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A REVIEW OF ARTIFICIAL INTELLIGENCE IN NUCLEAR POWER PLANTS

PREGLED UPORABE UMETNE INTELIGENCE V JEDRSKIH ELEKTRARNAH

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Abstract

Nuclear power plants are recognised as complex systems, where maintenance is critical for ensuring safety and operational stability. Time-based preventive maintenance programmes are employed in most nuclear power plants, relying on periodic inspections to prevent equipment failures. However, this method is considered resource-intensive and not always efficient. An alternative is offered by Artificial Intelligence and condition-based maintenance, which allow early fault detection, reduce unnecessary maintenance tasks, and lower operational costs. The potential of Artificial Intelligence in nuclear power plants is vast, ranging from operational improvements to predictive maintenance. Techniques such as Supervised and Unsupervised Learning are highlighted as essential tools for fault detection, pattern recognition, and predictive modelling. In Supervised Learning, known input-output pairs are used to train models, while Unsupervised Learning is employed to identify hidden patterns in unlabelled data, which is particularly useful in the large, unstructured datasets found commonly in nuclear power plants. The challenges in integrating Artificial Intelligence into nuclear power plant operations shall be noted, including the lack of standardised procedures for selecting and applying algorithms. Despite these challenges, AI-driven tools, including Deep Learning and hybrid models, have shown promising results in fault detection and prediction in nuclear power plants. These advancements support the broader goal of improving safety and operational efficiency. In conclusion, although Artificial Intelligence has not yet been adopted fully across all nuclear power plants, it is seen as a promising advancement for the future of nuclear energy operations. Its implementation enhances fault detection, reduces operational risks, and ensures more reliable energy production.

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Povzetek

Jedrske elektrarne so poznane kot kompleksni sistemi, njihovo vzdrževanje pa je ključno za zagotavljanje varnosti in zanesljivega obratovanja. Trenutno se v jedrskih elektrarnah uporablja princip časovno zasnovanega vzdrževanja, ki temelji na periodičnih pregledih za preprečevanje okvar. Pomembno je poudariti, da takšen pristop zahteva veliko porabo sredstev in ni vedno učinkovit. Alternativno lahko uvedemo vzdrževanje na podlagi stanja opreme z uporabo umetne inteligence ob predčasnem zaznavanju okvar, s čimer zmanjšamo stroške vzdrževanja in obratovanja. Potencial umetne inteligence v jedrski industriji je velik, od zagotavljanja zanesljive proizvodnje do vzdrževanja. Tehniki, kot sta nadzorovano in nenadzorovano učenje, sta izpostavljeni v članku, saj sta ključno orodje za zaznavanje napak, vzorcev in razvoja preventivnih modelov. Pri nadzorovanem učenju algoritem učimo z znanimi podatki, ki so klasificirani. Pri nenadzorovanem učenju algoritem učimo z veliko količino neklasificiranih podatkov, iz katerih model izlušči vzorce in zaznava odstopanje. Za integracijo umetne inteligence v jedrske elektrarne pa ostaja še veliko izzivov, med drugim tudi pomanjkanje standardnih pristopov. Ne glede na ponujene izzive pa orodja z uporabo umetne inteligence, globokega učenja in hibridnimi modeli obetajo pozitivne rezultate na področju zaznavanja napak in napovedovanja v jedrskih elektrarnah. Takšni napredki izboljšujejo varnost in omogočajo zanesljivo obratovanje. Čeprav umetna inteligenca še ni bila temeljno vpeljana v jedrsko industrijo, prikazuje pozitivne napredke za njeno prihodnost. Njena implementacija povečuje zaznavanje napak, zmanjšuje obratovalna tveganja ter zagotavlja stabilno in zanesljivo proizvodnjo električne energije.

1 INTRODUCTION

The use of Artificial Intelligence (AI) is on the rise in both the public and private sectors. As interest in this technology grows, the U.S. Nuclear Regulatory Commission has recognised this trend and published several documents addressing these topics. These publications serve as guidelines for the application of AI in nuclear power plants (NPP), and evaluate the current utilisation of these technologies within the industry [1]. Through AI adoption, some licensees aim to meet the requirements set forth in the Code of Federal Regulations. This shift allows for a transition from traditional time-based preventive maintenance (PM) methods to more advanced approaches facilitated by AI and condition-based maintenance (CBM) [2]. The use of AI is also recognised by the International Atomic Energy Agency, which established a working group in mid-2022 to research and implement AI in nuclear power.

