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Review

A Future with Machine Learning: Review of Condition Assessment of Structures and Mechanical Systems in Nuclear Facilities

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Abstract: The nuclear industry is exploring applications of Artificial Intelligence (AI), including autonomous control and management of reactors and components. A condition assessment framework that utilizes AI and sensor data is an important part of such an autonomous control system. A nuclear power plant has various structures, systems, and components (SSCs) such as piping-equipment that carries coolant to the reactor. Piping systems can degrade over time because of flow-accelerated corrosion and erosion. Any cracks and leakages can cause loss of coolant accident (LOCA). The current industry standards for conducting maintenance of vital SSCs can be time and cost-intensive. AI can play a greater role in the condition assessment and can be extended to recognize concrete degradation (chloride-induced damage and alkali–silica reaction) before cracks develop. This paper reviews developments in condition assessment and AI applications of structural and mechanical systems. The applicability of existing techniques to nuclear systems is somewhat limited because its response requires characterization of high and low-frequency vibration modes, whereas previous studies focus on systems where a single vibration mode can define the degraded state. Data assimilation and storage is another challenging aspect of autonomous control. Advances in AI and data mining world can help to address these challenges.

Keywords: condition assessment; artificial intelligence; deep learning; damage detection; signal processing; data management; nuclear piping; concrete; advanced reactors; digital twin

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1. Introduction

The energy sector and its industries are undergoing digitization with the rise of Artificial Intelligence (AI) and Big Data. Around the world, various applications of AI can be seen in image recognition, language processing, transportation, Global Positioning System (GPS), aviation, energy sector, and healthcare. The benefits of using AI in the industrial energy sector, such as oil, gas, coal, and nuclear power plants, span from operational cost reduction and increase in production efficiency to safeguarding life and property. In a power plant, asset management and predictive maintenance of critical infrastructure can be conducted with deep learning (DL) algorithms [1,2]. Robotics is another essential component of autonomous management of power plants that can aid operators in performing high-precision tasks in harsh environments [3]. With a rising demand for electricity, the nuclear industry is now exploring AI solutions for various tasks such as efficient operation, improvement in the reactor design and operation, optimization of complex actions, detection of anomalies, and development of digital twins [4]. Multiple past and ongoing studies are exploring autonomy and the concept of digital twins in advanced nuclear reactors [5–9]. Sensor data acquired from nuclear power plants can be utilized in autonomous control systems to demonstrate reliability as well as identify appropriate operator actions for the management of emergency and accident conditions [10,11].

The automation industry fuels the use of robots, computational systems, machine learning, control systems, information technology, and data handling to increase the quality of production without a significant increase in the costs of manufacturing [12]. It also defines various levels of automation that can range from acting independently without any human interference to providing strategic recommendations to the operator. Designing a level of autonomy for nuclear reactors and power plants can depend on the operational and system flexibility standards, safety requirements, and staffing protocols of the facility. The United States Department of Energy (DOE) focuses on the design and development of automation in the nuclear sector. DOE programs such as Modeling-Enhanced Innovations Trailblazing Nuclear Energy Reinvigoration (MEITNER) [13] and Generating Electricity Managed by Intelligent Nuclear Assets (GEMINA) [14] are a few of these recent initiatives. Similar digitally-focused programs are also being explored by other countries around the world such as France [15] and Korea [16,17].

The performance of an autonomous control and management system depends on the reliability of its digital twin and the accuracy of condition assessments. A Digital Twin (DT) serves as a virtual replica (*digital model*) of a real system that can be updated in real time by using data from sensors, and it also integrates the system's aging and performance history. It consists of three major components: the physical space, the virtual space, and the connected data that tie the physical and virtual space together. The concept of a DT was first introduced in 2003, by Dr. Grieves [18], for product lifecycle management. Since its inception, the DT concept has been applied successfully in various fields [19] such as space and aircraft industry [20–23], automobile industry [24,25], production and product design [26–28], health care [29], civil systems [30–34] and disaster management [35]. Additionally, many recent studies [36–42] explore digitization of the control and management processes in the nuclear sector by designing digital twins. Another study [43,44] proposes a conceptual framework for an integrated digital environment for fission and fusion nuclear power plants. It emphasizes the importance of condition assessment and extraction of data using non-destructive inspection techniques, such as health monitoring using real-time sensor data.

The DT is often connected to its real-life counterpart with the acquisition of real-time sensor data. The sensor data can be used to update the digital twin model such that the DT model replicates the functions of its real-life counterpart as well as captures the aging of its real-life counterpart. The replication of the functions and operations can be carried out with high-fidelity simulations. The aging of any system can be captured and predicted with a condition assessment framework. Thus, a condition assessment framework built using AI technology forms a part of the entire digital twin model. The AI typically uses sensor data acquired from the real-life system to predict anomalies, damage, aging and degradation in the system. However, AI can also be used to obtain synthetic real-time data in the case of sensor malfunctions, data manipulation, etc. Traditional ML techniques such as supervised or unsupervised learning can be used to achieve either of these goals.

As per the International Atomic Energy Agency (IAEA) [45], a nuclear power plant consists of various structures, systems, and components (SSCs), some of which are the pressure vessel, reactor vessel, concrete containment building, steam generator, piping-equipment systems, etc. The structural and functional integrity of a nuclear power plant depends on the health or condition of its SSCs. Previous research [46–54] highlights the importance of aging as well as post-hazard scenarios on the operational condition of SSCs and its direct impact on the Probabilistic Risk Assessment (PRA) of a nuclear power plant. Exposure to environmental factors such as extreme temperatures, natural hazards, radioactive zones, corrosive elements, etc., can cause the degradation of vital SSCs [55]. Predictive maintenance and detection of progressive degradation must be conducted using condition assessment frameworks to ensure safe operations. Some studies [56–61] develop preliminary condition assessment frameworks to detect degradation due to flow-accelerated corrosion and erosion in nuclear piping-equipment systems, whereas some others focus on modeling structural damage such as cracks in concrete structures or chemical damage in concrete due to chloride attack or Alkali–Silica Reaction (ASR) [62–67].

