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Nuclear Power Plant's Accident Scenario Identification through Artificial Intelligence Application: An Overview

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Abstract – *Nuclear energy has long been recognized as a low-carbon emission technology. However, the widespread adoption of nuclear power plants (NPPs) is hindered by the complexity of their man-machine-network integration systems, the occurrence of various faults, insufficient automation, and the challenges faced by human operators. In recent years, the development and utilization of artificial intelligence (AI) technology has presented both prospects and complexities in enhancing the functionality and security of nuclear reactors. This exponential growth of AI offers novel avenues to optimize the operation and ensure the safety of nuclear reactors. Artificial intelligence (AI) technologies have the potential to address the limitations and enhance the functionality of NPPs. In this review different AI techniques are investigated which can contribute to NPPs Accident Scenario Identification. By exploring the applications of AI in this context, we shed light on the potential benefits and advancements that can be achieved by integrating AI technologies into nuclear energy systems.*

Keywords: Nuclear Power Plant (NPP), Artificial Intelligence (AI), Fault Diagnosis, Accident Scenario Identification, Peaceful Nuclear Power Generation

I. Introduction:

Undoubtedly, nuclear power stands as a substantial and eco-friendly energy source capable of meeting the escalating energy requirements without emissions [1]. However, the operational costs associated with nuclear power plants have presented challenges in sustaining their operation. The expenses incurred by these plants are primarily attributed to the ongoing need for diligent monitoring and maintenance to ensure uninterrupted power generation and uphold safety standards. A typical nuclear plant accommodates numerous sensors, each tasked with monitoring distinct components to guarantee their optimal functionality.

However, nuclear power plants have witnessed various faults and accidents throughout history as depicted in Figure-1, highlighting the importance of safety and risk management in the operation of these facilities. While incidents at nuclear power plants are rare, their potential consequences necessitate constant vigilance and precautionary measures.

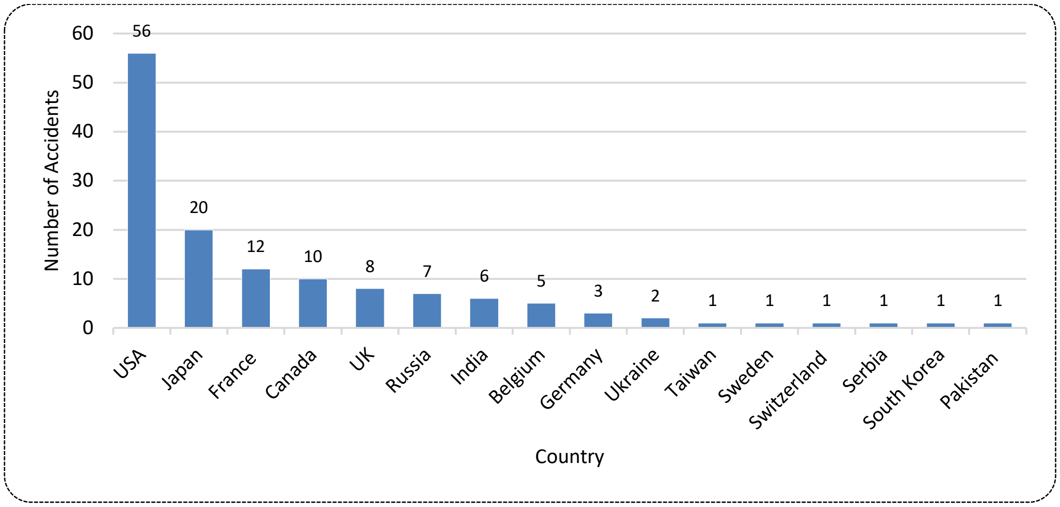

Figure 1. Number of Accidents Happened in World [2]

It is crucial to note that these accidents have spurred significant advancements in safety practices, emergency preparedness, and reactor design. The nuclear industry has implemented stringent regulations, enhanced safety features, and improved training for operators to prevent and mitigate such incidents in the future.

In recent years, artificial intelligence (AI) has gained considerable attention as a transformative technology with the potential to revolutionize various industries. AI encompasses a range of techniques and algorithms that enable machines to mimic human cognitive abilities, including perception, reasoning, and decision-making. By leveraging AI technologies, NPPs have the opportunity to overcome their inherent limitations and enhance operational efficiency and safety [3][4][5].

