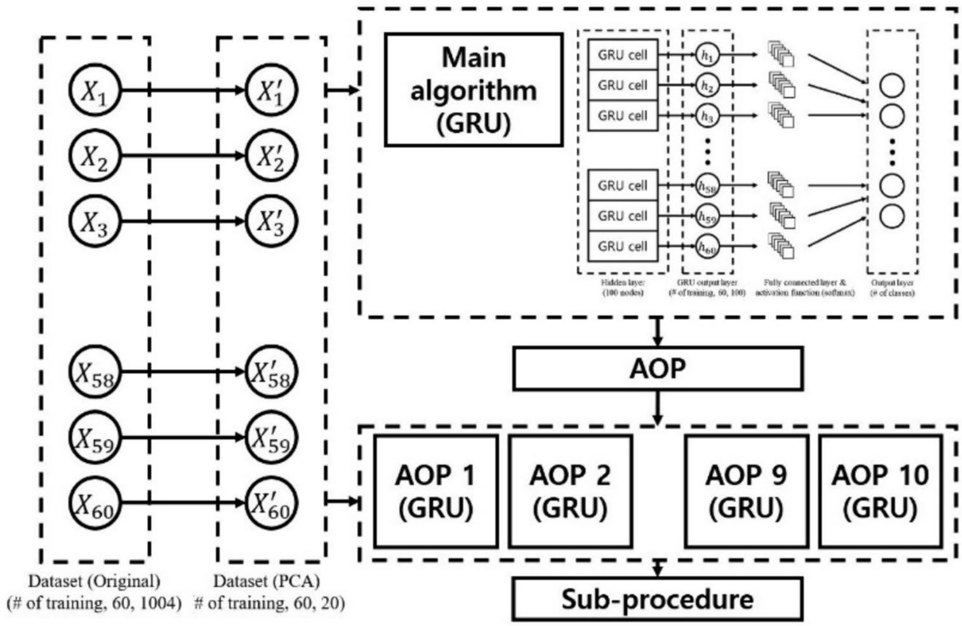


Fig. 3 Abnormal event diagnosis process utilizing GRU networks in two stages [39]

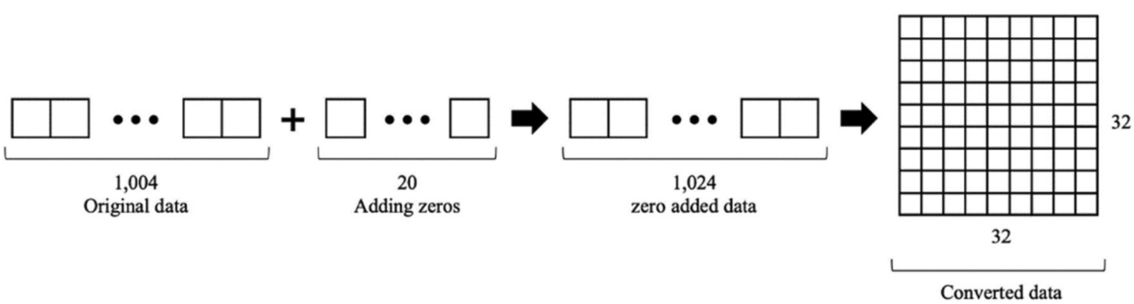


Fig. 4 Example of generating square 2D images from records of 1004 plant parameters [55]

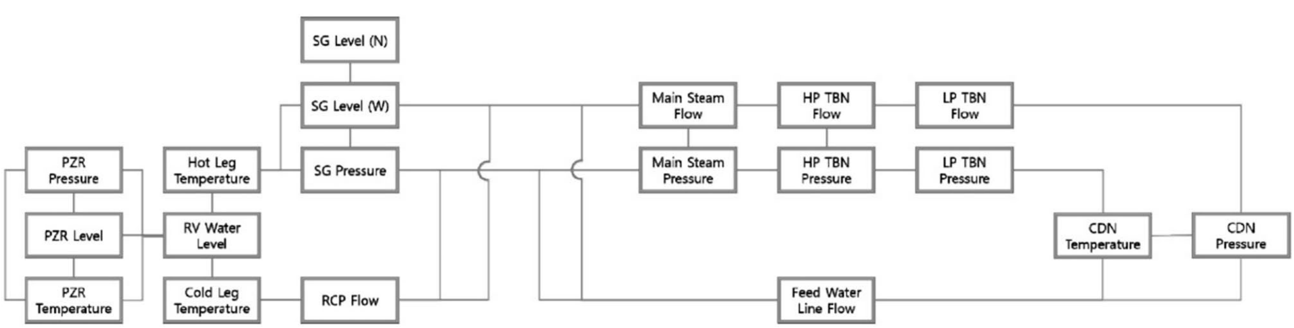


Fig. 5 Graph structure representing the physical relationships between plant parameters [56]. (*PZR* pressurizer, *RCP* reactor coolant pump, *SG* steam generator, *HP* high pressure, *LP* low pressure, *TBN* Turbine, *CDN* Condenser.)

Kim et al. employed autoencoders [58, 59]. An autoencoder is an ANN trained to reproduce input data. When the given data resembles the trained data, the input is accurately reconstructed. Conversely, when the given data differs significantly, the reconstruction error is higher compared to the trained data. Hence, by monitoring the residual between input and reconstructed input, situations that were not considered during training can be filtered out. Yang et al. and Kim et al. incorporated an LSTM-based autoencoder and variational autoencoder, respectively, to distinguish between trained and untrained situations for accident and abnormal diagnosis, respectively.

The success of such ANN-based approaches has led to further studies for enhancing their adaptability for real plants. Since the operating data of NPPs are typically confidential and the data for accident and abnormal events are rare, most studies have trained their models using datasets from plant simulators. However, differences exist between simulator data and plant field data in various aspects, and these differences may limit the application of data-driven models. For instance, the noise typical of field signals can degrade the performance of data-driven models. A test conducted by Shin et al. showed that only 2% Gaussian noise reduces the accuracy of a GRU-based diagnosis model by 55% [60]. To address this concern, the authors suggested implementing smoothing filters on time-series trends of plant parameters and augmenting the training data with artificial noise [60].

In addition to noise, there are also differences in the values and scales of the parameters, even when the overall trends are similar. Lee et al. tackled this problem by constructing a diagnosis model with high generalization ability using meta-learning methods [61]. First, they converted time-series records of plant parameters into images that can highlight the general trends instead of the specific values. Figure 6 shows an example of this conversion. Then they trained a CNN-based feature extracting neural network, which outputs reduced-dimensional representations of the training images, in the direction where the representations are clearly clustered according to the events. The inputs are classified to each event according to the distance of its representation from the prototypes, which are mean representations of the trained data for each event (i.e., prototypical learning). The generalization capability of the model using meta-learning and prototypical learning methods was demonstrated by a case study in which a model trained on simulator data was applied to a distinct dataset from a different plant simulator.

When multiple events occur simultaneously, operators may be confused by the intertwined symptoms of the events, in which case ANNs trained on single-event datasets may be limited. This limitation has been addressed with the GNN diagnosis model developed by Chae et al. [56]; however, the collection of training data for possible combinations of multiple events is required, which can be impractical. To address this impracticality, Cho et al. suggested a framework where the multi-abnormal events that should be trained as independent events are selected based on a one-versus-rest classifier [62]. In contrast, Shin et al. proposed a method utilizing only single-event training data [63]. In this method, multiple sub-models for each single event were utilized. The CNN-based sub-models determine whether the given situation corresponds to each event or not, and results of each model are aggregated to output the diagnosis result. The authors further employed an extremely randomized trees classifier to select the input parameters for each sub-model.

The black-box nature of ANNs is also an issue that needs to be addressed for practical applications. Since ANNs typically provide only diagnostic results without any explanation why such decisions were made, operators may be kept out of the loop and operator backup may be prohibited when the diagnosis fails [64, 65]. To solve this problem, Shin et al. interpreted their CNN diagnosis model using techniques such as saliency mapping, guided gradient-weighted class activation mapping, and deep learning important features with Shapley values [66]. Figure 7 illustrates an example outcome of these techniques for the input data of 60 s (y-axis) recording of 944 parameters (x-axis). The parameters contributing to diagnosing each event are highlighted based on their importance as measured by each technique. The authors validated these parameters by comparing them to the parameters illustrated in the entry conditions of AOPs

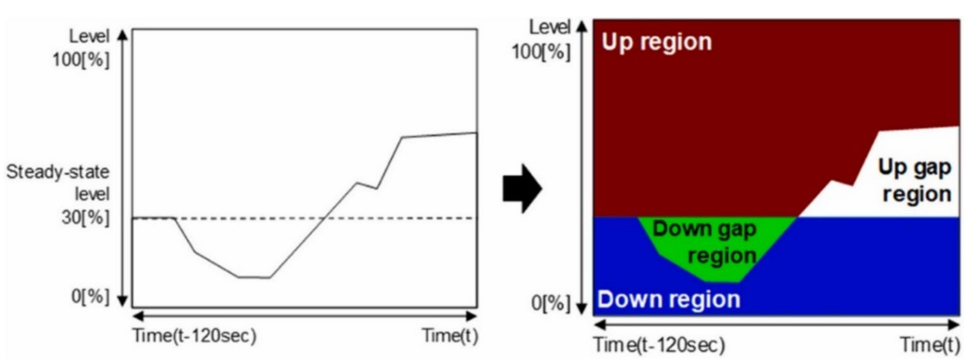


Fig. 6 Example of a trend image generation [61]. Each segmentation region that represents a parameter trend is color-coded