The use of AI technologies such as deep learning (DL) with its Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) can prove to be beneficial to emerging condition assessment frameworks. Digitization of data collected from nuclear power plants and appropriate feature extraction techniques can enable predictive maintenance of SSCs. However, the use of AI algorithms for the condition assessment of nuclear SSCs poses some challenges such as (i) data storage, handling, and management, (ii) cyber security, (iii) availability of computational resources, and (iv) reliability of diagnosis. This paper provides a summary of current and past projects for the condition assessment and structural health monitoring of nuclear SSCs as well as other structural and mechanical systems. This information is reviewed and discussed in Sections 2 and 3. The challenges of employing AI solutions to the predictive maintenance of industrial facilities such as nuclear power plants are described in Section 4. Section 5 provides important future directions in this area of research.

2. Past Condition Assessment Studies

Condition Assessment or Structural Health Monitoring (SHM) is used in the lifecycle management of SSCs, and to detect any damages during routine maintenance procedures. Various Non-Destructive Testing (NDT) techniques can be employed such as the use of ultrasonic waves, acoustic waves, chemicals, computer vision and imaging, sensors to obtain time-series data, etc. In power plants, typically sensors are installed at various locations to continuously measure sensor data. Data processing and feature extraction are carried out to detect any anomalies and damages in the structures and systems. NDT using continuously acquired sensor data from the plant can be conducted without halting any plant operations, thus reducing any loss of revenue from plant outages.

Recently, there has been an increase in the use of AI for the condition assessment frameworks [68–71]. The implementation of machine learning techniques is identified as an efficient approach for accurate data interpretation, integration, and extraction from the acquired sensor response. Data-driven machine learning approaches such as artificial neural networks (ANNs), support vector machines (SVMs), convolutional neural networks (CNNs), fuzzy logic, k-means clustering, and principal component analysis (PCA) have been employed with promising results for damage detection in recent studies. The following subsections provide a summary of past SHM and condition assessment studies that have been developed for various applications and different types of structural and mechanical systems. These studies represent the state-of-the-art for AI-based condition assessment in not only nuclear but also non-nuclear applications such as buildings, bridges, utility pipelines, aircraft, wind turbines, etc. Previously built algorithms that have shown good results for SHM in non-nuclear applications, such as machine learning, deep learning, signal processing, feature extraction, etc., can be applied to the nuclear energy sector as a baseline with future enhancements specific to the nuclear application. These studies provide valuable input for nuclear industry applications.

2.1. Structural Systems

Condition assessment or SHM is required to enhance the safety and reliability of structural systems, such as building frames, bridges, utility pipeline networks, etc., and to reduce the associated maintenance life-cycle costs. The advantages of using machine learning algorithms in such frameworks include feature learning, reduction of noise, data manipulation, and parallel computing. Features extracted from the sensor response of the structural system can be utilized to learn about the system's degraded state. Typically, extracted features include the modal attributes, Frequency Response Functions (FRFs), Fast-Fourier Transform (FFT), Power Spectral Density (PSD), Short-time Fourier transform (STFT), Wavelet transform (WT) and Hilbert–Huang transform (HHT). A condition monitoring strategy for nuclear piping systems is developed by a few studies [72–74] to detect damage by recording changes in the system's modal properties and acquired FFT plots. Modal attributes such as mode shapes, natural frequencies, damping ratios, resonant frequencies, etc., can be easier to obtain when compared to other feature extraction techniques. However, they can be insensitive to minor damage in multiple damage locations for large structures [75]. These features are also very sensitive to boundary conditions, sensor locations, and noise due to environmental effects on structures [75–77].

Some studies [78–83] utilize the system's FRFs to define damage indices as the learning parameter for ANNs. Using FRFs as a damage detection parameter requires prior information on the input excitation load. In these studies, structural systems, such as framed buildings, cantilever beams, bridge models, etc., are used to develop the health monitoring framework. Instead of extracting features and defining damage indices, the entire sensor response acquired from the structural system can also be used for condition assessment using high-performance CNNs. Past research [84] explores the use of CNNs to detect damage in an experimental stadium seating grandstand simulator by feeding the entire acceleration-time-series response into the neural network framework. In a similar study [85], one-dimensional CNN is employed for structural damage detection in a four-story steel building using the complete acceleration-time-series sensor response, and damage is introduced by loosening the bolts between various framing elements of the structure.

The development of CNNs was first conducted in 1998 [86] for handwritten character recognition using two-dimensional (2D) images. Since then, CNNs have been predominantly used for image classification and computer vision applications. In the field of SHM, CNNs can be utilized to extract damage-sensitive parameters from the images of acquired sensor data signals. Studies to identify structural anomalies in long-span bridges [87] and damage in steel jacket-type wind turbine foundations [88] use CNNs along with images of acceleration-time series signals as the input data. Other techniques such as ultrasonic signals, electromagnetic impedance signatures, and guided wave imaging can also be used to detect cracks or holes in structural plates using CNNs [89–91]. Pretrained CNNs such as ResNet, Alexnet, etc., and transfer learning algorithms can be employed for SHM or condition assessment in towers, concrete structures, and bridges [92–94].

In another approach, the time-series signals collected from sensors installed on the structural systems can be transformed to obtain frequency plots (FFT, PSD) or time-frequency plots (STFT, HHT, wavelet transform, and Teager–Huang transform). These plots can be further processed to extract damage-sensitive features for training the machine learning algorithms. Few past studies [95–97] explore the PSD of the sensor response as a promising damage assessment feature for bridges and structural beams. Either the entire PSD spectrum or the spectral moments obtained from the PSD spectrum can be used as damage-detection features along with unsupervised machine learning K-means clustering algorithm or the Kalman filtering technique. In a recent study [98], the PSD from nuclear piping-equipment systems is processed to extract a vector containing damage-sensitive information, and ANNs are used to conduct a post-hazard condition assessment of the systems. Damage indices can also be defined from time-frequency domain features, such as HHT [99–101] or STFT [102], to train supervised machine learning such as SVMs, ANNs, and CNNs and conduct condition monitoring of buildings, bridges, and nuclear piping systems.

2.2. Mechanical Systems

Mechanical equipment, turbines, and other power generation systems require regular inspections and maintenance for a seamless flow of operation and energy production. The condition assessment of such mechanical systems helps in reducing maintenance costs and preventing accidental failures. The health monitoring of mechanical systems such as wind turbine blades has been carried out in the past with various NDT techniques such as ultrasonic waves, acoustic emissions, radiographic waves, electromagnetic waves, etc. [103–108]. In most studies, a damage index or indicator is utilized to train machine learning algorithms such as ANNs [109], SVMs [110,111], CNNs [112] and decision trees [113], and diagnose the condition of the wind turbine. The most common causes of failure include mechanical defects in the bolted or welded connections between the turbine blade and the rotating motor. Fatigue build-up and cracks due to high winds can also be a leading factor for wind turbine damage. In 2019, a study [30] reviews the monitoring systems used in the digital twin models, by applying modern sensing techniques to a wind turbine. The measured sensor data are used to identify structural changes and deterioration. In addition to these studies, there have been efforts to develop digital twins for wind farms [33,34].

