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FEATURE EXTRACTION FOR UNCERTAINTY QUANTIFICATION AND REDUCTION OF NOISE IN CONDITION MONITORING USING DEEP LEARNING

Harleen K. Sandhu[1], **Saran S. Bodda**[2], **Serena Sauers**[2], **and Abhinav Gupta**[2]

[1]Department of CCEE, North Carolina State University
Raleigh, NC 27695, USA
e-mail: hksandhu@ncsu.edu

[2] Department of CCEE, North Carolina State University
Raleigh, NC 27695, USA
e-mail: {ssbodda,slsauers,agupta1}@ncsu.edu

Abstract. *The condition monitoring of structural and mechanical systems in an industrial facility is an important component of digital maintenance platforms. In a nuclear power plant, the structures, systems, and components are continuously monitored as a part of current maintenance procedures. Real-time sensor data collected from systems such as piping-equipment is fed into online condition monitoring programs. Deep learning algorithms such as neural networks can be used as powerful data-based engines to predict damage or aging in piping-equipment systems of nuclear power plants. Factors such as the quality and quantity of data available for training the deep learning algorithm can affect the performance of the condition monitoring framework. Typically, the computational efficiency of deep learning approaches is enhanced by utilizing signal processing and feature extraction techniques on data obtained from sensors installed on the system. This paper presentes a novel feature extraction methodology to quantify uncertainty in the acquired sensor data for the condition monitoring of nuclear piping-equipment systems. Uncertainty in the severity of degradation is classified as minor, moderate, and severe. Signal processing and feature extraction are implemented to calculate a vector of degradation-sensitive elements of interest and reduce the effect of noise in the data. Artificial neural networks are designed and trained using the extracted vector from the sensor response. The condition monitoring framework is tested on various nuclear piping-equipment configurations as well as load combinations.*

Keywords: Feature Extraction, Uncertainty Quantification, Condition Monitoring, Deep Learning, Nuclear Piping, Validation

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1 INTRODUCTION

As per the International Energy Agency, low-carbon electricity generation is important for achieving Net Zero Emissions by 2050 scenario. Nuclear energy is one of the clean energy solutions to meet the high demand for electricity. The energy sector and its industries, such as oil, gas, coal, and nuclear power plants, are undergoing digitization with the rise of Artificial Intelligence (AI) and Big Data. The benefits of using AI span from operational cost reduction and increase in production efficiency to safeguarding life and property. In a nuclear power plant, asset management and predictive maintenance of critical infrastructure can be conducted with deep learning (DL) algorithms [1, 2]. Processing of sensor data collected from nuclear power plants and appropriate feature extraction techniques can enable predictive maintenance of structures, systems, and components (SSCs). As part of the predictive maintenance, detection of progressive degradation must be conducted using condition monitoring frameworks to ensure safe operations.

The use of AI technologies such as Artificial Neural Networks (ANNs) can prove to be beneficial to emerging condition monitoring frameworks. The accuracy of an AI-based framework can vary significantly depending on the quality of data available for its training and testing. For condition monitoring frameworks, the sensitivity of features selected to train artificial networks can impact the ability to detect faults and anomalies in the system. dditionally, uncertainty in various parameters such as the severity of degradation and effects of ambient noise can reduce the predictive capability of an AI algorithm. This paper focuses on developing a condition monitoring framework for nuclear piping-equipment systems including the quantification of uncertainty, construction of a feature extraction technique, and design of ANNs to detect degradation such as flow-accelerated erosion and corrosion in the system.

Nuclear piping-equipment systems can experience degradation due to flow accelerated corrosion and erosion of the system. These phenomena cause thinning of the pipe walls, which results in a reduction of the system's structural strength and stiffness [3]. Degradation can be captured and characterized as a reduction in thickness of pipe-walls in the piping-equipment systems. Following a major external event, such as an earthquake, the emergency management of an NPP would require a thorough understanding of the degraded state of the SSCs. This necessitates a quick analysis of the acquired sensor data or even physical in-person inspection of the systems. In addition to a post-hazard scenario, nuclear equipment-piping systems can be subject to operational vibration loads (caused by mechanical equipment, fluid flow, pumps, water hammer phenomenon, etc.) and due to thermal cycles [4]. Degradation in the piping system can cause fatigue build-up and lead to sudden cracking and leakages.