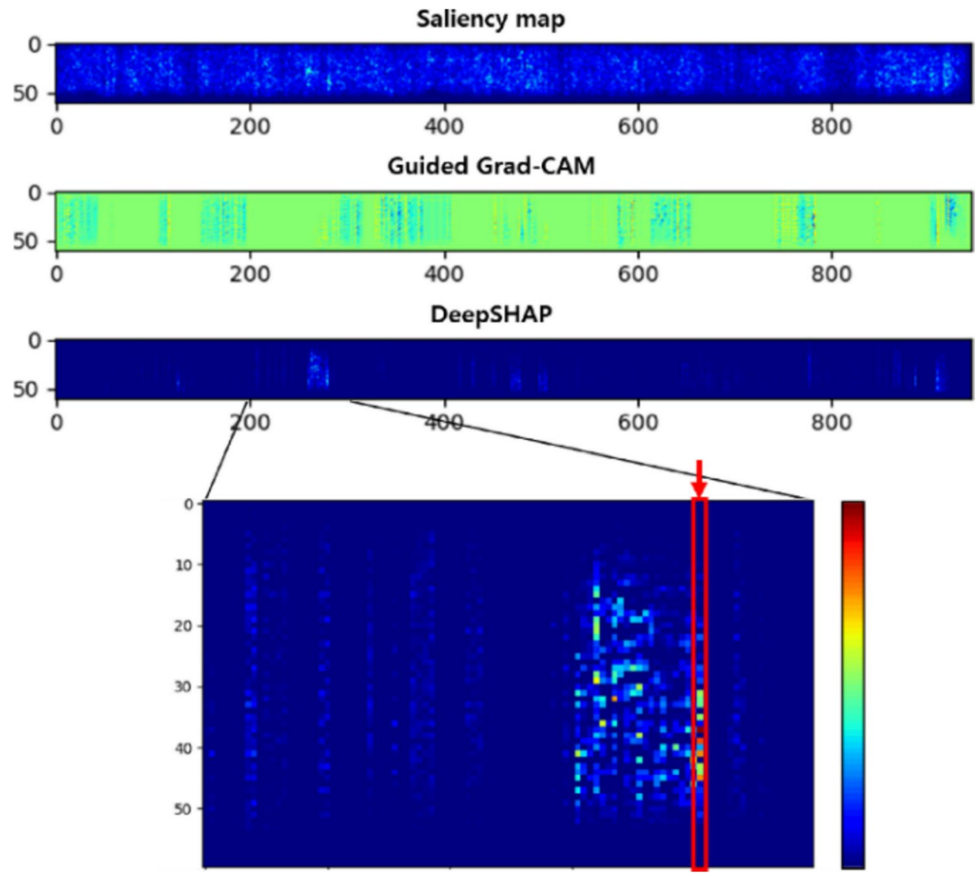


Fig. 7 Importance map of a plant parameter (x-axis) and time instant (y-axis) given by different interpretation techniques [66]

and constructing an ANN model using only these parameters. Similarly, Park et al. developed a diagnosis model using a light gradient boosting machine (LightGBM), a type of decision tree approach, and applied the Shapley values technique to identify diagnostic evidence [67]. Combining the LightGBM model, the interpretation technique, and an autoencoder model for classifying untrained situations, the authors designed a reliable intelligent diagnostic assistant and validated its effectiveness on several abnormal operation scenarios.

In addition to the studies introduced so far, other notable advances have been made. A diagnosis model that combines a CNN and LSTM has been suggested [68], attention mechanisms have been incorporated in a diagnosis model [69, 70], and an event diagnosis method utilizing infrared photography from drones has also been proposed [71].

Signal Validation

Validating the integrity of signals from sensors and plant systems is crucial not only for the diagnosis of events but also for all operational activities within NPPs. A common method for signal validation is to compare the signals with predictions of models trained on datasets with valid signals. If the given signals closely resemble the trained ones, the difference (i.e., residual) between the signals and the predictions will be minimal, and by establishing a threshold for this residual, invalid signals can be detected.

As discussed in the previous section, analytic models are limited due to the intricate nature of NPPs. Therefore, extensive research has focused on data-driven models such as auto-associative kernel regression (AAKR) [72, 73], singular value decomposition [74], and ANNs [75, 76]. Among them, ANNs have been highlighted since they can effectively capture complex relationships between sensor signals and operating conditions. For instance, Choi et al. suggested a signal validation algorithm with a VAE and LSTM [77]. By leveraging the ability of LSTMs to capture temporal patterns and the capability of VAEs to robustly reconstruct signals, the suggested method was able to be applied in emergency situations where signals rapidly vary. In a more recent advancement, Liu et al. applied a gate attention network (GAT) for detecting multiple faults in NPPs [78]. As shown in Fig. 8, sensor signals are fed into the graph structure and the hidden state h_{ij} and correlation values a_{ij} are updated, corresponding to each sensor and the relationship between sensors, respectively. Given the hidden state, the LSTM network predicts the signal values of the sensors. This reconstruction pipeline effectively captures both temporal (LSTM) and spatial (GAT) information. In addition, this

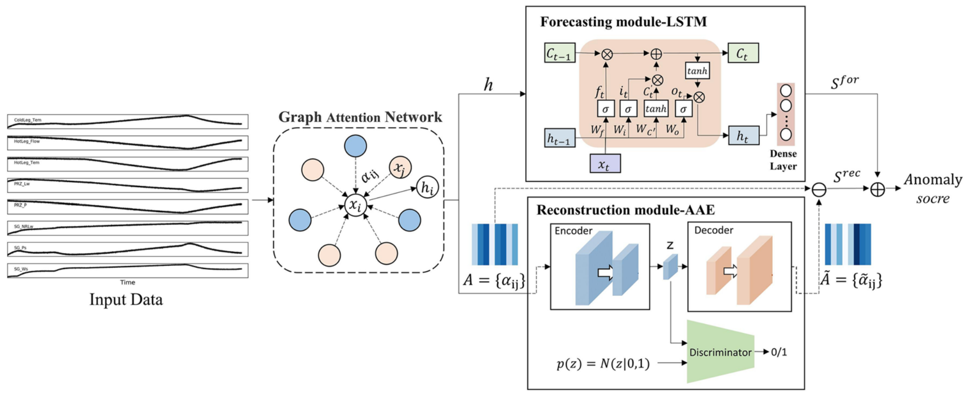


Fig. 8 Architecture of a developed sensor fault detection system with a GAT, LSTM, and adversarial autoencoder [78]

research deployed an additional pipeline for the correlation values with an adversarial autoencoder; this architecture thus utilizes two reconstruction errors, namely for sensor signals and correlations between sensors.

In contrast to the above signal validation approaches, Choi et al. suggested a novel approach for sensor fault detection using a consistency index [79]. Instead of utilizing datasets with valid signals, the authors artificially synthesized a dataset with faulty signals referring to sensor error modes reported in industrial data. They then assigned a consistency index of 1 to the valid signals and 0 or lower than 1 to the invalid signals and trained an LSTM network to predict the index of given input sequences. The authors further developed a sensor fault-tolerant accident diagnosis system that can isolate the impacts of faulty signals on event diagnosis using a GRU-decay network [40]. Finally, they integrated the sensor fault detection and fault-tolerant diagnosis systems, as shown in Fig. 9, and tested the integrated system on sensor faults during accidents, verifying its effectiveness [80].

Since invalid signals may stem from abnormal reactor states, attempts have been made to detect plant anomalies by validating signals [81]. Compared to the event diagnosis approaches, signal validation approaches require only normal operation data. This point has spurred the application of these methods for detecting plant anomalies caused by various factors. For instance, Gursel et al. employed a signal validation method to identify anomalous instances attributable to human error by NPP operators [82]. In this research, a generative adversarial network was utilized for anomaly detection, in which the residuals in the latent space of an ANN were compared. Likewise, Zhang et al. utilized AAKR for detecting cyberattacks on NPPs by monitoring network flow patterns and plant operating parameters [83, 84].

Furthermore, anomaly detection systems have been implemented with signal validation approaches on real operating nuclear reactors. Kim et al. applied an RNN-based online anomaly detection system to the operational records of a research reactor at the University of Wisconsin [85]. Similarly, an autoencoder-based anomaly detection system was applied to a real operating research reactor in the ROK (HANARO), as shown in Fig. 10 [86].

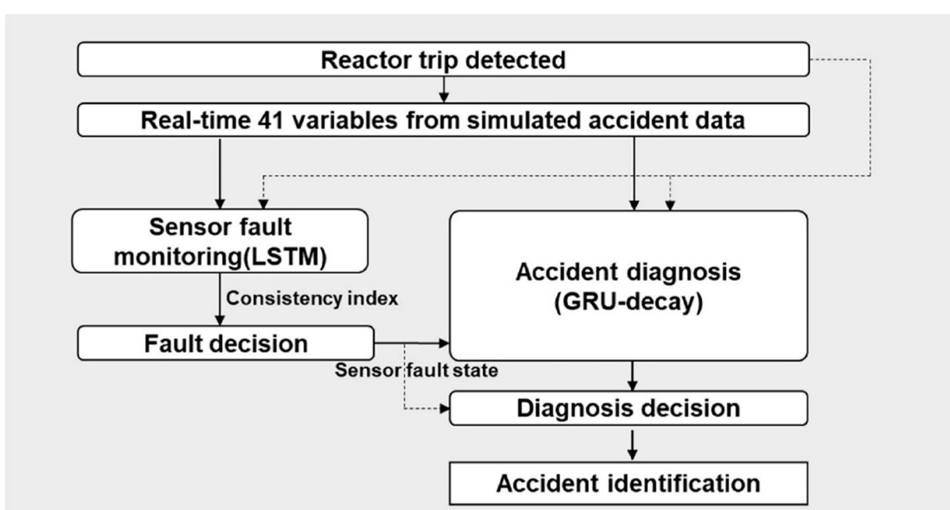


Fig. 9 Integrated sensor fault detection and fault-tolerant diagnosis systems [80]

Prediction

Simulating the plant behavior under a given operating scenario is fundamental for the operation of NPPs. Typically, simulations are conducted using analytic approaches such as thermal–hydraulic (TH) system codes and computational simulation codes for specific domains, such as reactor physics or materials behavior. The best estimation results obtained from these codes are considered analyzable and highly reliable, and accordingly, these codes are utilized in the design of reactors and form the backbone of plant simulators for operator training. However, it is worth noting that these codes demand substantial computational resources. For instance, TH system codes required 4.3 h and 1 h to simulate a single transient of a passive safety system [87] and a single accident scenario of an NPP [88], respectively. Therefore, to provide a more rapid and timely analysis when needed, fast surrogates of system codes can be utilized. Recently, deep-learning models have been intensively investigated as such surrogate models.