The wings of an aircraft can undergo excessive deformation or buckling due to dynamic loads or exhibit impact damage and fatigue crack propagation. Previous studies [114–117] carry out the condition assessment of aircraft wings using SHM and machine learning approaches. In addition to the wings of an aircraft, past work has also been focused on developing digital twins for the space and aircraft industry. In 2012, the National Aeronautics and Space Administration (NASA) re-defined the DT concept as "integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" [20]. This study proposes a DT application for a future NASA vehicle (*employed in space and controlled remotely*) that would enable a proactive approach instead of the traditional reactive approach toward the assessment of vehicular structural health. Another study [21] presents a conceptual DT model for predicting aircraft structural life and assessing its structural integrity. Simulations are carried out using a structural Finite Element Model (FEM) for the aircraft frame. After feeding the as-built structural information along with the time–history response of the aircraft frame for a virtual flight, the DT damage models can predict the progression of damage as well as the aircraft's new state. These DT models include SHM systems and Bayesian updating processes. Another study [22] demonstrates the use of guided wave responses for the SHM of an aircraft to predict damage. The 3D FEM aircraft model is created using Abaqus, and a Genetic Optimization Algorithm is used to select sensor locations. A recent study [23] also presents the application of Dynamic Bayesian Networks (DBN) for the SHM of an aircraft's wing. The FE models are created to include aircraft wing crack geometry and then compared to as-built models to predict structural damage using DBN. This approach allows for uncertainty incorporation into the digital twin models, in order to predict the probability of future structural failure. One study [118] explores the use of physics-informed neural networks (PINNs) to predict corrosion fatigue in aircraft wings. Cyclic loading as well as saline corrosion are considered. The physics driven methodology is used to simulate crack propagation due to fatigue and the neural network layers are used to detect damage due to corrosion. Cracks in the material are predicted using the proposed technique.

A lot of studies have been conducted for the autonomous control and maintenance of automobiles using machine learning and digital twin technology. Past research [24] demonstrates a digital twin model for predictive maintenance of an automobile brake system, by utilizing key technologies such as the Internet of Things (IoT) and Cyber-Physical Systems (CPS) to generate and analyze sensor data. Machine Learning algorithms such as filter and wrapper-based methods are used for the prediction process. Another study [25] presents a digital twin concept on monitoring sensors for the performance evaluation of propulsion drive systems in electric autonomous vehicles. In this study, the authors suggest the use of algorithms such as Kalman filters, support vector machines, neural network architectures, and deep learning techniques such as Convolutional Neural Nets, for future digital twin development. Physics-guided machine learning has also been proposed for detecting cyberattacks in electric vehicles by using physics-guided feature extraction to train a machine learning classifier algorithm such as RNNs [119].

Data integration and its extraction is an important aspect of condition assessment applications during product design and manufacturing. In 2016, the concept of AutomationML technology is proposed for data exchange between various systems comprising the digital twin data modeling process [26]. This included creating and defining a model (*industrial valves*), extracting key information, and developing an information system to provide component information to the consumer. Another study [27] demonstrates a simple condition assessment model of a bending test bench which includes the physical test bench, its digital model, and a data connection system, whereas different research [28] demonstrates the integration of sensor data and manufacturing data for the digital twin of physical machines. A case study is presented for a three-axis vertical milling machine. Sensor data are used to incorporate machine-specific features and predict surface roughness. This study proposes the future use of Artificial Neural networks (ANN), Genetic Algorithms (GA), and fuzzy logic as powerful tools to process a large amount of data that includes interdependent parameters.

A summary of current SHM and condition assessment applications, along with the employed ML algorithms and training features, is provided in Table 1. Some of the limitations of extending existing studies to nuclear applications are mentioned as follows:

- Most of the past studies are related to non-nuclear applications and the proposed frameworks are typically focused on detecting major damage such as cracks, notches, or fissures in the system. A condition assessment framework for nuclear structural and mechanical systems should be able to detect minor degradation as well as the onset of degradation, such as fatigue accumulation in piping systems and chemical reactions in concrete structures;
- Furthermore, the previous studies either employ large datasets collected directly from the sensors or define specific damage-sensitive indices to train the machine learning algorithms. In nuclear applications, the amount of time to take action against an anomaly in the system is very important and any erroneous or late decisions can result in nuclear accidents. Using large datasets, without any data preprocessing and feature extraction, can necessitate the installation of expensive computational resources;
- It is also shown that using damage indices defined by previous studies for non-nuclear applications can result in poor prediction accuracies because of the differences in the acquired dynamic response [56].

Thus, condition assessment frameworks built specifically for the nuclear energy sector need to be sensitive to minor degradation, define effective physics-based feature extraction techniques, demonstrate a verification and validation procedure, and produce safe and reliable results.

Table 1. SHM and condition assessment: State-of-the-art.

Applications	ML Algorithms	Training Features
Structural systems: steel and concrete buildings, bridge models, cantilever beams, stadium seating grandstand, wind turbine foundations, structural plates, towers, nuclear piping	ANNs, CNNs, SVMs, K-means clustering, Kalman filtering	FRFs, FFT, PSD, STFT, WT, HHT, time-series data, images of sensor data, ultrasonic signals, electromagnetic impedance signatures, guided wave imaging
Mechanical systems: wind turbine blades, aircraft wings, automobiles, product design	ANNs, CNNs, SVMs, DBN, GA, Fuzzy logic, Decision trees, Kalman filtering	Time-series data, guided waves, sensor data on machine-specific features, images of equipment

3. Current Initiatives in the Nuclear Industry

The condition assessment and maintenance of aging structural and mechanical systems in a nuclear power plant have been the focus of recent research. A continuously functioning condition assessment framework with digital twin integration capabilities can provide information on the structural health and the integrity of systems. The diagnosis from such a framework can act as an additional input to the operators towards making operational decisions. These frameworks can also be applied during the design and construction of new advanced nuclear reactors. Sensors and data acquisition systems can be in-built, and the construction process of new reactors can benefit from digital twin technologies [3,42,120].