It is essential to recognise that NPPs are complex systems composed of various interrelated systems and equipment, including electrical, mechanical, instrumentation and control systems. These components must operate reliably within specified parameters and require some type of maintenance. In most NPPs, PM programmes are implemented, consisting of scheduled activities aimed at ensuring the equipment's proper functioning. These PM programmes involve periodic inspections, and a systematic approach to record-keeping and scheduling maintenance activities. This structured framework helps to maintain equipment integrity and enhance overall operational safety [3].

Time-based preventive maintenance activities could, potentially, be replaced by CBM if faults are detected in advance. However, fault detection presents a complex challenge, particularly in large systems like NPPs. A significant issue arises when the volume of data collected is as extensive as that found in these facilities, making it difficult for manual systems to process and analyse all the available information effectively [2].

It is important to note that the data collected in NPPs are categorised into two main types: process instrumentation and control data, and, periodically, measured maintenance data. The first type, often called online monitoring (OLM), encompasses the plant's critical and non-critical parameters. These data are displayed in the control room, enabling the operators to monitor plant performance and health while being accessible to other personnel. The second type of data consist of measurements taken during outages and periodic equipment check-ups. These periodically gathered data play a vital role in maintaining the reliability and safety of the plant's operations. These data types form the foundation for effective PM strategies and operational decision-making in NPPs [4].

This paper outlines the data-gathering process in NPPs and elaborates on its significance. Chapter 3 discusses the most used advanced computational tools for AI. It is important to note that advancements in this field could potentially lead to significant improvements in the safety and operational reliability of NPPs. These technologies have the potential to decrease the number of faults and reduce operational costs greatly.

Chapter 4 focuses on the application of AI and Machine Learning (ML) in NPPs. The use of these technologies is increasing in various areas, including plant safety and security assessments, degradation modelling, fault diagnosis, prognosis, and overall plant operation and maintenance. By integrating AI and ML, NPPs can enhance their operational efficiency and safety measures, paving the way for a more reliable energy future.

2 DATA GATHERED IN NUCLEAR POWER PLANTS

The data collected in commercially operated NPPs are divided into two categories: process instruments and control data, and periodically measured data from maintenance activities. The OLM data include plant parameters for individual systems and their components, which are crucial for ensuring the plant’s safe and reliable operation [4]. These data are displayed in the control room on various screens and alarm panels, while some can be retrieved by the operating crew from the local panel. Given the enormous volume of data collected, processing them can become challenging, especially during accidents or abnormal operations. In such situations, the operators in the main control room follow established procedures designed to guide the crew through these critical and stressful steps. Their priority is to secure the safety of the reactor core and ensure a safe shutdown, all while minimising the risk of human error [5].

The OLM data are, typically, stored in large databases with limited sampling intervals, often set to one minute, allowing for efficient monitoring of the system`s performance history. These data can then be extracted from the database for further analysis and simulations, enabling the engineers to gain insights into the plant's operational status. In short, the OLM data are used to evaluate the health and reliability of the NPP processes, systems, and equipment [6].

In contrast, the second type of data rely on periodically gathered information from specific PM programmes, which include measurements of component parameters that may indicate the overall health of the components. These measurements can be taken through electrical or mechanical assessments, varying from once per cycle, to more or less frequently, thus providing critical insights into the condition of the components. Such evaluations are essential, as they can reflect the operational integrity of the components directly, potentially signalling a failure, or a state nearing failure [7].

Both types of data are instrumental in detecting deviations from stable and reliable operation within specific components and systems. However, with process instruments and control data, challenges arise from the sheer volume and complexity of the information collected, making manual analysis often inadequate for identifying significant deviations. To address this, alarm and trip values are established for specific measurements, offering a simplified approach to monitoring component states. While effective in alerting operators to faults, this method tends to react only after issues have manifested, necessitating timely intervention. In nuclear power plants, alarm thresholds are set conservatively at lower levels, to ensure that operators are notified promptly, enabling them to take the necessary precautions before situations escalate. On the other hand, periodically gathered data are typically evaluated by field professionals, who conduct thorough assessments of the components based on this information, allowing for informed maintenance decisions, and enhancing the overall safety and reliability of the plant.