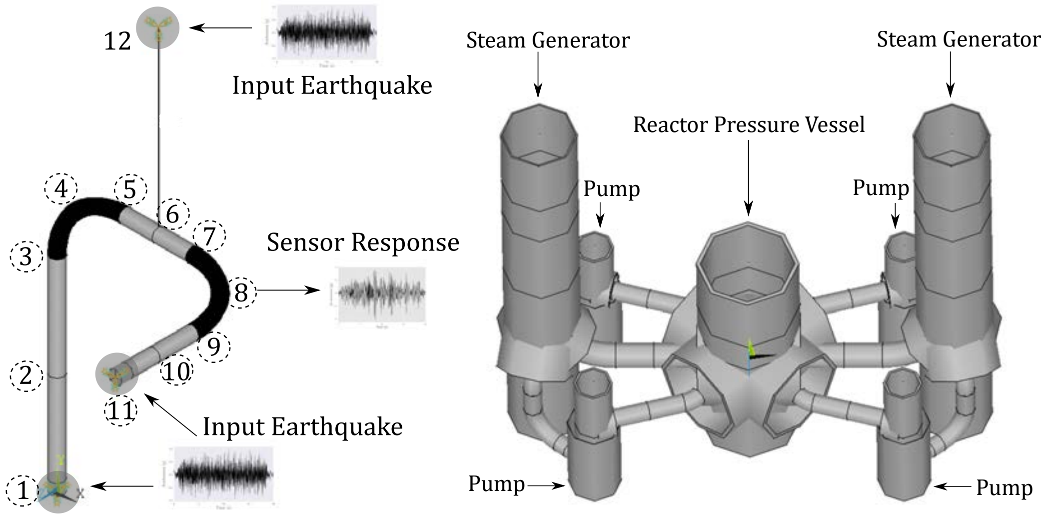
In current practice, NPPs use Non-Destructive Testing (NDT) for the lifecycle management of SSCs, and to detect any damages during routine maintenance procedures. Various NDT techniques are employed such as the use of ultrasonic waves, infrared waves, chemicals, etc. To detect degradation due to corrosion and erosion, the piping-equipment systems need to be scanned in their entirety by conventional NDT techniques which is time and cost-intensive. Despite the use of NDT techniques, multiple failures have occurred in the past due to undetected degradation locations in nuclear safety systems [3]. Therefore, it is quite critical to identify and retrofit such degraded locations in advance of a major crack and potential leakage scenario. An AI-powered condition monitoring framework can be beneficial for predicting degraded locations and their severity in nuclear piping-equipment systems, lowering maintenance costs, as well as extending the operating life of a nuclear power plant. In nuclear power plants, typically sensors are installed at various locations to continuously measure system response in the form of time-series signals. Condition monitoring 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.

In this study, a unique feature extraction technique is proposed for uncertainty quantification and reduction of noise as a part of a data-driven condition monitoring methodology. Signal processing is carried out to explore the use of power spectral density (PSD) as vibrational health-monitoring diagnostic quantities of interest. Uncertainty in the location and severity of degradation is considered by defining three classifications: minor, moderate, and severe. A novel vector of degradation-sensitive quantities is extracted from acquired sensor data. While ANNs are a useful tool for condition monitoring applications, a key step in using them lies in designing the architecture and determining key parameters that are most suitable for a particular application. A simple piping system is used to design the deep ANN architecture and characterize its key parameters for optimal performance. Then, the proposed design is tested by application to more complex and realistic nuclear piping-equipment systems. The proposed methodology can predict not only degraded locations but also identify the severity level. A condition assessment system with predictive capabilities can assist the nuclear power plant operators to stay well informed of the health of the systems, as well as make appropriate decisions to avoid future accidents.