3.1. Recent Efforts towards Automation in the Nuclear Industry

A unique and key aspect of automation in nuclear power plant safety relates to the critical role played by condition assessment of safety-related equipment. This is particularly critical in the development of autonomous monitoring and control systems. The accident at Three Mile Island nuclear plant illustrates this aspect quite explicitly. Any degradation in the safety-related piping and equipment at a nuclear plant has the potential to result in a loss of coolant which can eventually lead to a nuclear accident. Therefore, any autonomous monitoring and control system at a nuclear plant must rely on a robust condition monitoring system and alert the operators and stakeholders accordingly.

The future of nuclear energy and its operation with automated digital engineering seems to be the current focus of several United States Department of Energy (US-DOE) sponsored research projects. The US-DOE is investing in research targeting the automation of nuclear power plants with programs such as MEITNER [13] and GEMINA [14]. In a recent report [121], the Idaho National Lab attempts to build a digital twin of the Microreactor Agile Non-Nuclear Experimental Testbed (MAGNET) [122] by using continuous real-time capture of sensor data. The digital twin system consisting of machine learning algorithms is able to predict the high temperatures in piping systems that carry residual heat from the reactor core. The goal of the ongoing MEITNER program is to design cost-effective and safe advanced nuclear reactors. The use of modern equipment, high-fidelity simulation tools, and AI implementation is encouraged. With existing nuclear power plants undergoing retirement and relatively high construction costs of recent nuclear construction, this project has identified the need for safe, reliable nuclear reactors with low construction capital costs, quicker construction timelines, and modular manufacturing. Maintenance programs with condition assessment frameworks can utilize robotics for computer vision, visual sensing, data processing, damage detection using ML algorithms, cyber security, etc.

Under the MEITNER program, the NAMAC project aims to build an autonomous management and control system for advanced nuclear reactors [5,123]. Some studies [10,37] under the NAMAC project explore the design of a digital twin system for all aspects of an autonomous control system such as diagnosis, checking discrepancies, assessment of strategies, and prognosis. The loss-of-flow scenario is considered in a simulation-enabled digital twin of Experimental Breeder Reactor II. Machine learning algorithms, such as ANNs and Recurrent Neural Networks (RNNs), are utilized to identify the anomaly in operations, design a decision-making framework, and provide strategic recommendations to the operator for potential actions. Machine learning consists of statistical algorithms that create relationships between the input and output data. However, the lack of physics-based knowledge in a typical ML algorithm can result in erroneous predictions. As a part of NAMAC, previous studies [124,125] propose physics-guided machine learning as a solution to this problem. In these studies, a loss-of-flow scenario is selected for testing the physics-guided machine learning. An additional term representing the physical knowledge of the domain of application is added to the loss function in the machine learning algorithm. Additionally, physics-guided feature extraction from the collected time-series sensor data are also considered. The model is tested using RNNs as well as physics-guided RNNs, and it is found that the physics-guided machine learning framework is able to perform with higher accuracy and less uncertainty than a standalone machine learning framework. Another study in the NAMAC project [38] analyzes the effect of data coverage, such as real-time data outside the training database, on the performance of ANNs and RNNs for NAMAC. A framework to capture the epistemic uncertainty of neural networks (NNs) is proposed. Another study [126] develops a safety-significant factor using RNNs to capture a loss-of-flow accident and predict the peak temperature of fuel assemblies in the reactor core with only one sensor. The robustness of the proposed approach is also illustrated against sensor malfunctions and noisy signals.

Similar to the MEITNER program, program GEMINA targets building digital twin technology for next-gen nuclear reactors along with sophisticated Operation and Maintenance (O&M) programs. One of the outlined goals is to reduce O&M costs at nuclear power plants by 10 times their current expenditure. Achieving a cost-effective solution with condition assessment technology can enable economic competitiveness for the nuclear energy sector compared to the renewable energy industry. Under this goal, AI-based condition assessment of nuclear systems and their predictive maintenance is being explored. One of the sub-projects under the GEMINA program called maintenance of advanced reactor sensors and components (MARS) [127] is focused on designing sensors, data acquisition, and employing machine learning for fault detection in nuclear components and systems. Another program [128] is investigating ways to reduce O&M costs using condition assessment frameworks and predictive maintenance. A boiling water reactor is selected as the application case study which is also being used to design high-fidelity digital twins along with probabilistic machine learning algorithms [129]. A similar product focusing on the development of digital twins for molten-salt advanced reactor systems is being developed along with health monitoring capabilities and an intelligent controller system for the operator [130].

Another program by the US-DOE called the Nuclear Energy University Program (NEUP) aims to highlight the research conducted by the next generation of leaders in the nuclear energy sector. Multiple projects featuring the use of AI-based technologies are being conducted in the nuclear field. Online monitoring technology with diagnostic capability is being developed as a part of a current study [131]. The use of Bayesian networks is highlighted along with recommendations for an asset management platform. An ongoing project [132] investigates an autonomous system for monitoring the components of a nuclear reactor. The use of sensor technologies and robotics is proposed for data acquisition along with data-driven operational anomaly detection. Another project [133] is developing an autonomous control system with remote operational capabilities for advanced microreactors by using deep learning algorithms. Real-time data will be collected from a research reactor. One project [134] aims at developing physics-guided machine learning tools to accelerate fuel development and its qualification. A similar project [135] on physics-informed machine learning explores the processing and the acquired properties in metal additive manufacturing. One project [136] predicts void swelling in nuclear structural systems such as reactor steel by utilizing data-driven methodologies such as transfer learning, which is a subset of machine learning. Material testing for microstructural defects in nuclear construction is being studied in one project by using computer vision and machine learning techniques [137]. In addition to the above, probabilistic risk assessment (PRA) can also be enhanced by using machine learning models to reduce uncertainties in the existing data. In this ongoing project [138], a fire hazard at a nuclear power plant is considered and a framework is being developed to recognize parameters that highly affect the PRA of the nuclear facility. Another project [139] aims at designing a robotic platform to collect sensor data from the nuclear power plant, detect anomalies in the system, and perform diagnosis. This would form a part of an online monitoring system with maintenance and risk assessment capabilities.