A simple dataset collected from a motor-gearbox-pump skid will be examined for easier understanding. Typically, when a medium-voltage motor is involved with a larger pump, a comprehensive set of data is collected to indicate the skid's running parameters. For the electric motor, the temperature of the stator is monitored, often utilising six PT100 sensors or similar devices, with two sensors embedded in each phase at the hottest points. During the 1970s, the standard insulation system used for motors was Class B, which allows for a temperature rise of up to 80°C, as defined by the NEMA MG1 Standards.

In such horizontal machines, sleeve bearings made from Babbitt material with temperature monitoring are employed commonly, permitting operating temperatures to reach 130°C. Vibration monitoring is also implemented frequently, to track the vibrations of the bearings or housing, ensuring they remain within the maximum accepted values. Additionally, the temperatures and vibrations of the gearbox and pump are monitored, with operational values defined clearly. The system operates by transporting fluid at a specific temperature, so the temperatures and pressures at both the discharge and suction sides of the pump are measured typically.

With known operating parameters provided by the original equipment manufacturer and insights gained from operational experience, the limits of the system are established and adhered to throughout its operation. In cases of parameter deviations, or when alarm or trip values are reached, the skid is required to shut down, prompting the initiation of corrective maintenance. Such events can lead to economic consequences and impact the reliability of the plant and its systems. In NPPs each critical system is equipped with backup trains, to ensure that nuclear safety and plant reliability are not compromised by minor defects. However, even simple defects can diminish plant reliability, and introduce transients into the continuous operational cycle. Each transient can have specific effects on the plant, including necessitating shutdowns.

3 ADVANCED COMPUTATIONAL TOOLS

Advanced computational tools such as Artificial Intelligence, Machine Learning, Deep Learning (DL), and others in NPPs are on the rise, especially in health and reliability assessment. This chapter focuses on the advanced computational tools that form the backbone of AI applications in nuclear power plants. These tools, ranging from ML algorithms and neural networks to advanced simulations and probabilistic risk assessment models, offer robust platforms for addressing the unique challenges faced by nuclear energy systems. By leveraging cutting edge computational techniques, nuclear power plants can enhance their operational resilience, reduce human error, and anticipate failures before they occur. while maintaining strict regulatory compliance and safety standards. The chapter will delve into the specific categories of AI driven tools, their architectures, and their implementation strategies in the Nuclear domain.

3.1 Statistics and Computational Tools

Before going further into computational tools, it is essential to understand the core difference between statistics and computational tools. Statistics is a branch of mathematics, whereas computational tools such as AI, ML, and DL are subfields of advanced computing. Statistics focuses primarily on data collection, analysis, interpretation, presentation, and organisation. Its purpose is to uncover patterns, relationships, and trends within the given data, and draw conclusions based on a representative sample. Typically, statistics are applied to smaller datasets, and rely on mathematical methods to interpret and understand the data. By contrast, computational tools like AI and ML often handle vast amounts of data, leveraging algorithms to automate decision-making, predictions and other tasks, without requiring explicit human programming for every scenario. [8].

3.2 Artificial Intelligence and Machine Learning

AI is a field of Computer Science focused on developing advanced software systems designed to perceive their environment and learn to perform actions autonomously. ML, as a subfield of AI, allows machines to be trained using historical data. In ML systems, patterns, rules, or insights are identified from the collected data, which are then applied to make predictions or decisions [9].

A variety of approaches and techniques are encompassed within AI, including rule-based systems, search algorithms, and more advanced methods like Natural Language Processing, Robotics, and Computer Vision. In contrast, as previously mentioned, ML relies on algorithms trained to make predictions

- Supervised Learning,
- Unsupervised Learning,
- Reinforcement Learning,
- Recommender systems.

Deep Learning, a specialised subfield of ML, utilises multiple layers of neural networks to address complex problems. The primary distinction between AI and ML lies in the fact that, while ML focuses specifically on learning from data, AI encompasses a broader range of techniques, including those that do not necessarily involve data-driven learning.