2 APPLICATION SYSTEMS DESCRIPTION

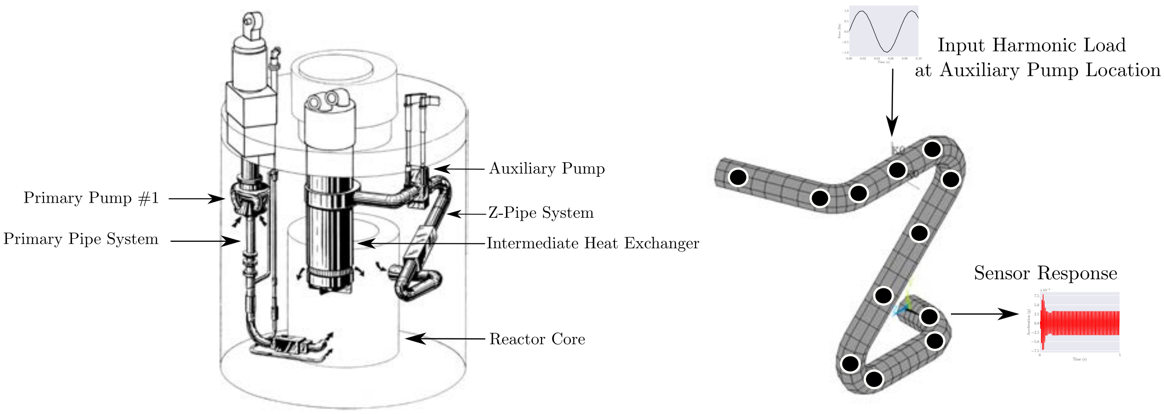
For developing the condition monitoring methodology, the first case study consists of a three-dimensional piping-equipment system with three straight-pipe elements, two bend-pipe elbow elements contained between two fixed anchors and a hanger support as shown in Figure 1a [5]. The system's vibration response is collected during an earthquake in order to create a sensor data repository. The acceleration-time-series sensor response is obtained by conducting high fidelity FE simulations against a collection of 100 real and synthetic earthquake input records [6, 7, 8]. A time-dependent earthquake time history analysis is conducted for each record with a damping ratio of 5% for the piping system. The sensor response at each of the nine nodes in the FE model is captured in the three orthogonal X, Y, and Z directions. For real structures, this can be achieved by installing triaxial accelerometers at sensor locations. Obtaining sensor data from all three directions also helps in generating a sufficient data repository for the ANN model.

In addition to the above, two realistic nuclear piping-equipment systems are selected to illustrate the effectiveness of the proposed condition assessment framework. A three-dimensional multi-branched piping-equipment system subjected to a post-hazard scenario (earthquake) is considered [9]. This configuration is representative of the primary systems of a two-loop reactor plant, consisting of a reactor vessel in the center, two steam generators on the sides of the reactor vessel, four primary pumps in the four quadrants around the center and interconnected piping systems, as shown in Figure 1b [10]. For demonstrating the condition monitoring of a nuclear piping system subjected to operational vibrating loads caused by pump operations, a coolant system called 'Z-pipe' system from EBRII [11, 12, 13, 14] is selected as shown in Figure 2a. The Z-pipe system is used to carry hot sodium from the reactor core subassemblies into the intermediate heat exchanger (IHX). It contains the auxiliary electromagnetic pump and is subjected to pump operational loads due to pump-induced vibrations. Twelve sensors are assumed to be placed at discontinuities in the systems such as elbows and nozzles, as well as long straight sections of pipe, as illustrated in Figure 1b.