Accident Scenario Identification plays a crucial role in NPP safety, enabling early detection and mitigation of potential accidents or abnormal situations. By harnessing AI techniques, such as machine learning algorithms, deep neural networks, and data analytics, NPPs can significantly enhance their ability to identify and classify accident scenarios accurately and efficiently [6][7].

This review will delve into various AI techniques that have been proposed or implemented in the context of Accident Scenario Identification in NPPs. It will explore the benefits and challenges associated with these AI-based approaches, as well as their potential to improve the overall safety, reliability, and operational performance of NPPs.

II. Artificial Intelligence Use in NPPs Operation and Maintenance

Enhancing the operational and maintenance (O&M) capabilities of nuclear power plants including stressed operators, insufficient automation and various faults as sketched in Figure-2 are of paramount importance in ensuring both safety and economic viability. Over time, the degradation of materials in NPP equipment can compromise its intended functionality, posing safety risks.

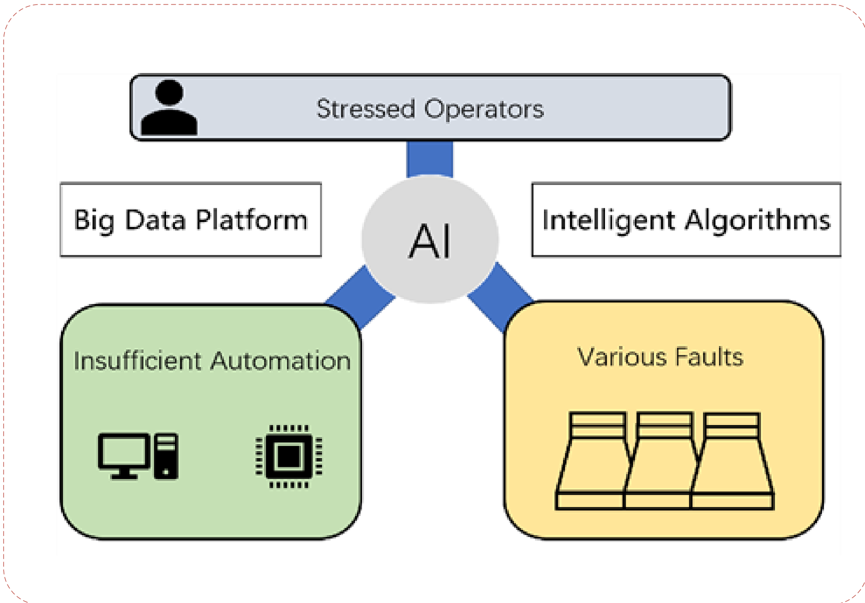

Figure 2. Artificial Intelligence in NPP Operation and Maintenance [8]

Furthermore, in order to remain competitive in a changing energy landscape that includes emerging alternatives like natural gas and wind power, the nuclear power industry must improve its economic performance. O&M costs constitute a significant portion, approximately 60% to 70%, of the total operating costs of a nuclear power plant, compared to fuel costs, which typically account for only around 15% to 30% of the total operating costs. Thus, reducing O&M expenses represents an effective approach to enhancing the economic feasibility of nuclear power plants and maintaining market competitiveness [9][10].

By prioritizing O&M improvements, NPPs can simultaneously bolster safety measures and address the economic challenges they face. This approach ensures the longevity and efficient operation of nuclear power plants, reinforcing their position as a reliable and sustainable source of energy in the evolving global energy landscape. Figure-3 illustrates the primary applications of AI techniques within the nuclear industry.