In this context, AI and ML are often used together, but it is important to note their differences and specific areas of application.

3.2.1 Supervised Learning

Supervised Learning is a type of AI learning that involves using training data with known input and output values. The observed data are input into the model along with the expected output values, allowing the model to be trained accurately. Once the training process is completed, the model is expected to predict outputs based on the new inputs with a certain degree of uncertainty. Various algorithms are used widely in Supervised Learning, including [11]:

Artificial Neural Networks (ANNs): These networks are composed of three types of layers, with each layer consisting of nodes, also known as neurons, as illustrated in Figure 1. Typically, a neural network includes an input, output, and multiple hidden layers. The layers are interconnected, and the nodes are associated with weights, representing each connection's significance. These weights are adjusted throughout the learning process. The number of inputs is determined by the dimensions of the input data, while the number of hidden layers and nodes defines the complexity of the model. The more complex the model, the greater its ability to capture intricate patterns in the data [12].

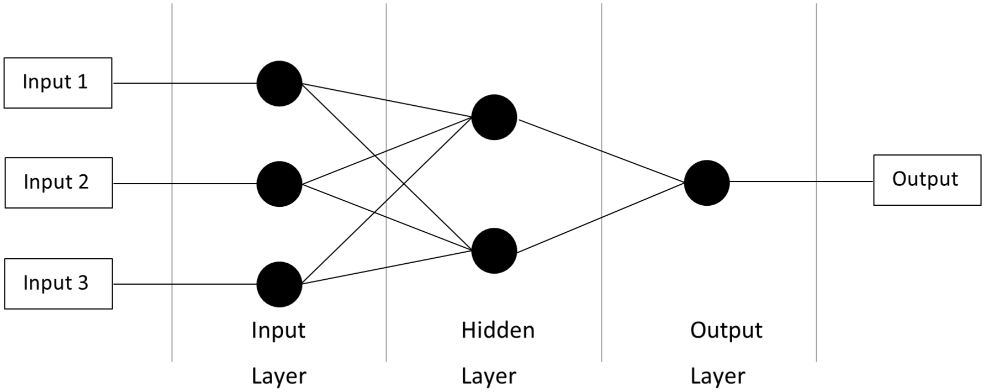

Figure 1: *Simple Artificial Neural Network*

Feedforward Neural Networks (FFNs): FFNs are the simplest type of Artificial Neural Networks. They consist of layers of nodes (neurons) that are connected through weights. In an FFN, the information travels in a single direction, from the input layer to the output layer, without looping back. These networks are used commonly in both regression and classification tasks [13].

Convolutional Neural Networks (CNNs): CNNs are designed specifically for processing grid-like data, such as images. They learn the spatial hierarchies of features automatically by using convolutional layers. These layers apply filters to the input data to capture important features like edges, textures and shapes, making CNNs highly effective for image classification, object detection and similar tasks [14]. CNNs were used in data diagnostics through images created from the data generated from large amounts of data gathered in NPPs [15].

Recurrent Neural Networks (RNNs): RNNs are distinguished by their ability to handle sequential data, as they have connections that form directed cycles. This allows them to retain information from previous inputs, making them suitable for time series analysis, and tasks involving sequential data like Natural Language Processing. RNNs use backpropagation through time, an optimisation algorithm that enables faster learning by adjusting weights efficiently based on errors from previous steps [16].

In addition to the algorithms mentioned, other methods are also used commonly, such as Decision Trees (DTs). These aim to create a tree-like model that predicts the output values based on a series of simple, predefined rules extracted from the features of the data. Random forests were developed to address the limitations of DTs, particularly the issue of overfitting. Overfitting occurs when a model performs exceptionally well on the training data, but fails to generalise

to new, unseen data [17]. Another important algorithm is the Support Vector Machine (SVM), used for classification and regression tasks. SVMs work by constructing a set of hyperplanes that separate different classes of data samples optimally. The goal is to maximise the margin between the classes, to improve the model's prediction accuracy and robustness.3.2.2
Unsupervised Learning