Various ANN-based surrogate models have been suggested according to their application domains. For instance, predicting future plant parameter trends can be useful for plant operators during accidents. However, predictions should be done in real-time for maximum effectiveness. To achieve real-time prediction, Radaideh et al. proposed a neural network–based time-series forecasting model [88]. The authors constructed simple ANNs and LSTM networks for each parameter, including core pressure, reactor water level, and fuel temperature, and trained them to predict future trends under an accident (i.e., loss of coolant accident [LOCA]). Similarly, Bae et al. employed ANNs, LSTM networks, and RNNs to forecast critical parameter trends for monitoring safety functions of the plant during emergencies, as shown in Fig. 11 [89]. The authors tested various multiple time step prediction strategies and also considered operator responses (i.e., device control). They concluded that the multi-input multi-output (MIMO) strategy is optimal and showed that a model with LSTM networks and the MIMO strategy can identify different future parameter trends under various accidents and operator actions. Expanding on this investigation, Ahn et al. further developed an operation validation system that raises an alarm when the current operator action could worsen future parameter trends [90].

Ryu et al. also conducted similar research [91], but rather than for operator support, their purpose was to reduce uncertainty in safety assessment by analyzing a wide spectrum of accident scenarios using a surrogate model instead of TH system codes. To achieve this, they proposed a novel deep-learning model, namely ensemble quantile recurrent neural network (eQRNN) with bidirectional LSTM networks, positional encoding, and quantile regression, as shown in Fig. 12. A comparison study showed its superiority compared to the sole LSTM network in previous studies.

Following these achievements, Kim et al. also exploited bidirectional LSTM networks [92]. The authors utilized sequence-to-sequence learning to retain a single predictive network and a conditional VAE to quantify the predictive uncertainty, expanding the prediction horizon up to 120 time steps. Other research on plant parameter prediction has focused on predictions under scenarios of control element withdrawal at full power [93], optimization of the training hyperparameters of LSTM networks with TH system code data of a boiling water reactor [94], interpretation of a

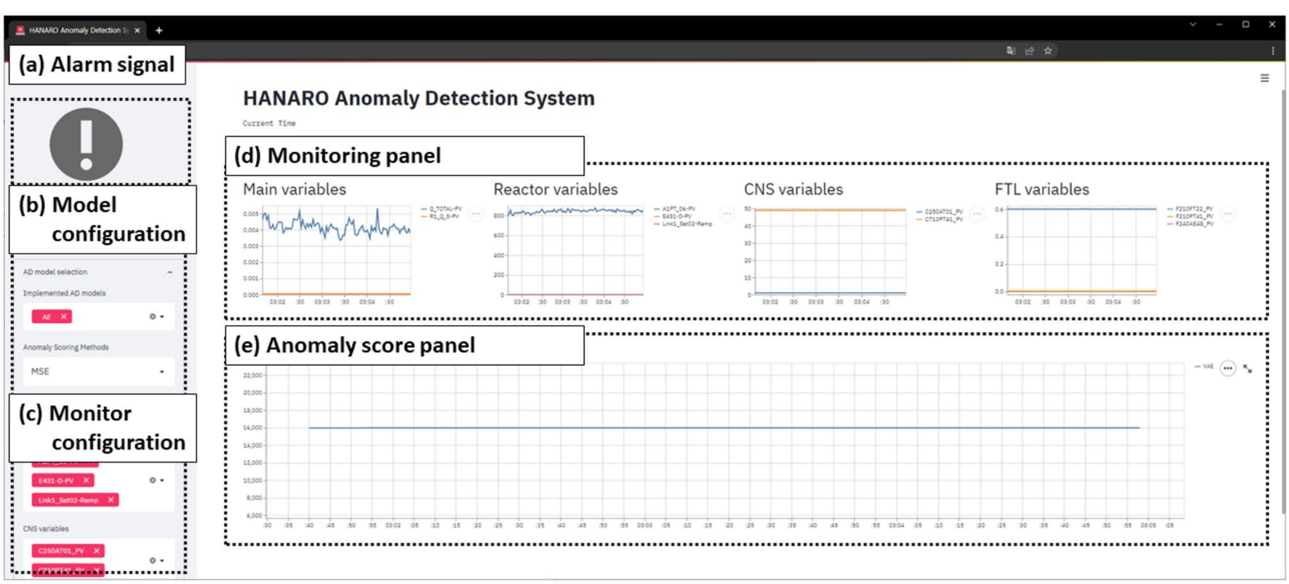


Fig. 10 User interface of the anomaly detection system implemented in HANARO [86]

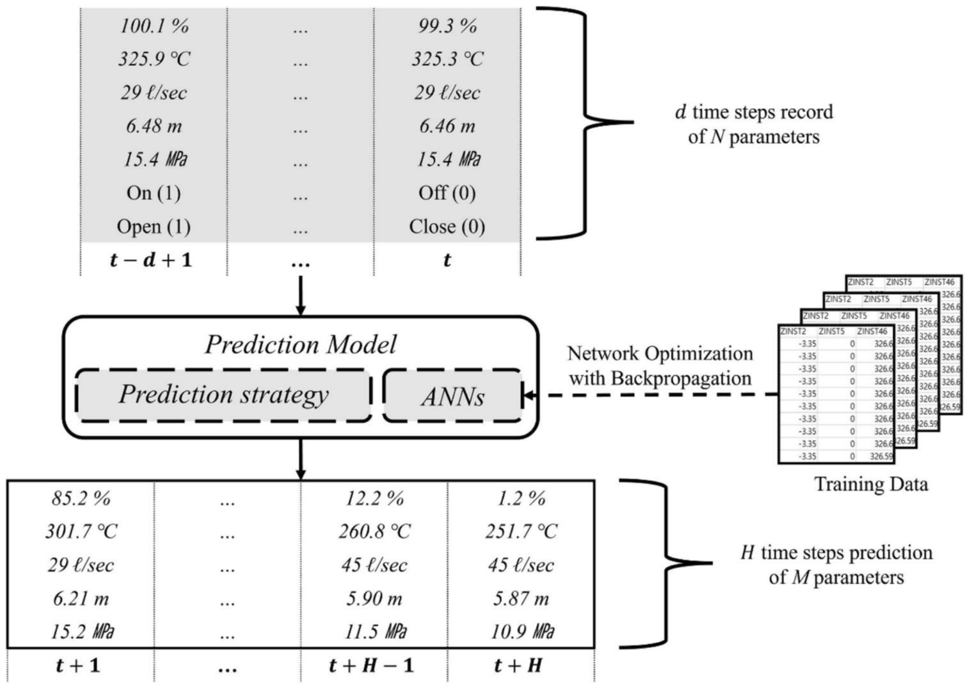


Fig. 11 Illustrative description of the parameter trend-prediction model [89]

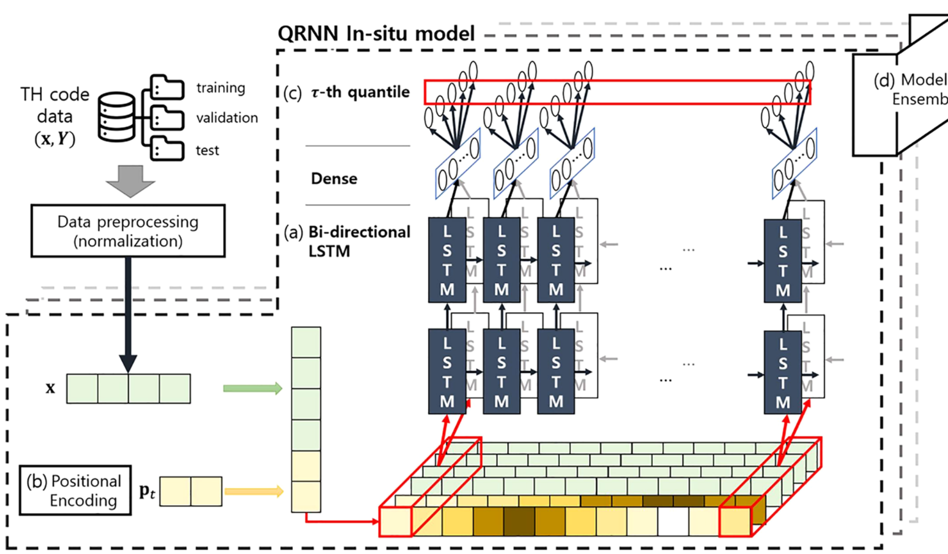


Fig. 12 Overall structure of eQRNN (left) and examples of prediction results (right) [91]

GRU prediction model using the SHAP technique [95], and application of transformer neural networks [96].

Alongside the prediction of future parameter trends, there is active investigation into using deep-learning methods to predict plant features, which can be useful for the operators but are typically not directly measurable and require significant computation time with analytic approaches. For example, fuzzy neural networks have been utilized to estimate severe accident features such as the break size [97] and critical flow [98] of LOCA, the reactor vessel water level [99] and hydrogen concentration [100] during a severe accident, the leakage rate in post-LOCA circumstances [101], and the remaining time for actuating the safety injection system (i.e., emergency core cooling system) in an accident [102].