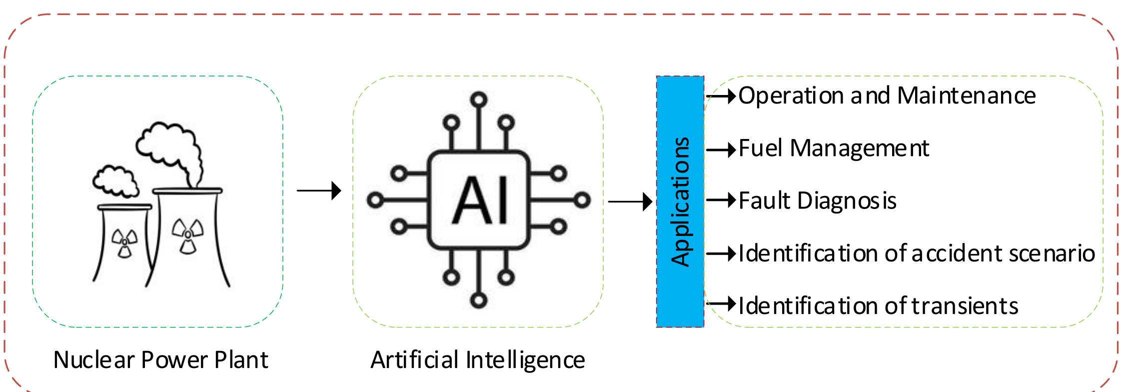

Figure 3. AI Applications in NPP

III. Artificial Intelligence in Accident Scenario Identification in NPP

Nuclear power plants safety measures are meticulously designed to prevent accidents from occurring during the plant's operational lifetime. However, it's essential to explore potential accident scenarios to ensure preparedness. Examples of such hypothetical events include abrupt rupture of the coolant pipe coupled to the reactor vessel, coolant pump breakdown in the running reactor core, or an unintended drop or ejection of a control rod.

Managing an accident scenario effectively necessitates operators to quickly evaluate complex signals and take decisive actions. One significant hypothesized accident is the Loss-of-Coolant Accident (LOCA), where a rapid reduction in coolant water occurs at a rate surpassing the reactor backup system's capabilities. Proper addressing of LOCA is critical, as there is maximum possibility it may proceed to damage to the reactor core. Consequently, every reactor is equipped with an backup core cooling arrangement exclusively designed to handle such scenarios.

Research in the field has also delved into the usage of AI in nuclear reactors during accident scenarios, as evidenced in Table 1. This exploration aims to enhance safety and response capabilities in the unlikely event of an accident.

Table 1. AI Techniques for Accident Scenario Identifications

Ref. No	Year of Publication	AI Technique	Observations
Nuclear Accidents Identification			
[11]	2015	Artificial Neural Network	The model exhibits precise accident classification even in the presence of noise levels up to 10%.
[12]	2019	Genetic programming	The model showcased remarkable accuracy, requiring minimal prior knowledge of the data.
Loss of Coolant Accident (LOCA)			
[13]	2009	Artificial Neural Network	Proved to be a highly effective operator support system for managing accidents.
[14]	2017	Fuzzy Neural Network	The model's predictive ability for break size is highly accurate, with RMS error of less than 0.7%.
[15]	2024	Fuzzy Neural Network	devised model accurately detects break locations and precisely estimates the size of the break.
[16]	2018	Artificial Neural Network	The utilization of interpolation pre-processing techniques to produce additional data has proven to be highly effective in improving the model's performance.
[17]	2019	Artificial Neural Network	The model demonstrated the capability to directly handle time-dependent signals and dynamically estimate break sizes in real-time.
Water Level Estimation Pressure Vessel			
[18]	2016	Fuzzy Neural Network	Aptly proficient in precisely gauging the water level of the reactor pressure vessel during accident scenarios.
[19]	2019	Artificial Neural Network	The deep neural network model showed the improved performance then neural fuzzy network.
Prediction of Hydrogen Concentration			
[20]	2016	Fuzzy Neural Network	The model's RMS error is below 5%
[21]	2015	Fuzzy Neural Network	Capable of forecasting the hydrogen concentration within the containment at a particular moment.

Nuclear Accidents Identification

A research discussed in [11], they employed ANN featuring Gaussian radial base functions to detect postulated NPP accidents in a pressurized water reactor. Training the ANN with data from computer simulations of Angra II NPP operating at 100% rated power. In this study they focused on three different types of design-based accident scenarios: loss of external electric power, loss of coolant accident, and steam generator tube rupture. Surprisingly, the model demonstrated accurate classification of all three types of accident scenarios, even in the presence of up to 10% noise in the signals.

Another study published in [12], in which they applied the genetic algorithm technique to detect the same three types of accident scenarios. Their findings showcased the effectiveness of genetic programming in accurately identifying the accident's nature in a short timeframe, requiring minimal prior knowledge of the data.