Unlike Supervised Learning, Unsupervised Learning is used to train models on large amounts of data where the label of the data is unknown. Unsupervised Learning is considered a highly promising method in AI, as labelling vast amounts of training data is often difficult. This allows models to be trained without human involvement or supervision. Additionally, one key advantage of these models is that, even in the early stages of their development, insight into the structure of the model can be gained. Similar to Supervised Learning, there are also various algorithms used in Unsupervised Learning:

Clustering analysis: This method enables data to be classified into branches and clusters, ensuring that the data within each cluster are more closely related than data from different clusters. This definition is based on the understanding that some data points exhibit greater similarity than others. Most clustering algorithms operate using numerical attributes, allowing similarity to be described through geometric analogies. There are numerous algorithms available for clustering data, including K-means, Spectral Clustering, Hierarchical Clustering, and more. Each of these algorithms employs distinct methodologies, such as partitional, hierarchical, density-based, grid-based, or model-based. By utilising these various approaches, clustering techniques can organise and analyse data effectively, revealing patterns and relationships that might otherwise go unnoticed [18].

Dimensionality Reduction: These algorithms are used to transform high-dimensional data into low-dimensional data when dealing with big data. It is important to note that this reduction process should not result in the loss of meaningful properties of the original data. In terms of data classification, these methods can be applied in various ways, such as creating superlinear traceable classification schemes, reducing the variance of classifiers, and removing noise. Traditionally, one of the most commonly used linear techniques is Principal Component Analysis (PCA). This method constructs a low-dimensional dataset, that retains as much of the original data's variability as possible by identifying a linear basis for reduced dimensionality. In recent years, more nonlinear techniques have been introduced, including global methods, multidimensional scaling, autoencoders, and Isomap, among others [19].

3.2.3 Reinforcement Learning

Reinforcement Learning is a learning approach involving the interaction of Artificial Intelligence with a dynamic environment. This technique focuses on learning sequential decision-making in complex problems and is inspired by the trial-and-error learning process observed in humans. Unlike Supervised Learning, where models learn from labelled data, Reinforcement Learning operates through feedback in the form of rewards or penalties, which are given based on the actions taken by the agent. This feedback mechanism allows the agent to learn and adapt over time, ultimately improving its performance in decision-making tasks [20].].

4 AN OVERVIEW OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN NUCLEAR POWER PLANTS

The fault detection methods are classified as model-based, signal-based and data-driven-based, and are analysed from on-line data. The method used most commonly is signal-based, and it is used for fault detection based on alarm and trip values. The model-based analysis is also well established, and they use output values from models and compare them with real-time on-line data. The data-based method is the most complex one, as it uses the historical data to learn. Through AI, the models are trained, and are capable of making predictions [21].

Many different types of algorithms can be employed in nuclear power plants, depending on the specific purpose of the task. For instance, models based on classification algorithms should be implemented when AI is utilised to analyse surface images to detect cracks in steel or concrete structures. In cases where large amounts of unstructured data, such as logs from operational experiences and OLM are available, unsupervised learning algorithms could potentially be utilised, particularly those based on clustering techniques.

However, a notable downside of this approach is that there are currently no established procedures for determining and incorporating the most suitable algorithm for each specific task. This lack of systematic guidance may hinder the effectiveness of algorithm selection and application in various scenarios within the nuclear power sector. Further challenges include handling missing data in vast datasets, ensuring sufficient training data quality, and the high cost of implementing AI systems, particularly in a legacy nuclear power plant infrastructure. Additionally, integrating AI technologies into existing NPP systems can pose significant technical and financial hurdles that require careful planning and investment.

4.1 Artificial Intelligence in nuclear power plant operation

The use of AI in operational contexts is welcomed highly, as operators must handle large amounts of data during both normal and abnormal operations. Numerous studies have employed computational data to assist in training predictive models. Given that NPPs typically operate in a stable manner, training models for specific faults and testing their detection capabilities can be challenging. The generated data originate from models of NPPs that are known to have specific faults [22, 23].

Prediction models were utilised to analyse the operations of a small light water reactor facility at Oregon State University, where positive results were reported. Despite the model's complexity, it learned them effectively and applied the reactor's features to make predictions. However, some behaviours remained undetected by the network [24].