(a) Simple Piping System (b) Primary system of a two-loop reactor plant

Figure 1: Nuclear piping-equipment systems subjected to a post-hazard scenario



(a) EBRII Primary Tank Layout [13] (b) Z-pipe system

Figure 2: EBRII and Z pipe system subjected to pump-induced vibrations

3 DESIGN OF CONDITION MONITORING FRAMEWORK

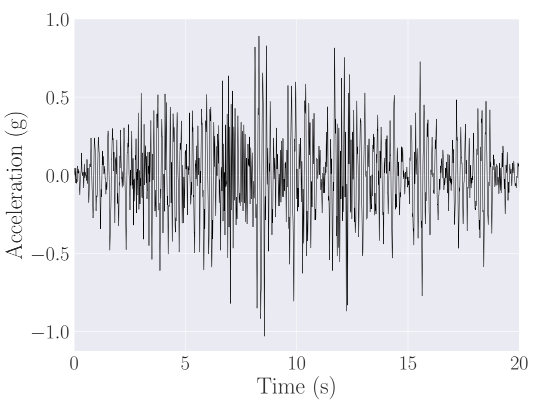
3.1 Uncertainty Quantification

Nuclear facilities consist of distributed piping-equipment systems that flow from one vessel to another, such as the pressure vessel, reactor vessel, steam generator, pumps, etc [15]. The attachments to these large vessels are modeled as anchors. Piping systems are also supported at intermediate locations using snubbers or hanger supports. Typically, the degradation due to erosion and corrosion occurs at discontinuities in the system such as the elbows, T-joints, nozzles, etc. [16, 17, 18, 19, 20, 21, 22]. A finite element model can incorporate degradation at such discontinuity locations in the piping system by considering a loss of thickness or Young's modulus which in effect translates into a reduction in stiffness. In this study, degradation is quantified by a reduction in the thickness of the pipe walls. Uncertainty in the location of degradation is quantified by incorporating degradation at one of the following locations of the simple-piping system: Nozzle node 1, and Elbow nodes 3,5,7,9.

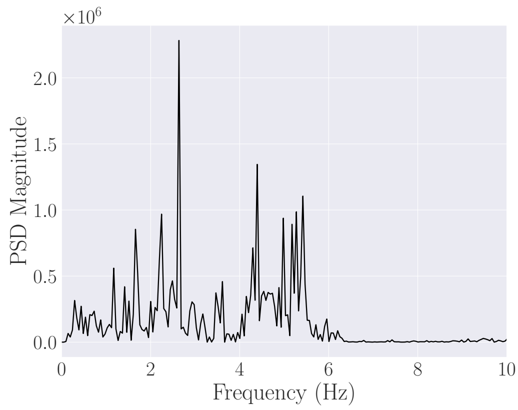
The severity of degradation is classified as minor, moderate, and severe corresponding to the amount of reduction in pipe-wall thickness at each location in the piping-equipment system. Detection of minor degradation is relatively more sensitive to uncertainty in the degree of degradation. Typically, the severity of degradation varies between multiple locations of the piping system. While some locations can experience minor degradation, others can exhibit effects of major degradation. Furthermore, considerable uncertainty exists in each level of degradation since the percentage of reduction in pipe-wall thickness for any level, such as minor degradation, would vary significantly amongst different locations. Therefore, a single distinct number for the percentage of degradation at a location should not be assigned for the severity classifications. The methodology proposed here quantifies this uncertainty by considering a lower bound and an upper bound of percentage pipe-wall thinning. The three levels of degradation can therefore be characterized as $[20\%,\ 30\%]$ for minor, $[45\%,\ 55\%]$ for moderate, and $[70\%,\ 80\%]$ for severe degradation. Then, Latin hypercube simulation (LHS) is used to generate random severity values for each degradation classification and these values are employed in the finite element model of the simple-piping system to collect a sensor response training database for the ANN [23, 24, 25, 26, 27, 28].

3.2 Feature Extraction

The time-series response (sensor data) collected from the piping system is processed to extract degradation-sensitive features. The change in the structural stiffness of the system due to pipe-wall thinning results in a change in the dynamic characteristics of the system. The change in the dynamic characteristics is reflected in the acquired acceleration-time-series response. In this study, the power spectral density (PSD) is explored as a potentially robust diagnostic quantity. The acquired sensor response is converted from the time domain (a typical acceleration-time-series) to the frequency domain (corresponding PSD) as shown in Figure 3. The PSD can be defined as the energy (or power) contained in a time-series response and can be used to calculate degradation-sensitive quantities such as the mean frequency, spectral moments, and ratio between the peak values of the frequency-domain spectrum. Some studies [29, 30] also define damage indices based on these values.