3.2. Condition Assessment of Piping-Equipment Systems

The piping-equipment systems in nuclear power plants are part of critical safety assessments and their integrity is essential for operating the plant as well as for managing any emergency or accident conditions. These systems can be subject to harsh environments due to high pressures and high temperatures. Typically, nuclear power plants conduct NDT of piping systems during scheduled outages as part of the maintenance procedures. Scanning the entire piping system is not feasible during an outage and is impractical. A condition assessment framework that collects sensor data from the plant's piping systems during normal operation can cut down the time required for maintenance by providing information to the maintenance crew on very few potential degraded locations.

NDT technologies include chemical penetrants, ultrasonic waves, eddy currents, magnetic waves, acoustic waves, radiography, etc. [140]. A recent study [141] explores guided ultrasonic waves for inspection of nuclear reactor piping systems and integration within a digital twin framework. Digital twins of the components are created using finite element simulations and wave propagation. Another study [142] employs AI tools such as CNN and Long-Short-Term-Memory (LSTM) to detect welding defects in vacuum vessel manufacturing. One research study [143] combines magnetically-coupled resonant wireless power transfer and eddy current testing along with machine learning PCA and ANN to detect cracks in aluminum tubes. Thermal sensing can also be used for leak inspection of nuclear waste disposal pipeline networks with fairly high accuracy [144]. Although the aforementioned NDT techniques show commendable results, they can be expensive, time-consuming, and difficult to employ. These methods often require manual setup of the equipment and highly trained professionals to conduct the NDT [145].

A recent study [56] investigates the role of deep learning in the post-hazard condition assessment of nuclear piping-equipment systems after an important external hazard such as an earthquake. It highlighted the need for an automated, efficient, and cost-effective framework to detect degraded locations in nuclear piping systems. Over time and constant use, the piping-equipment systems in a nuclear facility are subjected to flow-accelerated corrosion and erosion [146]. This leads to a thinning of pipe walls and an overall structural stiffness reduction. Degradation due to a reduction in pipe wall thickness can cause cracks, leaks, and nuclear accidents. Therefore, the research [56] focuses on detecting degradation due to pipe wall thinning at structural discontinuities of the system. In this study, a feature extraction method is proposed to generate a vector of degradation-sensitive quantities from the PSD plots of the acquired sensor response. High-fidelity finite element simulations are used to generate sensor data for two different nuclear piping-equipment systems, as shown in Figure 1a,b, subjected to seismic loads.

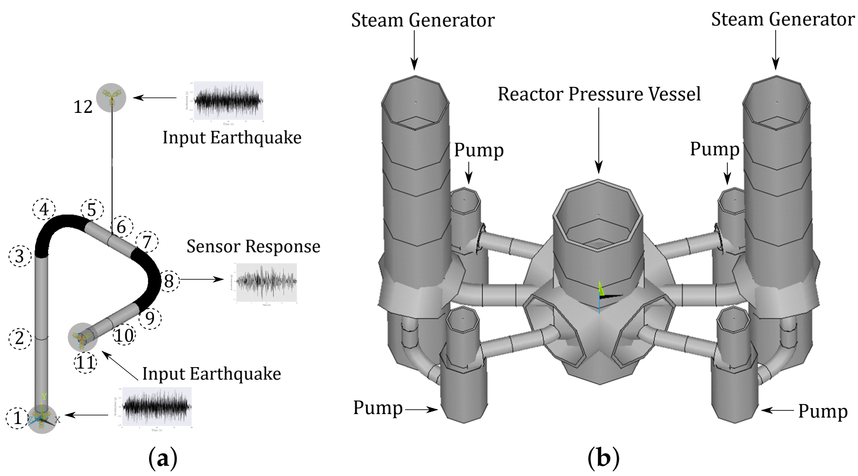


Figure 1. Nuclear piping-equipment systems [56]. (**a**) piping system 1; (**b**) piping system 2.

In addition to damaged locations, it also featured the detection of damage severity. Since multiple locations can undergo various levels of damage, this study classified damage as minor, moderate, and severe along with the incorporation of uncertainty corresponding to each severity level. The research demonstrated the limitations of directly incorporating the previously defined single damage indices in other structural applications such as buildings and bridges for the purpose of detecting degradation in nuclear piping-equipment systems. Deep learning algorithms are used to design an ANN for the post-hazard condition assessment framework, as shown in Figure 2. A sensor placement strategy is also explored. A 99% prediction accuracy is achieved for detecting degraded locations as well as their level of severity for the multi-branched piping system from a two-loop light water reactor, as shown in Figure 1b.

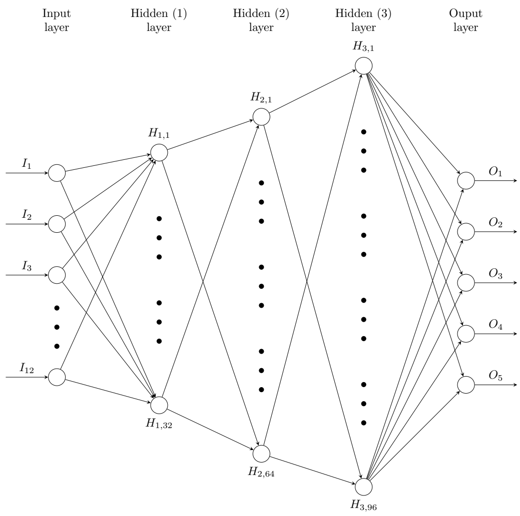


Figure 2. Deep neural network.

In addition to a post-hazardous scenario, the structural and mechanical systems of a nuclear power plant can be subject to various operational vibrations [147]. For example, the piping systems connected to pumps can undergo pump-induced vibrations. Experiencing continuous vibrations can cause additional stress on degraded locations, initiation of cyclic fatigue and cracks, and an increase in the chance of pipe rupture. Currently, a study is being conducted related to pump-induced vibrations in nuclear piping-equipment systems and the use of deep learning algorithms to detect degraded locations that may accumulate fatigue due to vibrations [59]. Furthermore, this condition assessment AI framework can be extended to include stress calculations, design code requirements for avoiding cyclic fatigue [148], and subsequent recommendations for the operator on pump operational speeds. A similar study, based on finite element simulations to collect sensor data, is able to achieve an error of only 2% [149] for detecting defects in welds of nuclear piping using deep fuzzy neural networks and finite element simulations to gather data on welding residual stresses.