Naimi et al. applied Machine Learning techniques to identify faults in NPPs, focusing initially on the detection of various faulty scenarios using neural networks. Subsequently, they employed K-Nearest Neighbours (KNN), SVM, and ensemble-based fault diagnosis methods for comparison. Among all the models tested, the KNN algorithm was identified as the most accurate and cost-efficient, although all the models were able to detect the presented faults [25].

A fault diagnostics method based on a semi-supervised classification approach was described by Ma and Jiang, who utilised data from operational NPPs in conjunction with data from a training simulator [26]. Young-Kuo et al. proposed a hybrid model that integrates PCA, signed directed graphs, and Elman Neural Networks for fault detection, fault isolation and severity estimation. Each component of this hybrid model contributes unique advantages, providing a robust foundation for future research in this area [27].

In recent years, hybrid models have been proposed for the operational analysis of NPPs. This trend can be attributed to the fact that individual models often possess specific strengths, and their integration allows for a more comprehensive approach to fault diagnostics and operational efficiency.

4.2 Artificial Intelligence in nuclear power plant maintenance

As mentioned, three methods of fault detection are used, and data-based methods are the most promising ones for AI applications. Nuclear power plants are critical facilities that need to run safely and within their parameters. Every deviation from normal operation can have an impact on the facility, environment, and economy of the plant. For normal operation, the plant needs to be well maintained; typically, the most successful plant runs on PM with weekly or daily routine check-ups on the equipment, or with periodic works on the components. As PM programmes are well established in NPPs, the only downside of these is their economic impact. The upgrade to PM would be (CBM), which would be viable when a fault detection system would be in place with close to 100% certainty. With CBM in place, unnecessary maintenance operations would not take place, and the cost would be reduced [28].

Data gathered from temperature, vibration and other sensors could be used for Unsupervised Learning with SVM or other algorithms [29]. Seker et al. studied RNNs for analysing a 5HP motor through spectral analysis in a coherent manner and neural networks. It was studied that, through backpropagation of the Elman's RNN, this model brings advantages to the concepts [30]. Qian and Liu studied four deep learning models, Deep-FFN, CNN, GRNN, and CRNN, for fault diagnosis of rotating machines, specifically bearings. After their study, those simple models were not able to extract the fault features accurately [31]. In another study, Qian and Liu developed a deep reinforcement learning that converges more slowly than typical deep learning models that have better stability. They show that, no matter if the data samples are small or large, the model will react and learn better if we interact with the model [32].

5 CONCLUSION

As mentioned throughout the article, the most important property of nuclear power plants is their safe and reliable operation. This can be achieved by following industry regulations and recommendations. It is essential that operational, maintenance and other procedures are established and aligned with the latest Standards and regulations. These procedures should be adhered to by personnel, and human errors must be minimised.

Even when procedures are followed, faults may occur due to human errors or random machine failures. Some machine faults have the potential to be detected beforehand but are often ignored, misinterpreted, or overlooked because of the vast amount of data available. With the help of AI and well-trained models, these faults could be detected in advance and subsequently prevented.

In the nuclear industry, AI is beginning to gain recognition, and some regulations have been established by the U.S. Nuclear Regulatory Commission. However, the use of AI remains an unfamiliar approach for many traditional NPP operators and personnel, as there are significant safety and operational risks involved.

A thorough study of AI and Machine Learning is necessary to train these models to a level of certainty that can earn the trust of the nuclear industry. It is important to note that these methods would not automatically regulate the plant but would instead serve as an alarm system for operators and other personnel, prompting them to respond to various indications. This ensures that human oversight remains central, with AI acting as a decision-support tool to enhance safety and operational reliability. It is also important to note that the use of AI in NPPs requires an interdisciplinary cooperation of computer scientists, nuclear engineers, regulatory subjects, and management for its successful implementation.

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Nomenclature

(Symbols)	(Symbol meaning)
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
DT	Decision Tree
FFN	Feedforward Neural Networks
KNN	K-Nearest Neighbor
ML	Machine Learning
NPP	Nuclear Power Plant
OLM	On-line monitoring
PCA	Principal Component Analysis
RNN	Recurrent Neural Networks
SVM	Support Vector Machines