Since NPPs comprise numerous mechanical components such as pumps, pipes and valves, deep-learning approaches for detecting any degradation of these components have been suggested. Chae et al. developed deep-learning models with CNNs and LSTM networks, respectively, that can predict the degree of pipe thinning based on vibration signals [103]. Lee et al. addressed the problem of small leakage detection, which is limited in traditional leakage detection methods, using bidirectional an LSTM network. In this research, the LSTM network was trained to predict the relative humidity of a leakage area based on the temperature and relative humidity at the measurement position and the distance between the leak area and the measurement position [104].

Like the aforementioned study by Ryu et al. [91], deep-learning models have also been utilized for plant safety assessment with TH system codes. In research conducted by Park et al. [105], an ANN was trained to predict wall temperature, which is a critical parameter affecting the heat transfer rate between the reactor and coolant, to save the computational time. Moreover, Chae et al. suggested the AI-utilized physics related information-based simulation method [106], in which a physics-informed neural network is deployed to solve partial differential equations, the foundation of TH system codes. Although the case studies were conducted in a highly limited manner, the results demonstrated the potential of neural networks to accelerate or substitute TH system codes.

Compared to the previous studies on resolving the computation burden of simulating numerous accident scenarios by substituting TH system codes with deep-learning models [91, 106], Bae et al. proposed a more conservative approach that integrates both deep learning and TH system codes [107]. In this research, the authors introduced Deep-SAILS, short for deep learning-based searching algorithm of informative limit surfaces/states/scenarios. This algorithm aims to reduce the computational burden by directing the TH system code to intensively simulate the scenarios close to the limit surface, referring to the boundary between accident scenarios with and without plant damage. Since the surface is ambiguous at the beginning, a deep-learning model designed to predict a critical parameter that determines plant damage or not repetitively estimates the surface, directs the TH system code, learns the simulation results, and estimates the surface again. Figure 13 shows an example of the result with Deep-SAILS.

Autonomous Control

NPPs are equipped with automation systems such as PID controllers, programmable logic controllers, and field-programmable gate arrays. However, these systems play limited predefined roles, while most complex decision making has been made by plant operators [108]. Yet recent trends are pushing for a higher degree of automation. Even though the reliability of mechanical systems has increased, the risk of human error remains a significant concern for satisfying the stringent risk requirements for NPPs. Essentially, a high level of automation can prevent or reduce the impact of human error. The development of SMRs has further emphasized the importance of automation, as the loss of economies of scale in SMRs can be compensated by implementing automated systems while minimizing the number of operators required per modular reactor [109].

Nowadays, the advancement of AI technology, as well as its success in various NPP operational tasks such as diagnosis, signal validation, and prediction, is increasing the possibility of achieving such higher levels of automation [110]. Autonomous control, as an

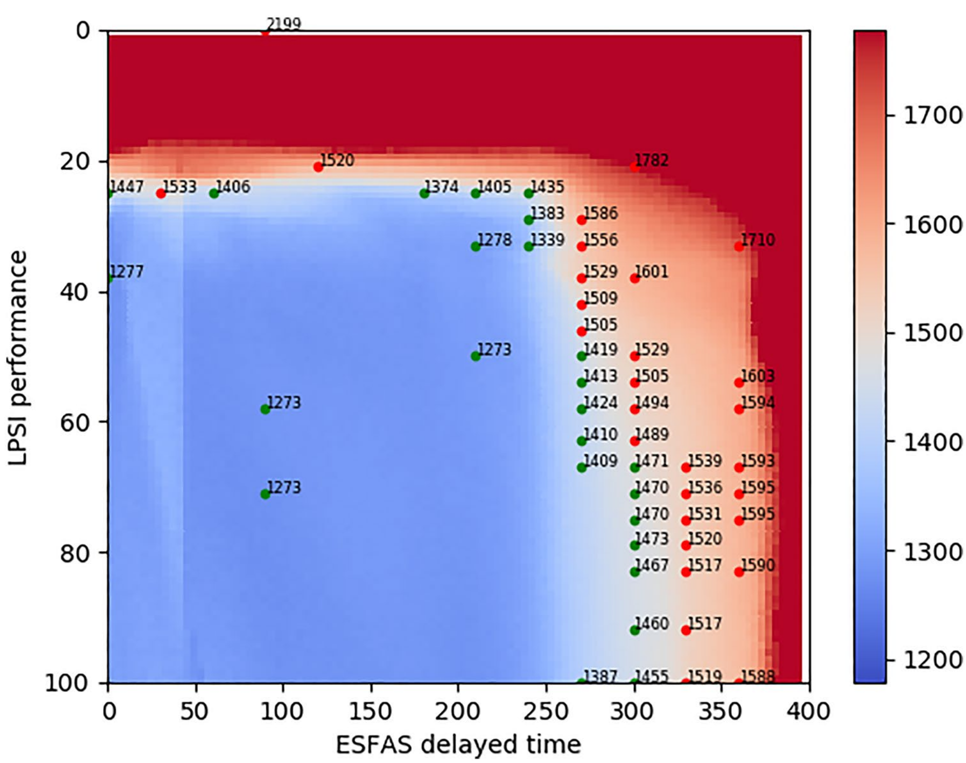


Fig. 13 Limit surface (white region between red and blue areas) estimated by the deep-learning model and simulated scenarios (green and red dots), which are mostly located near the surface [107]

essential component for high-level automation, has also been addressed using AI technology [111]. For instance, at the component level, Na et al. designed a genetic fuzzy controller that can adjust the water level of NPP steam generators [112]. Similarly, Mehrdad et al. proposed a reactor core power controller for electricity load following using RNNs and fuzzy systems [113]. In addition, Mousakazemi et al. fine-tuned PID controllers for reactor core power using the PSO algorithm [114].

Autonomous control has also been investigated at the system level with detailed frameworks integrating multiple functions. Lee et al. proposed a function-based hierarchical framework for the autonomous operation of safety systems during emergency operations, outlined in Fig. 14 [115]. In the case study, an LSTM network was designed following the suggested framework and trained using simulated emergency operation records of well-trained students presuming the actions of plant operators. Kim et al. further expanded this framework and proposed a conceptual design of an autonomous emergency operation system (A-EOS) integrating separate LSTM networks for autonomous control and accident diagnosis, and rule-based systems for performance monitoring and strategy selection [116]. The authors also implemented a prototype A-EOS in a simplified NPP simulator, as shown in Fig. 15.

In the last decade, deep reinforcement learning (DRL), which combines deep learning with classical reinforcement learning (RL) methods, has emerged as a promising approach for implementing autonomous control systems in NPPs [108, 117, 118]. Unlike classical approaches, DRL trains autonomous agents using limited feedback on their trial-and-error experiences, making it well suited for complex systems such as NPPs. Early attempts with NPP simulators have shown promising results. For example, Lee et al. utilized RL to train an LSTM network model capable of selecting appropriate actions for reactor power control during power increase operations in NPPs [119]. Integrating the RL-based agent with rule-based systems, the authors proposed an algorithm for autonomous power increase operations, as depicted in Fig. 16. Similarly, Park et al. implemented a DRL algorithm to train an autonomous agent to control the pressurizer pressure and water level during the reactor heating process [120].

There is also research on incorporating classical approaches with DRL. For instance, Lee et al. suggested a PID controller tuned by DRL and compared its performance with a standalone DRL agent and a classical PID controller on pressurizer level and pressure control tasks during cold shutdown operations of an NPP [121]. Similarly, Wei et al. proposed a novel model predictive control method in which the model parameters are optimized by DRL and applied the method to reactivity control for reactor power change [122].

One challenge with DRL-based approaches is training the agent to achieve multiple objectives simultaneously. This can be accomplished by properly harmonizing the training feedback for each objective. However, this clearly requires significant human intervention. To address this challenge, Kim et al. introduced a prediction-based strategy [123] in which an LSTM network predicts the future trends of plant parameters for possible combinations of candidate actions for each objective when there is a conflict in controlling certain components. These predicted trends are then scored

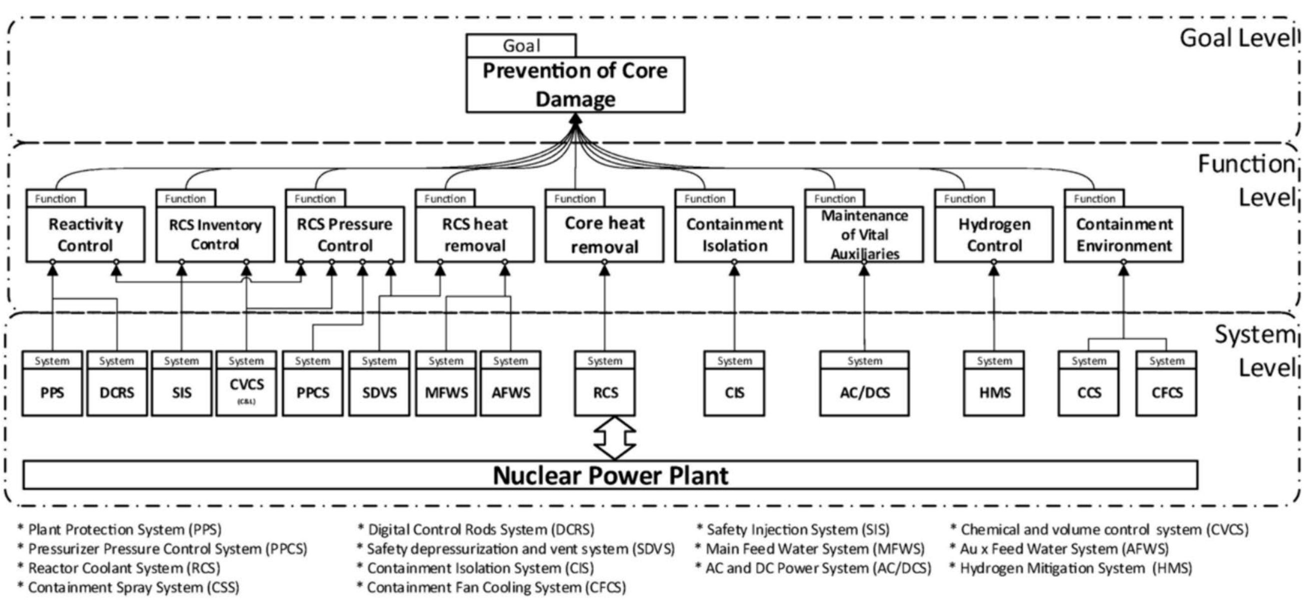


Fig. 14 Function-based hierarchical framework for the autonomous operation of NPP safety systems [115]