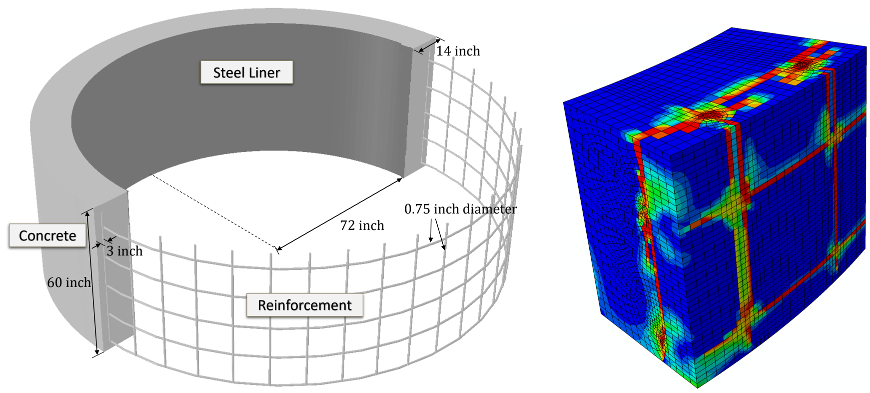
Although the aforementioned studies achieve significant success in detecting damage using simulated sensor data, the validation of the condition assessment framework and its machine learning algorithms needs to be conducted. Uncertainty due to noise, multiple degraded locations, non-uniform degradation severity, etc., are some of the factors that can affect real-time sensor data collected from an actual nuclear power plant. However, acquiring sensor data from nuclear power plants can require additional security and regulatory clearances. Therefore, there is a need for studies focusing on the experimental validation of existing AI-based condition assessment frameworks for nuclear applications. Past experimental research [57] to detect flow-accelerated corrosion in nuclear piping systems utilizes laboratory designs to construct pipe networks similar to the secondary loop of a nuclear power plant. The damage is introduced by thinning the pipe walls using chemicals over a period of 10 days. Acquired sensor data are transformed using HHT and the performance of machine learning algorithms such as SVM, CNN, and LSTM is compared. Only LSTM is able to predict non-uniform damage in the piping system with 96% accuracy.

3.3. Condition Assessment in Concrete Structures

In any nuclear plant, a substantial part of the structure is made up of concrete. The functionality of these concrete structural systems extends from serving as the building's load-bearing capacity to radiation containment and leak tightness [150]. In addition to withstanding external hazards (such as earthquakes, floods, tornadoes, impacts, etc.), concrete used in power plants must retain its strength throughout the operating lifetime of the plant. Aging in concrete due to chemical reactions such as chloride-induced degradation or Alkali-Silica Reaction (ASR) can lead to degraded systems with less than desirable resiliency. Critical infrastructures such as nuclear power plants are currently over about four to five decades old and require condition assessment techniques to detect aging-related degradation in concrete.

One study [151] highlights the need for classifying defects in nuclear concrete structures using NDT techniques. Various ML algorithms such as SVMs, Decision Trees, Logistic Regression, k-Nearest Neighbor (kNN), and Naive Bayes are compared. In addition to that, the study also proposes an integration strategy to combine the output results from various ML techniques by using statistical operations such as sums, averages, and square-root-of-sums-of-squares. The integration strategy aims to establish redundancies in the predicted outputs from various ML algorithms. It is observed that higher performance and reliability are achieved by an integration of classification prediction. Concrete used for shielding any radiation at nuclear power plants can also experience strength reduction over decades of use. A study [152] explores the use of the Least-Squares SVM machine learning algorithm to calculate the current strength of radiation shielding concrete. The results show a Root Mean Square Error (RSME) of less than 3% in predicting the overall concrete strength.

A recent study [63] aims to simulate chloride-induced damage in concrete and its detection using deep learning algorithms. Most of the advanced small modular reactor designs [153,154] assume an underground concrete containment that houses the nuclear reactor for the nuclear power plant. A soil rich in chlorides can interact with adjacent concrete structures to eventually corrode the underlying reinforcement bars and increase the internal stresses developed in the concrete. This can lead to localized and major cracking of concrete structural systems. Chloride degradation at early stages can be detected through the use of a systematic structural health monitoring (SHM) approach. This research [63] develops an integrated SHM framework for propagating various uncertainties through a multi-step chloride simulation and detecting non-uniform chloride degradation using a physics-trained AI algorithm. The uncertainties in chloride concentration and concrete properties are propagated in the simulations of chloride diffusion, reinforcement corrosion, and corrosion-induced concrete damage. Then, a novel methodology is developed by conducting a simulation-based NDT using finite element (FE) models that can represent the non-uniform degradation in a cylindrical ring concrete structure (Figure 3).



(**a**) (**b**)

Figure 3. FEM of concrete ring structure [63]. (**a**) concrete ring structure; (**b**) degradation in model.

A physics-based feature extraction method is developed to identify degraded-sensitive features. Lastly, an ANN model is created by learning from a data repository of degraded-sensitive features to predict the severity of degradation at multiple degraded zones. Degradation-sensitive features are extracted to train an ANN, as shown in Figure 4, to detect chloride-induced degradation locations and their severity with 97% accuracy.

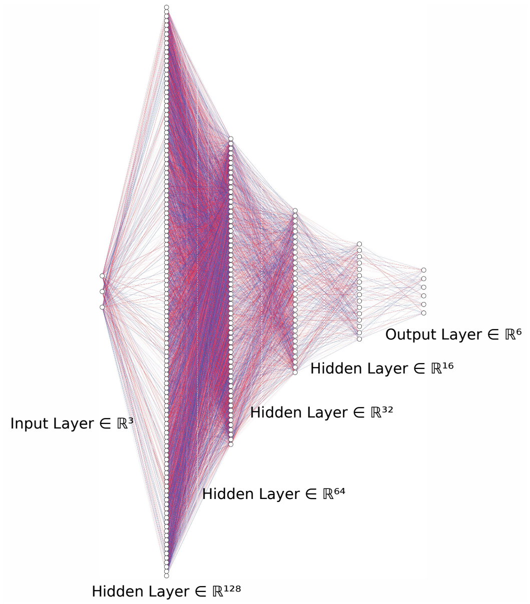


Figure 4. Improved artificial neural network model [63].