Loss of Coolant Accident (LOCA)

One different approach discussed in[13], in this study they produced time-based transient data for NPP operation using a thermal hydraulic code. Assuming the core to be in equilibrium, they developed a plant operator support system named the symptom-based diagnostic system. This diagnostic package was designed using an artificial neural network and put to the test with a pilot study on large break LOCA. Impressively, the system successfully detected transient changes in parameter values during the process, distinguishing them from values observed during normal functioning. As a result, the artificial neural network-based system was deemed a promising operator aid system during unconventional circumstances for accident management.

Study published in [14], they introduced a cascaded fuzzy neural network model to forecast break sizes in LOCA. They employed a hybrid method, combining a GA and a least squares method to train the model collecting the data from the same modular accident analysis program discussed in [15]. The results showed that the cascaded fuzzy neural network outperformed with a RMS error of only 0.7%.

In research published [15] utilized a probabilistic neural network in conjunction with a fuzzy neural network to detect break locations (cold-leg, hot-leg, or steam generator tubes) in LOCA. The model's accuracy was verified using data attained from mathematical modeling achieved through modular accident analysis program code. It effectively recognized break positions and estimated their sizes with high precision.

In [16], they explored various ANN architectures for break size assessment during LOCA. They found that producing a larger number of data points through interpolation in data preparation significantly improved the robustness of the ANN model. The model trained with cubic spline interpolation as a pre-processing step established the best robustness.

The method investigated in [17], successfully developed an ANN model skilled in handling time-dependent signals for dynamic assessment of break sizes in LOCA in real-time. They claimed that this model could support NPP operators in preparation of proper accident management countermeasures.

In the event of a LOCA, coolant water is quickly drained from the pressure vessels of the reactor, containing the nuclear core. It may lead to a rise in the temperature of the fuel cladding tube, causing rapid oxidation and hydrogen liberation. Maintaining the hydrogen concentration below 4% is essential to preserve the capacity of the pressure vessels and avoid explosions.

Pressure Vessel Water Level Estimation

A method discussed in [18], implemented a cascaded fuzzy neural network to determine vessel water levels in reactor during severe accidents. The model is designed by using simulated data from the modular accident analysis program code, demonstrated satisfactory performance.

In [19], a deep neural network for estimating water levels in the pressure vessels of reactor in severe accidents situations is implemented by using the data set from[18]. Their deep neural network achieved superior results with at 0.78% error level maximum.

Prediction of Hydrogen Concentration

In [20], a cascaded fuzzy neural network to forecast hydrogen concentration in NPP containment in severe accident situations. Their results shows more accuracy as compared to conventional fuzzy neural networks used in [21].

Observations:

Nuclear power reactors present intricate and challenging engineering systems with numerous components and interdependent systems. Ensuring their safe operation and compliance with regulatory guidelines requires precise functioning. Nevertheless, the dynamic nature of nuclear power plant objectives, evolving needs, and transient regulatory guidelines have resulted in varying AI focuses in the sector over time. The lack of real effective data is a persistent issue, specifically considering the catastrophic consequences of system failures.

Selecting the most suitable AI techniques for specific purposes is complicated due to variations in AI systems developed by different scholars based on diverse datasets. To claim accuracy and identify the best technique, collaborative efforts through an interlaboratory work frame or a round-robin program using the same database for developing AI tools for specific purposes are essential.

A significant apprehension in implementing AI in the nuclear industry, where millions of lives are at stake, is its black box nature. The data embedded within AI networks lacks transparency and understanding for developers and scientists. This necessitates caution and highlights the critical importance of comprehending the behavior of developed AI models, especially in the dynamic situations inherent to nuclear reactors. The lack of transparency makes these intelligent systems susceptible to being fooled and targeted by hackers, which raises security concerns.

Studies have shown that deep neural network models, often used in AI applications, can be easily fooled in image classification tasks, posing a potential challenge for their use in critical scenarios such as nuclear accidents.

Conclusion:

Nuclear power reactors represent intricate and technological challenging engineering systems. The concept of utilizing artificial intelligence in various nuclear industry applications is not a new development. However, a significant obstacle in creating advanced AI models for real-time application in the nuclear industry is because of lack of a valid database, particularly concerning accident scenarios. While AI has made remarkable advancements in recent times, but its black box nature presents a substantial challenge for its integration into the nuclear industry, as it leaves these systems vulnerable to potential deception. Further research and focused exploration of artificial intelligence applications tailored to the specific needs of the nuclear industry are imperative before such systems can be fully embraced and deployed.

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