(a) Acceleration-Time Series



(b) Power Spectral Density

Figure 3: Signal Processing

In this study, for a preliminary investigation, the maximum PSD (PSD_{max}) value is extracted from each sensor's response as the degradation-sensitive feature for training the ANN. An initial design of an ANN is considered with one hidden layer. Additionally, one damage index developed in a previous study [30] by extracting information from the PSD of the signal is also used as a training feature for the initial ANN representation. A total of $4,500$ simulations are conducted on the simple-piping system. Approximately 70% of the simulations are used for training and 30% are used for testing the neural network's prediction capabilities. A prediction accuracy of 45% is obtained by using PSD_{max} as a degradation-sensitive feature and 67% by using the pre-defined damage index [30]. This illustrates that the initial implementation of ANN is not learning sufficient information from the extracted features. While single damage indices have performed well for buildings, bridges, and utility pipeline networks, they fail to capture minor damage-sensitive information in the case of nuclear piping-equipment systems. Enhancement of the proposed framework is required for efficient feature extraction and design of ANN specific to the application of nuclear piping-equipment systems.

After careful analysis of the PSD response, it is observed that the maximum PSD value extracted from the degraded system's sensor response is almost equal to the corresponding value obtained from the non-degraded piping system configuration Figure 4. Therefore, to define a powerful degradation-sensitive feature, the maximum change in the PSD sensor response between the non-degraded system and the degraded system must be extracted.

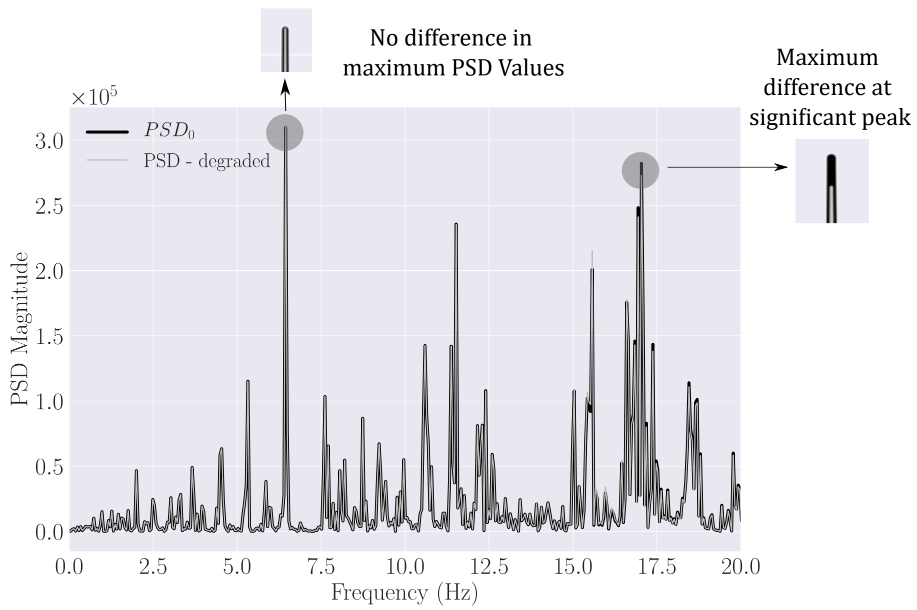


Figure 4: PSD Pattern Recognition and Feature Extraction

The approach proposed in this study collects PSD values at certain significant peaks (within 20% of the maximum PSD value), calculates the corresponding differences between the degraded and the non-degraded response, and extracts the maximum difference ($\Delta_{max}PSD$) as the degradation-sensitive feature using Equation 1 and Equation 2. The consideration of only top 20% of sensor response also helps eliminate the uncertainty due to ambient vibrations. These ambient vibrations can cause noise in the acquired sensor response and are usually reflected in the lower peaks of the PSD. The elimination of such noise and its uncertainty is carried out by excluding the lower 80% of the PSD signal.