Similar to chloride-induced degradation, ASR can impact the structural resiliency of nuclear concrete systems. Over time, the alkali in concrete can react with the silica present in the aggregate to produce a gel. In the presence of moisture, this gel expands inside the concrete and leads to cracking. Such degradation of concrete structures at nuclear power plants can result in a significant reduction in their resiliency. Therefore, it is essential to monitor the effects of ASR in concrete well before any cracks are allowed to develop. The development of an efficient condition assessment framework depends on the quality of simulation models that can accurately represent the degradation in a structure. An ongoing study [62] is being conducted to simulate the ASR-induced damage in concrete structures, such that the total strain progression and the anisotropic expansion of concrete can be precisely visualized. Future steps would require collecting data from the simulated models and designing a machine-learning framework to detect ASR-induced damage with confidence.

Another study [66] evaluates ASR in concrete and its detection using deep learning algorithms. However, this study is not focused on nuclear applications of concrete structures. NDT is carried out using acoustic emission signals and their continuous wavelet transform (CWT) for feature extraction. Two deep learning algorithms (CNN and autoencoders) are compared for their prediction capabilities. It is found that the CNN is able to detect degradation with 85% accuracy, whereas the autoencoder generated results with 80% accuracy.

4. Challenges in Using AI Algorithms

While nuclear energy generates emission-free electricity, competing with renewable energy sources requires the nuclear energy sector to demonstrate reliability, sustainability, and profitability. As existing nuclear reactors request license renewals and newer advanced reactor designs enter the market, it is essential to develop systems with safe operational and predictive capabilities at low costs. Construction optimization, predictive maintenance, fault detection, and advanced control systems are some of the recently seen applications of AI in the nuclear sector. Sensor data captured from nuclear reactors and their systems along with physics-based machine-learning techniques can pave the way for digital twin technology. A sustainable future with nuclear energy can be achieved with AI-powered solutions. However, the use of AI for developing cutting-edge digital twins and condition assessment frameworks can be subjected to challenges such as data acquisition and management, requiring computational resources and incurring costs, cyber-attacks, security, etc. [155]. More research is required to ensure accountability for using data-driven machine learning algorithms and their interpretability for a robust design.

Data quality: The performance of most AI algorithms depends on the amount and quality of available training data. Current sensor data and previous data on operational anomalies from nuclear power generation facilities are not publicly available. To access such data, security clearance and prior approvals from regulatory agencies are required. Even before obtaining clearance, it is essential to demonstrate a working digital twin model with condition assessment capabilities. This necessitates the use of simulated as well as experimental data which may or may not represent the characteristics of real-time sensor data.

Data availability: The accuracy of an AI-based framework can vary significantly depending on the data available for its training and testing. Limited data can be augmented to create a larger database for training the machine learning framework, but the process for quality assurance of data augmentation techniques (such as generative adversarial networks and neural style-transfer) needs to be investigated [156–158].

Data handling: For condition assessment frameworks, the sensitivity of features selected to train artificial networks can impact the ability to detect faults and anomalies in the system. In the case of detecting damage in nuclear piping-equipment systems, a large amount of sensor data can be collected on a daily basis, making data processing and storage a challenging task. Data mining can assist in the appropriate feature extraction, pattern recognition, classification, and labeling for such large sets of data [159]. Sensor data are typically collected in the form of a time-series signal. Time Series Data Mining (TSDM) consisting of data preprocessing, fault detection, classification, and prediction can be a beneficial tool for the condition assessment frameworks [160].

Computational costs: AI algorithms, specifically in the field of deep learning, require considerable computational power in terms of the number of cores, Graphical Processing Units (GPUs), Tensor Processing Units (TPUs), etc., to perform a condition assessment of systems within stringent time periods. In recent years, High-Performance Computing (HPC) systems, cloud computing, and parallel processing have emerged as possible solutions to the computational complexity of AI applications. However, installation and maintenance of such tools can be expensive. Future research on designing machine learning algorithms for condition assessment of systems needs to focus on reducing the computational complexity of the algorithm by preprocessing the data, investigating data distribution techniques, carrying out sensitivity analysis, and calculating the total energy consumption [161–163].

Data security: The AI technology used to provide reliable and cost-effective programs for the nuclear energy sector can also be used by hackers or terrorists to breach confidential nuclear plant data. Malware can be updated continuously using AI to avoid detection by online security platforms. Data manipulation is one of the main targets of cyber attacks, where false positives can trigger erroneous actions and consequences at a nuclear power plant. Software bugs can also hamper the performance of AI in digital twins and their condition assessment frameworks. Currently, the United States Nuclear Regulatory Commission (USNRC) is seeking AI-based applications for preventing cyber attacks at nuclear power plants [164]. Some past studies outline the use of big data [165] and Bayesian networks [166,167] for cyber security measures in the nuclear energy sector, but more research can be conducted specifically towards preventing data manipulation in condition assessment frameworks. One study [168] explores the use of ANNs to detect false signals as a result of cyberattacks and alert the operators. A three-loop reactor plant simulation model is created to acquire sensor signals. The proposed ANN is able to detect anomalies in the data and predict original sensor data with less than 1.5% error. Data manipulation during a cyberattack can also be achieved by injecting augmented or noisy data into the stream of sensor signals. One study [169] considers the detection of augmented data for data manipulation as a part of accident prediction for a pressurized water reactor. The use of WaveNet machine learning architecture demonstrates robustness against any data acquired from a malfunctioning sensor such as random noise. A similar study [170] investigates data augmentation to include random noise in the acquired signals from a simulator test bed. The accuracy to detect a loss of coolant accident and a steam generator tube rupture is compared using three different machine learning algorithms such as support vector machines, decision trees, and multilayer perceptron. A recent study [171] focuses on recovering lost sensor data using convolutional neural networks. Strain monitoring sensor data are collected from a beam simulator and experimental frame structure. However, the proposed methodology requires availability of previously acquired sensor data for recovery of lost signals. Another study [172] explores the use of generative adversarial nets and autoencoders for data anomaly detection. Unsupervised machine learning algorithms and computer vision techniques are considered for learning from the images of time-series sensor data. A full-scale bridge is used to collect sensor data and conduct validation of the proposed framework.