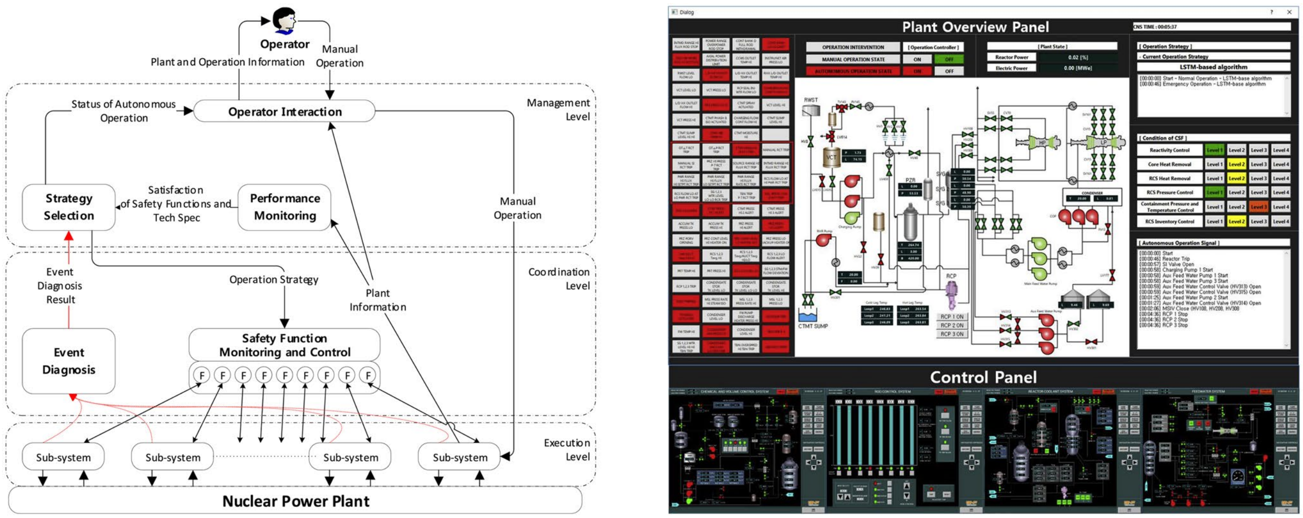


Fig. 15 Functional architecture of the A-EOS (left) and human–machine interface of its prototype (right) [116]

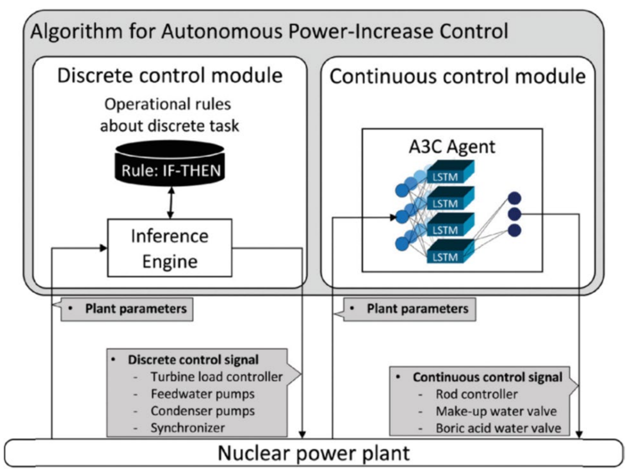


Fig. 16 Schematic of the algorithm for autonomous power increase control in an NPP, where rule-based controls and continuous controls, illustrated in the operating procedures, are automated by rule-based logics and a DRL agent, respectively [119]

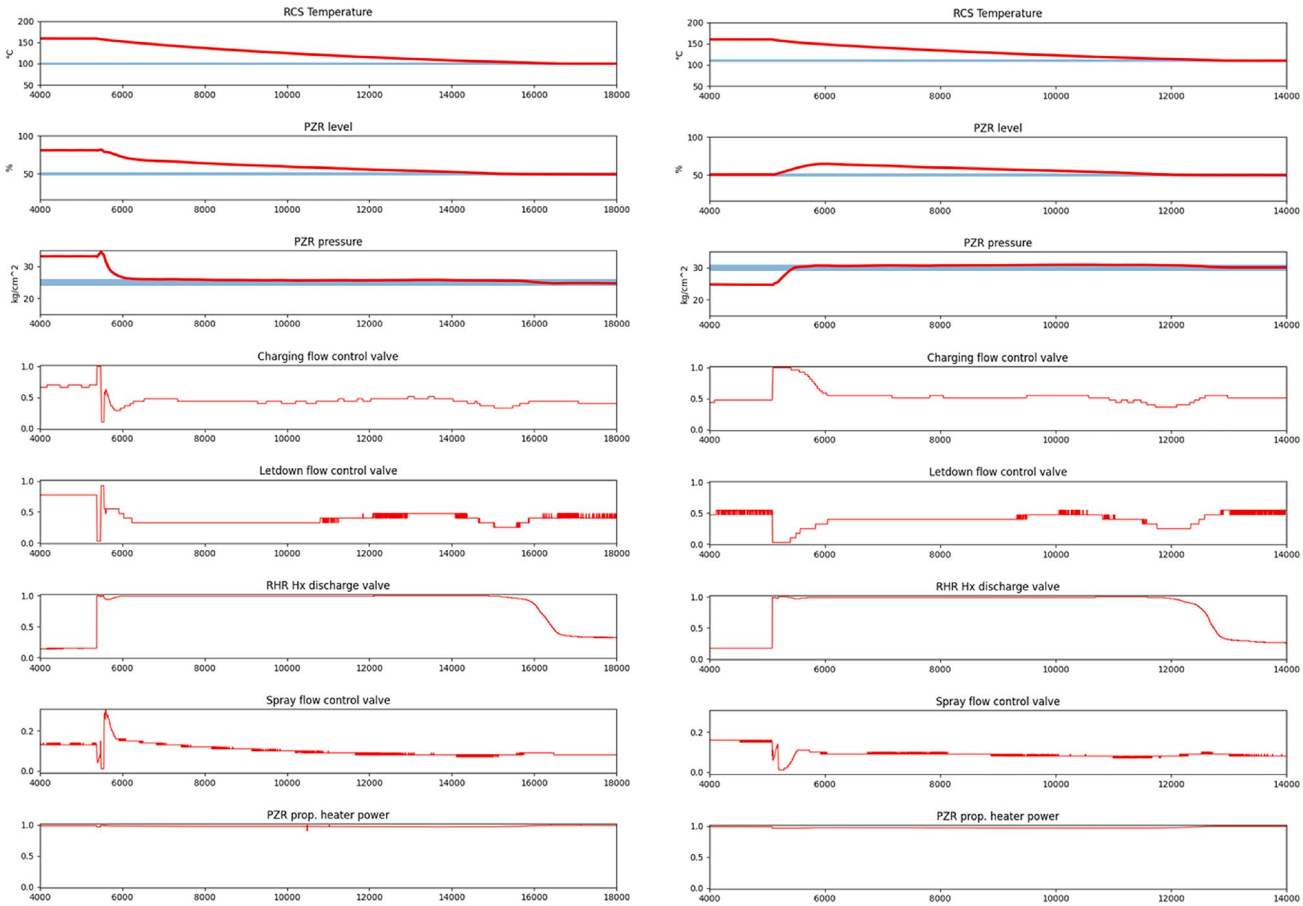
based on the limiting conditions for NPP operation, and the action with the optimal score is selected.

Another recent advancement addressing multi-objective operation has been achieved by Bae et al. [124]. In their research, the authors designed a DRL algorithm to provide positive feedback only when the objectives are achieved, unlike previous studies where positive feedback was continuously given based on the distance from a predefined operational path. The authors addressed the challenge of sparse feedback by employing advanced DRL algorithms and tested their approach on the reactor heating process in an NPP. As a result, the trained agent identified a way to increase the temperature while properly adjusting the pressure and volume of the reactor coolant with very limited feedback. In addition, the agent succeeded to some extent in untrained objectives, such as decreasing the temperature, as shown in Fig. 17.

Conclusion and Perspectives

Recent advancements in AI technologies, particularly the emergence of deep learning, have spurred applications across various industries, including safety–critical infrastructure. NPPs, as representatives of such infrastructure, have also embraced AI technologies. This paper introduced the current progress of AI applications with a particular focus on plant operations and plant operators. Figure 18 summarizes the introduced applications. As illustrated in this figure, AI techniques are incorporated based on their efficacy and alignment with the objectives of the target application. While our discussion here covered four application domains—event diagnosis, signal validation, prediction, and autonomous control—it is important to note that active investigations are being conducted beyond these domains.

As highlighted in this paper, much of the extensive research on AI applications for NPP operations has been conducted in the ROK. The main factor contributing to this is the advanced adoption of digital technologies in Korean NPPs. Figure 19 illustrates the MCR of the APR1400, a plant currently installed in the ROK and exported to the United Arab Emirates [125]. In addition to the devices visible in the image, such as personal computers and the large display panel, the instrumentation and control system and its software are fully digitalized in this plant. In addition, Korea Hydro & Nuclear Power Co., Ltd., the vendor of NPPs in the ROK, has established a centralized monitoring & diagnosis center [126] and is currently developing a digital twin



(a) Adjusting the level and pressure (b) Adjusting the pressure only

Fig. 17 Operating records of the DRL agent for the untrained objective of decreasing temperature [124]

of the man–machine interface system (MMIS) deployed in Korean NPPs [127]. This industrial progress has supported ambitious research endeavors in the application of AI technologies for NPP operations.