$$\Delta_{peak_i} PSD = \frac{(PSD_{peak_i} - PSD_{0,peak_i})}{PSD_{0,peak_i}} \times 100\% \tag{1}$$

$$\Delta_{max} PSD = absmax(\Delta_{peak_i} PSD) \tag{2}$$

where PSD_{peak_i} is the PSD value of i^{th} peak selected from the degraded sensor response, and $PSD_{peak_{i,0}}$ is the corresponding PSD value of i^{th} peak selected from the non-degraded sensor response.

In addition, the corresponding frequency (ω_Δ) at which the maximum PSD difference occurs and the corresponding PSD value from the non-degraded response ($PSD_{0,\Delta}$) are also extracted. Instead of extracting only one degradation-sensitive feature (the maximum PSD value), a novel methodology is proposed by incorporating four degradation-sensitive quantities of interest (QoIs), as shown in Table 1. The richness of collected data is enhanced by extracting the frequency corresponding to the maximum difference in PSD response. This also ensures uniqueness between the data captured from various degraded locations where a similar $\Delta_{max} PSD$ may be observed at different frequencies. With the new approach, four quantities of interest per sensor response are fed into the ANN model.

QoIs	Definition	Sample Values
PSD_{max}	Max PSD from degraded response	$3.1E+05$
$\Delta_{max} PSD$	Max difference at significant PSD peaks	3%
ω_Δ	Frequency corresponding to ΔPSD_{max}	17 Hz
$PSD_{0,\Delta}$	non-degraded PSD corresponding to ΔPSD_{max}	$2.8E+05$

Table 1: Feature Extraction with Four Quantities of Interest

3.3 Deep Learning Network

Machine-learning techniques have been employed for structural health monitoring applications in building and bridges [31, 32, 33]. This paper explores deep learning techniques for the condition monitoring of nuclear piping-equipment systems. Artificial neural networks (ANNs) are built to replicate the human brain, with multiple neurons connected to each other like a web. Implementation of an ANN requires a careful characterization of its architecture and key parameters such as learning rate, batch size, number of epochs, activation functions for each layer, dropout, number of layers and neurons in each layer, etc. The architecture and capability of the network change with the number of neurons in each layer and the number of constructed hidden layers. For deep learning purposes, the single layer neural network can be expanded by adding additional hidden layers which allows for a higher level of accuracy in prediction. Once the ANN architecture and parameters are designed, the input features are fed into the ANN.

In this study, a multilayer perceptron (MLP) ANN is developed for detecting the degradation in piping-equipment system. The performance of the proposed framework to the architecture of the ANN and the parameters used for its design are investigated to design a robust network, as shown below:

1. ***Optimizer*:** Stochastic Gradient Descent (SGD), Adaptive Moment (Adam), Root Mean Square Propagation (RMSProp) and Adaptive Gradient (AdaGrad).

2. ***Learning rate*****:** 0.001, 0.005, 0.01 and 0.1.
3. ***Batch size*****:** 8, 16, 32 and 64.
4. ***Dropout*****:** Various dropout values of $0.1, 0.3, 0.5, 0.9$ are tested to avoid overfitting with lower dropout values and loss of training data with higher dropouts.
5. ***Activation function*****:** ReLU, sigmoid, hyperbolic tangent, softmax and PReLU.
6. ***Number of hidden layers*****:** 1, 2, 3 and 4 with varying number of neurons per layer.
7. ***Epochs*****:** An epoch is defined as a forward and backward pass when training an ANN. 2000 epochs are specified in the algorithm, along with early stopping criteria to avoid overfitting the data. The models are trained over 2000 epochs for all the possible hyper-parameter combinations to obtain the best validation accuracy.