Interpretability and physics-guided machine learning: Machine learning is now utilized in many high-stake decision applications such as health care systems, autonomous vehicles, industrial applications, etc. There is a need to avoid using machine learning as a black box for outputting answers. Most of the previous and ongoing research lacks the interpretability of machine learning models. An interpretable model or Explainable Artificial Intelligence (XAI) refers to an AI algorithm that can be interpreted by humans for robustness and causality [173–175]. The main purpose of interpretable machine learning is to make the output prediction understandable to a human, for example, an operator in the case of nuclear applications. By utilizing interpretable ML, erroneous decisions based on false predictions from AI networks can be avoided. Physics-based machine learning techniques for condition assessment can provide a better insight into this issue [176]. Physics-guided machine learning approaches, such as physics-informed neural networks (PINNs), can result in efficient learning, reduction of computational costs, more reliable predictions, and greater interpretability of the results [177]. In PINNs, another term is added to the loss function of the neural networks which represents the knowledge of physical laws from a system. This term can also function as a regularizer for the neural networks [178]. In one study [179], a random forest regressor is used for feature extraction using fusion physics, and a physics-guided neural network is designed to predict the optimal parameters for plasmas used in nuclear fusion. Some studies [180,181] investigate the power of PINNs to solve nuclear reactor equations. Optimization of nuclear fuel assemblies is also carried out by employing physics-informed reinforcement learning [182]. In this study, the physics-informed reinforcement learning algorithm outperforms the traditional stochastic optimization algorithms by increasing computational efficiency. Much of the focus in physics-informed neural networks for nuclear applications has focused on detecting emergency or accident conditions. Research is needed to advance and apply the condition assessment to structural and mechanical systems in a nuclear power plant, such that degradation can be detected at an early stage in order to avoid the initiation of an emergency or accident condition.

5. Recommendations for Future Research

Significant work is being conducted toward automating processes for the nuclear energy sector worldwide, as mentioned in the previous sections. Some of the machine learning algorithms used for nuclear applications include artificial neural networks, support vector machines, clustering algorithms, dimensionality reduction algorithms, data mining, Bayesian methods, and image digitization. However, more areas need to be explored before AI technology is validated for its application to existing as well as new nuclear power plants. Some of the recommendations for future research are:

1. The initial success of AI-based condition assessment frameworks needs to be validated against laboratory experiments or real-time data from nuclear power plants. Sensor data should be collected from mechanical systems such as piping attached to equipment, as well as structural concrete systems being tested for chemical reactions and cracks. Compared to simulated sensor data, experimental/on-site sensor data are

expected to include some variations that can affect the performance of AI algorithms. Real-time data can be noisy due to surrounding vibrations, environmental effects, or sensor malfunctions. Typically, structures and systems undergo non-uniform degradation. However, high-fidelity modeling of non-uniform degradation in finite element software is challenging. Uncertainty in various parameters, such as degradation severity and a number of simultaneously degraded locations, can also impact the quality of signals acquired from as-built systems;
2. The effects of data scarcity on the predictive capabilities of a machine-learning framework need to be studied. Techniques such as data augmentation and damage-sensitive feature extraction can be explored as possible solutions;
3. Data handling, from its acquisition, storage, and processing, is one of the biggest challenges in autonomous industrial applications. Continuous streams of acquired data from nuclear power plants have to be appropriately stored and handled. The use of cloud-based storage services, data mining technology, and effective data preprocessing needs to be demonstrated;
4. The overall objective of using automation in the nuclear energy sector is to reduce construction, operations, and maintenance costs. However, AI implementation in itself can incur high computational costs. The total energy usage of various AI algorithms and their computational costs for installation and employment need to be calculated. A comparison study would enable the nuclear industry to make informed decisions on the performance of AI-based frameworks versus the incurred expenditure;
5. For public and government safety, it is essential to conduct research on cyber-safe automation platforms. Designs that demonstrate resiliency against malware and unauthorized access data by hackers need to be developed;
6. Since the performance of condition assessment frameworks at a nuclear facility is vital to its safety, an interpretable machine learning algorithm can enhance the reliability of such condition assessment frameworks. Some simpler machine learning algorithms such as linear regression, decision trees, random forest, etc., are favorable for interpretability when compared to deep learning such as neural networks. However, the accuracy of complex algorithms such as ANNs, CNNs, and RNNs can outperform other interpretable models. The balance between the explainability and accuracy of various AI algorithms should be examined for future applications in the nuclear industry, including the use of physics-guided machine learning;
7. The use of computer vision for new nuclear construction needs to be investigated during the construction phase to create "as-built" digital twins which would enable significant advances in condition assessment. It can also enhance worker safety, asset management, and reduce maintenance costs.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
ASR	Alkali–Silica Reaction
CNN	Convolutional Neural Network
CPS	Cyber-Physical Systems
CWT	Continuous Wavelet Transform
DBN	Dynamic Bayesian Networks
DL	Deep Learning
DT	Digital Twin
FEM	Finite Element Model
FFT	Fast-Fourier Transform
FRF	Frequency Response Functions
XAI	Explainable Artificial Intelligence
GA	Genetic Algorithms
GE	General Electric
GEMINA	Generating Electricity Managed by Intelligent Nuclear Assets
GPS	Global Positioning System
GPU	Graphical Processing Units
HHT	Hilbert–Huang Transform
HPC	High-Performance Computing
IAEA	International Atomic Energy Agency
IoT	Internet of Things
kNN	k-Nearest Neighbor
LOCA	Loss of Coolant Action
LSTM	Long-Short-Term-Memory
MAGNET	Microreactor Agile Non-Nuclear Experimental Testbed
MARS	Maintenance of Advanced Reactor Sensors and Components
MDPI	Multidisciplinary Digital Publishing Institute
MEITNER	Modeling-Enhanced Innovations Trailblazing Nuclear Energy Reinvigoration
ML	Machine Learning
NAMAC	Development of a Nearly Autonomous Management and Control System
NASA	National Aeronautics and Space Administration
NDT	Non-Destructive Testing
NEUP	Nuclear Energy University Program
NN	Neural Networks
O&M	Operation and Maintenance
PCA	Principal Component Analysis
PINN	Physics-Informed Neural NetworkS
PRA	Probabilistic Risk Assessment
PSD	Power Spectral Density
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SHM	Structural Health Monitoring
SSCs	Structures, Systems, and Components
STFT	Short-Time Fourier Transform
SVM	Support Vector Machines
TPU	Tensor Processing Units
TSDM	Time Series Data Mining
US-DOE	United States Department of Energy
US-NRC	United States-Nuclear Regulatory Commission
WT	Wavelet Transform
2D	Two-Dimensional

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