However, limitations remain that must be addressed for practical adoption in real NPPs. Much of the research conducted thus far has relied on data from TH system codes or NPP simulators due to the confidentiality of operational data from actual plants. While this has enabled significant progress, there is a concern that AI models trained solely on artificial data may not perform optimally when deployed in real plants. This issue has been partially addressed, as discussed here in Sect. “Event Diagnosis” about event diagnosis; however, further research and development should be conducted to ensure robust performance with field data.

Another critical limitation is the validation and verification (V&V) of software implementing AI technology. As highly safety–critical infrastructures, NPPs require a high degree of reliability for their components and software. Current V&V processes are well suited for software with deterministic logic but may not be directly applicable to software with AI technology, as deep-learning models are sets of logical units that perform incomprehensible logics. Therefore, new V&V methodologies specifically tailored to AI-based software are needed.

A similar limitation is on the regulatory side. Regulatory bodies such as the Nuclear Safety and Security Commission of Korea and the Nuclear Regulatory Commission (NRC) of the U.S. are responsible for regulating everything related to nuclear safety in accordance with strict standards. However, there is no precedent for regulatory experience regarding AI applications, which may cause a period of stagnation. To avoid such a period, regulatory bodies should establish an organizational framework to review AI applications in advance, as exemplified by the activities of the NRC [128].

While addressing these drawbacks, further research should also suggest proper systematic frameworks for efficiently harmonizing human operators and machine systems including AI technologies. The cognitive process

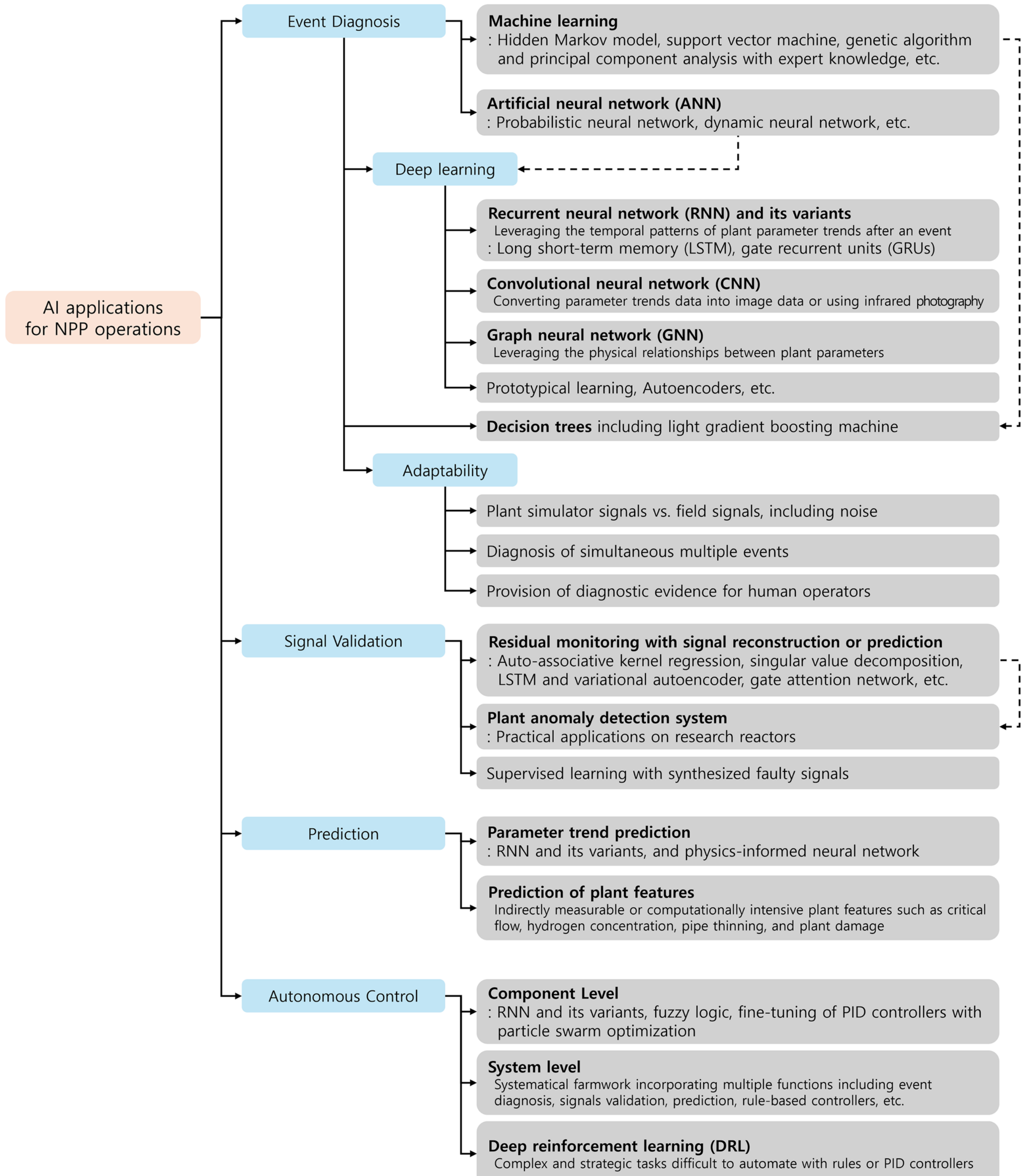


Fig. 18 Illustrative summary of the introduced AI applications for plant operations

of human operators should be taken into account [65] for diluting the information given to the operators [129] and selecting the proper tasks to be automated [130]. We believe that AI technology integrated with such appropriate schemes can reduce the burden of plant operators and ultimately improve the safety of NPPs.

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Data availability The dataset used in this study are available upon request from the corresponding author.

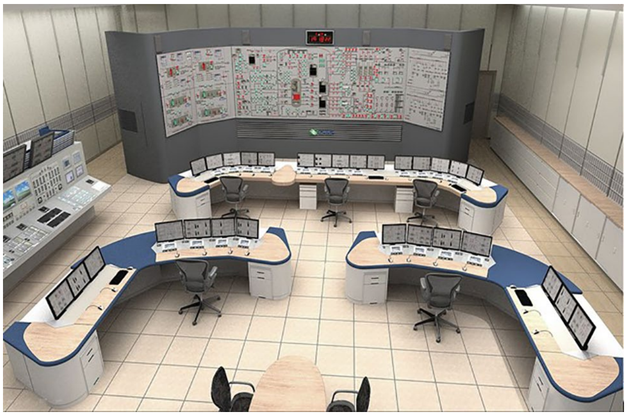

Fig. 19 Digitalized main control room of the APR1400 [125]