Computationally, all the ANN designs took the same amount of time and resources for training and testing. It is observed that the ANN with 3 hidden layers gives the best validation accuracy of 97% with batch size of 16, a learning rate of 0.001, and a dropout of 0.5. After finalizing the architecture of the proposed ANN as shown in Figure 5, data is extracted from the simple-piping system for testing the accuracy with which the model can predict degraded locations. A testing accuracy of 97% is achieved with the framework proposed in this study.

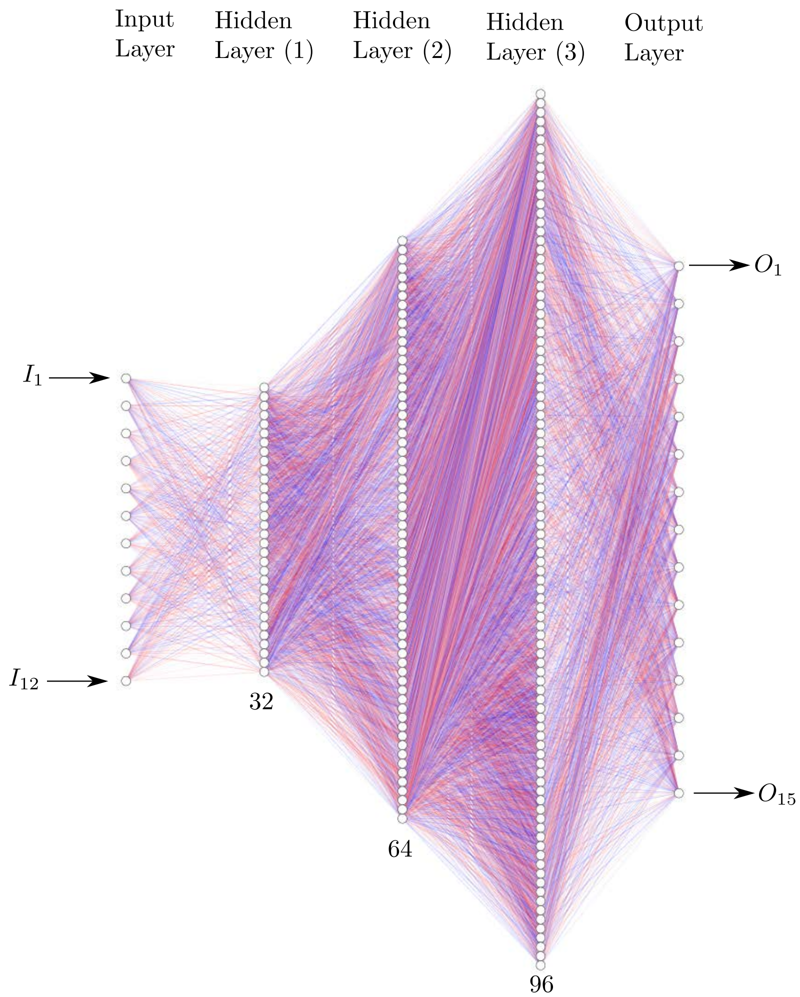


Figure 5: MLP ANN Design

4 RESULTS

Current non-destructive testing (NDT) practices in nuclear equipment and piping models only include detection of degraded locations. However, knowledge of the severity in degradation can be extremely helpful to detect and identify degradation as minor versus moderate or major. Therefore, the proposed approach is extended to incorporate this objective of uncertainty quantification. Furthermore, optimal sensor placement is necessary to reduce computational costs while maintaining a certain level of accuracy. According to standard industry practices, sensors are placed at the elbows and T-joints of piping systems. Some sensors are also placed on long spans of straight piping elements. Reduced sensors are considered to study the effects of the aforementioned sensor placement strategy.