References

1. K. Jin, J. Cho, S.-Y. Kim, Machine learning-based categorization of source terms for risk assessment of nuclear power plants. Nucl. Eng. Technol. **54**(9), 3336–3346 (2022)
2. H. Kim et al., Random forest classifier for real-time chemical leak source tracking using fence-monitoring sensors. Korean J. Chem. Eng. **35**(6), 1231–1239 (2018)
3. E. Broughton, The Bhopal disaster and its aftermath: a review. Environ. Health **4**(1), 6 (2005)
4. J.M. Broughton et al., A scenario of the Three Mile Island unit 2 accident. Nucl. Technol. **87**(1), 34–53 (1989)
5. The Fukushima Daiichi Accident. International Atomic Energy Agency, Vienna (2015)
6. S. Jung, Facility siting and plant layout optimization for chemical process safety. Korean J. Chem. Eng. **33**(1), 1–7 (2016)
7. W. So et al., Optimal layout of additional facilities for minimization of domino effects based on worst-case scenarios. Korean J. Chem. Eng. **28**(3), 656–666 (2011)
8. C. Eo, J.M. Lee, Safety distance analysis to prevent pipeline chain accidents. Korean J. Chem. Eng. **39**(5), 1158–1164 (2022)
9. L. Guo et al., Mathematical programming model of process plant safety layout using the equipment vulnerability index. Korean J. Chem. Eng. **40**(4), 727–739 (2023)
10. H.S. Lee et al., Reduction of thermal radiation by steam in flare stack system. Korean J. Chem. Eng. **29**(10), 1310–1320 (2012)
11. S. Kabir, M. Taleb-Berrouane, Y. Papadopoulos, Dynamic reliability assessment of flare systems by combining fault tree analysis and Bayesian networks. Energy Sour. Part A: Recov. Utiliz. Environ. Effects **45**(2), 4305–4322 (2023)
12. Y. Jo et al., Dynamic analysis of a flare network: Gas blow-by and depressurization system. Korean J. Chem. Eng. **39**(4), 838–852 (2022)
13. Safety of Nuclear Power Plants, *Design* (International Atomic Energy Agency, Vienna, 2016)
14. J.-E. Yang et al., The role of risk-informed approaches for advanced reactors in Korea. Nucl. Eng. Des. **417**, 112805 (2024)
15. P. C. Cacciabue, Guide to applying human factors methods: Human error and accident management in safety-critical systems. Springer Science & Business Media (2004)
16. S. French et al., Human reliability analysis: a critique and review for managers. Saf. Sci. **49**(6), 753–763 (2011)
17. S. Kariuki, K. Löwe, Integrating human factors into process hazard analysis. Reliab. Eng. Syst. Saf. **92**(12), 1764–1773 (2007)
18. H. R. Greenberg, J.J. Cramer, Risk assessment and risk management for the chemical process industry. John Wiley & Sons (1991)
19. M. Jahangiri et al., Human error analysis in a permit to work system: a case study in a chemical plant. Saf. Health Work **7**(1), 6–11 (2016)
20. W. Jo, S.J. Lee, Bayesian belief network-based human reliability analysis methodology for start-up and shutdown operations in nuclear power plants. Ann. Nucl. Energy **179**, 109403 (2022)
21. Operational performance of information system for nuclear power plant. Available from: https://opis.kins.re.kr/opis.
22. G. Heo et al., Recent research towards integrated deterministic-probabilistic safety assessment in Korea. Nucl. Eng. Technol. **53**(11), 3465–3473 (2021)
23. T. Satoh, S. Kobashi, M. Saito, Development of an advanced man-machine system for Japanese PWR plants. Int. Atom. Energy Agency (IAEA). 235–243 (1994)
24. S.H. Chang et al., Development of an advanced human–machine interface for next generation nuclear power plants. Reliab. Eng. Syst. Saf. **64**(1), 109–126 (1999)
25. M.S. Lee et al., Development of human factors validation system for the advanced control room of APR1400. J. Nucl. Sci. Technol. **46**(1), 90–101 (2009)
26. L. Das et al., Toward preventing accidents in process industries by inferring the cognitive state of control room operators through eye tracking. ACS Sustain. Chem. Eng. **6**(2), 2517–2528 (2018)
27. C. Ko et al., Development of augmented virtual reality-based operator training system for accident prevention in a refinery. Korean J. Chem. Eng. **38**(8), 1566–1577 (2021)
28. J.M. Yang et al., Design and implementation of an integrated safety management system for compressed natural gas stations using ubiquitous sensor network. Korean J. Chem. Eng. **31**(3), 393–401 (2014)
29. O. Vinyals et al., Grandmaster level in StarCraft II using multi-agent reinforcement learning. Nature **575**(7782), 350–354 (2019)
30. A. Ramesh, et al., Hierarchical text-conditional image generation with clip latents. arXiv preprint arXiv:2204.06125, **1**(2): 3 (2022)
31. D.M. Himmelblau, Applications of artificial neural networks in chemical engineering. Korean J. Chem. Eng. **17**(4), 373–392 (2000)
32. H. Lee et al., Data-driven fault detection for chemical processes using autoencoder with data augmentation. Korean J. Chem. Eng. **38**(12), 2406–2422 (2021)
33. Y. Xia et al., Incipient fault diagnosis for centrifugal chillers using kernel entropy component analysis and voting based extreme learning machine. Korean J. Chem. Eng. **39**(3), 504–514 (2022)
34. S. Son, Determining adsorbent performance degradation in pressure swing adsorption using a deep learning algorithm and one-dimensional simulator. Korean J. Chem. Eng. **40**(11), 2602–2611 (2023)
35. Q. Wang et al., Deep-learning modeling and control optimization framework for intelligent thermal power plants: A practice on superheated steam temperature. Korean J. Chem. Eng. **38**(10), 1983–2002 (2021)
36. J. Kim, S. Lee, P. H. Seong, Autonomous nuclear power plants with artificial intelligence. Springer Nature **94** (2023)
37. J. Hartmann, J. Hyvärinen, V. Rintala, The operator and the seven small modular reactors — an estimate of the number of reactors that a single reactor operator can safely operate. Nucl. Eng. Des. **418**, 112929 (2024)
38. K. Moshkbar-Bakhshayesh, M.B. Ghofrani, Transient identification in nuclear power plants: a review. Prog. Nucl. Energy **67**, 23–32 (2013)

39. J.M. Kim et al., Abnormality diagnosis model for nuclear power plants using two-stage gated recurrent units. Nucl. Eng. Technol. **52**(9), 2009–2016 (2020)
40. J. Choi, S.J. Lee, A sensor fault-tolerant accident diagnosis system. Sensors **20**(20), 5839 (2020)
41. J. Ma, J. Jiang, Applications of fault detection and diagnosis methods in nuclear power plants: a review. Prog. Nucl. Energy **53**(3), 255–266 (2011)
42. K.-C. Kwon, J.-H. Kim, Accident identification in nuclear power plants using hidden Markov models. Eng. Appl. Artif. Intell. **12**(4), 491–501 (1999)
43. Z. Yangping, Z. Bingquan, W. DongXin, Application of genetic algorithms to fault diagnosis in nuclear power plants. Reliab. Eng. Syst. Saf. **67**(2), 153–160 (2000)
44. S. Rocco, E. Zio, A support vector machine integrated system for the classification of operation anomalies in nuclear components and systems. Reliab. Eng. Syst. Safety **92**(5): 593–600 (2007)
45. S. Park, J. Park, G. Heo, Transient diagnosis and prognosis for secondary system in nuclear power plants. Nucl. Eng. Technol. **48**(5), 1184–1191 (2016)
46. S.W. Cheon, S.H. Chang, Application of neural networks to a connectionist expert system for transient identification in nuclear power plants. Nucl. Technol. **102**(2), 177–191 (1993)
47. Y. Ohga, H. Seki, Abnormal event identification in nuclear power plants using a neural network and knowledge processing. Nucl. Technol. **101**(2), 159–167 (1993)
48. E.B. Bartlett, R.E. Uhrig, Nuclear power plant status diagnostics using an artificial neural network. Nucl. Technol. **97**(3), 272–281 (1992)
49. Y. Bartal, J. Lin, R.E. Uhrig, Nuclear power plant transient diagnostics using artificial neural networks that allow "don't-know" classifications. Nucl. Technol. **110**(3), 436–449 (1995)
50. S.J. Lee, P.H. Seong, A dynamic neural network based accident diagnosis advisory system for nuclear power plants. Prog. Nucl. Energy **46**(3), 268–281 (2005)
51. K. Mo, S.J. Lee, P.H. Seong, A dynamic neural network aggregation model for transient diagnosis in nuclear power plants. Prog. Nucl. Energy **49**(3), 262–272 (2007)
52. S. Hochreiter, J. Schmidhuber, Long short-term memory. Neural Comput. **9**(8), 1735–1780 (1997)
53. K. Cho, et al., Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078, (2014)
54. J. Yang, J. Kim, An accident diagnosis algorithm using long short-term memory. Nucl. Eng. Technol. **50**(4), 582–588 (2018)
55. G. Lee, S.J. Lee, C. Lee, A convolutional neural network model for abnormality diagnosis in a nuclear power plant. Appl. Soft Comput. **99**, 106874 (2021)
56. Y.H. Chae et al., Graph neural network based multiple accident diagnosis in nuclear power plants: data optimization to represent the system configuration. Nucl. Eng. Technol. **54**(8), 2859–2870 (2022)
57. F. Scarselli et al., The Graph neural network model. IEEE Trans. Neural Networks **20**(1), 61–80 (2009)
58. J. Yang, J. Kim, Accident diagnosis algorithm with untrained accident identification during power-increasing operation. Reliab. Eng. Syst. Saf. **202**, 107032 (2020)
59. H. Kim, A.M. Arigi, J. Kim, Development of a diagnostic algorithm for abnormal situations using long short-term memory and variational autoencoder. Ann. Nucl. Energy **153**, 108077 (2021)
60. J.H. Shin, J.M. Kim, S.J. Lee, Abnormal state diagnosis model tolerant to noise in plant data. Nucl. Eng. Technol. **53**(4), 1181–1188 (2021)
61. H.-J. Lee, D. Lee, J. Kim, Event diagnosis method for a nuclear power plant using meta-learning. Nucl. Eng. Technol (2024)
62. S.G. Cho et al., Multi-abnormality attention diagnosis model using one-vs-rest classifier in a nuclear power plant. J. Nucl. Eng. **4**, 467–483 (2023). https://doi.org/10.3390/jne4030033
63. J.H. Shin et al., Approach to diagnosing multiple abnormal events with single-event training data. Nucl. Eng. Technol. **56**(2), 558–567 (2024)
64. M.R. Endsley, E.O. Kiris, The out-of-the-loop performance problem and level of control in automation. Hum. Factors **37**(2), 381–394 (1995)
65. S.-J. Lee, P.-H. Seong, Development of an integrated decision support system to aid cognitive activities of operators. Nucl. Eng. Technol. **39**(6), 703–716 (2007)
66. J.H. Shin et al., An interpretable convolutional neural network for nuclear power plant abnormal events. Appl. Soft Comput. **132**, 109792 (2023)
67. J.H. Park et al., A reliable intelligent diagnostic assistant for nuclear power plants using explainable artificial intelligence of GRU-AE, LightGBM and SHAP. Nucl. Eng. Technol. **54**(4), 1271–1287 (2022)
68. I. Ramezani, N. Vosoughi, M.B. Ghofrani, Application of deep learning techniques for nuclear power plant transient identification. Ann. Nucl. Energy **194**, 110113 (2023)
69. T. Zhang et al., Abnormal event detection in nuclear power plants via attention networks. Energies **16**(18), 6745 (2023)
70. F. Dong et al., Attention-based time series analysis for data-driven anomaly detection in nuclear power plants. Nucl. Eng. Des. **404**, 112161 (2023)
71. I. Jae Jin, D. Yeong Lim, and I. Cheol Bang, Development of fault diagnosis for nuclear power plant using deep learning and infrared sensor equipped UAV. Ann. Nucl. Energy **181**, 109577 (2023)
72. J. Garvey et al., Validation of on-line monitoring techniques to nuclear plant data. Nucl. Eng. Technol. **39**(2), 133 (2007)
73. F.D. Maio et al., Fault detection in nuclear power plants components by a combination of statistical methods. IEEE Trans. Reliab. **62**(4), 833–845 (2013)
74. S. Mandal et al., Sensor fault detection in Nuclear Power Plant using statistical methods. Nucl. Eng. Des. **324**, 103–110 (2017)
75. K. Hadad, et al., Enhanced neural network based fault detection of a VVER nuclear power plant with the aid of principal component analysis. IEEE Trans. Nucl. Sci (2008)
76. A. Messai et al., On-line fault detection of a fuel rod temperature measurement sensor in a nuclear reactor core using ANNs. Prog. Nucl. Energy **79**, 8–21 (2015)
77. Y. Choi, G. Yoon, J. Kim, Unsupervised learning algorithm for signal validation in emergency situations at nuclear power plants. Nucl. Eng. Technol. **54**(4), 1230–1244 (2022)
78. S. Liu et al., Graph attention Network-Based model for multiple fault detection and identification of sensors in nuclear power plant. Nucl. Eng. Des. **419**, 112949 (2024)
79. J. Choi, S.J. Lee, Consistency index-based sensor fault detection system for nuclear power plant emergency situations using an LSTM network. Sensors **20**(6), 1651 (2020)
80. J. Choi, S.J. Lee, RNN-based integrated system for real-time sensor fault detection and fault-informed accident diagnosis in nuclear power plant accidents. Nucl. Eng. Technol. **55**(3), 814–826 (2023)
81. K. Nabeshima et al., Nuclear reactor monitoring with the combination of neural network and expert system. Math. Comput. Simul **60**(3), 233–244 (2002)
82. E. Gursel et al., Using artificial intelligence to detect human errors in nuclear power plants: a case in operation and maintenance. Nucl. Eng. Technol. **55**(2), 603–622 (2023)
83. F. Zhang, J.W. Hines, J.B. Coble, A robust cybersecurity solution platform architecture for digital instrumentation and control

systems in nuclear power facilities. Nucl. Technol. **206**(7), 939–950 (2020)
84. F. Zhang et al., Multilayer data-driven cyber-attack detection system for industrial control systems based on network, system, and process data. IEEE Trans. Industr. Inf. **15**(7), 4362–4369 (2019)
85. M. Kim et al., RNN-based online anomaly detection in nuclear reactors for highly imbalanced datasets with uncertainty. Nucl. Eng. Des. **364**, 110699 (2020)
86. S. Ryu et al., Development of deep autoencoder-based anomaly detection system for HANARO. Nucl. Eng. Technol. **55**(2), 475–483 (2023)
87. L. Puppo et al., Failure identification in a nuclear passive safety system by Monte Carlo simulation with adaptive Kriging. Nucl. Eng. Des. **380**, 111308 (2021)
88. M.I. Radaideh et al., Neural-based time series forecasting of loss of coolant accidents in nuclear power plants. Expert Syst. Appl. **160**, 113699 (2020)
89. J. Bae, G. Kim, S.J. Lee, Real-time prediction of nuclear power plant parameter trends following operator actions. Expert Syst. Appl. **186**, 115848 (2021)
90. J. Ahn et al., Operation validation system to prevent human errors in nuclear power plants. Nucl. Eng. Des. **397**, 111949 (2022)
91. S. Ryu et al., Probabilistic deep learning model as a tool for supporting the fast simulation of a thermal–hydraulic code. Expert Syst. Appl. **200**, 116966 (2022)
92. H. Kim, J. Kim, Long-term prediction of safety parameters with uncertainty estimation in emergency situations at nuclear power plants. Nucl. Eng. Technol. **55**(5), 1630–1643 (2023)
93. F. Isuwa Wapachi, and A. Diab, Time-series forecasting of a typical PWR system response under control element assembly withdrawal at full power. Nucl. Eng. Design, **413**, 112472 (2023)
94. J. Song, S. Kim, A machine learning informed prediction of severe accident progressions in nuclear power plants. Nucl. Eng. Technol. (2024)
95. Y. Fu, et al., An interpretable time series data prediction framework for severe accidents in nuclear power plants. Entropy, **25**, https://doi.org/10.3390/e25081160 (2023)
96. H. Tohver, R. de Oliveira, M. Jeltsov, Interpretable time series forecasting of NPP parameters in accident scenarios. Nucl. Eng. Des. **403**, 112145 (2023)
97. M.G. Na et al., Estimation of break location and size for loss of coolant accidents using neural networks. Nucl. Eng. Des. **232**(3), 289–300 (2004)
98. Y.J. An et al., Critical flow prediction using simplified cascade fuzzy neural networks. Ann. Nucl. Energy **136**, 107047 (2020)
99. S.H. Park et al., prediction of the reactor vessel water level using fuzzy neural networks in severe accident circumstances of NPPS. Nucl. Eng. Technol. **46**(3), 373–380 (2014)
100. D.Y. Kim et al., Prediction of hydrogen concentration in containment during severe accidents using fuzzy neural network. Nucl. Eng. Technol. **47**(2), 139–147 (2015)
101. D.Y. Kim et al., Prediction of leak flow rate using fuzzy neural networks in severe post-loca circumstances. IEEE Trans. Nucl. Sci. **61**(6), 3644–3652 (2014)
102. H.S. Jo et al., Prediction of golden time for recovering SISs using deep fuzzy neural networks with rule-dropout. Nucl. Eng. Technol. **53**(12), 4014–4021 (2021)
103. Y.H. Chae et al., A methodology for diagnosing FAC induced pipe thinning using accelerometers and deep learning models. Ann. Nucl. Energy **143**, 107501 (2020)
104. S. H. Lee, H. S. Jo, and M. G. Na, Relative humidity prediction of a leakage area for small RCS leakage quantification by applying the Bi-LSTM neural networks. Nucl. Eng. Technol. (2023)
105. H.M. Park, J.H. Lee, K.D. Kim, Wall temperature prediction at critical heat flux using a machine learning model. Ann. Nucl. Energy **141**, 107334 (2020)
106. Y.H. Chae et al., Development of a data-driven simulation framework using physics-informed neural network. Ann. Nucl. Energy **189**, 109840 (2023)
107. J. Bae, J.W. Park, S.J. Lee, Limit surface/states searching algorithm with a deep neural network and Monte Carlo dropout for nuclear power plant safety assessment. Appl. Soft Comput. **124**, 109007 (2022)
108. A. Gong, et al., Possibilities of reinforcement learning for nuclear power plants: Evidence on current applications and beyond. Nucl. Eng. Technol. (2024)
109. R.T. Wood, B.R. Upadhyaya, D.C. Floyd, An autonomous control framework for advanced reactors. Nucl. Eng. Technol. **49**(5), 896–904 (2017)
110. H. Basher, J. Neal, and L. UT-Battelle, Autonomous control of nuclear power plants. United States. Department of Energy (2003)
111. G. Zhou, D. Tan, Review of nuclear power plant control research: Neural network-based methods. Ann. Nucl. Energy **181**, 109513 (2023)
112. N. Man Gyun, Design of a genetic fuzzy controller for the nuclear steam generator water level control. IEEE Trans. Nucl. Sci. **45**(4), 2261–2271 (1998)
113. M. Boroushaki et al., An intelligent nuclear reactor core controller for load following operations, using recurrent neural networks and fuzzy systems. Ann. Nucl. Energy **30**(1), 63–80 (2003)
114. S.M.H. Mousakazemi, N. Ayoobian, G.R. Ansarifar, Control of the pressurized water nuclear reactors power using optimized proportional–integral–derivative controller with particle swarm optimization algorithm. Nucl. Eng. Technol. **50**(6), 877–885 (2018)
115. D. Lee, P.H. Seong, J. Kim, Autonomous operation algorithm for safety systems of nuclear power plants by using long-short term memory and function-based hierarchical framework. Ann. Nucl. Energy **119**, 287–299 (2018)
116. J. Kim et al., Conceptual design of autonomous emergency operation system for nuclear power plants and its prototype. Nucl. Eng. Technol. **52**(2), 308–322 (2020)
117. H.A. Saeed et al., Autonomous control model for emergency operation of small modular reactor. Ann. Nucl. Energy **190**, 109874 (2023)
118. J. Li et al., The application of deep reinforcement learning in coordinated control of nuclear reactors. J. Phys. Conf. Ser. **2113**(1), 012030 (2021)
119. D. Lee, A.M. Arigi, J. Kim, Algorithm for autonomous power-increase operation using deep reinforcement learning and a rule-based system. IEEE Access **8**, 196727–196746 (2020)
120. J. Park et al., Control automation in the heat-up mode of a nuclear power plant using reinforcement learning. Prog. Nucl. Energy **145**, 104107 (2022)
121. D. Lee, et al., Comparison of deep reinforcement learning and PID controllers for automatic cold shutdown operation. Energies, **15**, https://doi.org/10.3390/en15082834 (2022)
122. L. Wei et al., Neural network model predictive control of core power of Qinshan nuclear power plant based on reinforcement learning. Ann. Nucl. Energy **207**, 110702 (2024)
123. J.M. Kim, J. Bae, S.J. Lee, Strategy to coordinate actions through a plant parameter prediction model during startup operation of a nuclear power plant. Nucl. Eng. Technol. **55**(3), 839–849 (2023)
124. J. Bae, J.M. Kim, S.J. Lee, Deep reinforcement learning for a multi-objective operation in a nuclear power plant. Nucl. Eng. Technol. **55**(9), 3277–3290 (2023)
125. A. Arigi, and J. Kim, HRA methodology development for digital main control rooms of NPPs. 2600–2607 (2020)

126. J.H. Min, D.-W. Kim, C.-Y. Park, Demonstration of the validity of the early warning in online monitoring system for nuclear power plants. Nucl. Eng. Des. **349**, 56–62 (2019)
127. S. Lee, W.W. Ko, *Basic Concepts of APR1400 MMIS Digital Twin using Virtualization Technology, in Korean Nuclear Society Virtual Spring Meeting* (Korean Nuclear Society, Virtual, 2020)
128. M. Dennis, et al., Artificial intelligence strategic plan: Fiscal Years 2023–2027 (2023)
129. J.H. Kim, P.H. Seong, The effect of information types on diagnostic strategies in the information aid. Reliab. Eng. Syst. Saf. **92**(2), 171–186 (2007)
130. J.S. Kang, S.J. Lee, Concept of an intelligent operator support system for initial emergency responses in nuclear power plants. Nucl. Eng. Technol. **54**(7), 2453–2466 (2022)