The results obtained from implementing the condition monitoring methodology to all application piping-equipment systems using the enhanced ANN are shown in Table 2. It is observed that the proposed ANN can detect degraded locations as well as degradation severity with 97% prediction accuracy for the simple-piping system subjected to an earthquake. Even with reduced sensor placements, the artificial neural network is able to predict degraded locations satisfactorily at 96% accuracy. An optimal number of sensors can reduce the computational and economic costs of installing numerous sensors whilst maintaining the integrity of the condition monitoring framework. For the primary system of a two-loop reactor plant, using a single degradation-sensitive quantity of interest delivered a low accuracy of 14% for predicting degraded locations. However, the accuracy of predictions increased to 99% for degraded locations and 99% for degraded locations as well as degradation severity levels if a vector of four degradation-sensitive quantities is extracted from the sensor response. Next, the proposed condition monitoring methodology is implemented on the Z-pipe system and an accuracy of 97% is achieved to detect degraded locations and their severity levels. These prediction results illustrate the effectiveness of the proposed framework in monitoring degradation locations in nuclear piping-equipment systems.

Case Study	**Training Features** (*QoI: Quantity of interest)	**Predict Locations**	**Predict Locations and Severity**
Simple-Piping	1 QoI: PSD_{max}	60%	-
	Damage Index [30]	76%	-
	Vector: 4 QoIs, 9 sensors	97%	97%
	Vector: 4 QoIs, 4 sensors	96%	96%
Primary system of a two-loop reactor plant	1 QoI: PSD_{max}	14%	5%
	Vector: 4 QoIs	99%	99%
Z-pipe system from EBRII	1 QoI: PSD_{max}	86%	74%
	Vector: 4 QoIs, 12 sensors	99%	97%
	Vector: 4 QoIs, 8 sensors	98%	97%

Table 2: Application of Condition Monitoring Framework

5 CONCLUSIONS

The nuclear industry is exploring applications of Artificial Intelligence (AI), including autonomous control and management of reactors and components. A condition monitoring framework, that utilizes AI and sensor data, is an important part of such an autonomous control system. The current industry standards for conducting maintenance of vital SSCs can be time and cost-intensive. AI can play a greater role in condition monitoring to recognize degradation (such as flow-accelerated erosion and corrosion in nuclear piping-equipment) before cracks develop. Data quality, affected by uncertainty quantification and the presence of noise, is a challenging aspect of AI applications. This paper proposes a feature extraction technique for data-driven condition monitoring of nuclear piping-equipment systems. Uncertainty in the severity of degradation and its location is incorporated in the framework. The presence of noise in the data is eliminated by proposing a unique vector of degradation-sensitive features. A simple-piping system is used to design the framework, and its applicability is tested on realistic piping-equipment configurations with different loading conditions, such as earthquake loads and operational vibration loads. The key conclusions of this study are:

- Uncertainty quantification is carried out by considering various levels of degradation severity as minor, moderate and severe. These levels represent the percentage of pipe-wall thickness reduction due to erosion and corrosion. Potential degraded locations are also varied including numerous elbows and nozzles in the system.

- Feature extraction is investigated and a novel technique is proposed to reduce ambient noise and enhance the quality of data available for training the AI algorithm. Changes in the PSD response are observed and a vector containing four quantities of degradation-sensitive features with substantial information about the degraded state of the piping system is extracted.

- A deep learning algorithm using an MLP ANN is designed specifically for the application of nuclear piping-equipment systems, including its architecture and parameters.

- The proposed condition monitoring framework is able to detect degraded locations along with the severity of degradation as minor, moderate, or severe, with 97% accuracy for the simple-piping system subjected to a post-hazard scenario.

- The effects of sensor placement are illustrated by reducing the number of available sensors. The proposed feature extraction technique with a vector of degradation-sensitive quantities enriches the quality of information in the training data. Therefore, even with reduced sensor placements, the artificial neural network is able to predict degraded locations satisfactorily.

- To check the efficacy of the proposed feature extraction technique and AI development, it is applied to a reactor coolant loop piping-equipment system, and a 99% accuracy is achieved in detecting degradation locations and the corresponding severity levels.

- The Z-pipe system from EBRII is also considered by subjecting it to pump-induced normal operational loads and a 97% accuracy is achieved in this case.

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